Meteorological Drought Prediction Using a Multi-Model Ensemble Approach

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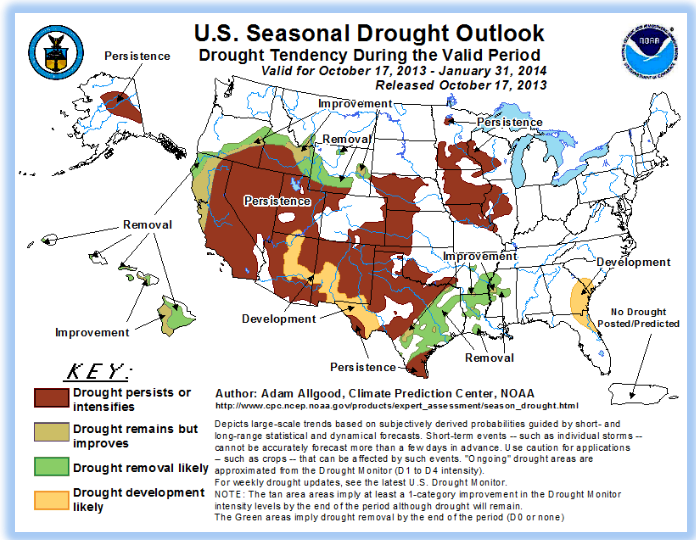
Objectives

- 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.



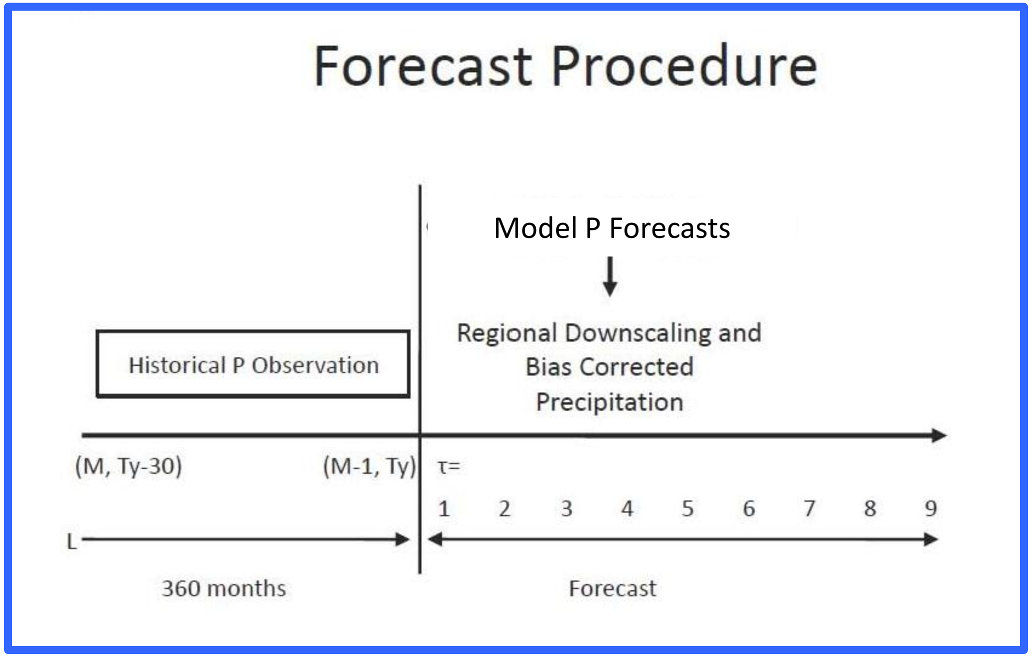
Phrase-II NMME Forecast Providers

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

* 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).



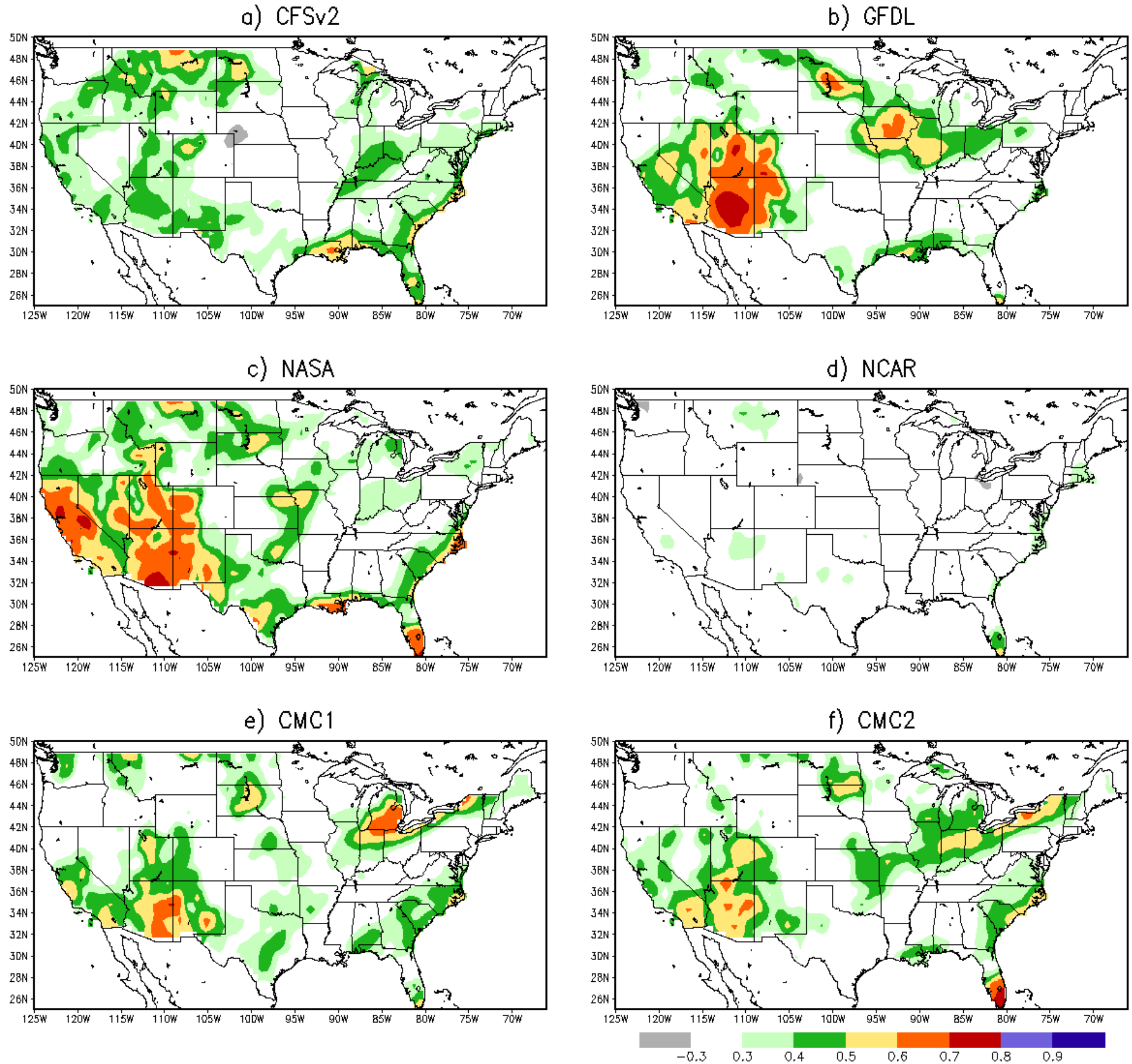
Yoon et al. (2012)

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

$$p_{bc} = F_{ana}^{-1}(F_{hnd}(p))$$

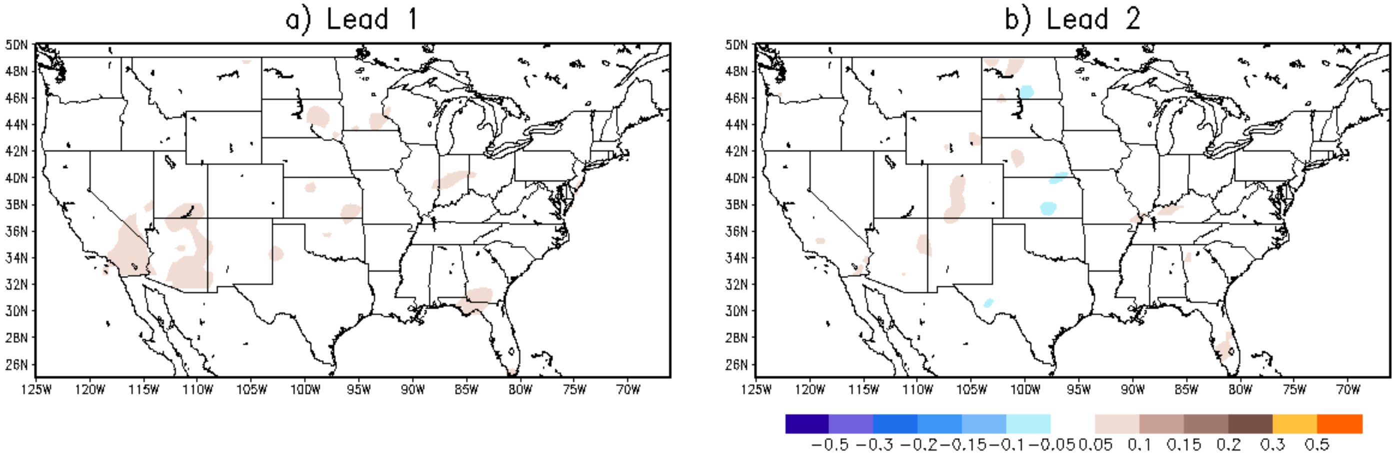
ACC of P Anomaly for Jan (Month-1 Fcst)



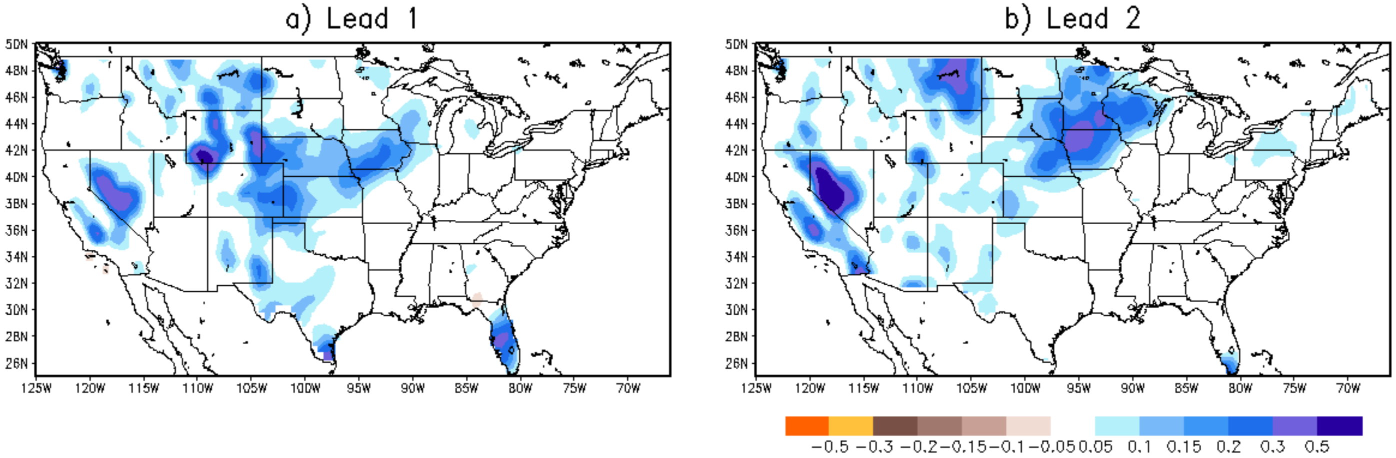
- ACC vary among models.
- For Jan, P forecast skill is higher over the Southwest.
- Comparing to other models, NCAR model has lower P forecast skill.

Differences Between w/o BCSD for CFSv2 Jan Fcst

Panom ACC

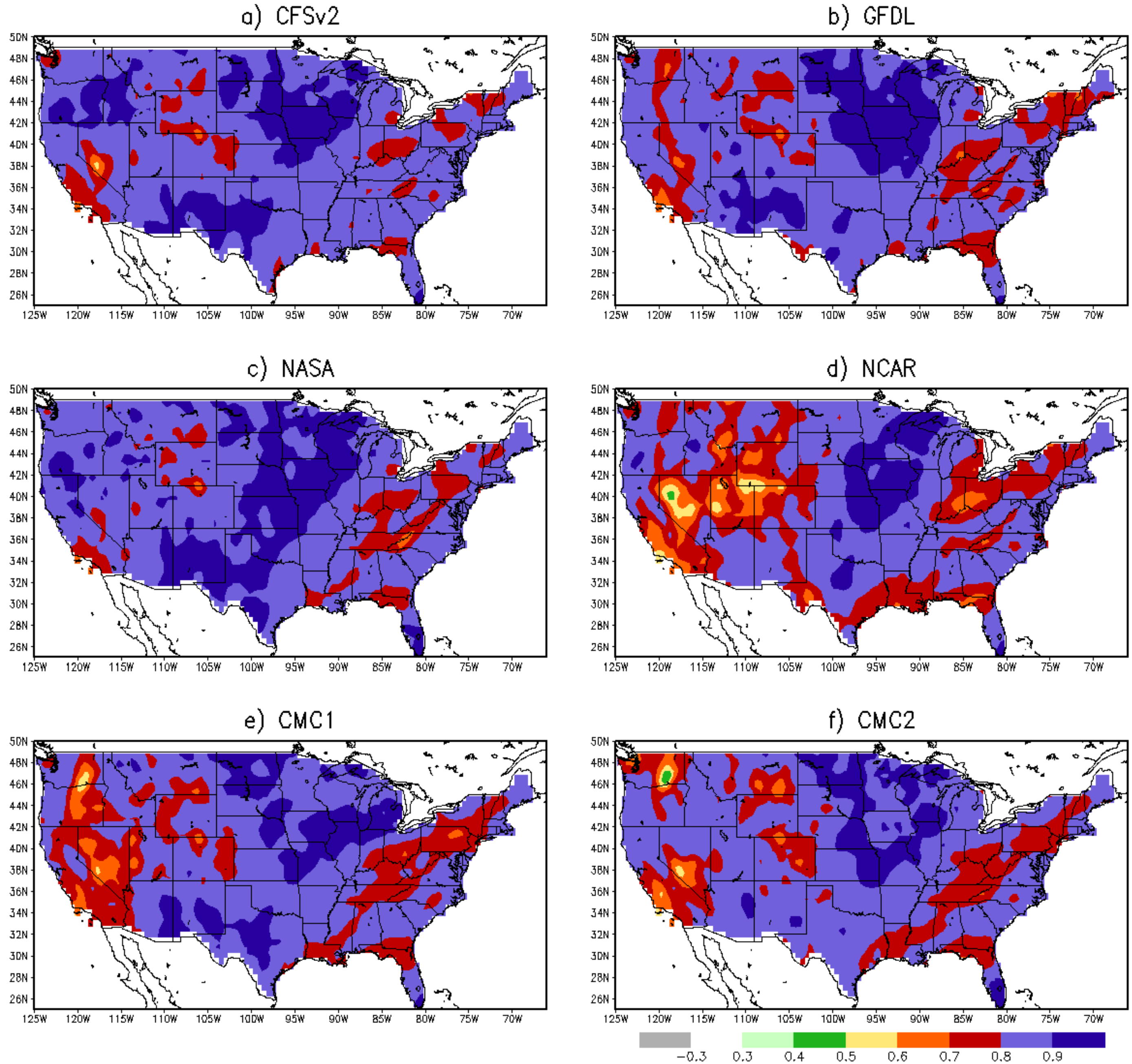


Panom RMSE

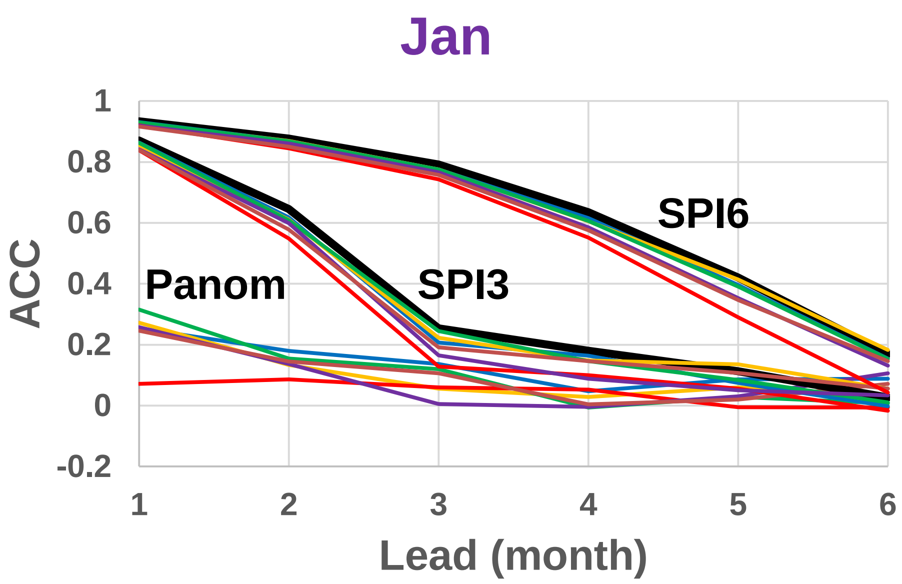


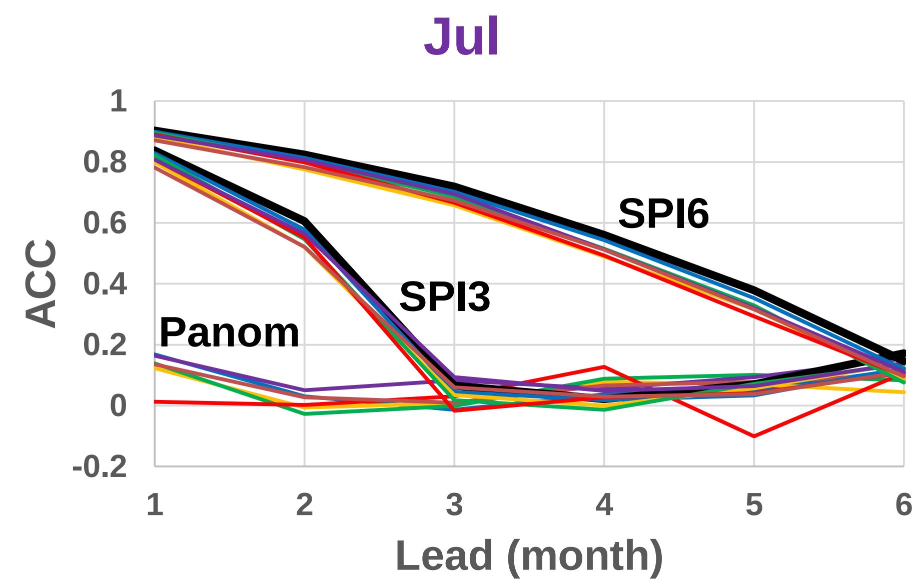
- Differences in ACC are small.
- BCSD improves RMSE.
- For CFSv2, most improvements are over Western U.S. and the Midwest.

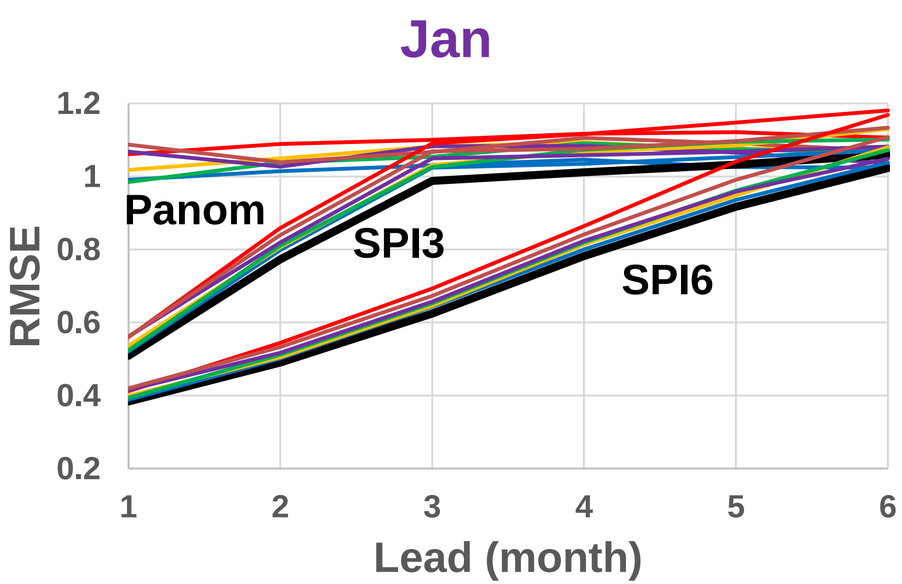
ACC of SPI3 for Jan (Month-1 Fcst)



- 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.


Jan
ACC
Panom
SPI3
SPI6
1
0.8
0.6
0.4
0.2
0
-0.2
1
2
3
4
5
6
Lead (month)


Jul
ACC
Panom
SPI3
SPI6
1
0.8
0.6
0.4
0.2
0
-0.2
1
2
3
4
5
6
Lead (month)


Jan
RMSE
Panom
SPI3
SPI6
1.2
1
0.8
0.6
0.4
0.2
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2
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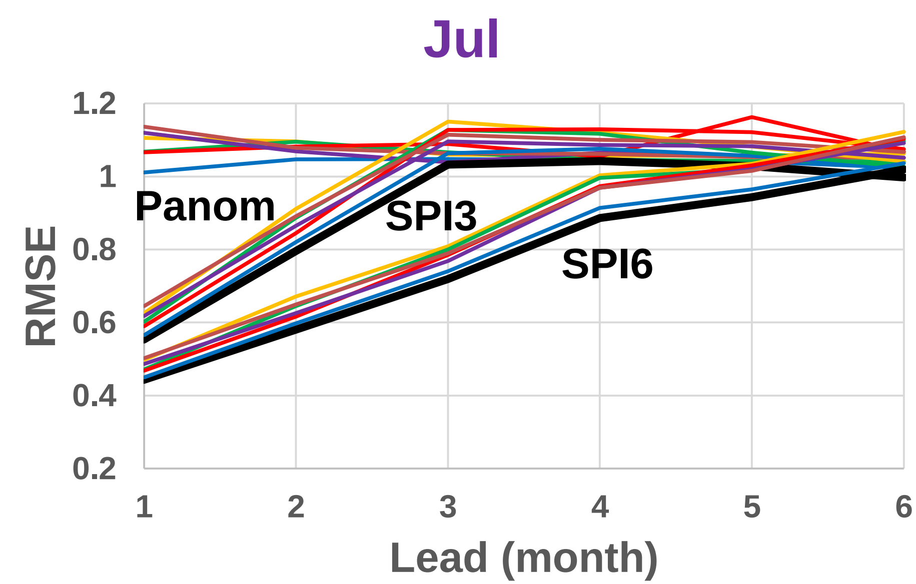
5
6
Lead (month)


Jul
RMSE
Panom
SPI3
SPI6
1.2
1
0.8
0.6
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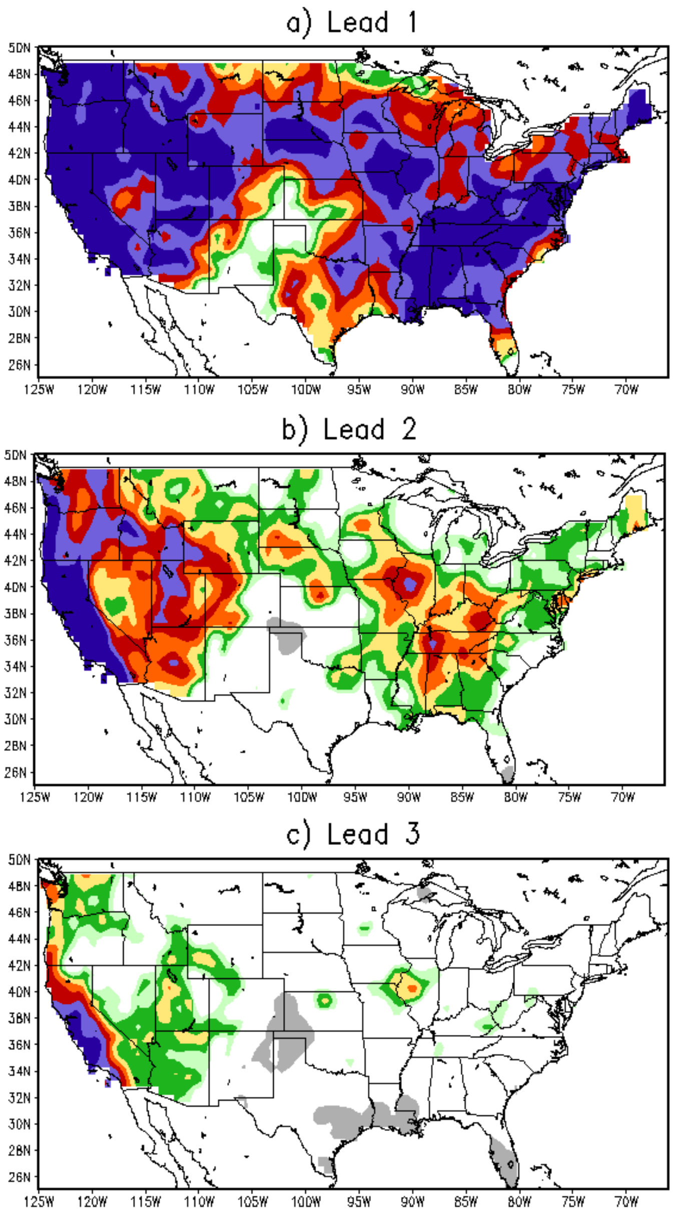
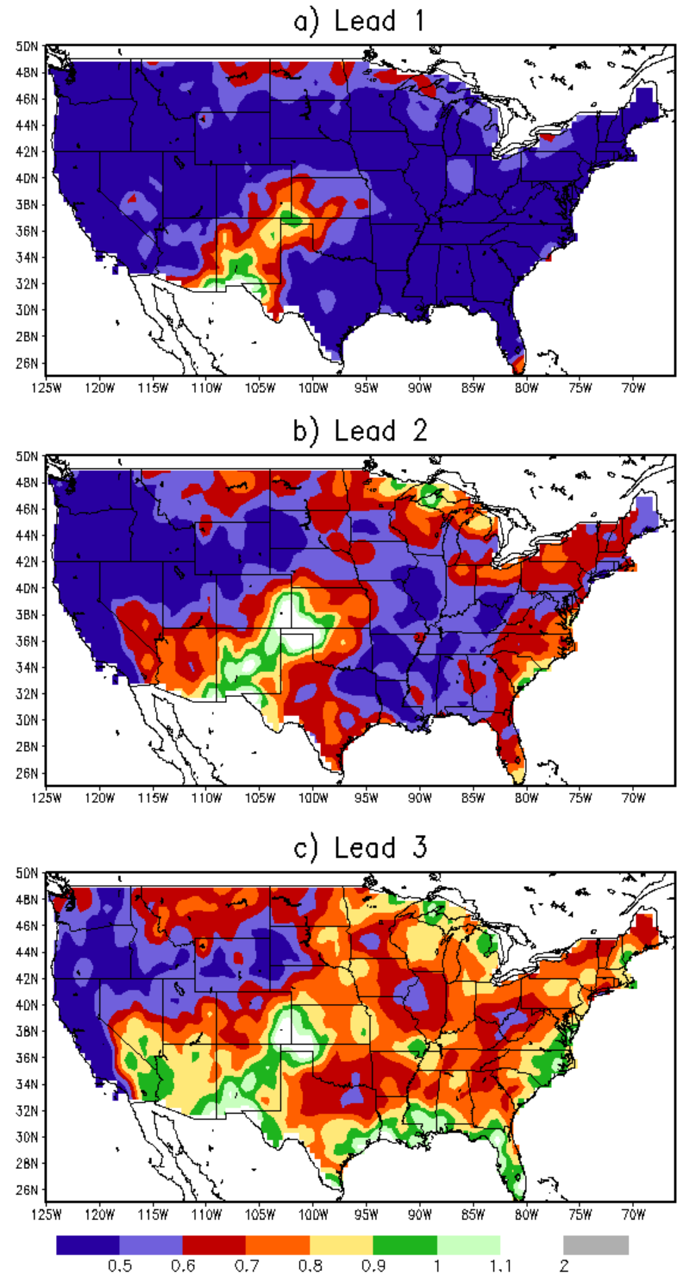
4
5
6
Lead (month)

Persistence



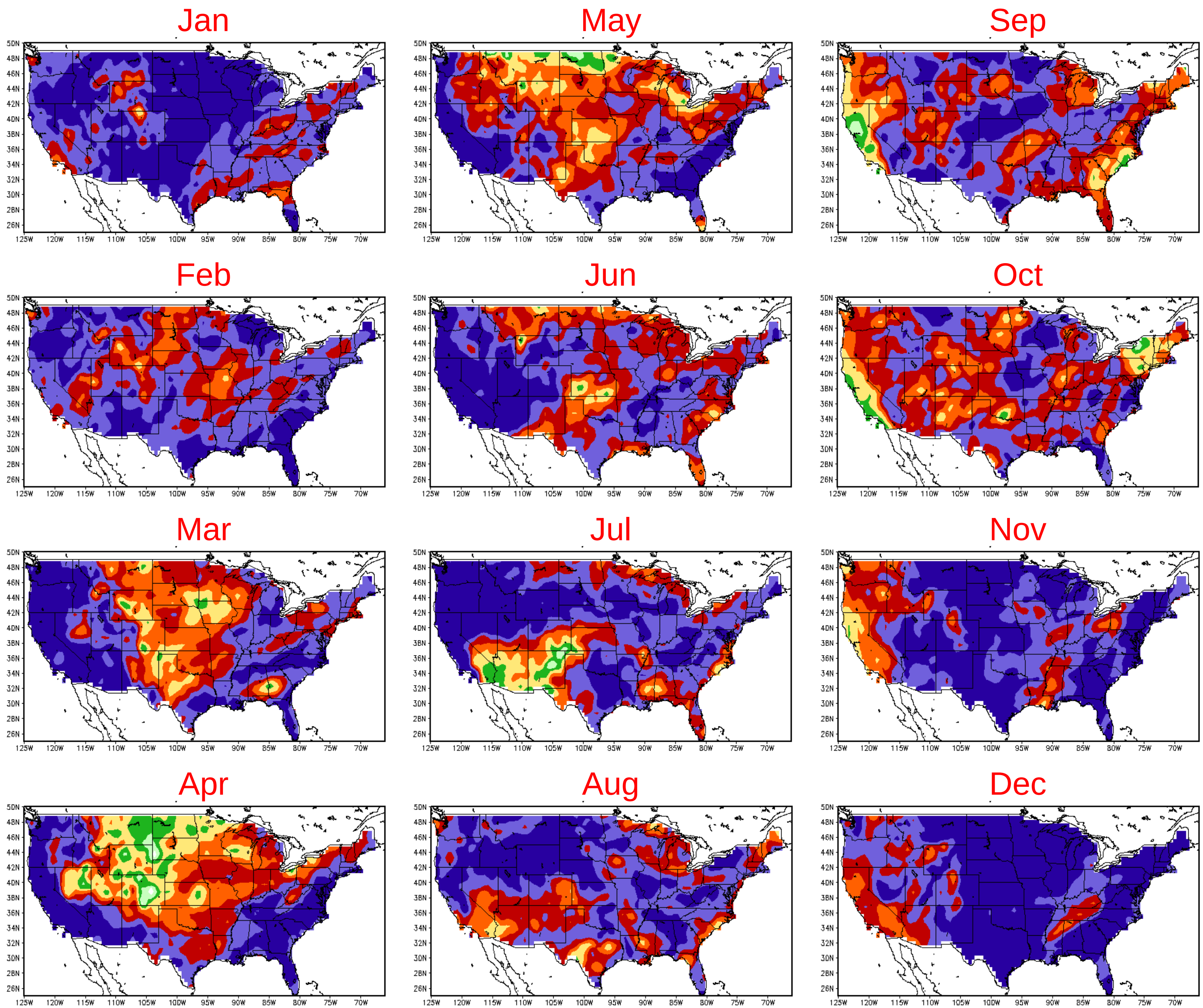
Ensemble with BCSD



RMSE of SPI6 for Jul Fcst

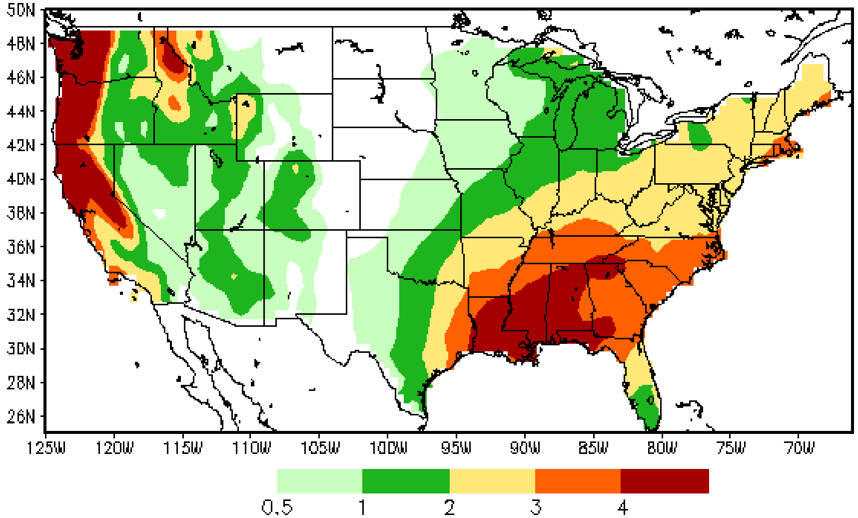
- NMME Ensemble forecasts after BCSD have higher skill than those based on persistence.

RMSE of SPI3 (Month-1 Fcst)

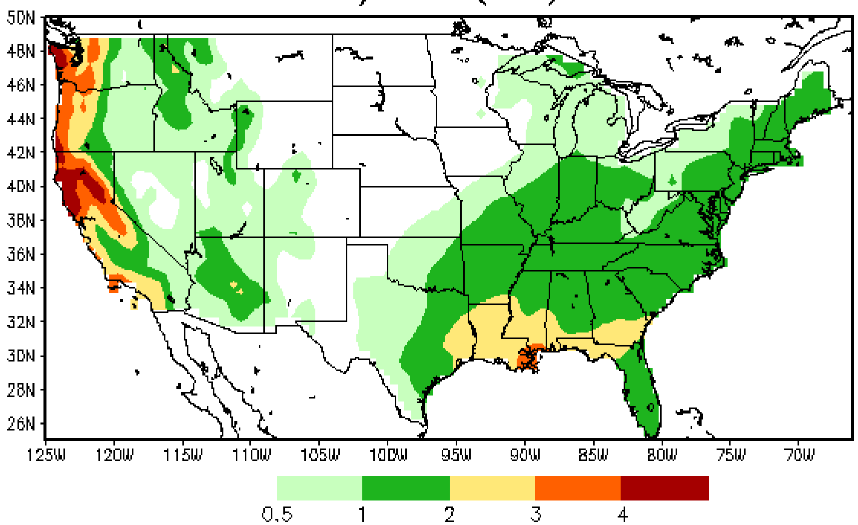


P Climatology (mm/day)

a) Mean (Jan)



b) STD (Jan)

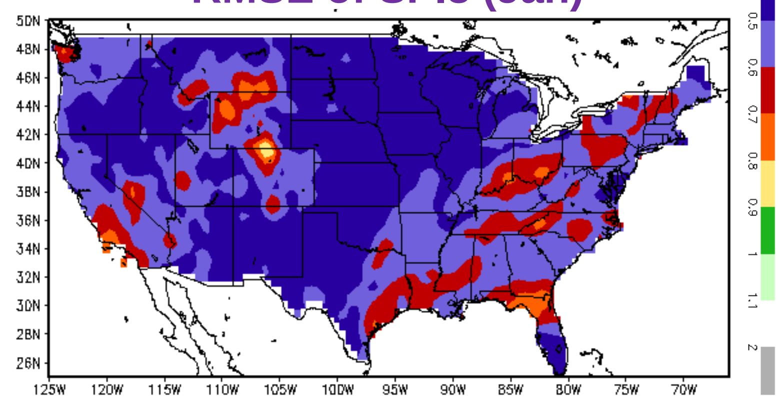


Why forecasts skill is different across the U.S.?

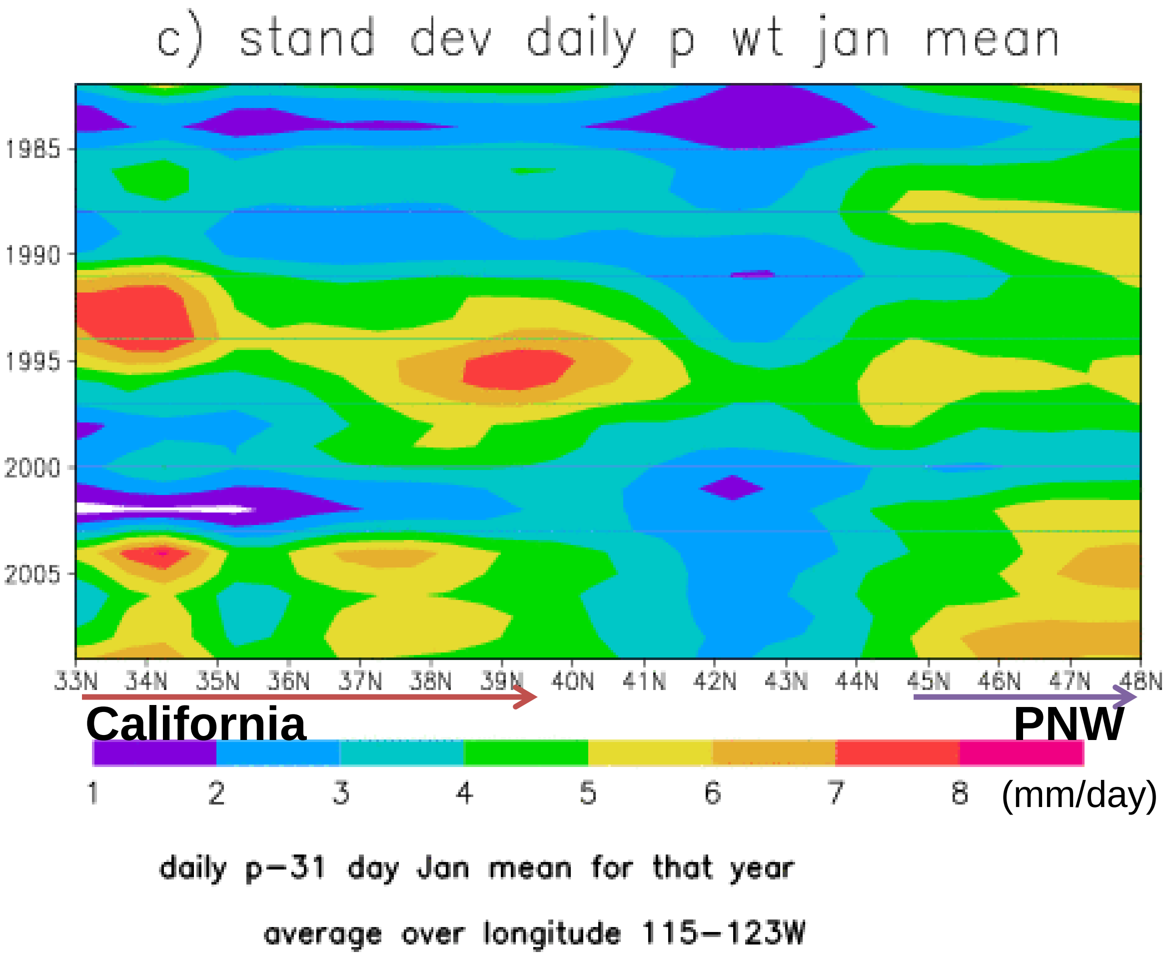
- Central U.S. has higher skill:
  Climatology and the interannual variability for the central U.S. in January are low, so skill is higher (Quan et al. 2012).

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

RMSE of SPI3 (Jan)



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

- NMME SPI Outlooks:

http://www.cpc.ncep.noaa.gov/products/Drought/Monitoring/spi_outlooks_3.shtml

- Contacts:

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