

# Spatial Analysis of Regional Climate Experiments: Functional ANOVA and Heat Stress

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# Outline

- Comparing winter precipitation.
  - NARCCAP NCEP-driven runs.
  - Single-factor functional analysis of variance.
- A preliminary study of heat stress.
  - NARCCAP GFDL-driven timeslice/regional climate model.
  - Two-factor functional analysis of variance.

# NARCCAP

- North American Regional Climate Change Assessment Program ([www.narccap.ucar.edu](http://www.narccap.ucar.edu))
  - NCAR, ISU, CCCma, OURANOS, LLNL, GFDL, Hadley, Scripps, PNNL, USSC, etc.
  - NSF, NOAA, DOE, EPA
- *Systematically investigate the uncertainties in regional scale projections of future climate* and produce high resolution climate change projections using multiple RCM and multiple GCM simulations.
- 4 GCMs provide boundary conditions for 6 RCMs
  - balanced half-fraction

# NCEP Experiment

- Six regional models
  - **CRCM** (OURANOS/UQAM), **ECPC** (UC San Diego/Scripps), **HRM3** (Hadley Centre), **MM5I** (Iowa State U.), **RCM3** (UC Santa Cruz), **WRFP** (PNNL)
- Boundary conditions supplied by NCEP Reanalysis II.
- 1981 – 2000 (20 years)
- Average daily precipitation (mm) – winter (DJF)
- Interpolated to a common grid:  $120 \times 98 = 11,760$  grid boxes

CRCM

ECPC

HRM3

MM5I

RCM3

WRFP

Yr 1

Yr 2

Yr 3

⋮

⋮

⋮

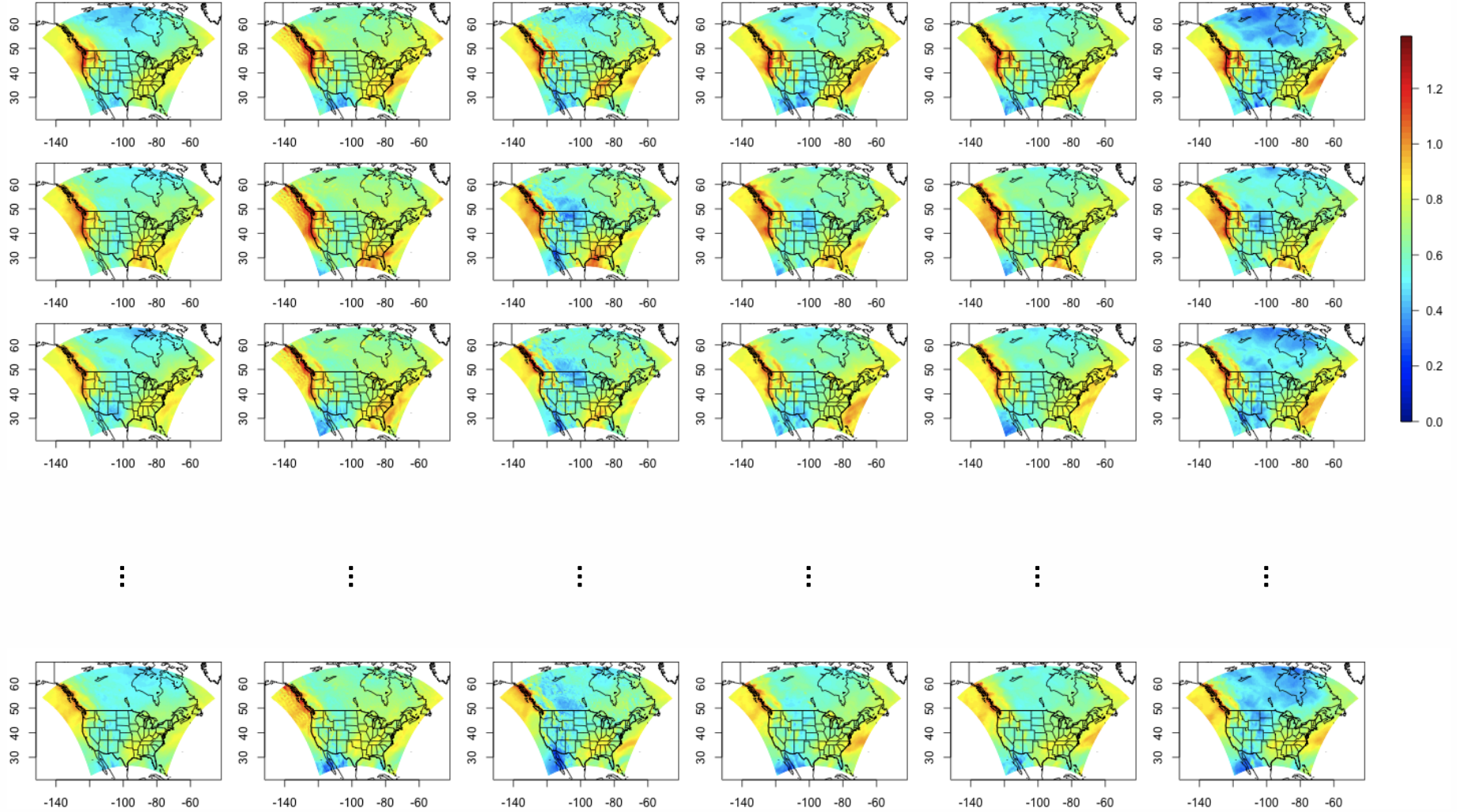
⋮

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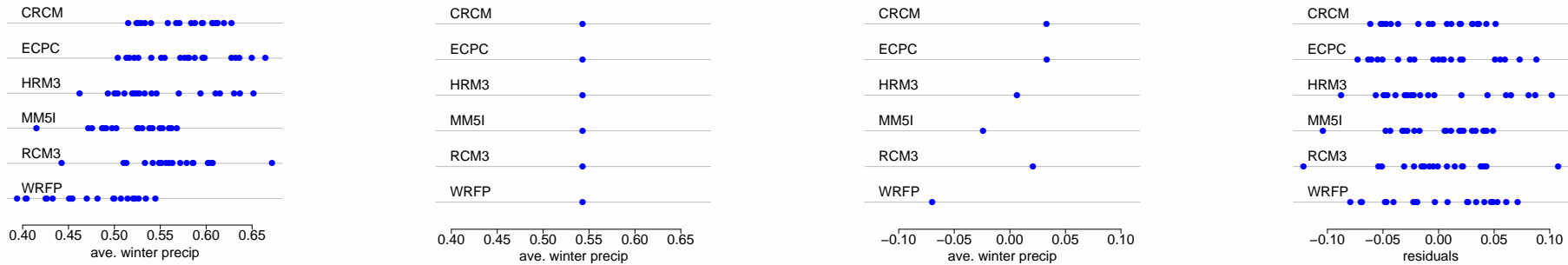
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Yr 20



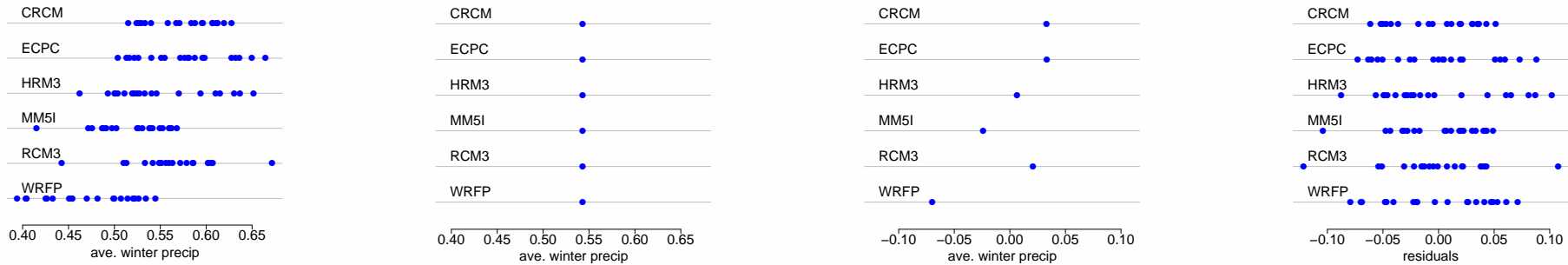
# Analysis of Variance



$$Y_{ij} = \mu + \alpha_i + \epsilon_{ij}$$

- For every grid box (this grid-box is in eastern Nebraska):
  - $Y_{ij}$  is the response (transformed precipitation) for the  $i$ th model and the  $j$ th year.
  - $\mu$  is a common mean
  - $\alpha_i$  is a RCM-specific effect
  - $\epsilon_{ij}$  is the error or residual

# Analysis of Variance



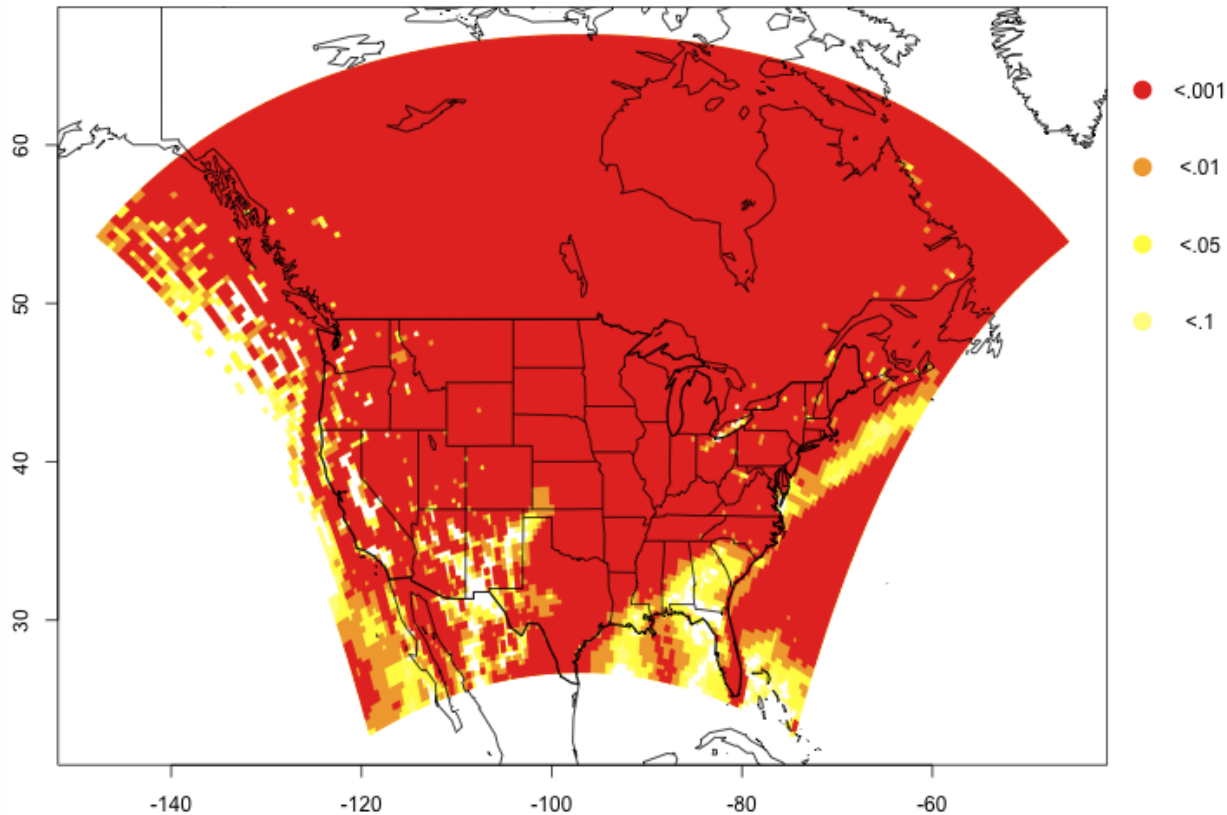
$$Y_{ij} = \mu + \alpha_i + \epsilon_{ij}$$

- Testing the null hypothesis  $H_0 : \alpha_1 = \dots = \alpha_6 = 0$ :

	df	SS	MS	F	p-value	
RCM	5	0.163	0.0326	15.3	1.75e-11	***
Residual	114	0.243	0.00213			

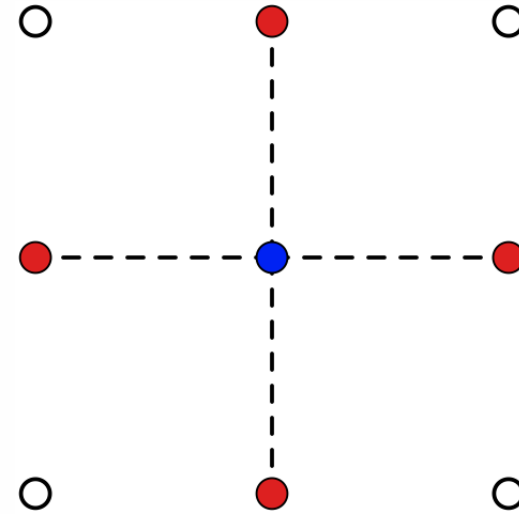
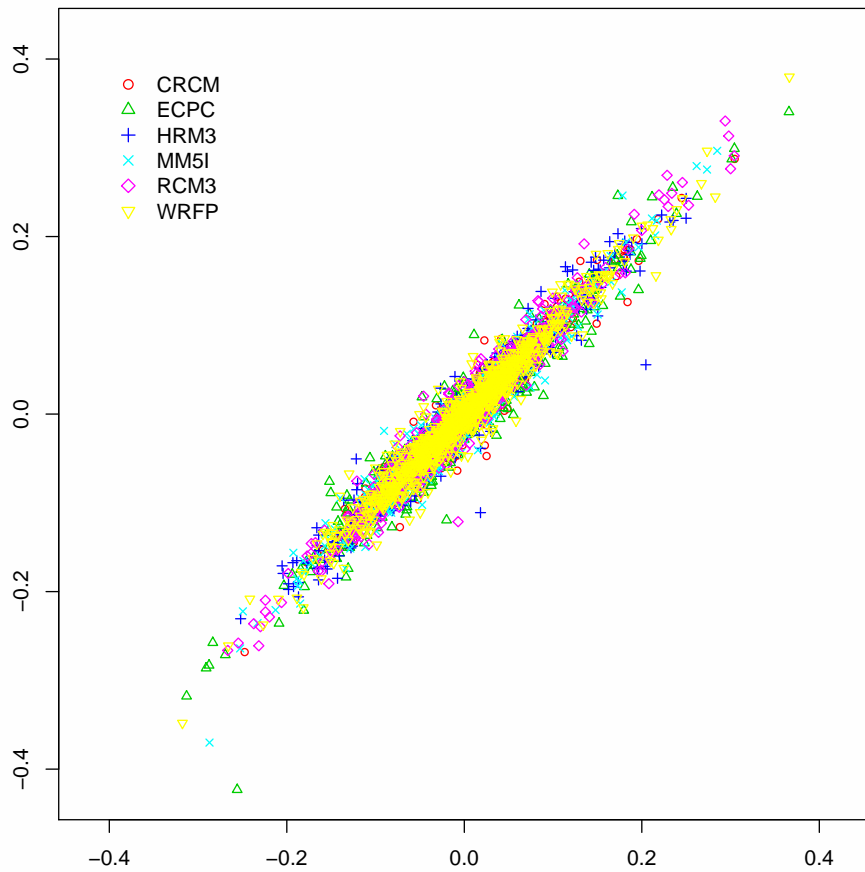
- Conclusion: strong evidence of differences in the RCM means.

# Analysis of Variance



Map of pointwise p-values: strong evidence of differences in RCM means over nearly every grid box in the domain ???

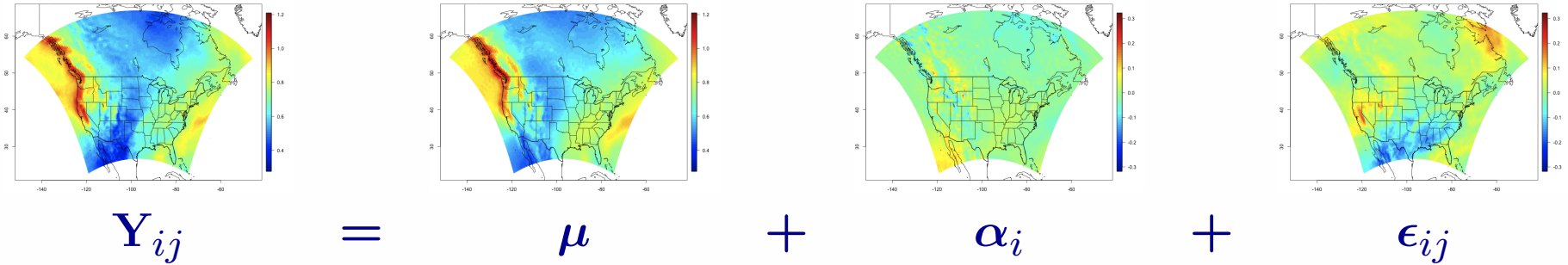




- Problem: correlated residuals at neighboring grid-boxes.

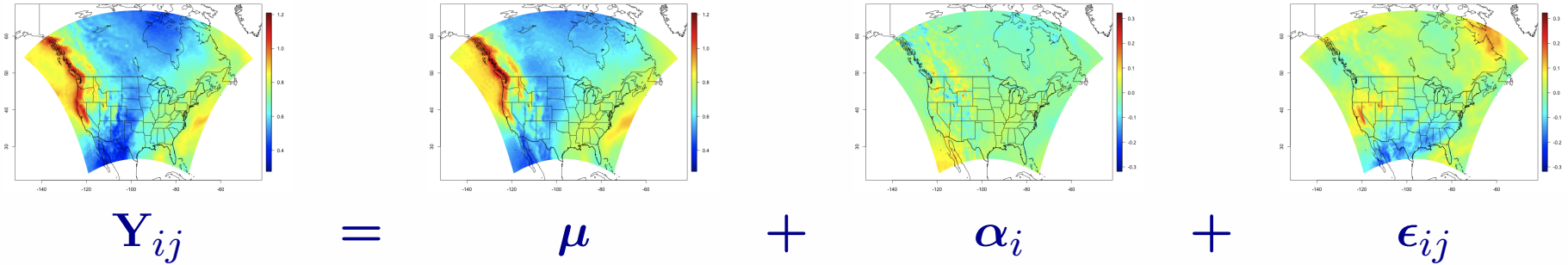
- ★ Result: invalid inference – any conclusions based on the p-value map are suspect.

# Functional Analysis of Variance

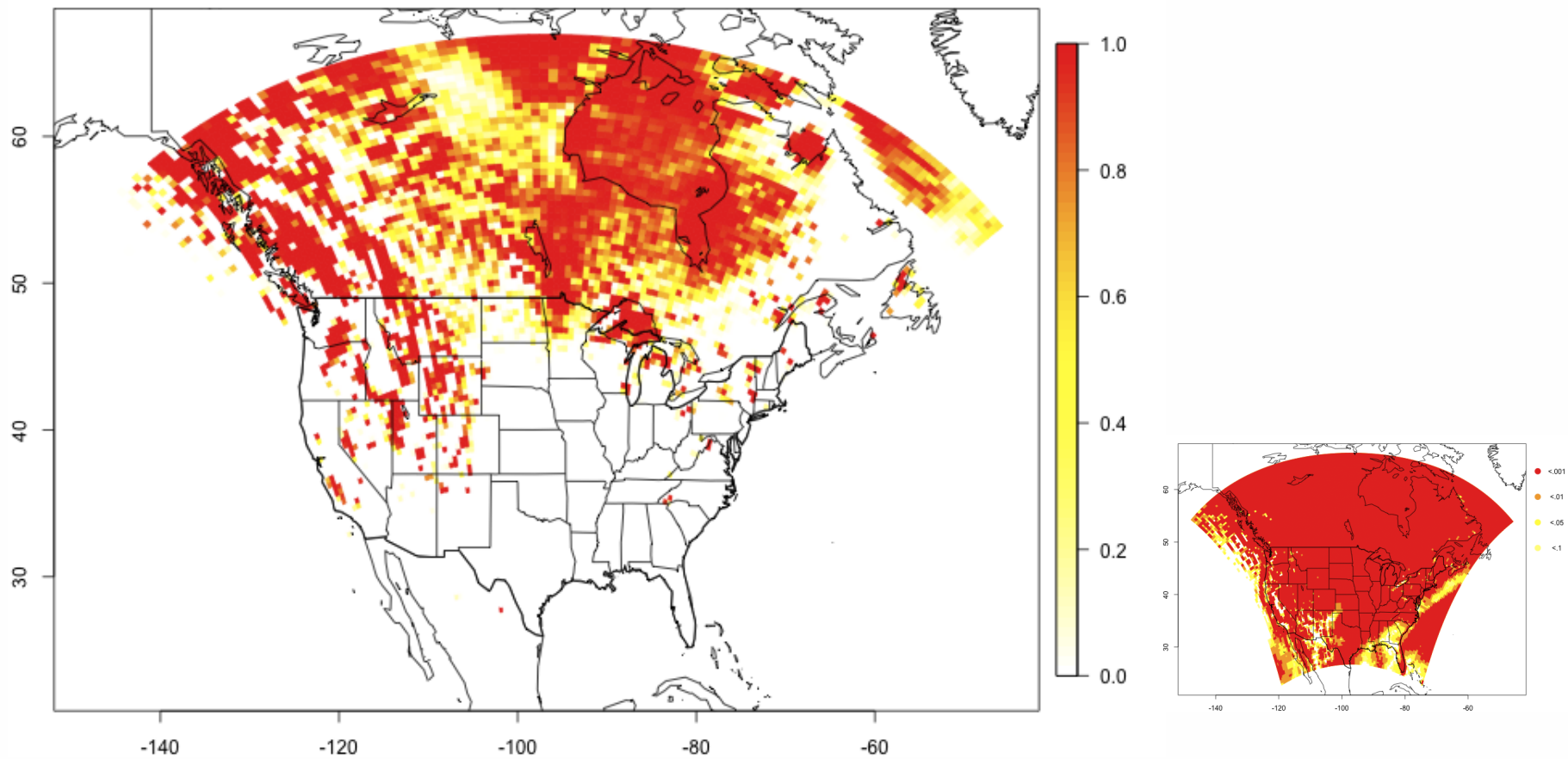


- The goal is to partition the variation into specific effects:
  - $Y_{ij}$  is the vector response (transformed precipitation) for the  $i$ th model and  $j$ th year.
  - $\mu$  is the vector mean common to all RCMs
  - $\alpha_i$  is the vector RCM-specific effect
  - $\epsilon_{ij}$  is the vector residual.

# Functional Analysis of Variance



- The innovation is that each of these effects is a *surface*.
- Each effect is considered a realization from a random process.
- Gaussian fields are often used as prior distributions; inferences about the effects involve conditioning on the observed output fields.
- Kaufman and Sain (2009, submitted).



$$\hat{P}[s_{\alpha}^2 > s_{\epsilon}^2]$$

Pointwise probabilities that the model-to-model variation is larger than the year-to-year variation (analogous to small p-values in a traditional ANOVA).

# A Statistical Model

- A common approach involves a three-level hierarchy:

Data model:  $[data|process, parameters]$   
Process model:  $[process|parameters]$   
Prior model:  $[parameters]$

- Simplifies the problem by factoring a complicated distribution into a series of conditional distributions.
- Inference involves sampling the posterior distribution:

$$[process, parameters|data] \propto [data|process, parameters][process|parameters][parameters]$$

# A Statistical Model

- A hierarchical structure:

Data model:  $\mathbf{Y}_{ij} \sim \mathcal{N}(\boldsymbol{\mu}_i, \sigma_i^2 \mathbf{V}(\phi_i)), \quad i = 1, \dots, 6, j = 1, \dots, 20$

Process model:  $\boldsymbol{\mu}_i \sim \mathcal{N}(\boldsymbol{\mu}, \sigma^2 \mathbf{V}(\phi))$

Prior model:  $\boldsymbol{\mu} \sim \mathcal{N}(\mathbf{NCEP}, \sigma_\mu^2 \mathbf{V}(\phi_\mu))$

- $\{\mathbf{Y}_{ij}\}$  are (transformed) daily average precipitation fields
  - $\{\boldsymbol{\mu}_i\}$  are model specific means;  $\boldsymbol{\mu}$  is the “grand” mean
  - $\{\sigma_i^2\}, \sigma^2, \sigma_\mu^2$  are scale parameters
  - $\{\phi_i\}, \phi, \phi_\mu$  are spatial dependence parameters
- Prior distributions on scale and spatial dependence parameters are non-informative.

# A Statistical Model

- An alternative (ANOVA) formulation:

$$Y_{ij} = \text{NCEP} + \eta + \alpha_i + \epsilon_{ij}, \quad i = 1, \dots, 6, j = 1, \dots, 20$$

- $\eta$  is a common component to all fields and explains variation beyond NCEP.
    - \*  $\mu = \text{NCEP} + \eta$ .
  - $\{\alpha_i\}$  are RCM-specific components.
    - \*  $\mu_i = \text{NCEP} + \eta + \alpha_i$ .
  - $\{\epsilon_{ij}\}$  represent year-to-year variation.
- Sain, Kaufman, and Tebaldi (2009, in preparation)

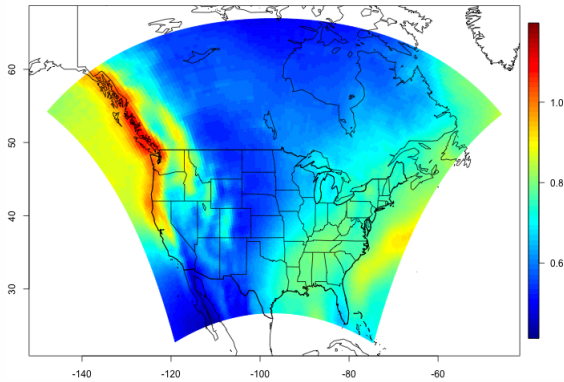
# NCEP Experiment

- Recall the functional ANOVA model:

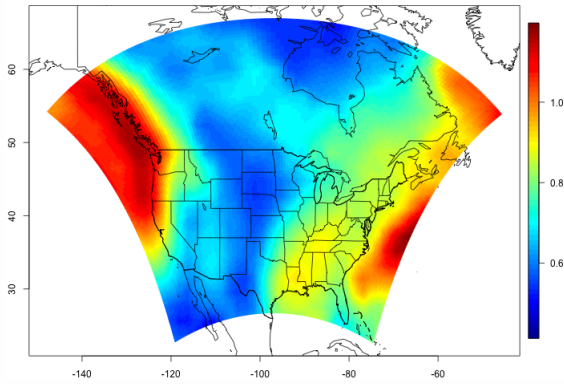
$$Y_{ij} = \text{NCEP} + \eta + \alpha_i + \epsilon_{ij}, \quad i = 1, \dots, 6, j = 1, \dots, 20$$

- Compare  $\mu$  to NCEP – how do the RCMs on average compare to the driving model?
- Compare  $\{\alpha_i\}$  – how consistent are the RCMs and how do they compare with each other?
- By drawing samples from the posterior (ensemble), we can address these questions giving insight to the sources of uncertainty in the collection of RCM output.

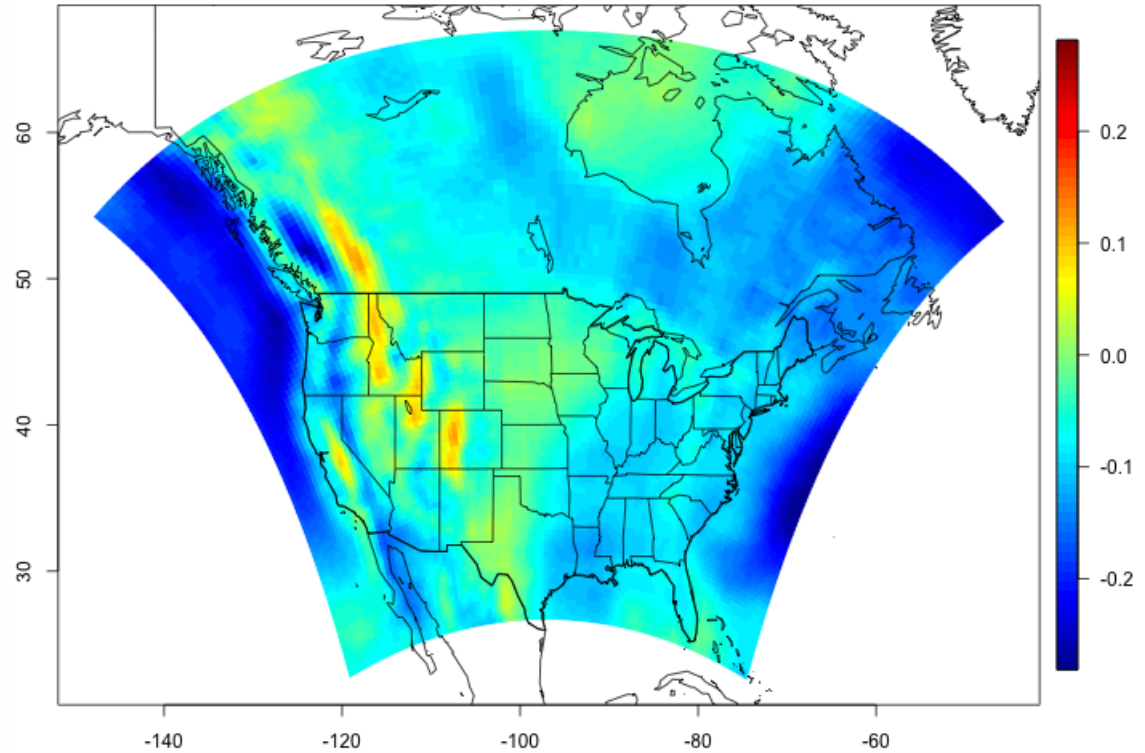




$\mu$

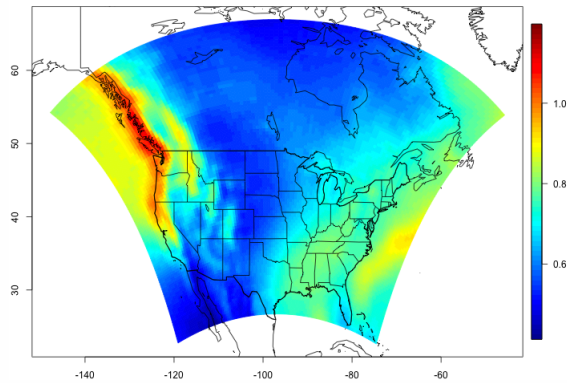


NCEP

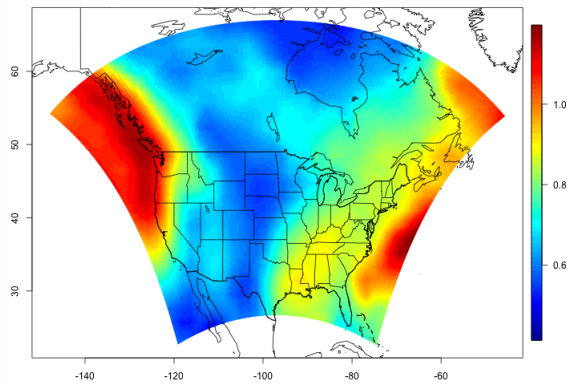


$\mu - \text{NCEP}$

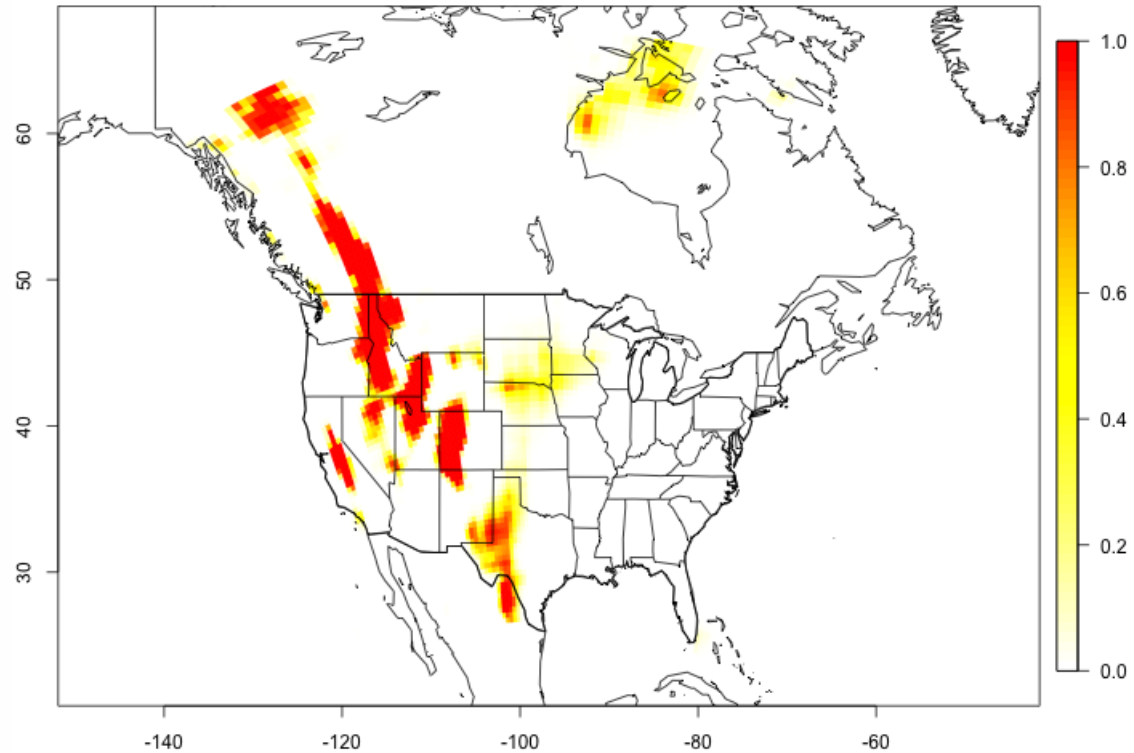
- Difference between posterior mean for  $\mu$  and the mean NCEP.
- Average daily winter precipitation (transformed).



$\mu$

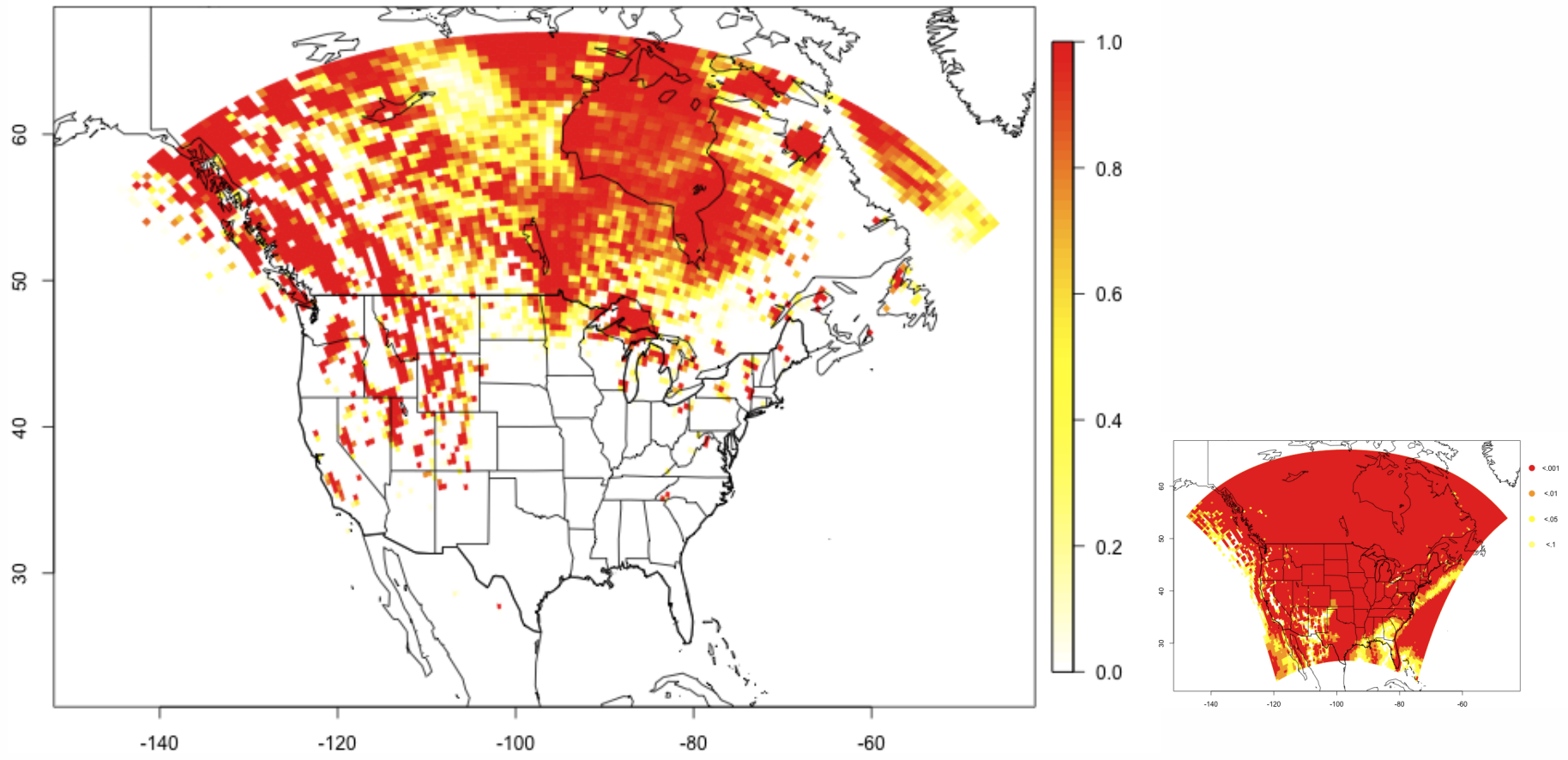


NCEP



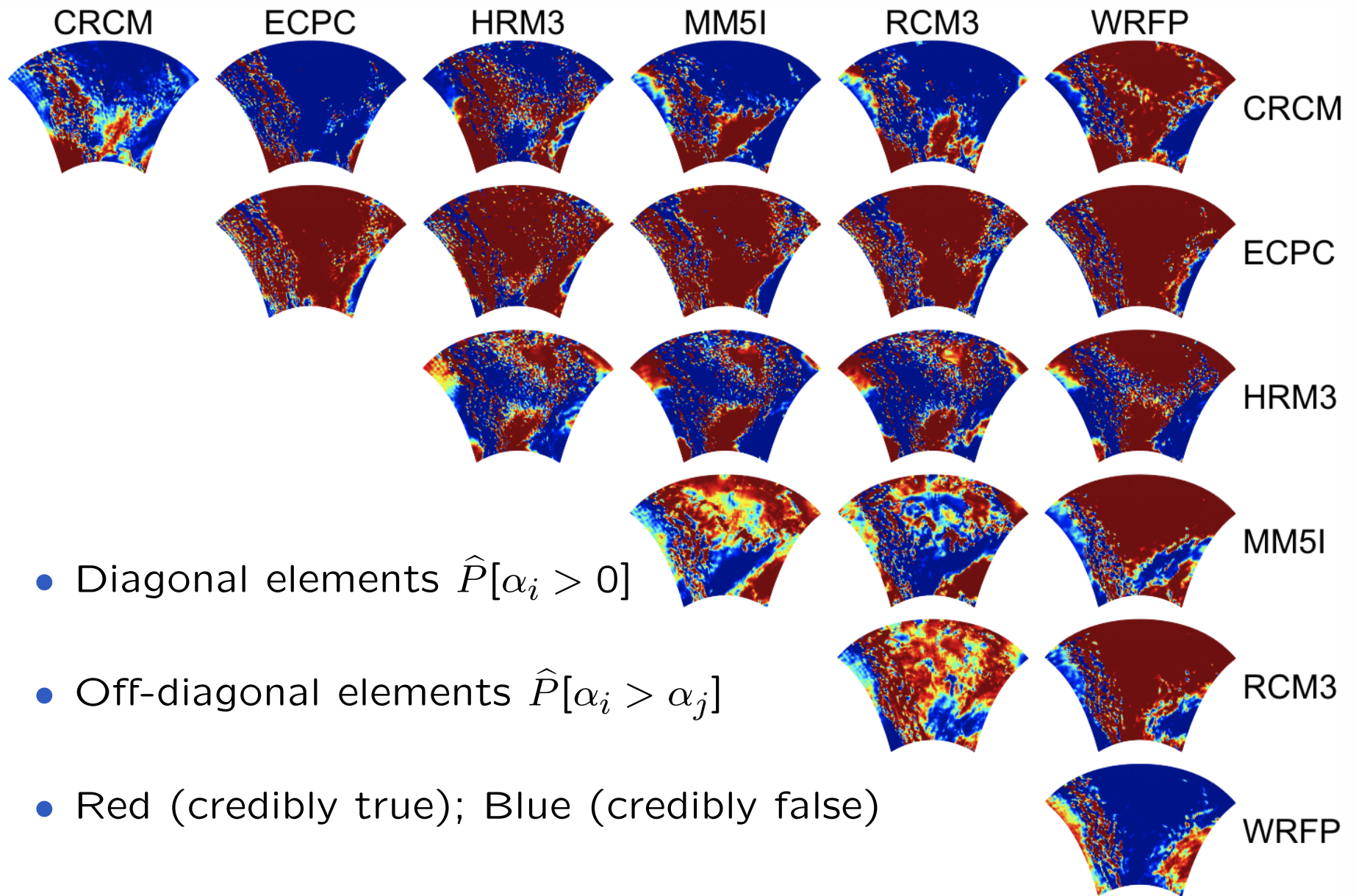
$\hat{P}[\mu > \text{NCEP}]$

Pointwise probabilities that draws from the posterior distribution of  $\mu$  are greater than the mean NCEP field. Red (credibly true); white (credibly false).



$$\hat{P}[s_{\alpha}^2 > s_{\epsilon}^2]$$

Pointwise probabilities that the model-to-model variation is larger than the year-to-year variation.



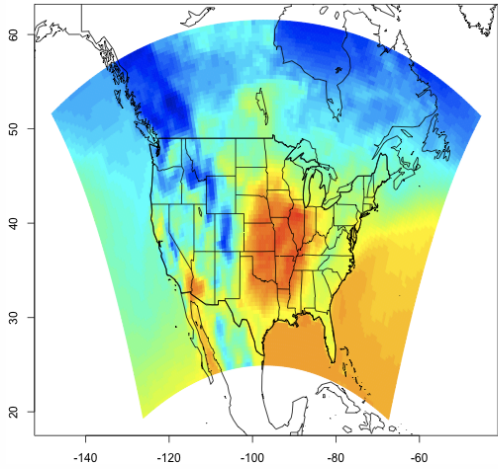
# Heat Stress: A Preliminary Study

- Two types of dynamic downscaling: a GFDL time-slice and a GFDL-driven RCM (RCM3; UC Santa Cruz).
  - Geophysical Fluid Dynamics Laboratory (GFDL; NOAA)
- Both timeslice and RCM use the A2 scenario.
- Current (1971-2000) and future (2041-2070) runs.
- Focus on summer (May-September) heat stress.
  - Output interpolated to a common grid (134 × 83).
- Examine differences in the two models as well as changing heat stress in North America.

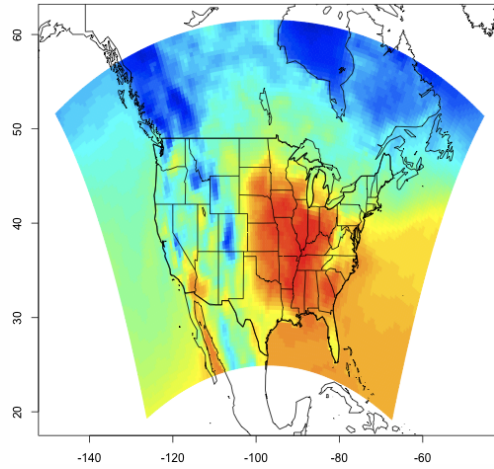
# What is a Heat Wave/Heat Stress?

- “...an extended period of unusually high atmosphere-related heat stress, which causes temporary modifications in lifestyle, and which may have adverse health consequences for the affected population.”
  - Intensity and duration and local climatology.
- We adopt the definition of heat stress put forth by Meehl and Tebaldi (2004) in their study of global climate models: **maximum of the 3-day running mean of the overnight minimum temperature.**
  - Captures persistence and (lack of) overnight cooling.

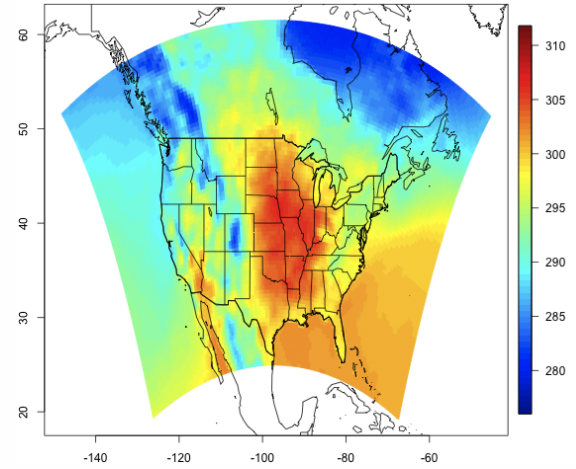
# Heat Stress (Timeslice)



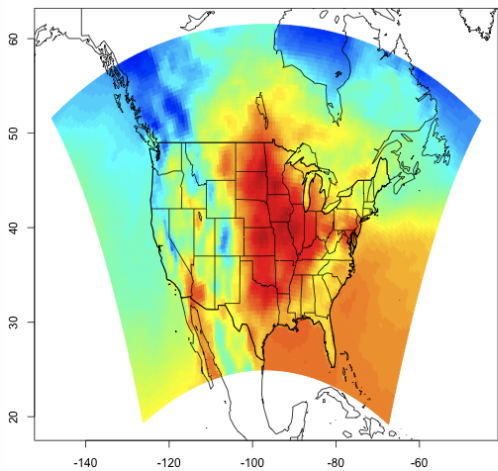
1980



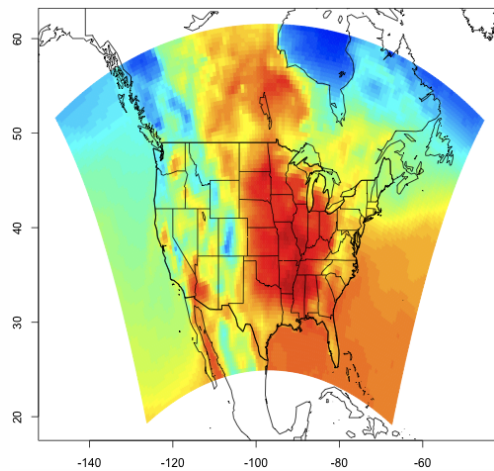
1990



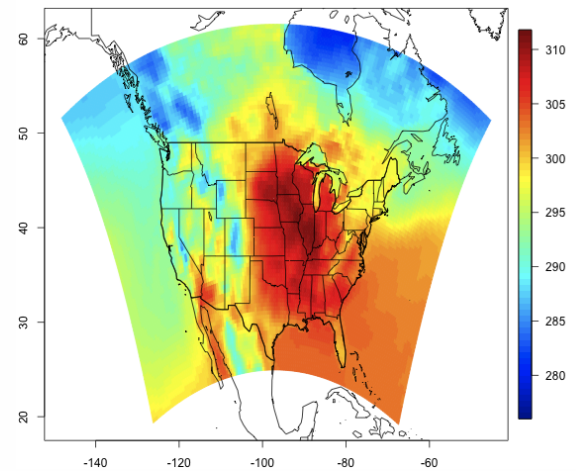
2000



2050

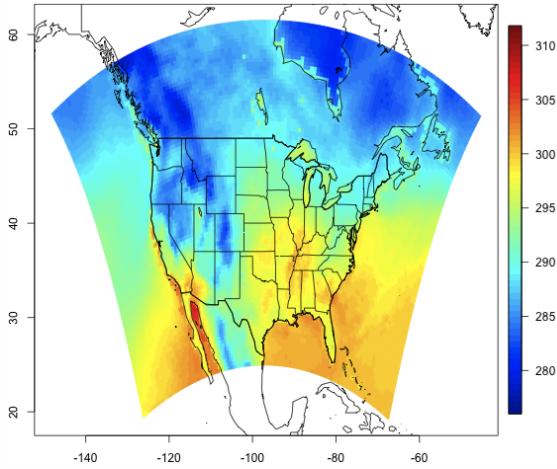


2060

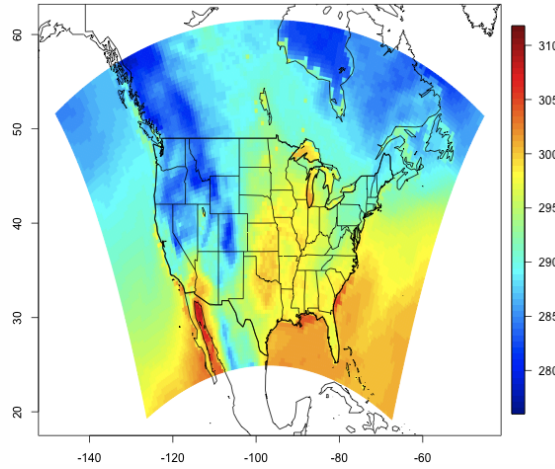


2070

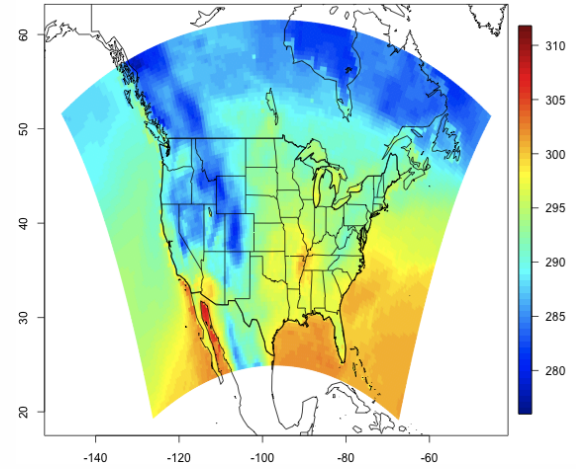
# Heat Stress (RCM)



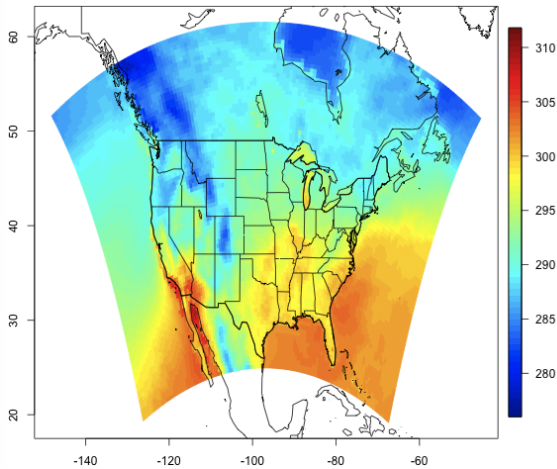
1980



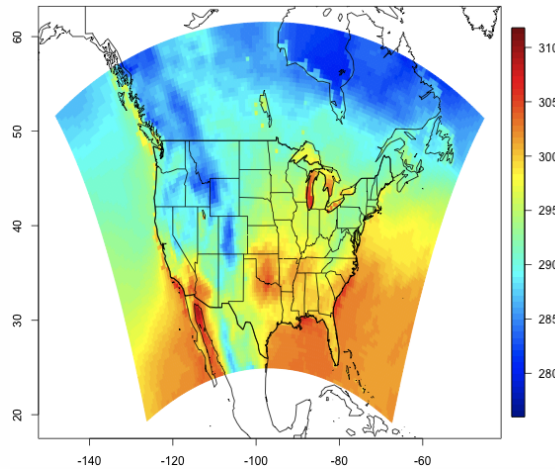
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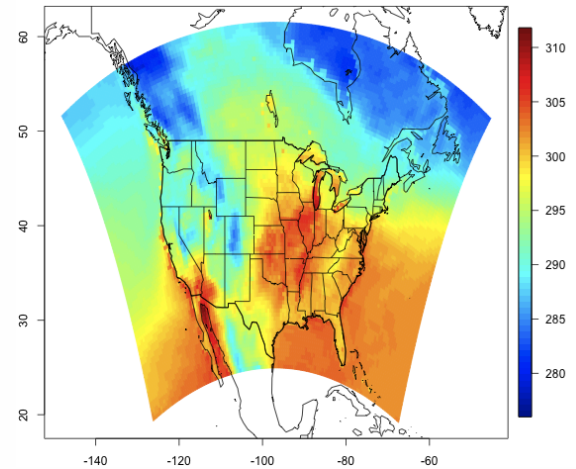
2000



2050



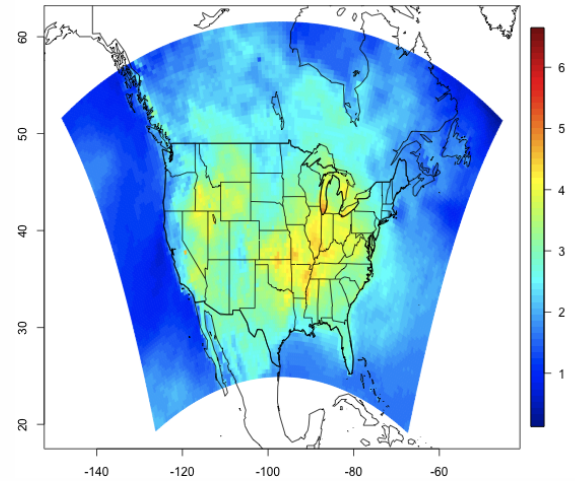
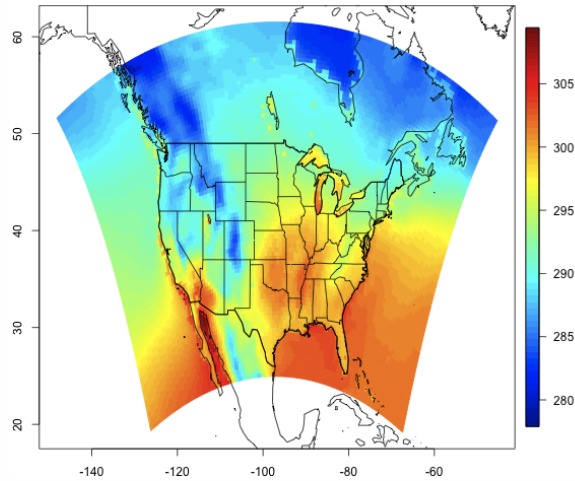
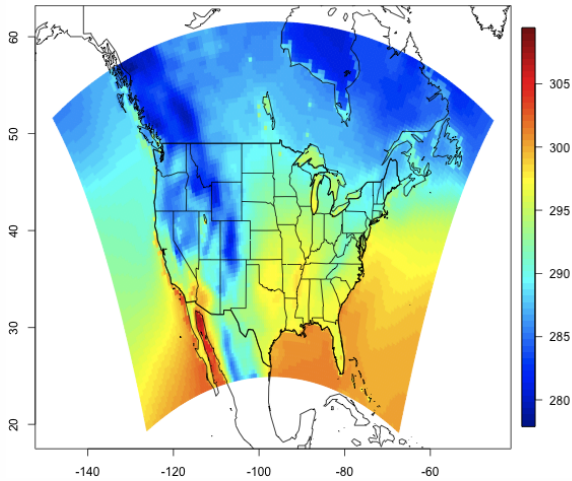
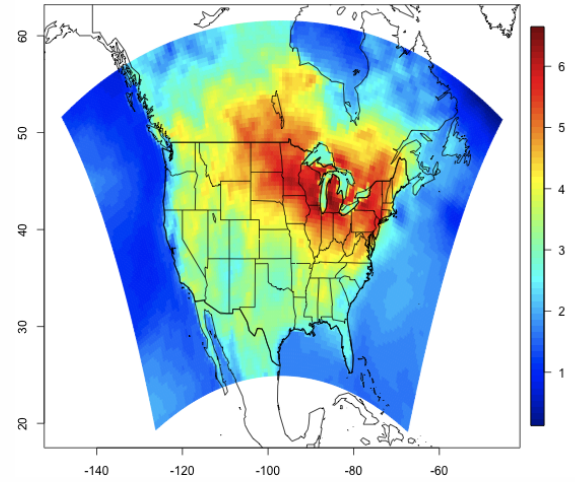
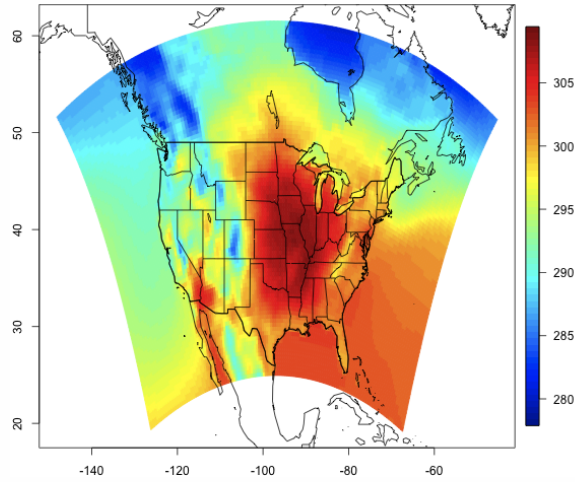
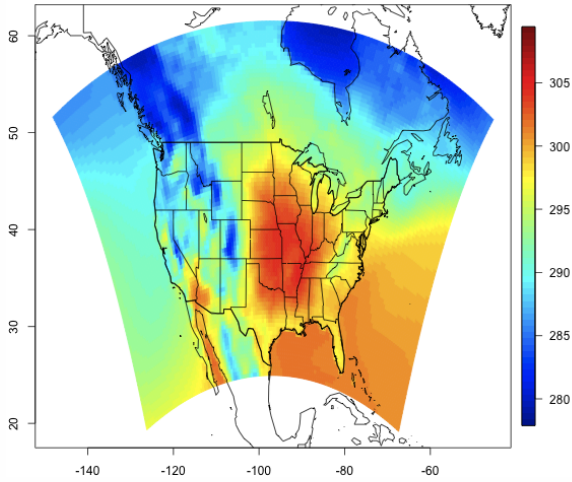
2060



2070



# Heat Stress (Means)



Current

Future

Difference

# A Functional ANOVA Model

- Let  $Y_{ijt}$  denote the  $i$ th model (timeslice vs RCM;  $i = 0, 1$ ), the  $j$ th run (current vs future;  $j = 0, 1$ ), at the  $t$ th time ( $t = 1, \dots, 30$ ):

$$Y_{ijt} = \alpha_0 + i\alpha_1 + j\alpha_2 + ij\alpha_3 + \epsilon_{ijt}$$

- Assume each component is generated from a Markov random field:

$$\begin{aligned} \alpha_0 &\sim \mathcal{N}(\mu_{curr}, \Sigma(\theta_0)) & \alpha_1 &\sim \mathcal{N}(\mathbf{0}, \Sigma(\theta_1)) \\ \alpha_2 &\sim \mathcal{N}(\mu_{diff}, \Sigma(\theta_2)) & \alpha_3 &\sim \mathcal{N}(\mathbf{0}, \Sigma(\theta_3)) \end{aligned}$$

- $\mu_{curr}$  and  $\mu_{diff}$  are average fields of the current and difference in heat stress computed from the driving global GFDL model.

# A Functional ANOVA Model

- The error term,  $\epsilon_{ijt}$  is broken up into two pieces:

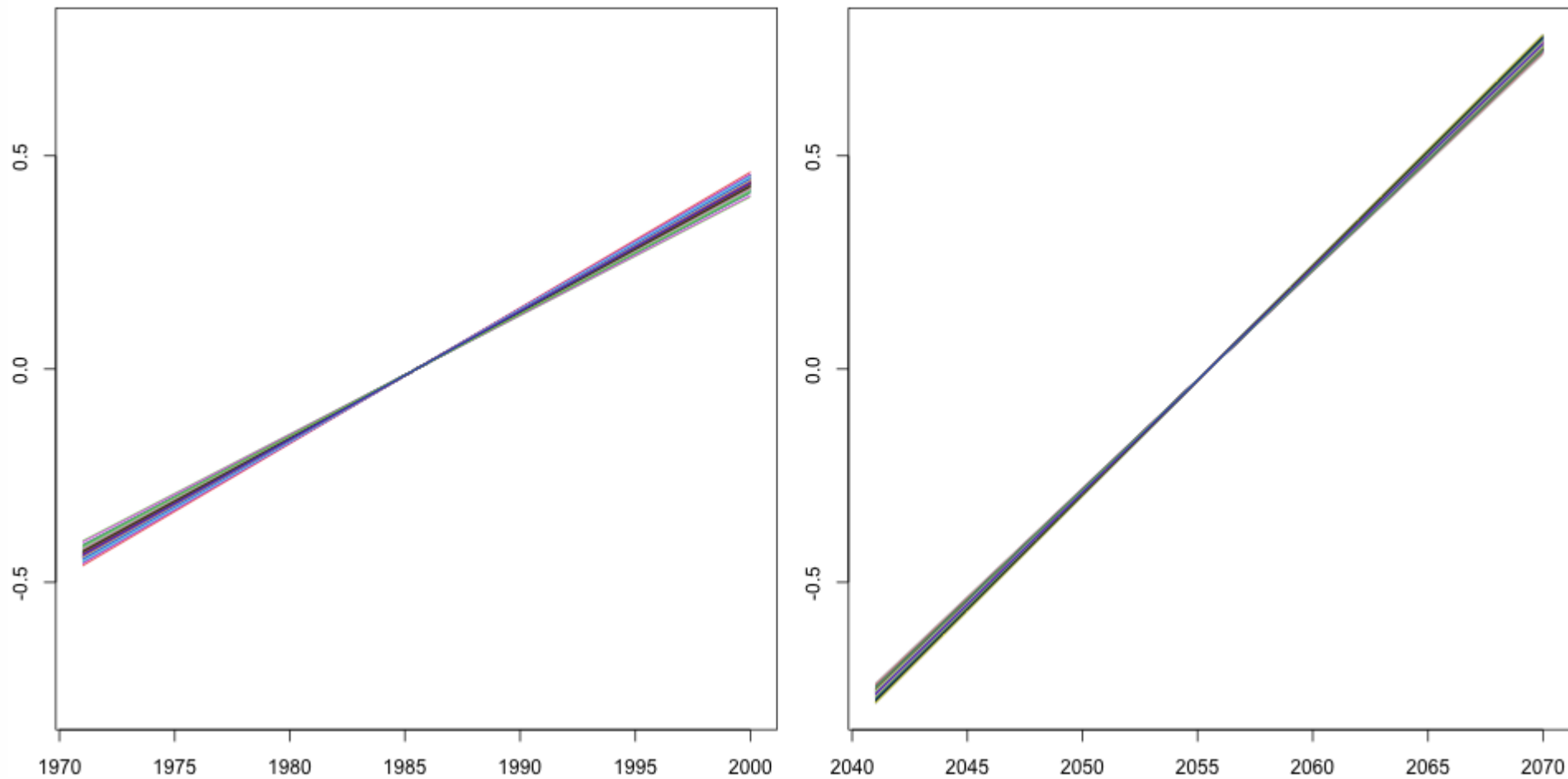
$$\epsilon_{ijt} = \gamma_j(t - 15.5) + \eta_t$$

where

$$\gamma_j \sim \mathcal{N}(\gamma_j^*, \sigma_\gamma^2)$$

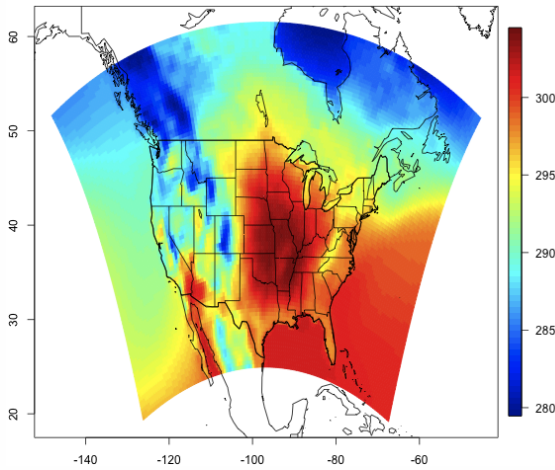
$$\eta_t \sim \mathcal{N}(0, \Sigma(\theta_t))$$

- $\gamma_j^*$  are average slopes from the control and future runs of the driving global GFDL model.

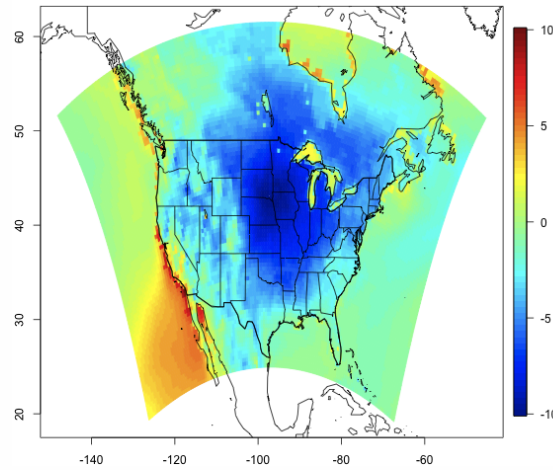


100 draws from the posterior of  $\gamma_0$  (left) and  $\gamma_1$  (right).

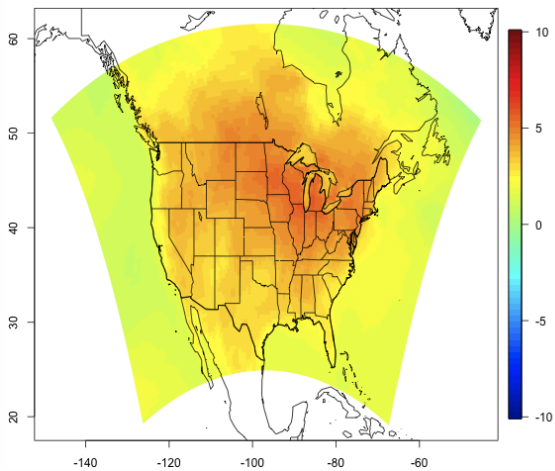
# Posterior Means



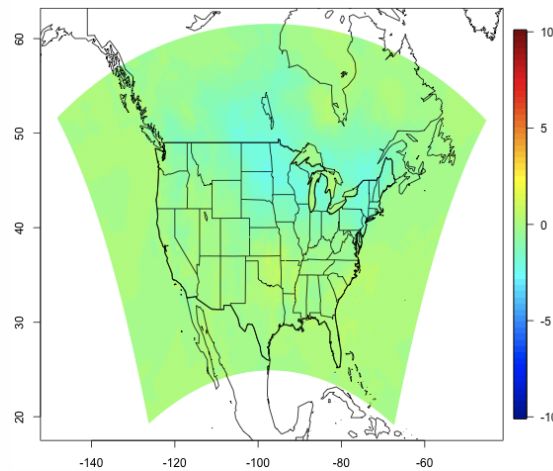
$\bar{\alpha}_0$



$\bar{\alpha}_1$



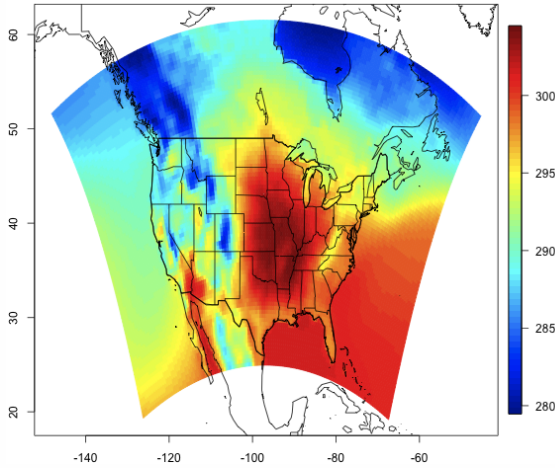
$\bar{\alpha}_2$



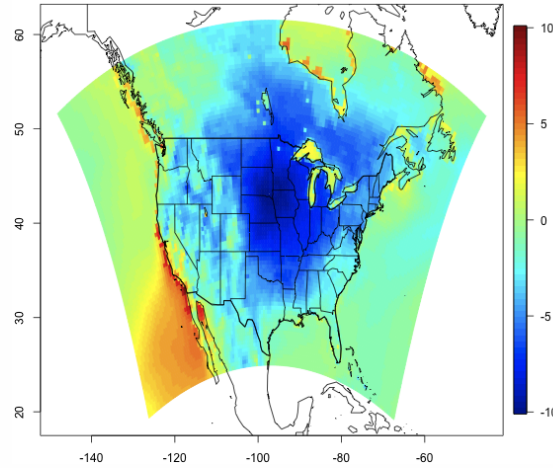
$\bar{\alpha}_3$

- $\alpha_0$  represents current timeslice.
- $\alpha_1$  adjusts for current RCM.
- $\alpha_2$  adjusts for future run.
- $\alpha_3$  is an interaction.

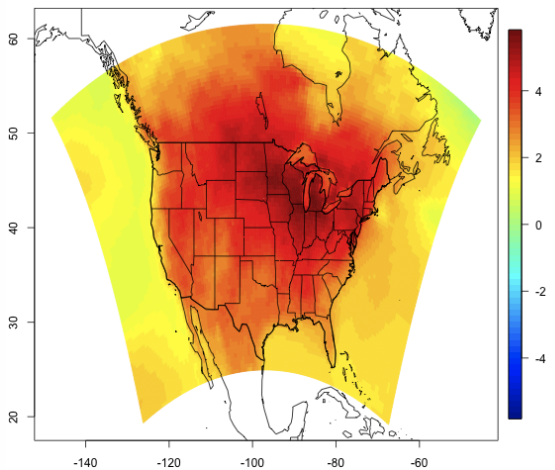
# Posterior Means



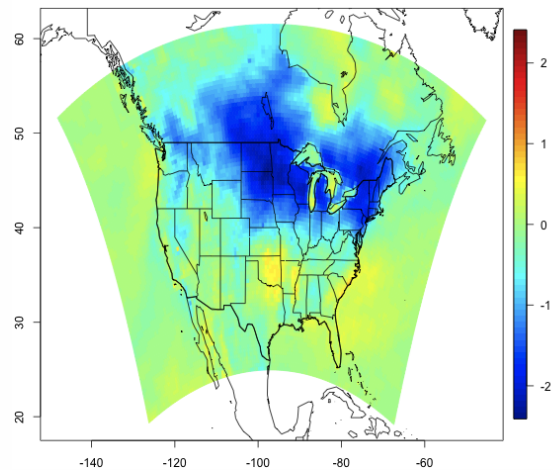
$\bar{\alpha}_0$



$\bar{\alpha}_1$



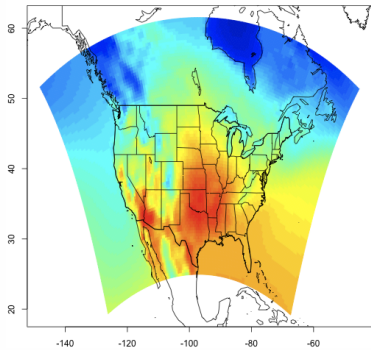
$\bar{\alpha}_2$



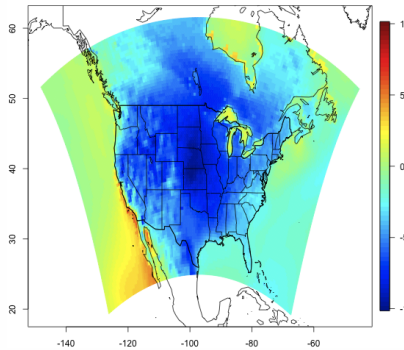
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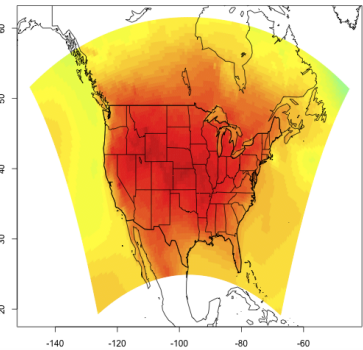
# A Quick Look at Temperatures



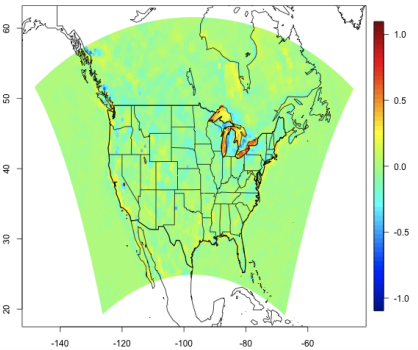
$\bar{\alpha}_0$



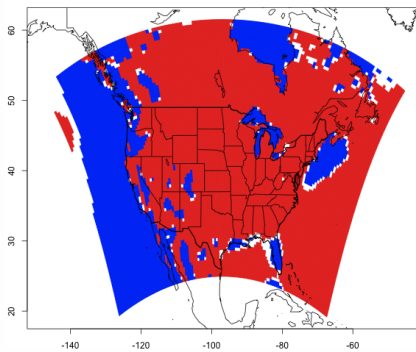
$\bar{\alpha}_1$



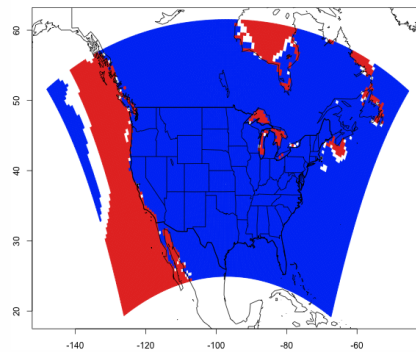
$\bar{\alpha}_2$



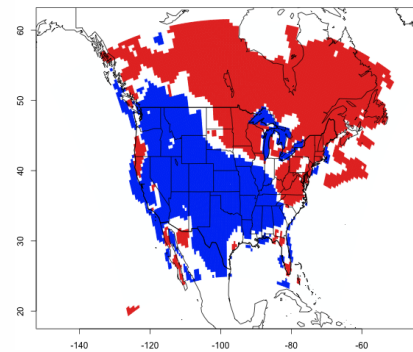
$\bar{\alpha}_3$



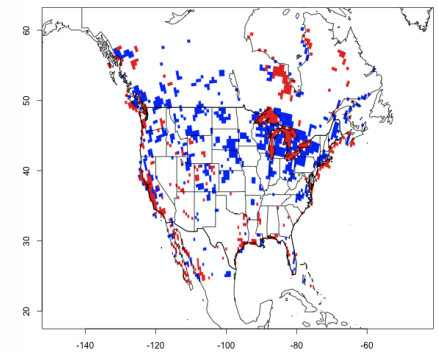
$\hat{P}[\alpha_0 > \mu_{curr}]$



$\hat{P}[\alpha_1 > 0]$

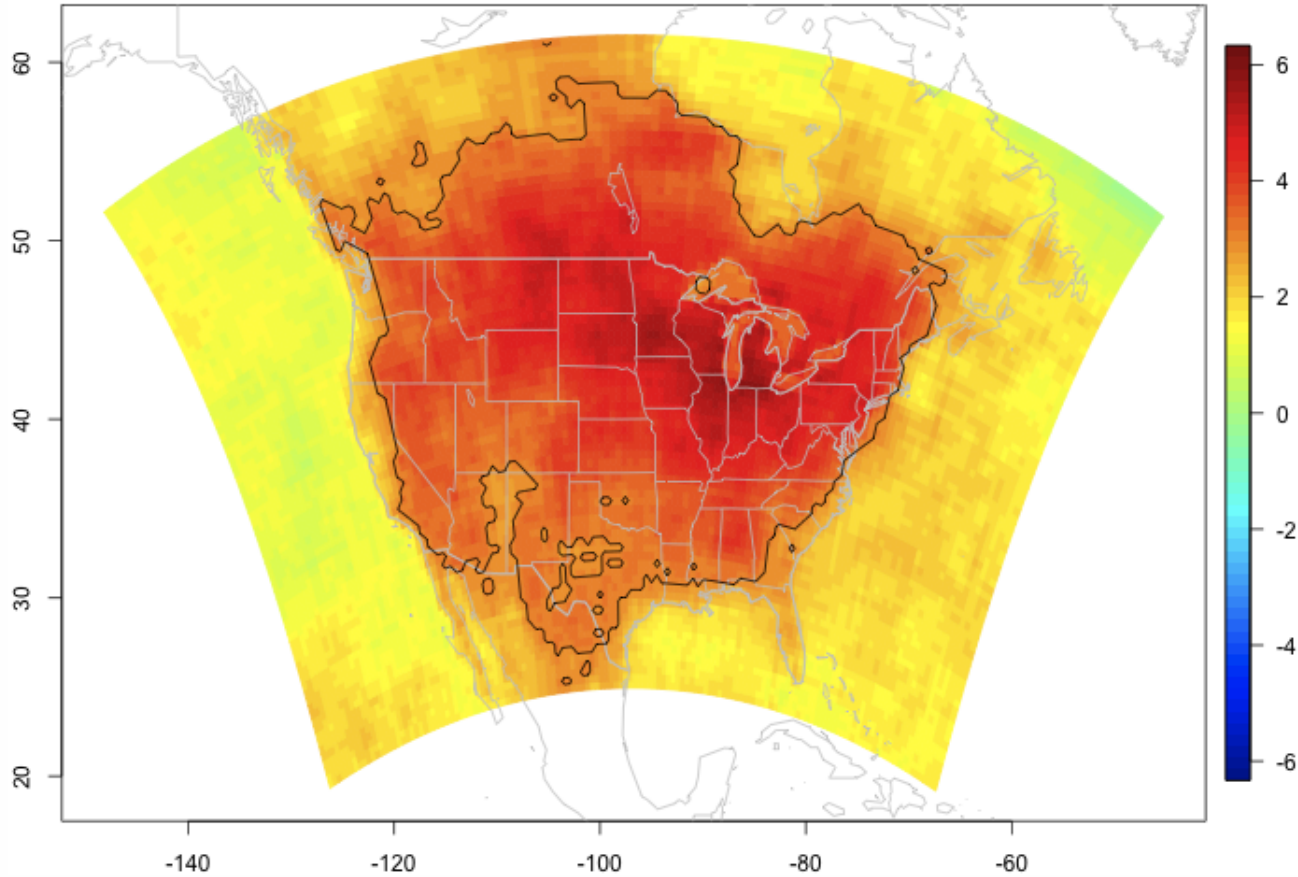


$\hat{P}[\alpha_2 > \mu_{diff}]$



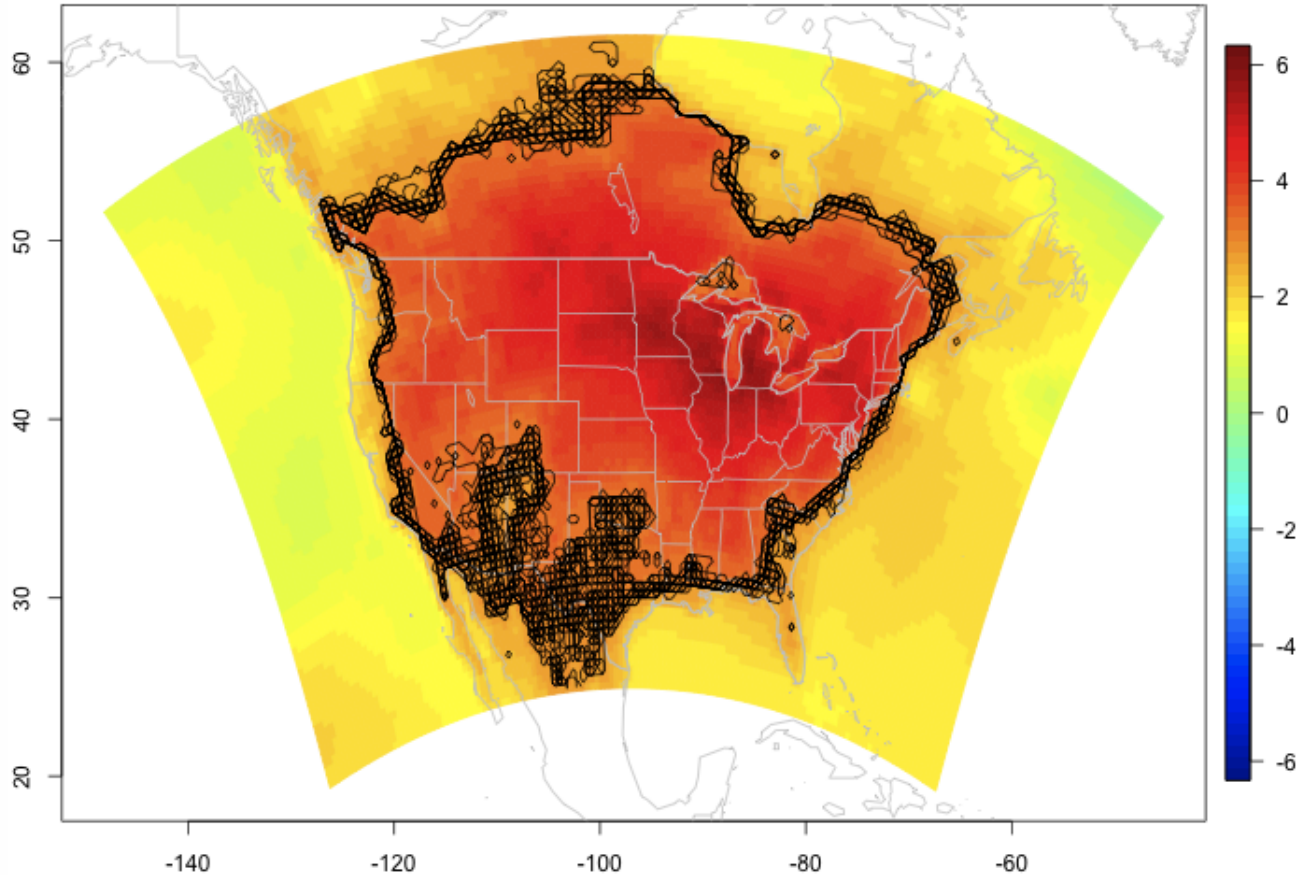
$\hat{P}[\alpha_3 > 0]$

JJA Ave Temp –  $p < 0.05$  – blue;  $p > 0.95$  – red.

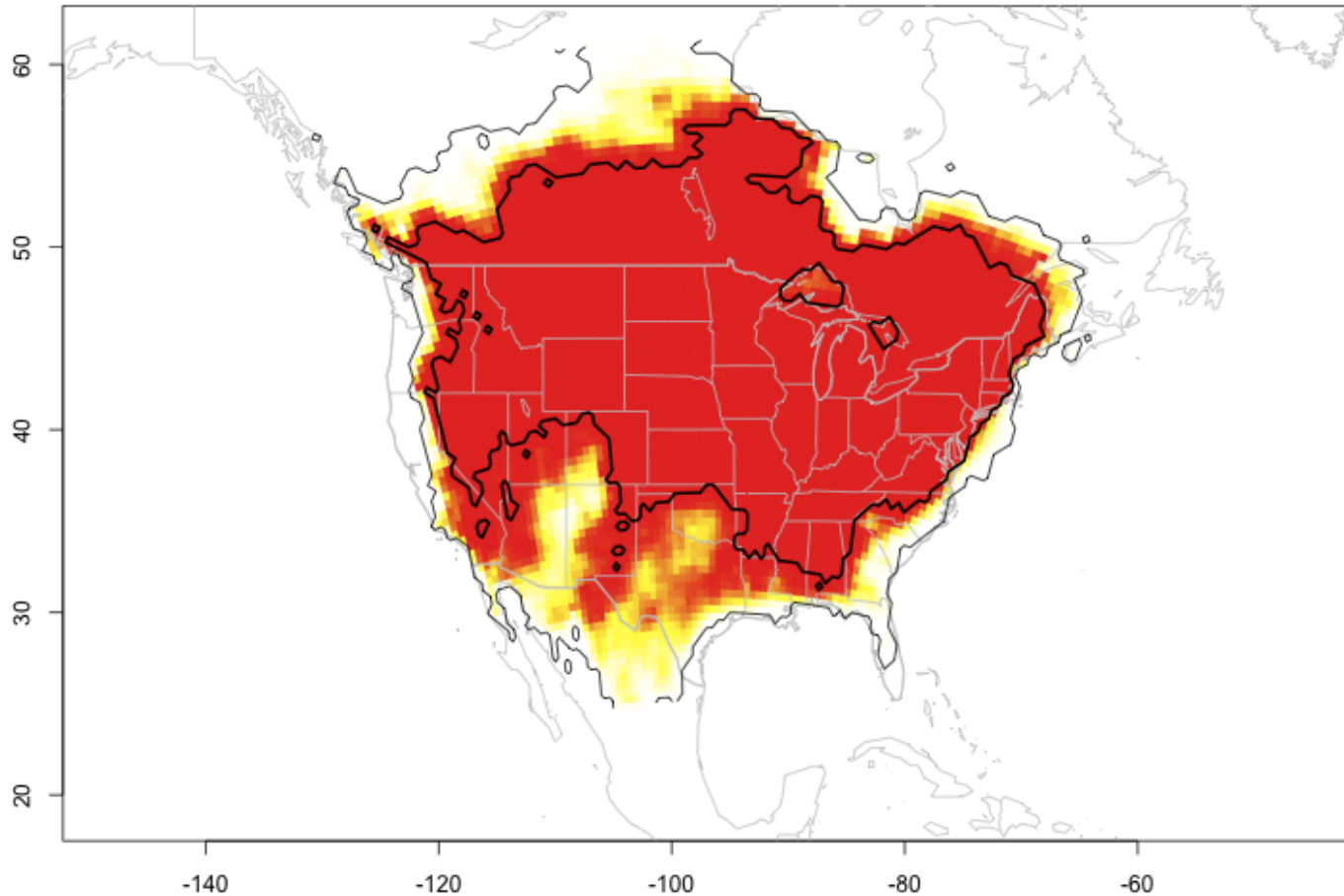


- A single draw from the posterior for  $\alpha_2$ .
- Contour represents an increase in heat stress by 3.0 degrees.

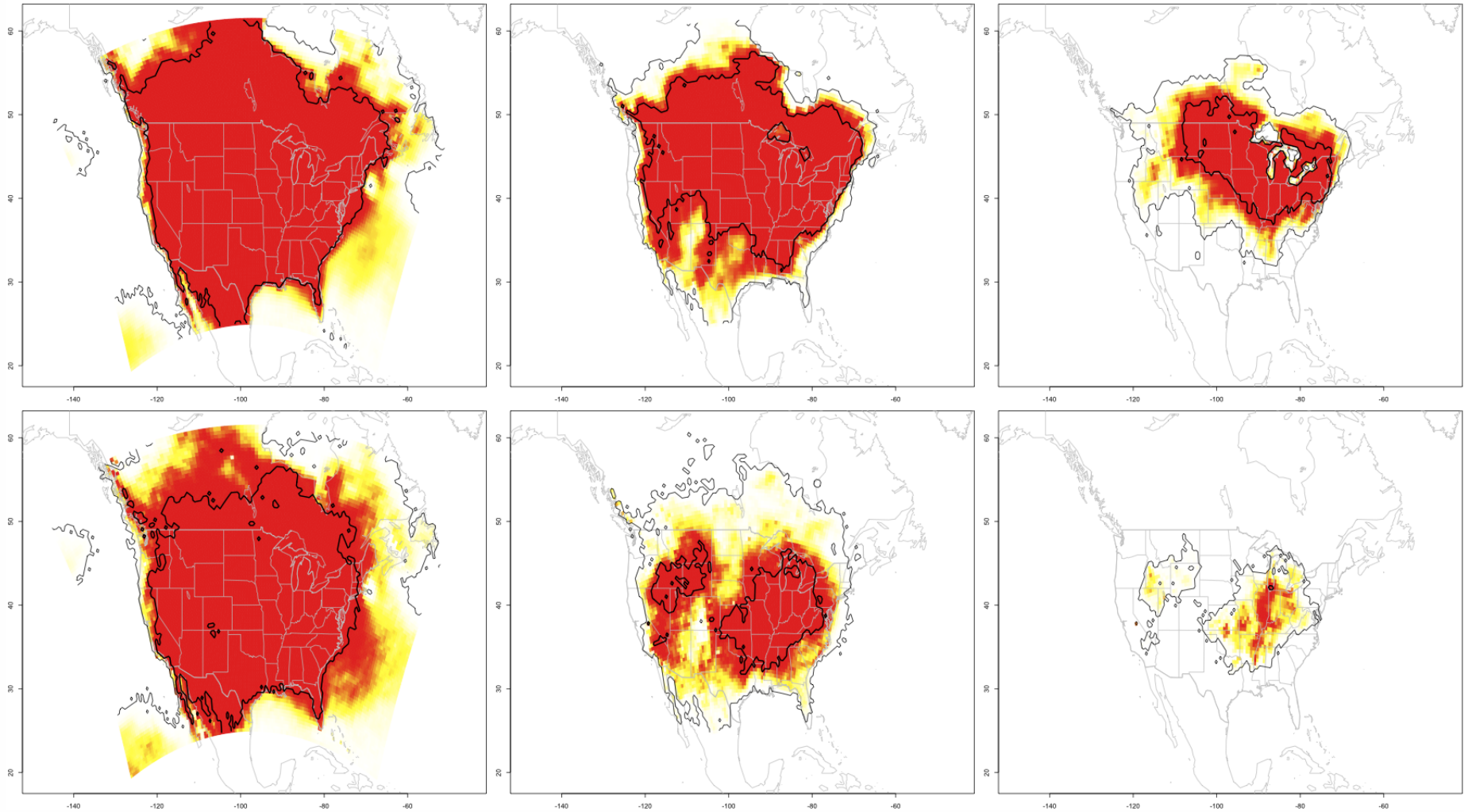




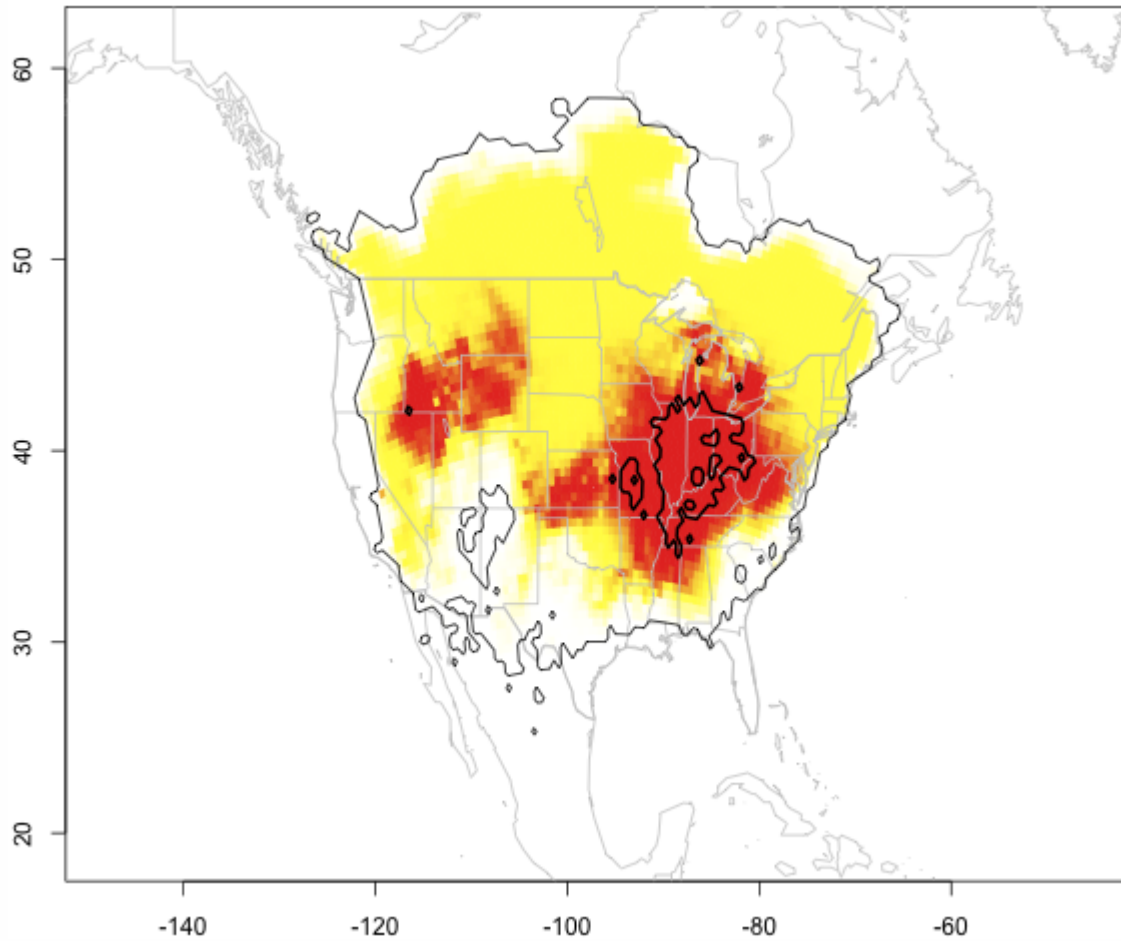
- Posterior mean for  $\alpha_2$ .
- Contour lines represent an increase in heat stress by 3.0 degrees for 20 randomly sampled draws from the posterior of  $\alpha_2$ .



- Pointwise posterior probability that  $\alpha_2(\mathbf{s}) > 3.0$ .
- Regions where all draws are greater than 3.0 (inside wide contour) or where no draws were greater than 3.0 (outside thin contour).



Varying thresholds ( $\tau = 2.0, 3.0, 4.0$ ) for timeslice ( $\alpha_2$ ; top) and RCM ( $\alpha_2 + \alpha_3$ ; bottom).



Pointwise probability for change greater than 3.0 for both models.

# Questions?



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*Thank You!*