

Super-Ensemble Statistical Forecasting of Monthly Precipitation over the Contiguous US, with Improvements from Ocean-Area Precipitation Predictors

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Definitions

- Ensemble: A weighted mean of multiple estimates
 - Traditionally used for GCM forecast runs with different initial conditions
- Statistical Ensemble: A weighted mean of different statistical estimates
 - Ensemble members may have different predictors, different predictor regions, or use different statistical models to give different estimates
- Super Ensemble: Use ensemble-averaging weights that reflect the accuracy of each member



Predictor & Predictand Areas: N.H. Oceans and Contiguous US

Regions for predictors: OI SST and GPCP P

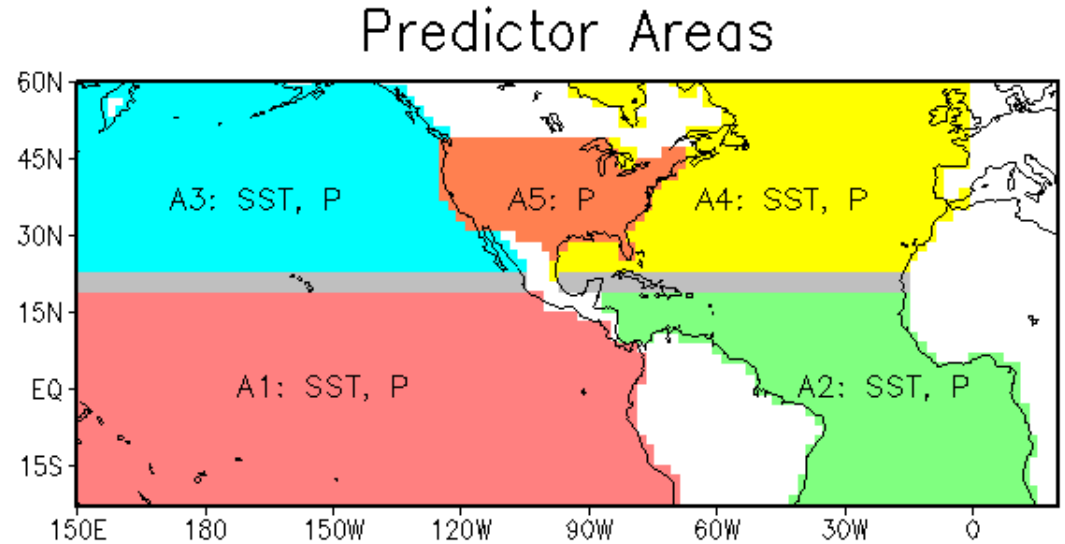
4 Ocean predictor areas with 20°N-23°N overlap

Regions likely to influence P_{US} , similar to Lau et al. (2002) areas

Predictors for ensemble:

- Ocean area $SST_k(t-1)$
- US area $P_{US}(t-1)$
- Ocean area $P_k(t-1)$

Always predict $P_{US}(t)$ anoms



Two Models: CCA and JEOF

- CCA
 - Decomposes predictor and predictand fields using EOFs
- JEOF
 - Simultaneous EOF of normalized predictor and predictand fields
- Predictors are leading SST and P, predictand is US P
- Super-ensemble weights use cross-validation skill of each forecast



Data & Evaluations

- GPCP precipitation and OI SST
 - 1997-2014 1dd GPCP averaged to monthly, compute anomalies
- Cross-validation testing of 0-lead monthly forecasts
 - Omit all data for the year of analysis and 3 months on either side of the year
 - Data from month $t-1$ to predict month t
- Correlations used to evaluate skill and improvements

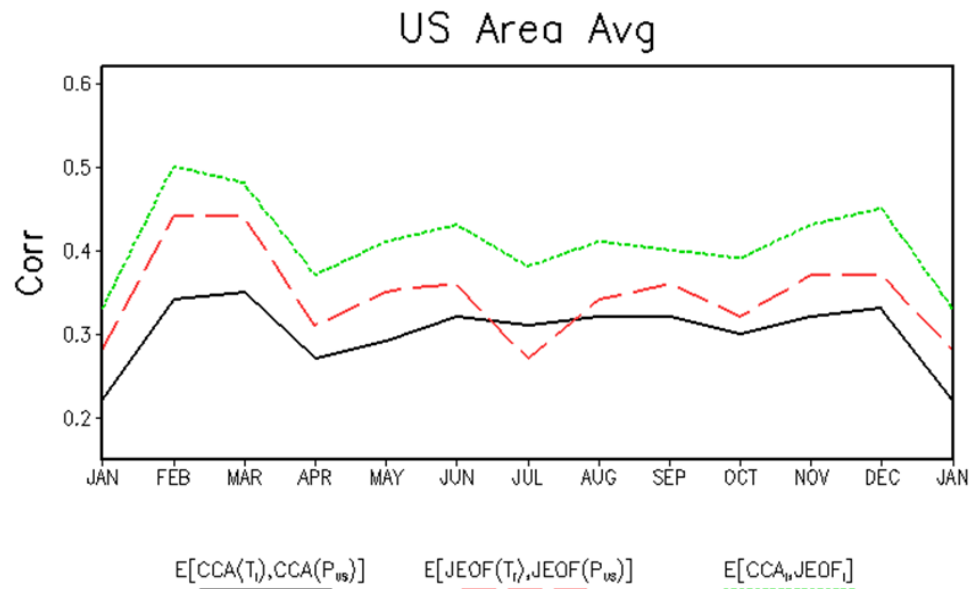
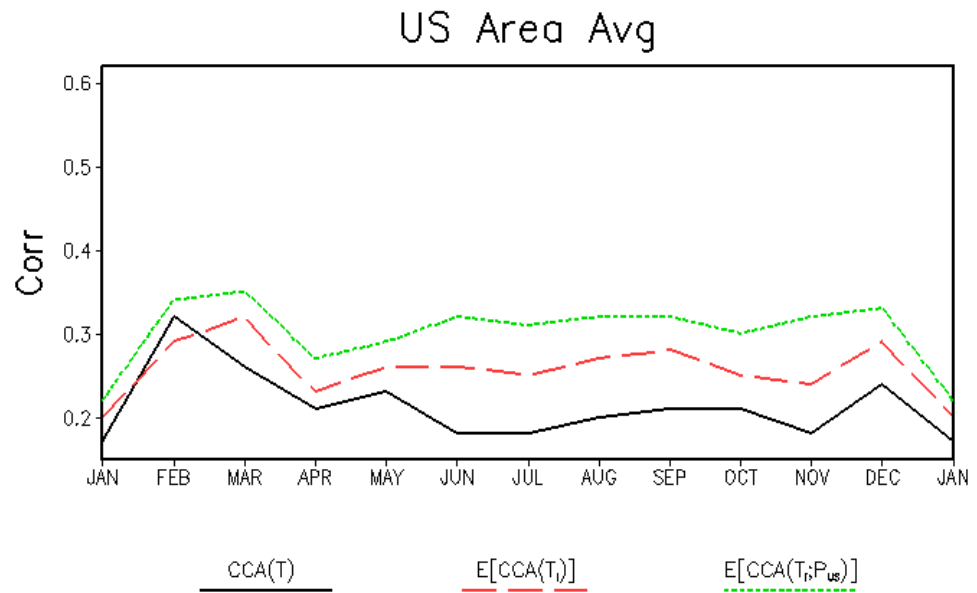
Annual Cycle of US Average Skill

Ensemble CCA using SST(t-1) regions better than CCA using the same SST(t-1) combined (upper panel)

Ensemble improved more when including prediction from $P_{US}(t-1)$

Using SST(t-1) and $P_{US}(t-1)$ predictors, JEOF better than CCA and using both is best (lower panel)

More models and super ensemble method gives improvements



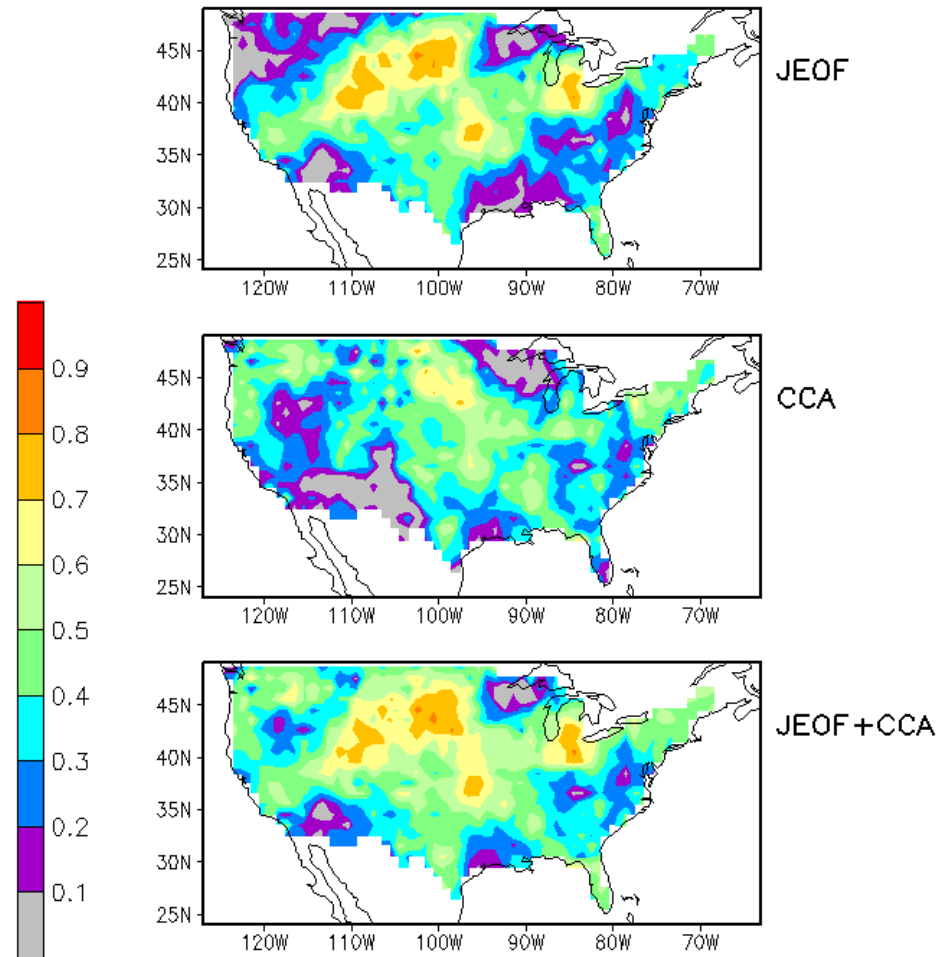
Cross-Validation Precipitation Anomaly Correlation: June, no oceanic precipitation

JEOF and CCA skill patterns similar, but not identical

Regions of high skill different in different models

Super ensemble using both takes the best of each

Jun X-Val Ens Corr [P(m),F(m-1)]



GPCP 1997-2014: No Ocean Prec

Cross-Validation Precipitation Anomaly Correlation: December, no oceanic precipitation

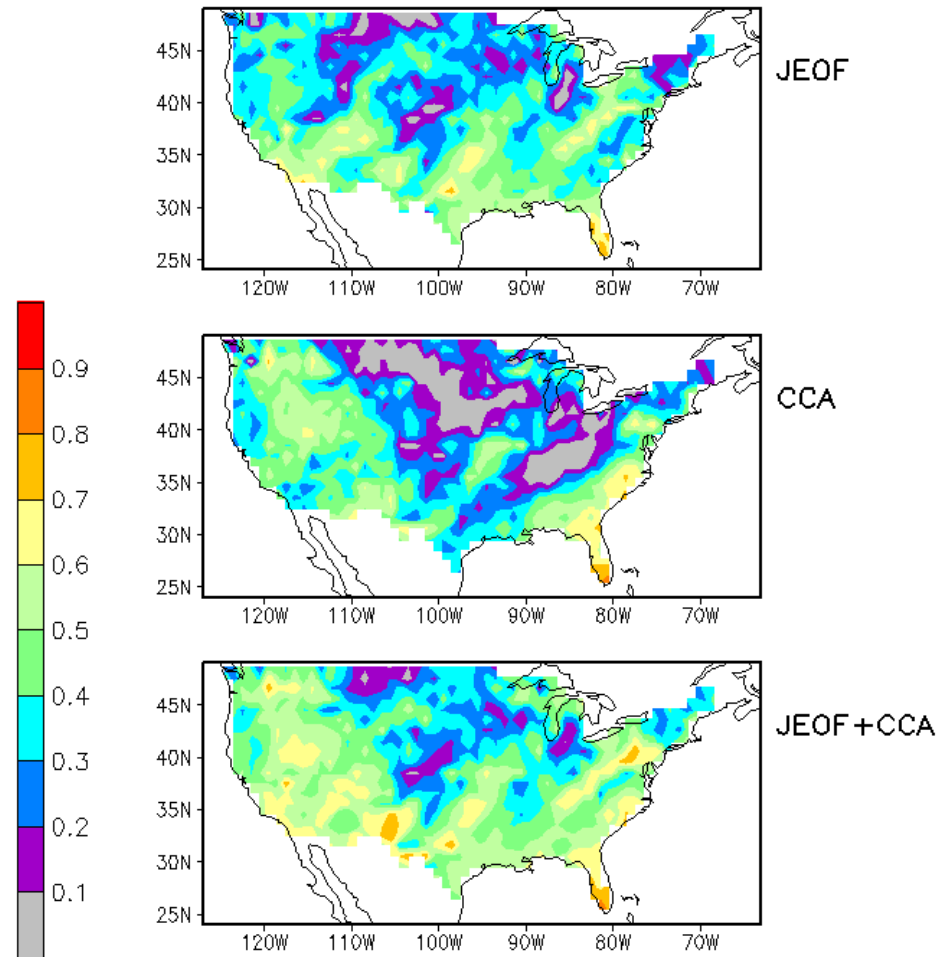
Both JEOF and CCA show skill gaps but in different regions

Using both expands the region of good skill

Methods Conclusions:

- 1) Ensembles dividing predictors into regions improves skill
- 2) Using ensemble members from multiple models also improves skill

Dec X-Val Ens Corr [P(m),F(m-1)]

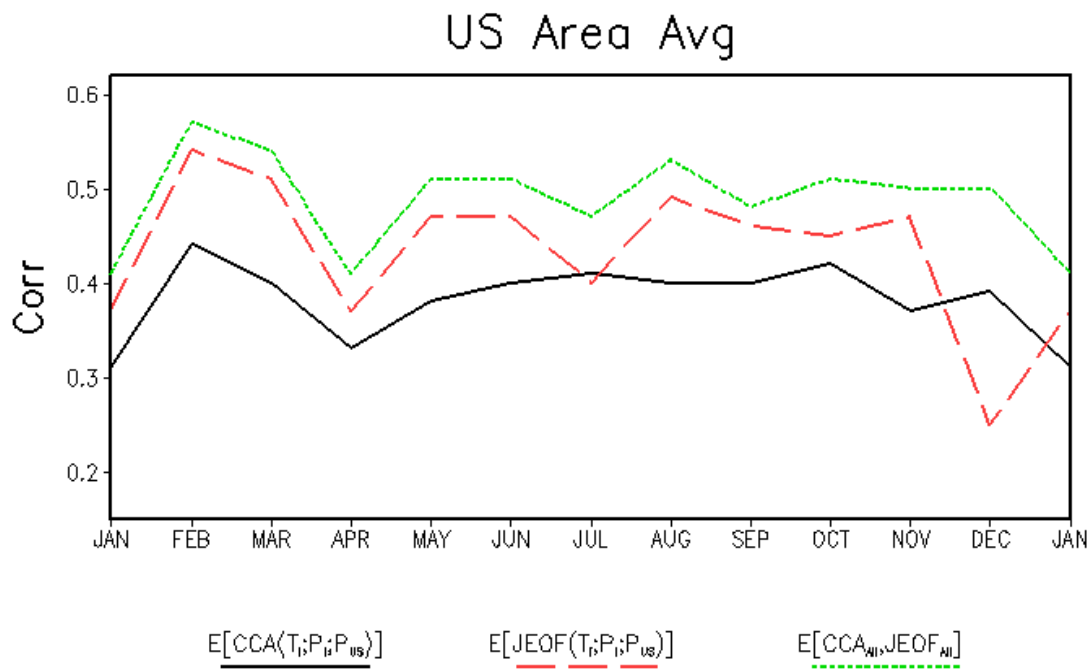


GPCP 1997–2014: No Ocean Prec

Including Oceanic Precipitation in 4 Regions

Skill increases when including members with ocean area P(t-1) predictors

JEOF better than CCA, using both is best

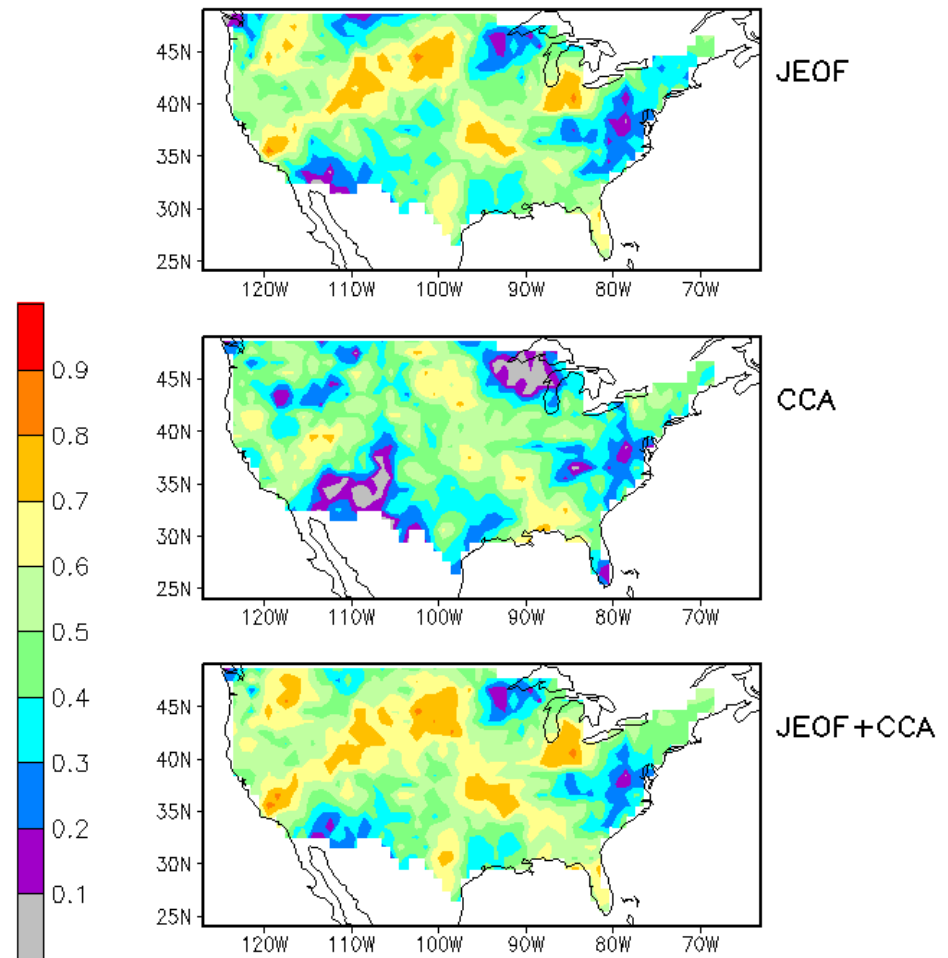


Cross-Validation Precipitation Anomaly Correlation: June, with oceanic precipitation

Ocean P ensemble members improve both
JEOF and CCA

JEOF still better, and combining them still gives
higher skill

Jun X-Val Ens Corr [P(m),F(m-1)]



GPCP 1997-2014: With Ocean Prec

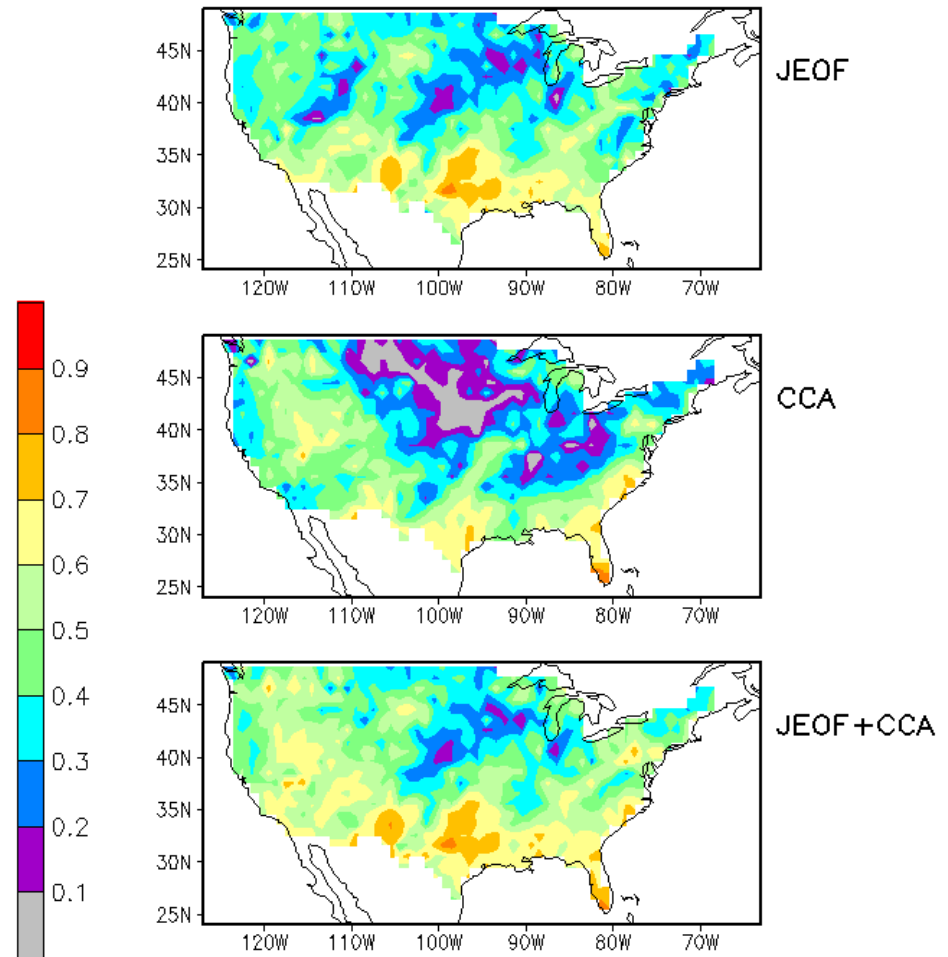
Cross-Validation Precipitation Anomaly Correlation: December, with oceanic precipitation

More regions with higher skill than the case with no oceanic precipitation: satellite-based P improves the forecast

Best skill apparently from ENSO

Low-skill regions for both JEOF and CCA not improved by combining them

Dec X-Val Ens Corr [P(m),F(m-1)]



GPCP 1997-2014: With Ocean Prec

Skill from more than ENSO

- Skill from Tropical Pacific area SST or Precip important but not the whole story
- Combining with forecasts using SST and Precip from other regions doubles average correlation
- All averages omit no-skill regions (correlations < 0)

Temporal cross-validation correlations against GPCP computed for each month (1997-2014), averaged over the contiguous US and annually.

Predictors	CCA	JEOF
T_{TPac}	0.20	0.18
P_{TPac}	0.21	0.23
$E[T_i, P_{\text{US}}]$	0.31	0.35
$E[T_i, P_i, P_{\text{US}}]$	0.39	0.45

Overall Improvements from oceanic precipitation

- Adding satellite-based $P_i(t-1)$ predictors improves ensembles

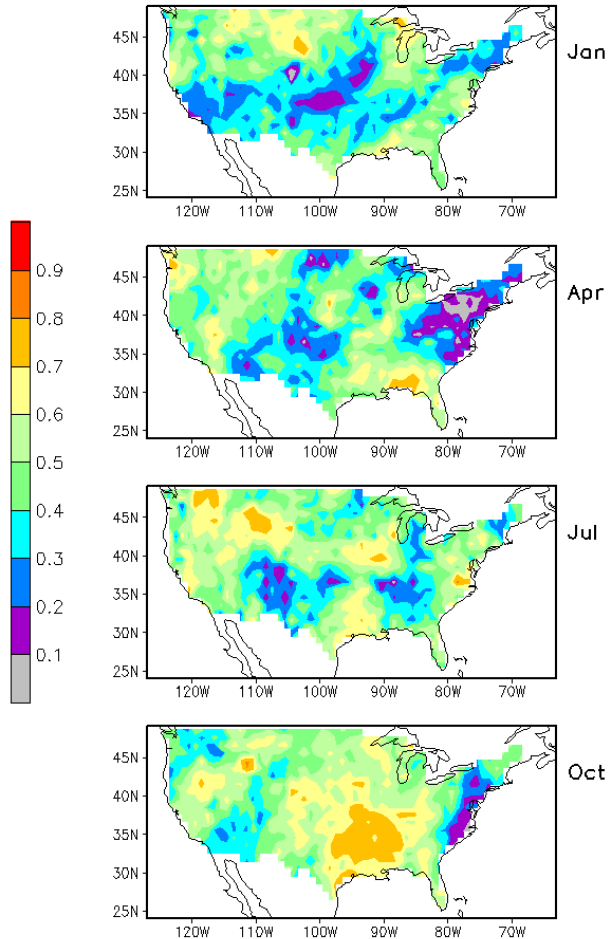
Temporal cross-validation correlations against GPCP computed for each month (1997-2014), averaged over the contiguous US and annually.

Predictors	CCA	JEOF	JEOF+CCA
$E[T_i, P_{US}]$	0.31	0.35	0.42
$E[T_i, P_i, P_{US}]$	0.39	0.45	0.50

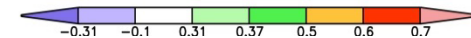
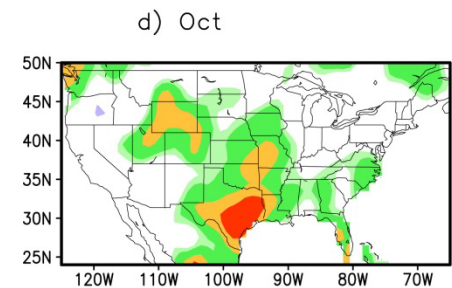
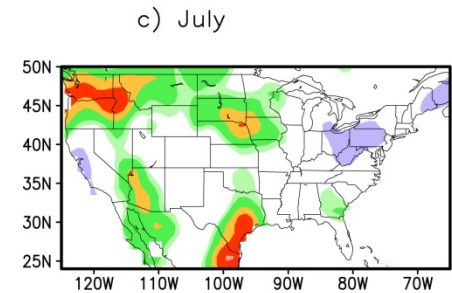
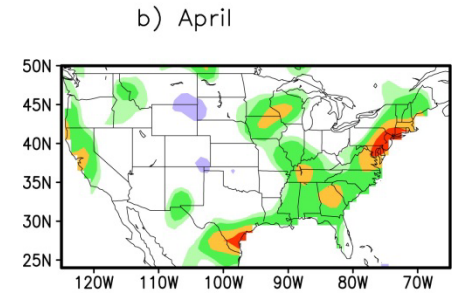
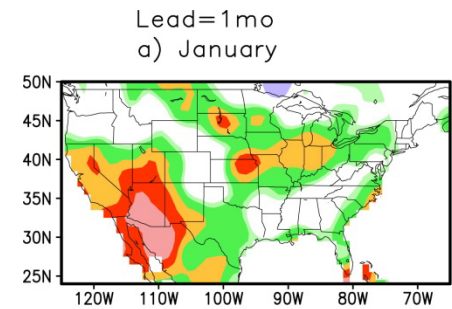
Comparisons to Similar NAMME Tests

Similar Skill Levels but in Different Regions

X-Val Ens Corr [P(m),F(m-1)]



GPCP 1997-2014: With Ocean Prec



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From Mo and Lettenmaier (2014, J. Hydromet.)

Conclusions

- Super-ensemble-statistical forecast are better than non-ensemble forecasts
 - Method improvements include using multiple statistical models and super-ensemble averaging weights
- Ocean-area precipitation predictors improve US-area precipitation forecasts
 - Additional predictors add skillful members to the ensemble and give higher ensemble skill
 - Many other predictors may give skill and improve the forecast, including different statistical predictors and estimates from numerical models; more testing is needed