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Forecasting Seasonal Streamflow Using a Stacked Recurrent Neural Network

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Providing accurate seasonal (1-6 months) forecasts of streamflow is critical for applications ranging from optimizing water management to hydropower generation. In this study we evaluate the performance of stacked Long Short Term Memory (LSTM) neural networks, which maintain an internal set of states and are therefore well-suited to modeling dynamical processes.

Existing LSTM models applied to hydrological modeling use all available historical information to forecast contemporaneous output. This modeling approach breaks down for long-term forecasts because some of the observations used as input are not available in the future (e.g., from remote sensing and in situ sensors). To solve this deficiency we train a stacked LSTM model where the first network encodes the historical information in its hidden states and cells. These states and cells are then used to initialize the second LSTM which uses meteorological forecasts to create streamflow forecasts at various horizons. This method allows the model to learn general hydrological relationships in the temporal domain across different catchment types and project them into the future up to 6 months ahead.

Using meteorological time series from NOAA's Climate Forecast System (CFS), remote sensing data including snow cover, vegetation and surface temperature from NASA's MODIS sensors, SNOTEL sensor data, static catchment attributes, and streamflow data from USGS we train a stacked LSTM model on 100 basins, and evaluate predictions on out-of-sample periods from these same basins. We perform sensitivity analysis on the effects of remote sensing data, in-situ sensors, and static catchment attributes to understand the informational content of these various inputs under various model architectures. Finally, we benchmark our model to forecasts derived from simple climatological averages and to forecasts created by a single LSTM that excludes all inputs without forecasts.