



Hydrological modelling using machine and deep learning models across multiple case studies

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Machine learning (ML) and deep learning (DL) models can play an important role when it comes to modelling complicated processes. Such capability is necessary for hydrological and climate-related applications. Generally, ML models utilize precipitation and temperature time series of a basin as input to develop a lumped rainfall-runoff model to simulate streamflow at the basin outlet. However, when it is divided into several sub-basins, Graph Neural Networks (GNN) can consider each sub-basin as a node and link them together using a connectivity matrix to account for spatial variations of hydroclimatic variables. In this study, GNN and various ML models with different types of architecture, ranging from neural networks, tree-based structure, and gradient boosting, were exploited for daily streamflow simulation over different case studies. For each case study, the basin was divided into a few sub-basins for which daily precipitation and temperature data were aggregated and used as input. For training GNN, the connection matrix of sub-basins was also used as input. Basically, 75% of historical records were utilized to train GNN and different ML models, e.g., artificial neural networks, support vector machine, decision tree, random forest, eXtreme Gradient Boosting (XGBoost), Light Gradient-Boosting Machine (LightGBM), and Category Boosting (CatBoost), while the rest was used for testing. Streamflow simulation was conducted with/without considering seasonality impact and lag times. The obtained results clearly demonstrate that considering seasonality and time lags can enhance accuracy of streamflow predictions based on Kling–Gupta efficiency (KGE). Furthermore, GNN with seasonality impact and time lags achieved promising results across different case studies with $KGE > 0.85$ for training and $KGE > 0.59$ for testing data, respectively. Among ML models, boosting models, e.g., LightGBM and XGBoost, performed slightly better than other ML models. Finally, this comparative analysis provides valuable insights for ML/DL applications in climate change impact assessments.

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