Performance-based multimodel probabilistic climate change scenarios

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• Goal: Production of regional climate outlooks for the coming century
• Initial focus: Evolution of mean regional temperatures; eventually continuing with variability, precipitation…
• Methodology: Multimodel ensemble, combined in the framework of a linear Bayesian probability model
  – Coefficients derived by fitting to simulations of 20th-century climate (20C3M runs from IPCC AR4)
  – Bayesian estimation employed, in keeping with probabilistic framework
  – Model formulations with varying degrees of complexity explored
Regional definitions as in the IPCC SAR...
AOGCMs may exhibit significant regional temperature biases

Central American sector (CAM), raw temperature series

Anomalies (relative to each model’s 1961-1990 climatology)
Incoherence not limited to interannual variations
Mean regional temperatures are simulated with more fidelity than are regional temperature trends.
Probability model structures compared

- A: $Y_{ik} \sim N(\mu_{ik}, \sigma^2)$ (variance of Y is uniform...)
- B: $Y_{ik} \sim N(\mu_{ik}, \sigma_k^2)$ (or regionally dependent...)
- C: $\beta_{jk} \sim MVN(\mu_{\beta}^{(j)}, \Sigma)$ (cov(\beta) modeled explicitly)

The last of these represents a multilevel, or hierarchical structure:

1: Regional series of obs and simulations
2: Global structure for parent distribution of $\beta$

- Priors are “diffuse” (i.e. non-informative) with the qualified exception of $\Sigma$, for which a scale matrix must be specified to at least an order of magnitude.
Probability model C as a graph (DAG)

- $\beta_{jk}$
- $\mu_{ik}$
- $\sigma_k^2$
- $Y_{ik}$
- $\beta_k^0$
- $x_{ijk}$
- $\sum_\beta$
- $R_\beta$
- regions k
- models j
- years i
Regional input covariance exhibits varying degrees of structure…
Some model comparison statistics (mean annual temperature)

<table>
<thead>
<tr>
<th>Model</th>
<th>Dbar</th>
<th>Dhat</th>
<th>DIC</th>
<th>pD</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>2532</td>
<td>2217</td>
<td>2847</td>
<td>315.3</td>
</tr>
<tr>
<td>B</td>
<td>1768</td>
<td>1429</td>
<td>2108</td>
<td>339.4</td>
</tr>
<tr>
<td>C</td>
<td>1735</td>
<td>1505</td>
<td>1964</td>
<td>229.8</td>
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</table>

Dbar: Mean of the posterior deviance: \(\text{mean}(-2 \log(p(y|\theta)))\)

Dhat: Posterior deviance computed from mean \(\theta\): \(-2 \log(p|(y|\theta_{\text{bar}}))\)


pD: Effective number of parameters in the model.

Conclusion: Model B a lot better than A; C a little better than B
Some fitted series…

**ALA ann: Obs, unweighted model mean, fitted values**

<table>
<thead>
<tr>
<th>Year</th>
<th>T anom</th>
<th>obs</th>
<th>fit</th>
<th>mean</th>
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</thead>
<tbody>
<tr>
<td>1900</td>
<td>−0.50</td>
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<td></td>
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<tr>
<td>1920</td>
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<td></td>
<td></td>
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<tr>
<td>1940</td>
<td>0.5</td>
<td></td>
<td></td>
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<tr>
<td>1960</td>
<td>1.0</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>1980</td>
<td>−0.4</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>2000</td>
<td>0.6</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

**SEA ann: Obs, unweighted model mean, fitted values**

<table>
<thead>
<tr>
<th>Year</th>
<th>T anom</th>
<th>obs</th>
<th>fit</th>
<th>mean</th>
</tr>
</thead>
<tbody>
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<td>1900</td>
<td>−0.4</td>
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<tr>
<td>1920</td>
<td>−0.2</td>
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<tr>
<td>1940</td>
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<td>0.6</td>
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</tbody>
</table>

**Model A**

**Model B**
Fitted series, cont'd

ALA ann: Obs, unweighted model mean, fitted values

Sea ann: Obs, unweighted model mean, fitted values

Model B

Model C
Model structure and estimation of $\beta_{jk}$

Distributions of beta

Variance distributions for beta
Prior distribution of \( \text{cov}(\beta) \) is “imprinted” by the data.

Prior correlation for \( \beta \):
A blank slate.

Posterior correlation:
(Weak) structure is present.
Cross-validation

- Computed with respect to decadal means
- “Leave-10-out”, with model fitted to remaining data. Nine values / region

Comparison over all regions

<table>
<thead>
<tr>
<th>Season</th>
<th>F</th>
<th>P (ν₁=ν₂=198)</th>
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<tbody>
<tr>
<td>Ann</td>
<td>4.38</td>
<td>1.16E-23</td>
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<tr>
<td>DJF</td>
<td>2.58</td>
<td>3.05E-11</td>
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<tr>
<td>JJA</td>
<td>3.32</td>
<td>1.22E-16</td>
</tr>
</tbody>
</table>

Region by region (annual mean)
Coefficients are applied to the SRES scenario simulations to generate the final temperature projections.

- ALA annual temperature change for SRES a2
- NAS annual temperature change for SRES a2
- CAM annual temperature change for SRES a2
- SEA annual temperature change for SRES a2
Stationarity assumptions cannot be ignored…
Summary

• Regional temperature projections are generated for the 21st century
• Based on IPCC 20C3M experiments, SRES scenario simulations
• AOGCM outputs combined in the framework of a Bayesian hierarchical linear model of limited complexity
• Relaxation of constraint that \( \sum_j \beta_{jk} = 1 \) allows resultant to “escape the envelope” of the underlying simulations
• Projections appear to be an improvement over the unweighted mean of the contributing AOGCMs. This improvement is greatest for the annual mean, decreasing but still present for DJF and JJA
• There is an implicit assumption of stationarity, and with this comes the unavoidable responsibility of choosing good (or at least defensible) assumptions in model building. So what else is new?