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Large-scale evaluation of temporal trends in ANN behaviour for daily flow forecasts in Canadian catchments.

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Modelling accurate rainfall-runoff (RR) simulations is a longstanding contest in hydrological research. These models often treat the RR relationship as stationary; in other words, model parameters are assumed to be fixed, time-invariant values. In reality, the RR relationship is continuously changing due to factors such as climate change, rapid urban growth, and construction of hydraulic infrastructure. Therefore, there is a need for hydrological models to be able to adapt to these changes.

The suitability of machine learning (ML) models for flow forecasting has been well established over the past 3 decades. One advantage of such models is their ability to rapidly and continuously adapt to the non-stationary relationship between rainfall and runoff generation. However, changes in model performance and model adaptation in an operational context have not received much attention from the research community.

We present a large-scale framework for daily flow forecasting models in Canada (>100 catchments). In our framework, local artificial neural network (ANN) ensembles models are automatically trained to forecast flow on an individual catchment basis using openly available daily hydrometeorological timeseries data. The collection of catchments taken from across Canada have highly heterogenous soil groups, land use, and climate. We propose several experiments that are designed to evaluate the robustness of ANN-based flow forecasting across time. Using the most recent year of observations for validation, we evaluate the effects of incrementally providing increasing amounts of historic observations. Similarly, we quantify changes to ANN model parameters (weights and biases) across increasing historic training data. Finally, we analyse feature importance across time using multiple feature importance algorithms. Our research aims to provide guidance on initial model training and adaptive learning, as ML-based approaches become increasingly adapted for operational use.