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Adaptive Bias Correction for Improved Subseasonal Forecasting

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Improving our ability to forecast the weather and climate is of interest to all sectors of the economy and government agencies from the local to the national level. In fact, weather forecasts 0-10 days ahead and climate forecasts seasons to decades ahead are currently used operationally in decision-making, and the accuracy and reliability of these forecasts has improved consistently in recent decades. However, many critical applications require subseasonal forecasts with lead times in between these two timescales. Subseasonal forecasting—predicting temperature and precipitation 2-6 weeks ahead—is indeed critical for effective water allocation, wildfire management, and drought and flood mitigation. Yet, accurate forecasts for the subseasonal regime are still lacking due to the chaotic nature of weather.

While short-term forecasting accuracy is largely sustained by physics-based dynamical models, these deterministic methods have limited subseasonal accuracy due to chaos. Indeed, subseasonal forecasting has long been considered a “predictability desert” due to its complex dependence on both local weather and global climate variables. Nevertheless, recent large-scale research efforts have advanced the subseasonal capabilities of operational physics-based models, while parallel efforts have demonstrated the value of machine learning and deep learning methods in improving subseasonal forecasting.

To counter the systematic errors of dynamical models at longer lead times, we introduce an *adaptive bias correction* (ABC) method that combines state-of-the-art dynamical forecasts with observations using machine learning. We evaluate our adaptive bias correction method in the contiguous U.S. over the years 2011-2020 and demonstrate consistent improvement over standard meteorological baselines, state-of-the-art learning models, and the leading subseasonal dynamical models, as measured by root mean squared error and uncentered anomaly correlation skill. When applied to the United States' operational climate forecast system (CFSv2), ABC improves temperature forecasting skill by 20-47% and precipitation forecasting skill by 200-350%. When applied to the leading subseasonal model from the European Centre for Medium-Range Weather Forecasts (ECMWF), ABC improves temperature forecasting skill by 8-38% and precipitation forecasting skill by 40-80%.

Overall, we find that de-biasing dynamical forecasts with our learned adaptive bias correction method yields an effective and computationally inexpensive strategy for generating improved subseasonal forecasts and building the next generation of subseasonal forecasting benchmarks. To facilitate future subseasonal benchmarking and development, we release our model code through the subseasonal_toolkit Python package and our routinely updated SubseasonalClimateUSA dataset through the subseasonal_data Python package.