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Recent Developments and Ongoing Challenges in Operational Seasonal Prediction at CPC

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1. Introduction

The current seasonal forecast process at NOAA's Climate Prediction Center (CPC) dates back to 1995, and involves issuing temperature and precipitation forecasts for the upcoming 13 three-month overlapping seasons. Statistical and dynamical models are both used to inform the forecast process, with an objective consolidation introduced in 2006 (O'Lenic *et al.*, 2008). Beginning in 2011, forecasts from the National Multi-Model Ensemble (NMME) have been available to forecasters and used heavily in constructing official outlooks. A looming issue for seasonal forecasts, especially temperature, is the role of long-term trends – much of the skill of seasonal temperature forecasts can be attributed to the fact that above-normal temperatures are observed more in real time than over the reference climatology (currently 1981-2010).The first section will detail some recent developments in seasonal forecasting using empirical forecast techniques, as well as post-processing of dynamical guidance and subsequent consolidation across suites of forecast guidance. The second section will discuss research results related to a project that explores how to better handle long-term trends in seasonal forecasts.

2. Developments in the seasonal forecast process

Beginning in 2016 there have been multiple efforts to update the legacy empirical tools suite that forms the basis of the seasonal forecasts. Post-processing and calibration of dynamical model data from the NMME has been prioritized, and most recently a new consolidation of the statistical and dynamical forecast tools has been developed and made available to forecasters in real time.

Since 2017, three new empirical forecast tools have been derived and used in the forecast process:

- ENSO-OCN: This empirical model uses the official CPC Niño 3.4 consolidation forecast as a predictor in a linear regression model. The 15-year optimal climate normal (OCN; running 15-year mean anomaly relative to reference climatology) is removed prior to regression and then added back in the end. The process uses a leave-one-year-out cross validation to generate skill metrics and calibrate the forecast anomalies using linear regression. Probabilistic temperature and precipitation (precipitation data are subject to a square root correction)

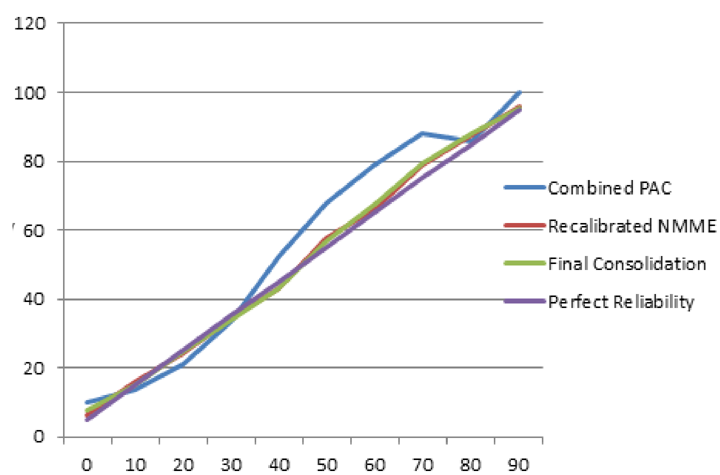

Fig. 1 Reliability diagram of lead-1 temperature forecasts valid for DJF from the NMME and final consolidation forecast over North America from 1981-2018. The blue line shows the reliability of the mean of individually PAC-calibrated NMME models, while the red line shows the reliability after the second pass PAC calibration. The final consolidation and perfect reliability are in green and purple, respectively.

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forecasts are created by using the model's residual error to fit a single Gaussian distribution around the forecast anomaly.

- CCA: The current operational canonical correlation analysis (CCA) used for Niño 3.4 prediction is extended to temperature and precipitation by changing the predictands. This forecast system currently uses sea surface temperature (SST) and sea level pressure anomalies as predictors. A forward-moving hindcast from 1995 onward is used to calculate skill and calibrate using regression. Probability forecasts are likewise calculated by using the unexplained variance from the regression calibration process.
- SST Constructed Analog: A long-time favorite of CPC forecasters, this product has been reinvigorated by using its cross-validated hindcast to generate probabilistic forecasts.

The NMME dynamical model suite is currently calibrated using probability anomaly correlation (PAC; van den Dool *et al.* 2017). In real time this process works by calibrating each model and then averaging across models using equal weights; this can lead to under-confident forecasts (Fig. 1). This issue can be understood intuitively by considering two models – one that is skillful and one that is not skillful. The probabilities from the model with no skill are damped to climatology in the PAC calibration process; however, some portion of the probability anomalies from the skillful model is retained. In this case the forecaster would not want to consider the skill-less model, however it has the effect of further damping the skillful model when included in the final, averaged product. To address this as part of the new consolidation process, the NMME constituent model forecasts are combined by weighting according to their PAC coefficients as a function of grid point. This combination is then subject to a second pass PAC calibration, thus eliminating the under-confidence. The statistical models are likewise combined into a statistical model constituent. The NMME and statistical combinations are then consolidated by weighting based on PAC coefficient and calibrating over the entire hindcast – this yields the final consolidation that can serve as a first guess for the official forecast. This process continues to update in real time, so model biases and the PAC coefficients are based on the maximum amount of available data.

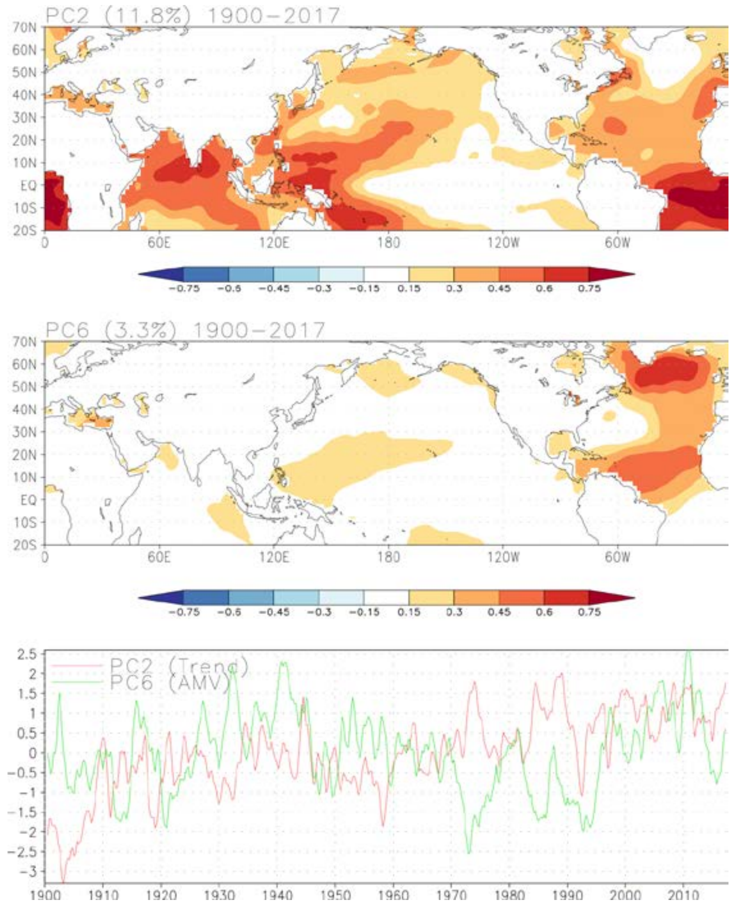

Fig. 2 Loading patterns for the non-stationary trend (PC2, top panel) and AMV (PC6, middle panel) shown as correlations between the PCs and SST anomalies from 1900-2017. The bottom panel shows the PC times series over the 1900-2017 period.

3. Ongoing challenges – Long-term trends

An ongoing challenge in seasonal climate forecasting is how to optimally handle long-term trends. We know, for instance, that CPC's seasonal temperature forecast skill is largely due to observed long-term warming trends (*e.g.* Peng *et al.*, 2012). At first glance this might seem to indicate that beyond the linear trend there is little seasonal forecast skill. However, the apparent skill in predicting interannual and even decadal variability can be muted by the dominance of long-term trends in forecasts and observations. Therefore separating secular warming from decadal and interannual climate variability is potentially important for short-term climate prediction. Furthermore, distinguishing between climate variability as a function of time scale can provide an on-the-fly attribution of forecast and observed seasonal climate anomalies.

Historically CPC has incorporated trends through the OCN tool, which takes advantage of the fact that the fixed 30-year WMO climatology is not likely the ideal ‘first guess’ for seasonal temperature and precipitation. One can test for the ideal number of preceding years, which will varying seasonally and spatially, but a fixed 15-year OCN is a simple and reasonable method currently used.

An ongoing research project has attempted to deal with the issue of trends by decomposing seasonal SST data following Guan and Nigam (2008). A rotated, extended EOF analysis of 20th century SST anomalies yields principal components (PCs) that correspond to variability ranging from ENSO to the secular trend. Preliminary results showed that using the trend PC or a linear trend line was better than the OCN-15 at reconstructing seasonal temperature anomalies. Adding a PC corresponding to Atlantic multidecadal variability (AMV) closed the gap between the linear trend line and the SST PC comprising the secular trend. The overarching idea is that it would be desirable to have a small subset of physically-grounded time series (*e.g.* derived from SST) through which one might attribute climate anomalies to variability on decadal time scales or longer.

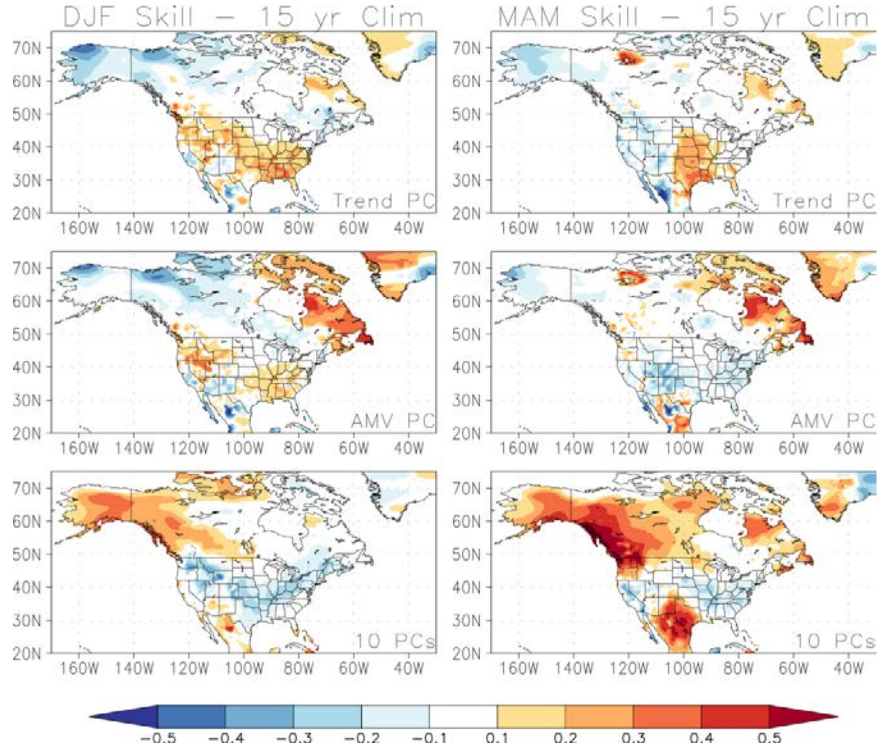

Fig. 3 Anomaly correlation between the temperature hindcast and observations where anomalies are with respect to a trailing 15-year climatology. Left (right) column is for lead-3 DJF (MAM) forecasts. From top to bottom rows: forecast using trend PC as predictor, forecast using AMV PC as predictor, forecast using the leading 10 PCs as predictors.

These preliminary results, however, were data dependent reconstructions, and so an experiment was devised that would test these PCs in a predictive capacity. Starting in 1980, the extended, rotated EOF analysis is computed for 1900-1980 using ERSSTv5, and various PCs are used as predictors. Temperature and precipitation data (GHCN+CAMS and CPC’s gauge-based reconstruction, respectively) from 1950-1980 is used in a linear regression model to generate a forecast for seasons in 1981, using no future data. This process is repeated for each year from 1981 to 2017 resulting in a forward moving hindcast. Figure 2 shows the loading patterns associated with the long-term trend and AMV and their PC time series. Hindcast skill is calculated using anomaly correlation coefficients, and results are compared to the skill of an OCN-15 forecast. This process is repeated using a fixed climatology (anomalies relative to fixed mean and zeroed out in correlation calculation), a trailing 30-year WMO climatology (*i.e.* using 1951-1980 climatology from 1981-1990), and a trailing 15-year climatology (zeroing out OCN).

To emphasize the empirical model skill relative to OCN, Figures 3 and 4 show the skill of three reconstructions (trend alone, AMV along, and the leading 10 PCs) relative to a trailing 15-year climatology, for each of the four meteorological seasons. The AMV component seems to yield skillful temperature forecasts relative to OCN over the Plains during JJA and over much of southern Canada during SON. The Trend PC provides little value relative to OCN in this framework with marginal and mixed temperature results. The role of ENSO can be seen in the skill of temperature forecasts using the 10 leading PCs (ENSO variability is contained in three to four of the leading patterns), especially during the transition seasons. The results with respect to precipitation are difficult to interpret (not shown). The skill with respect to a trailing 15-year climatology is surprisingly high, but this might point to the relative futility of OCN-based precipitation forecasts, at least as compared to temperature forecasts. Precipitation climatologies are more stationary than temperature, and these results may suggest that longer climate base periods are more appropriate for precipitation forecasts.

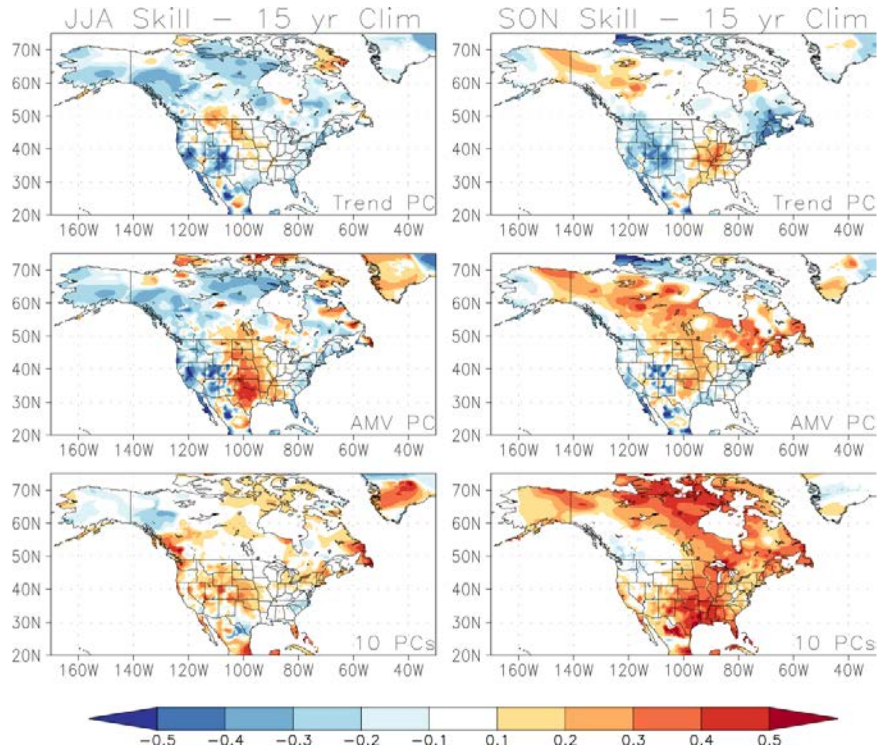

Fig. 4 Same as Fig. 3, except for JJA (left column) and SON (right column).

Overall the results of the forward-moving hindcast experiment are mixed – OCN proves difficult to beat on independent data for temperature forecasts, but OCN may be ill-advised for precipitation forecasts. Some ideas for future directions include using a Hadley-OI blended dataset from 1900-present, which would be more akin to the Guan and Nigam (2008) method. Because ERSST uses recent data in its reconstruction of past data, it may not be as well suited to analyses targeting variability on decadal or longer time scales. The forward-moving approach is intentionally restrictive, but even outside of a prediction framework this analysis can be useful for monitoring and attribution of SST anomalies and associated climate impacts.

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