Integration of decadal climate trends into the Bayesian Joint Probability (BJP) calibration of North American Multi-Model Ensemble (NMME) temperature and precipitation forecasts

Dan Collins (NOAA/CPC), Johnna Infanti (Innovim/CPC), Sarah Strazzo (Embry-Riddle Aeronautical University), Andrew Schepen (CSIRO), QJ Wang (University of Melbourne)

North American Multi-Model Ensemble (NMME) hindcasts and forecasts of temperature and precipitation are post-processed using the Calibration, Bridging, and Merging (CBaM) methodology at the Climate Prediction Center (CPC) to improve skill and reliability over raw dynamical model forecasts.



Fig. 1: Temperature and precipitation trends in June-August (JJA) for observations (top) and Raw NMME lead 1 hindcasts (bottom)

However, dynamical models often incorrectly represent decadal trends (Fig. 1), potentially reducing skill and impacting calibrated probabilities in regions and seasons with strong trend. A trend parameter is added to Bayesian Joint Probability (BJP) calibration, BJP+T, that correlates with observed trend in order to correct dynamical model decadal trends. Summer seasons are more impacted by temperature trends (see Fig. 1(a), western US and AK). We expect that JJA forecasts will be improved more by the addition of explicit trend. We find increased temperature skill over regions with large trend when comparing BJP+T to BJP in individual models (Fig. 2 left). Reliability of MME probability is increased in some cases, e.g. below normal precipitation (Fig. 2 right).



Fig. 2: BJP+T - BJP upper and lower tercile average t2m Brier Skill Score for CFSv2 (lead 1, JJA) (left) and NMME BJP+T and BJP lower tercile prate reliability (right)

Though calibrated skill increases when adding explicit trend, most of the benefit of CBaM is from merging calibration with bridging through Bayesian Model Averaging (BMA). Results are modest, but positive for merged t2m or prate (Fig. 3).



Fig. 3: BJP+T - BJP upper and lower tercile average t2m Brier Skill Score for NMME (lead 1, JJA) (left) and prate (right)

Extreme skill results are mixed. Temperature does not show as large of an increase from addition of trend. Precipitation shows the largest increase in the winter months (Dec-Feb, DJF). This likely is due to stronger precipitation trend in DJF (Fig. 4).



Fig. 4: DJF observed prate trend (left); 1 month lead BJP+T - BJP BSS difference for 80th and 20th prate percentiles for DJF (right)

However, MME and individual model (e.g., CFSv2) precipitation probability reliability is increased by addition of explicit trend, particularly for extremes falling into the 80th percentile (Fig. 5).



Fig. 5: Reliability of CFSv2 (left) and NMME BJP+T and BJP 80th percentile precipitation (right) for lead 1 DJF

References: Strazzo S, Collins DC, Schepen A, et al (2019) Application of a Hybrid Statistical–Dynamical System to Seasonal Prediction of North Americar Temperature and Precipitation. Mon Weather Rev 147:607-625. https://doi.org/10.1175/MWR-D-18-0156.1 Shao, Y, Wang, Q. J., Schepen, A., & Ryu, D. (2020). Embedding trend into seasonal temperature forecasts through statistical calibration of GCM outputs. International Journal of Climatology, n/a(n/a). https://doi.org/10.1002/joc.6788





Supplemental Material 1: Example of raw model temperature trends (initialized June, lead 1, predicting July-Sept)



Supplemental Material 1: Example of BJP calibrated temperature trends (initialized June, lead 1, predicting July-Sept)