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Improving sub-seasonal drought forecasting via machine learning to leverage climate data at different spatial scales

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Droughts are one of the most dangerous natural hazards that are affecting societies, with an economic impact amounting to over 9 billion euros per year in Europe. Drought events usually originate from a precipitation deficit, which can then cause water shortages, agricultural losses, and environmental degradation. Despite the numerous efforts and recent advances in predicting weather and extreme weather events, accurately forecasting rainfall remains a challenge, especially at sub-seasonal lead-times. In this case, the reference period is short enough for the atmosphere to retain a memory of its initial conditions, but also long enough for oceanic variability to affect atmospheric circulation. However, the relative contribution of climate teleconnections and local atmospheric conditions to the genesis of total precipitation at sub-seasonal scale remains unclear. In this work, we aim to address this gap by advancing the Climate State Intelligence (CSI) framework to examine the impact of both teleconnection patterns and local atmospheric conditions on monthly total precipitation. We then use the information gained to forecast total precipitation with a one-month lead time, and we test three different Machine Learning (ML) models: (i) Extreme Learning Machine (ELM); (ii) Fully Connected Neural Network; (iii) Convolutional Neural Network (CNN). We finally assess the skill of our ML-based precipitation forecasts in predicting the Standardized Precipitation Index (SPI), using the ECMWF Extended Range forecasts as a benchmark. Our framework is developed within the CLImate INTelligence (CLINT) project and applied in the Rhine Delta area, in the Netherlands. Initial findings indicate that combining global and local climate contexts into ML-based models significantly improves state-of-the-art drought forecast accuracy, thus representing a promising option to timely prompt anticipatory drought management measures.