# Recent Developments and Ongoing Challenges in Operational Seasonal Prediction at CPC

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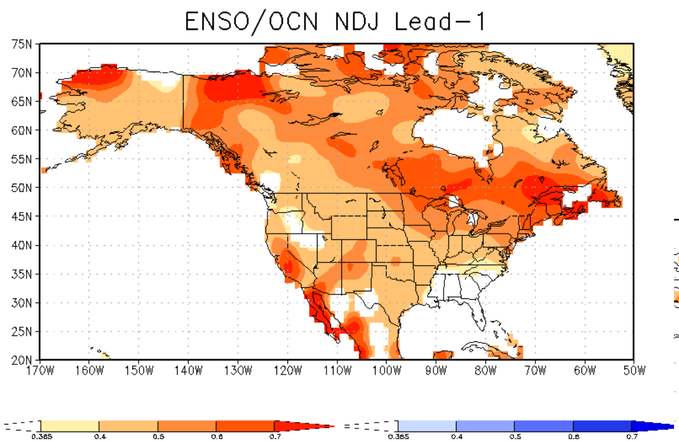
# CPC’s Seasonal Forecast Process

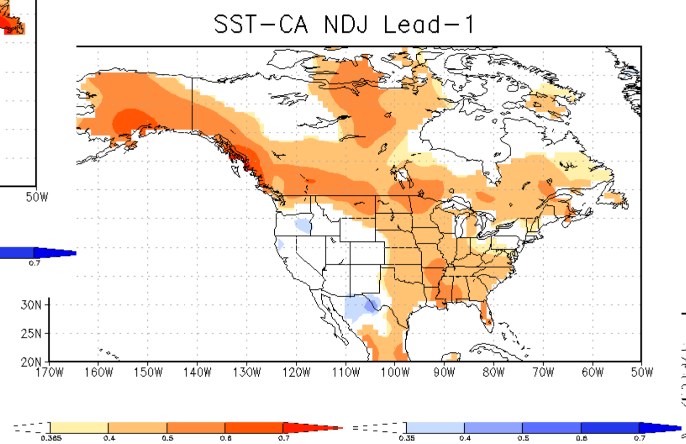
- The current seasonal forecast process began in its present form in 1995.
- Informed by various dynamical and statistical tools.
  - These have been evaluated by an objective consolidation process that was implemented in 2006 (O’Lenic et al., 2008).
- Beginning in 2011, forecasts from the National Multi-model Ensemble (NMME) system have been available to forecasters.
- Since 2016 there have been multiple efforts to update the legacy empirical tools, better calibrate the dynamical model suite, and create a new consolidation of the statistical and dynamical forecast tools.

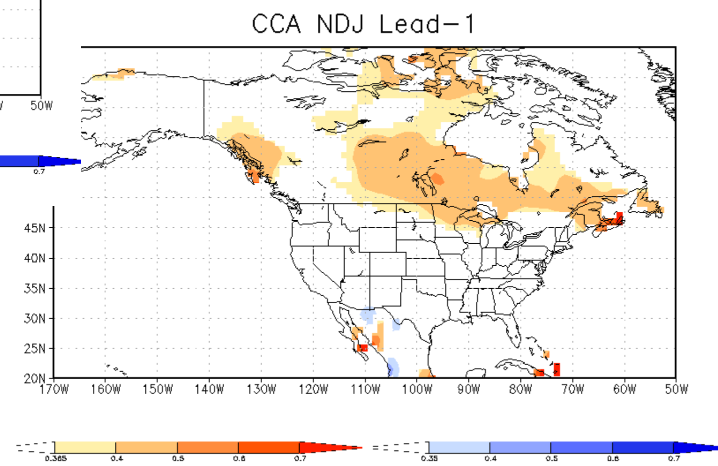
# Empirical Forecast Tools

- Since 2017, there are three new empirical forecast tools available to CPC forecasters:
  - ENSO-OCN
    - This empirical model uses the CPC Niño 3.4 consolidation forecast as a predictor (not a perfect-prog system) in a linear regression model.
    - The 15-year OCN is removed prior to that model construction and then added back in at the end. The process uses leave-one-year-out cross validation to construct skill metrics and calibrate the forecast anomalies using simple linear regression.
    - Probabilistic forecasts are created by using the model's residual error in a single Gaussian distribution around the forecast anomaly.
  - CCA
    - The current operational CCA used for ENSO prediction was extended to temperature and precipitation prediction by swapping out the predictands. Currently uses SST and SLP as predictors.
    - Forward-moving hindcast is constructed without using future data from 1995-present to calculate skill metrics and to calibrate. Probability forecasts are likewise constructed using the unexplained variance from the linear regression model.
  - 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 of temperature and precipitation.

# Current Forecast Examples

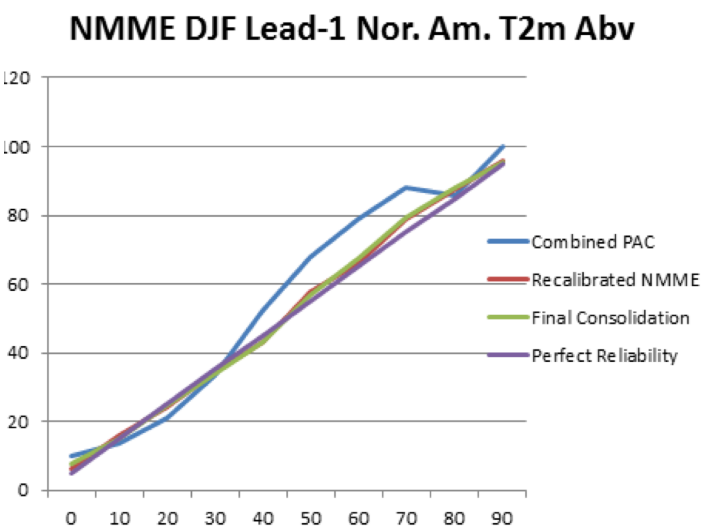


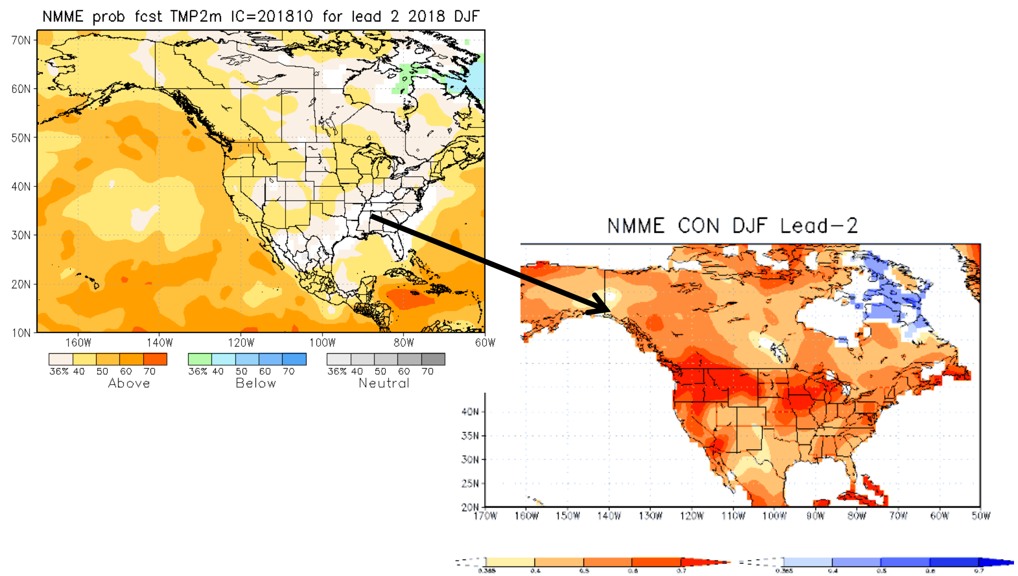



# NMME Calibration

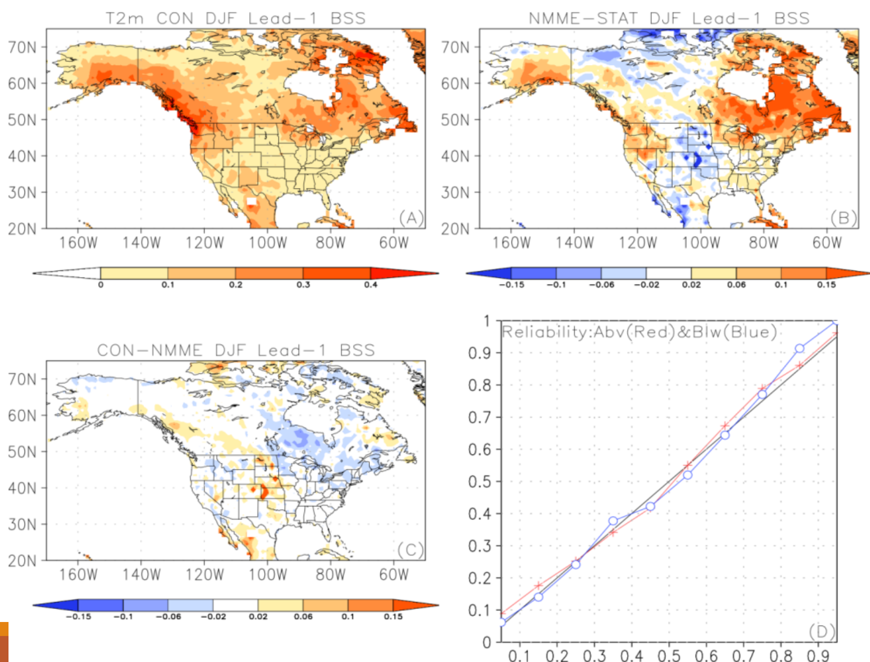
- The NMME model suite is currently calibrated using probability anomaly correlation (PAC; van den Dool 2017).
  - Each constituent model is calibrated, and results are averaged together.
  - However, this can lead to under-confident forecasts
  - A second-pass PAC calibration can help – along with updating model bias in real-time.

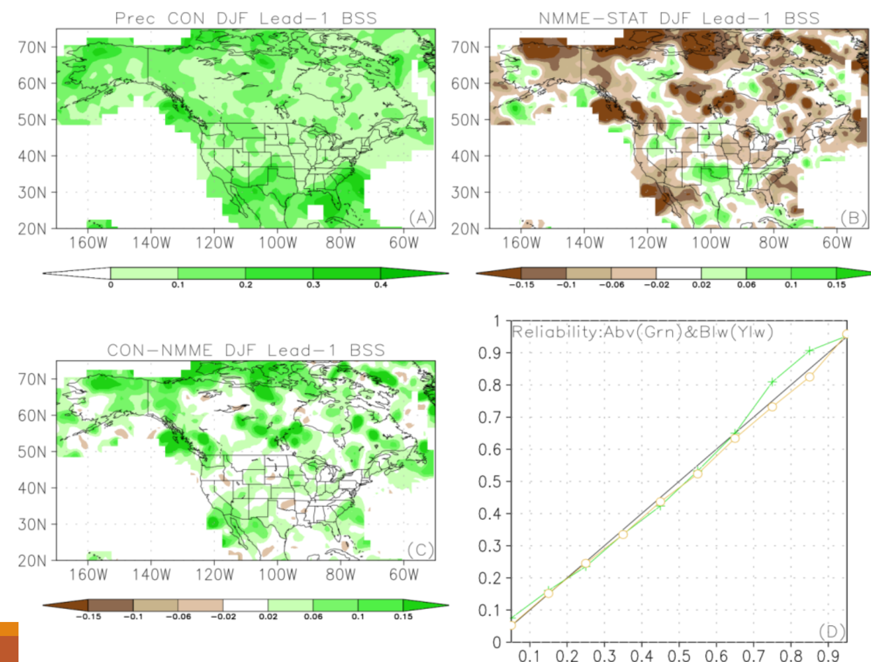


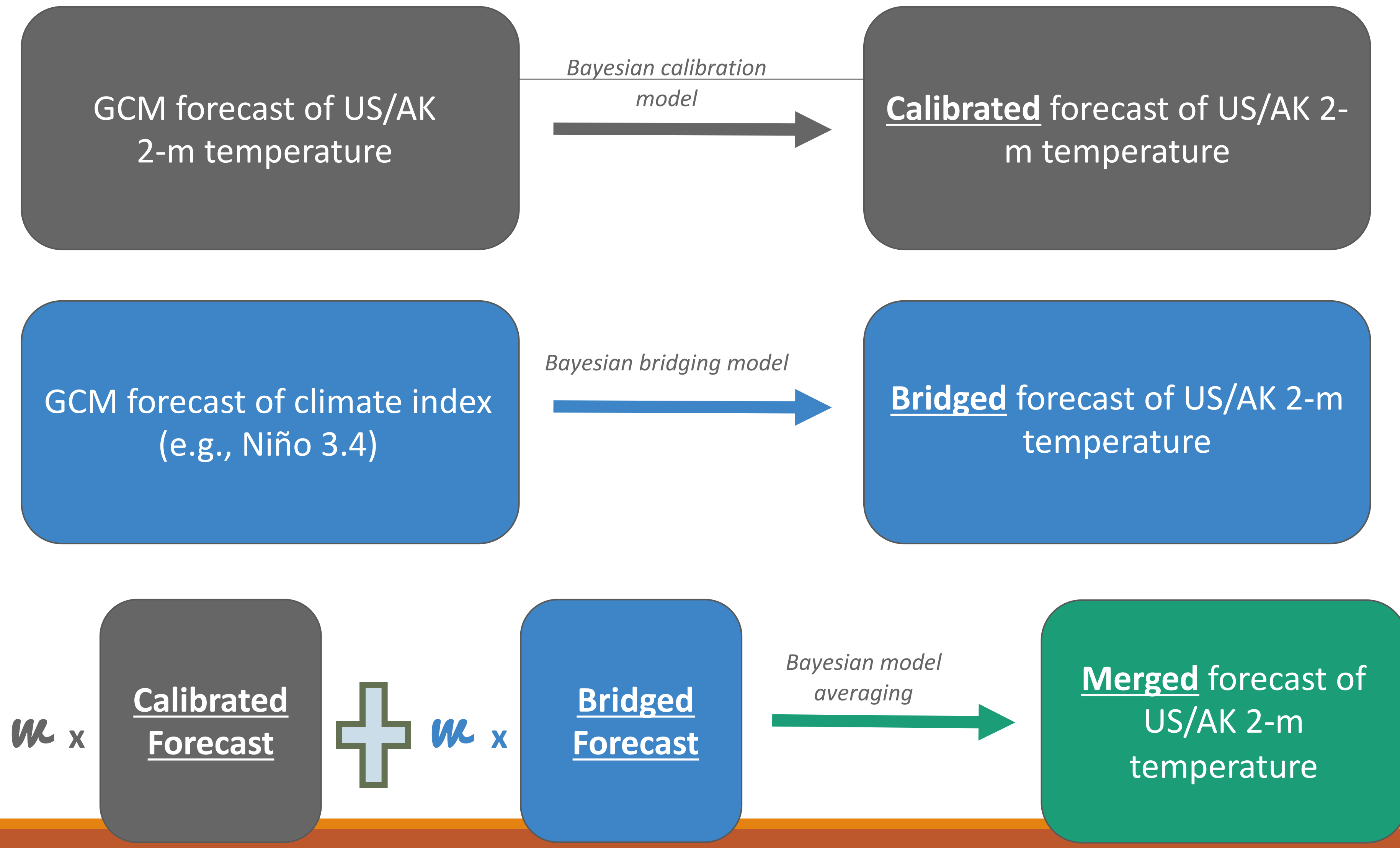
# New Forecast Consolidation

- NMME and statistical model suite are each PAC-calibrated in separate 'streams' – dynamical and statistical, respectively.
- The dynamical and statistical constituents are then combined by weighting based on PAC coefficient and then calibrating over the entire hindcast.



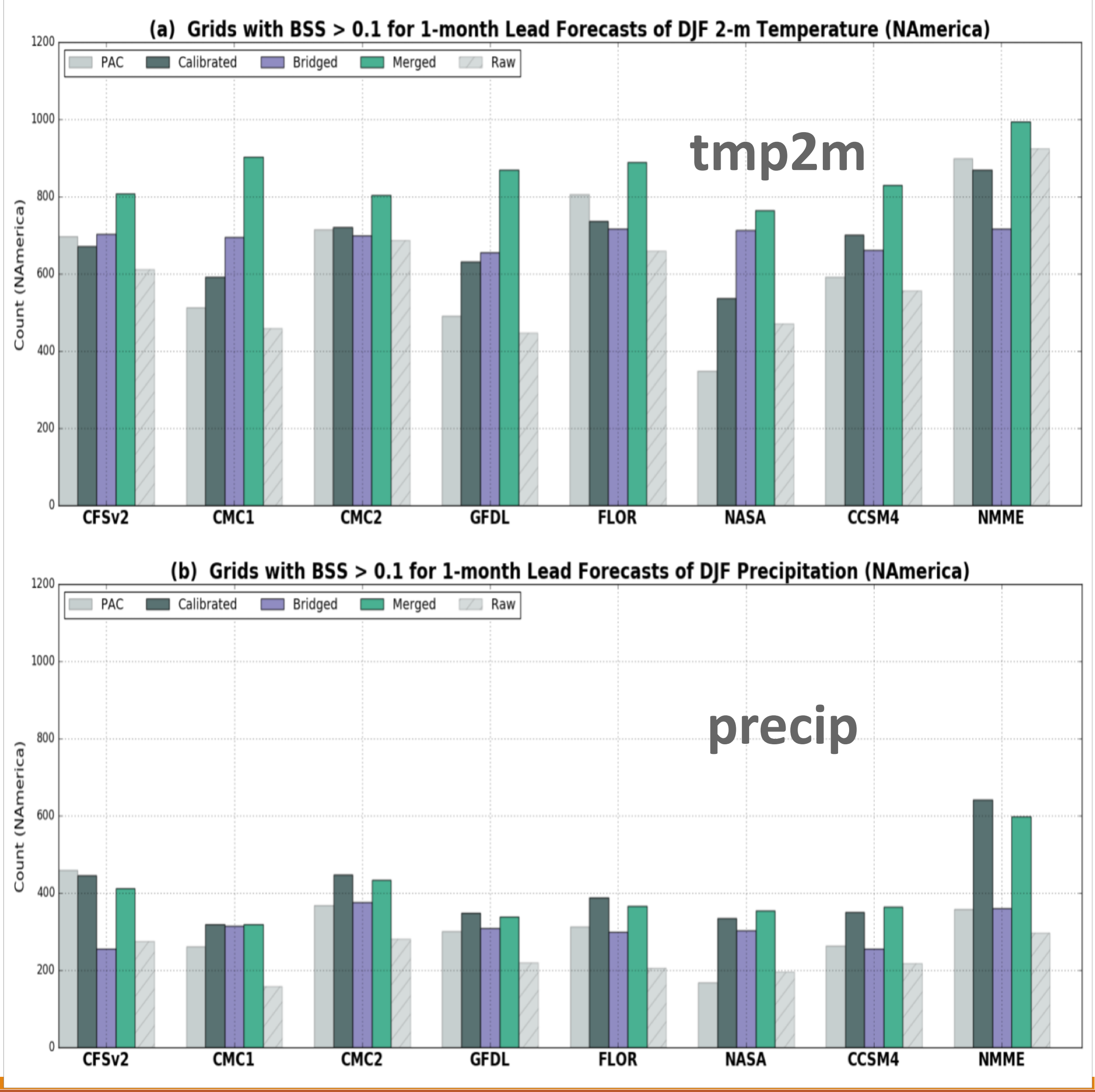
# Calibration, Bridging, and Merging (CBaM)



# CBaM Performance: Hindcast

- Bridging improves forecast skill across some regions of the northern U.S., resulting in higher spatial coverage of merged forecast skill (green)

- In the hindcast period, CBaM forecasts tend to yield positive skill for more grid points than PAC or raw forecasts



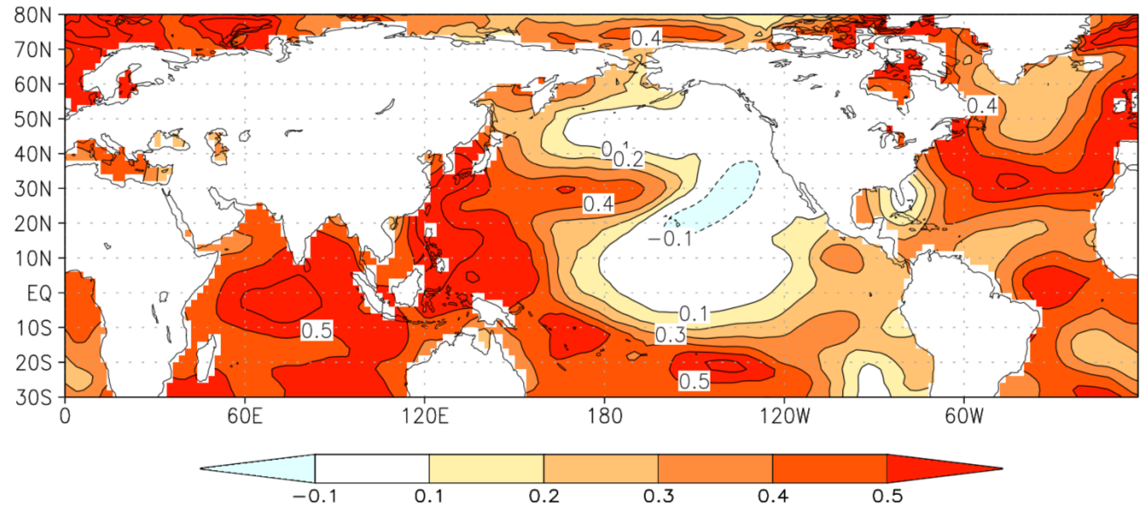
# Ongoing Challenges - Trends

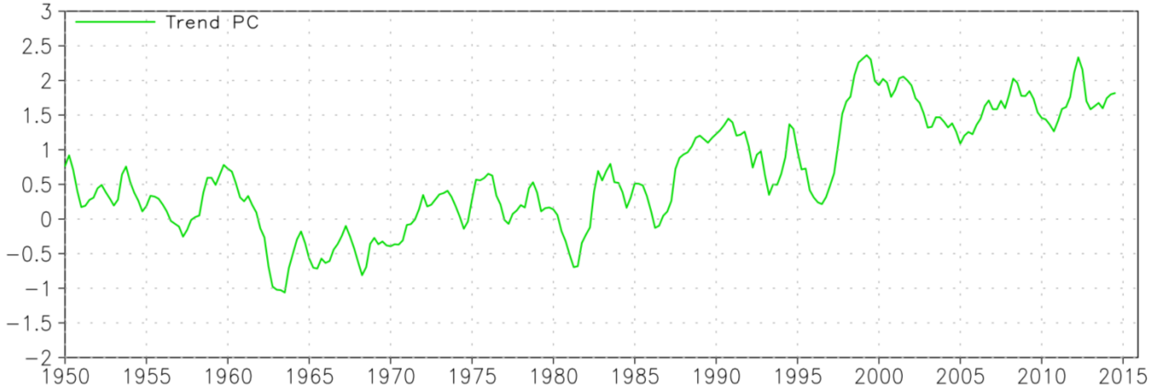
- CPC’s seasonal temperature forecast skill is largely due to the observed long-term warming trend (e.g. Peng et al., 2012).
- The apparent skill in predicting interannual and decadal variability can be muted by the dominance of the long-term trend in forecasts and observations.
- Separating secular warming from decadal variability is potentially important for short-term climate prediction (~years).
- Furthermore, distinguishing between interannual variability and (multi)decadal variability can provide an on-the-fly attribution of forecast seasonal climate anomalies.

# How do we deal with trends?

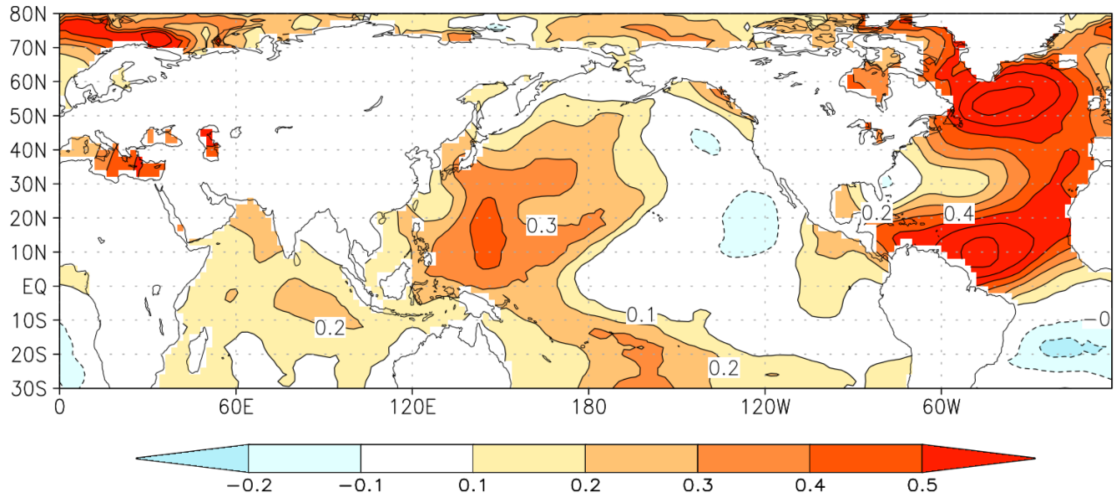
- 15-year optimal climate normals (OCN)
  - This tool takes advantage of the fact that the fixed 30-year WMO climatology is not the ideal ‘first guess’ for seasonal temperature and precipitation.
  - Variants include changing the number of preceding years in calculating OCN, as well as EOCN.
- Time series derived from spatiotemporal analysis of the SST anomaly field (e.g. Guan and Nigam 2008).
  - Uses Hadley SST data from 1900-2015 over 20$^{o}$S-70$^{o}$N, 0-360$^{o}$ domain.
  - Rotated, extended EOF analysis of seasonal SST anomalies.
  - Not apparently sensitive to domain (Atlantic vs. Pacific vs. both).
  - Trend is the leading PC, explaining 15.2% of variance. By comparison, subsequent patterns whose centers of action are in the equatorial Pacific combine to explain 27.9% of variance.

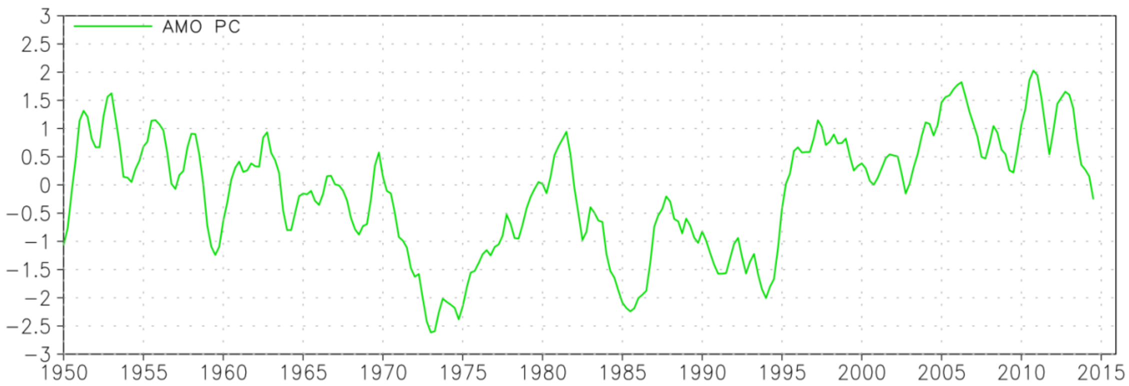
# SST PCs – Trend ($1^{st}$ PC)



# SST PCs – AMV (5th PC)



# Land Surface Temp and PCs

| | Globally Averaged Land Surface Temperature Anomalies |
|---|---|
| Trend PC | 0.76 |
| AMO PC | 0.46 |
| Leading ENSO PC | 0.20 |

Note: Correlations are from 1950-2015; temperature data is GHCN+CAMS.

# Previous Results and Conclusions

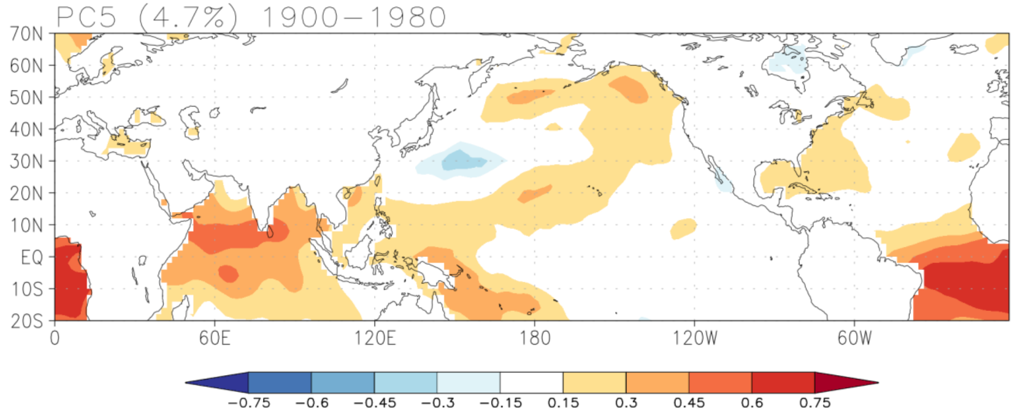
- OCN-15, the linear trend, and PC reconstructions, unsurprisingly yield very similar spatial patterns over the 1965-2015 period.
- The PC reconstructions appear better than OCN, but worse than the linear trend.
  - Adding the AMV PC as a predictor in the same way as the trend PC closes the gap between the PC reconstructions and the linear trend.
  - These were data-dependent reconstructions, *not* actual prediction skill. That said, linear trends are the most data-dependent and thus likely to contain the most artificial skill.
- A time series corresponding to long-term trends is desirable when it is derived in the context of interannual and decadal variability.
- Use of SST is preferred given its usefulness as a slowly-varying boundary condition in seasonal prediction.
- Linear removal of the 1$^{st}$ PC from statistical and dynamical forecast guidance can isolate interannual and decadal variability from long-term trends.
  - This will allow for better attribution of both observed and forecast climate anomalies.

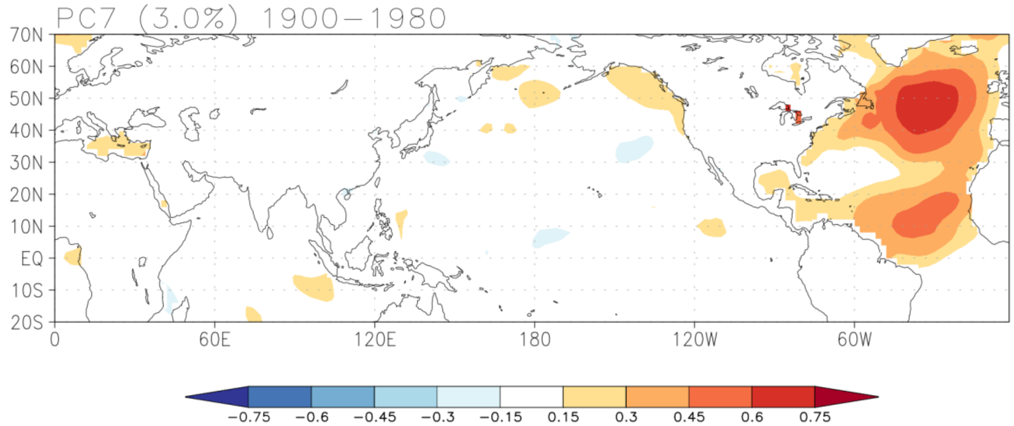
# Current Experiment

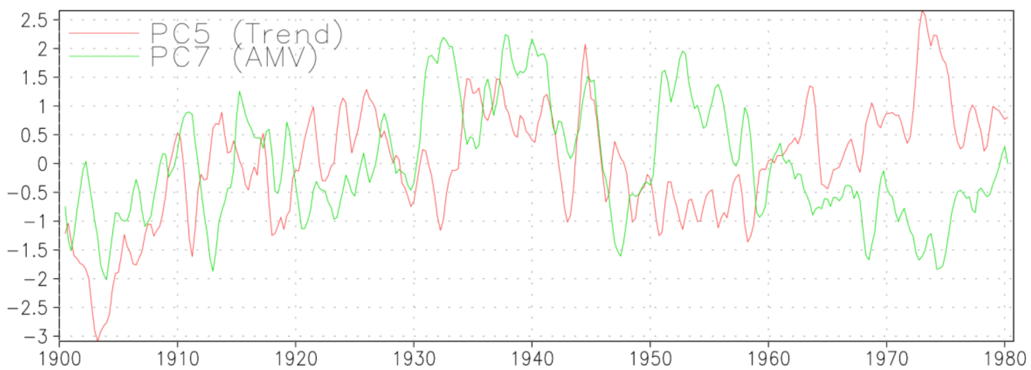
- Use ERSSTv5 to reproduce Hadley analysis – Hadley does not update in real time like ERSSTv5.
  - Five season window, nonoverlapping seasons.
  - Leading 11 patterns are subject to varimax rotation.
- Starting in 1980, rerun analysis each year to get latest patterns and principal components.
- Use 1950 to 'present' training period to construct forward-moving temperature and precipitation hindcast, using no future data.
  - Data: GHCN+CAMS for temperature; Gauge-based monthly precip analysis
- The target periods (predictands) are the 12 overlapping seasons.
- At the end of the hindcast construction, I have a forecast (as a function of lead) for each three month season from AMJ 1980 to near present.

# Differences from the Hadley analysis

- A big difference became obvious between the Hadley and ERSSTv5 analyses:
  - The principal component most closely corresponding to the long-term trend is higher frequency and also incorporates Atlantic Nino variability.
- The other PCs corresponding to decadal variability and ENSO, for example, are similar (correlations of ~0.8 or higher).

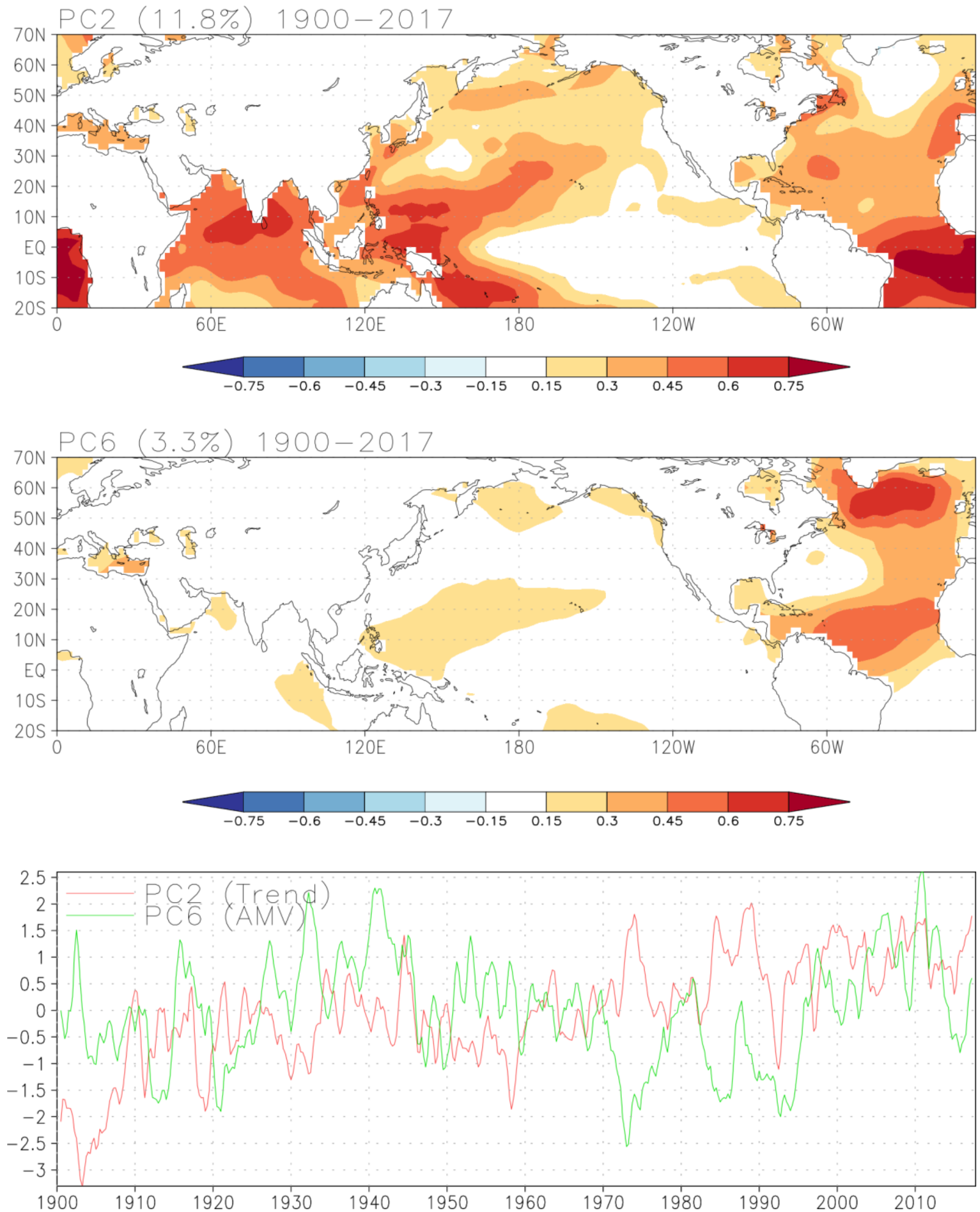



# ‘Trend’ and AMV spatial patterns in 1980

Spatial patterns are correlations between the PC and SST anomalies from 1900 onward. Shading interval is 0.15 with the zero contour emitted.

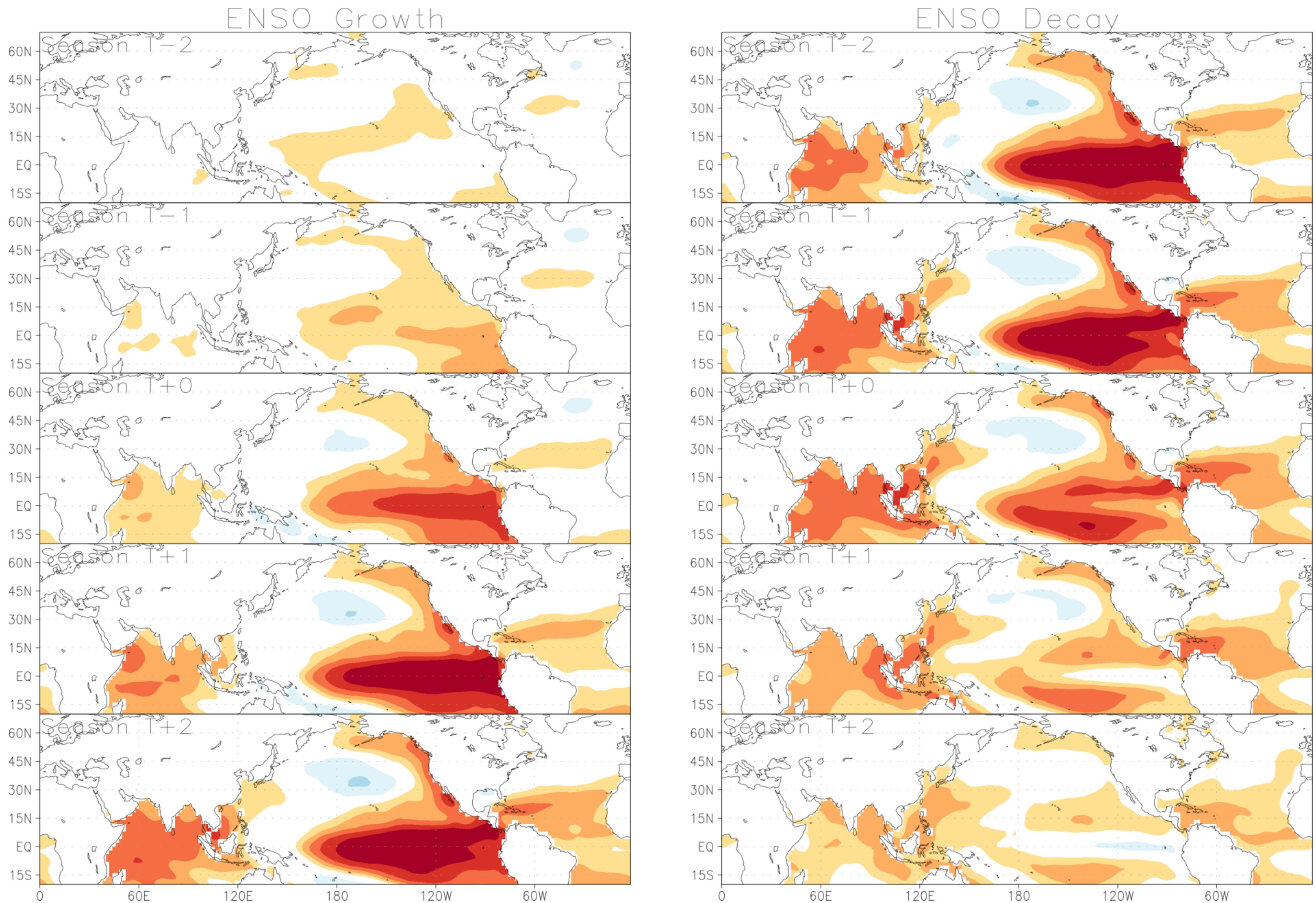



# ‘Trend’ and AMV spatial patterns in 2017

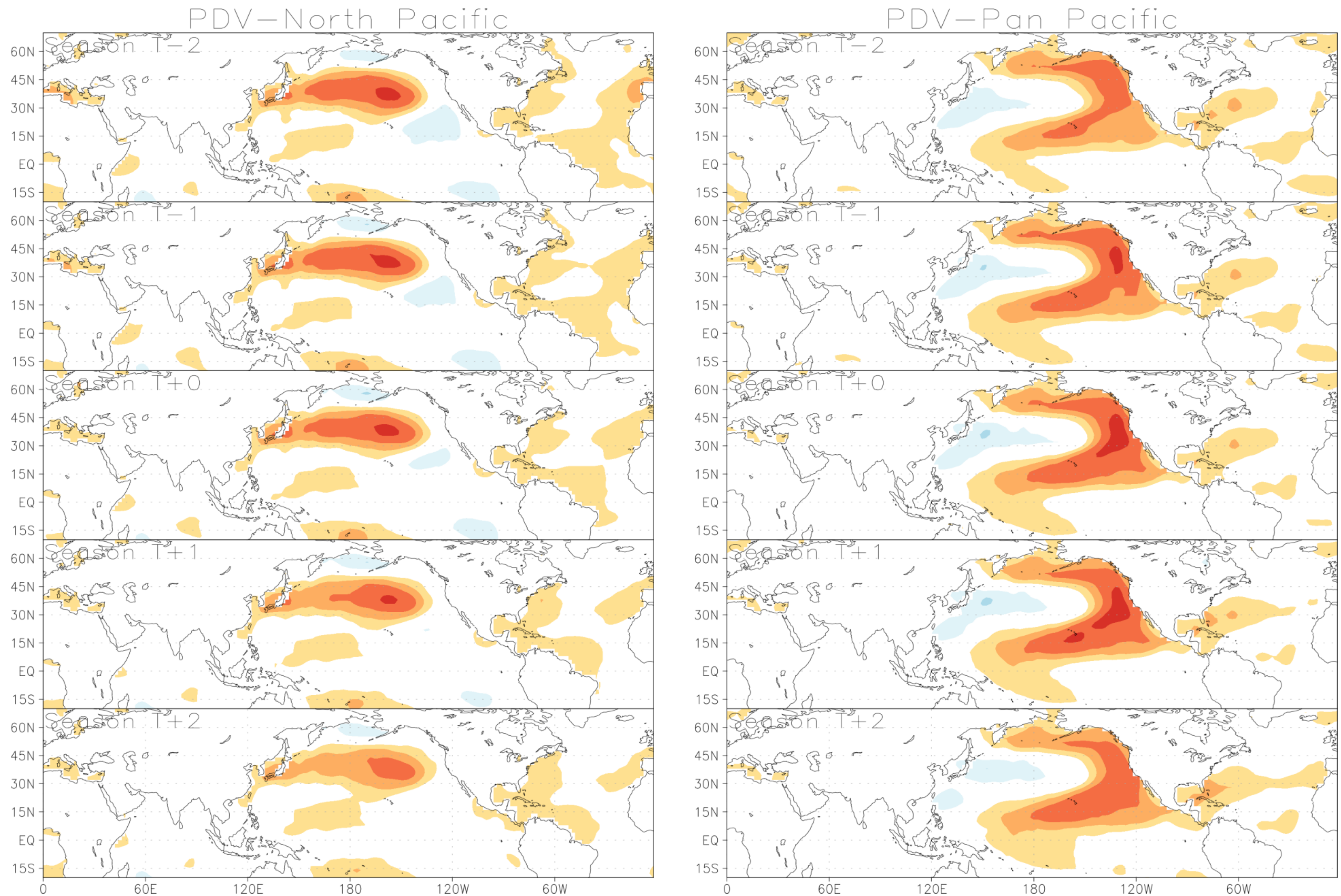
Spatial patterns are correlations between the PC and SST anomalies from 1900 onward. Shading interval is 0.15 with the zero contour emitted.

# Other Leading Patterns of SST Variability

- ENSO growth and decay are the dominant patterns – an intuitive result
- Pacific decadal variability and non-canonical ENSO also emerge as leading patterns – as in the original Guan and Nigam analysis.
- Key patterns:
  - ENSO Growth
  - ENSO Decay
  - Trend/Atlantic Niño
  - PDV North Pacific
  - PDV Pan Pacific
  - AMV
  - Non-canonical ENSO




Lead-lag correlations between ENSO PCs and SSTs from 1900-present. Shading interval is 0.15 with the zero contour omitted.

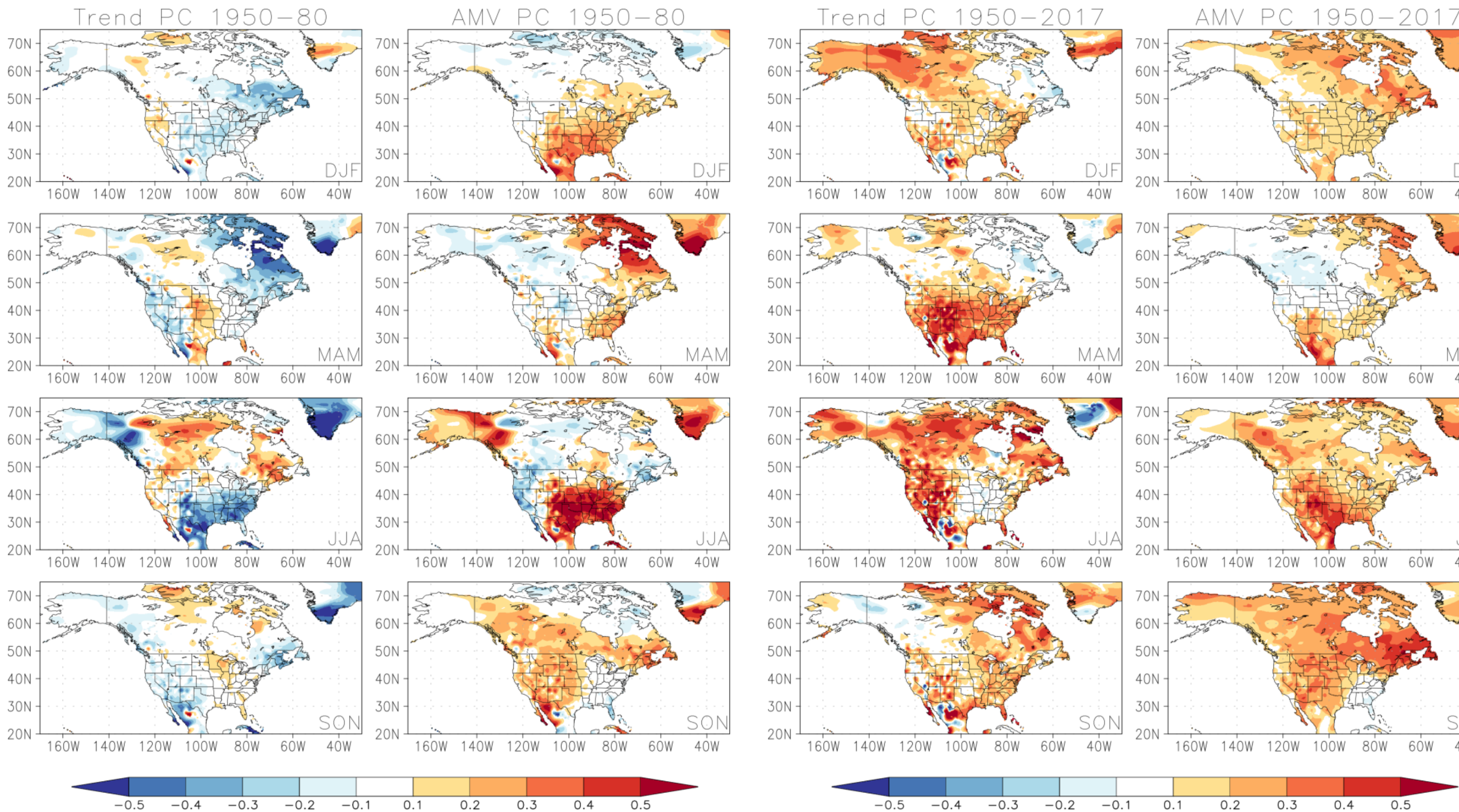



Lead-lag correlations between Pacific decadal variability PCs and SSTs from 1900-present. Shading interval is 0.15 with the zero contour omitted.

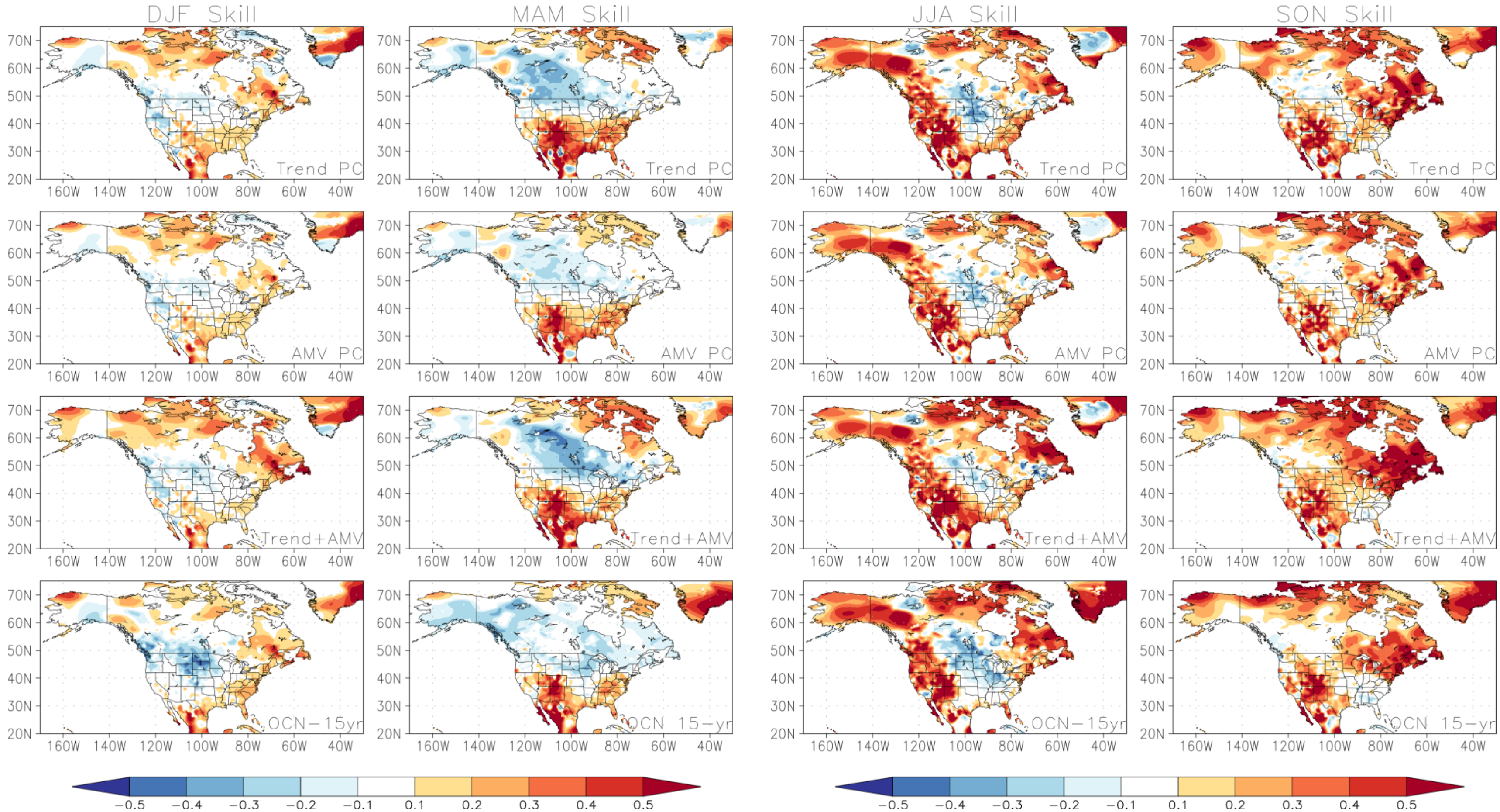
# Analysis of generated hindcast

- Hindcast generated using no future data is compared to observations.
- Skill is calculated using correlation coefficients and compared to 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 climo from 1981-1990), and a trailing 15-year climatology (zeroing out OCN).

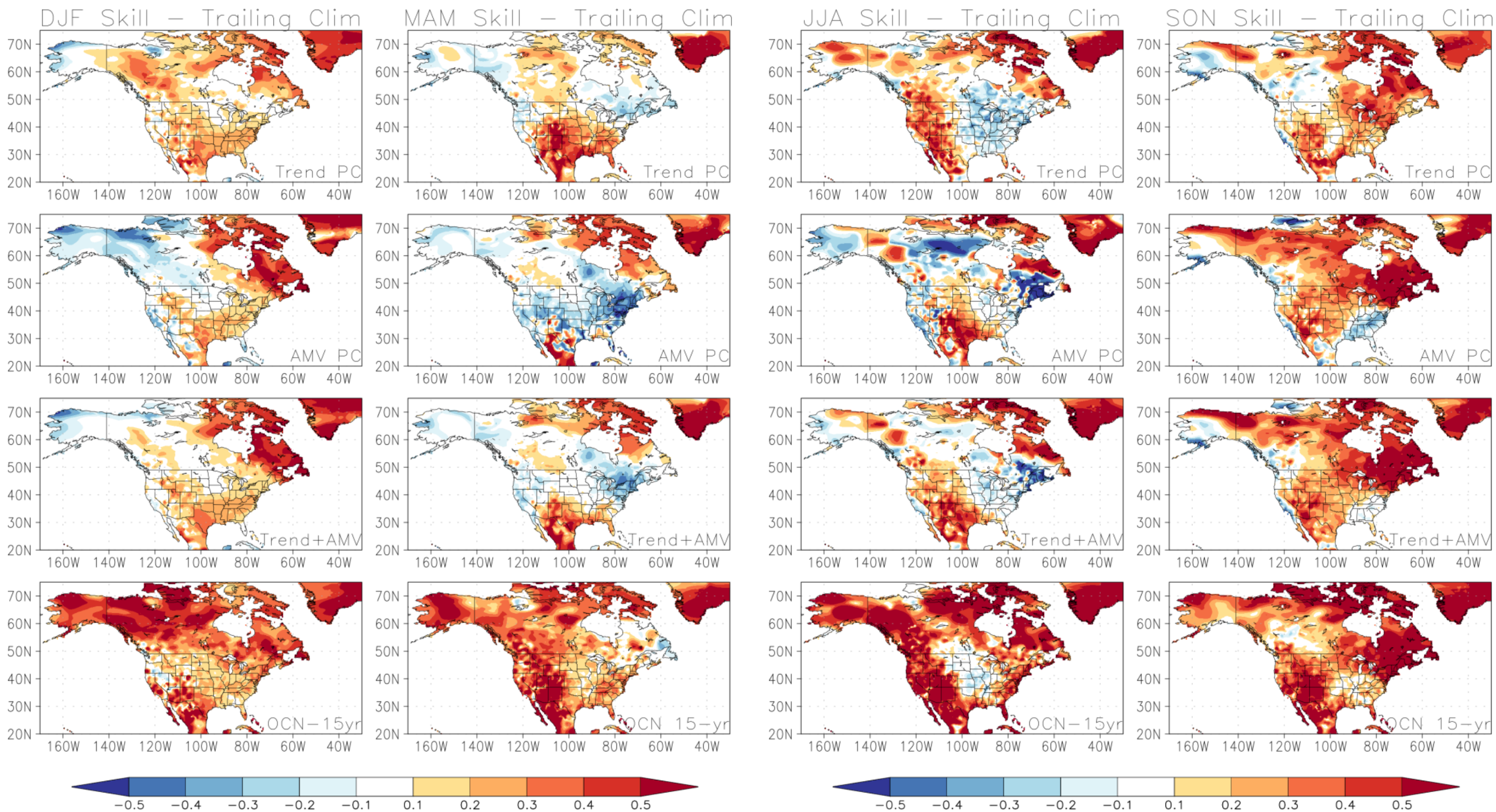
# Correlations between PCs and temperature at a lag corresponding to lead-3 forecast



# Skill [r(fcst,obs)] of lead-3 forecast from 1980-present



# Skill (AC) of lead-3 forecast from 1980-present (trailing WMO climos)



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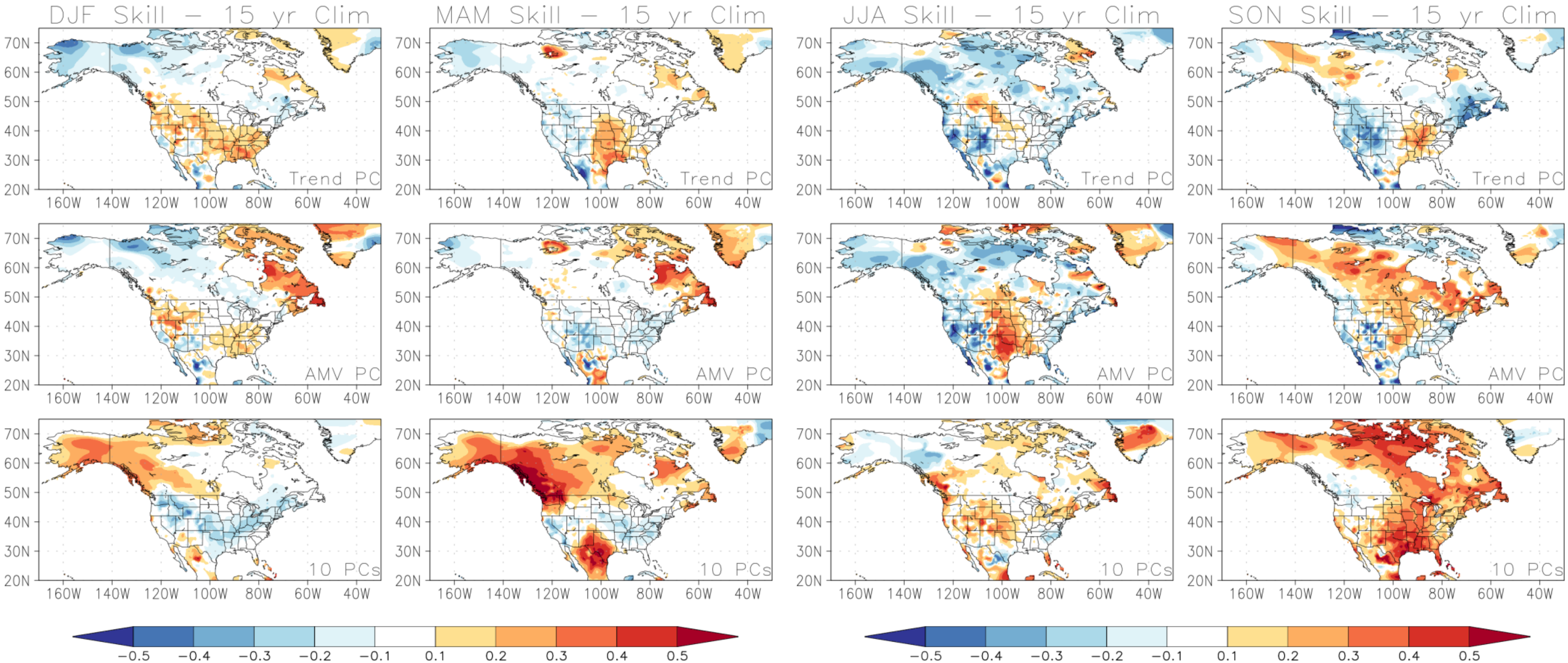
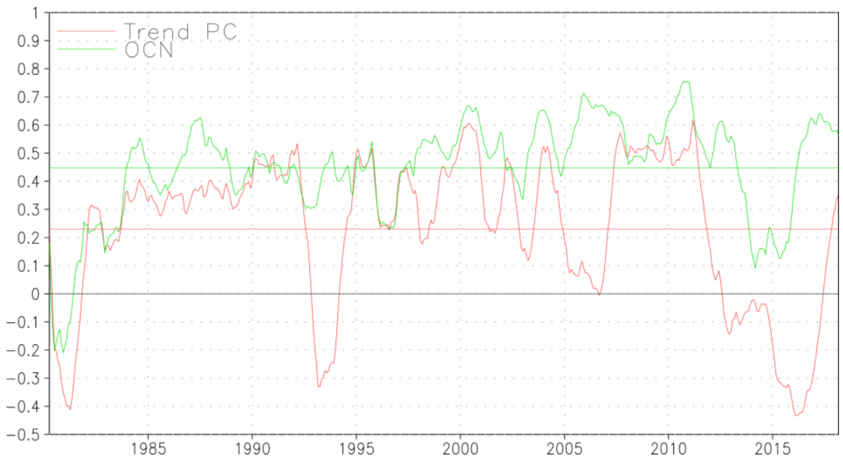
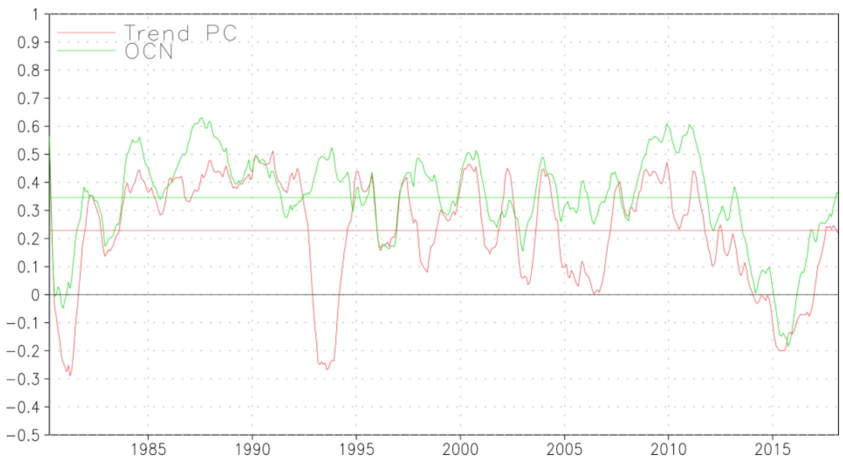


# Time series of spatial correlations




Top panel: time series of anomaly correlation for the Trend PC and OCN-15, with a 12-month running mean applied.

Bottom panel: time series of pattern correlation for the same.

Anomalies in each case are relative to the trailing WMO climo.

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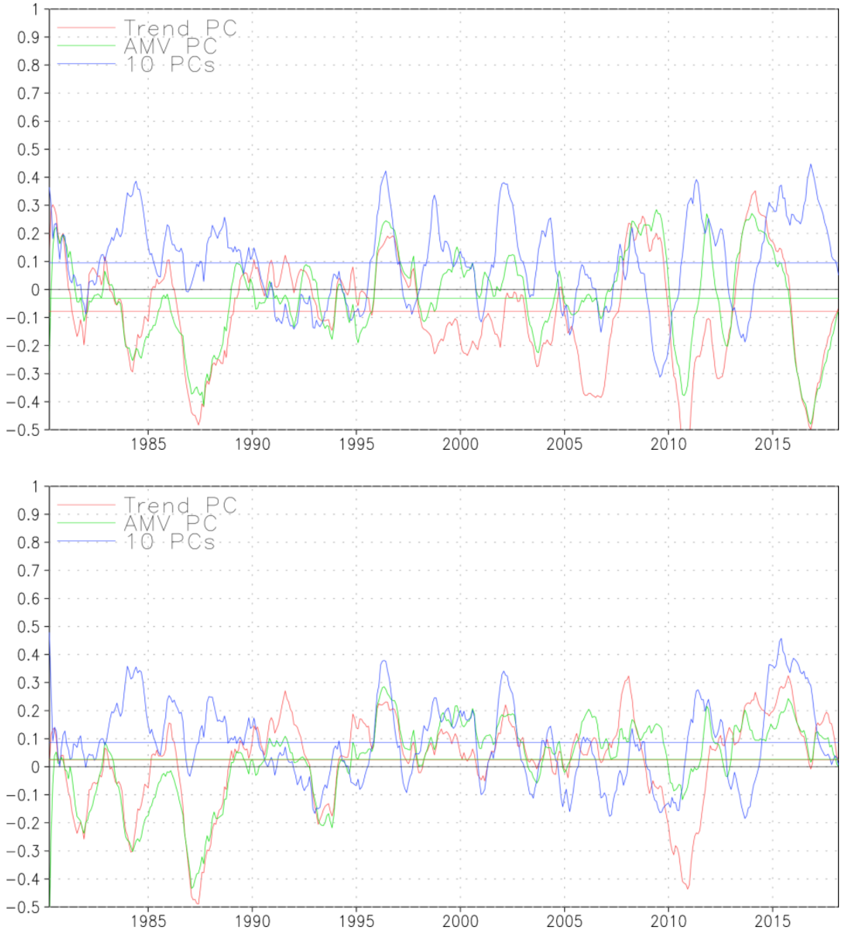



Top panel: time series of anomaly correlation for the Trend PC, AMV PC, and the leading 10 PCs, all with a 12-month running mean applied.

Bottom panel: time series of pattern correlation for the same.

Anomalies in each case are relative to the preceding 15 years.

# Making a probabilistic forecast

- We have a time series of forecasts and observations at each grid point from AMJ 1980 onward
- Use linear regression equation to calibrate forecasts
- Apply a single Gaussian distribution using where the variance is equal to the variance unexplained by the regression model [$\sigma_f=\sigma_c\sqrt{(1-r^2)}$]
- Question/problem:
  - I've done this calculation, but the 'skill' when using the PC regression forecasts *and* OCN largely seems to be a function of the changing climatology from, for example, 1950-1980 in the early hindcasts to 1950-2017 in later hindcasts.
  - I could use hindcast anomalies relative to older climatologies, but those are not internal correlation coefficients – this apparent 'skill' might just come from the bias which would be incorporated in the intercept term.

# Prelim Conclusions

- Temperature forecasts from PC regressions and OCN seem to have similar skill in first pass – all likely just from slowly changing climatology.
- Anomaly correlations using trailing climatology shows the strength of the OCN – but is it just less cold biased?
- Relative to a running 15-year climatology, PC regressions are largely skill-less, though AMV seems to have a stable footprint over the central CONUS in summer and fall.
- Precipitation results are tough to interpret – skill relative to a trailing 15-year climatology surprisingly good, but why?
  - OCN precipitation forecasts seem bad over the CONUS
  - Longer precipitation climatology periods are better (more stationary).
- Is forward-moving approach too restrictive?

# Ideas for Future Directions

- Use Hadley-OI blended dataset from 1900-present.
  - We have this locally from 1948-present already.
  - This might yield a more robust and independent secular trend component akin to the seminal analysis.
- Use 20CR data from 1900 to present for training, prediction, and verification.
- Outside of a prediction framework, this analysis can be useful for monitoring and attribution of SST anomalies and associated climate impacts.

# Ongoing Challenges: Moving Beyond ENSO and Trends

- How can we move seasonal prediction beyond ENSO and long-term trends?
  - Despite recent progress in revamping empirical tools and objectively combining empirical and dynamical guidance, we are still lacking in a few key areas:
    - Better real-time model diagnostics – where are forecast climate anomalies coming from?
    - Incorporating recent advances in understanding relationships between sea ice, snow cover, stratospheric circulation, and wintertime tropospheric circulation.
    - Applying modern methods of data science where appropriate.
      - Given more available data (e.g. 20CR, longer model free runs, etc.), are we in a better position to use nonlinear statistical approaches?

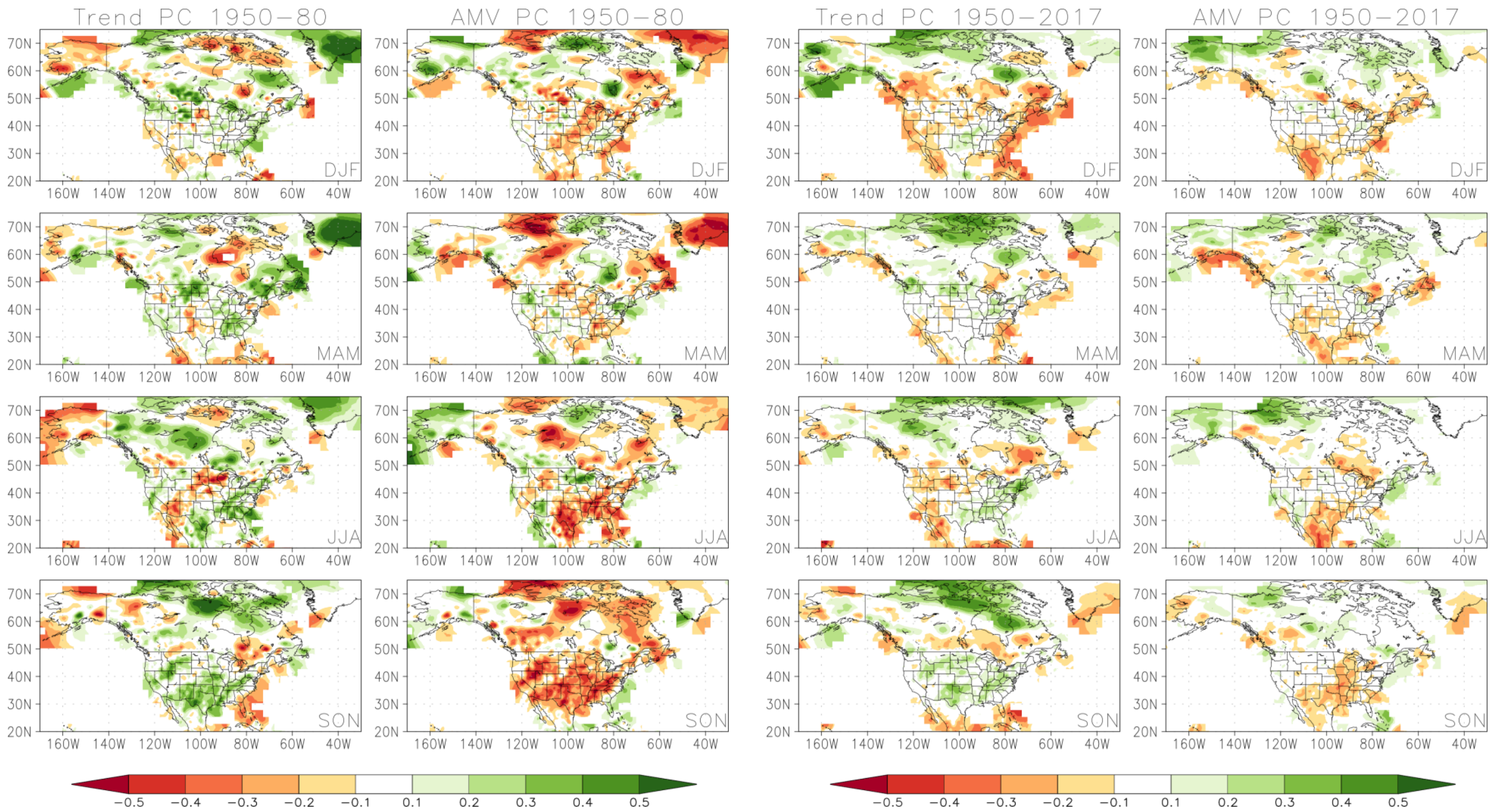
# Two FY19 Projects

- A project is being undertaken to address potential NAO/AO prediction skill in the context of a statistical and/or hybrid model.
  - Broadly seeking to reproduce key aspects of Wang et al. (2017) paper and extend to the North Pacific – while generating real-time output.
    - This expands the pool of predictors beyond SSTs and closely related variables.
  - Deep dive into NMME models – patterns of variability independent of ENSO and the secular trend.
- Second effort is a pilot project to use neural networks to predict ENSO variability
  - This is a limited experiment to test whether neural networks can provide nuanced information pertaining to asymmetry of ENSO development and associated empirical predictors.
  - Eventual targets of machine learning efforts would be temperature and precipitation – however we need to have some exposure to modern data science methods in a systematic way.

# Additional Slides

# Precipitation Results

# Correlations between PCs and precipitation at a lag corresponding to lead-3 forecast



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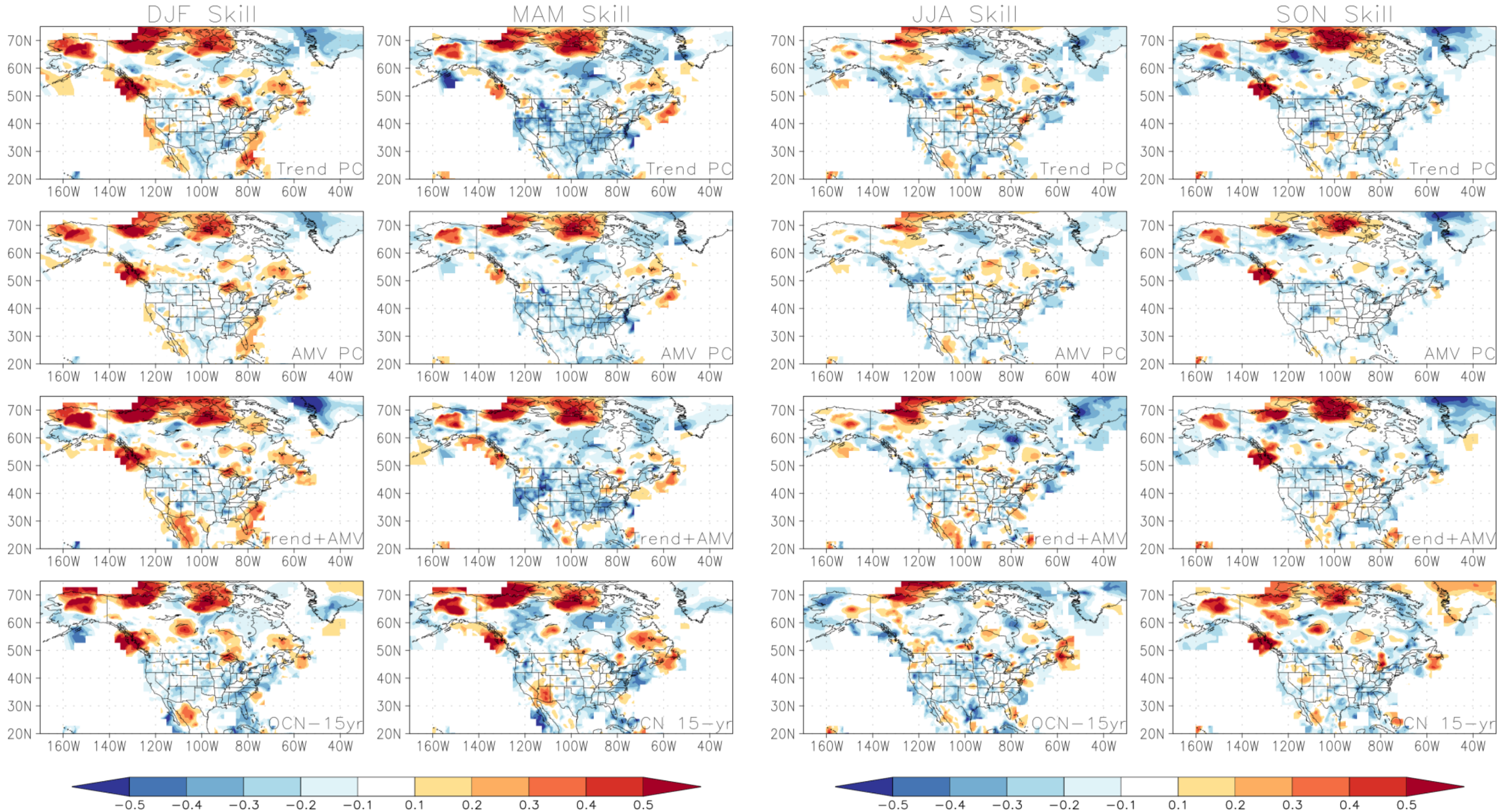

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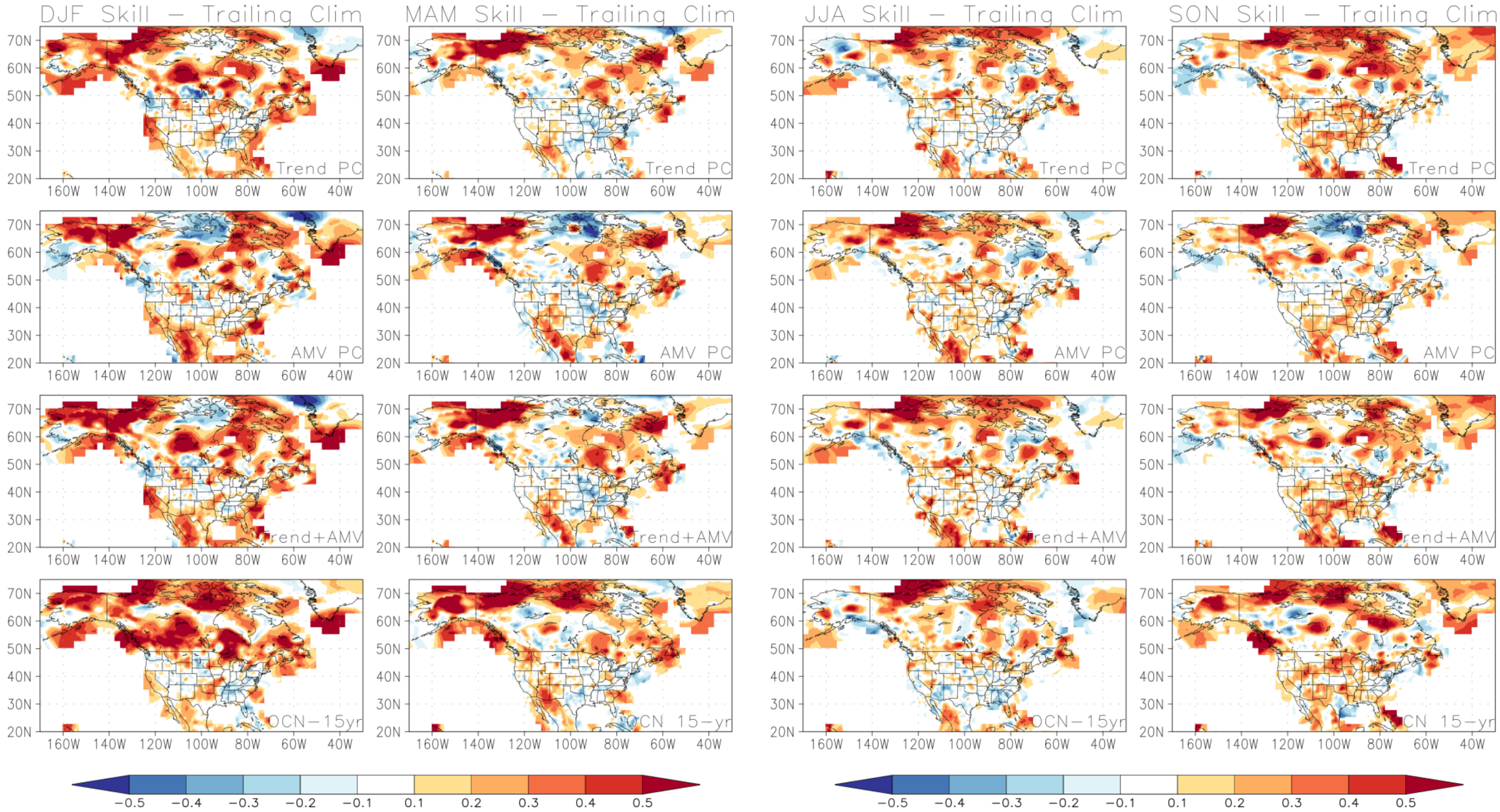

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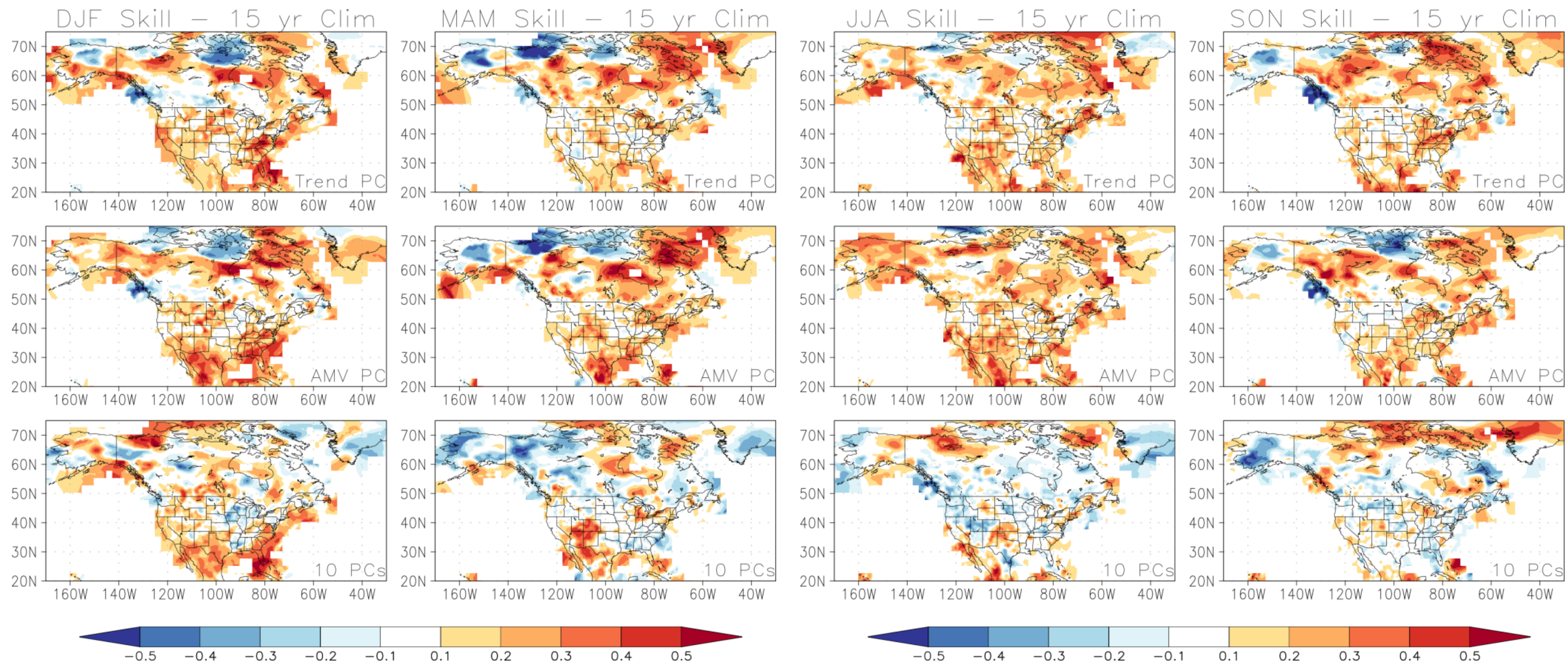

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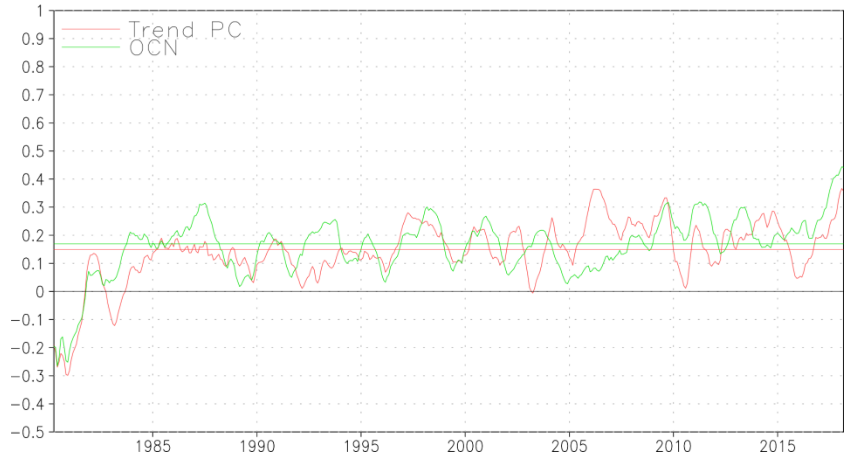


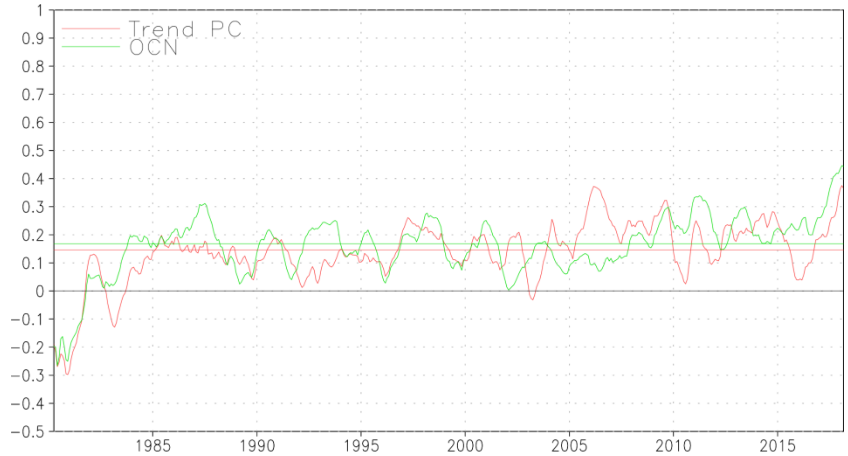


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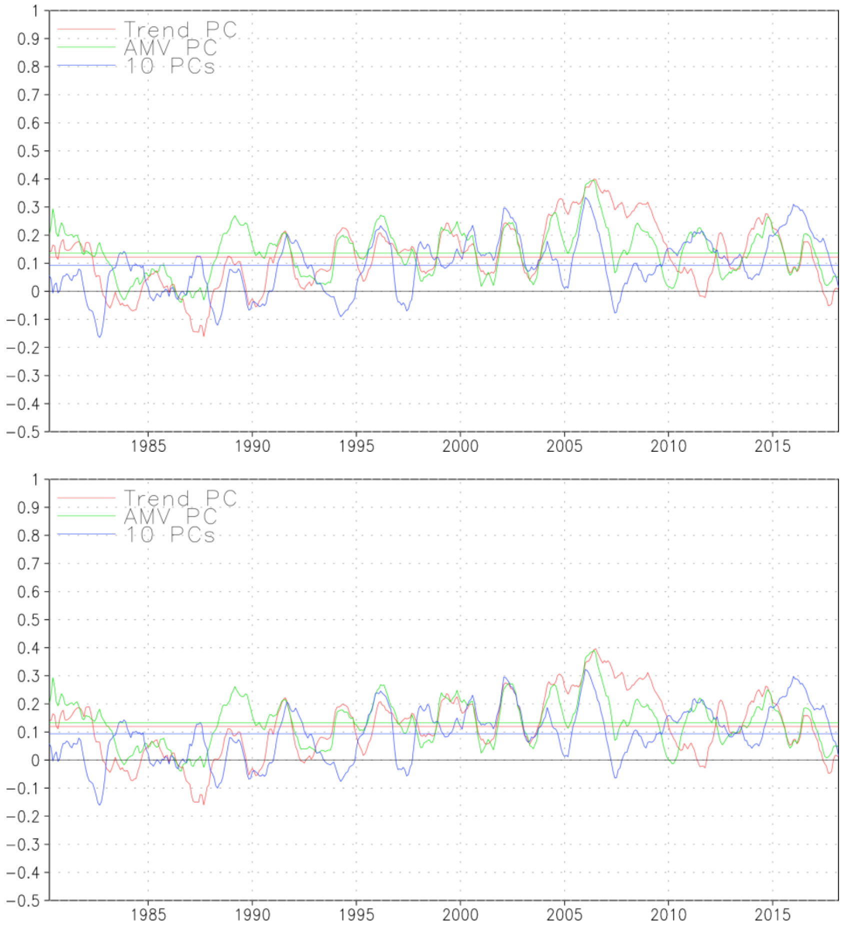


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