Accounting for spatial-temporal rainfall variability in river flow prediction in the data scarce River Mayanja catchment, Upper White Nile basin using a hybrid ConvLSTM-LSTM model

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ABSTRACT

Limited hydro-meteorological datasets resulting from sparse observation networks, particularly in developing countries constrain the development and application of robust hydrological models and hinder accurate representation of rainfall spatial heterogeneity. This study applied a novel hybrid ConvLSTM-LSTM model that enables consideration of spatial-temporal variation of rainfall. Additionally, limited studies have applied the ConvLSTM-LSTM for river flow prediction particularly in data scarce catchments. The applied hybrid ConvLSTM-LSTM complements in situ observed rainfall with gridded Tropical Applications of Meteorology using Satellite (TAMSAT) remotely sensed data for daily river flow prediction in a data scarce upper Mayanja catchment in central Uganda. The ConvLSTM-LSTM model was parallelly trained and tested using two branches including the ConvLSTM and LSTM branch. The ConvLSTM branch was trained using a 0.0375^0x0.0375^0 resolution TAMSAT gridded dataset whereas the LSTM branch was trained using in situ observed daily time series. The two branches were subsequently concatenated side by side then passed through a linear layer to obtain the final river flow output. The performance of the developed hybrid was compared to two standalone deep learning networks (LSTM and transformer) and a process based Hydrologic Engineering Center – Hydrologic Modeling System (HEC-HMS) with gridded rainfall. Comparison was based on two objective metrics including the Nash-Sutcliffe Efficiency (NSE) and Root Mean Square Error (RMSE), and two signature indices including the percent bias in Flow Duration Curve (FDC) high-segment volume (%BiasFHV) and percent bias in FDC low-segment volume (%BiasFLV). The study results indicate that the ConvLSTM-LSTM outperformed all models during the training and testing period given the two-objective metrics. ConvLSTM-LSTM achieved an NSE of 0.60 and RMSE of 5.71 m^3/s for the test set while LSTM had an NSE of 0.43 and RMSE of 7.03 m^3/s and HEC-HMS achieved an NSE of 0.34 and RMSE of 7.39 m^3/s. Additionally, the ConvLSTM-LSTM model performed best in capturing peaks with a %BiasFHV of -27.0 while the HEC-HMS scored the least %BiasFHV of -29.2. However, ConvLSTM-LSTM demonstrated the worst performance in predicting low flows with a %BiasFLV of 117 while HEC-HMS achieved the best performance with %BiasFLV of 21.5. The study results indicate that incorporating spatial-temporal rainfall variability in the modelling framework using the hybrid ConvLSTM-LSTM improves performance over process-based and standalone deep learning models in predicting daily river flows. Additionally, ConvLSTM-LSTM model could contribute to development of reliable flood early warning systems. However, the model may not be well suited for low flow conditions and should be applied carefully. Furthermore, low NSE values observed are largely attributed to limited historical observations. Future research will look at integrating machine learning and process-based models to complement their strengths in simulating daily river flows.

Keywords: deep learning; data scarcity; spatial-temporal modeling; ConvLSTM-LSTM.