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.

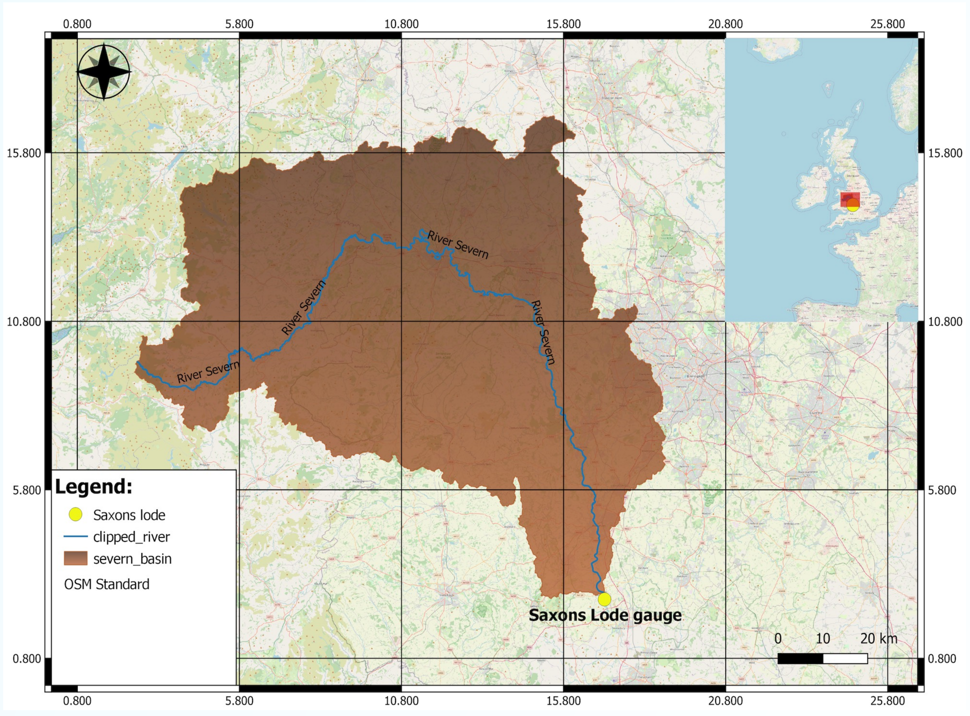

Figure 3 : The River Severn study area

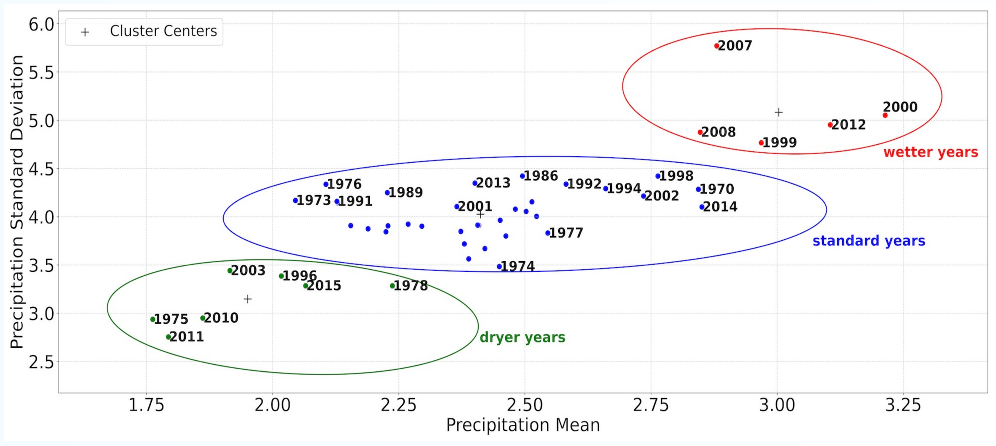

Figure 6 : Clusters on annual mean and standard deviation of daily rainfall. Three Distinct Yearly Precipitation Patterns: dryer years in green, standard years in blue, and wetter years in red

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.

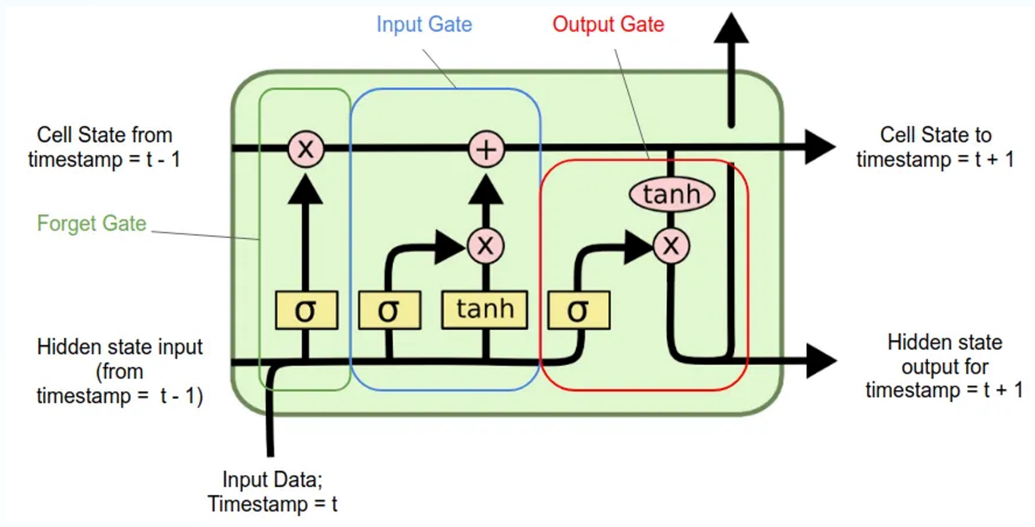

Figure 1 : Structure of the LSTM neuron, including different gates [2]

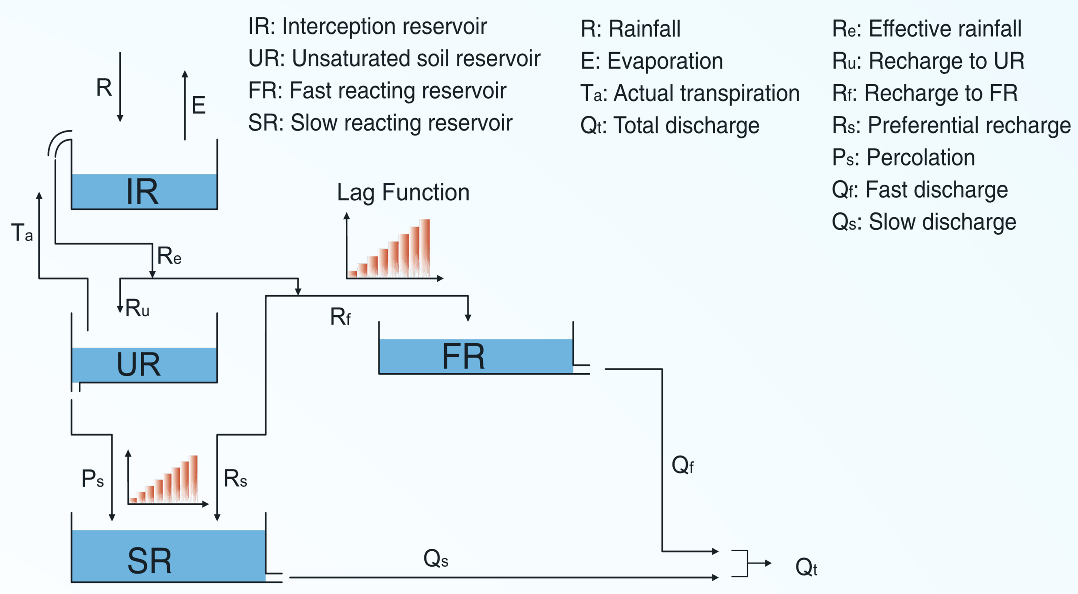

Figure 2 : Structural diagram of the Flex[TM] model[3]

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 :

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

Where $\overline{Q_0}$ 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

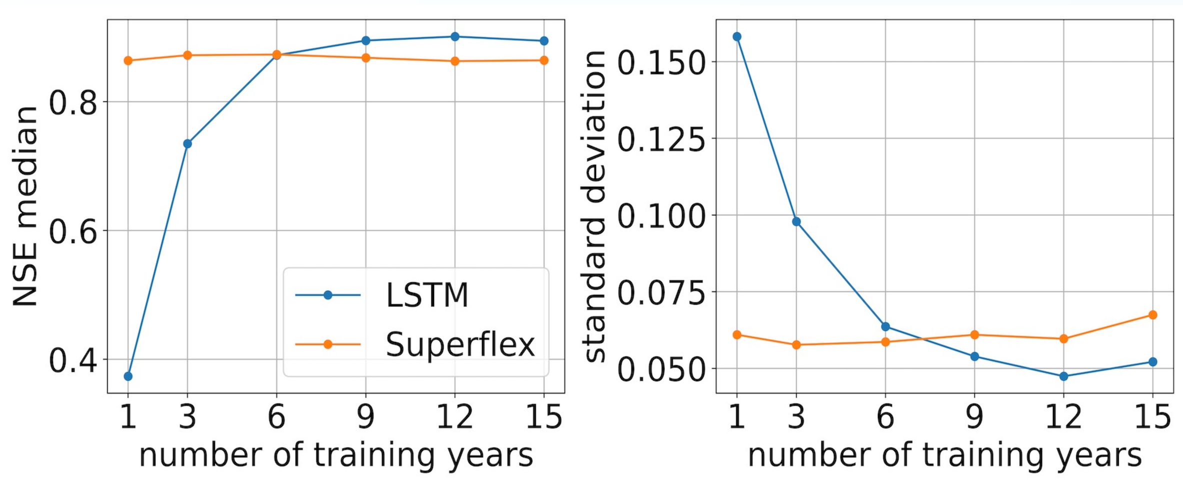

Figure 5 : Comparison between the LSTM and Superflex models across the Median NSE and the standard deviation

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

2) Impact of the hydrometeorological typology

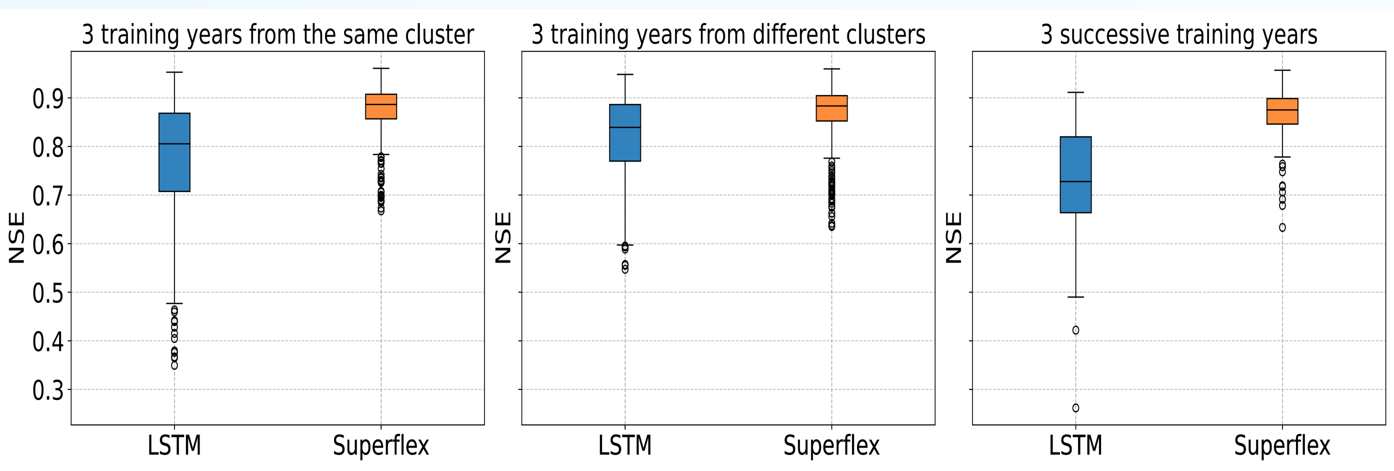

Figure 7 : Boxplots illustrating the distribution of the NSE performance metric for both the LSTM and Superflex models across three distinct scenarios: 3 training years from the same cluster (right), 3 training years from different clusters (middle), and 3 successive training years (left)

- 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**

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.

References

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Conférence SHF « Prévision des crues et des inondations – Avancées, valorisation et perspectives » ; 28-30 novembre 2023 – Toulouse