Advances in AI-based Subseasonal to Seasonal Forecasting

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Capitalizing on the recent availability of long-term data records of mean atmospheric and climate fields based on high-resolution reanalysis, machine learning architectures offer an alternative to physics-based numerical weather predictions of subseasonal to seasonal and annual means. We introduce a novel Deep UNet-based Ensemble (DUNE) architecture, employing multi-encoder-decoder structures with residual blocks. This architecture produced AI-based monthly, seasonal, and annual mean forecasts of 2-meter temperatures (T2m) over the US from a prior year, outperforming persistence, climatology, and multiple linear regression, and is comparable to NOAA operational seasonal forecasts from a prior two-week seasonal forecast. The DUNE forecast outputs are at 0.25 degrees compared to 2.0 degrees for NOAA. Heidke monthly statistics are comparable, and RMSE and ACC error statistics for mean monthly and seasonal forecasts are better than those of recent AI-based daily forecasts. A unique capability of AI-trained inference forecasts is the ability to generate forecasts in seconds, enabling the generation of hundreds of ensemble forecasts. We propose that AI S2S forecasts be considered for addition to the ensemble of S2S forecast models.