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Improving CPC's Handling of Long-term Temperature Trends

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1. Introduction

It is well documented that CPC's seasonal temperature forecast skill derives largely from long-term warming trends over the United States (*e.g.* Peng *et al.* 2012). Most recently this was explored in a presentation at the 41st Climate Diagnostics and Prediction Workshop (Baxter 2017), wherein it was shown that CPC's deterministic seasonal forecast skill from 1995 to the present is not as good as a categorically warm forecast (a forecast where every grid cell is depicted as favoring temperatures in the upper tercile). Given this research result, it is imperative that CPC incorporate long-term trends as rigorously as possible and in a way that isolates long-term climatic changes from interannual and decadal variability. Indeed, analysis of climate variability on subseasonal to seasonal time scales is where CPC is uniquely adept.

Forecasting seasonal and subseasonal variability explicitly is where known skill is unclear. For example, the long-term Heidke skill score when above-normal is the favored forecast temperature category is near +30. However, the same skill score when below-normal is forecast falls all the way to +5. This, along with inspection of reliability diagrams, reveals a systemic cold bias in the official forecasts. To be sure this is counterintuitive considering that CPC outlooks do forecast above-normal temperatures more than the other two categories. It would be ideal to separate interannual and even decadal variability from long-term trends in order to better understand, and potentially improve, forecast skill related to various phenomena.

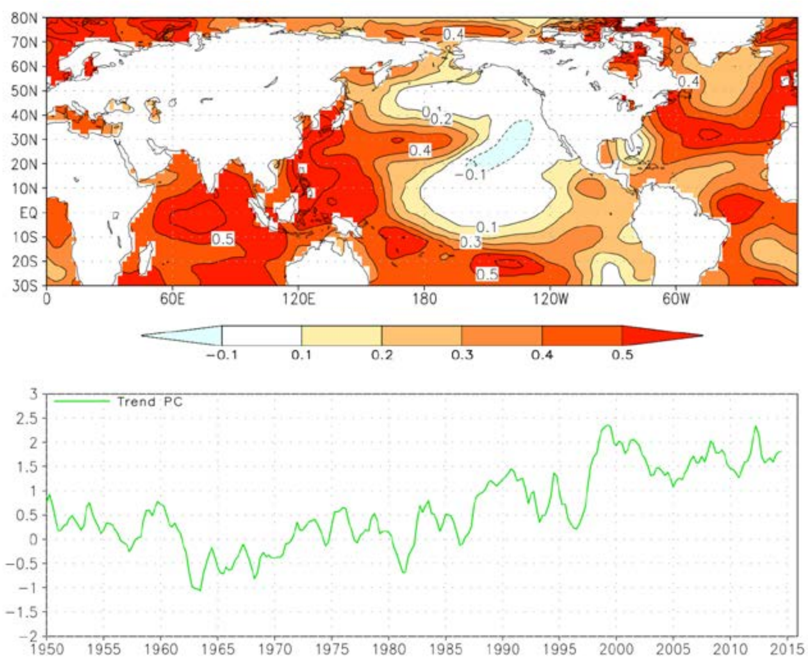

Fig. 1 Top: Correlations of the 1st PC with ERSSTv4 data from 1950-2015. Contour interval is 0.1 with the zero contour omitted. Bottom: 1st PC is plotted from 1950-2015. A clear positive trend is notable.

Two common forecast tools used to incorporate long-term trends are the linear trend and optimal climate normals (OCN). The latter is defined here as the running 15-year average temperature anomaly, which varies as a function of target season. OCN, as the name implies, generates forecast skill simply from the fact the base climatology used operationally (an aging 30-year fixed period) is inadequate, if one considers the point of a climatology to be providing your first-guess expectation at seasonal climate. The usefulness of an OCN forecast disappears if the base climatology is the OCN averaging period. Linear trends do not suffer from that shortcoming, but do suffer from the fact that variability other than long-term trends can easily be aliased into it, a characteristic shared by OCN as well. An alternative technique is introduced here, where the leading principal component of spatio-

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temporal seasonal SST variability during the 20th century is used as the trend time series. This approach grounds the treatment of long-term trends in an important physical field within the context of other interannual and decadal variability.

2. Methods

Linear trends, OCN, and regressions of the 1st PC of SST variability are used in reconstruction of seasonal temperature anomalies from 1965-2015. Temperature data is from the GHCN+CAMS dataset. The trend principal component is derived using rotated, extended EOF analysis of three-month, non-overlapping seasonal SST anomalies (Hadley SST data) from 1900-2015, following Guan and Nigam (2008). The domain of the analysis is 20oS-90oN, 0-360o. The nonstationary trend is the leading principal component, explaining 15.2% of the variance. North Atlantic decadal variability emerges as the 5th principal component; this plays some role in the low-frequency component of North American temperature anomalies.

Trends are calculated using least squares regression over the 1950-2015 period, and are used to reconstruct the seasonal temperature anomalies from 1965-2015. The PC reconstructions use a one year lag regression between the principal component and the target season. Regression analysis is performed over the 1950-2015 period, and anomalies are reconstructed for the 1965-2015 period. OCN is the average temperature anomaly over the previous 15 years for a given meteorological season, starting in 1965.

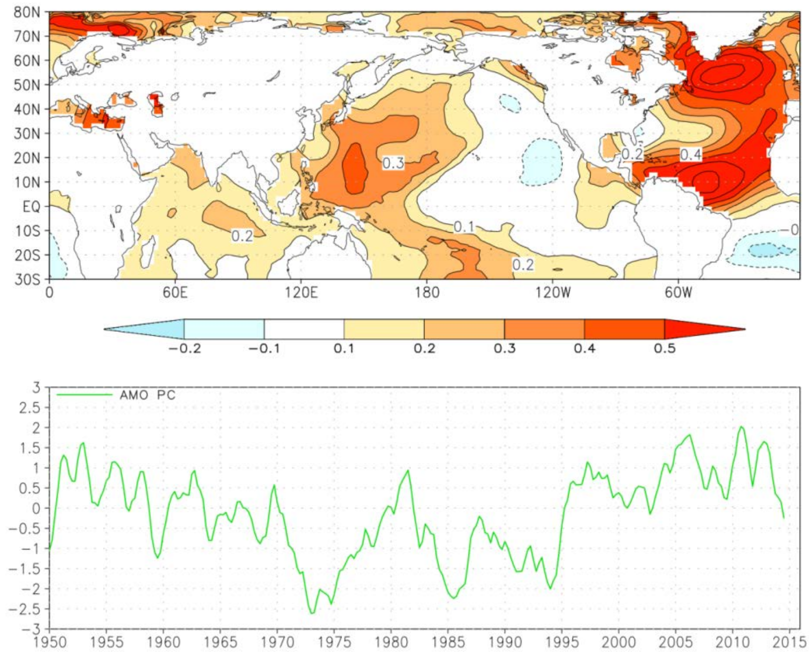

Fig. 2 Same as Fig. 1, but for the 5th PC comprising decadal variability associated with the AMO.

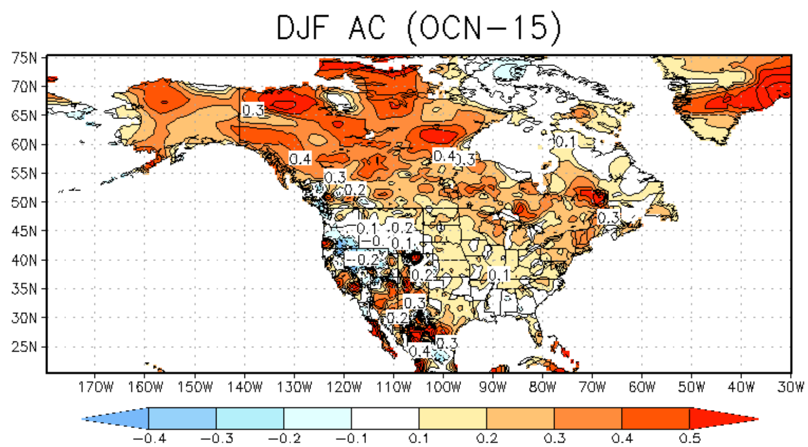

Fig. 3 Correlations between the OCN-based temperature reconstructions and observed temperature anomalies from 1965-2015 for northern winter. Contour/shading interval is 0.1 with the zero contour omitted.

3. Results

Figure 1 shows correlations of the 1st PC with ERSSTv4 data over the 1950-2015 period, along with the associated time series. A clear but nonstationary trend is evident. Importantly, this trend is temporally independent of other canonical SST variability, including ENSO. Figure 2 is the same except for the 5th PC comprising Atlantic decadal variability, usually identified as the Atlantic Multidecadal Oscillation (AMO). While only the most recent 65 years are plotted in the time series, the decadal tendency is obvious.

For the sake of brevity, only meteorological winter is discussed here, though the analysis is complete for all four meteorological seasons with essentially the same results. Figure 3 shows the anomaly correlation between the OCN forecast anomalies and the observed anomalies over the 1965-2015 period. Positive correlations exist across northern North America including parts of the northern CONUS, while correlations are weak over much of the central and eastern CONUS. Anomaly correlations are notably high over much of Southwest, where temperature trends are known to be prominent. Figure 4 shows the same but for the linear trend reconstructions. Importantly, this is a largely data dependent reconstruction, so this should not be taken as forecast skill. The spatial structure is nearly identical to OCN, though the magnitude of the correlations is generally higher. The SST PC reconstruction (Fig. 5) contains nearly identical spatial structure as well, with magnitudes that are fairly close to those associated with the linear trend. Figures 6 and 7 show the difference in anomaly correlations between the analysis using the SST PC and OCN and linear trends, respectively. Here it is clear that the SST PC is better than the OCN reconstruction, but somewhat worse than the linear trend. The addition of the 5th PC (AMO) to the regression and reconstruction analysis eliminates all or most of that gap (Fig. 8).

Because of the similarity between long-term trends and the 1st PC in time, their similar correlation footprints are unsurprising. However, the SST-rooted analysis has the advantage of being able to discriminate between long-term trends and decadal variability, and does not risk any obvious ENSO aliasing. OCN by its nature does not actually yield predictive information about a nonstationary climate. This becomes obvious when one considers that the next year ought to be warmer than the previous 15 years when only considering secular climate warming.

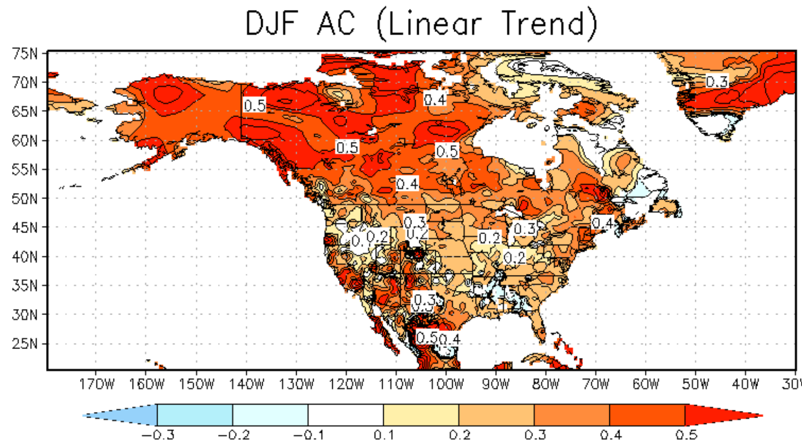

Fig. 4 Same as Fig. 3, but for reconstructions using the linear trend.

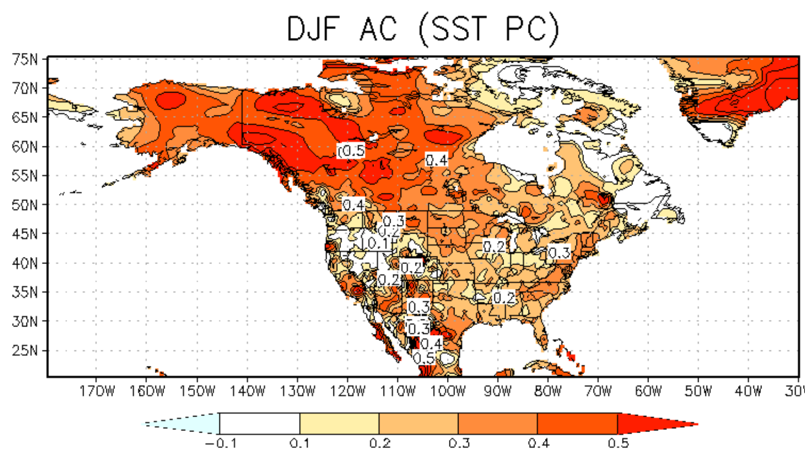

Fig. 5 Same as Fig. 3, but for reconstructions using the 1^{st} PC of spatio-temporal SST variability.

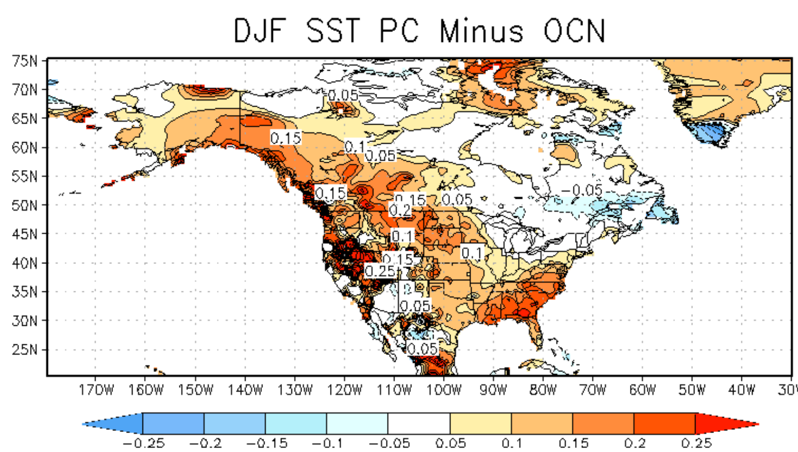

Fig. 6 The difference between Fig. 5 and Fig. 3. Contour/shading interval is 0.05 with the zero contour omitted.

4. Conclusions

A time series corresponding to long-term trends is desirable especially when it is derived in the context of interannual and decadal variability. The use of SST in this regard is preferred given its usefulness as a slowly-varying boundary condition in seasonal climate prediction. Other physical fields could be explored in similar analyses, but the SST-rooted analysis is well-documented and physically robust.

Linear removal of the 1st PC from statistical and dynamical forecast guidance can isolate interannual and decadal variability from long-term trends. In this way we can better attribute both observed and forecast climate anomalies. In light of this pilot analysis, next steps include an independent hindcast experiment and the extension to overlapping 3-month seasons. From that point forecasts of trend-based anomalies and associated probabilities can be made and used in the seasonal forecast process.

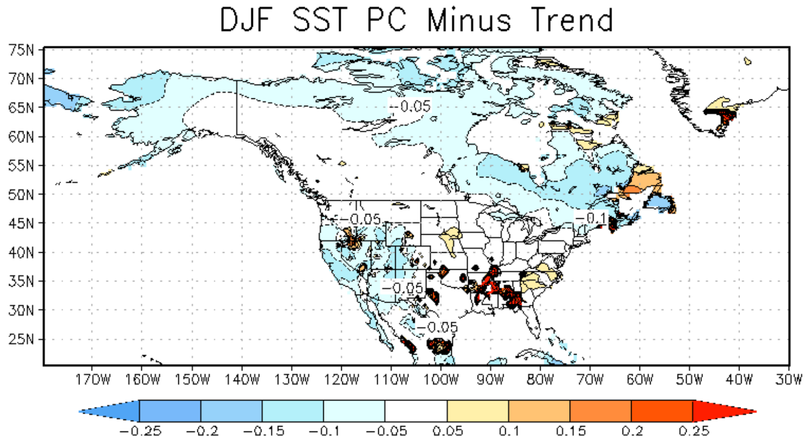

Fig. 7 The difference between Fig. 5 and Fig. 4. Contour/shading interval is 0.05 with the zero contour omitted.

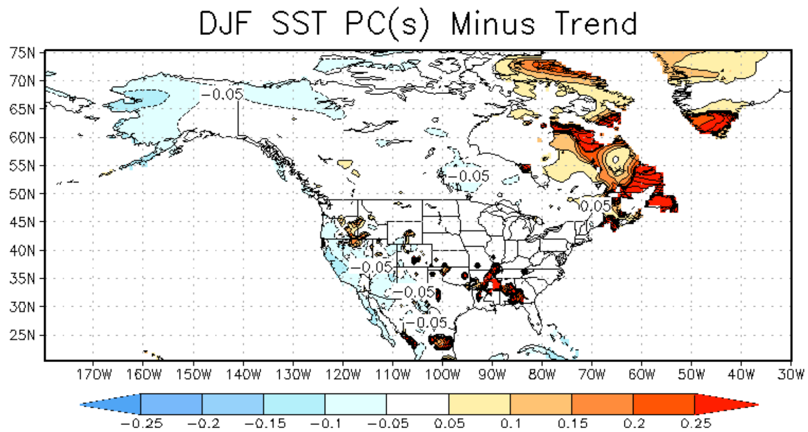

Fig. 8 The difference between a reconstruction using the 1st and 5th PCs and Fig. 4. This shows the potential added benefit of including decadal variability.

References

Baxter, S.: 2017. Evaluating CPC's operational seasonal temperature forecasts: Why aren't we beating a categorically warm forecast? *Climate Prediction S&T Digest, NWS Science and Technology Infusion Climate Bulletin Supplement, 41st NOAA Climate Diagnostics and Prediction Workshop*, Orono, ME, DOC/NOAA, 61-63, doi:10.7289/V5JS9NH0.

Guan, B., and S. Nigam, 2008: Pacific sea surface temperatures in the twentieth century: An evolution-centric analysis of variability and trend. *J. Climate*, **21**, 2790–2809, doi:https:// doi.org/10.1175/2007JCLI2076.1

Peng, P., A. Kumar, M. S. Halpert, and A. Barnston, 2012: An analysis of CPC's operational 0.5 month lead seasonal outlooks. *Wea. Forecasting*, **27**, 898–917, doi:10.1175/WAF-D-11-00143.1.