NMME Precipitation and Temperature Forecasts for the Continental United States and Europe

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## NMME Models

<table>
<thead>
<tr>
<th>Model name</th>
<th>Modeling center</th>
<th>Available period</th>
<th>Ensemble size</th>
<th>Lead times</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCSM3</td>
<td>NCAR/ COLA/ RSMAS</td>
<td>1982-present</td>
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<td>0.5-11.5</td>
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<td>CMC</td>
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<td>NCEP</td>
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<td>NASA</td>
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<td>GFDL2.1</td>
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<td>FLORb01</td>
<td>GFDL</td>
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</table>
Decomposition of the potential skill

(a) High Quality

(b) Unconditional Bias

(c) Conditional Bias

(d) Poor Association
Decomposition of the potential skill (2)

\[ SS = \rho_{fx}^2 - \left[ \rho_{fx} - \frac{\sigma_f}{\sigma_x} \right]^2 + \left[ \frac{\mu_f - \mu_x}{\sigma_x} \right]^2 = PS - SREL - SME \]

- \( \rho_{fx} \) = correlation coefficient between observations and forecasts
- \( \mu_f \) and \( \mu_x \) = forecast and observation means
- \( \sigma_f \) and \( \sigma_x \) = forecast and observation standard deviations

- PS = Potential skill
- SREL = Slope reliability factor (it quantifies conditional biases)
- SME = Standardized mean error (it quantifies unconditional biases)

The PS decreases quickly after the shortest lead time; there are large unconditional biases (temperature).
The PS decreases quickly after the shortest lead time; there are large unconditional biases (precipitation)
The droughts tend to be better forecasted than the floods.
Multi-model averaging

Development of a multi-model averaging procedure to increase the forecast skill of these models. The technique is based on Bayesian updating, and it assigns weights that define the likelihood of historical outcomes $y_i$ ($i=1, \ldots, N$) given the forecast $\theta$.

$$w_i = \frac{f_{\theta}(\theta | y_i)}{\sum_{j=1}^{N} f_{\theta}(\theta | y_j)}$$

We compare five approaches to multi-model averaging approaches based on:

- the equal-weighted eight-single-model ensemble forecasts (EW-8);
- the Bayesian-weighted single-model ensemble forecasts (BMA-8);
- the Bayesian-weighted model members (BMA-94);
- the Bayesian-weighted principal components of the single-model ensemble forecasts (BMA-PCA-8);
- and the Bayesian-weighted principal components of the 94 model members (BMA-PCA-94).
Bayesian updating generally improves the skill (precipitation)
Bayesian updating generally improves the skill (temperature)
Bayesian updating removed unconditional biases but introduced some conditional biases.
Extreme precipitation and temperature events
None of the multi-model approaches can consistently capture the extreme events
Conclusions

• The skill of eight NMME models in forecasting precipitation and temperature across the continental United States and Europe decreases rapidly for increasing lead times.
• The actual skill is predominantly affected by unconditional biases.
• There is no model or merging technique that performs consistently well in forecasting extreme precipitation and temperature events.
• The application of a Bayesian updating method leads to increases in potential skill and reduction in unconditional biases at the expenses of larger conditional biases.
• Accounting for the correlation among GCMs and within the members of the same model does not lead to a significant benefit.

Questions?
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