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Oral
We introduce a hybrid method that integrates deep learning with model-analog forecasting, a straightforward yet effective approach that generates forecasts from similar initial climate states in a repository of model simulations. This hybrid framework employs a convolutional neural network to estimate state-dependent weights to identify analog states. The advantage of our method lies in its physical interpretability, offering insights into initial-error-sensitive regions through estimated weights and the ability to trace the physically-based temporal evolution of the system through analog forecasting. We evaluate our approach using the Community Earth System Model Version 2 Large Ensemble to forecast the El Niño–Southern Oscillation (ENSO) on a seasonal-to-annual time scale. Results show a 10% improvement in forecasting sea surface temperature anomalies over the equatorial Pacific at 9–12 months leads compared to the traditional model-analog technique. Furthermore, our hybrid model demonstrates improvements in boreal winter and spring initialization when evaluated against a reanalysis dataset. Our deep learning-based approach reveals state-dependent sensitivity linked to various seasonally varying physical processes, including the Pacific Meridional Modes, equatorial recharge oscillator, and stochastic wind forcing. Notably, disparities emerge in the sensitivity associated with El Niño and La Niña events. We find that sea surface temperature over the tropical Pacific plays a more crucial role in El Niño forecasting, while zonal wind stress over the same region exhibits greater significance in La Niña prediction. This approach has broad implications for forecasting diverse climate phenomena, including regional temperature and precipitation, which are challenging for the traditional model-analog forecasting method.
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