Assessing Uncertainty in Regional Climate Experiments

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Goals

- Describe the distribution of model output.

- Understanding sources of variation.
  - GCM, RCM, GCM×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 = “Climate” + Spatially correlated residual/“internal response model variability”

\[ \mu_{ijt}(s) = \mu(s) + i\alpha(s) + j\beta(s) + ij(\alpha\beta)(s) + \gamma t, \]

= Common + RCM + GCM + Interaction + Time

- \( i, j = -1, 1 \) (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

Model Year
A Functional ANOVA Model

- A single-factor ANOVA model:

\[ Z_{it}(s) = \mu(s) + h_i(s) + \epsilon_{it}(s) \]

\[ = \text{Common} + \text{RCM} + \text{Error} \]

- 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 \( h_i(s), \text{ Posterior Means} \)
Results (A Posterior Draw)

$h_i(s)$

Residuals

Model
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:

\[ Z_{it}(s) = \mu(s) + h_i(s) + \epsilon_{it}(s) \]

\[ = \text{Common} + \text{RCM} + \text{Error} \]

- The key difference is the prior on \( h_1(s), h_2(s), h_3(s) \) is Gaussian with mean 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, $\Sigma_h$, 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 $w$ that minimizes the variance of $\sum_i w_i h_i(s)$ is the solution to

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

- Other ideas: maximize variance (principal components), etc.
A Proposal for Combining Model Output

\[ \hat{\Sigma}_h = \begin{pmatrix} 2.05 & 0.66 & 0.37 \\ 0.94 & 0.50 & \end{pmatrix} \]

\[ \hat{w} = \begin{pmatrix} 0.14 \\ 0.54 \\ 0.32 \end{pmatrix} \]
Extremes

- Spatial scaling of return levels.
- Comparing spatial distributions of extremes.
Questions?

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