

# Separation of interannual signals into decadal and shorter time scales in dynamical ensembles for seasonal forecasting

Dan Collins, Emerson LaJoie, and Jon Gottschalck

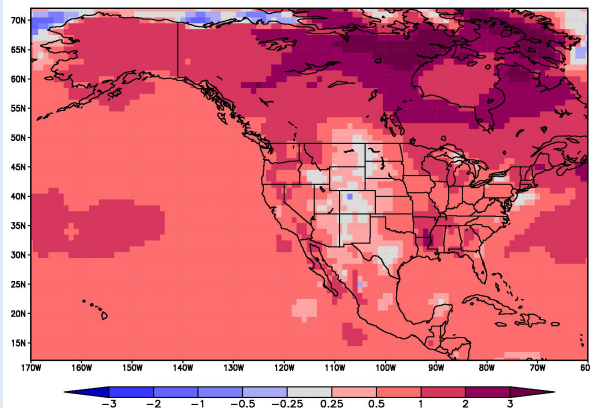
NOAA Climate Prediction Center



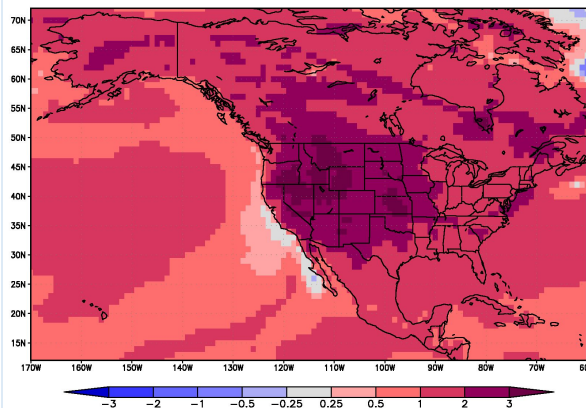
# Background

- We analyze the skill and errors of ensemble model systems related to longer decadal timescales and shorter interannual timescales.
- Much of the skill of seasonal forecasts can be attributed to decadal timescale temperature trends.
- Ensemble models have probabilistic skill that is independent of decadal timescale variability.
- This provides a potential diagnostic of model errors and seasonal forecasting tool.

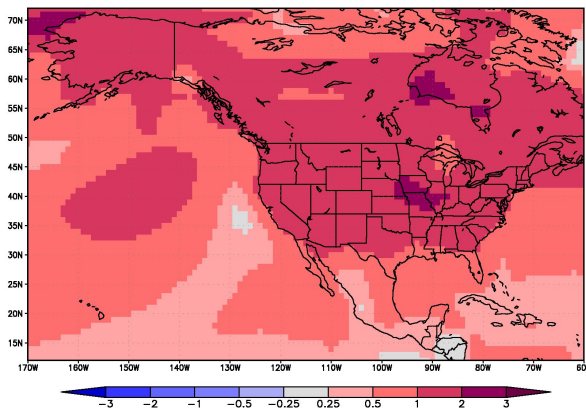




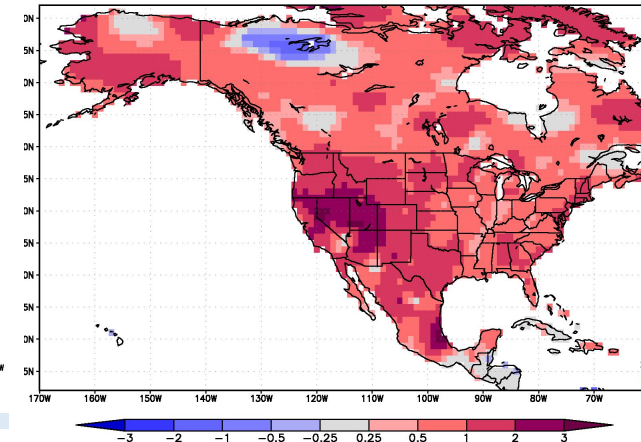
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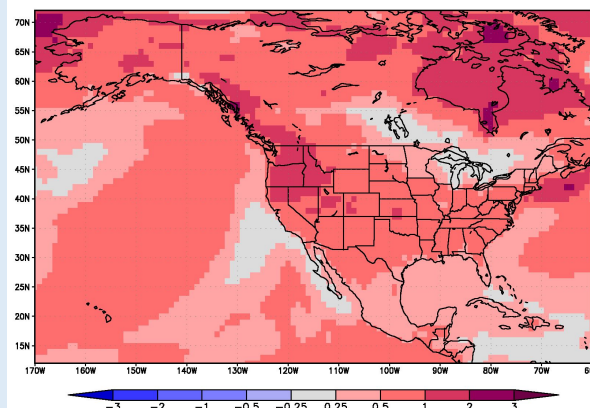
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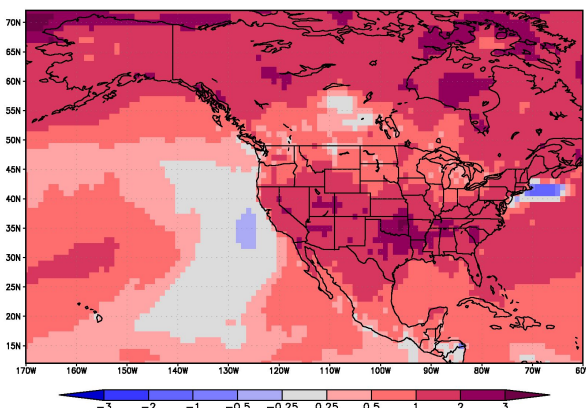
CanCM4i



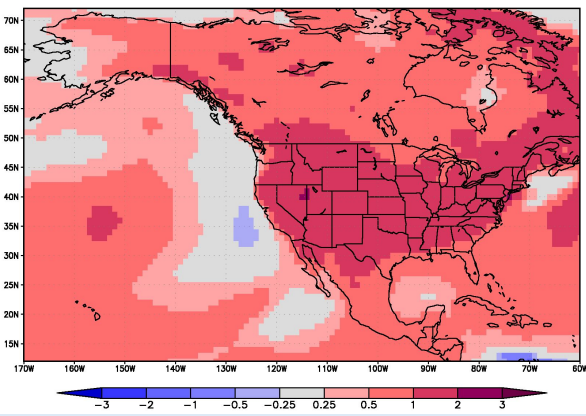
Observed JJA trends



GEM5 NEMO



NASA



NCAR

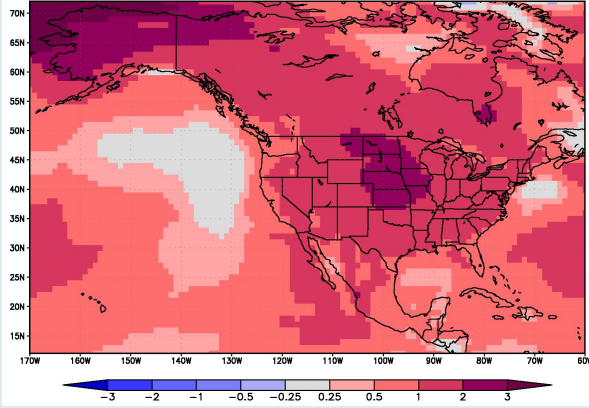
Summer /  
JJA

**Linear Trends based on NMME model lead-1 JJA temperature forecasts vs. observed trends:**

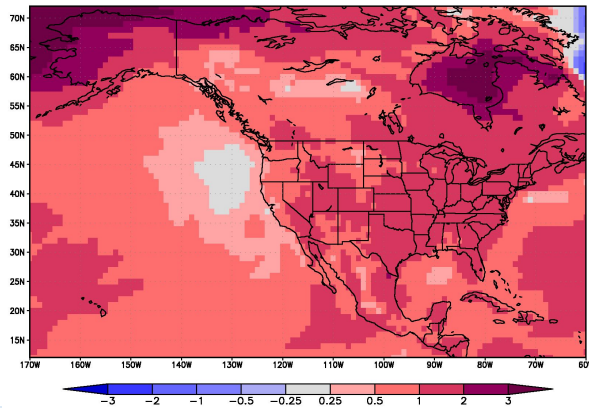
Warm season trends are nearly uniformly positive but somewhat different between models and observations.



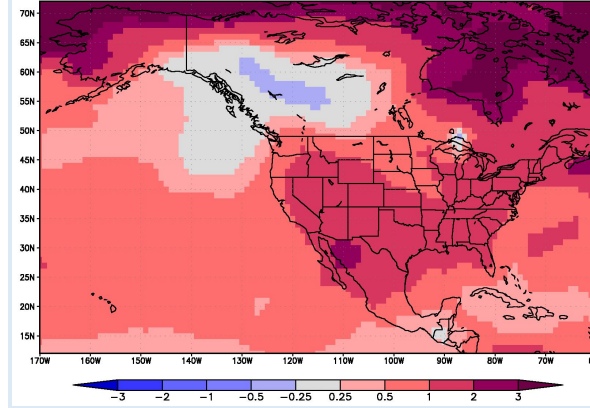
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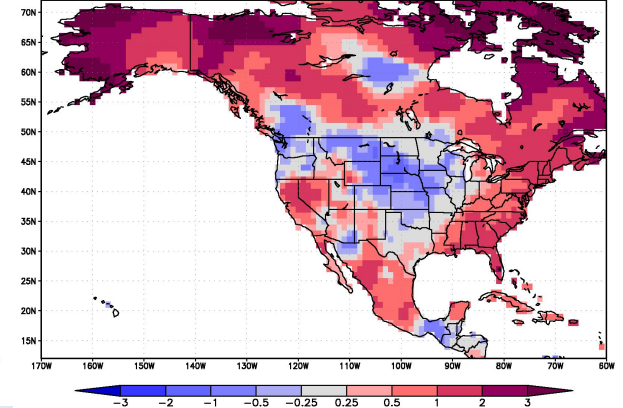
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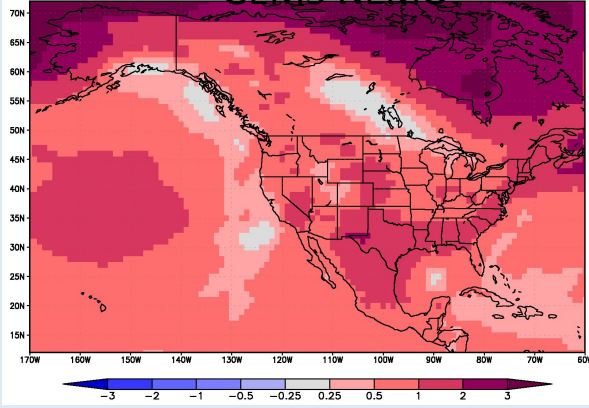
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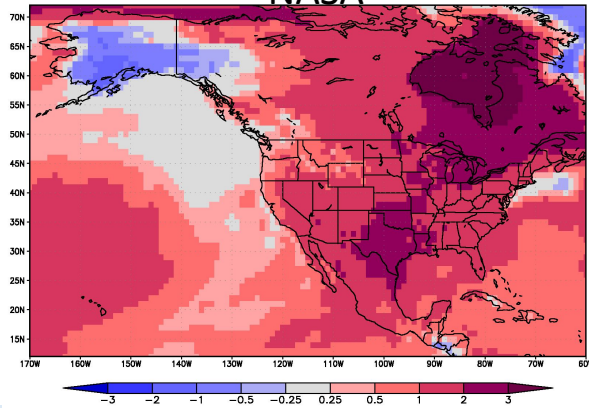
Observed DJF Trends



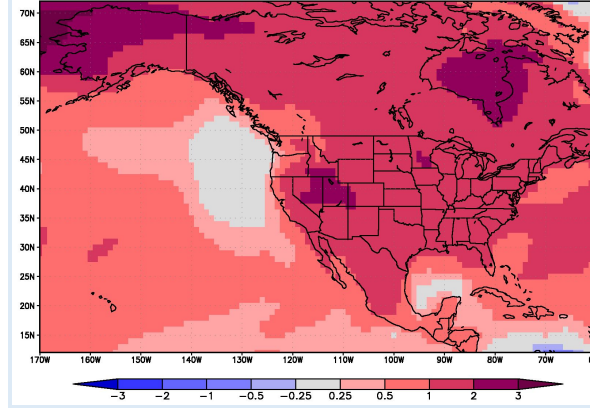
GEM5 NEMO



NASA



NCAR



# Winter / DJF

**Linear Trends based on NMME model lead-1 DJF temperature forecasts vs. observed trends:**

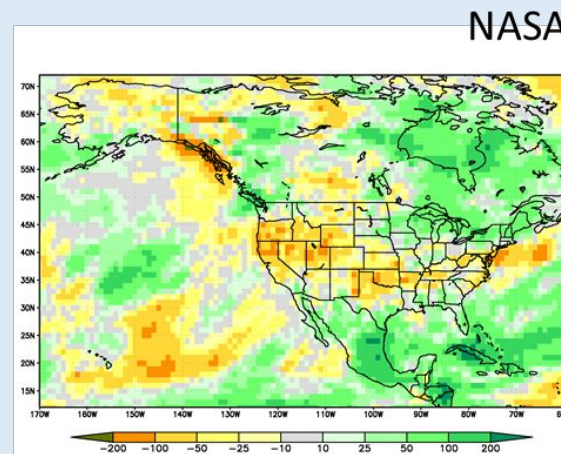
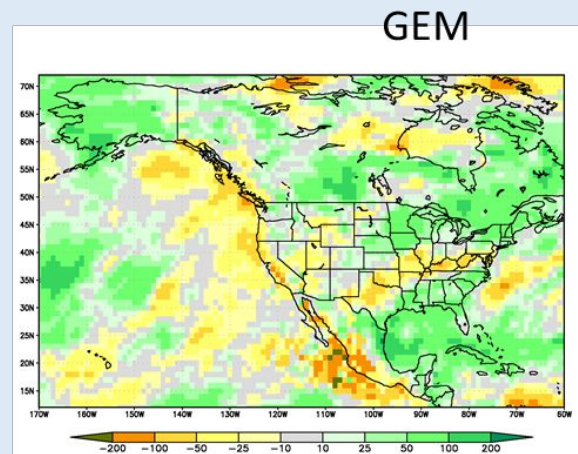
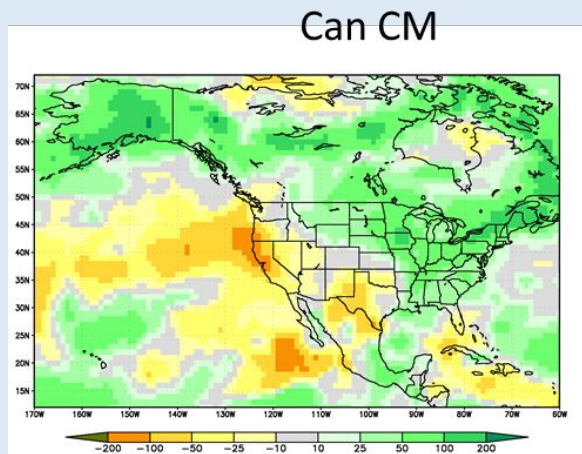
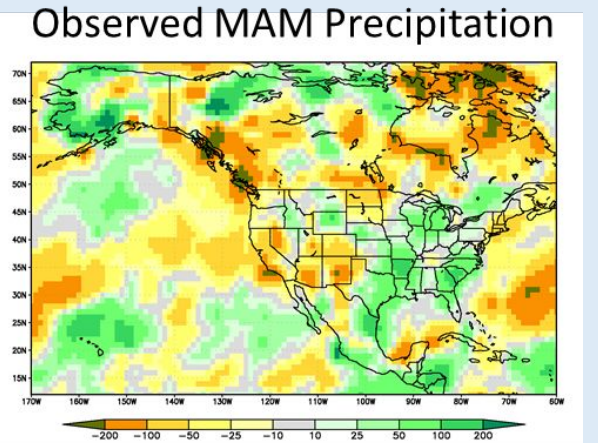
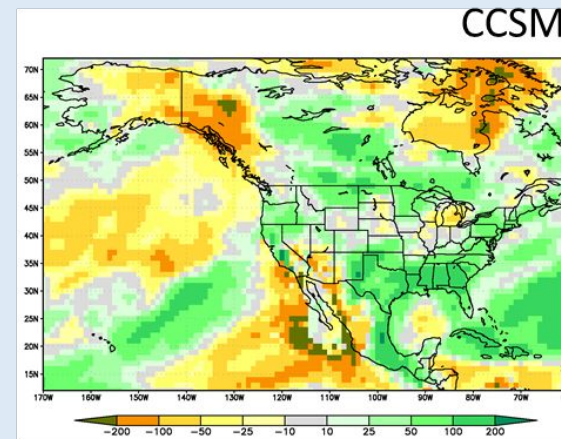
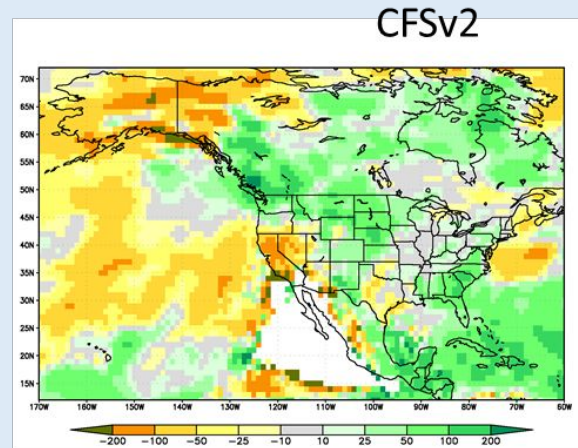
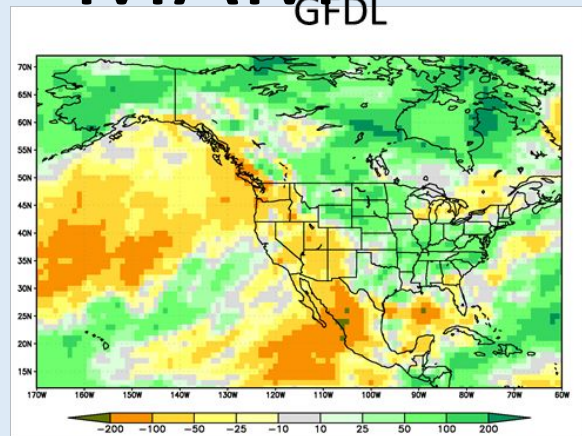
Dynamical model winter trends are more uniformly towards warmer conditions across the domain and greater than observed trends in many areas of North America.





# Precipitation standardized linear trends:

## MAM



- **Trend predictor**: Slowly varying representation of decadal variability / climate change
  - *CPC uses the Optimum Climate Normal (Huang, van den Dool, & Barnston 1996)*
  - *We also tested the linear variation of observed temperatures with time (Cross-validation is used to limit overfitting)*

**Ensemble regression (ER)** post-processing and calibration of dynamical models uses a standard linear regression model of the form:

$$F^* = a + bF$$

$F$  = *model forecast*

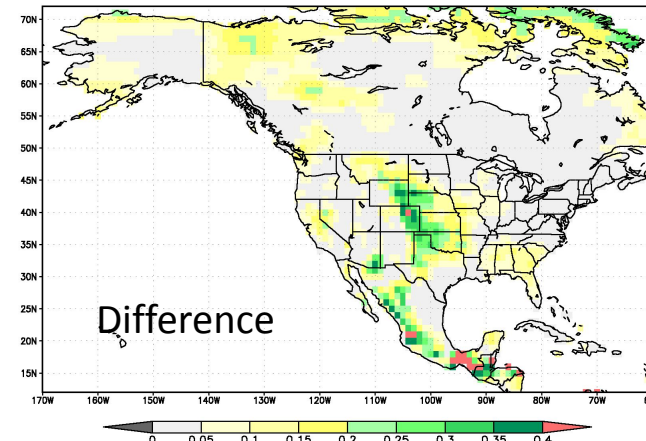
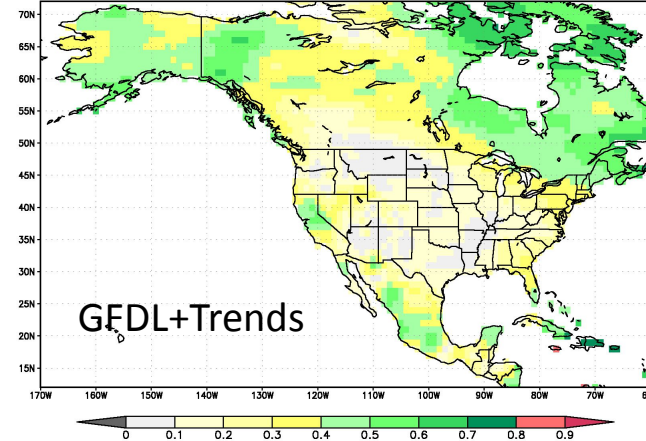
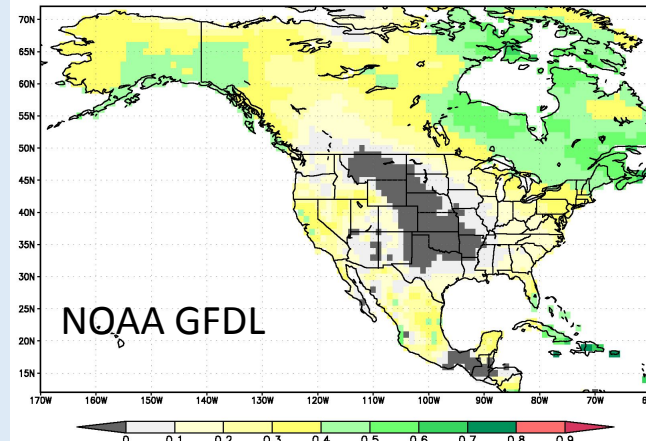
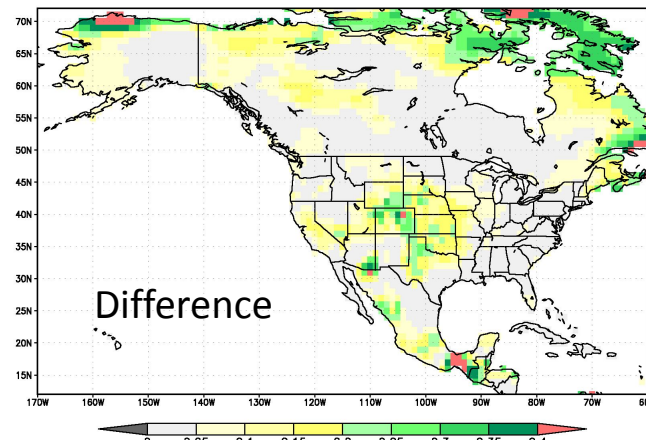
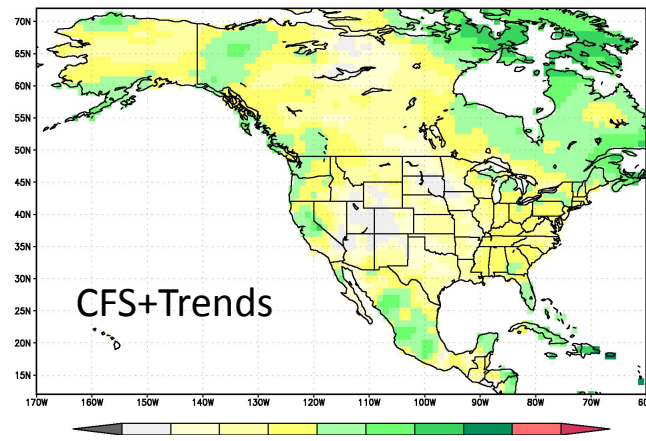
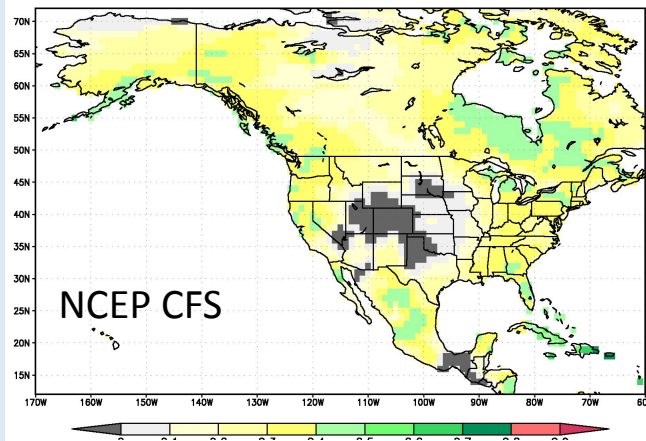
$F^*$  = *corrected model forecast*

We propose to use a decadal trend predictor  $T$ , in addition to model forecasts  $F$  (Krakauer, 2019):

$$F^* = c + dF + eT$$



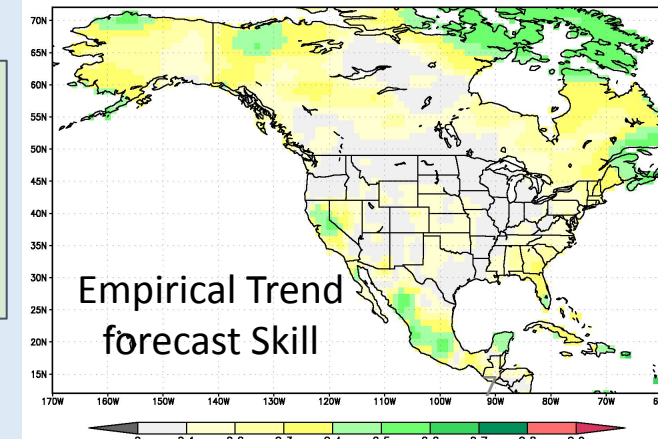




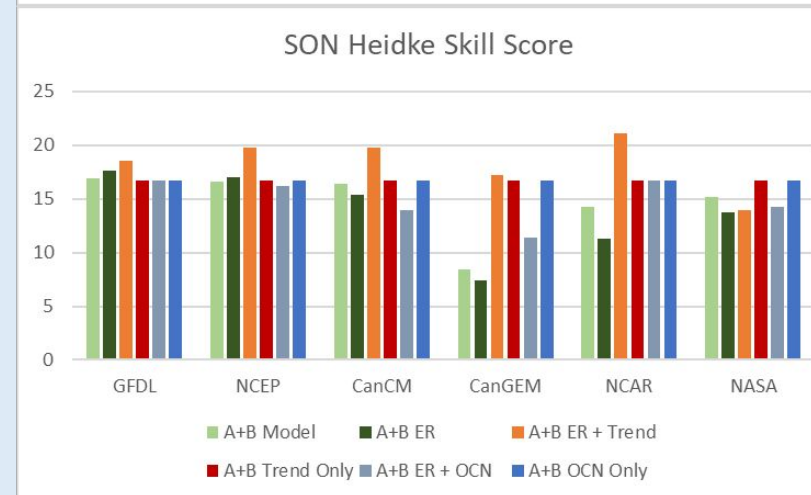
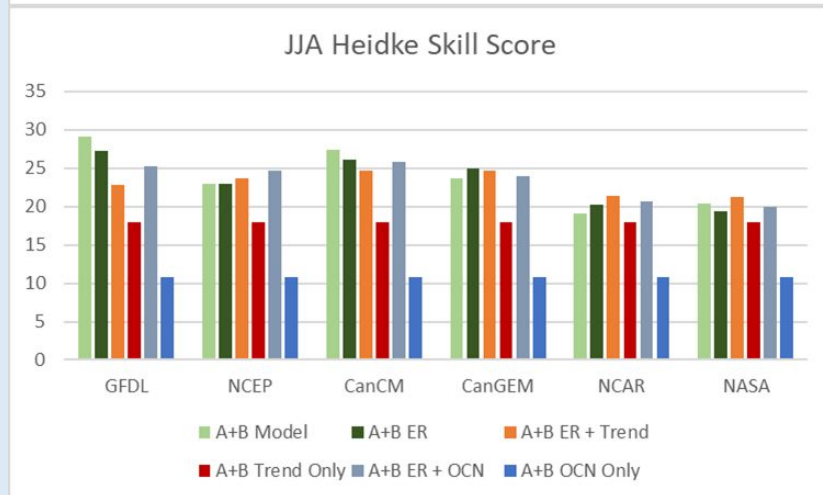
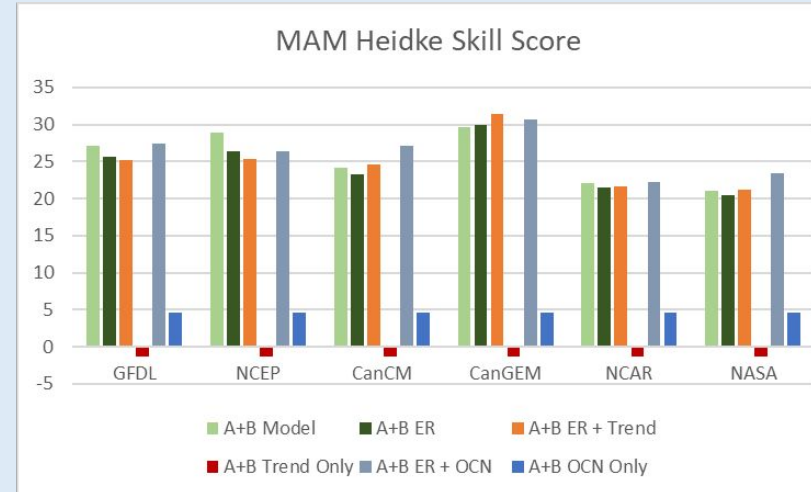
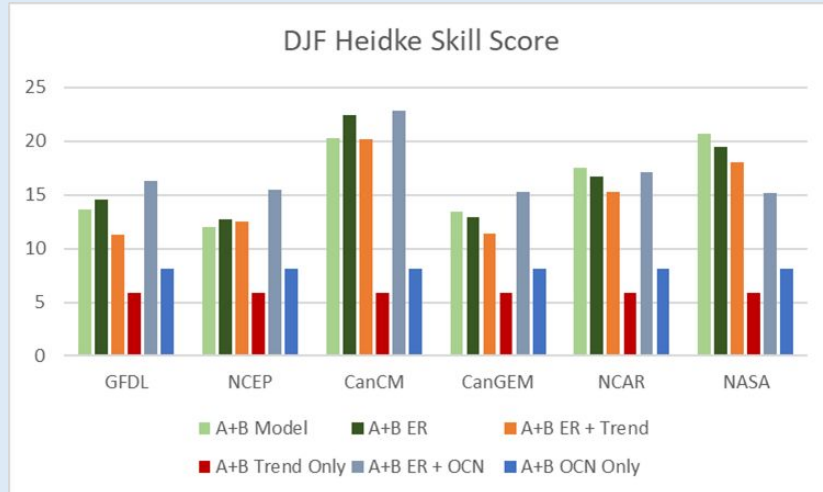
Addition of the decadal trend predictor uniformly increases the apparent **signal**.

No change to signal where dynamical model predicts trend or trends are small.

## Correlation Signal from Calibrated Model + Decadal Trends: Anomaly Correlations for lead-1 DJF Temperature



OCN predictor improves Heidke Skill Score (HSS) for DJF Temperatures while Linear Trend predictor improves skill in SON, when trends are greatest



HSS,  
Temperature

Non-EC,  
Above and  
Below  
Normal



Post-processing using Ensemble Regression with OCN, gray bars, performs best overall



# CFSv2 DJF forecasts: Raw, ER, OCN+ER, Obs.

2014-15

2015-16

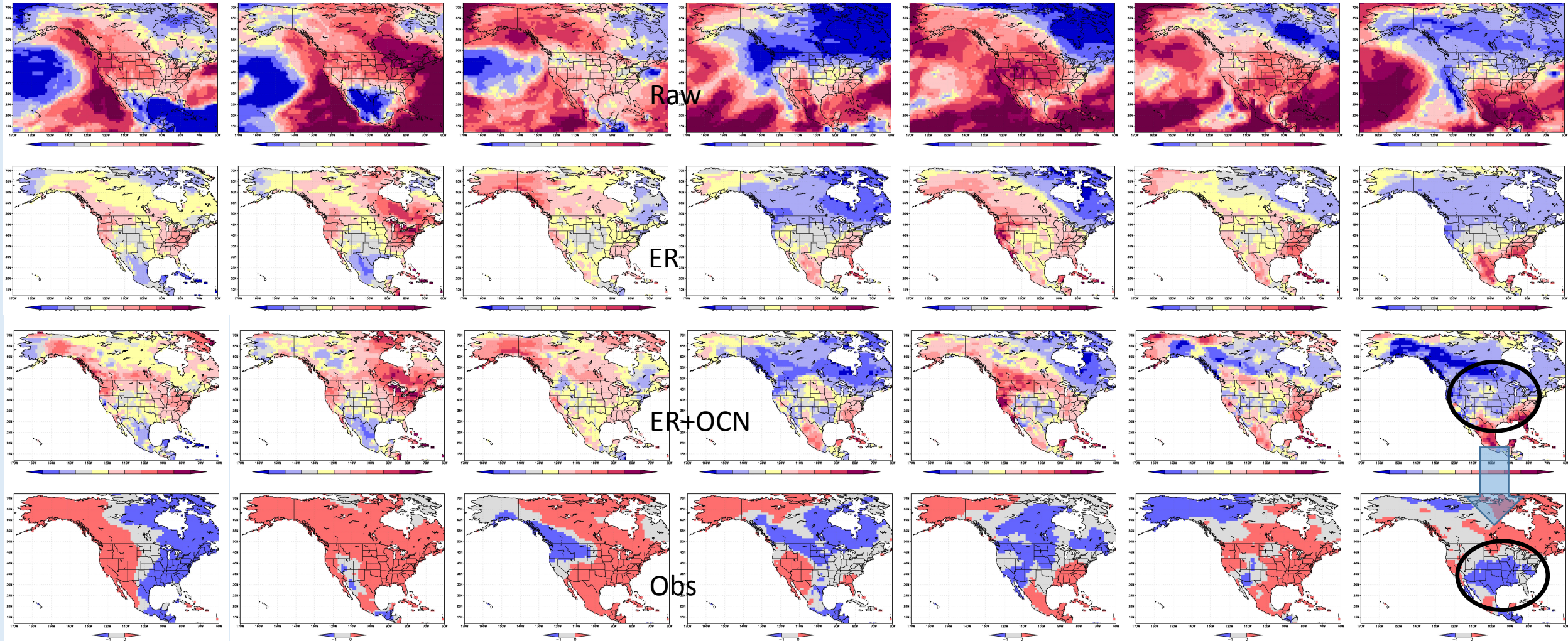
2016-17

2017-18

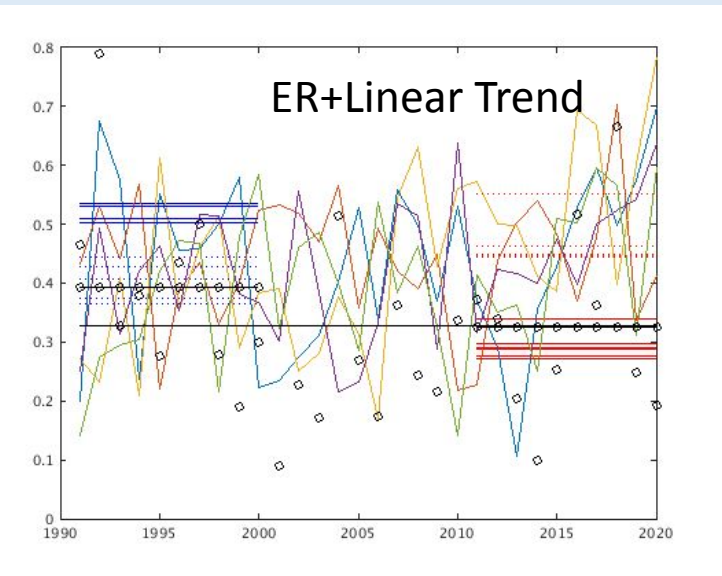
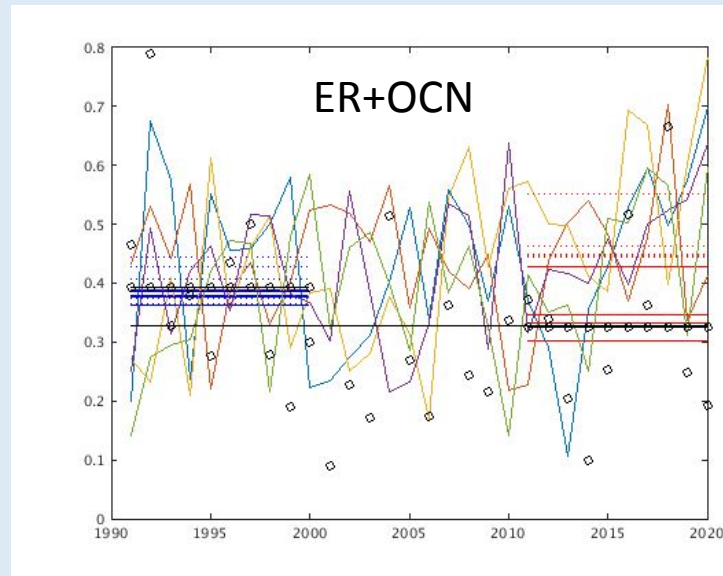
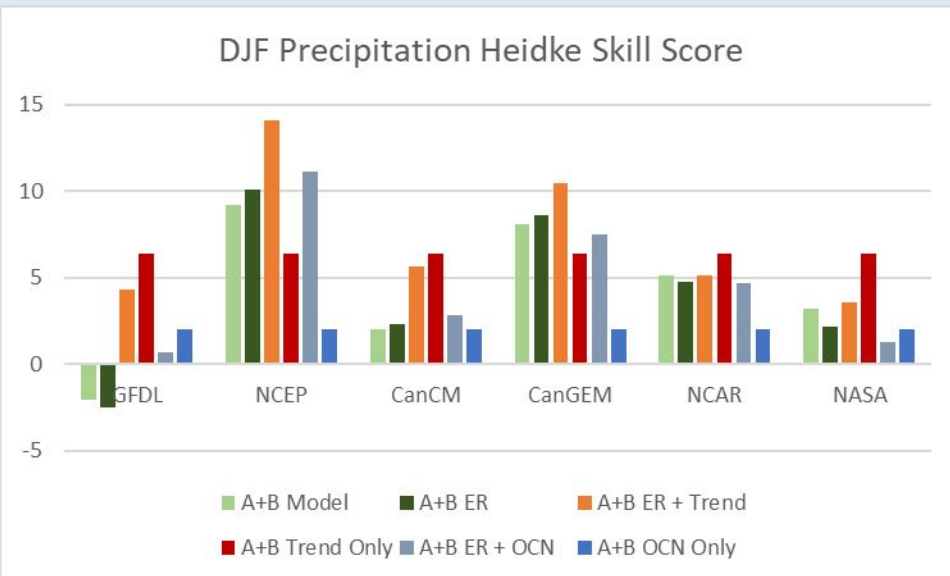
2018-19

2019-20

2020-21



# DJF Precipitation HSS for CONUS + AK



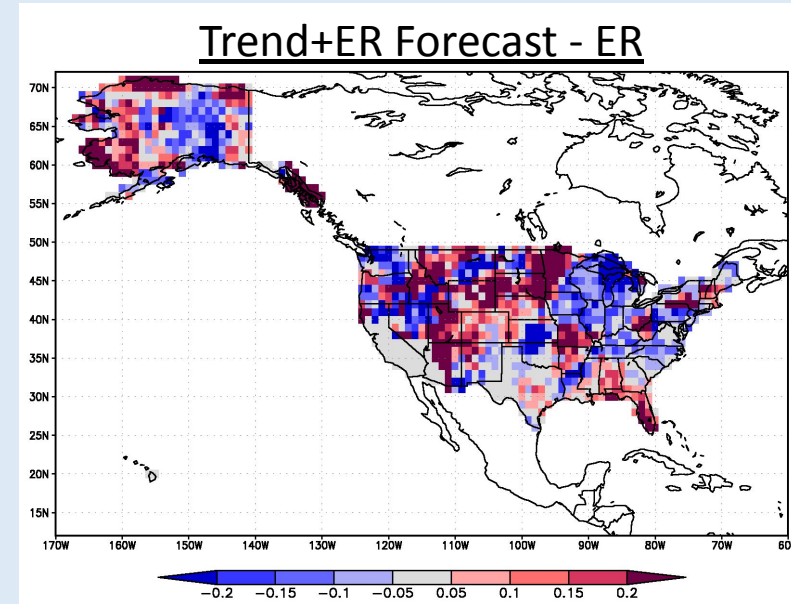
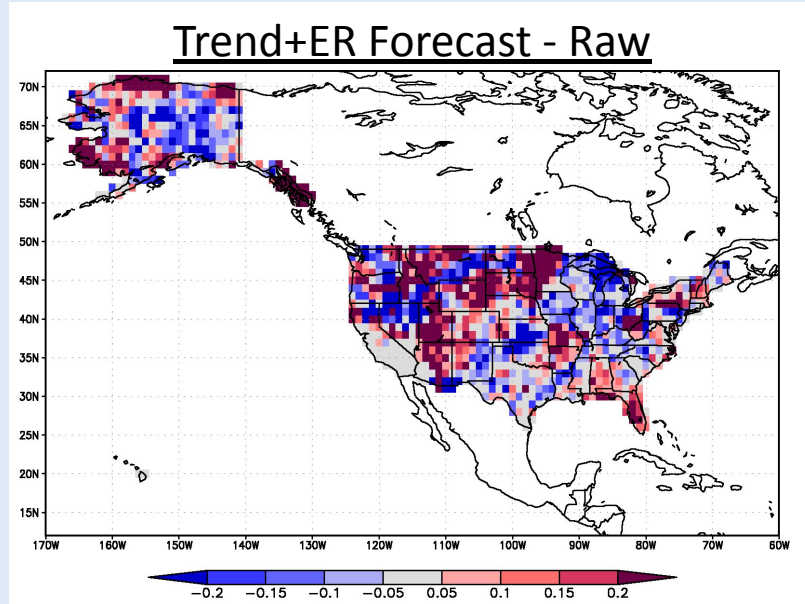
- ER + Linear Trend (orange bars) most skillful in winter (with an overall drying trend)
- However, frequency of above normal (horizontal lines) is less than observed (circles) in recent decade





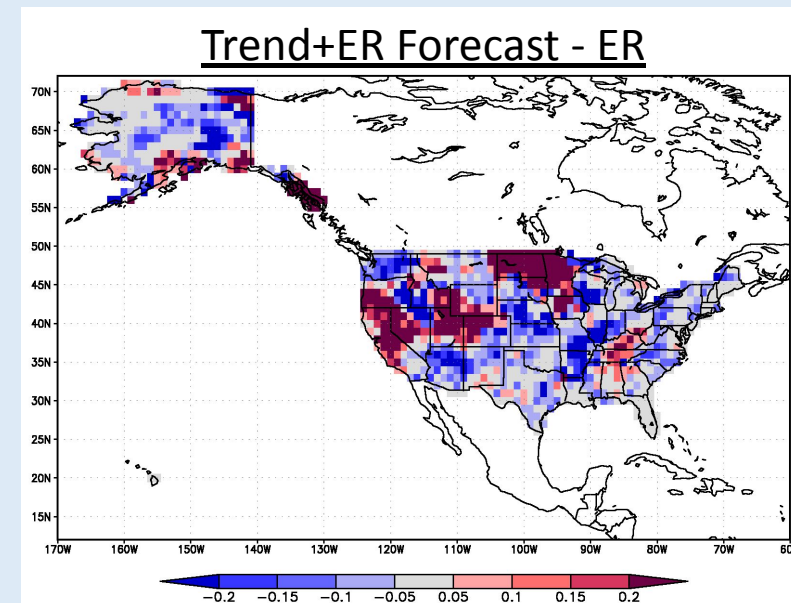
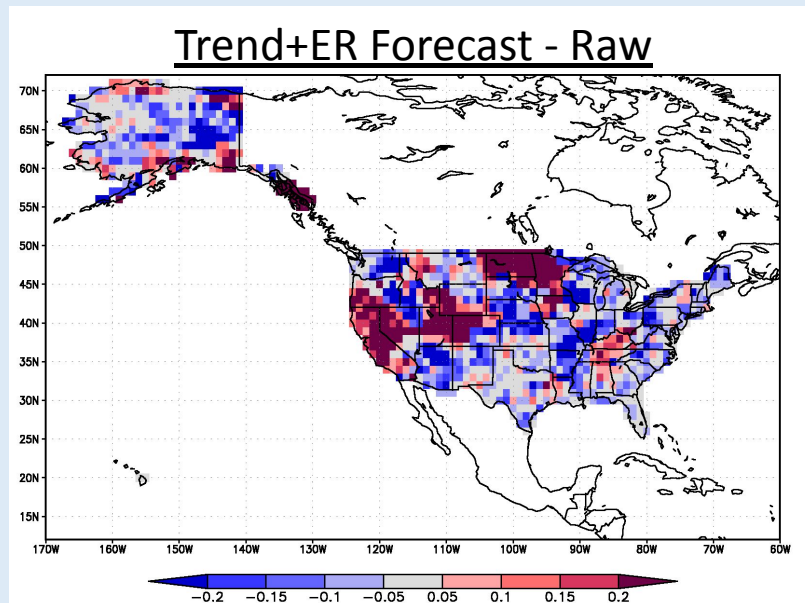
# $\Delta$ HSS for CFSv2 Precipitation

SON

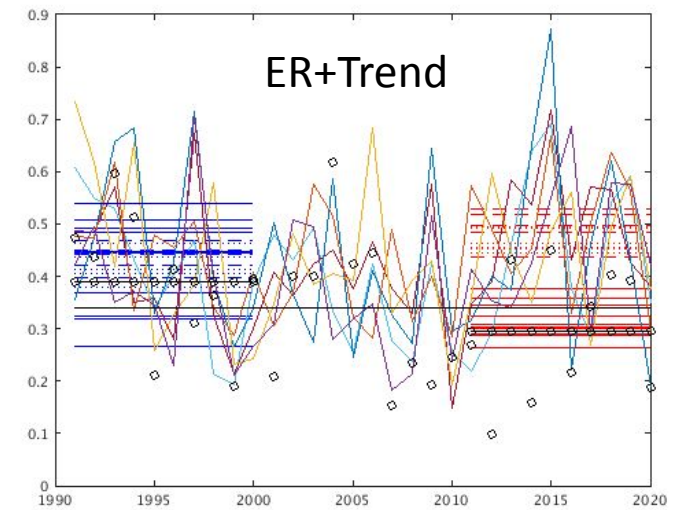
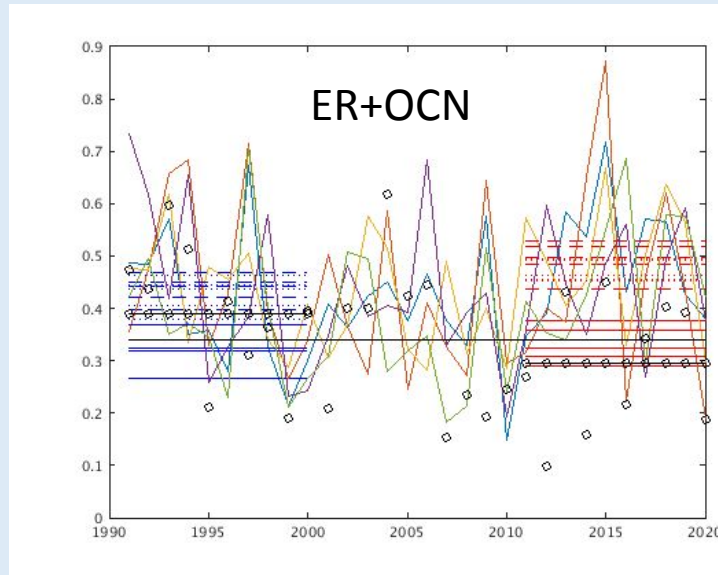
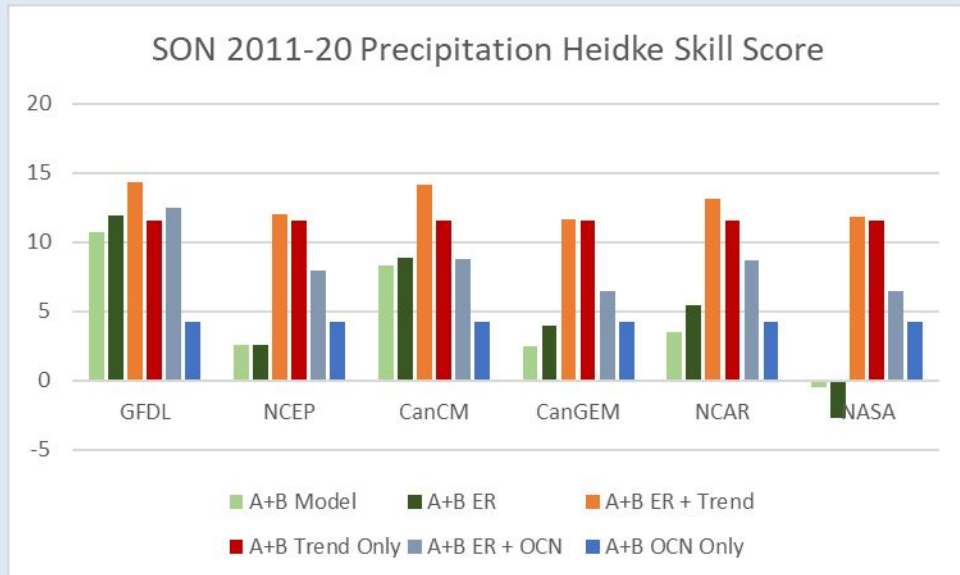


- Red areas show improvement of Heidke skill score using trend-aware post-processed forecasts over both simple post-processed and raw model forecasts

DJF



# SON Precipitation HSS for CONUS + AK



- Drying trend;
- ER+OCN improves skill, while ER + linear trend improvement is greater

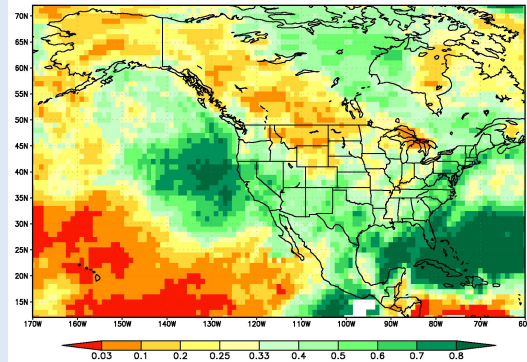




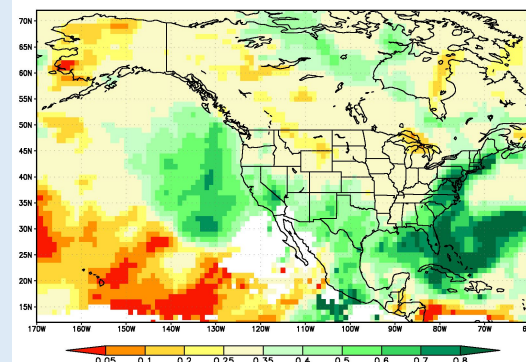
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Raw, ER, ER w/Trends, Obs.

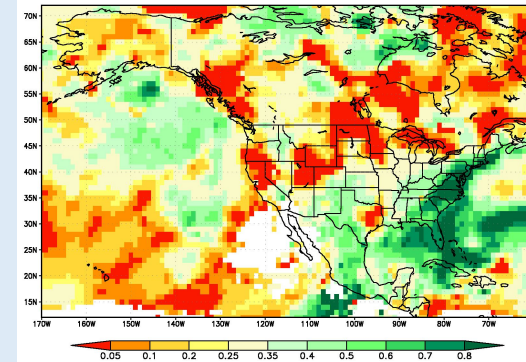
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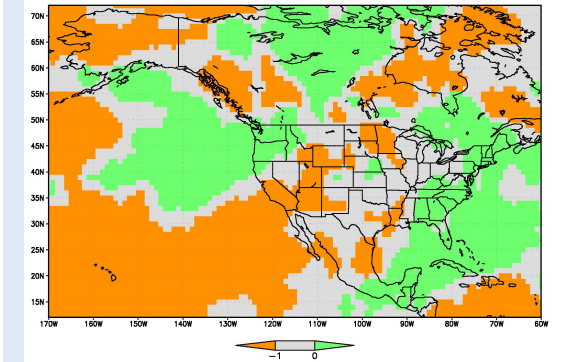
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ER

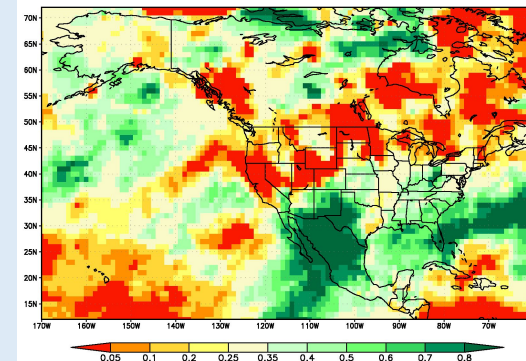
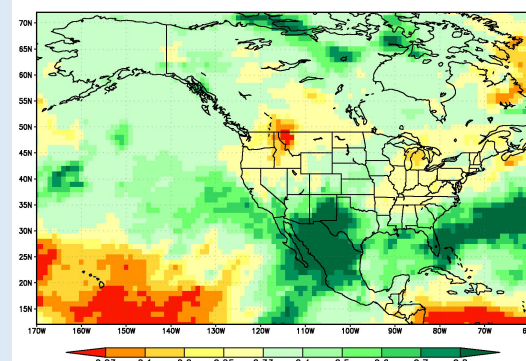
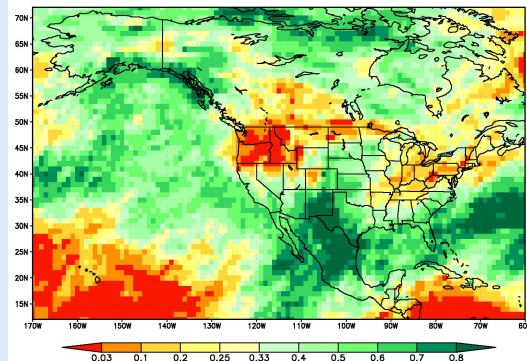


ER+Trend



Observed Tercile

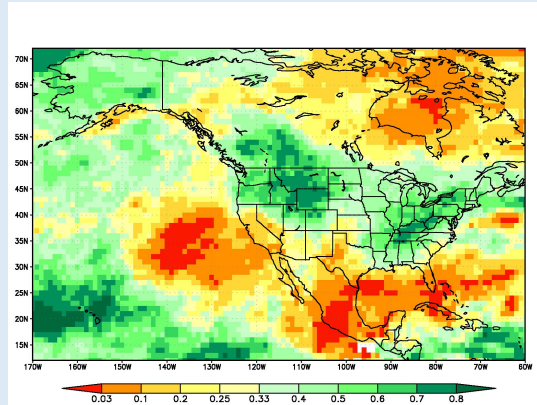
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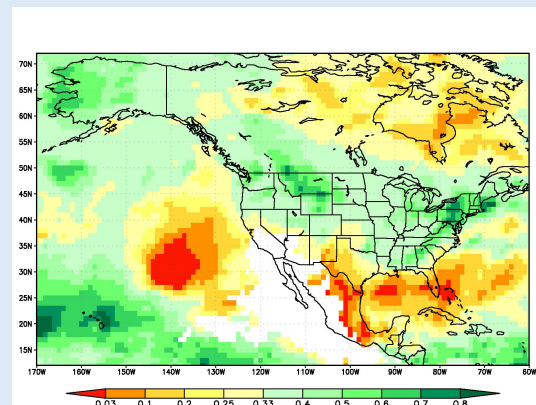
# Winter (DJF) 2020-21 Precipitation forecasts:

Raw, ER, ER w/Trends, Observed

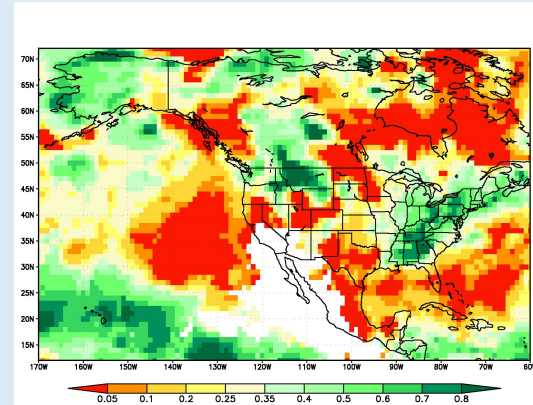
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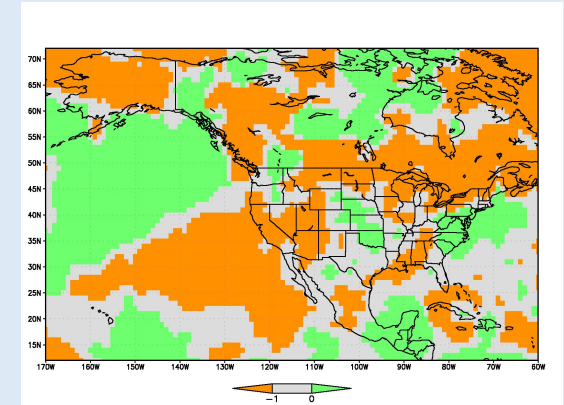
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ER

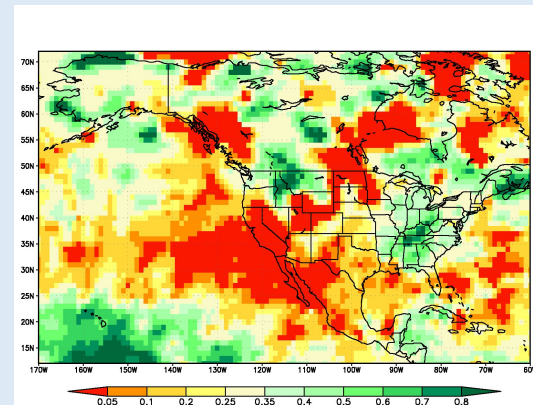
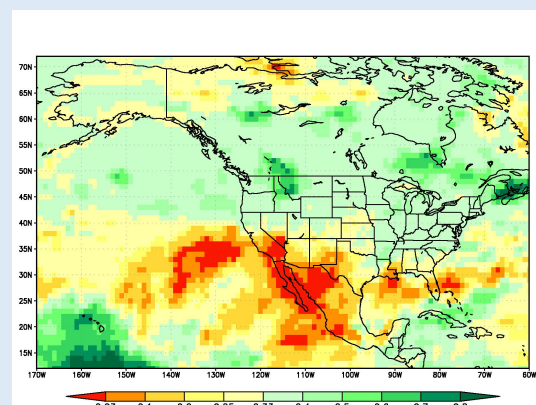
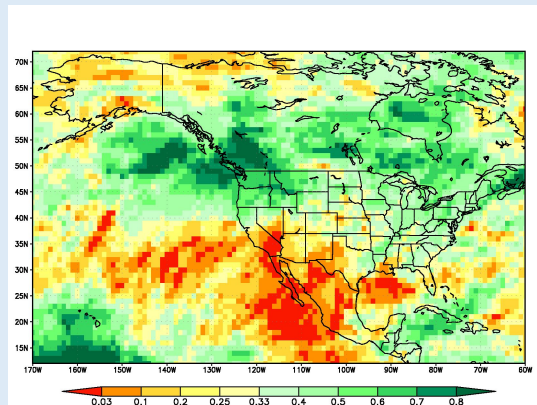


ER+Trend



Observed Tercile

GFDL



# Summary

- Biases in dynamical models are separated into decadal and shorter timescale variability
- Models appear to have biases associated specifically with longer timescales, varying by season and location
- Correction or removal of longer/decadal timescale errors increases skill
- Separation of model error by timescale is a potential diagnostic that may help determine sources of model error

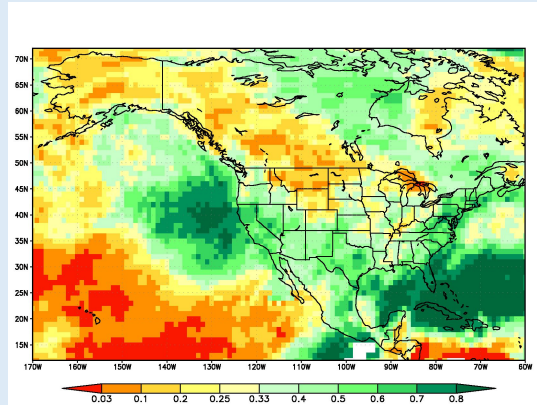




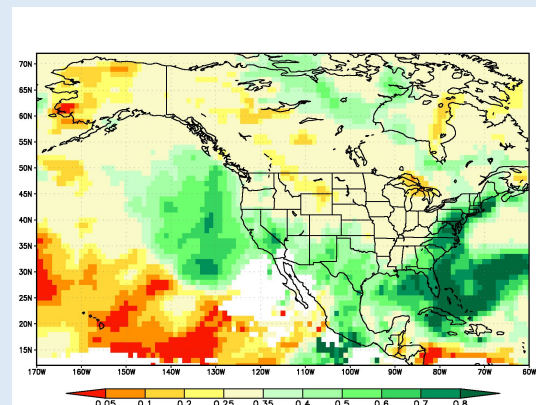
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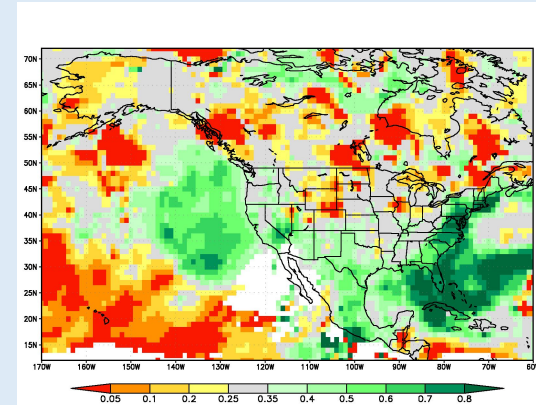
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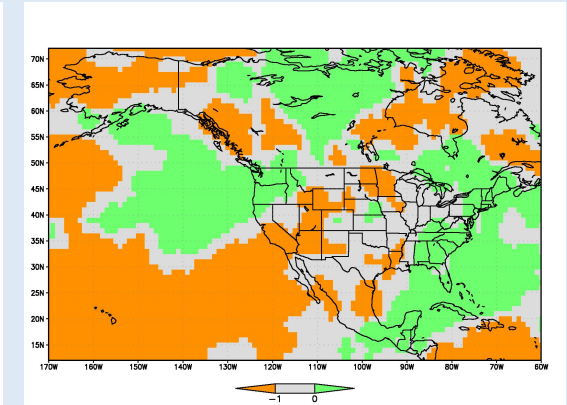
Raw



ER

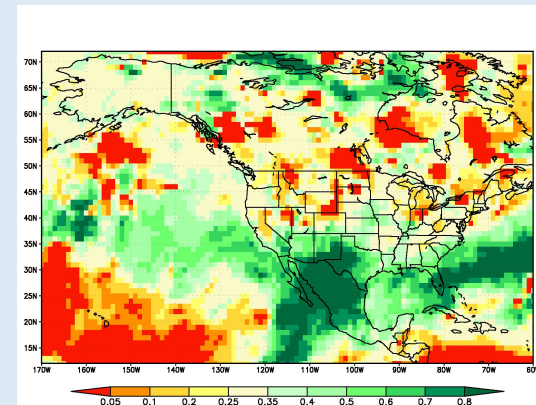
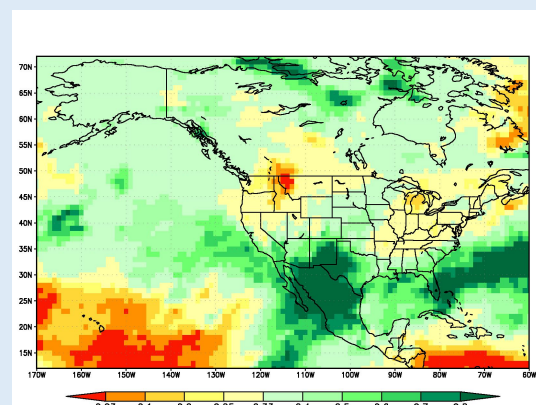
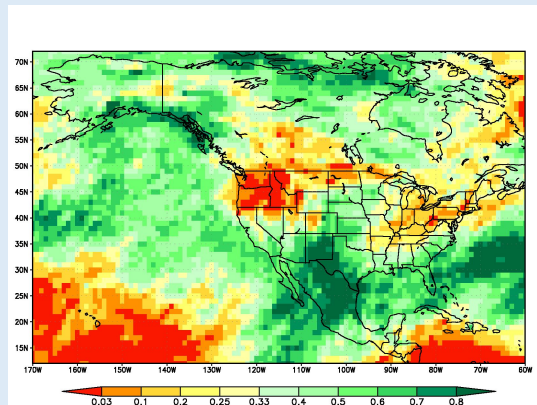


ER+OCN



Observed Tercile

GFDL

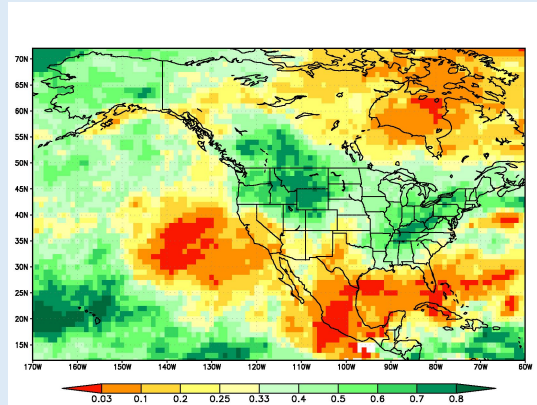




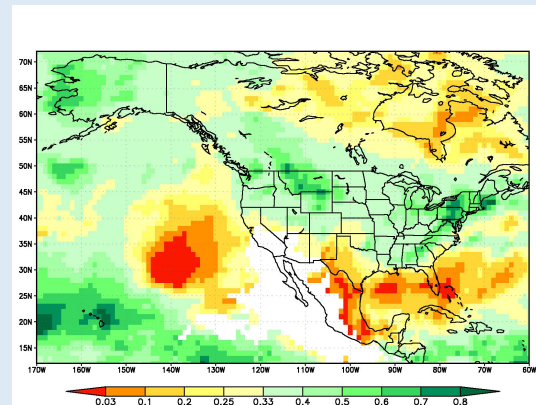
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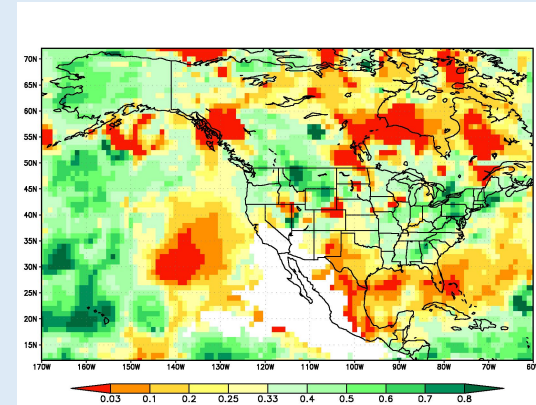
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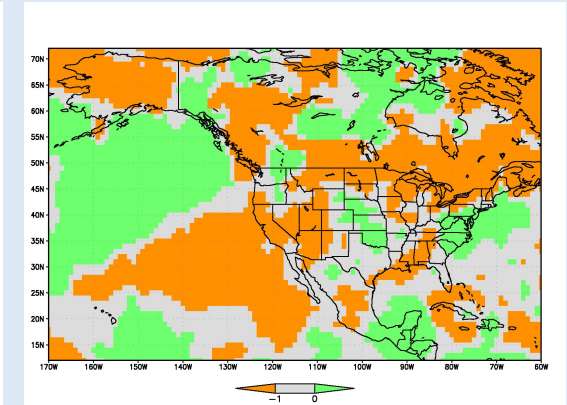
Raw



ER



ER+OCN



Observed Tercile

GFDL

