Super Ensemble Statistical Short-Range Precipitation Forecasts over the US and Improvements from Ocean-Area Precipitation Predictors

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Definitions

- Ensemble: A weighted mean of multiple realistic estimates
  - Traditionally used with dynamic GCM forecast runs with different initial conditions
  - Average used to estimate the expected value

- Statistical Ensemble: A weighted mean of different statistical estimates
  - Ensemble members may have different predictors or predictor regions or use different statistical models

- Super Ensemble: Use weights that reflect the accuracy of each ensemble member

Improvements

- Ensemble-statistical forecasting
  - Developed & tested by Shen et al. 2001 & Lau et al. 2002
  - Ensemble CCA improved seasonal U.S. T forecasts (Mo 2003)

- Method Improvements
  - Ensemble members for differences in predictor regions, predictor types, and statistical models
  - Optimal super-ensemble formed

- Data Improvements: include satellite ocean-area precipitation predictors

Statistical Super Ensemble Method

- Find predictors, p_1, p_2, …, p_n, for some property, g
- Separate models for each prediction, $f_1(p_1)$=g_1, …, $f_n(p_n)$=g_n
- Compute the n member ensemble, E[g] = $\sum_{i=1}^{n} w_n g_n$
- Optimal weights proportional to the correlation squared
- Use cross-validation to compute optimal weights

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

Region standard deviations, for OI SST anomalies (upper) and GPCP P anomalies (lower)

4 Ocean predictor areas:

1) Trop Pacific (23°S-23°N, 150°E-80°W)
2) Trop Atlantic (23°S-23°N, 90°W-20°E)
3) N. Pacific (20°N-60°N, 150°E-100°W)
4) N. Atlantic (20°N-60°N, 100°W-0°W)

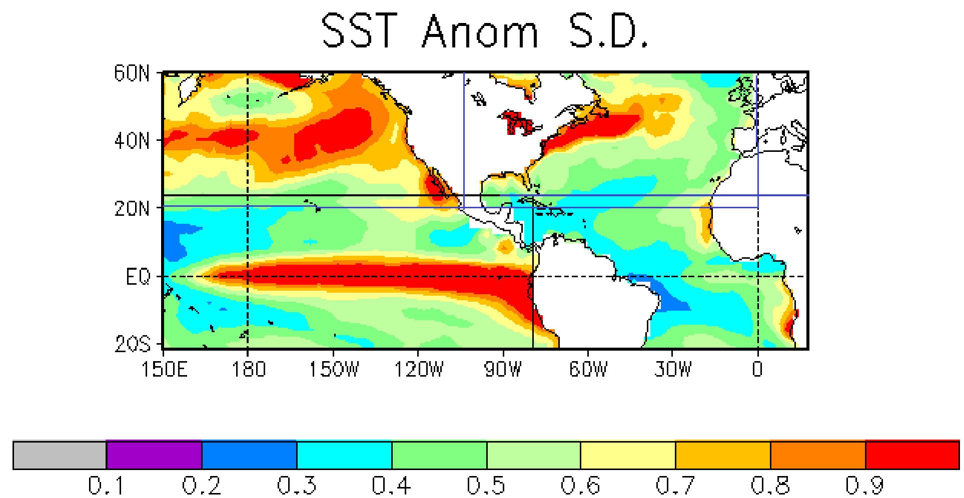
Some overlap in ocean areas

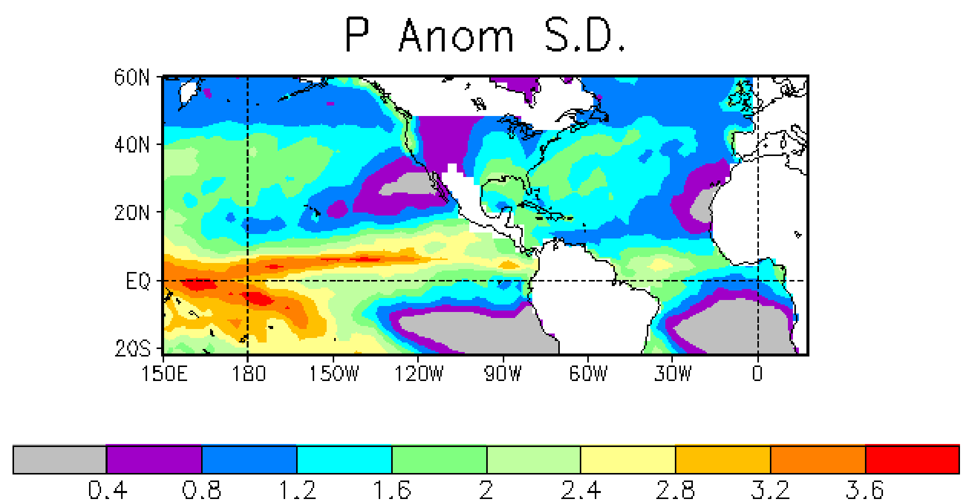
Regions likely to influence P_{US}, similar to Lau et al. (2002) areas

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





One Model: Canonical Correlation Analysis (CCA)

- Used by Barnett, Banston, many others
  - Decompose predictor and predictand fields using EOFs
  - Compute CCA in spectral space
  - X-val tuning indicates that using 20 CCA modes is best

- Correlation between predictor field and the time-lagged US precipitation field used for forecast

- Separate CCA for each predictor type and region

Another: Joint Empirical Orthogonal Analysis (JEOF)

- JEOF is EOF of several fields stacked together
- Normalize predictor and time-lagged US P fields, stack together and perform EOF
- JEOF for each predictor type and region
- X-val tuning shows that 5 JEOF modes is best
- For both CCA & JEOF anomalies are forecasts, and preliminary test show separate models for different seasons are not needed

Super-Ensemble Weights

- For OI at a point, spatial correlations = 1 and weights are a function of noise/signal error variance

$$w_i = \frac{1}{1+\eta_i^2}$$

- Assume that each ensemble, x_i, is a linear function of the truth, x, with random error & maybe bias

$$x_i = \alpha_i x + \beta_i + \varepsilon_i$$

- Using definitions of variance and correlation, and we can show that weights are a function of squared correlation, $w_i = r_i^2$

- Normalize weights to avoid damping or inflation of variance, compute maps of weights

Data & Evaluations

- GPCP monthly precipitation and OI monthly SST inputs
  - 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

All-area SST CCA vs ensemble SST CCA

- CCA skill using all SST together < skill of ensemble from divided SST_i regions, i=1 to 4
- Non-ensemble SST skill similar to skill using $P_{US}(t-1)$
- All averages omit no-skill regions (correlations < 0)

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

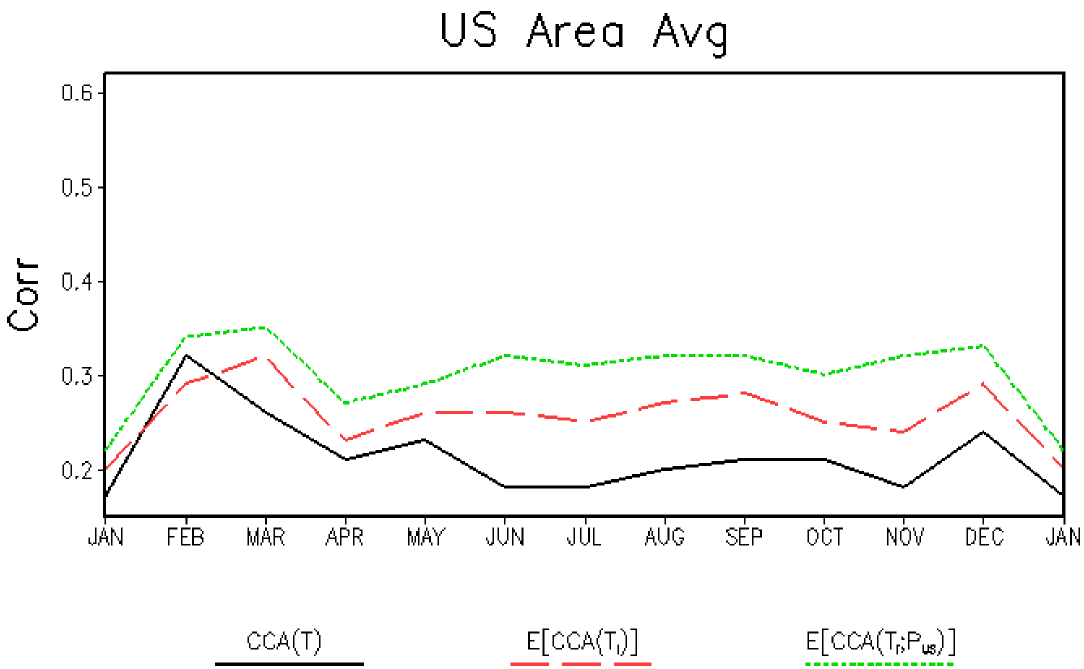
Predictors	CCA
SST(t-1)	0.22
$E[SST_i(t-1)]$	0.26
$P_{US}(t-1)$	0.22

Annual Cycle of US Average Correlation Skill

Multiple-CCA ensemble using SST(t-1) in regions almost always better than CCA using the same SST(t-1) combined

Spring-summer months most improved

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

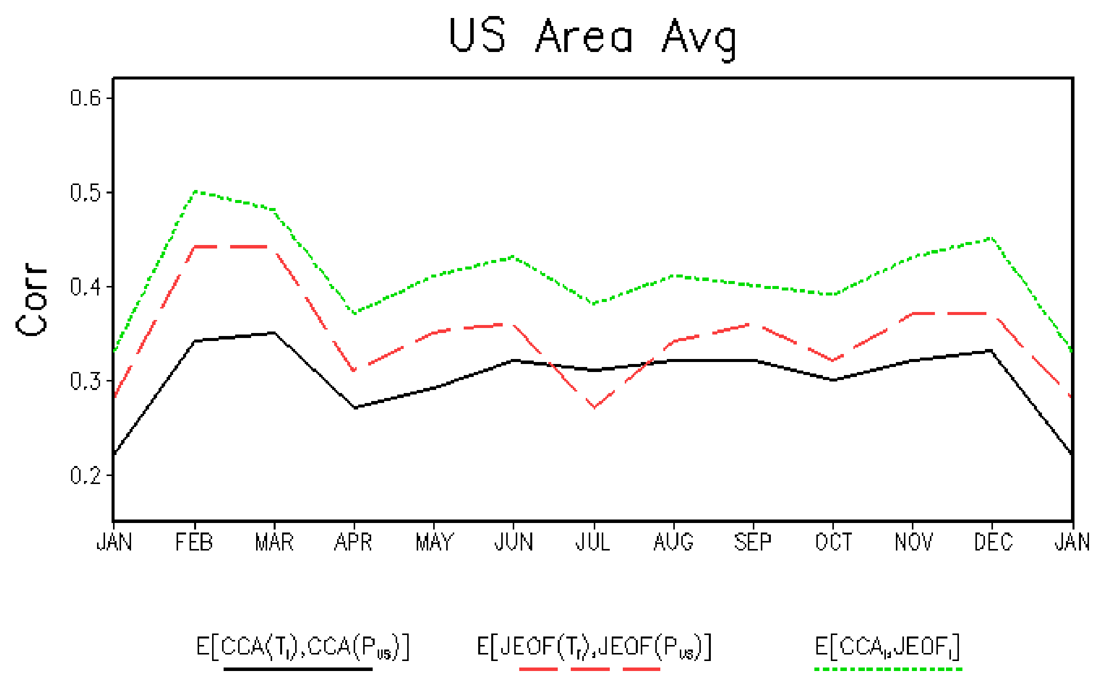


CCA vs JEOF, Annual Cycle of US Average Correlation

Ensemble using SST(t-1) and P_{US}(t-1); no oceanic P predictor members

JEOF typically better than CCA

Improved more if both JEOF and CCA members used in ensemble

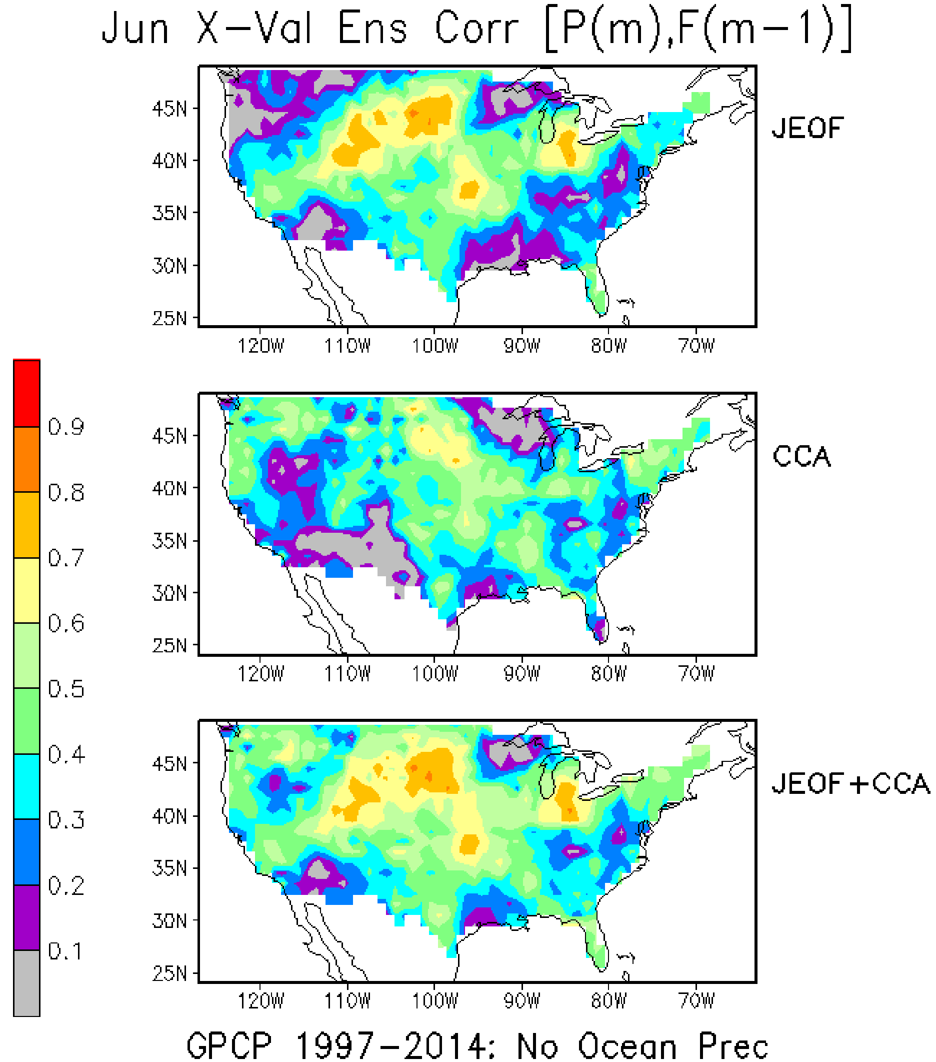


Cross-Validation Precipitation Anomaly Correlation: June, no oceanic precipitation

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



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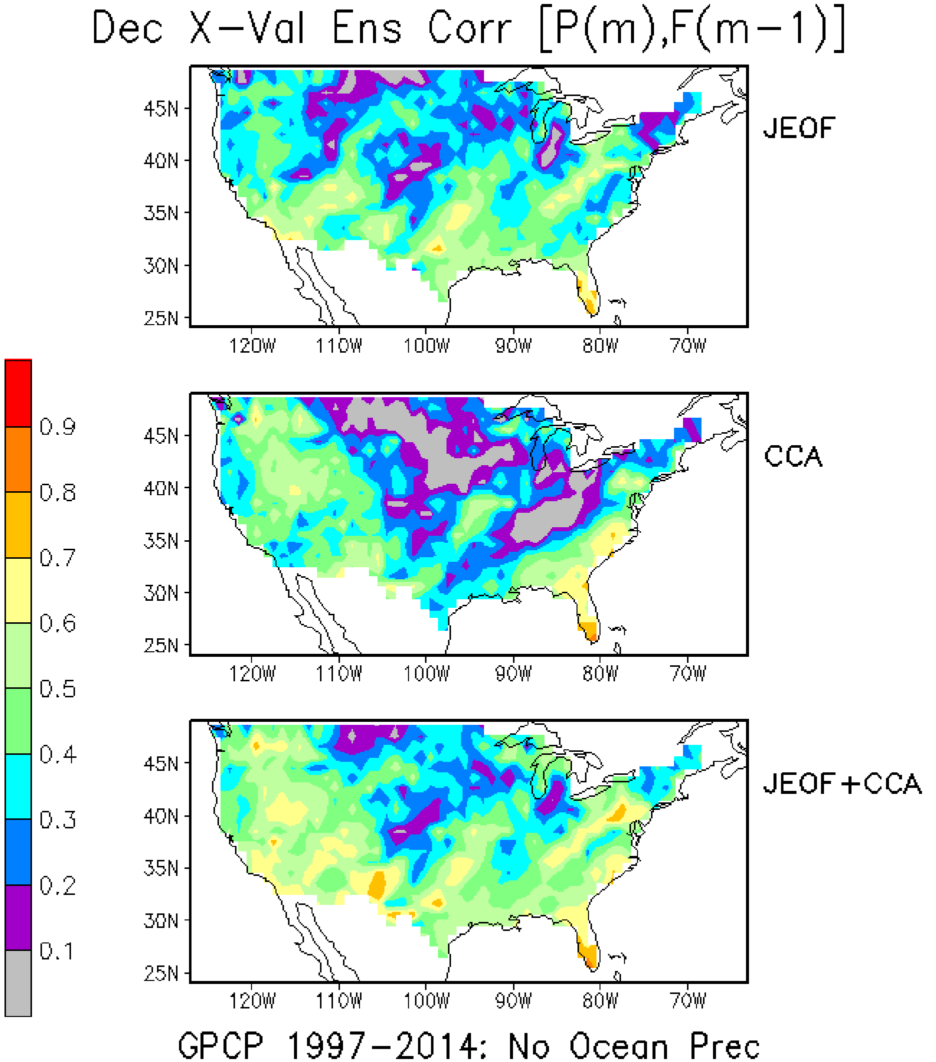
Cross-Validation Precipitation Anomaly Correlation: December, no oceanic precipitation

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 noticeably improves skill



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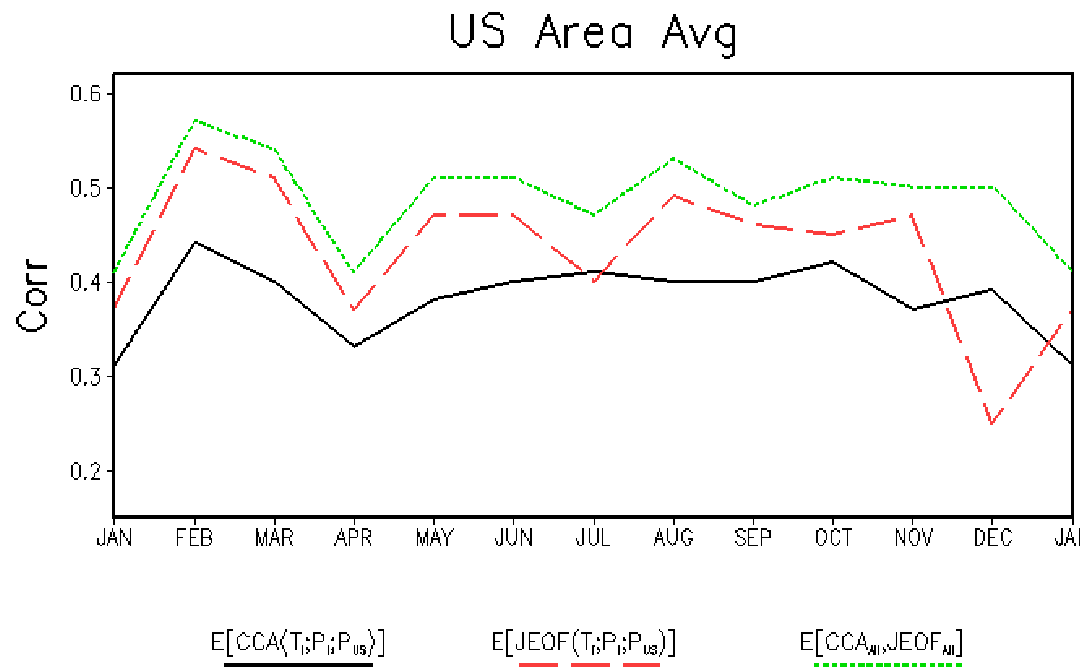
Including Oceanic Precipitation in 4 Regions

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

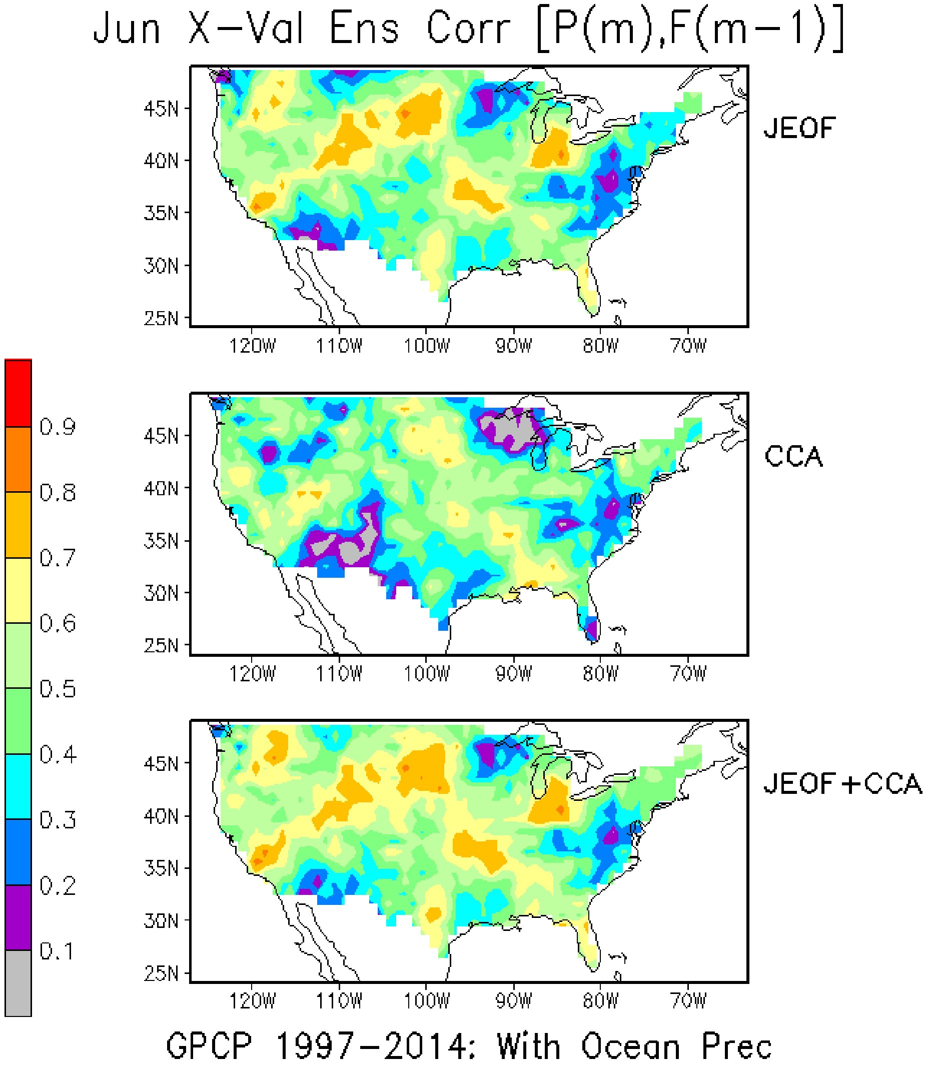
JEOF better than CCA, using both is best



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

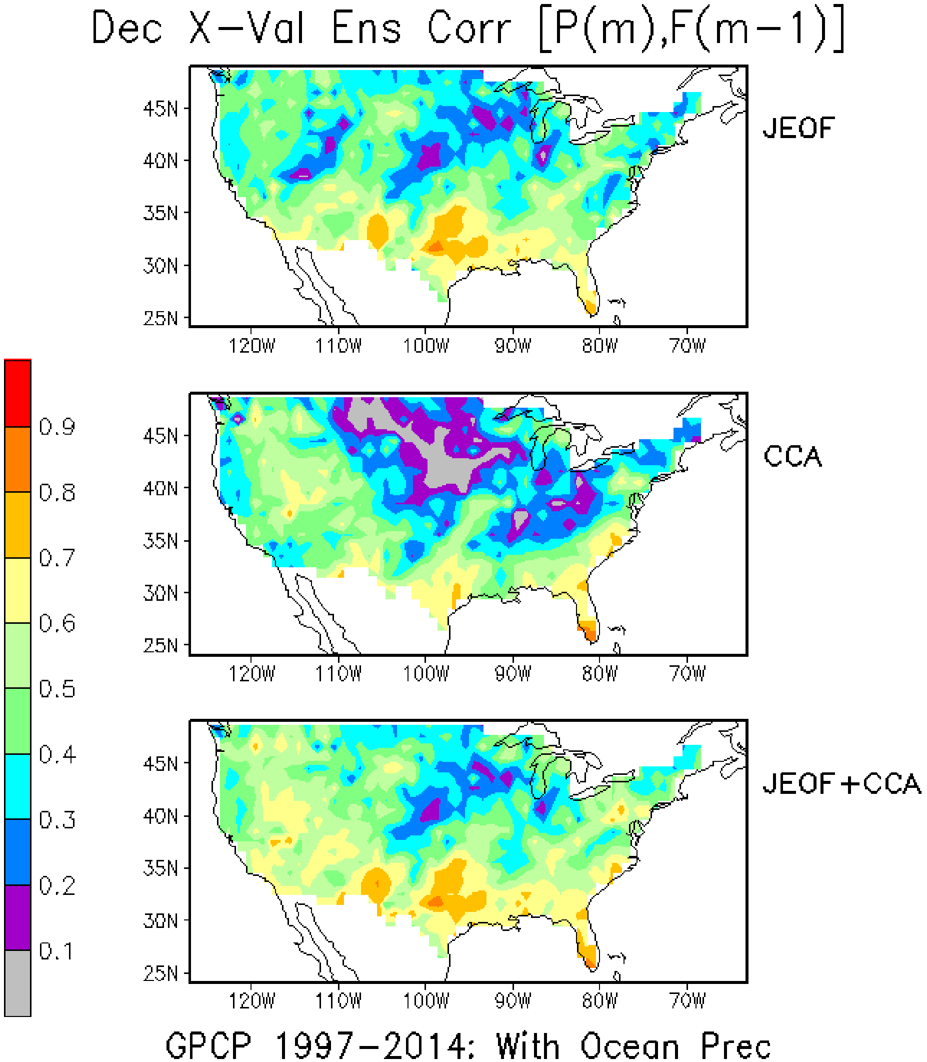


Cross-Validation Precipitation Anomaly Correlation: December, with oceanic precipitation

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



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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

Temporal 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
$E[T_i, P_{US}]$	0.31	0.35
$E[T_i, P_i, P_{US}]$	0.39	0.45

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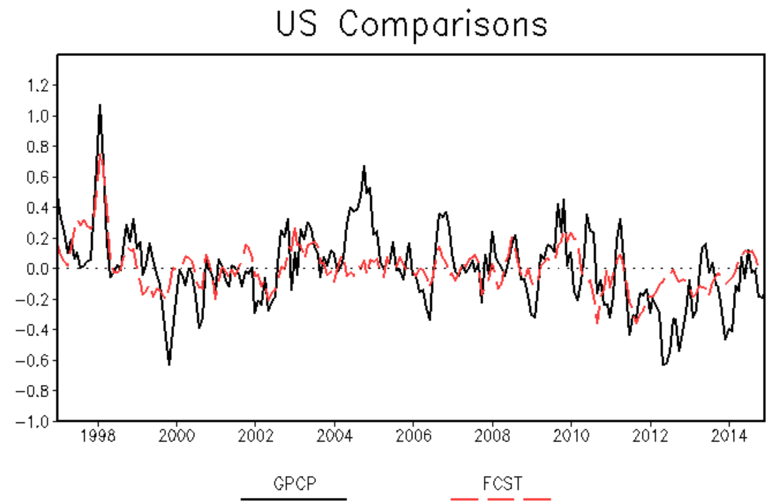
Overall Improvements from oceanic precipitation

- Adding satellite-based $P_i(t-1)$ predictors improves ensembles
- JEOF method slightly better than CCA but best-skill regions are different

Temporal 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

US Area-Average of Forecasts vs GPCP

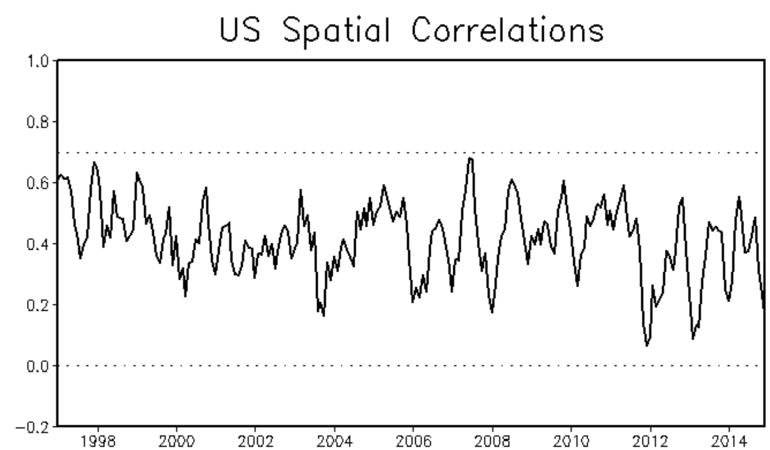


Monthly values 3-mon smoothed

Most large variations consistent, but with important misses

Tends to damp when it misses

Climate variations like ENSO help the correlation (avg 0.41)



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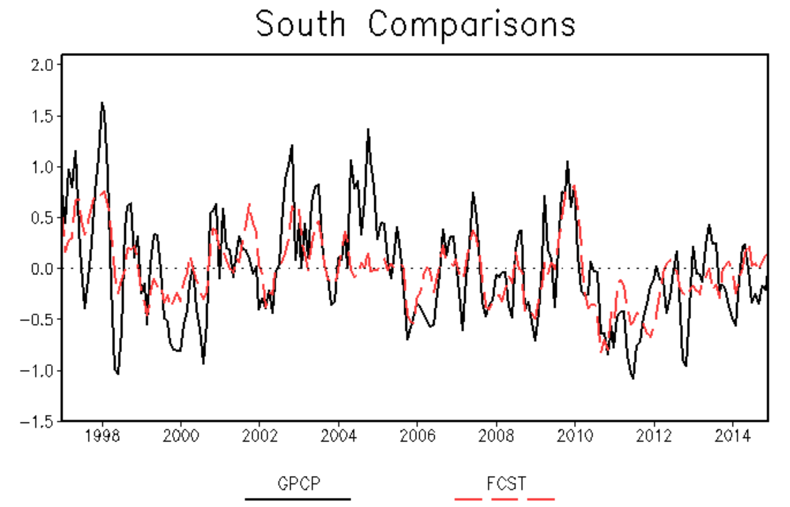
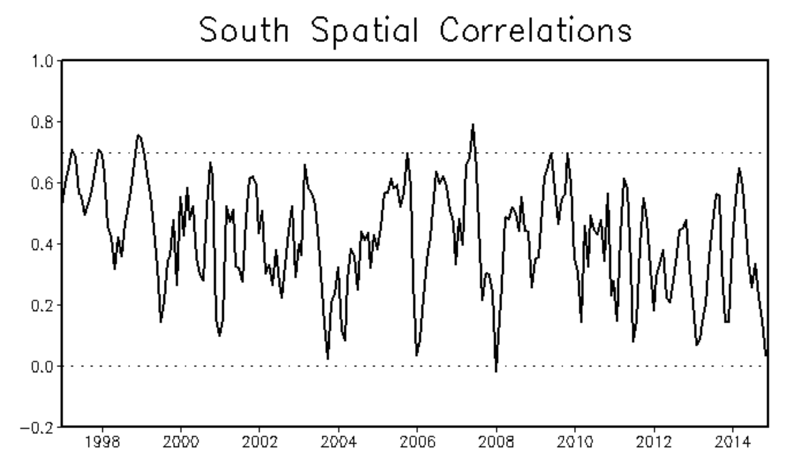
US Area South of 35°N Forecasts vs GPCP



Monthly values 3-mon smoothed

Region influenced by ENSO

Fewer misses and correlation slightly better than for entire US (avg 0.42)



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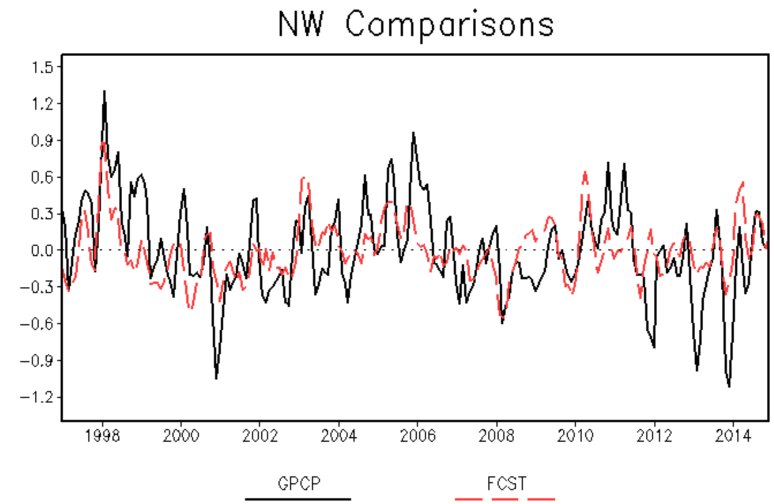
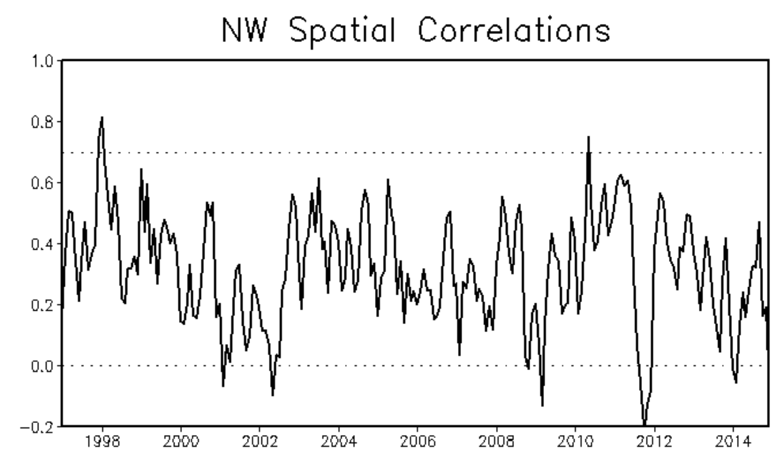
US North of 35°N, West of 100°W
Forecasts vs GPCP



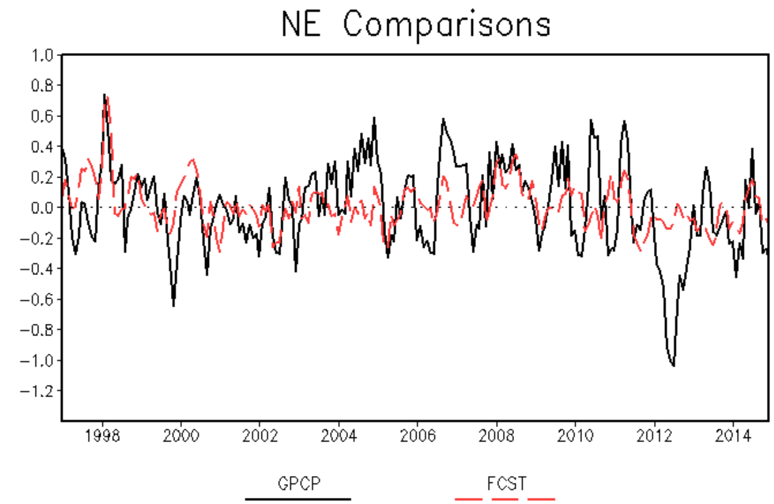
Monthly values 3-mon smoothed

Multi-decadal variations clear

More misses, correlation lower than entire US (avg 0.32)



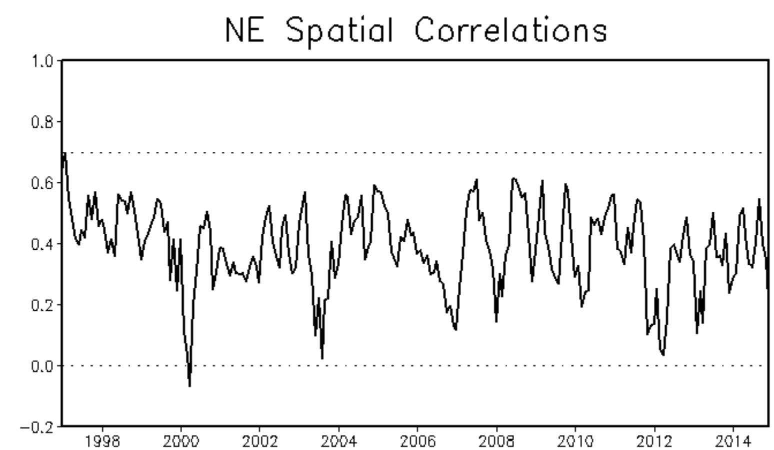
US North of 35°N, East of 100°W
Forecasts vs GPCP



Monthly values 3-mon smoothed

Forecast misses slight multi-decadal variations and some extremes

More misses, correlation slightly lower than entire US (avg 0.39)



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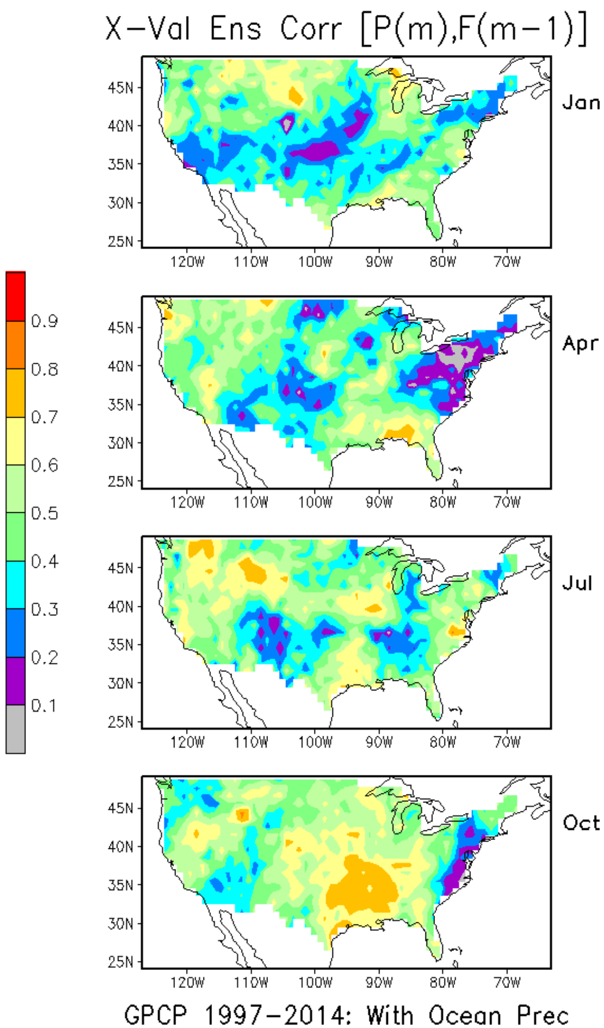
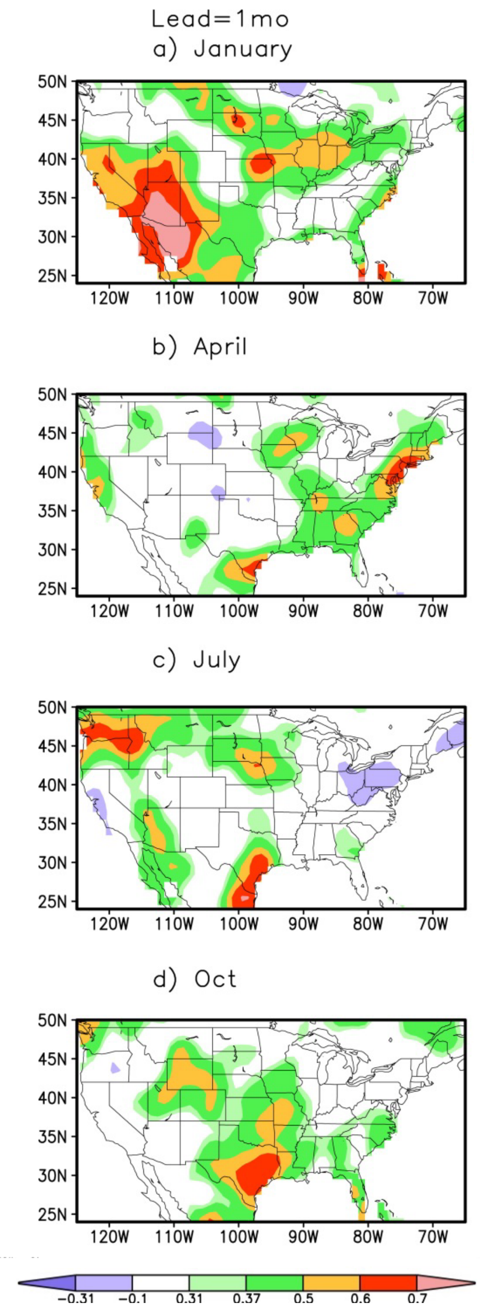
Comparisons to Similar NAMME Tests

Similar Skill Levels but in Different Regions





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

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3-Category Validation

- For each month use the 18 years to define the lowest, middle, and highest third (below normal, normal, above normal categories)

- Find the % time forecast is in the correct third (hit)

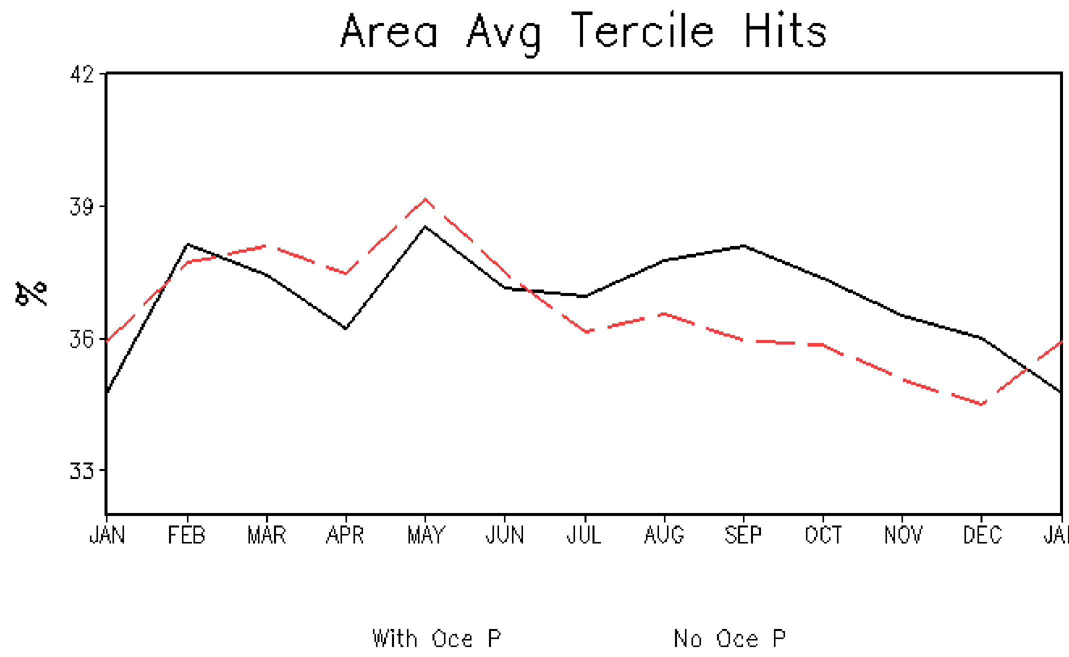
- Find the % time forecast misses by 2 categories (bad miss)

Averages for Each Month: Hits With & Without Ocean P

% Hits: forecast in correct third

Average does not change much over year

Sometimes more hits when ocean P not used, but typically better with ocean P



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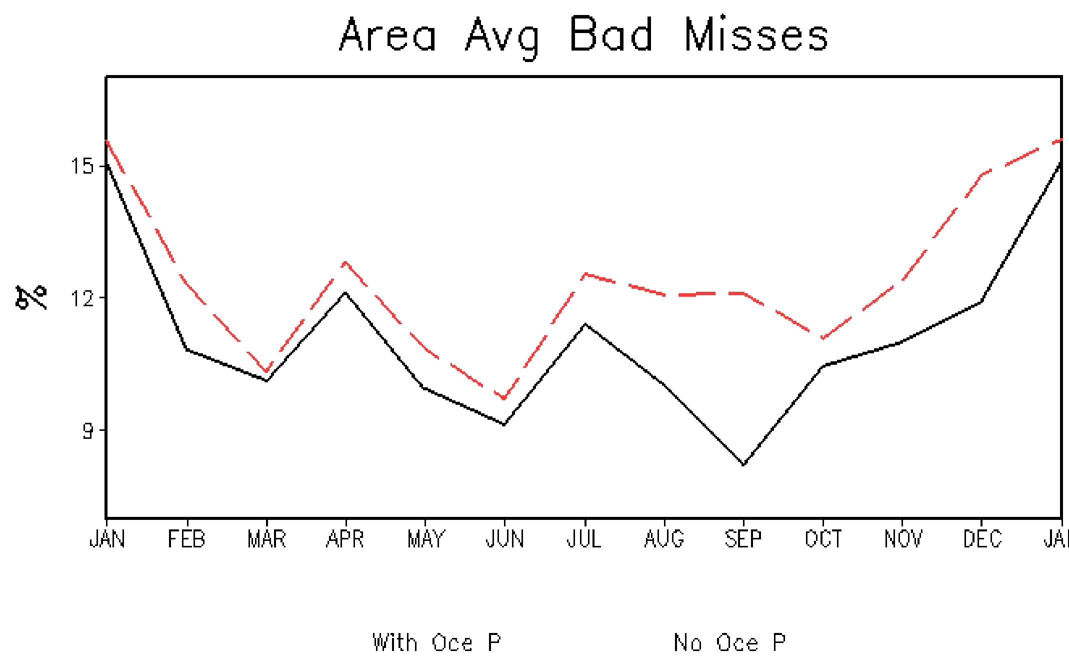
Tercile Averages for Each Month: Bad Misses With & Without Ocean P

% Bad Misses: forecast upper & validate lower third or forecast lower & validate upper third

Using ocean P reduces bad misses



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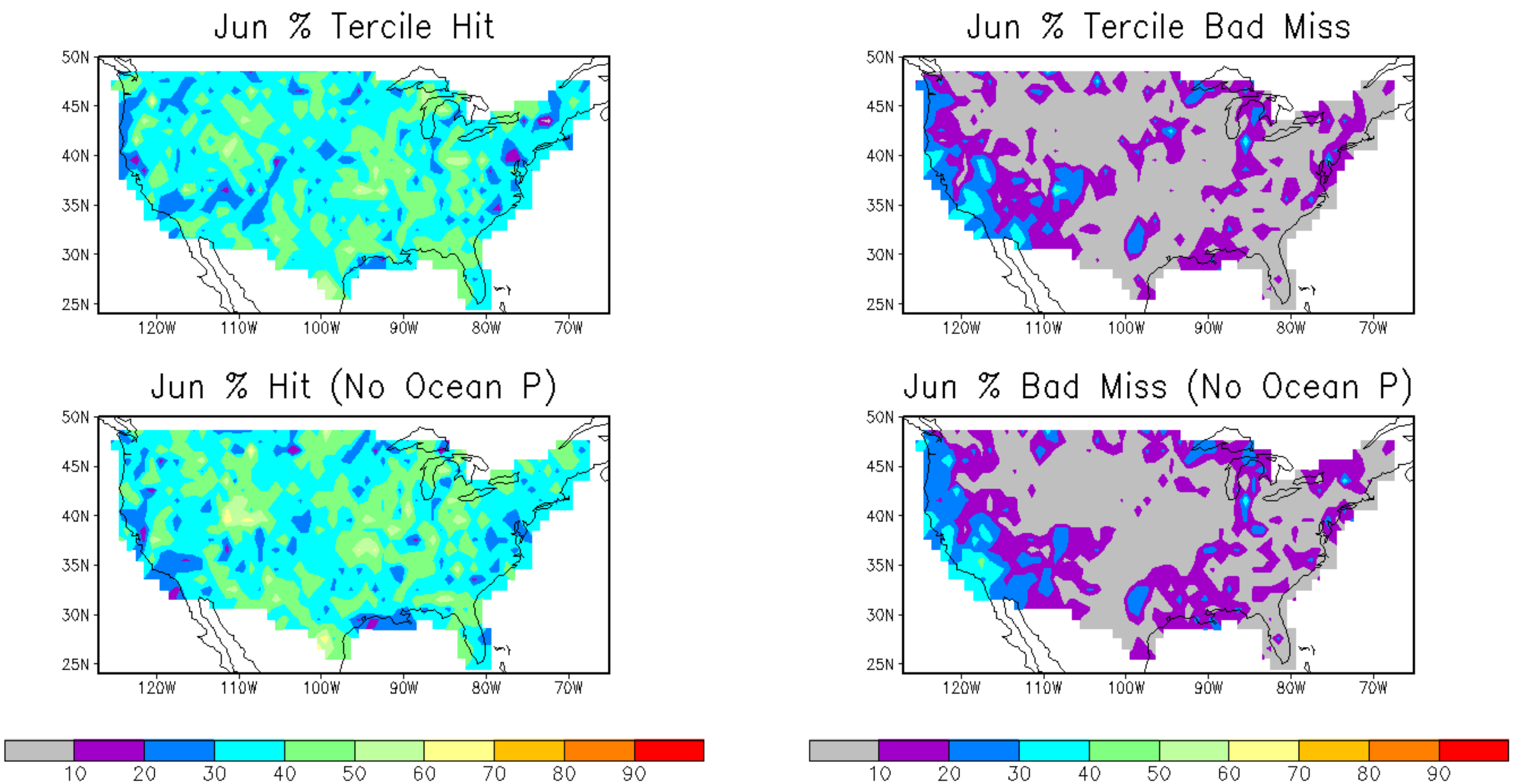
Monthly June Maps: Hits & Bad Misses

Ocean P has little impact on Hits

Differences are clearer in bad misses, especially western areas



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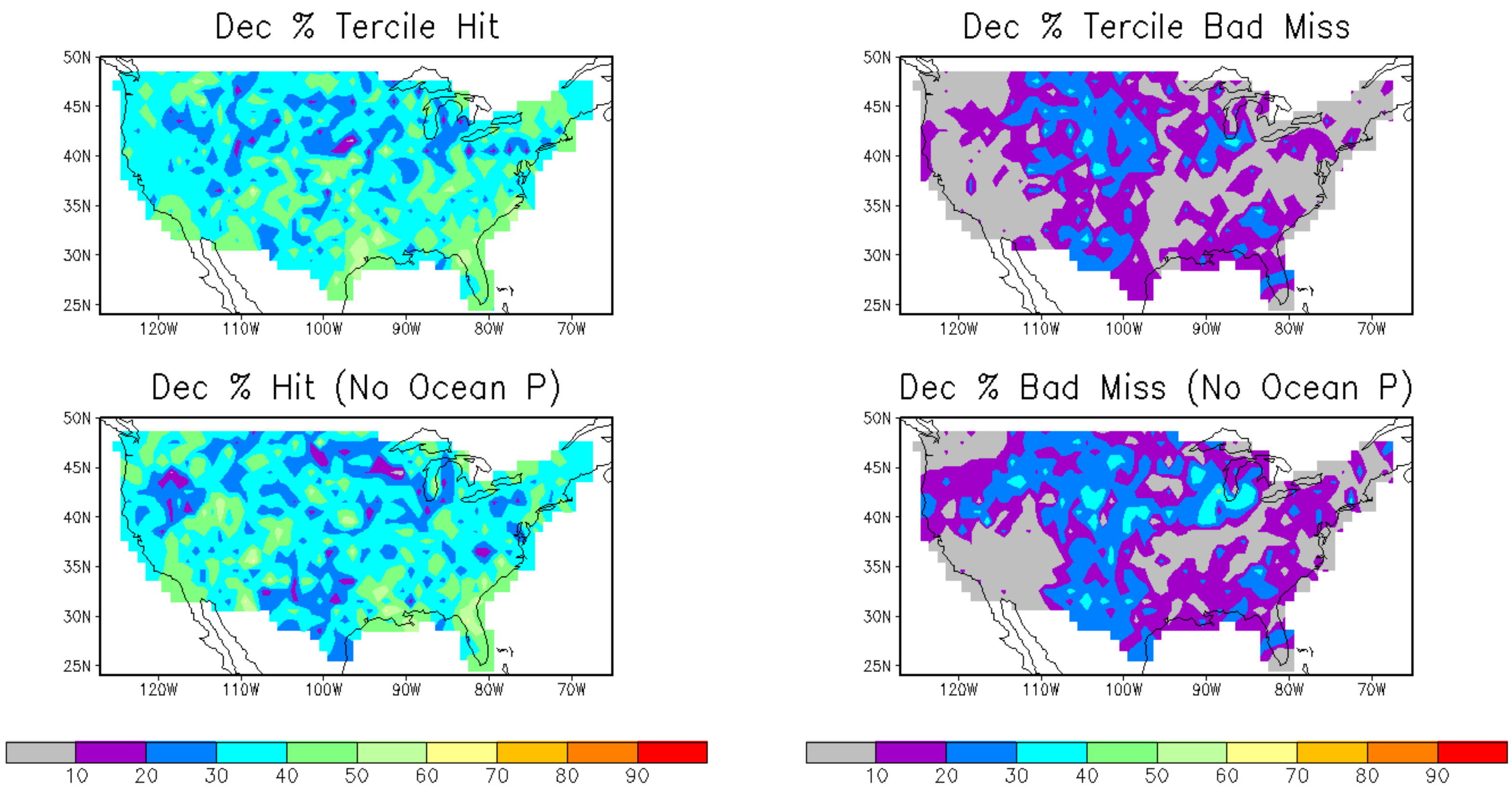
Monthly December Maps: Hits & Bad Misses

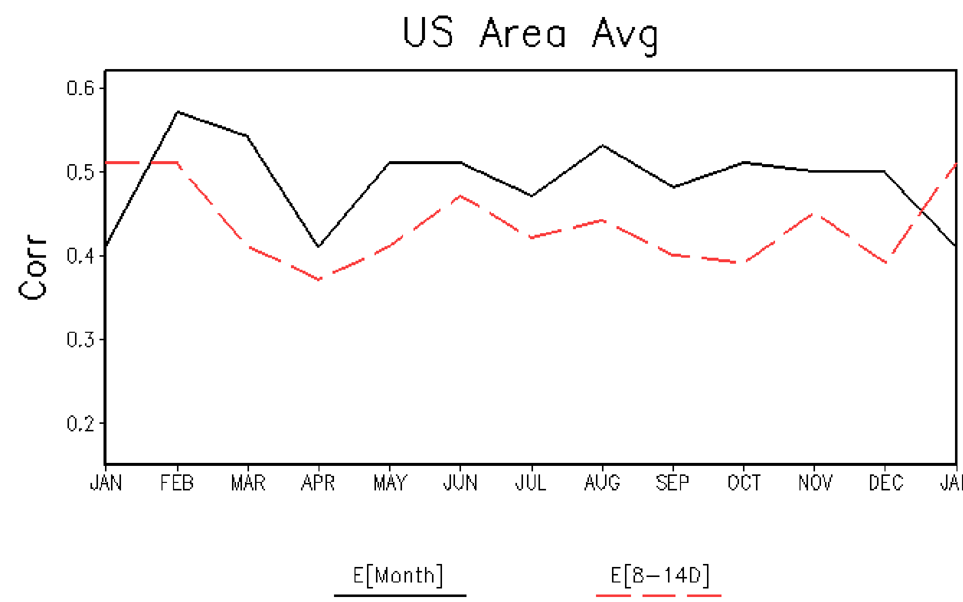
Ocean P has more impact on hits in December

Again differences are clearer in bad misses, most in mid west and southeast



Testing 8-14 Day Forecast

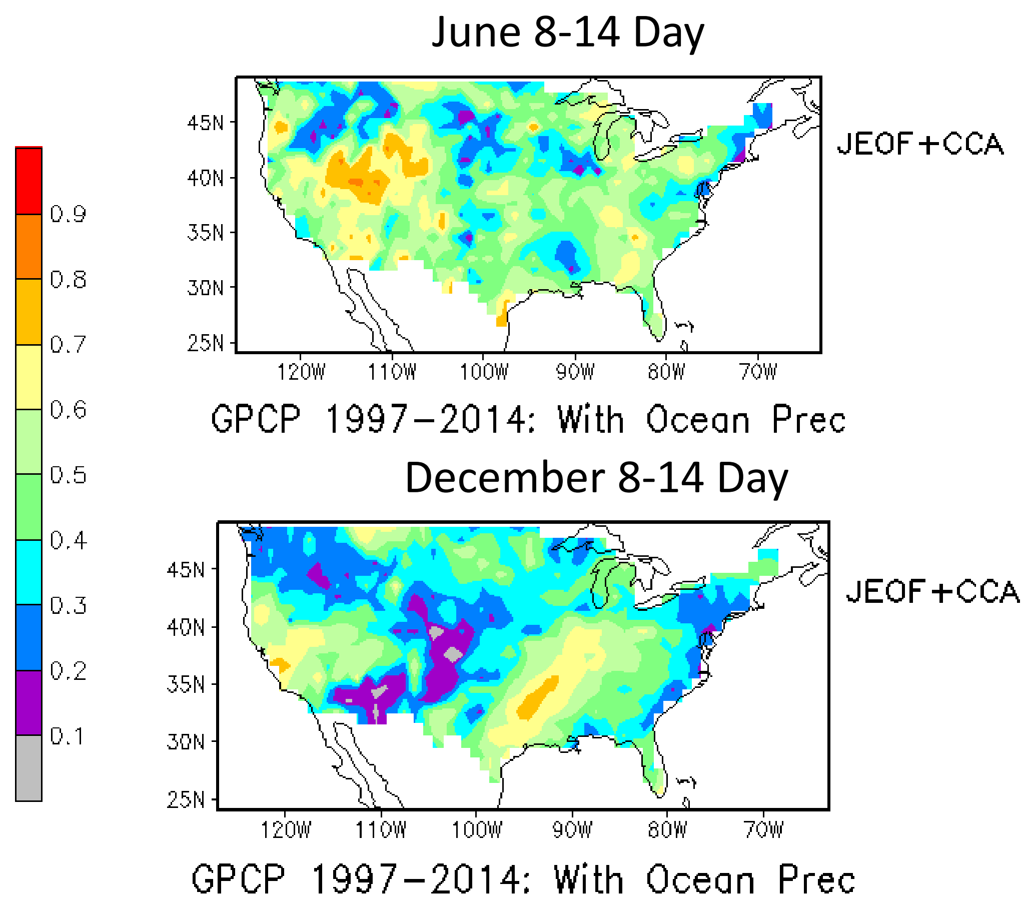
- Forecast for day 8-14 average of each month as test
- Predictors: SST for previous month, P for last week of previous month
- Ensembles of CCA+JEOF, all predictors
- Average skill similar to monthly skill but usually slightly lower



8-14 Day 1-Week Forecast Skill Patterns

Different from monthly patterns with larger areas of low skill

Need to independently test all forecasts of interest



Conclusions

- Super-ensemble-statistical forecast better than comparable non-ensemble forecasts
- JEOF better than CCA and multiple linear models gets additional information from the same predictors
- Ocean-area precipitation predictors improves US-area precipitation forecasts

Next Steps

- Need to more fully develop and test methods and new data sources
  - More lead times & more predictors
  - Other regions, test both T & P predictions
  - Funding likely needed to get more people working on the project
- Super ensembles can incorporate both statistical and dynamic predictions
- Need interested partners for improvements to become part of operational forecasts