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Forecasting streamflow using Artificial Neural Network (ANN) with different spatial discretizations of the watershed : use case on the Au Saumon watershed in Quebec (Canada).

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Improving streamflow forecasts helps in reducing socio-economical impacts of hydrological-related damages. Among them, improving hydropower production is a challenge, even more so in a context of climate change. Deep learning models drew the attention of scientists working on forecasting models based on physical laws, since they got recognition in other domains. Artificial Neural Network (ANN) offer promising performance for streamflow forecasts, including good accuracy and lesser time to run compared to traditional physically-based models.

The objective of this study is to compare different spatial discretization schemes of inputs in an ANN model for streamflow forecast. The study focuses on the "Au Saumon" watershed in Southern Quebec (Canada) during summer periods, with a forecast window of 7 days at a daily timestep. Parameterization of the ANN was a key preliminary step: the number of neurons in the hidden layer was first optimized, leading to 6 neurons. The model was trained on a 11-year dataset (2000-2005 and 2007-2011) followed by model validation on one dry (2012) and one wet (2006) year to take into account extreme hydrologic regimes.

To lead this study, the physically-based hydrological 'Hydrotel' model is the reference to compare our results. The model defines watershed heterogeneity using hydrological units based on land uses, soil types, and topography, called Relative Homogeneous Hydrological Units (RHHU). The Nash-Sutcliffe Efficiency score (NSE) is the main evaluation criteria calculated. In a preliminary step, we have to ensure the ANN model can satisfactorily mimic Hydrotel. With the same model inputs, that is same variables and same spatial discretizations of variables (total precipitation, daily maximum and minimum temperatures, and soil surface humidity), the ANN forecasts were found to be better than those of Hydrotel for one to 7-day forecasts.

Three different watershed spatial discretizations were tested: global, fully distributed, and semi-distributed. For the global model, hydrometeorological data used as inputs to the ANN model were averaged across all RHHUs. The complexity is reduced with loss of spatial details and heterogeneity. For the fully distributed model, a regular grid was defined with six cells of 28x28km2 covering all the watershed. For the semi-distributed model, spatial distribution of the input data was that of the RHHUs. For this discretization, the state variables (soil moisture and outflow) were updated at each forecast timestep, whether on all RHHUs, or only on the RHHU of the outlet.

Depending on the spatial discretization of inputs used, the accuracy differed. The fully distributed model offered the least performance, with NSE values of 0.85 ,while the global model surprisingly performed better with a 0.93 NSE. Moreover, updating soil moisture on all the RHHUs of the semi-distributed model improved the NSE across the entire window of forecast.

This research will assess the ANN model performance developed using ERA5-land precipitation and temperature reanalysis and ground observations of soil moisture. Given the promising results obtained with the fully and semi distributed models, our ANN model will be tested with state variables retrieved from satellite data, such as surface soil moisture from SMAP and SMOS missions.