ABSTRACT CONTRIBUTION

Identifying relevant large-scale predictors for sub-seasonal precipitation forecast in the southwestern US using explainable neural networks

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The last few years have seen an ever growing interest in weather predictions on sub-seasonal time scales ranging from 2 weeks to about 2 months. By forecasting aggregated weather statistics, such as weekly precipitation, it has indeed become possible to overcome the theoretical predictability limit of 2 weeks, bringing life to time scales which historically have been known as the "predictability desert". The growing success at these time scales is largely due to the identification of weather and climate processes providing sub-seasonal predictability, such as the Madden-Julian Oscillation (MJO) and anomaly patterns of global sea surface temperature (SST), sea surface salinity (SSS), soil moisture and snow cover. Although much has been gained by these studies, a comprehensive analysis of potential predictors and their relative relevance to forecast sub-seasonal rainfall is still missing.

At the same time, data-driven machine learning (ML) models have proved to be excellent candidates to tackle two common challenges in weather forecasting: (i) resolving the non-linear relationships inherent to the chaotic climate system and (ii) handling the steadily growing amounts of Earth observational data. Not surprisingly, a variety of studies have already displayed the potential of ML models to improve the state-of-the-art dynamical weather prediction models currently in use for sub-seasonal predictions, in particular for temperatures, precipitation and the MJO. It seems therefore inevitable that the future of sub-seasonal prediction lies in the combination of both the dynamical, process-based and the statistical, data-driven approach.

In the advent of this new age of combined Neural Earth System Modeling, we want to provide insight and guidance for future studies (i) to what extent large-scale teleconnections on the sub-seasonal scale can be resolved by purely data-driven models and (ii) what the relative contributions of the individual large-scale predictors are to make a skillful forecast. To this end, we build recurrent neural networks to predict sub-seasonal precipitation based on a variety of large-scale predictors derived from oceanic, atmospheric and terrestrial sources. As a second step, we apply layer-wise relevance propagation to examine the relative importance of different climate modes and processes in skillful forecasts.

Preliminary results show that our data-driven ML approach achieves moderate skill over our target region of the southern US. The ML model shows highest confidence and accuracy for winter precipitation. By investigating the relative importance for skillful predictions of wet winter periods, we find that on short time scales (2 weeks) water vapor transport is the most important predictor while on longer time scales (3 months) summer SST of the Great Lakes are more important. For dry winter periods, the most important predictor comes from global warming.