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Comparison of a conceptual rainfall-runoff model with an artificial neural network model for streamflow prediction

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Introduction

Accurate streamflow forecasting can minimize negative impacts of hydrological events

Two models were compared for daily streamflow forecasting:

- Traditional conceptual rainfall-runoff (hydrological) model
- Artificial neural network (ANN) model

Methodology

1) The adopted ANN model is a long short-term memory (LSTM) architecture with two hidden layers, each with 256 neurons. It was computed using Neuralhydrology library¹

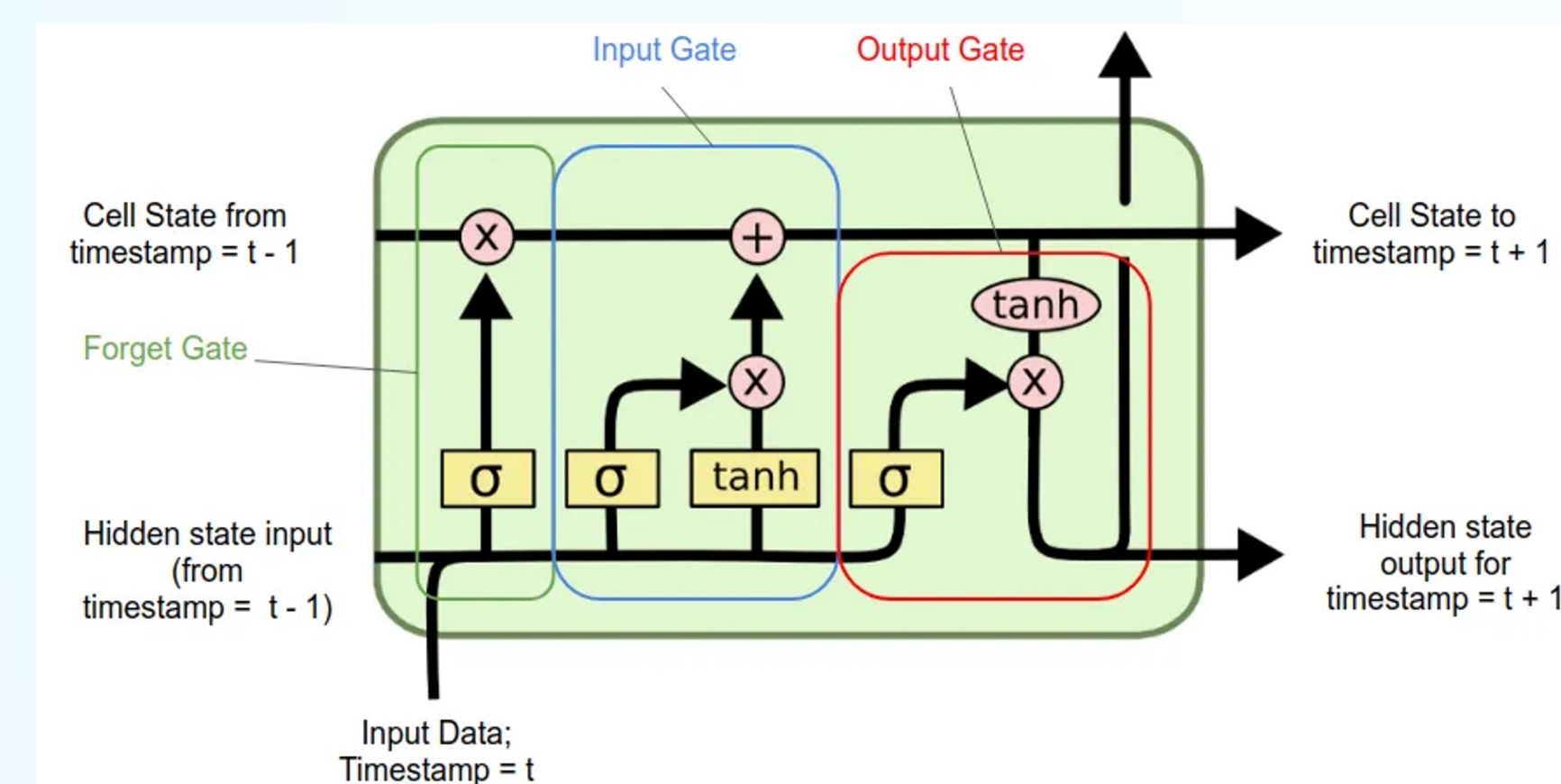


Figure 1 : Structure of the LSTM neuron.

We can see the different gates inside of an LSTM neuron²

2) The conceptual hydrological model called Superflex is used as a reference.

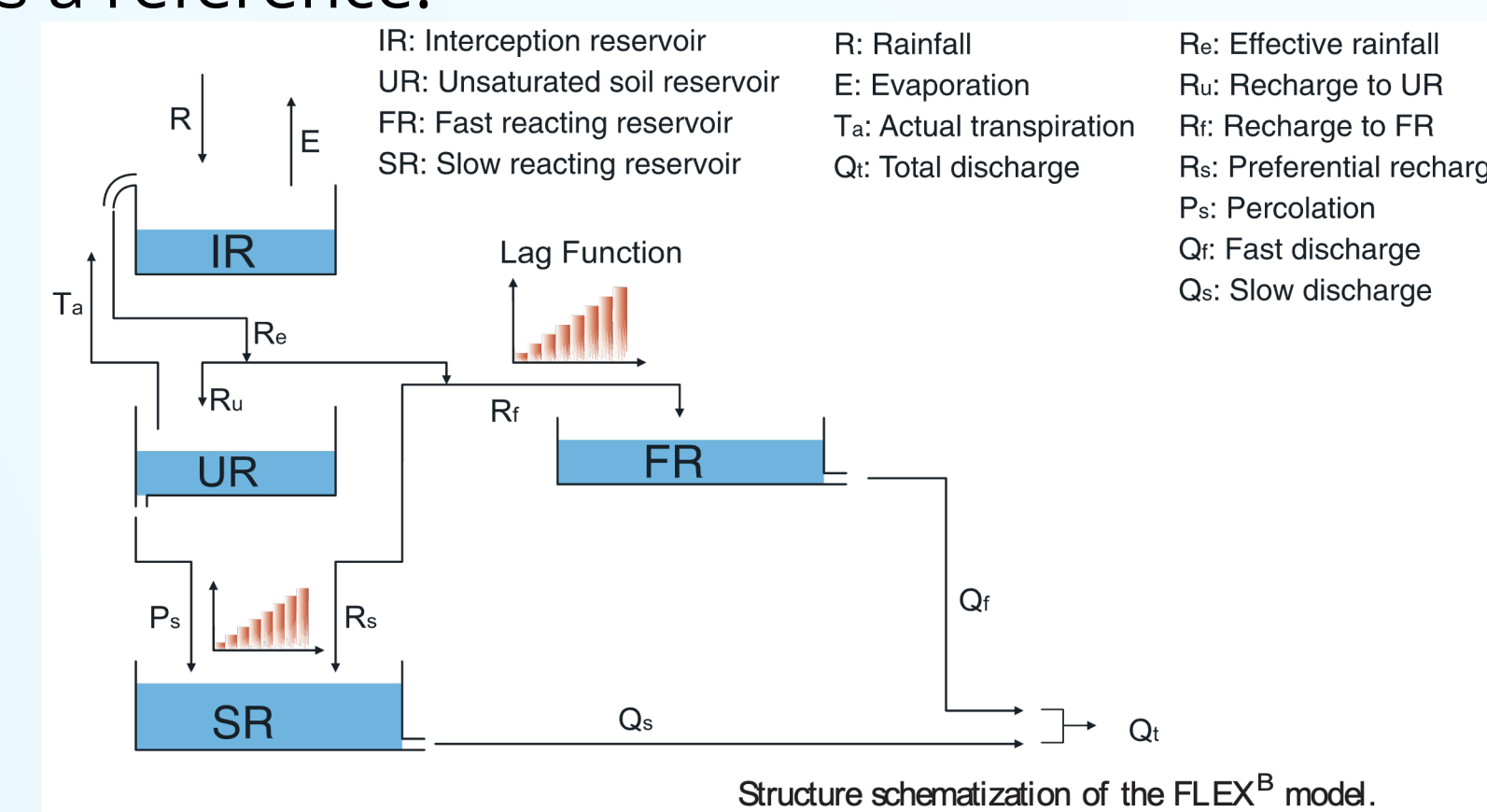


Figure 2 : Structural diagram of the FlexTM model³

3) The Severn River basin was chosen for this study.

- The River Severn is Great Britain's longest river, spanning 220 miles with an average flow rate of 107 m³/s. It is the most voluminous river in England and Wales.
- The flow was measured at Saxon Lode.
- The data were obtained from the ERA5 database⁴

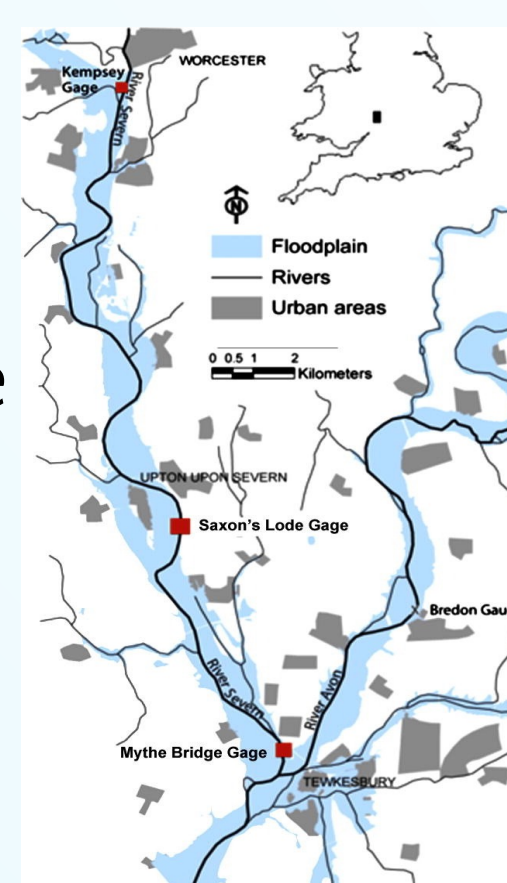


Figure 3 : The River Severn study area⁵

Methodology

4) The models are :

- Trained between 1 and 13 years dataset from 2004 to 2017
- Validated on a 2-year dataset from 2018 to 2020
- The Severn catchment in the United Kingdom was used as a test case

The same inputs meteorological forcings were used for both models : Total precipitation, Daily maximum and minimum temperatures, Daylight duration, Mean surface downward short-wave radiation flux, and Vapor pressure.

5) Models evaluated using Nash-Sutcliffe Efficiency (NSE) score

$$NSE = 1 - \frac{\sum_{t=1}^T (Q_0^t - Q_m^t)^2}{\sum_{t=1}^T (Q_0^t - \bar{Q}_0)^2}$$

Where \bar{Q}_0 is the mean discharges, Q_m is modeled discharge. Q_0^t is observed discharge at time t.

If a model has no estimation error, NSE equals 1; if its error equals the variance of the observed data, NSE equals 0.

Results

1) NSE score as a function of the number of training years for both LSTM and Superflex

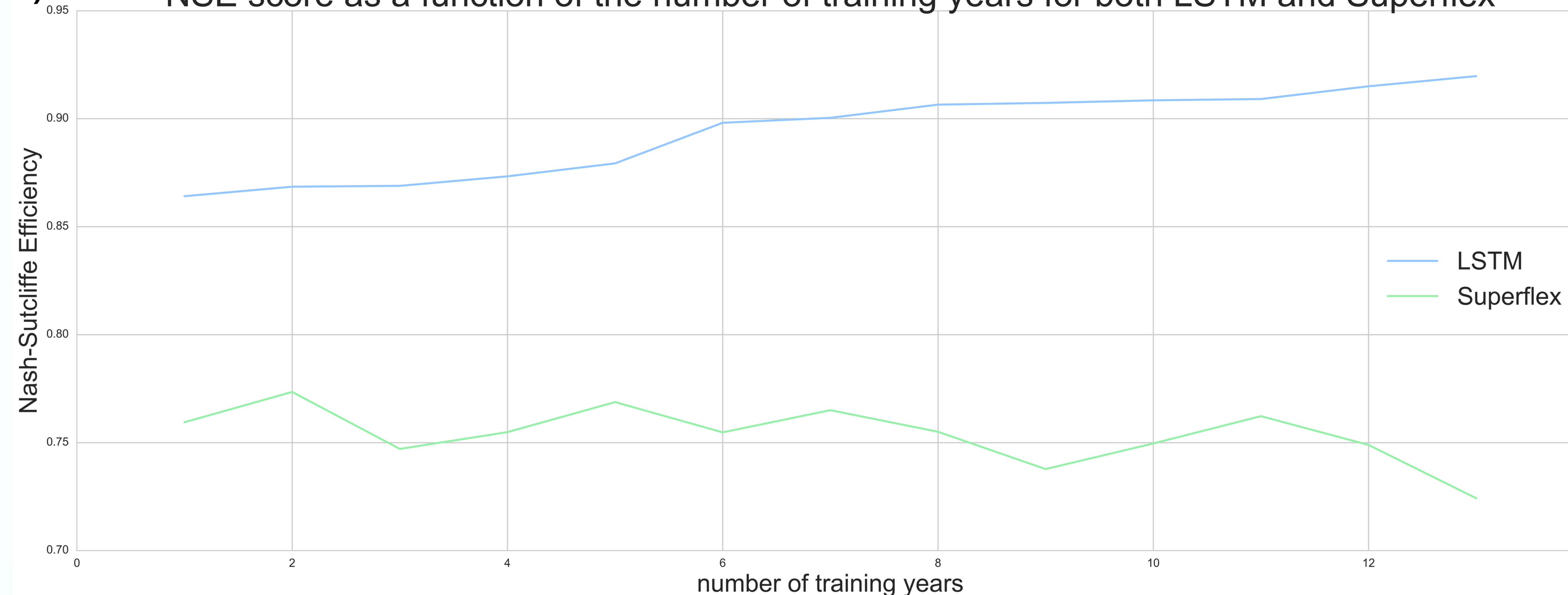


Figure 4 : NSE score as a function of the number of training years for LSTM (in blue) and Superflex (in green)

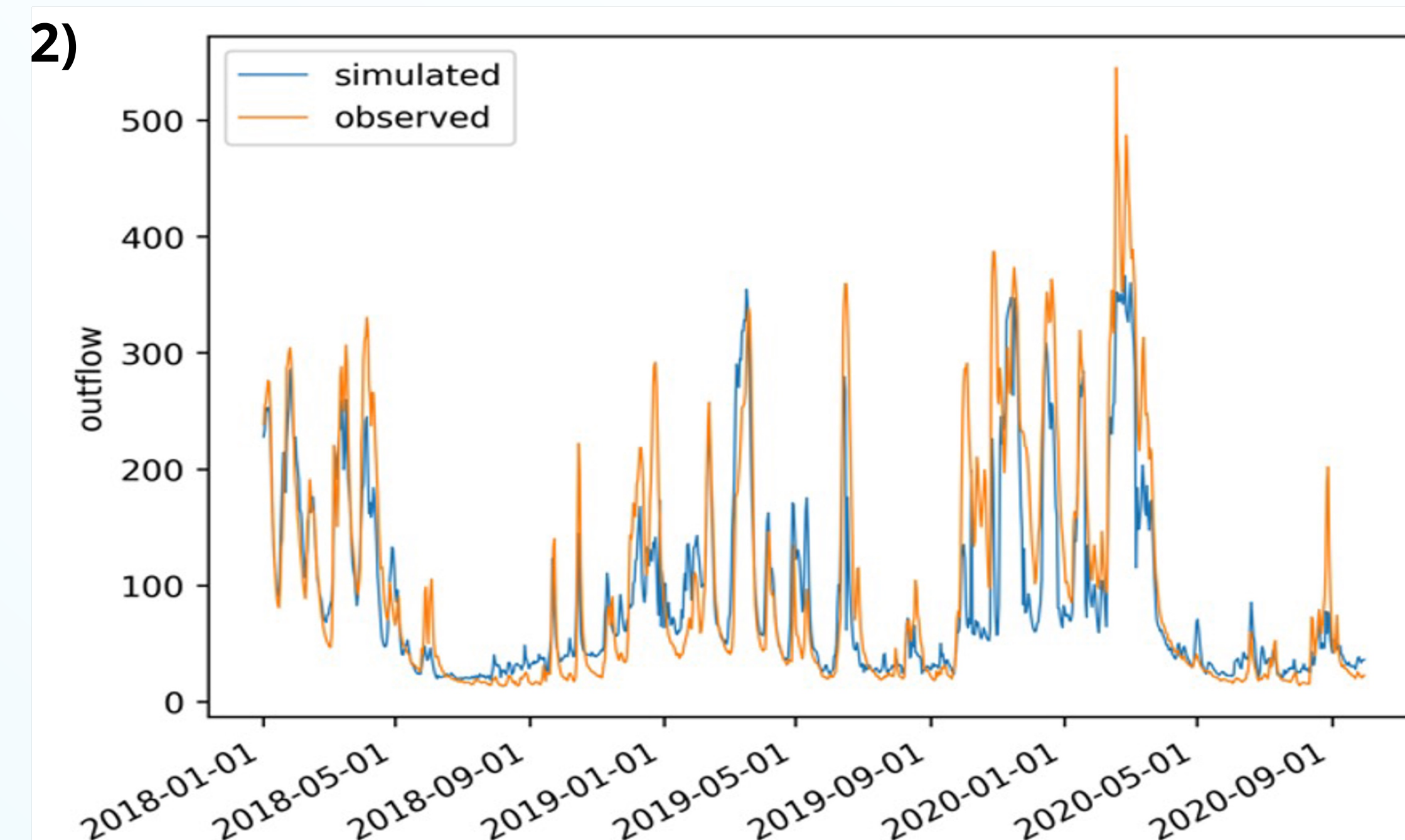


Figure 5 : Comparison of simulated outflow (in blue) and observed outflow (in orange) over the validation period for the LSTM.

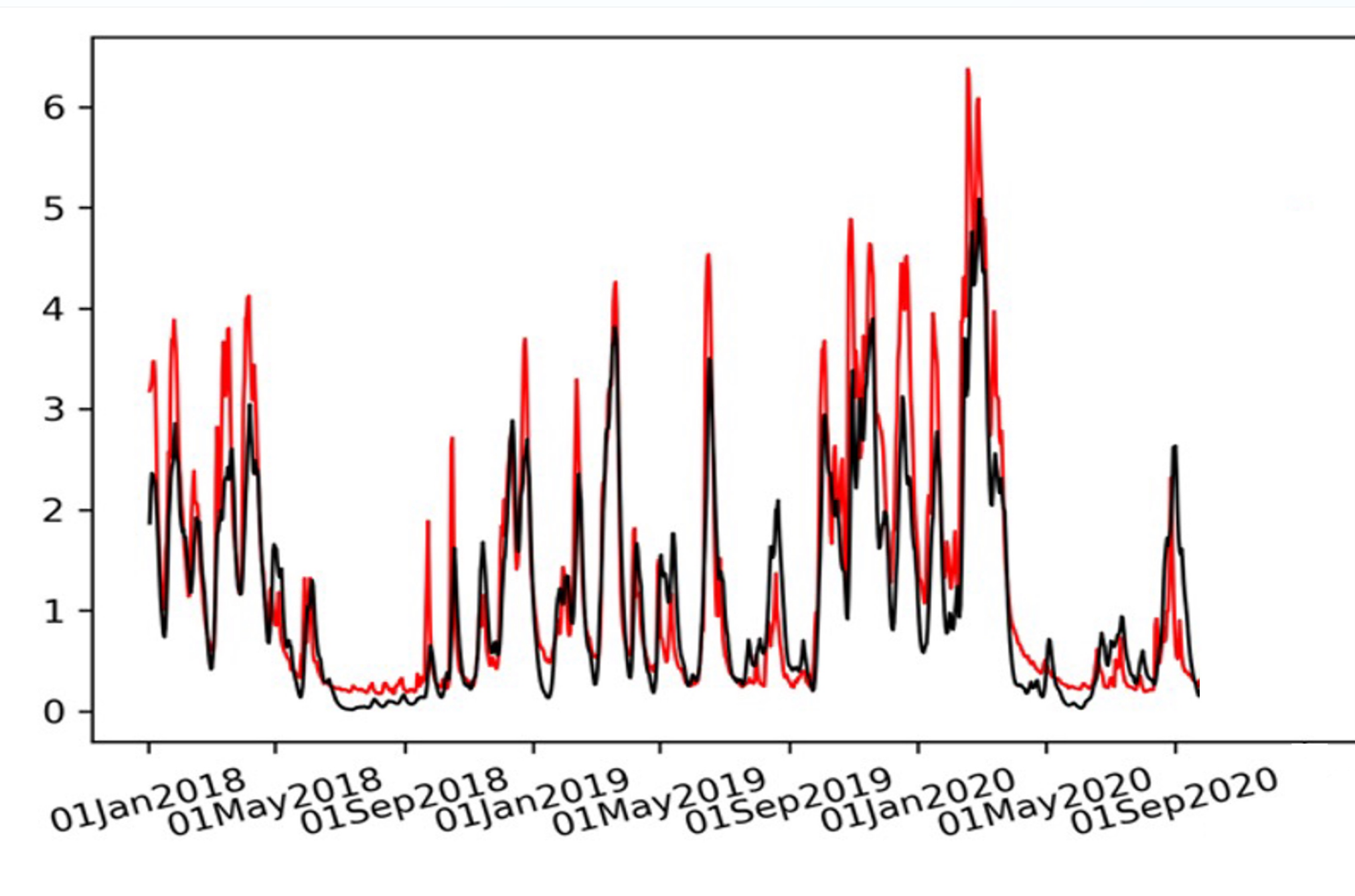


Figure 6 : Comparison of simulated outflow (in black) and observed outflow (in red) over the validation period for SuperFlex.⁶

Results

3) LSTM model provides more accurate one-day forecasts than the hydrological model Superflex

• Average NSE score of 0.99 achieved by LSTM model for the training period, and 0.85 for the validation period

• NSE score of 0.84 achieved by the Superflex model for the training period, and 0.74 for the validation period

Conclusion

• ANN model showed promising results compared to a state-of-the-art conceptual hydrologic model in the study

• Further comparisons between both models will be conducted using different training dataset periods and different catchments

• Additional tests will provide more information on the capabilities of the LSTM model and confirm its effectiveness

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