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COMPARISON OF AN ARTIFICIAL NEURAL NETWORK WITH A CONCEPTUAL RAINFALL-RUNOFF MODEL FOR STREAMFLOW PREDICTION

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Introduction

The effectiveness of Machine Learning models, such as rainfall-runoff models, is influenced by the amount of data available. How does this sensitivity compare to that of more traditional models, and what approaches can be employed to alleviate it?

A comparison was conducted between two models for daily streamflow forecasting: a traditional conceptual rainfall-runoff (hydrological) model and an Artificial Neural Network (ANN) model, considering both data size and dataset typology.

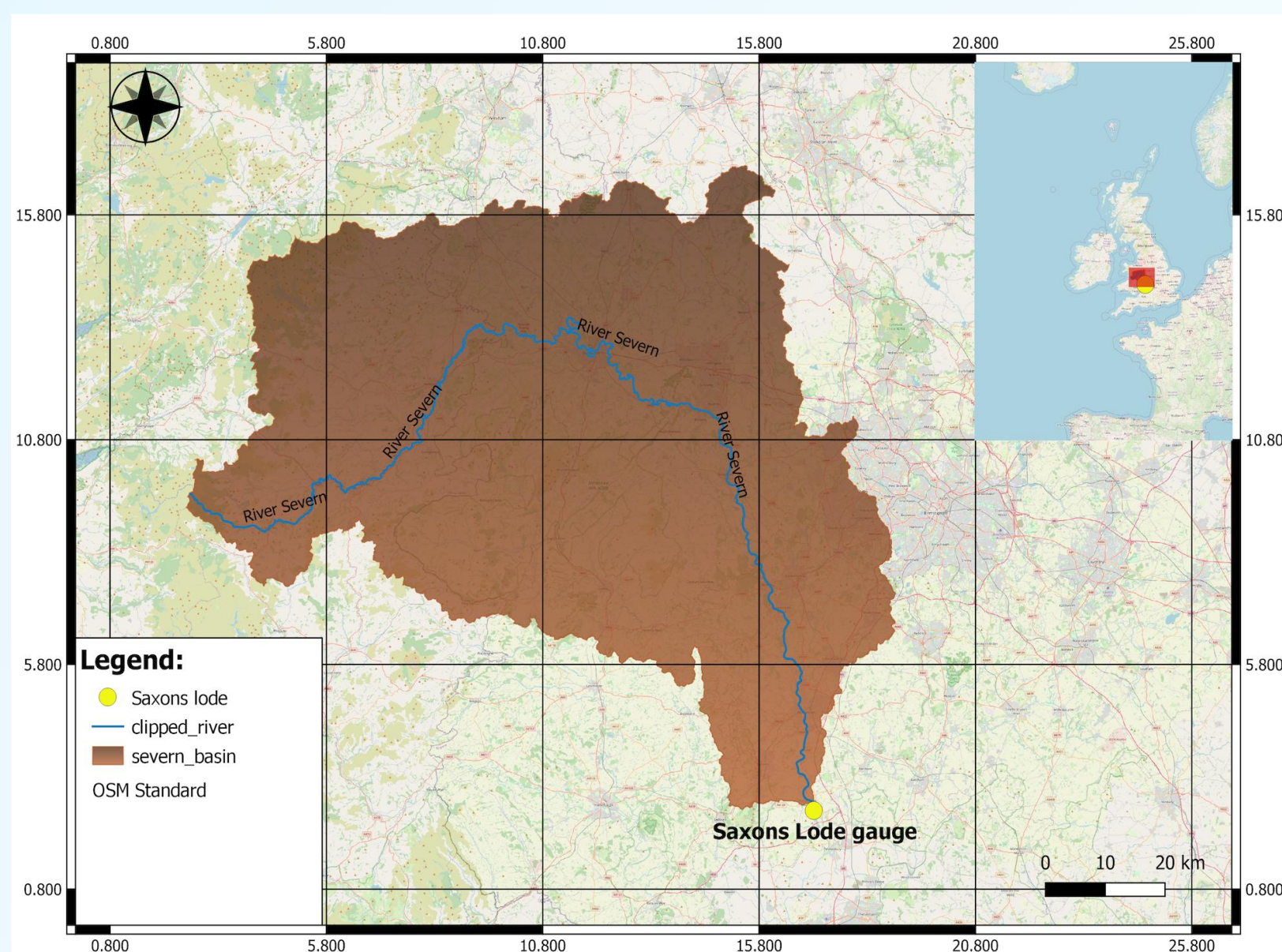


Figure 3 : The River Severn study area

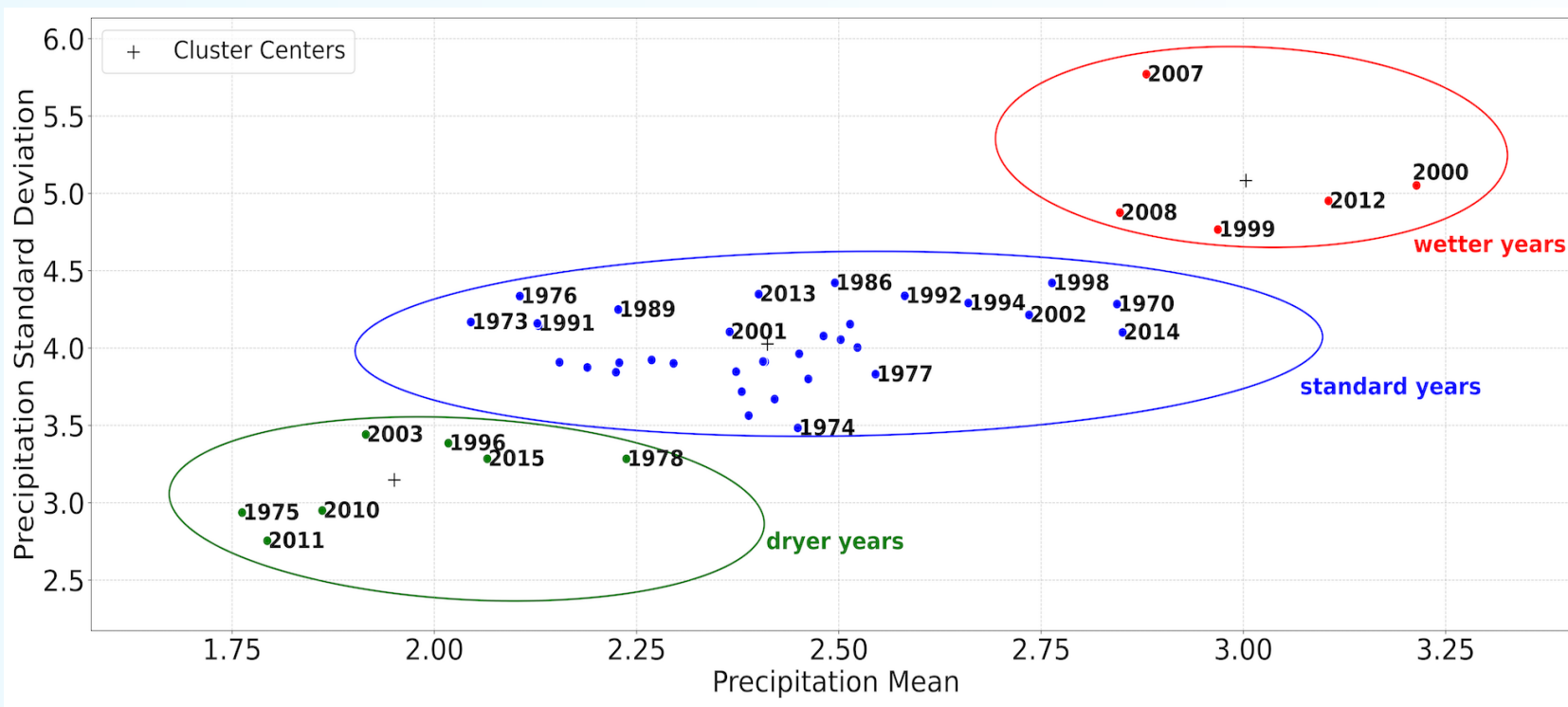


Figure 6 : Clusters on annual mean and standard deviation of daily rainfall. Three Distinct Yearly Precipitation Patterns: drier years in green, standard years in blue, and wetter years in red

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 library [1].

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

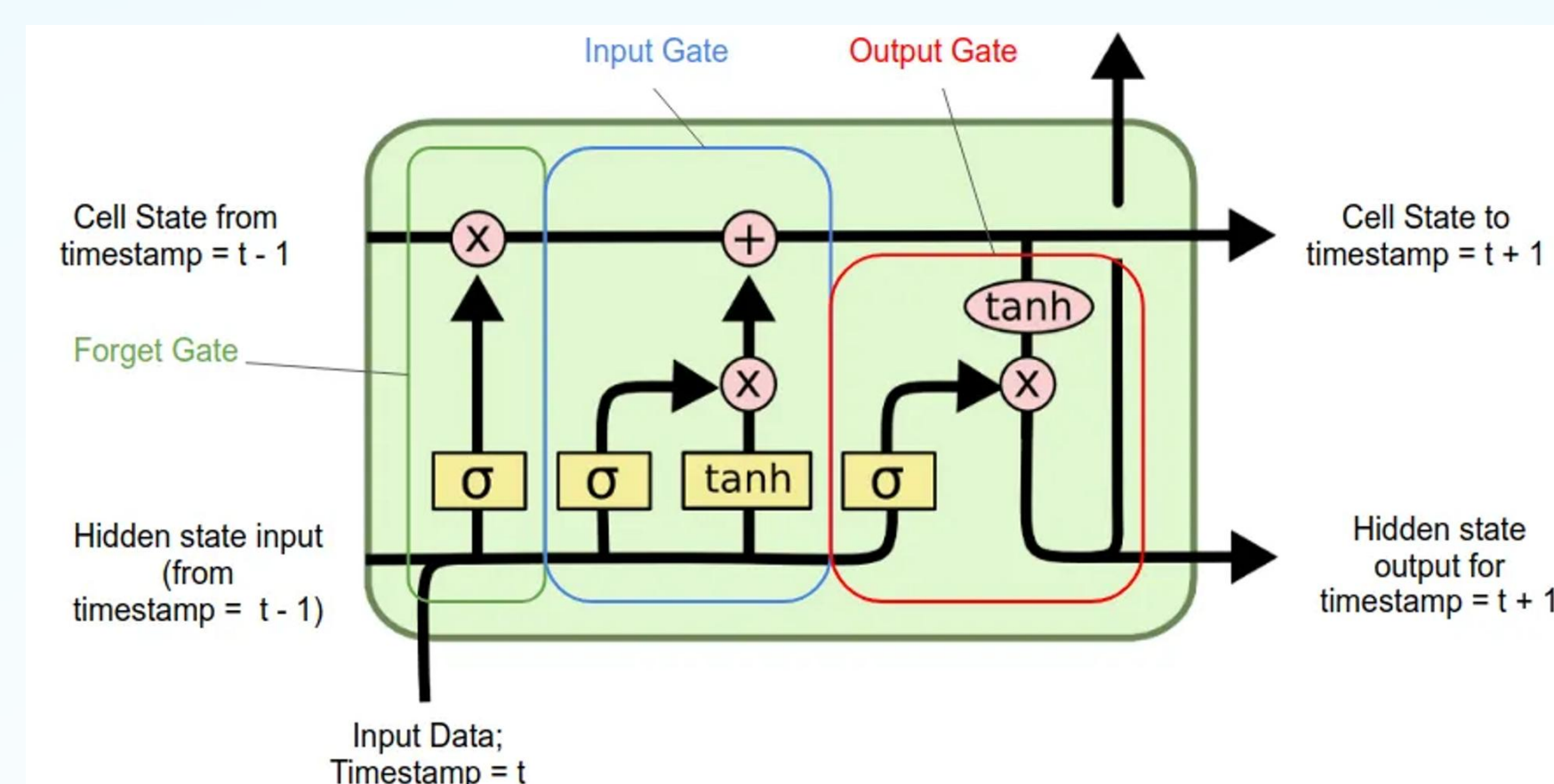


Figure 1 : Structure of the LSTM neuron, including different gates [2]

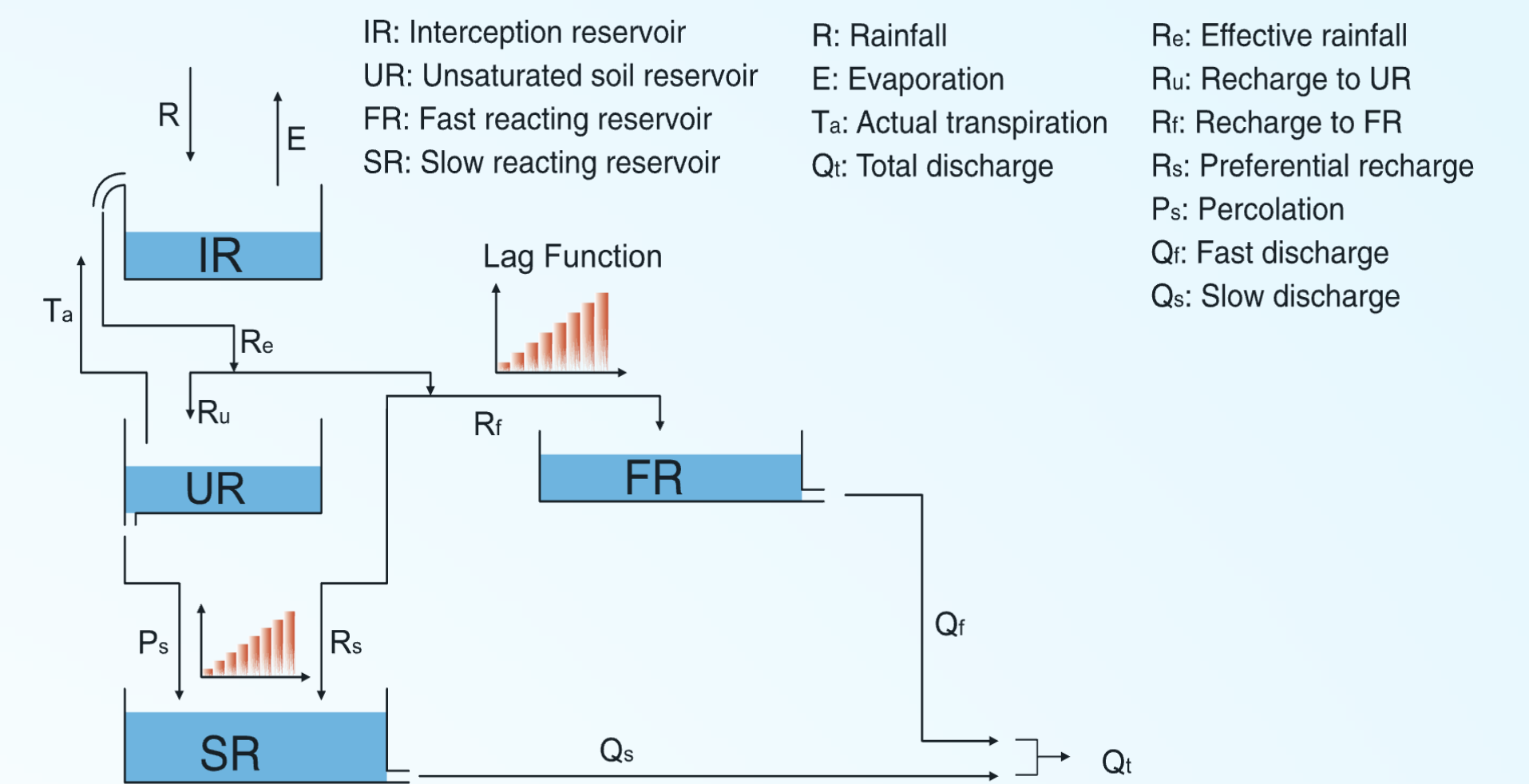


Figure 2 : Structural diagram of the Flex™ model[3]

CAMEL-GB dataset [4] provides inputs for both models: Precipitation, Potential evapotranspiration corrected, Temperature, Wind speed, Specific humidity, Downward shortwave radiation, Long-wave radiation, Discharge.

Training dataset: 1976 to 2004.
Validation dataset: 2005 to 2014.

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

- The Severn River is the longest in Great Britain, 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 Saxons Lode.

4) Impact of training data size experiment :

- Both LSTM and Superflex models were trained on each year of the training phase and evaluated for each year of the validation phase.
- They were then trained with varying numbers of training years (3, 6, 9, 12 and 15 years).

5) Impact of hydrometeorological typology experiment :

- The dataset was classified according to annual hydrological typology using a K-means clustering approach.
- The models were trained using various three-year training data subsets from the same cluster and evaluated for each year of the validation phase.
- The models were also trained using distinct three-year training data subsets, each year originating from a different cluster.

6) The models are 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 discharge over time, Q_m is the modelled discharge. Q_0^t is the observed discharge at time t .

If a model has no estimation error, $NSE=1$.

If the error equals the variance of the observed data, $NSE=0$.

Results

1) Impact of training data size :

- For 1-year training: Superflex overperform LSTM
- As the number of training years extends: Superflex NSE remains stable while LSTM NSE increases
- At 6-year training: LSTM start overperforming Superflex



Figure 4 : Average NSE according to validation year obtained by Superflex (orange) and LSTM (blue) models. Each graph represents a fixed number of training years from 1 to 15

- LSTM model :
 - From 1 to 6 years: significant reduction in the standard deviation
 - Beyond 9 years: the standard deviation stabilizes, and the NSE Median reaches a plateau
- Superflex model : Remains stable

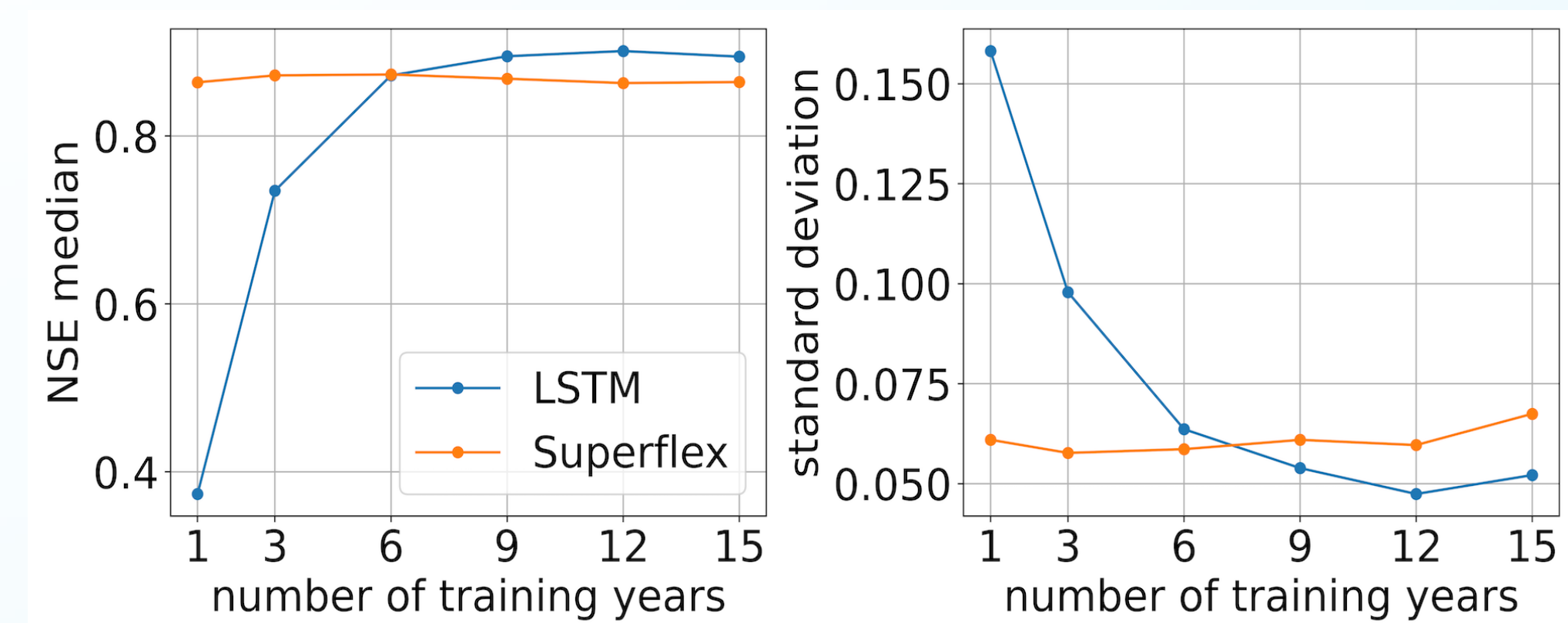
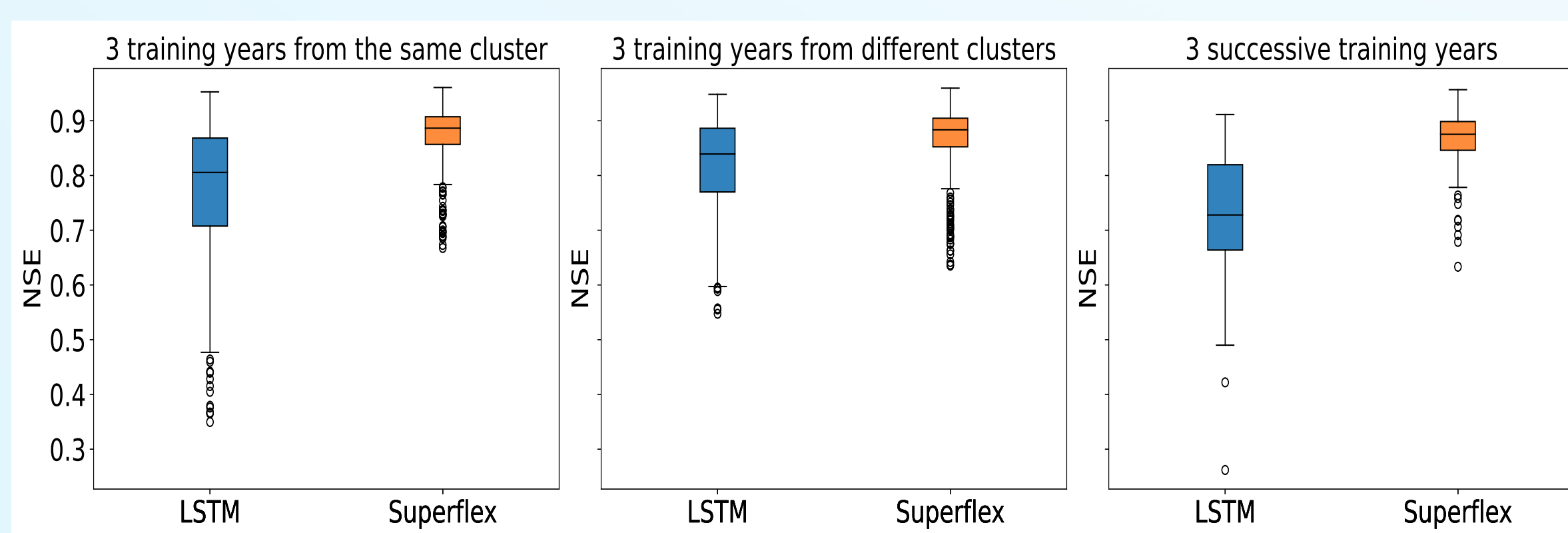


Figure 5 : Comparison between the LSTM and Superflex models across the Median NSE and the standard deviation

- LSTM is more sensitive to data size than Superflex**

2) Impact of the hydrometeorological typology



- Median values:
 - For LSTM: the median value is variable between the scenarios and higher with different clusters scenario.
 - For Superflex, the median value remains uniform
- Range between the maximum and minimum values:
 - For LSTM model, training years from different clusters has the smaller range.
 - For Superflex model, it's remains uniform across the different scenarios.

- LSTM shows better performance when trained using data from different clusters**

Figure 7 : Boxplots illustrating the distribution of the NSE performance metric for both the LSTM and Superflex models across three distinct scenarios: 3 training years from the same cluster (right), 3 training years from different clusters (middle), and 3 successive training years (left)

Conclusion

- ANN model showed promising results compared to a state-of-the-art conceptual hydrologic model in the study
- LSTM is sensitive to data size and hydrometeorological characteristics when compared to Superflex.
- This sensitivity can be mitigated to some extent by training the model on large data size (15 years or greater).
- For smaller dataset, this sensitivity can be mitigated by training the model on diverse hydrometeorological conditions.

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