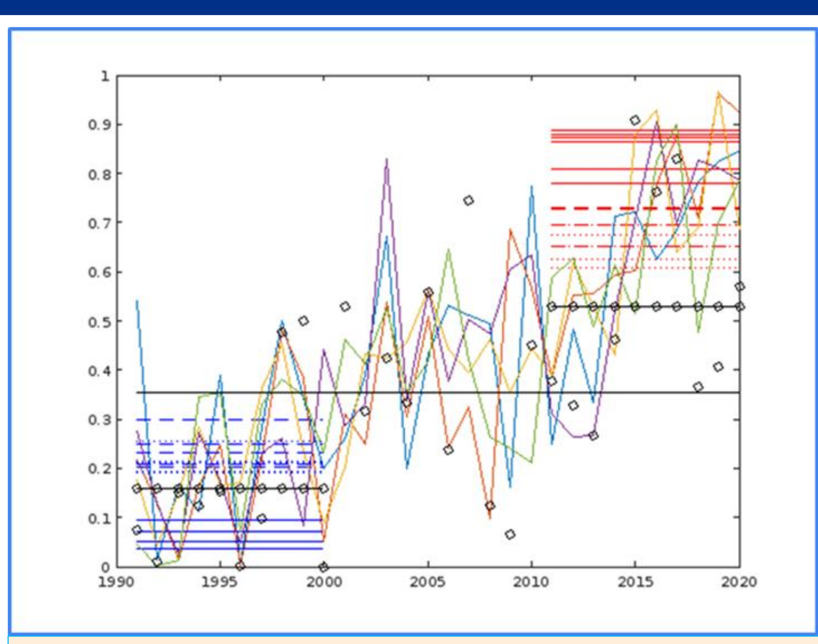
Climate change aware bias correction and calibration of global climate models for seasonal forecasting

Dan Collins
NOAA/NCEP Climate Prediction Center
dan.collins@noaa.gov

Outline

- Global climate models (GCM) and multi-model ensembles (e.g., North American Multi-Model Ensemble, Copernicus) are a primary tool for the prediction of seasonal variations in temperature and precipitation.
- Multi-decadal timescale variability, including anthropogenic climate change, is a primary source of predictability on seasonal timescales.
- GCM seasonal forecasts should contain decadal-timescale signals through initialization, predicting shorter timescale interannual variability.
- In addition, there may be changes in the impacts of interannual climate phenomena, such as the El Nino Southern Oscillation (ENSO) over decadal timescales.
- Generally in the validation and post-processing of seasonal forecasts, signals related to various climate forcings and timescales are evaluated simultaneously.
- In this analysis, we analyze the skill and errors of dynamical models related to longer decadal timescales and shorter interannual timescales.
- It is found that much of the skill of seasonal forecasts can be attributed to decadal timescale temperature trends.
- However, decadal variability appears poorly represented in seasonal forecasts (including the shortest lead times of one month forecasts).
- Statistical correction of the decadal signals in seasonal forecasts is shown to improve skill on seasonal timescales.
- "Climate change aware" evaluation of GCMs reveals model errors in decadal variability and skill that is independent of decadal variability.

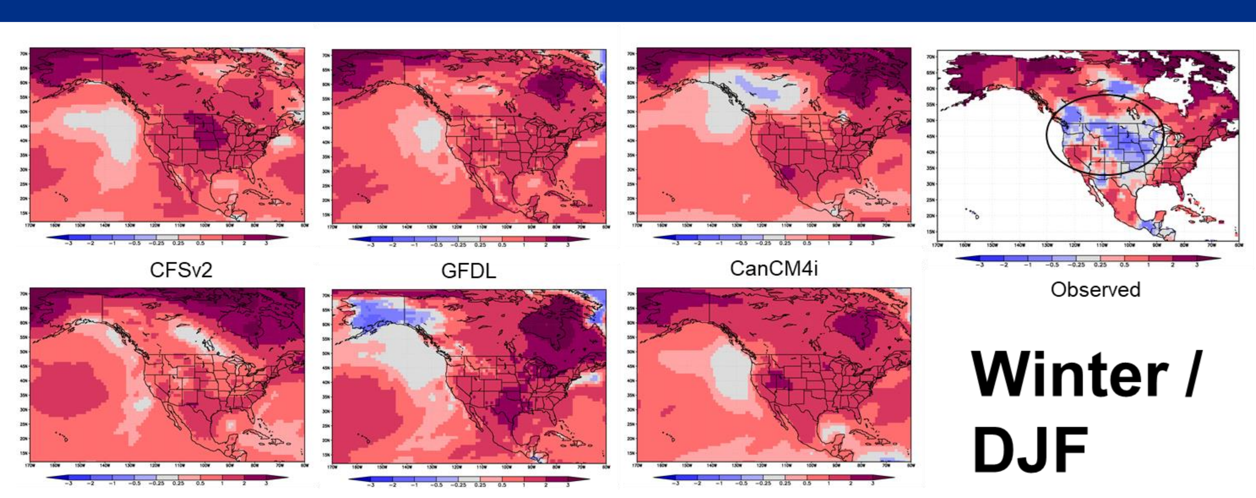
Forecasting seasonal variability under climate change



- Climate change alters the frequency above normal (as well as near and below normal) seasonal temperatures. [Coverage across N America shown.]
- By definition, above normal occurs 33% of seasons over the 30-year climatology period, but over 50% in last 10 years (horizontal black line).
- Ensemble models predict above normal more often than occurs in observations in this 10-year period. (dotted red lines).

Frequency of above normal seasonal temperatures across a 30-year hindcast

Seasonal Forecast Model & Observed Trends

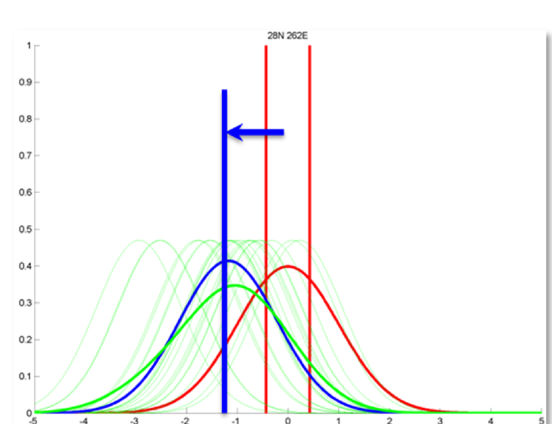


Winter / DJF

Methodology

- Bias correction and calibration of model derived probabilities are essential component of the forecast process and known to improve skill. While post-processing typically derives statistics from multi-decadal hindcasts to apply to real-time forecasts, skill and biases may be conditional on the timescale of signals from seasonal to decadal.
- North American Multimodel Ensemble seasonal hindcasts from 1991-2020
- Leave-3-Years-Out-Following Cross-Validation
- Linear Regression is used to bias correct forecasts and calibrate probabilities to represent model error.

Ensemble Regression (Unger et al, 2009) is used to calibrate ensemble model forecast probabilities with the addition of statistical predictions of climate change.



$$F^* = a + bF$$

F = *model forecast*

F^* = *corrected forecast*

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

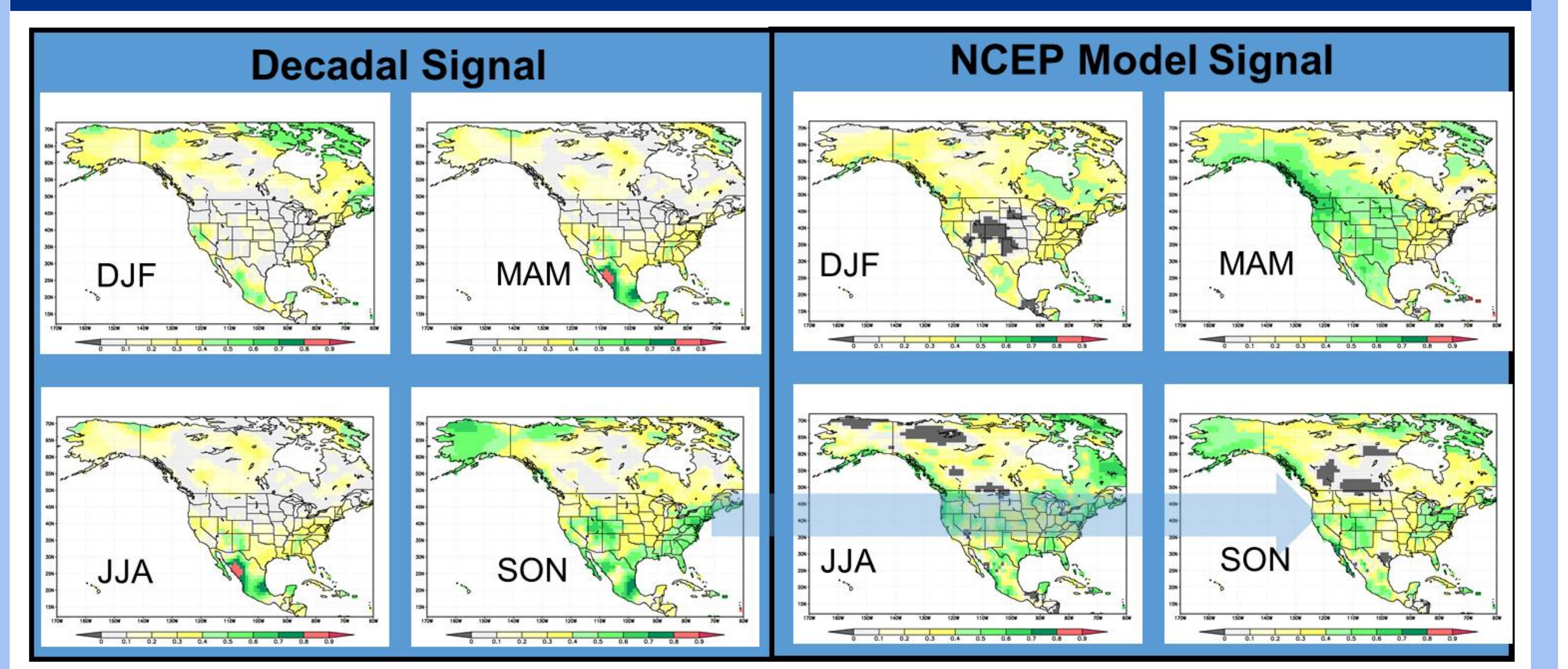
T = climate trend predictor

Trend is predicted using two methods:

1) Optimum Climate Normal (OCN): 10-year running mean (Huang et al, 1996)
2) Linear trend

Figure: Probability density functions for climatology (red), a single ensemble mean regression forecast (blue), and the same ensemble regression forecast (dark green).
The normal probability density functions in light green represent errors for the individual ensemble members.

Comparison of seasonal forecast skill and trends



- Correlations of cross-validated multi-decadal linear trends to observations (left 4 maps) are similar to dynamical model forecast correlations (right).
- In some seasons (e.g. SON), skill of a cross-validated linear trend exceeds model forecast skill.

Conclusions

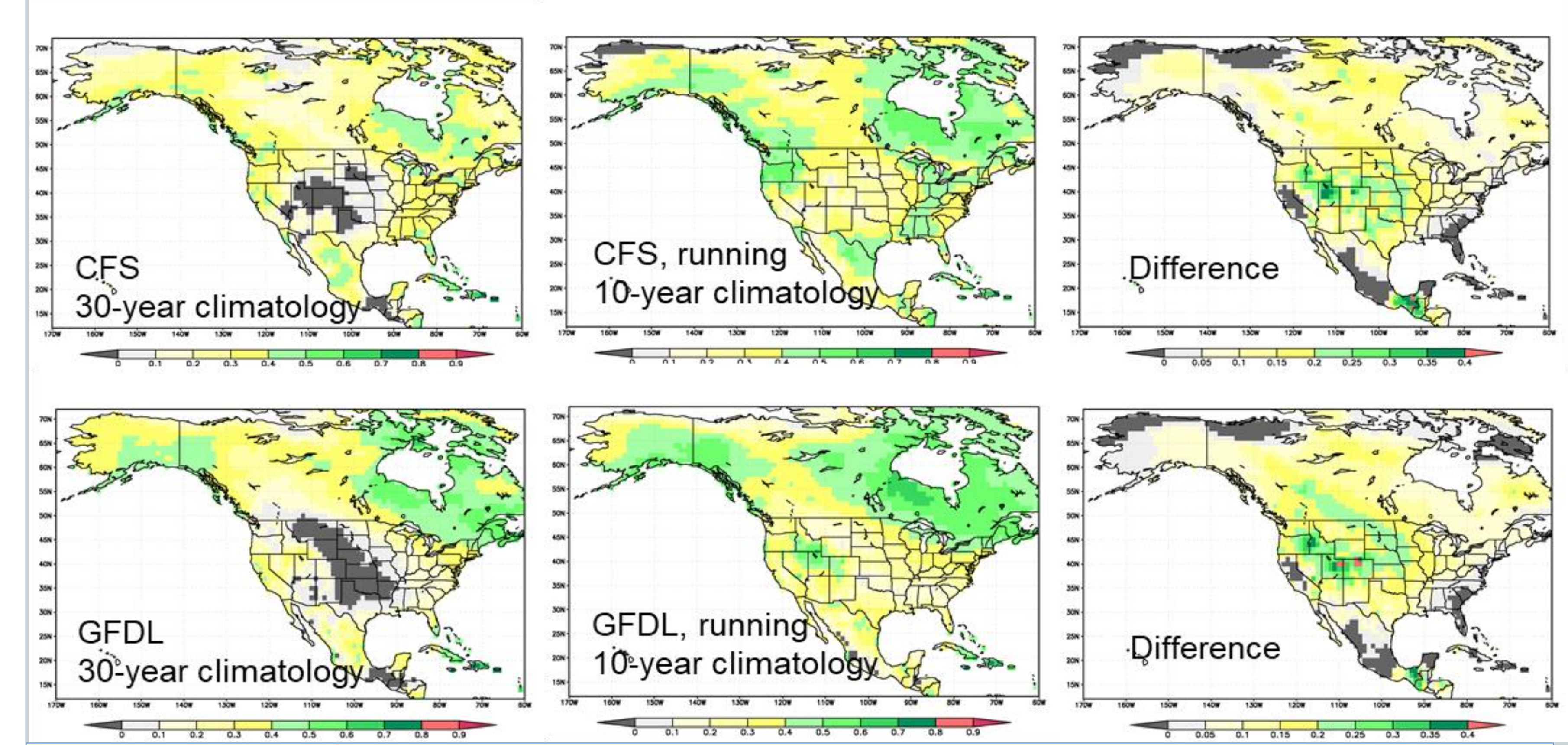
- Separation of forecast signals into 1) decadal and 2) shorter-timescale interannual variability provides new diagnostics of model error, and can be significant to the validation of both seasonal and decadal predictions.
- Climate change impacts seasonal forecasts, changing the frequency of above and below normal temperatures and precipitation in both models and observations.
- Model biases in decadal trends appear in the first month of the forecasts.
- Models have greater skill in predicting anomalies relative to the most recent observed 10-year climatology, than the 30-year hindcast climatology.
- Climate change aware post-processing can correct decadal timescale biases and increase skill.

Future Work:

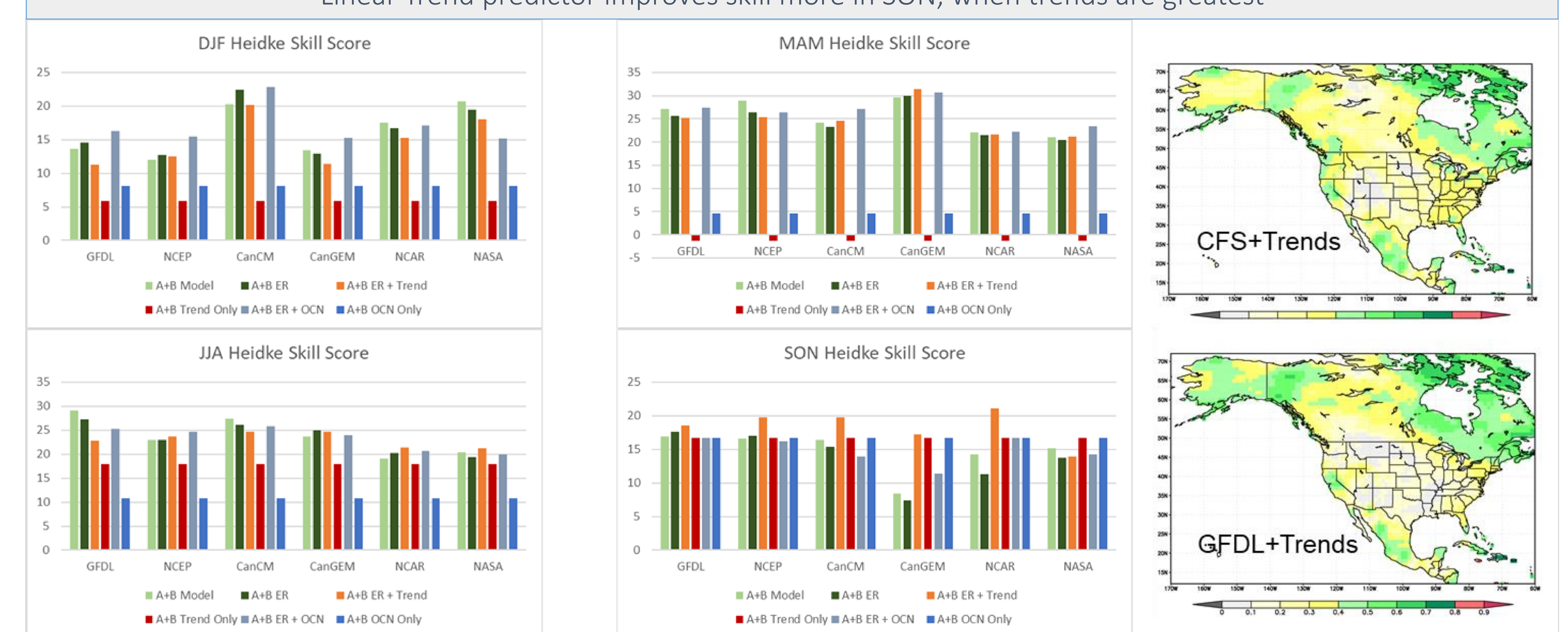
- Diagnose model errors associated with El Nino Southern Oscillation (ENSO) variability and impact of ENSO-related errors on model decadal trends.
- Evaluate if observed trends are in the range of model trends from ensemble members.

Results

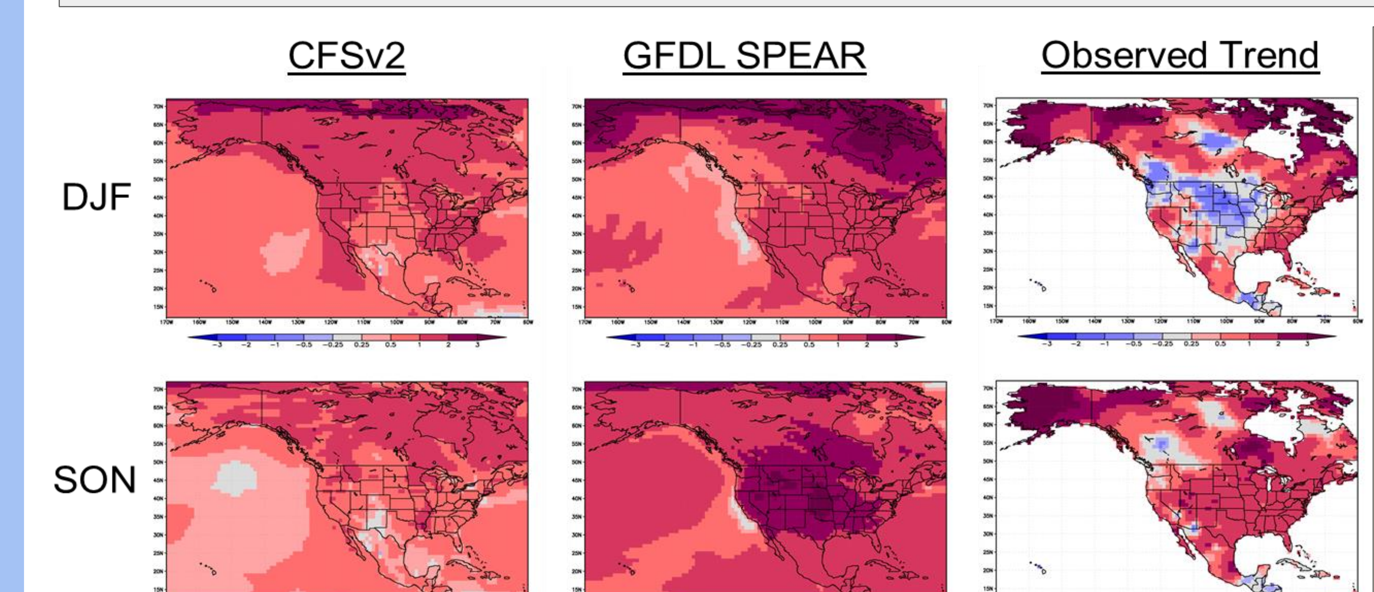
- Correlation of model forecast anomalies to observations relative to a running 10-year climatology have greater skill compared to the correlation of anomalies relative to a standard 30-year climatology.
- When decadal signals are effectively removed, models predict the smaller remaining interannual variability.



Optimum Climate Normal (10-year running mean) predictor improves Heidke Skill Score (HSS) for DJF Temperatures while Linear Trend predictor improves skill more in SON, when trends are greatest



Post-processing using Ensemble Regression plus OCN, gray bars, has greatest hit rate for 3-category forecasts of above, near and below normal temperatures.



Comparison of linear trend across the 30-year hindcast period from zero-lead initialized December, January, and February monthly forecasts to observed trends

Zero-lead one-month forecasts show errors in multi-decadal trends across the 30-year hindcast period despite climate change signals in initialization.

References

- Unger, D. A., van den Dool, H., O'Lenic, E., & Collins, D. (2009). Ensemble Regression. Monthly Weather Review, 137(7), 2365-2379. https://doi.org/10.1175/2008MWR2605.1