



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

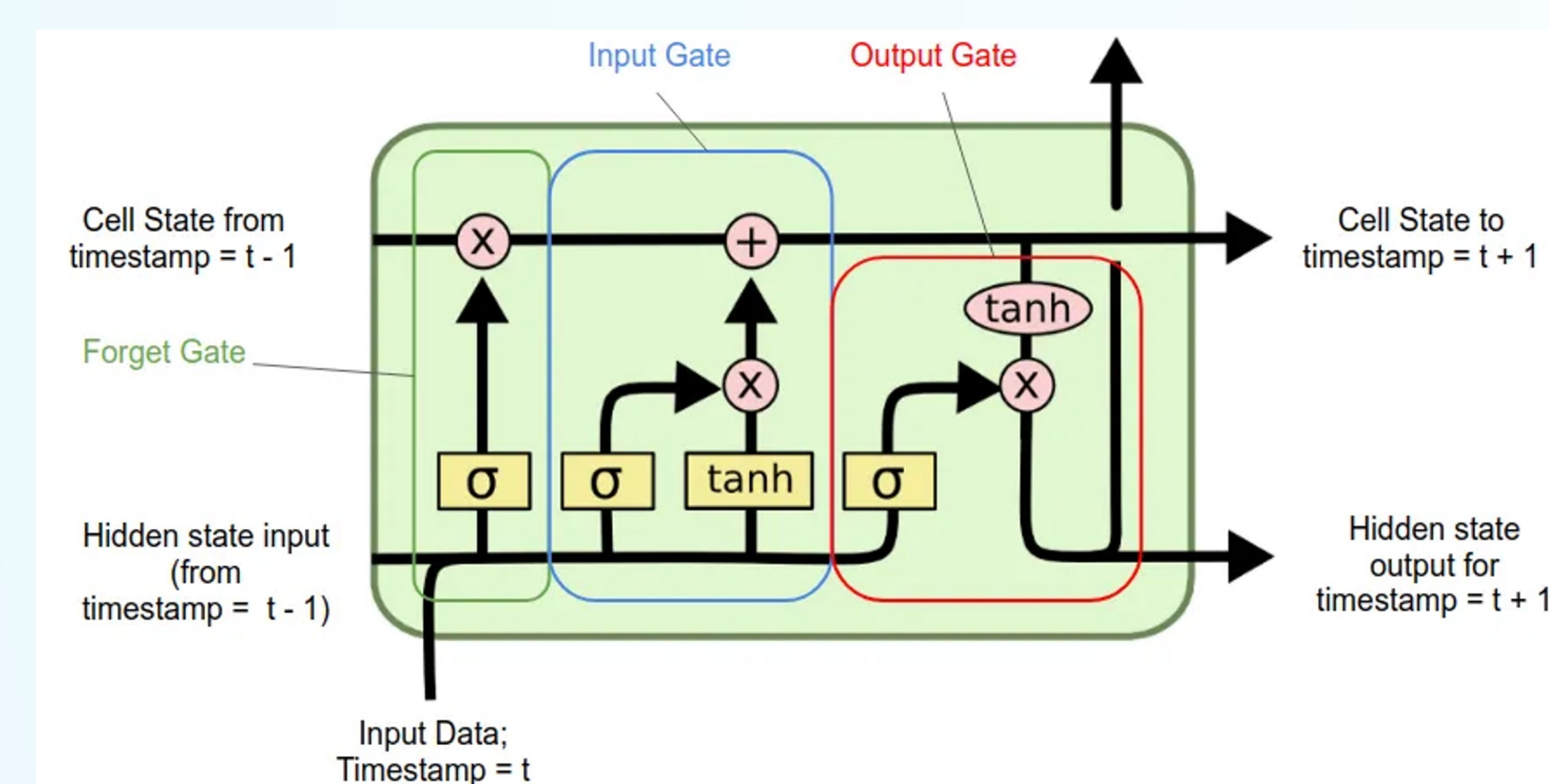


Figure 1 : Structure of the LSTM neuron.

We can see the different gates inside of an LSTM neuron²

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

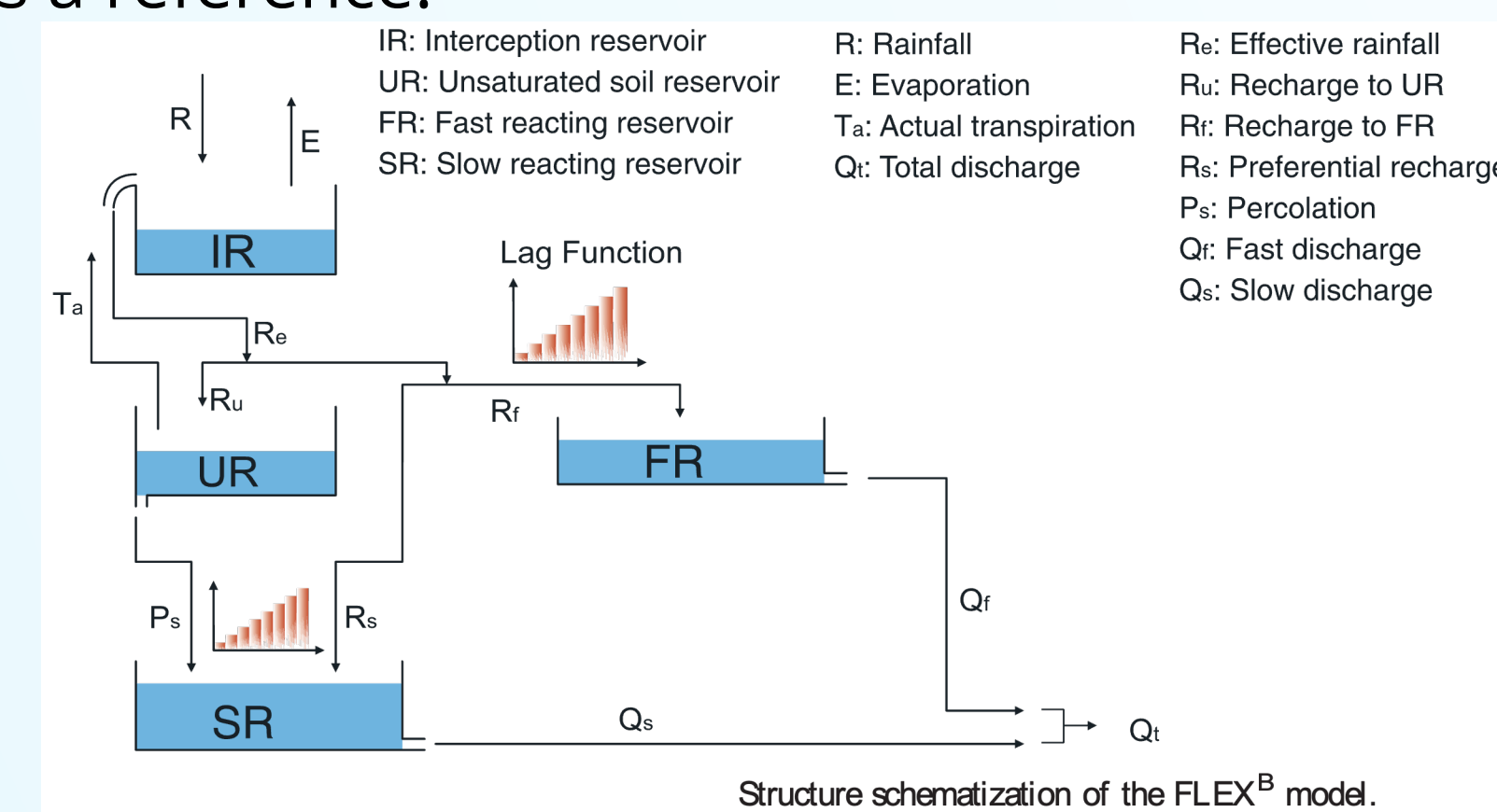


Figure 2 : Structural diagram of the Flex™ model³

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

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

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

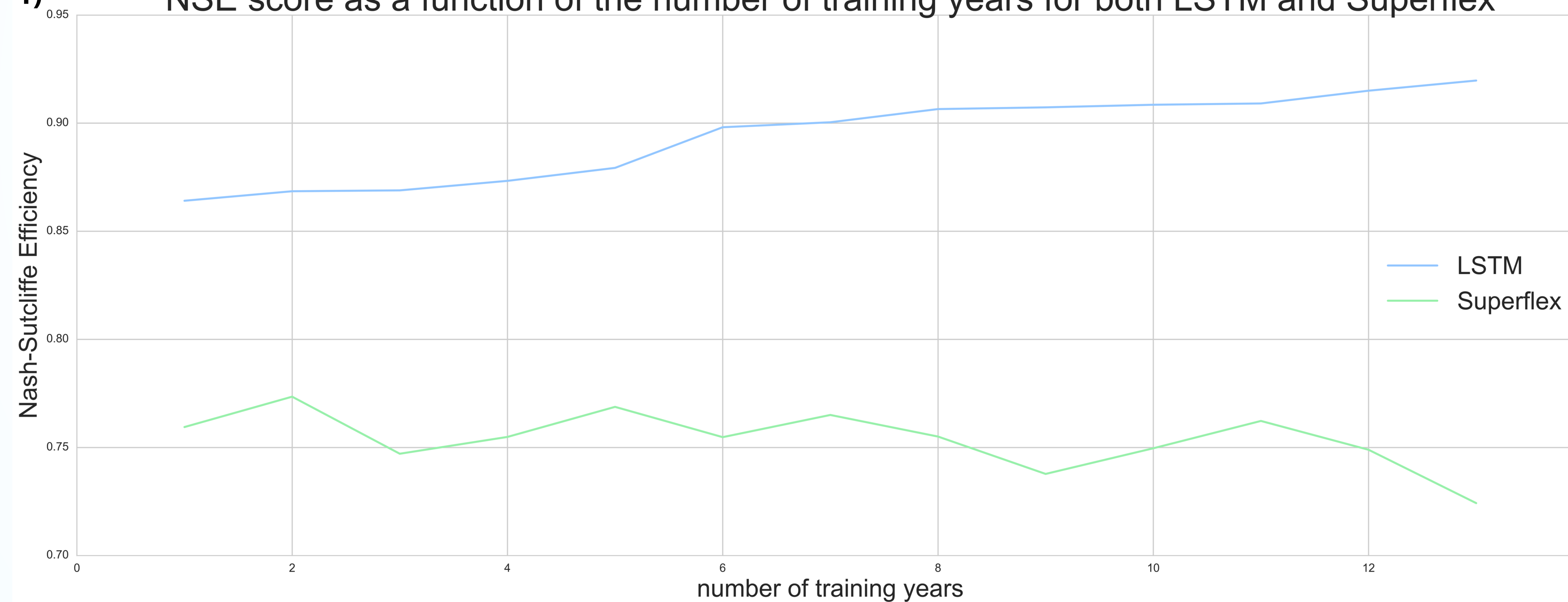


Figure 4 : NSE score as a function of the number of training years for LSTM (in blue) and Superflex (in green)

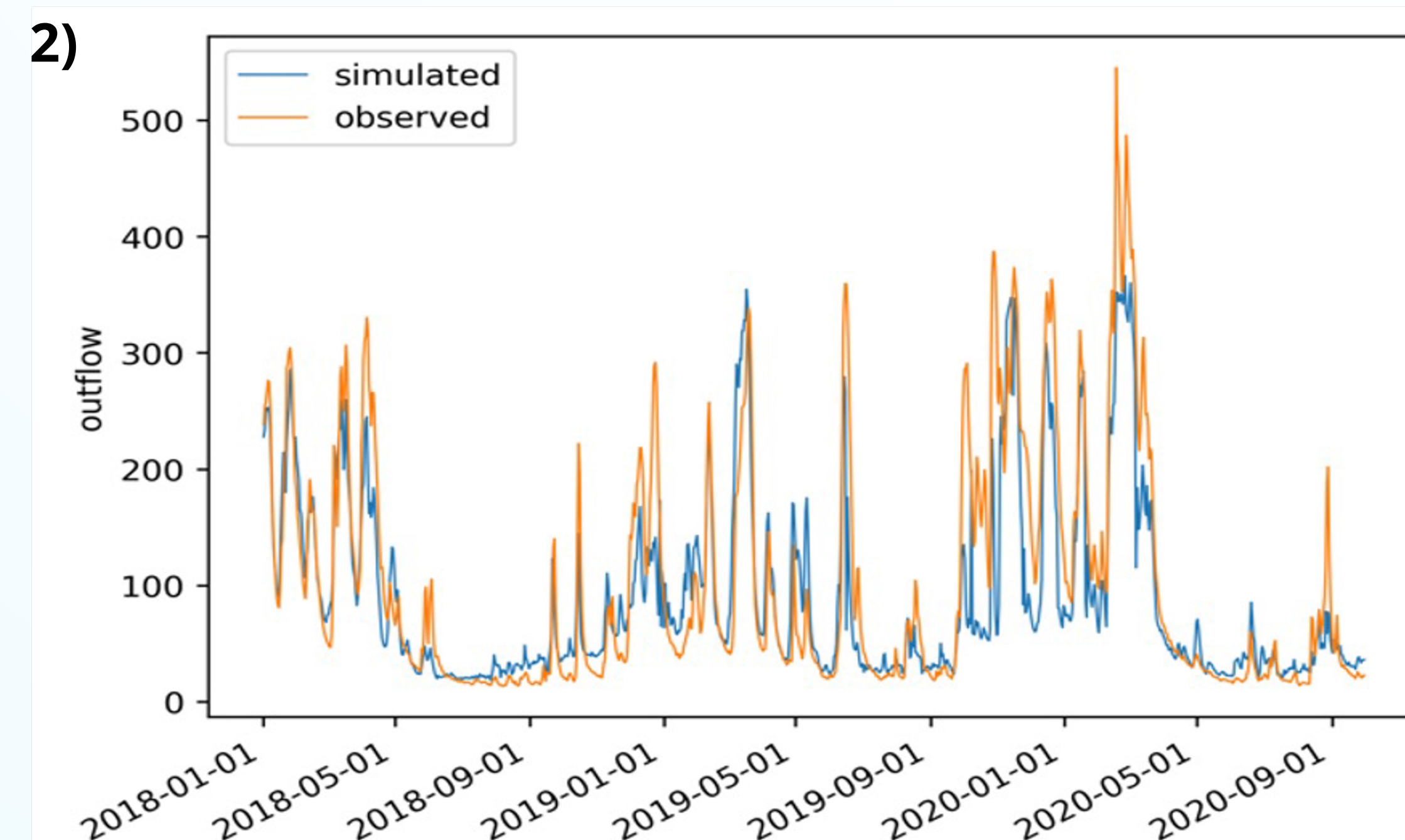


Figure 5 : Comparison of simulated outflow (in blue) and observed outflow (in orange) over the validation period for the LSTM.

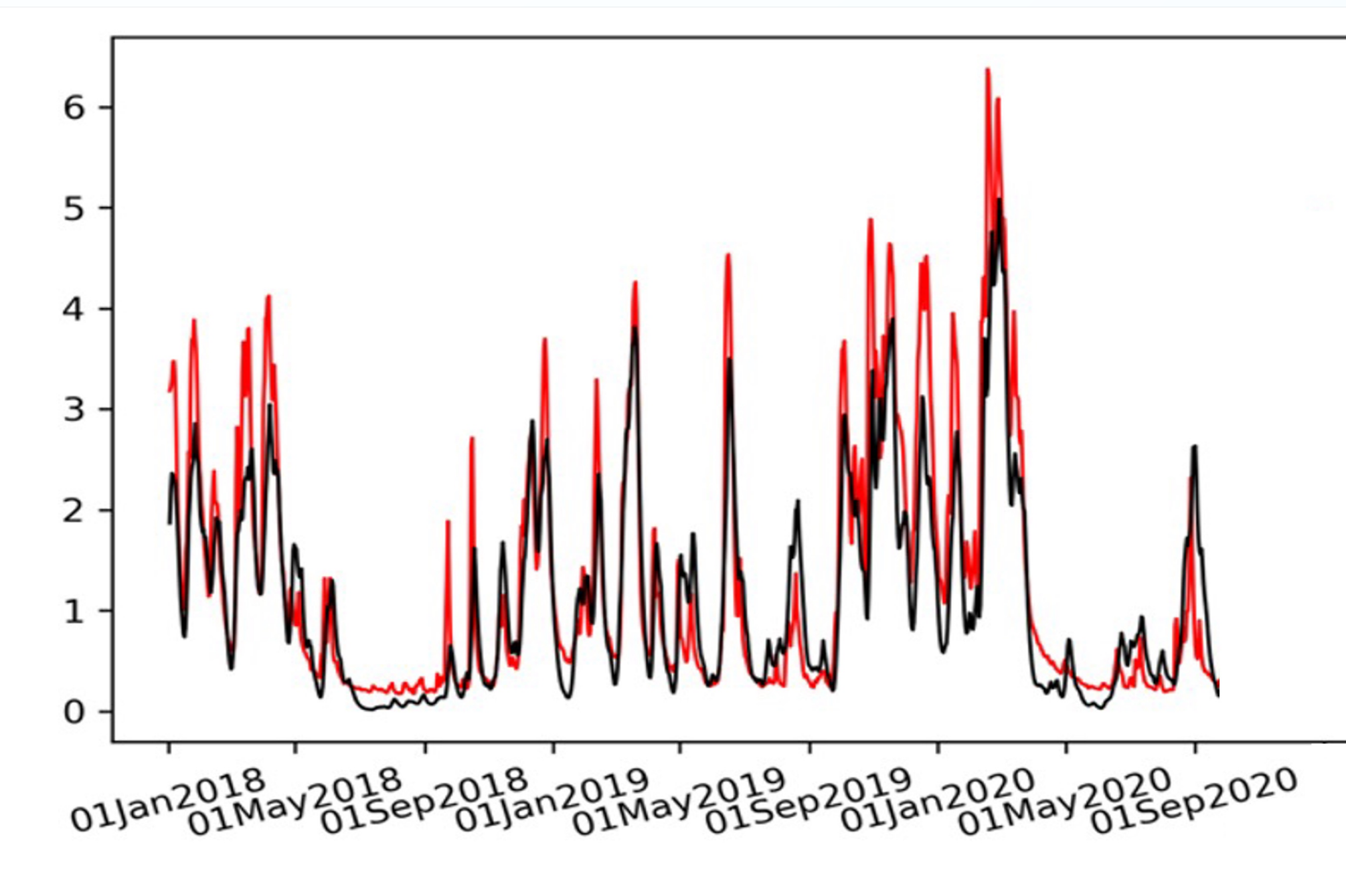


Figure 6 : Comparison of simulated outflow (in black) and observed outflow (in red) over the validation period for SuperFlex.⁶

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

References

1. Kratzert, F., Gauch, M., Nearing, G. & Klotz, D. NeuralHydrology – A Python library for Deep Learning research in hydrology. Journal of Open Source Software vol. 7 4050 (2022).
2. Varsamopoulos, Savvas & Bertels, Koen & Almudever, Carmen. (2018). Designing neural network based decoders for surface codes.
3. Fenicia, F., Savenije, H. H. G., Matgen, P. & Pfister, L. A comparison of alternative multiobjective calibration strategies for hydrological modeling. Water Resources Research vol. 43 (2007).
4. Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., Thépaut, J.-N. (2023): ERA5 hourly data on pressure levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). DOI: 10.24381/cds.bd0915c6 (Accessed on DD-MMM-YYYY)
5. Neal, J. et al. Estimating River Channel Bathymetry in Large Scale Flood Inundation Models. Water Resources Research vol. 57 (2021).
6. PFE STES, Modélisation hydrologique pluie-débit sur la rivière Severn (UK), Freychet Julien

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