Uncertainty and regional climate experiments

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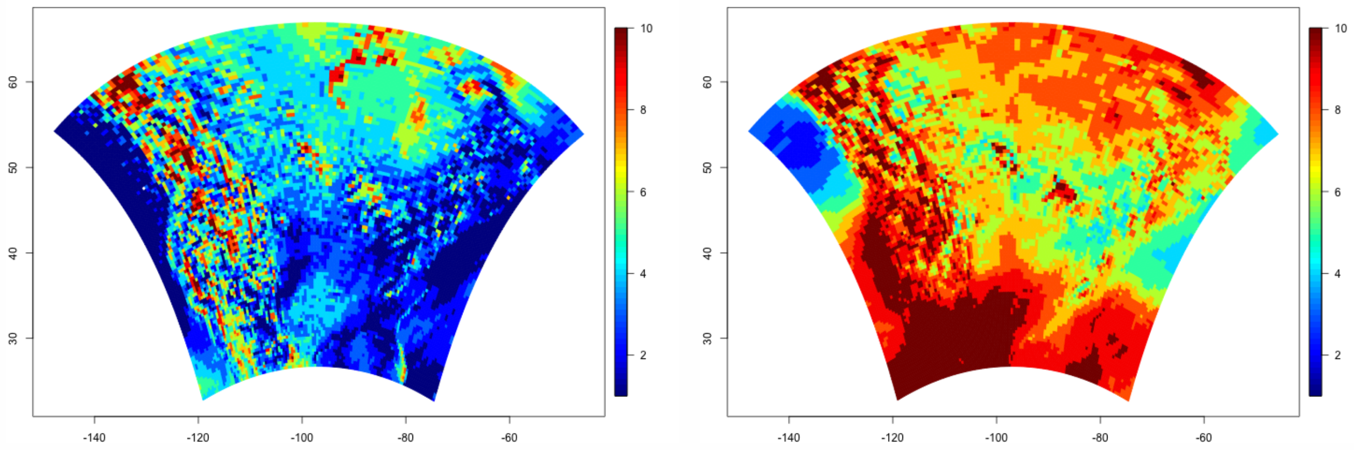
Goals

- Examining sources of variability/uncertainty
  - GCM, RCM, scenario, interactions, physical processes, etc.
- Projections of climate change – combining across models
- Survey of other projects
  - Multivariate, extremes, correlated models, etc.

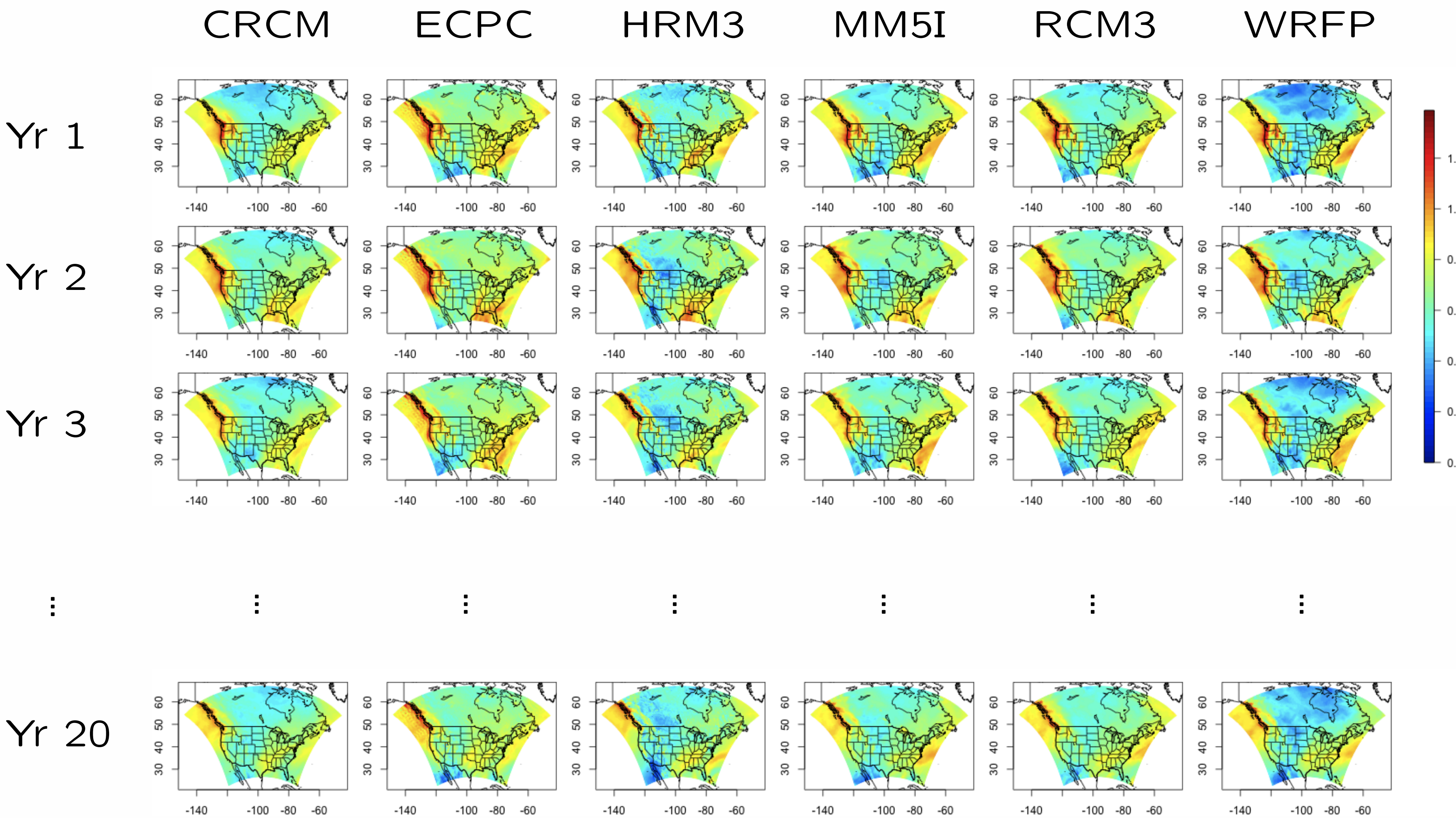


The NARCCAP Design

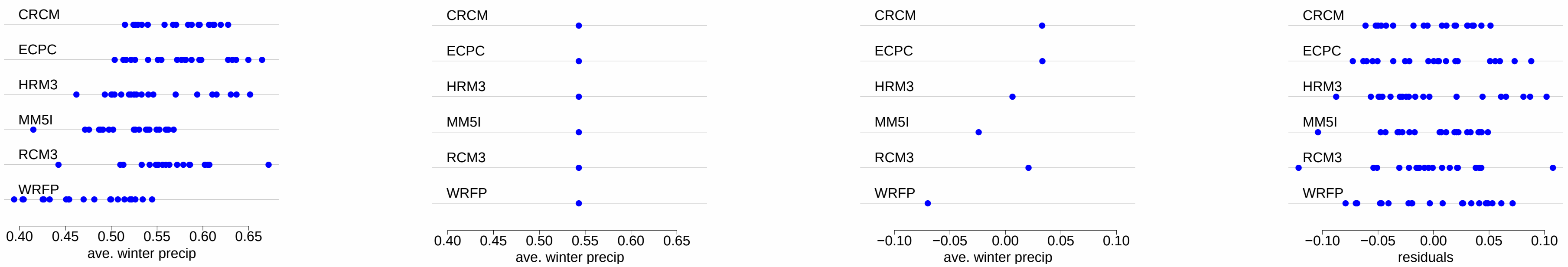
	Phase I	Phase II			
	NCEP	GFDL	CGCM3	HADCM3	CCSM
CRCM	**finished**		finished		finished
ECP2	**finished**	running		planned	
HRM3	**finished**	planned		finished	
MM5I	**finished**			planned	finished
RCM3	**finished**	finished	finished		
WRFG	**finished**		running		finished

Phase I:

- 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
Yr 20
-140
-100
-80
-60
30
40
50
60
0.0
0.2
0.4
0.6
0.8
1.0
1.2

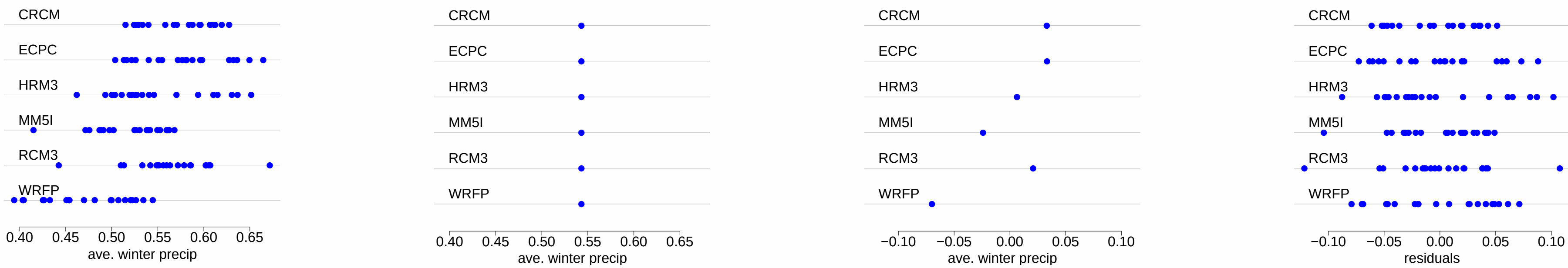
Analysis of Variance



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

- For every grid box (this grid-box is in eastern Nebraska):
  - Y_{ij} is the (transformed) precipitation for the ith model and the jth year.
  - μ is a common mean
  - α_i is a RCM-specific effect
  - ϵ_{ij} is the error or residual

Analysis of Variance



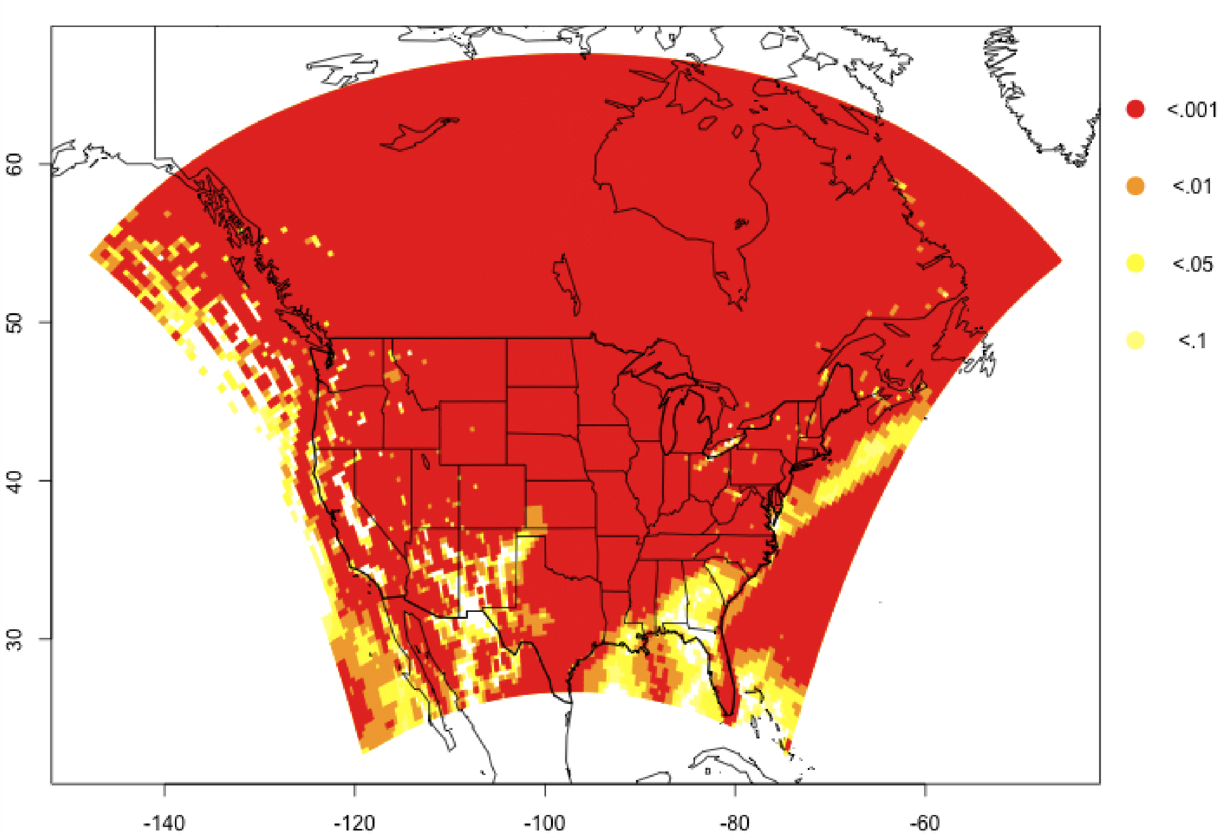
$$Y_{ij} = \mu + \alpha_i + \epsilon_{ij}$$

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

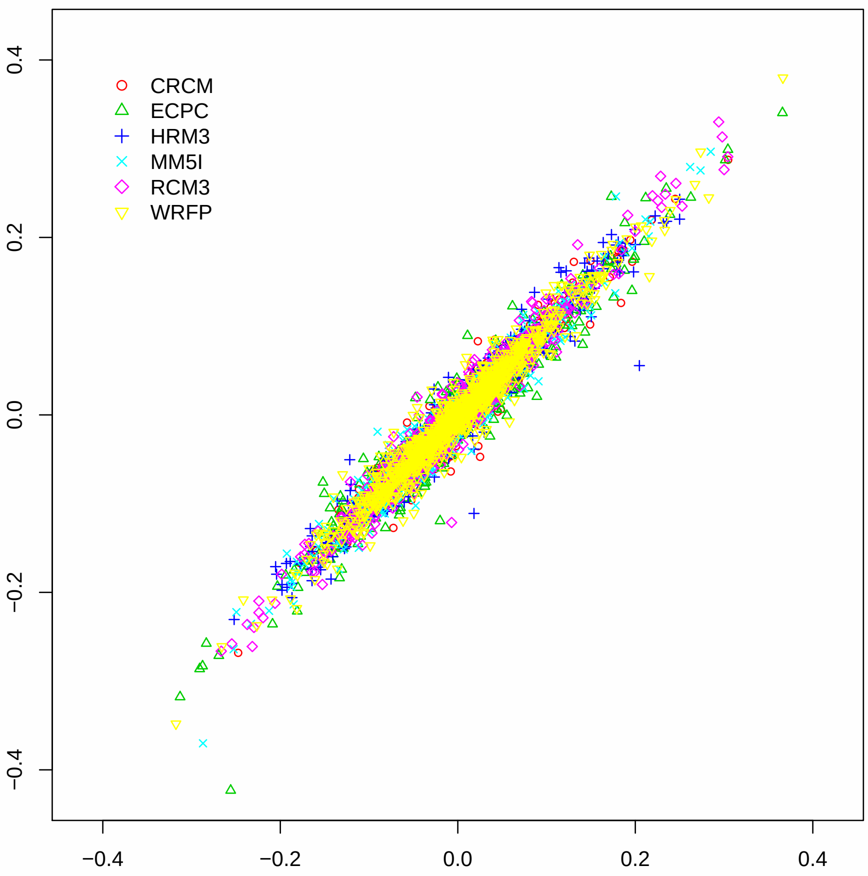
	df	SS	MS	F	p-value	
RCM	5	0.163	0.0326	15.3	1.75e-11	$\star\star\star$
Residual	114	0.243	0.00213			

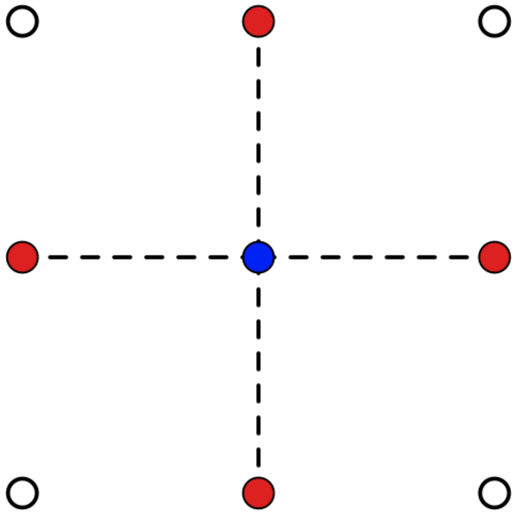
- Conclusion: strong evidence of differences in the RCM means.

Analysis of Variance



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

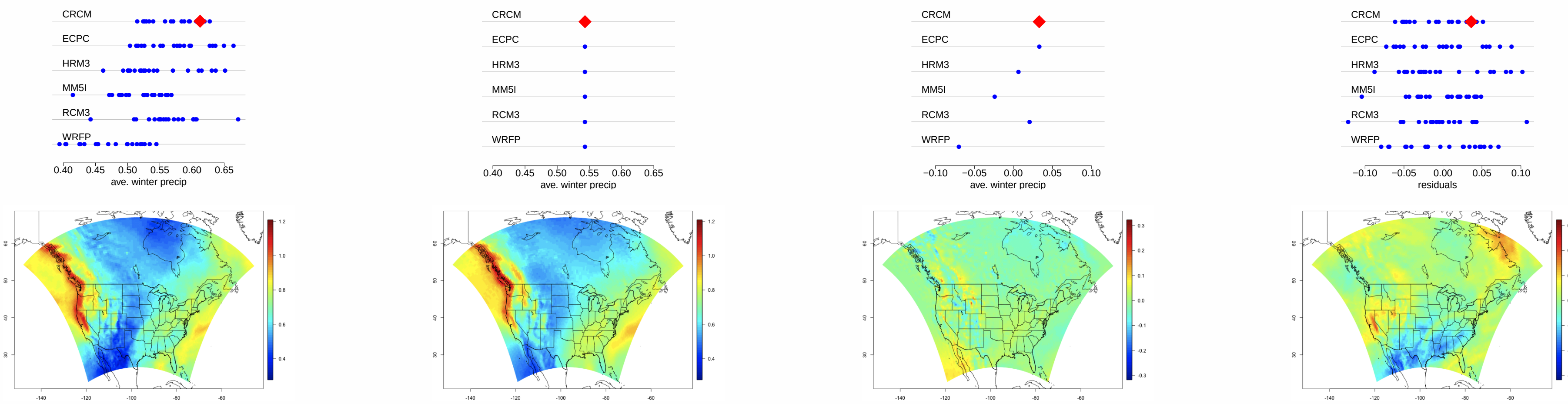




- Problem: correlated residuals at neighboring grid-boxes.

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

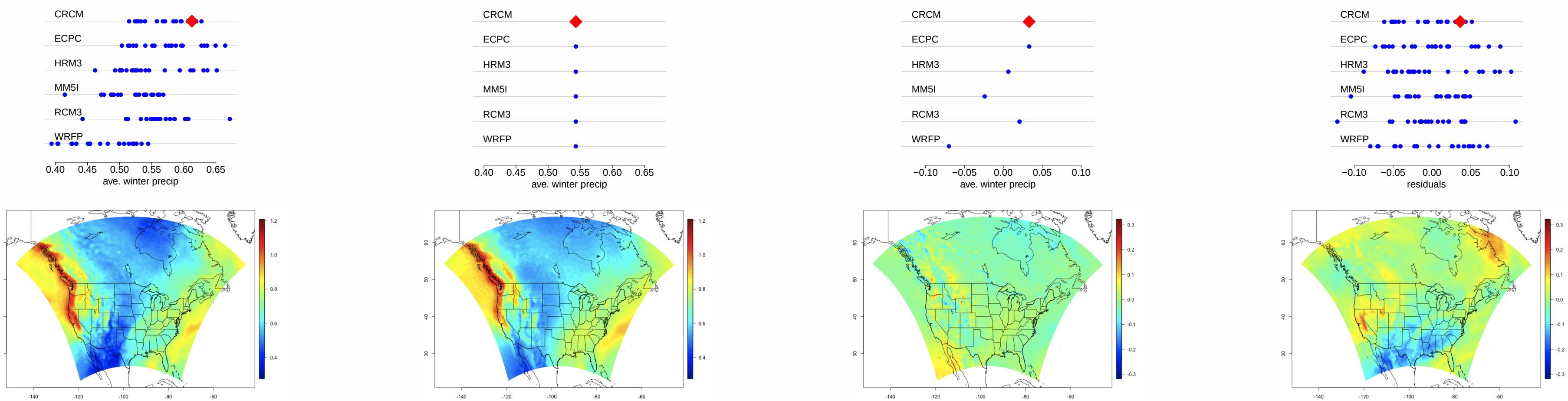
Functional Analysis of Variance



$$\mathbf{Y}_{ij} = \boldsymbol{\mu} + \boldsymbol{\alpha}_i + \boldsymbol{\epsilon}_{ij}$$

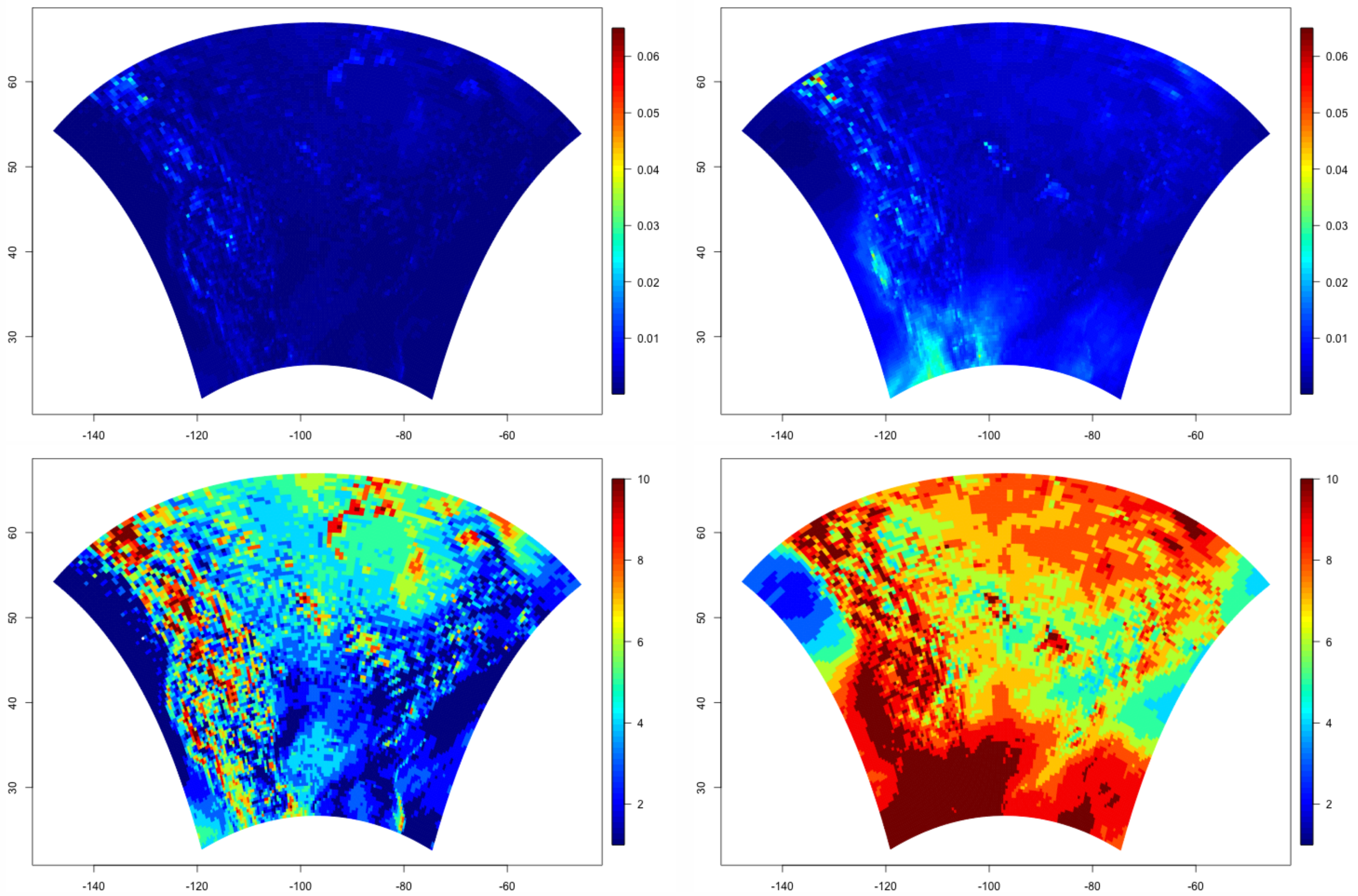
- $\mathbf{Y}_{ij}$ is the vector of (transformed) precipitation for the ith model and jth year.
- $\boldsymbol{\mu}$ is the vector mean common to all RCMs
- $\boldsymbol{\alpha}_i$ is the vector RCM-specific effect
- $\boldsymbol{\epsilon}_{ij}$ is the vector residual.

Functional Analysis of Variance

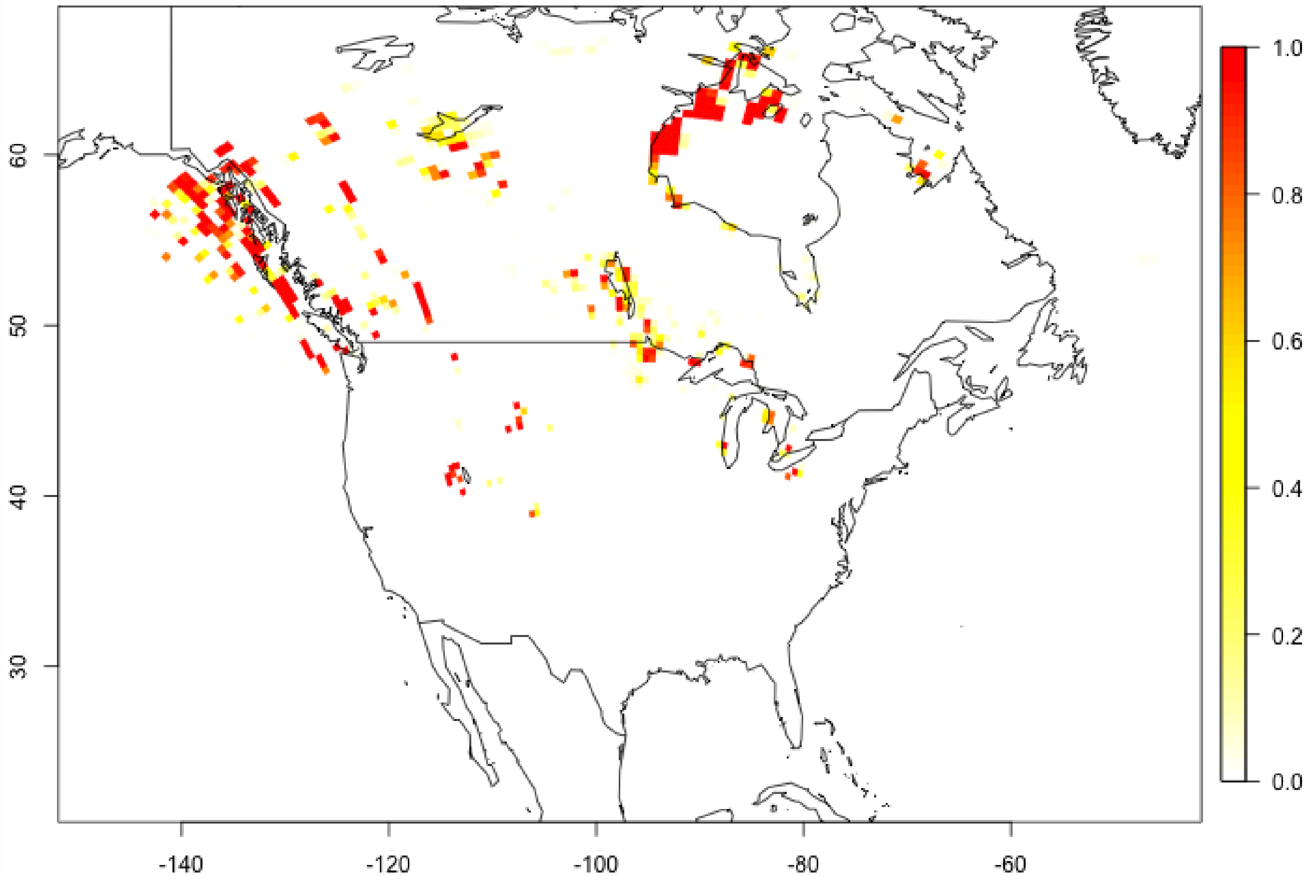


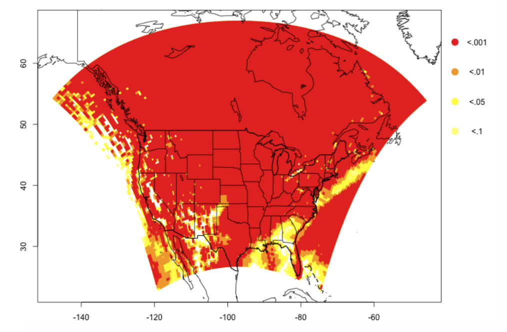
$$\mathbf{Y}_{ij} = \boldsymbol{\mu} + \boldsymbol{\alpha}_i + \boldsymbol{\epsilon}_{ij}$$

- 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 (2010), Sain, Nychka and Mearns (2010).



Posterior means of model-to-model variation (left column) and residual or year-to-year variation (right column). Color scheme for bottom row based on quantiles.





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

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).

Another example

- Two datasets and three regional models.
- Summer (JJA) average temperature.
  - (Seasonal temp/precip, extreme precip, heat stress, bivariate...)
- Current: 1971-2000; Future: 2041-2070.
- All models use A2 scenario for future emissions.
- All data/model output interpolated to common 114×102 grid.
  - 11628 gridboxes

Another example

Datasets:

- **CRU**: UEA Climate Research Unit's Global Climate Dataset (1970-2002).

- **UDEL**: Data from Willmott, Matsuura, and Collaborators at the University of Delaware (1979-2006).

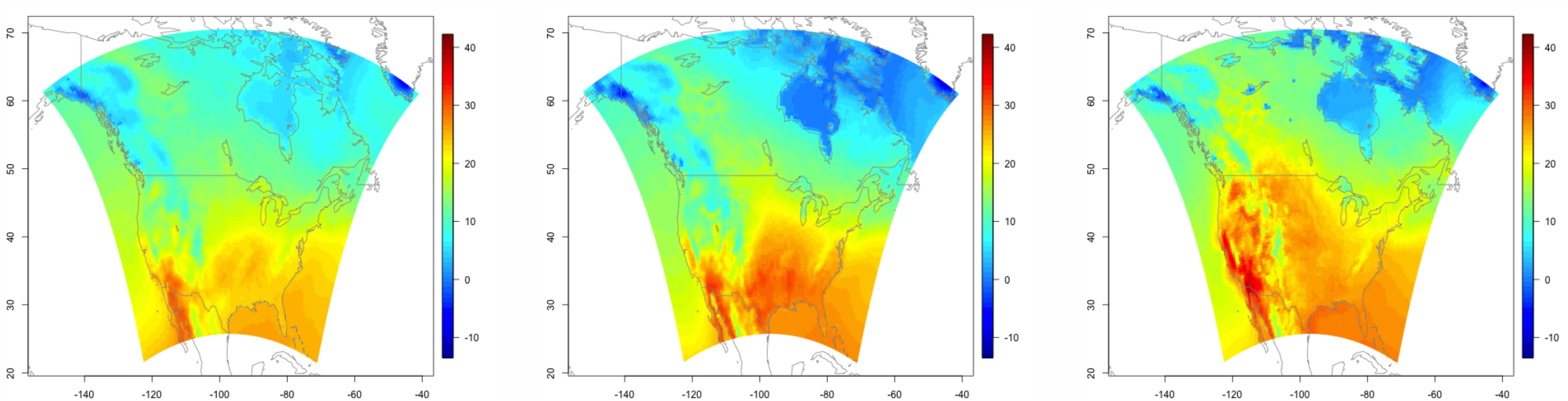
Models:

- **GFDL/RCM3**: UC Santa Cruz's Regional Climate Model; driven by NOAA's Geophysical Fluid Dynamics Laboratory GCM
- **CGCM3/CRCM**: OURANOS' Canadian Regional Climate Model; driven by CCCma's Third Generation Coupled Global Climate Model.
- **HadCM3/HRM3**: Hadley Centre's Hadley Regional Model; driven by Hadley Centre Coupled Model.

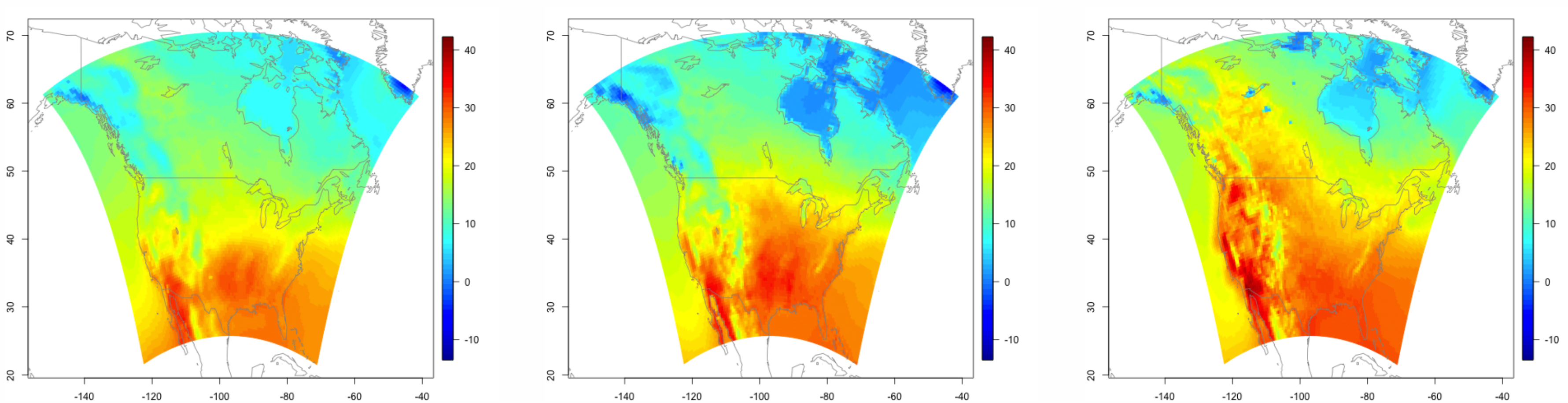
A Preview

RCM3 CRCM HRM3

2000



2070



A Hierarchical Model

Data Model:

$$\mathbf{Y}_{it} \sim \mathcal{N}\left(\mathbf{H}_i \mu_i, \boldsymbol{\Sigma}_{\mathbf{Y}_i}\right), \quad i = 1, 2; t = 1, \ldots, N_i$$

$$\mathbf{Z}^0_{it} \sim \mathcal{N}\left(\mu^0_i, \boldsymbol{\Sigma}_{\mathbf{Z}^0_i}\right), \quad i = 1, 2, 3; t = 1, \ldots, 30$$

$$\mathbf{Z}^1_{it} \sim \mathcal{N}\left(\mu^1_i, \boldsymbol{\Sigma}_{\mathbf{Z}^1_i}\right), \quad i = 1, 2, 3; t = 1, \ldots, 30$$

Process Model:

$$\boldsymbol{\mu}_i \sim \mathcal{N}\left(\boldsymbol{\mu}, \boldsymbol{\Sigma}_{\boldsymbol{\mu}_i}\right), \quad i = 1, 2$$

$$\boldsymbol{\mu}^0_i \sim \mathcal{N}\left(\boldsymbol{\mu}, \boldsymbol{\Sigma}_{\boldsymbol{\mu}_0}\right), \quad i = 1, 2, 3$$

$$\boldsymbol{\mu}^1_i \sim \mathcal{N}\left(\boldsymbol{\mu}^0_i + \boldsymbol{\Delta}, \boldsymbol{\Sigma}_{\boldsymbol{\mu}_1}\right), \quad i = 1, 2, 3$$

Prior Model:

$$\boldsymbol{\mu} \sim \mathcal{N}\left(\boldsymbol{\mu}_{\text{NCEP}}, \boldsymbol{\Sigma}_{\boldsymbol{\mu}}\right), \quad \boldsymbol{\Sigma}_{\boldsymbol{\mu}} = \sigma^2_{\boldsymbol{\mu}} \mathbf{I}, \quad \sigma^2_{\boldsymbol{\mu}} >> 0$$

$$\boldsymbol{\Delta} \sim \mathcal{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_{\boldsymbol{\Delta}}\right), \quad \boldsymbol{\Sigma}_{\boldsymbol{\Delta}} = \sigma^2_{\boldsymbol{\Delta}} \mathbf{I}, \quad \sigma^2_{\boldsymbol{\Delta}} >> 0$$

$$
\begin{aligned}
\mathbf{Y}_{it} &= \mathbf{H}_i\,(\boldsymbol{\mu}+\boldsymbol{\alpha}_i)+\boldsymbol{\epsilon}_{it} \\
\mathbf{Z}^0_{it} &= \boldsymbol{\mu}+\boldsymbol{\beta}_i+\boldsymbol{\epsilon}^0_{it} \\
\mathbf{Z}^1_{it} &= \boldsymbol{\mu}+\boldsymbol{\Delta}+\boldsymbol{\gamma}_i+\boldsymbol{\epsilon}^1_{it} \\
&= \boldsymbol{\mu}+\boldsymbol{\Delta}+\boldsymbol{\beta}_i+\boldsymbol{\eta}_i+\boldsymbol{\epsilon}^1_{it}
\end{aligned}
$$

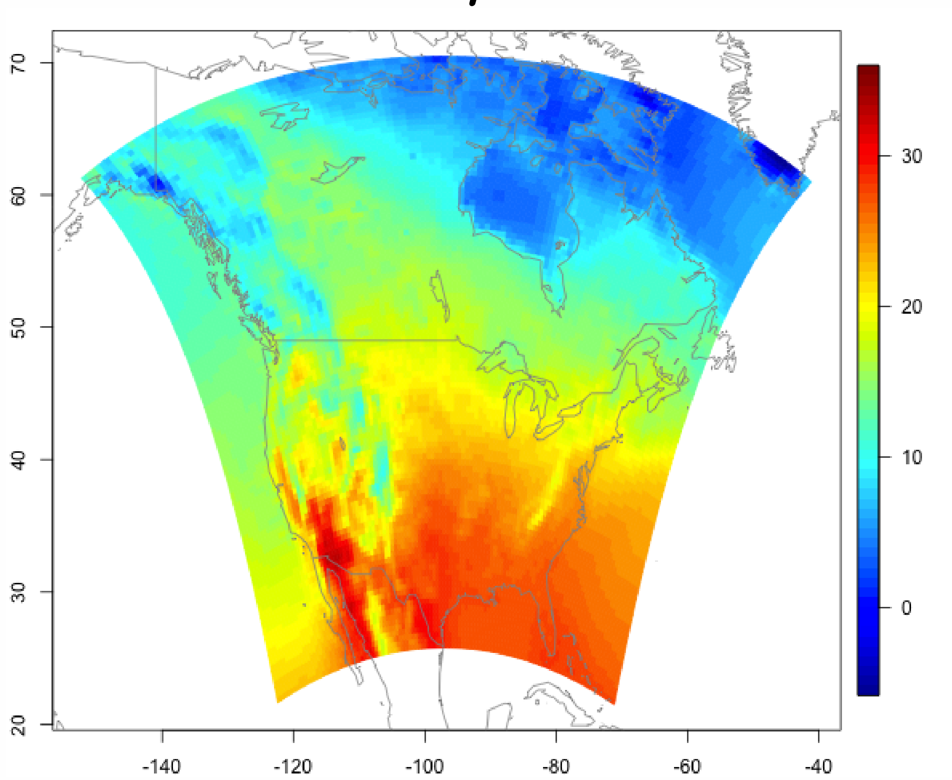
- Each yearly season of a dataset or current run of an RCM has a common "climate" ($\boldsymbol{\mu}$) plus individual model-specific deviations ($\boldsymbol{\alpha}_i/\boldsymbol{\beta}_i$) plus year-to-year variation ($\boldsymbol{\epsilon}_{it}/\boldsymbol{\epsilon}^0_{it}$).

- Each yearly season of a future run of an RCM has a common "climate" ($\boldsymbol{\mu}$) plus a common deviation or change ($\boldsymbol{\Delta}$), plus individual model-specific deviations ($\boldsymbol{\gamma}_i$), plus year-to-year variation ($\boldsymbol{\epsilon}^1_{it}$).

- Note that $\boldsymbol{\gamma}_i$ can be thought of as a model-specific deviation plus an interaction.

Posterior Mean Fields (Current)

μ

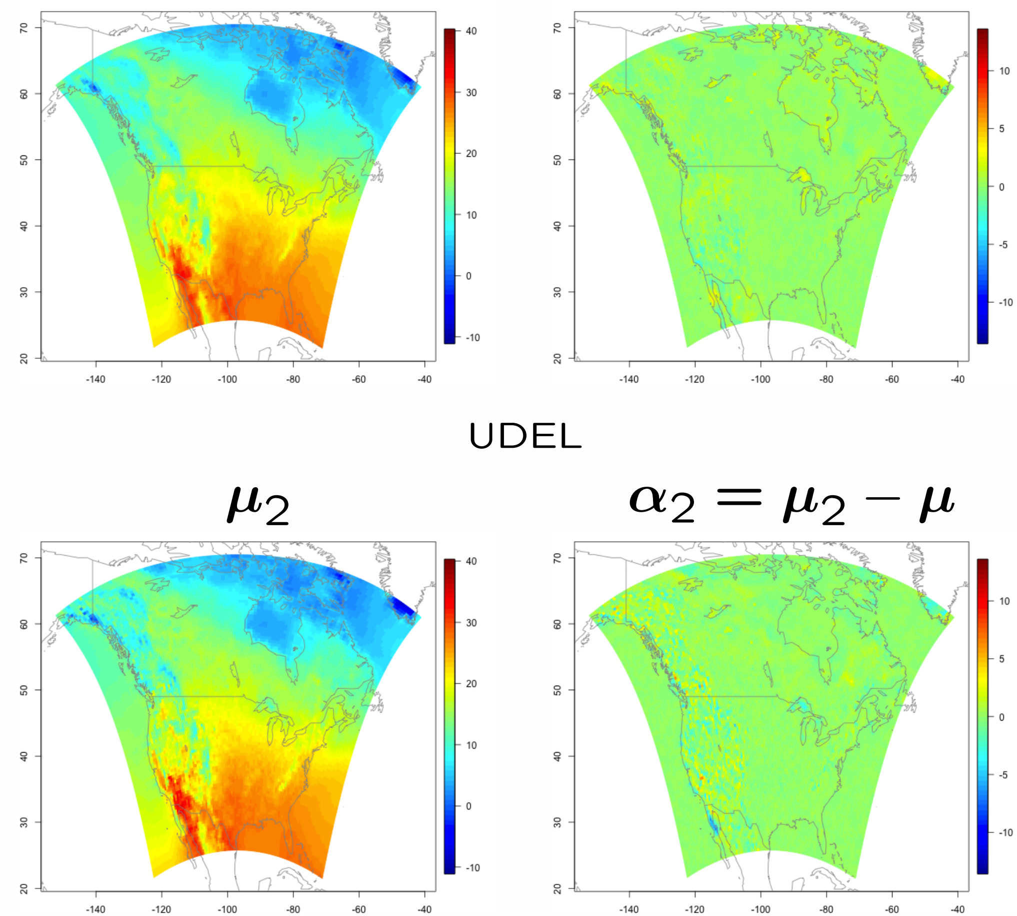


CRU

μ_1 $\qquad$ $\alpha_1 = \mu_1 - \mu$

UDEL

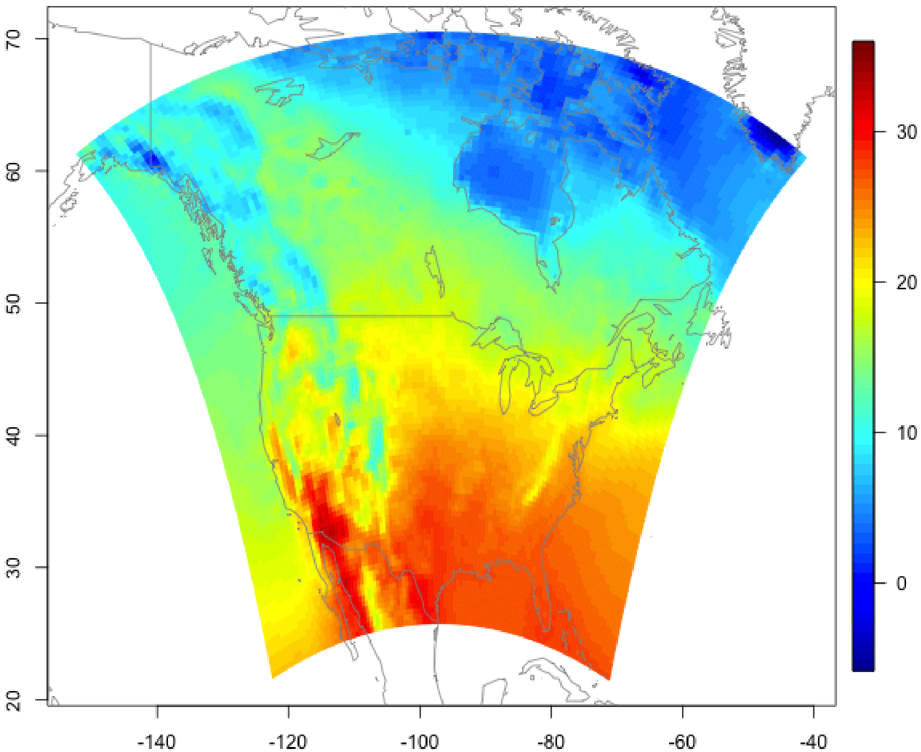
μ_2 $\qquad$ $\alpha_2 = \mu_2 - \mu$



Differences in observational datasets.

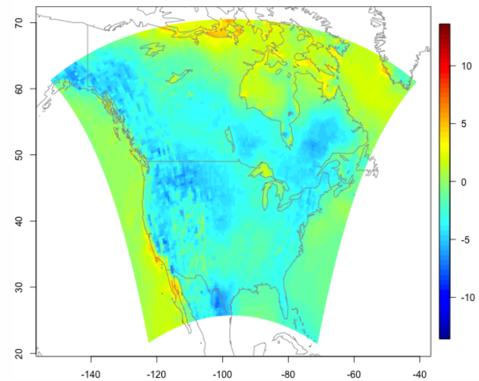
Posterior Mean Fields (Current)

μ



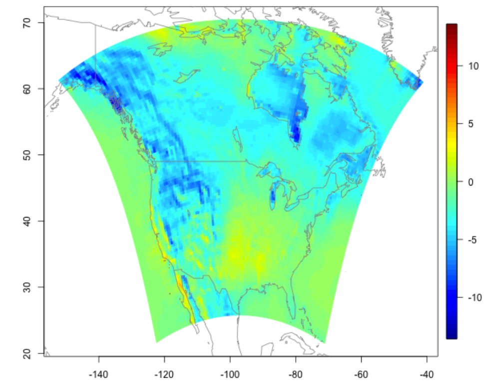
RCM3

$\beta_1 = \mu_1^0 - \mu$



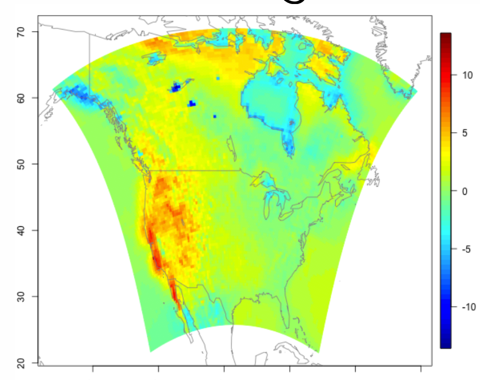
CRCM

$\beta_2 = \mu_2^0 - \mu$



HRM3

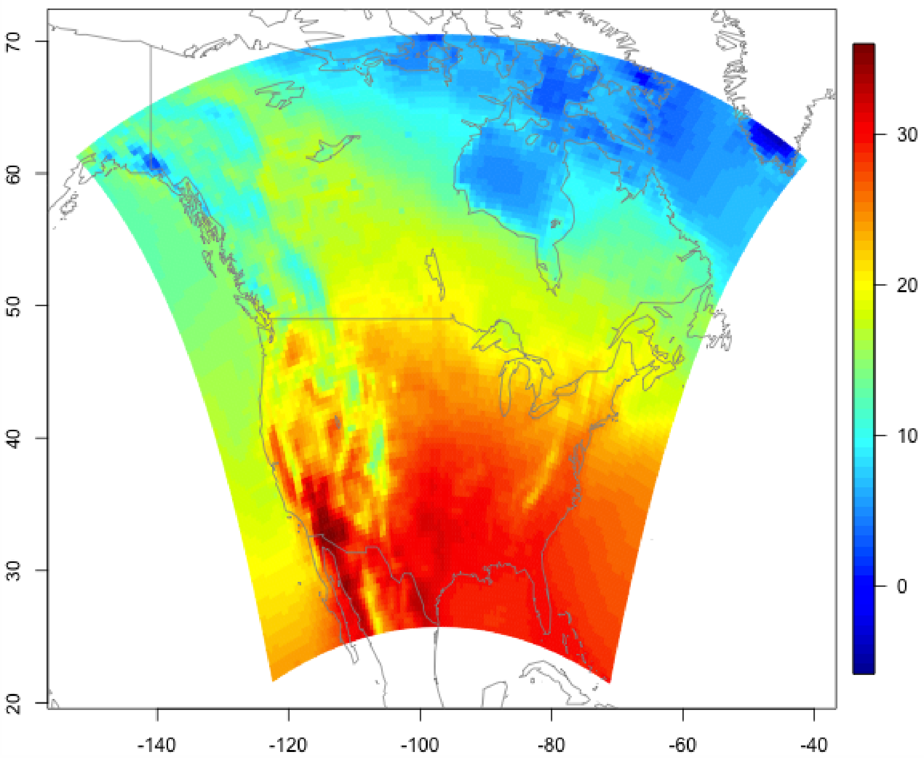
$\beta_3 = \mu_3^0 - \mu$



Differences in current runs.

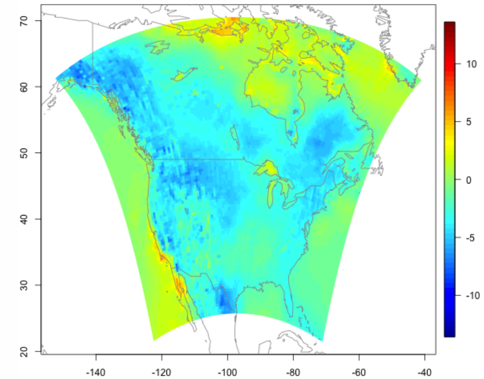
Posterior Mean Fields (Future)

$\boldsymbol{\mu}^1$



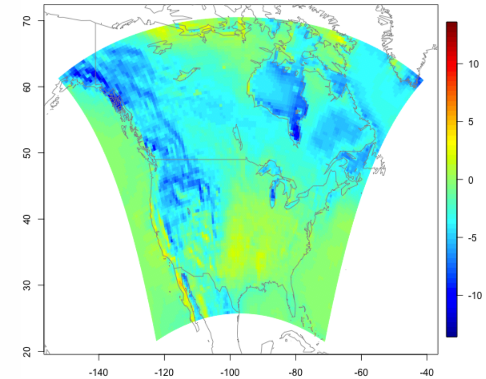
RCM3

$\gamma_1 = \boldsymbol{\mu}_1^1 - \boldsymbol{\mu}^1$



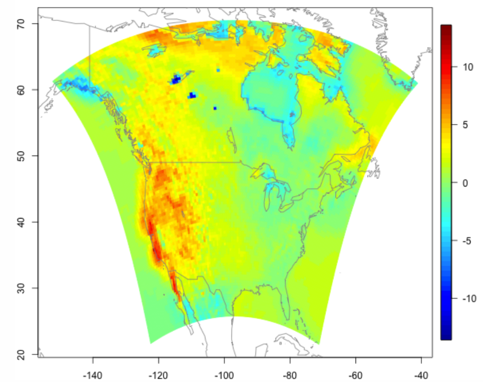
CRCM

$\gamma_2 = \boldsymbol{\mu}_2^1 - \boldsymbol{\mu}^1$



HRM3

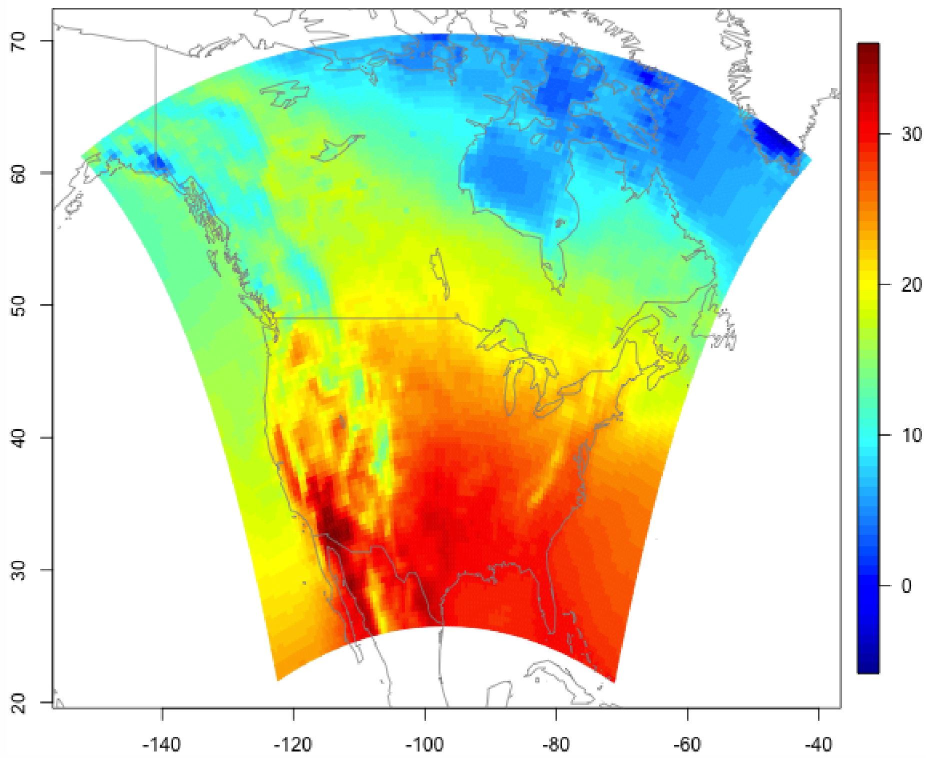
$\gamma_3 = \boldsymbol{\mu}_3^1 - \boldsymbol{\mu}^1$



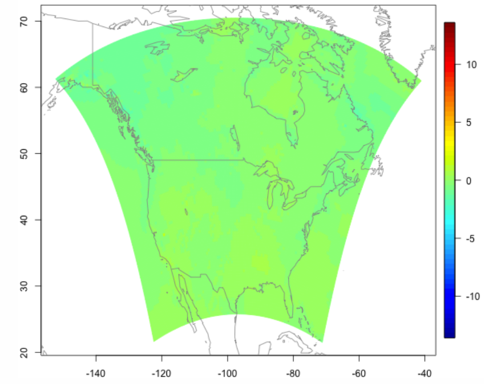
Differences in future runs.

Posterior Mean Fields (Future)

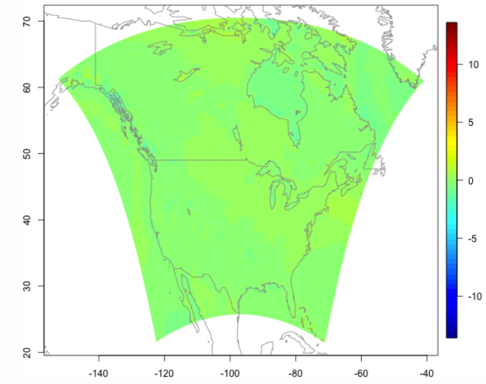
μ^1



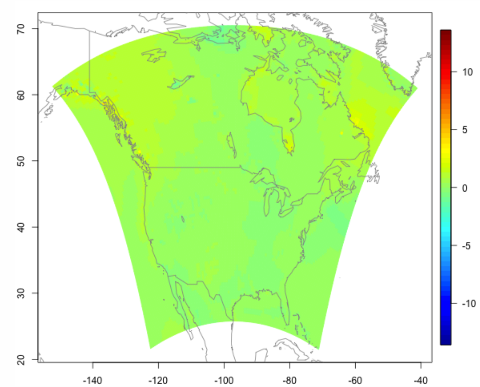
η_1 (RCM3)



η_2 (CRCM)

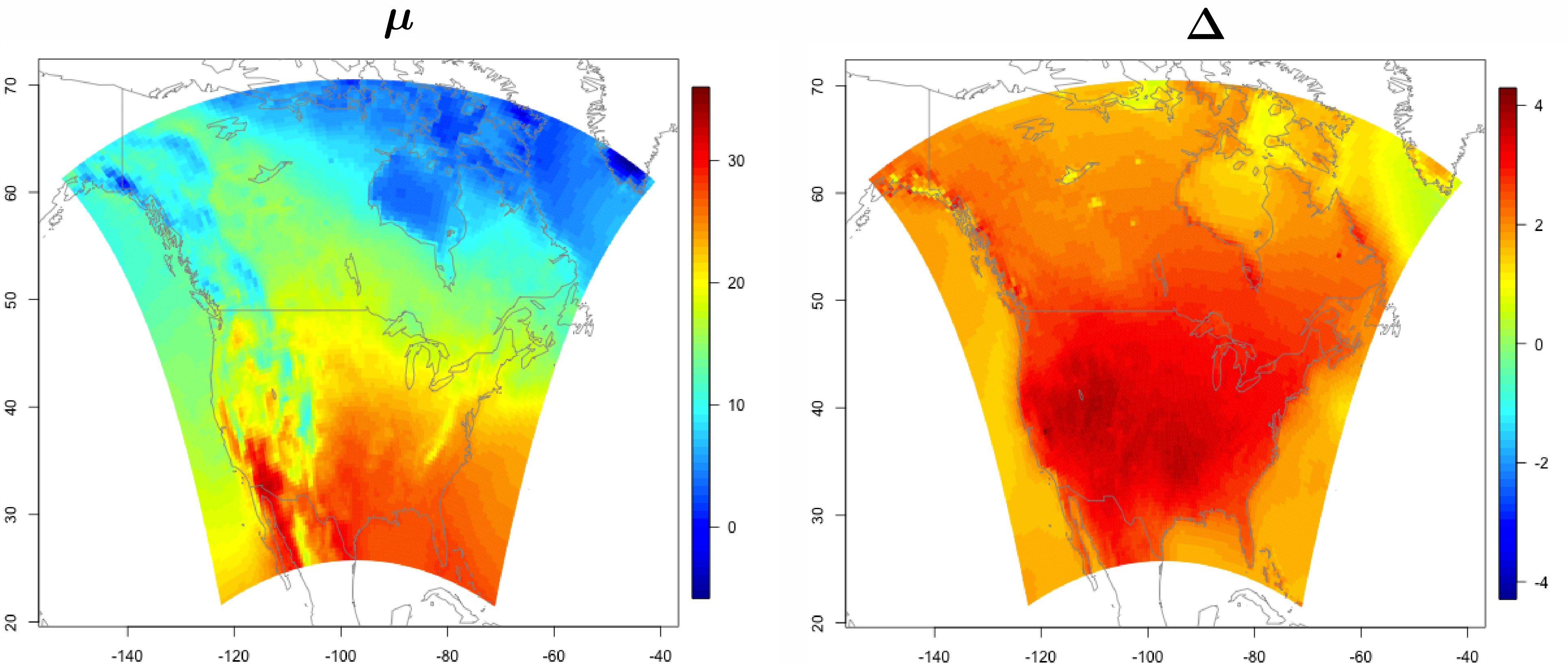


η_3 (HRM3)



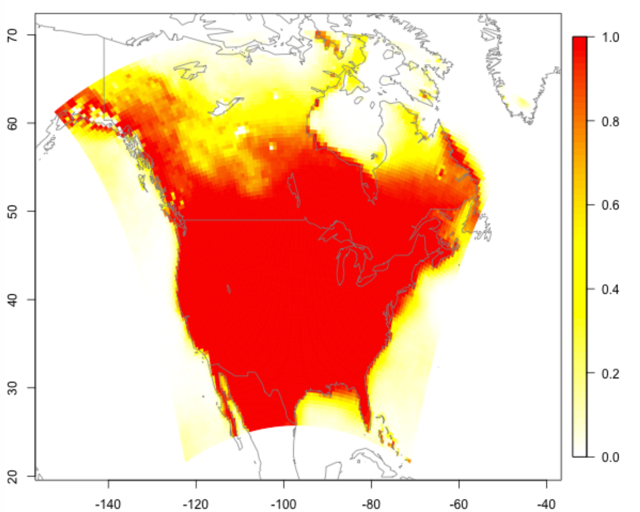
Interactions - RCMs responding to scenario forcing in different ways.

Posterior Mean Fields

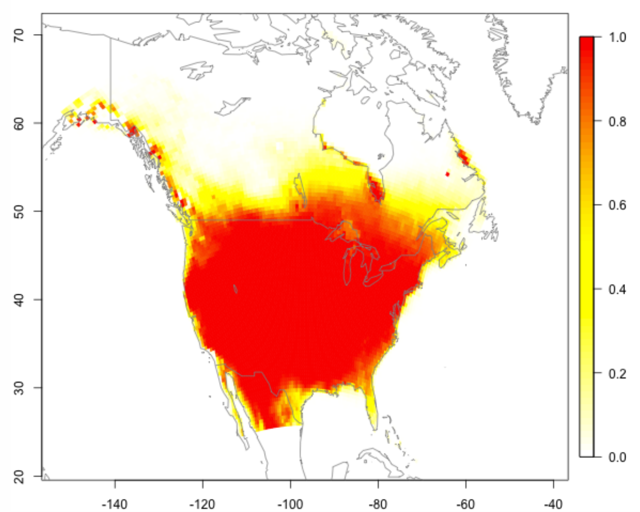


$\triangle$ Uncertainty

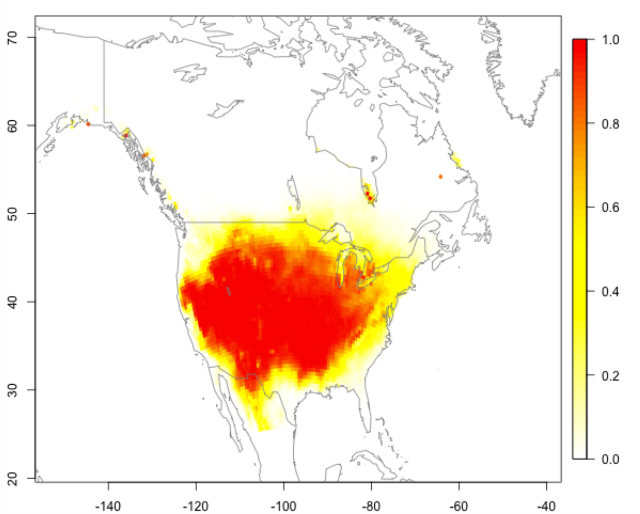
$P[\Delta > 2.0]$



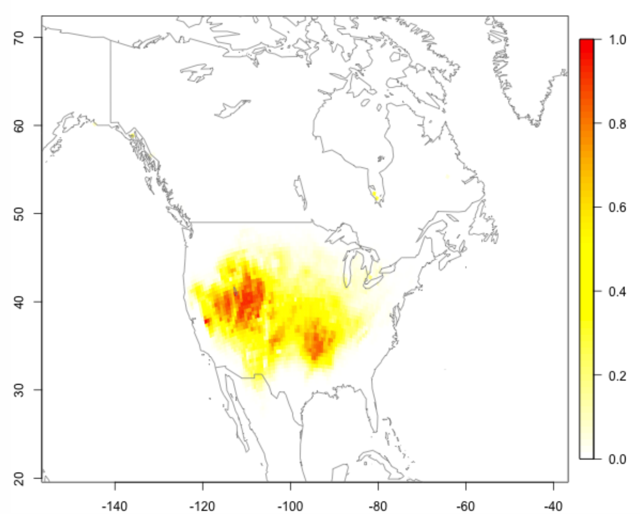
$P[\Delta > 2.5]$



$P[\Delta > 3.0]$

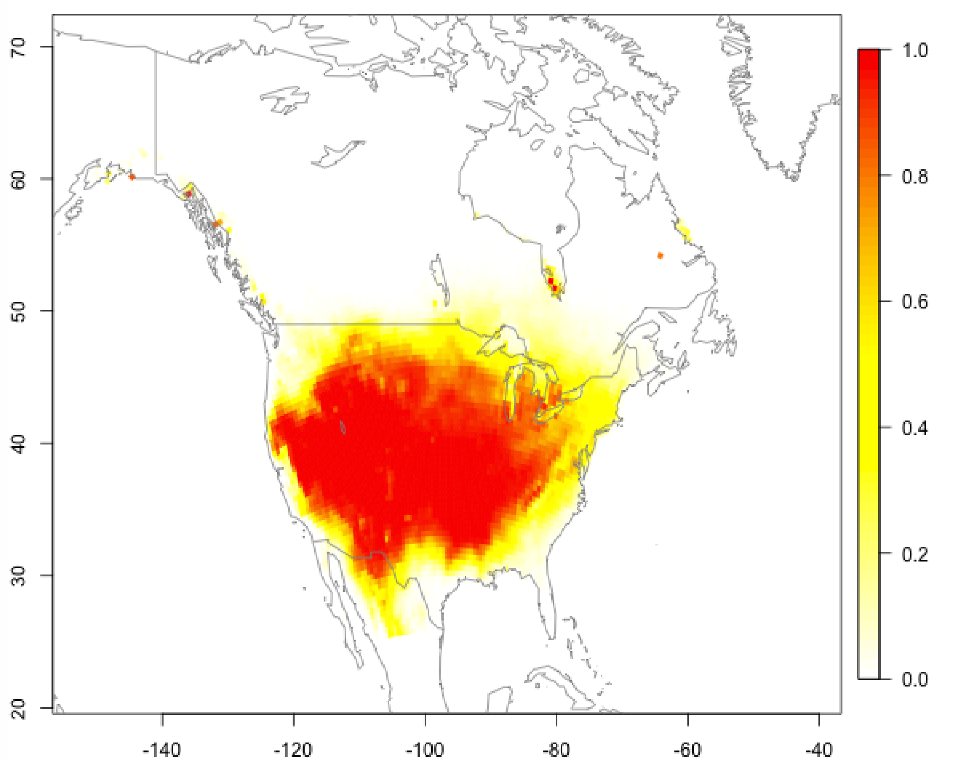


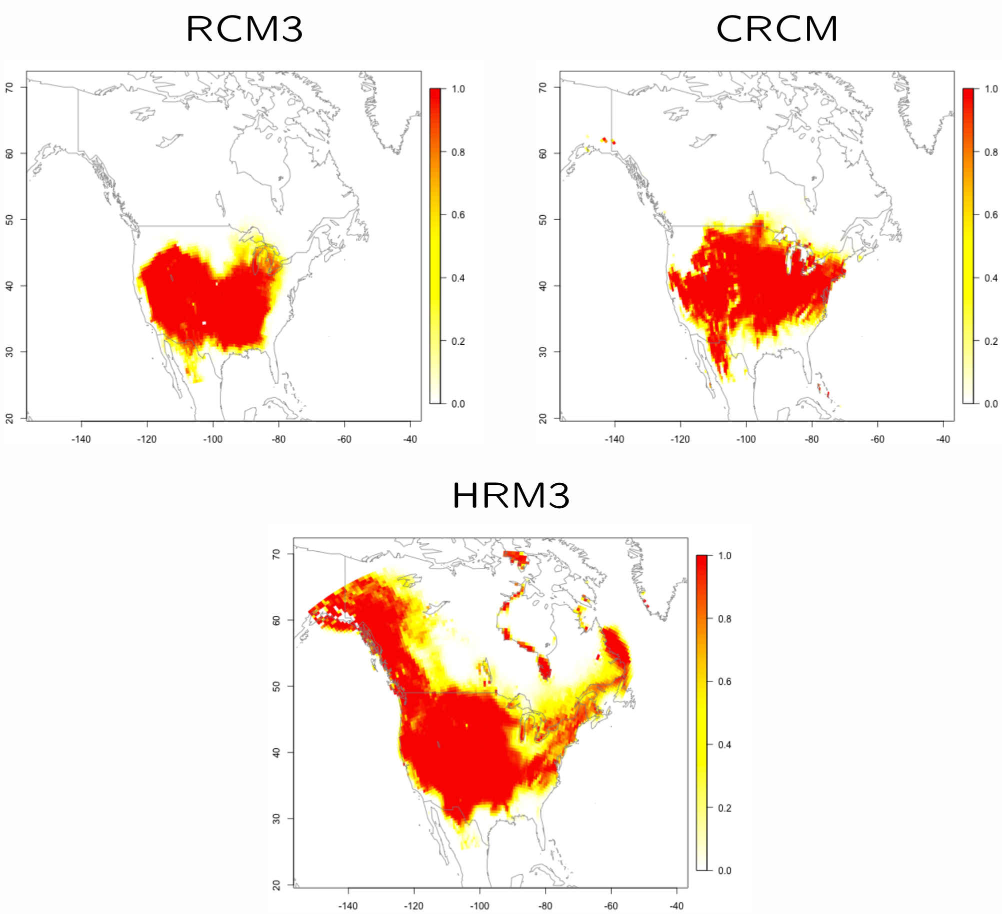
$P[\Delta > 3.5]$



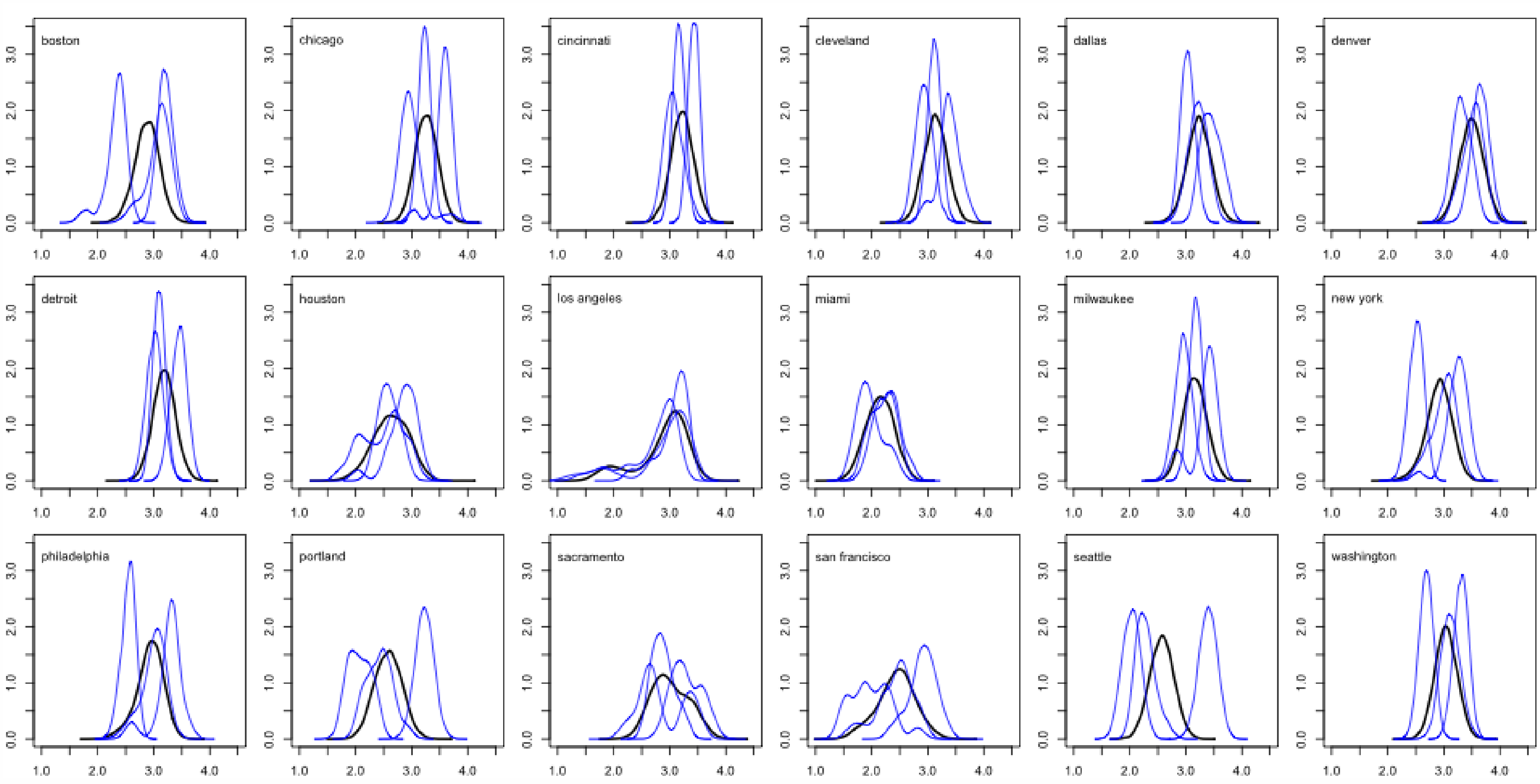
Δ Uncertainty

$P[\Delta > 3]$

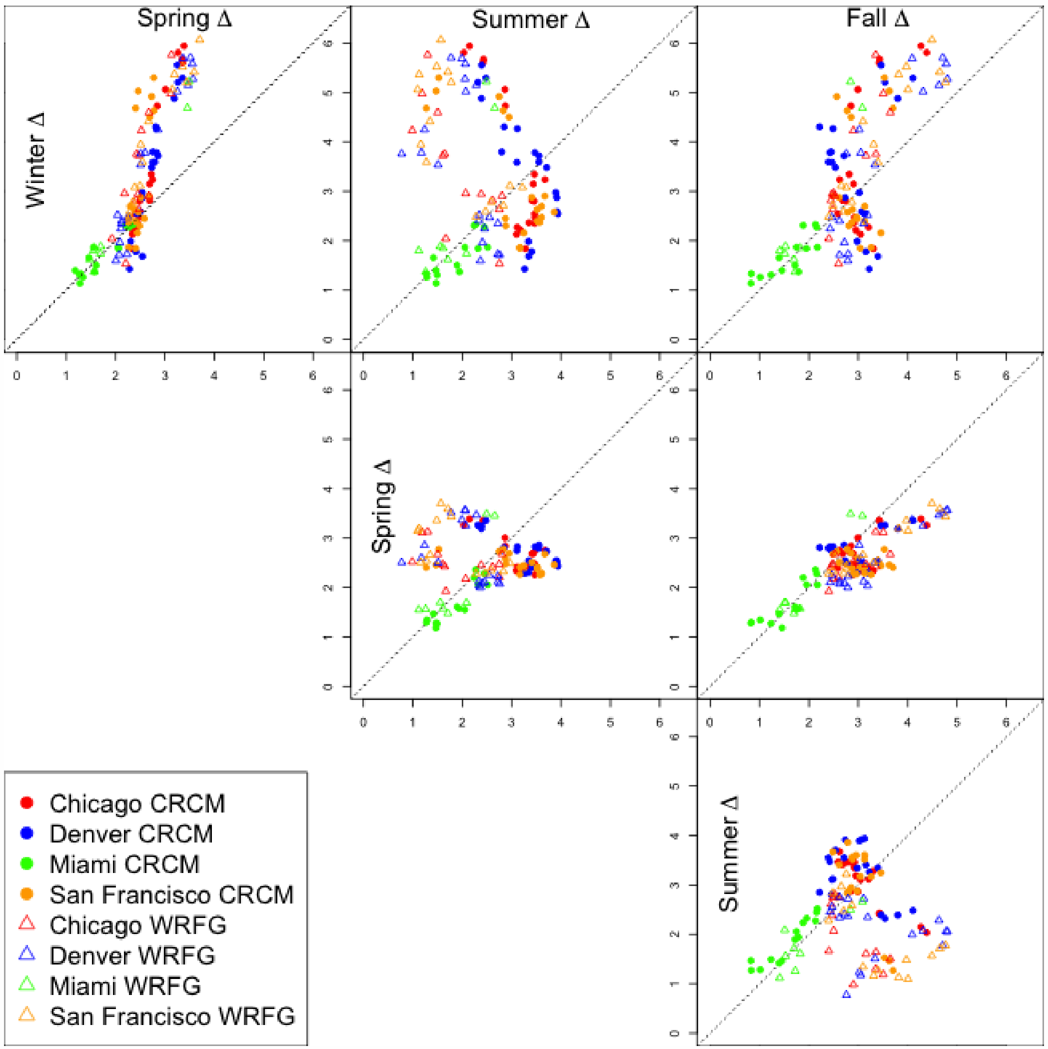




△ Uncertainty



Other Topics: Multivariate



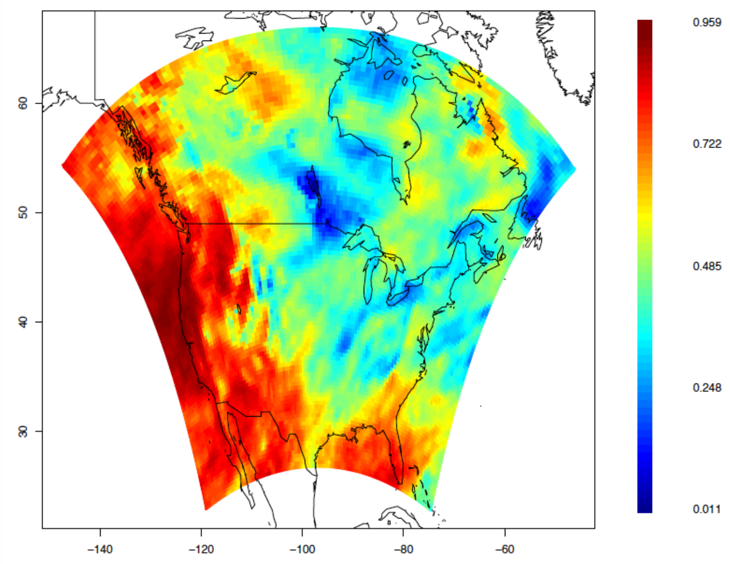
Seasonal temperature changes for selected CMSAs based on a multivariate spatial model. Extensions focused on representing a profile for whole year.

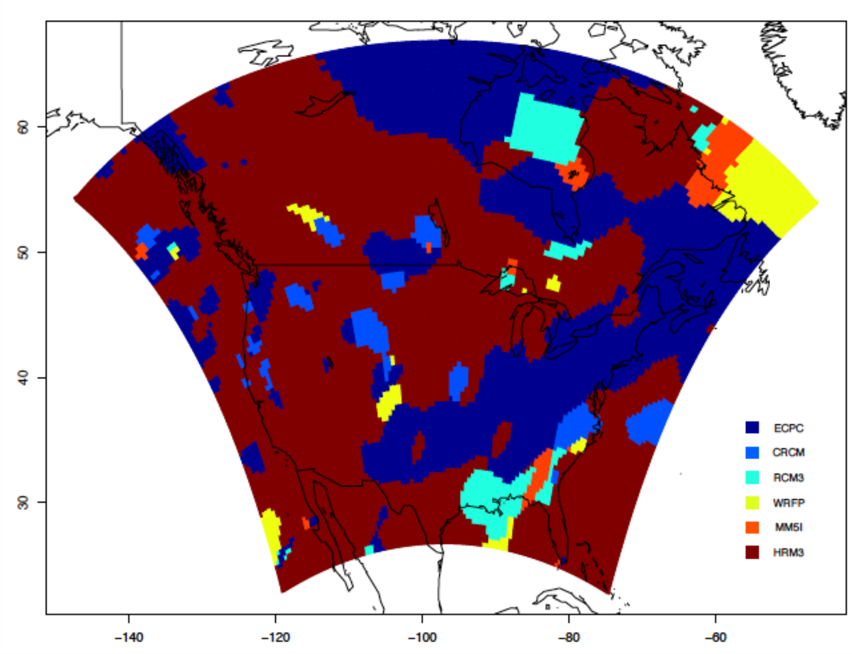
With T. Greasby, NCAR.

Other Topics: Correlated Models

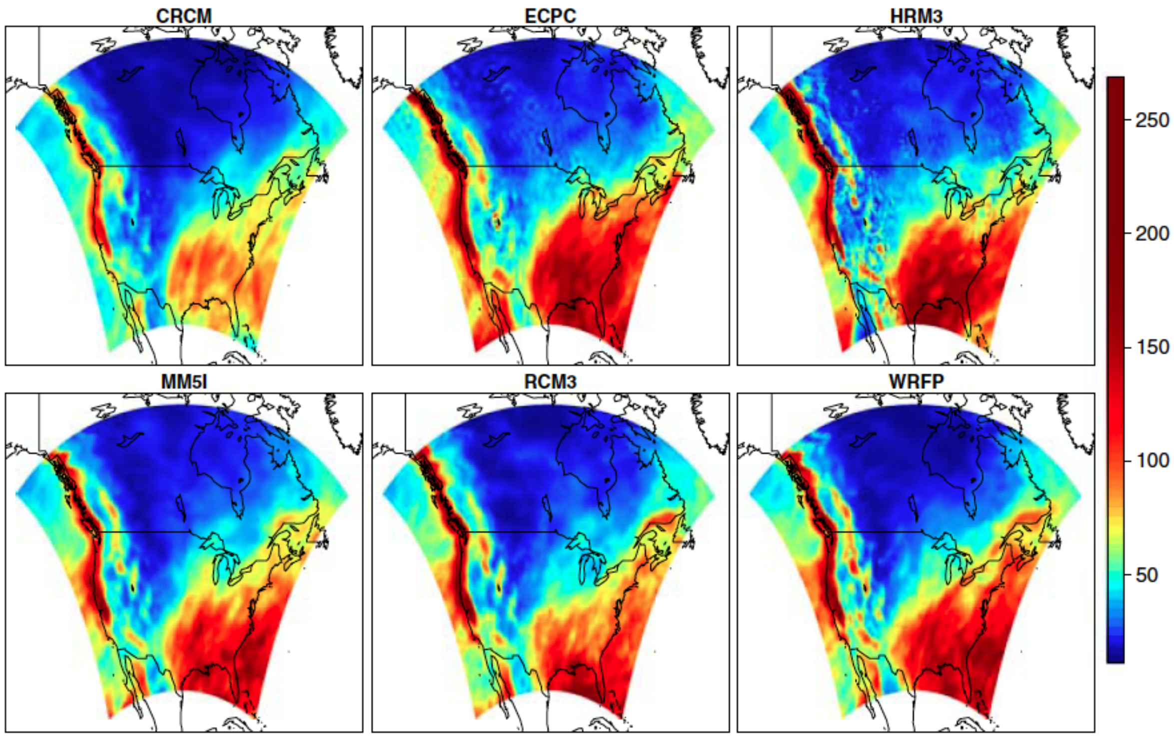
A fundamental concern with combining model output from different models is model-to-model correlations. Latent variable modeling provides a unique view into these correlations and how to combine models.

With W. Christensen, BYU.



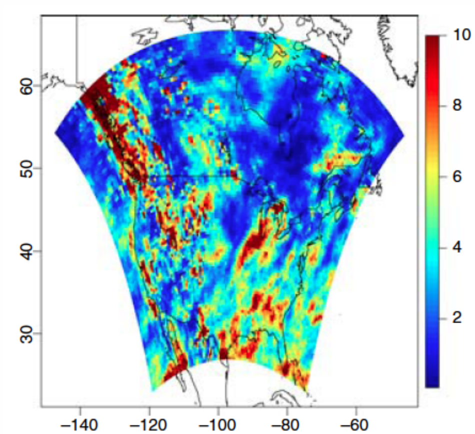


Other Topics: Extremes



100-year return levels for winter precipitation based on a hierarchical Bayesian spatial model based on the GEV representation for extremes.

With D. Cooley, CSU.



Questions?

Many opportunities for visits and collaboration: ASP, RSVP, SIParCs, GSP, IMAGe, Theme-of-the-Year,...

`ssain@ucar.edu`
`http://www.image.ucar.edu/~ssain`

Thank You!

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