Background

NOAA SBIR: Probabilistic Subseasonal Weather Forecasts for the Energy & Agriculture Sector

Main Objectives:

- **Optimize** subseasonal forecast skill through ensemble calibration & clustering; pattern recognition/analog forecasts
- **Investigate** CFSv2 & ECMWF to develop a multi-model prediction
- **Implement** an objective confidence scheme based on forecast skill for each relevant variable
- **Support** decision making in the energy and agricultural sectors
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Multi-model framework

Forecast provides:
✧ Useful probabilities for decision making
✧ Qualitative insights into plausible scenarios
✧ No useful information beyond climatology

Schematic of anticipated forecast scheme:

- CFSv2
  - only
- CFSv2 + ECMWF
- MME
- Analog + MM
Evaluation of multi-model forecasts (CFSv2 & ECMWF) in a staged manner:

1) Produce parallel forecasts using CFSv2 & ECMWF
2) Implement a multi-model ensemble, equally weighted
3) Determine the weight of each model based on the relative skills of the two models
## Hindcast Selection for this Study

<table>
<thead>
<tr>
<th>Model</th>
<th>CFSV2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ensemble/day</td>
<td>4</td>
</tr>
<tr>
<td>Initialization</td>
<td>Three times per day*</td>
</tr>
<tr>
<td>Forecast lead time</td>
<td>45 days</td>
</tr>
<tr>
<td>Hindcast period</td>
<td>1999-2010</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>ECMWF</th>
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</thead>
<tbody>
<tr>
<td>Ensemble/day</td>
<td>11</td>
</tr>
<tr>
<td>Initialization</td>
<td>Twice per week (Mo/Thu)</td>
</tr>
<tr>
<td>Forecast lead time</td>
<td>45 days</td>
</tr>
<tr>
<td>Hindcast period</td>
<td>1996-2015*</td>
</tr>
</tbody>
</table>

Saha et al. 2010, 2013  
[http://cfs.ncep.noaa.gov](http://cfs.ncep.noaa.gov)

*20 year hindcast available for each operational forecast cycle
Verification Metrics

• Continuous Rank Probability Score (CRPS):

  \[ \text{CRPS} = 0 \]  – perfect score

  \[
  \text{CRPS} = \int_{-\infty}^{\infty} \left( F(y_i) - H(y_i - y_o) \right)^2 dy
  \]
  \[
  H(y) = 1, \quad y_i \geq y_o
  \]
  \[
  H(y) = 0, \quad y_i < y_o
  \]

• Error-Spread Skill Score (ESS):

  \[ ESS = 1 - \frac{ES_{EPS}}{ES_{clm}} \]
  with \[ ES = \left( s_i^2 - e_i^2 - e_i s_i g_i \right)^2 \]

  \[ ESS = 1 \]  – perfect score
Results

Temperature

Precipitation

[Maps of temperature and precipitation across the United States]
Temperature Results - DJF

- Strong regional dependence
- EC tends to perform better than CFS for most regions
- Useful forecasts up to week 4 for some regions
- Both models have difficulties beyond day 10 for the western regions, with EC performing worst than CFS
Temperature Results - JJA

- Strong regional dependence
- Both models perform worst compared to winter
- Some potential benefits of the multi-model approach
Precipitation Results - DJF

- Strong regional dependence
- Both models perform worst compared to temperature
- Useful forecasts up to week 3 for some regions
Both models perform worst compared to temperature
Useful forecasts up to week 1 for most regions
Challenge - limited data for some regions
Boreal Winter

- MJO (VPM) index using 200 hPa velocity potential instead of OLR, similar to Ventrice et al., 2013
- The VPM index enhances the capability of detection of large-scale tropical convection that is asymmetric about the equator.
• DJF air temperature: Extended prediction skill for some regions when the ECMWF model is initialized during strong MJO Phases 5-7
• No change in prediction skill during JJA (no shown)
Summary

• Overall the EC is more skillful compared to CFSv2
• There is some advantage to using a multi-model approach, but the results vary with season and region

Challenges:
• Using the operational version of the models (larger ensemble size (51/16)) could lead to better results
• Limited amount of forecast to assess the impact of teleconnections (e.g., MJO), especially for precipitation
• Finding the best multi-model solution
• Finding the optimum way to communicate the forecast skill data to end users.