Meteorological Drought Prediction Using a Multi-Model Ensemble Approach

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Objectives

- To improve drought prediction capability through the use of multi-model ensemble forecasts to support CPC’s Drought Outlook activities.
- To conduct an assessment of SPI predictive skill using NMME retrospective forecasts from 1982 to 2010.

- Funding for this research is supported by CPO MAPP.
<table>
<thead>
<tr>
<th>Model</th>
<th>Hindcast Period</th>
<th>No. of Member</th>
<th>Arrangement of Members</th>
<th>Lead (months)</th>
<th>Model Resolution: Atmosphere</th>
<th>Model Resolution: Ocean</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCEP-CFSv2</td>
<td>1982-2010</td>
<td>24(20)</td>
<td>4 members (0,6,12,18Z) every 5th day</td>
<td>0-9</td>
<td>T126L64</td>
<td>MOM4 L40 0.25 deg Eq</td>
<td>Saha et al. (2010)</td>
</tr>
<tr>
<td>GFDL-CM2.1</td>
<td>1982-2010</td>
<td>10</td>
<td>All 1st of the month 0Z</td>
<td>0-11</td>
<td>2x2.5deg L24</td>
<td>MOM4 L50 0.30 deg Eq</td>
<td>Delworth et al. (2006)</td>
</tr>
<tr>
<td>CMC1-CanCM3</td>
<td>1981-2010</td>
<td>10</td>
<td>All 1st of the month 0Z</td>
<td>0-11</td>
<td>CanAM3 T63L31</td>
<td>CanOM4 L40 0.94 deg Eq</td>
<td>Merryfield et al. (2012)</td>
</tr>
<tr>
<td>CMC2-CanCM4</td>
<td>1981-2010</td>
<td>10</td>
<td>All 1st of the month 0Z</td>
<td>0-11</td>
<td>CanAM4 T63L35</td>
<td>CanOM4 L40 0.94 deg Eq</td>
<td>Merryfield et al. (2012)</td>
</tr>
<tr>
<td>NCAR-CCSM3.0</td>
<td>1982-2010</td>
<td>6</td>
<td>All 1st of the month</td>
<td>0-11</td>
<td>T85L26</td>
<td>POP L40 0.3 deg Eq</td>
<td>Kirtman and Min (2009)</td>
</tr>
<tr>
<td>NASA-GEOS5</td>
<td>1981-2010</td>
<td>11</td>
<td>4 members every 5th days; 7 members on the last day of the previous month</td>
<td>0-9</td>
<td>1x1.25deg L72</td>
<td>MOM4 L40 1/4 deg at Eq</td>
<td>Rienecker et al. (2008)</td>
</tr>
</tbody>
</table>

* Slide is by courtesy of Huug Vandendool, Qin Zhang, and Emily Becker.
SPI Prediction

- The bias correction and spatial downscaling (BCSD) method based on the probability distribution functions was applied to each member and each lead of the P hindcasts.
- The corrected P forecasts were then appended to CPC unified P analysis to form a P time series for computing 3-month and 6-month SPIs (SPI3 and SPI6).

Yoon et al. (2012)
Bias Correction and Spatial Downscaling (BCSD)

- BCSD corrects both the mean and STD of the ensemble hindcasts in the normal space.
- For month M and lead time t, CDF based on model hindcasts, $F_{hnd}(p)$, is computed at each grid point using all ensemble members excluding target year Y.
- Similarly, CDF of the corresponding P analysis, $F_{ana}(p)$, is computed.
- At each grid point, the percentile of $P(Y, t, M)$ is determined according to the CDF of the hindcasts.
- The bias-corrected percentile for target year Y is then obtained from the inverse CDF of the P analysis based on the percentile calculated from the CDF of the hindcasts, that is

$$p_{bc} = F_{ana}^{-1}(F_{hnd}(p))$$
ACC vary among models.
- For Jan, P forecast skill is higher over the Southwest.
- Comparing to other models, NCAR model has lower P forecast skill.
Differences Between w/o BCSD for CFSv2 Jan Fcst

- Differences in ACC are small.
- BCSD improves RMSE.
- For CFSv2, most improvements are over Western U.S. and the Midwest.
ACC of SPI3 for Jan (Month-1 Fcst)

- Small variations among models.
- Model with lower P forecast skill (e.g., NCAR) has lower SPI3 forecast skill.
- High skill is contributed by P observations.
NMME Ensemble forecasts after BCSD have higher skill than those based on persistence.
RMSE of SPI3 (Month-1 Fcst)
Climatology and the interannual variability for the central U.S. in January are low, so skill is higher (Quan et al. 2012).

- Central U.S. has higher skill: Wet regions have higher variability, and rainfall depends on low-level moisture transport, which is more difficult to predict in atmospheric models. The Gulf states, eastern U.S., and the west Coast have lower skill:

Why forecasts skill is different across the U.S.?
Why skill over CA is lower than PNW in Jan?

- Rainfall in California and PNW is influenced by interannual variability, such as ENSO and SSTAs from the North Pacific.

- However, rainfall in California is also influenced by the intraseasonal variability, such as MJO or 22-day waves that are difficult to predict.
Summary

• BCSD improves RMSE, but not ACC.
• P observation is a dominant factor contributing to the SPI forecast skill.
• NMME SPI ensemble forecasts are superior than those based on persistence and individual models.
• NMME SPI6 forecasts are skillful up to four months.
• SPI forecast skill is regionally and seasonally dependent.
• SPI predictive skill at a region corresponds to local rainfall climatology and variability.
• California is difficult to forecast in January because its rainfall is not only influenced by interannual variability (e.g., ENSO) but also intraseasonal variability (e.g., MJO).
Thank you and Questions

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