A Deep Learning Approach for reconstructing suspended sediment load and forecasting under various climate change scenarios

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1. Context and Objectives

The dynamics of sediments in rivers play a crucial role in the transport of contaminants, particularly radionuclides. In the case of the Rhône River, where several nuclear facilities discharge into the waterway, understanding sediment transport is especially important. Numerous studies have already demonstrated the effectiveness of machine learning models in accurately estimating hydrological phenomena, including suspended sediment load. These models have become valuable tools for improving our understanding of sediment dynamics and assessing the risks associated with radionuclide transport, especially in the event of accidental releases.

1. Development of Data-driven methodologies to capture suspended sediment load dynamics in the tributaries of the Rhône river with the goal of filling the OSR database.
2. Proposing a novel approach to model suspended sediment load in data scarce rivers based on Transfer Learning.
3. Application of Deep Learning models to assess the impact of climate change by using streamflow projections based on different scenarios.

2. Methodology

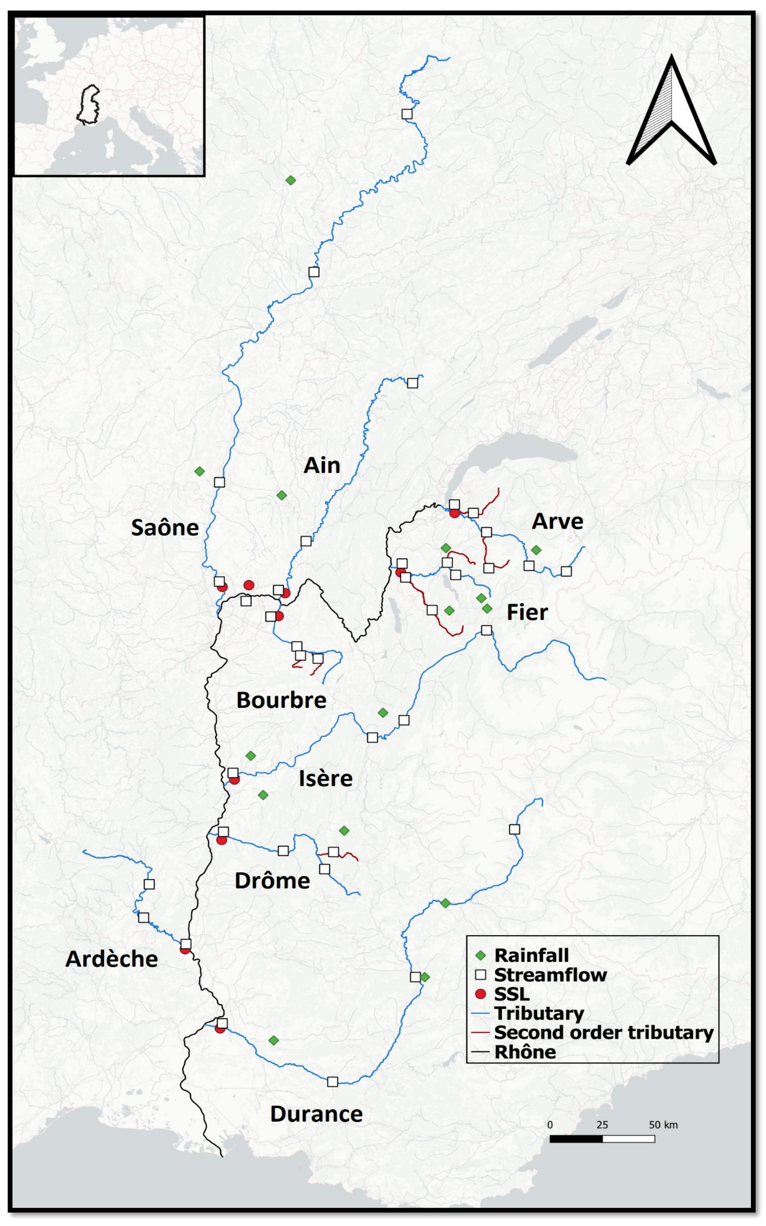

Figure 1: Study area and measuring stations

1. Using of the availability of different measuring stations of streamflow and rainfall data across each river to estimate hourly suspended sediment load at the downstream.
2. Evaluating 3 different types of models (Table 1) in 8 tributaries of the Rhône river.
3. Proposing a Transfer Learning approach based on the CNN-LSTM model for the Ardèche tributary that contains a small number of valid measures.
4. For monthly modelling: proposing a Transformer based model, with an evaluation it on a test set and then an application to project the SSL according to different climate scenarios.

By incorporating multiple variables, the ML models overcome the limitation of the rating curve model, which relies solely on a single streamflow variable

The use of deep learning models allows the capturing of temporal dependencies which can be interpreted as transit time through the river system.

Model	Type	Inputs
SiRCA	Rating curve model	Downstream streamflow
Random Forest	Machine Learning	Multiple streamflow and rainfall data across the river
CNN-LSTM, Transformer	Deep Learning	Multiple lagged streamflow and rainfall data across the river

Table 1: Models description

3. Results

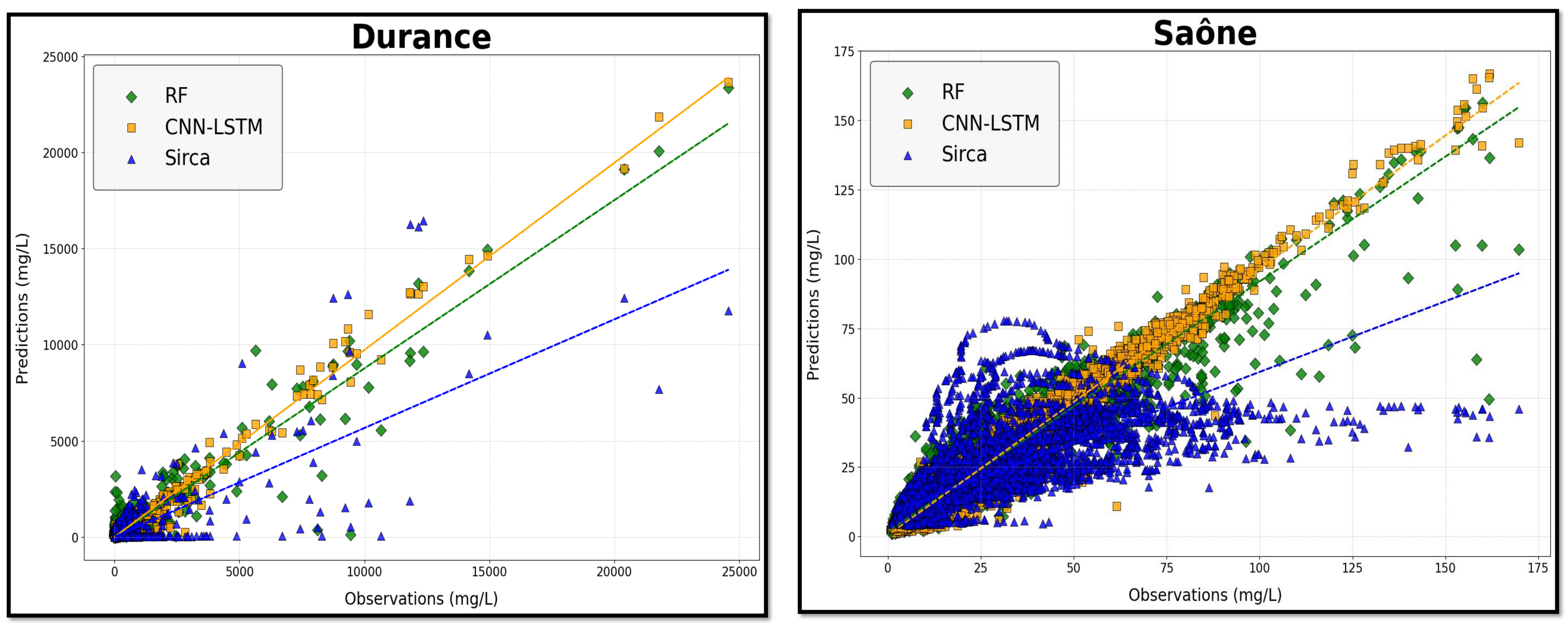

Figure 2: Measured vs Predicted SSL with different models

- For the Transfer Learning approach :
- First: Seek to establish clusters of rivers (Figure 4).
- Second: Train the CNN-LSTM model on a river (e.g. Saône) and then finetune it on a small part of a river on the same cluster (e.g. Isère) while freezing the first layers to and evaluate the performance change.
- Finally: Apply it on the Ardèche Cluster (pretraining on Durance) and do a simulation that is compared with the physical model CasteaurX (Figure 4)

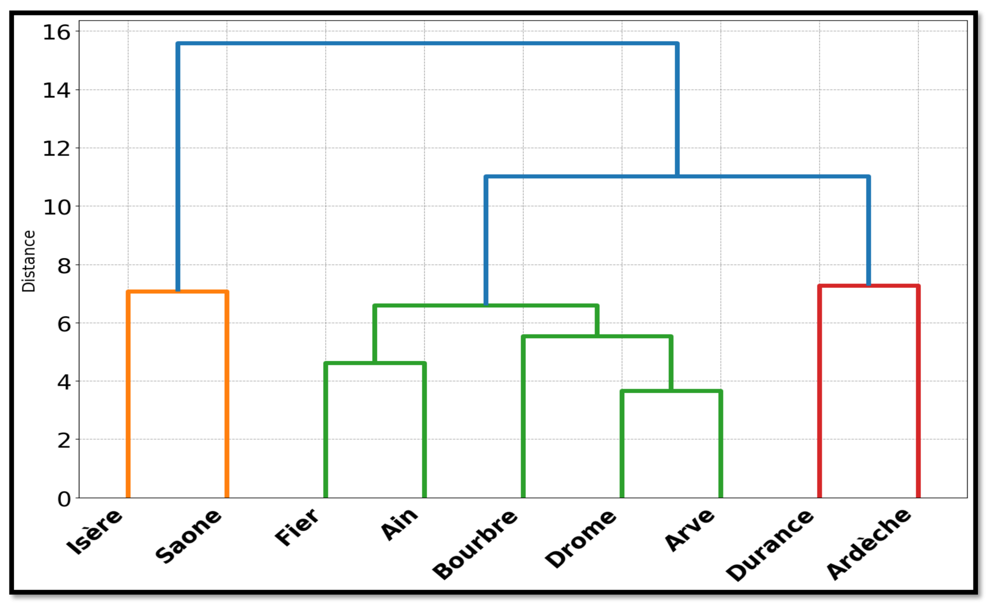

Figure 3: Hierarchical clustering of Rivers

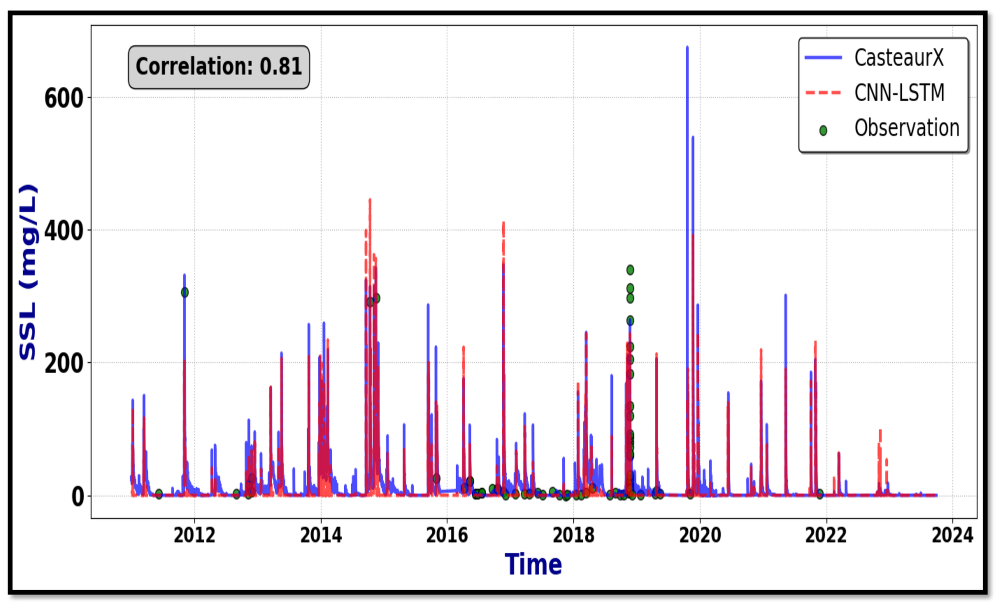

Figure 4: Simulated SSL on Ardèche

- Evaluate the Transformer model in estimating monthly SSL (Figure 5) using streamflow from 3 different stations.
- Use the projections of different climate scenarios of the same stations to forecast SLL.
- Compare the maximum monthly forecasted SSL per 10-year window with historical data (Figure 6).

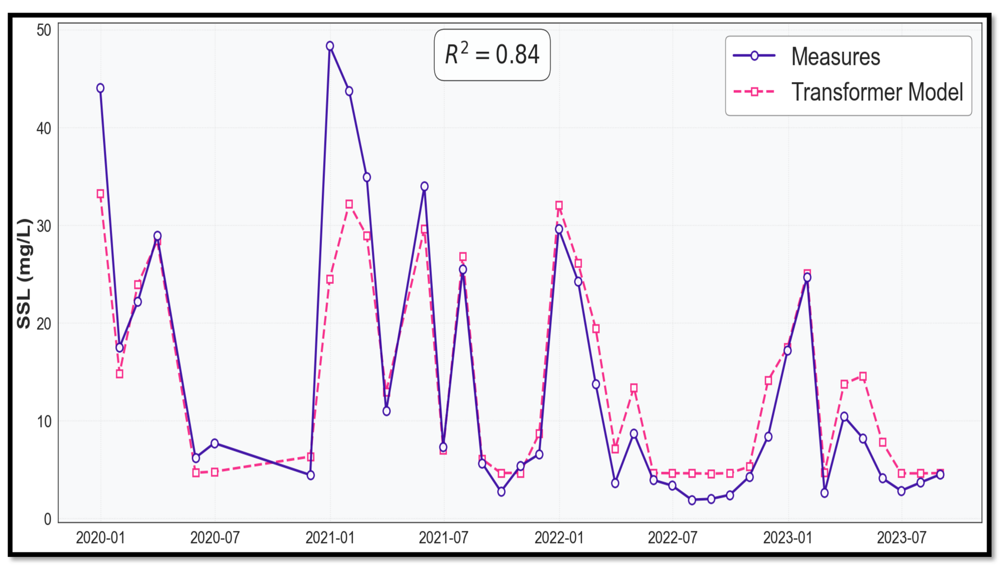

Figure 5: Measured vs Predicted monthly SSL in the Saône river

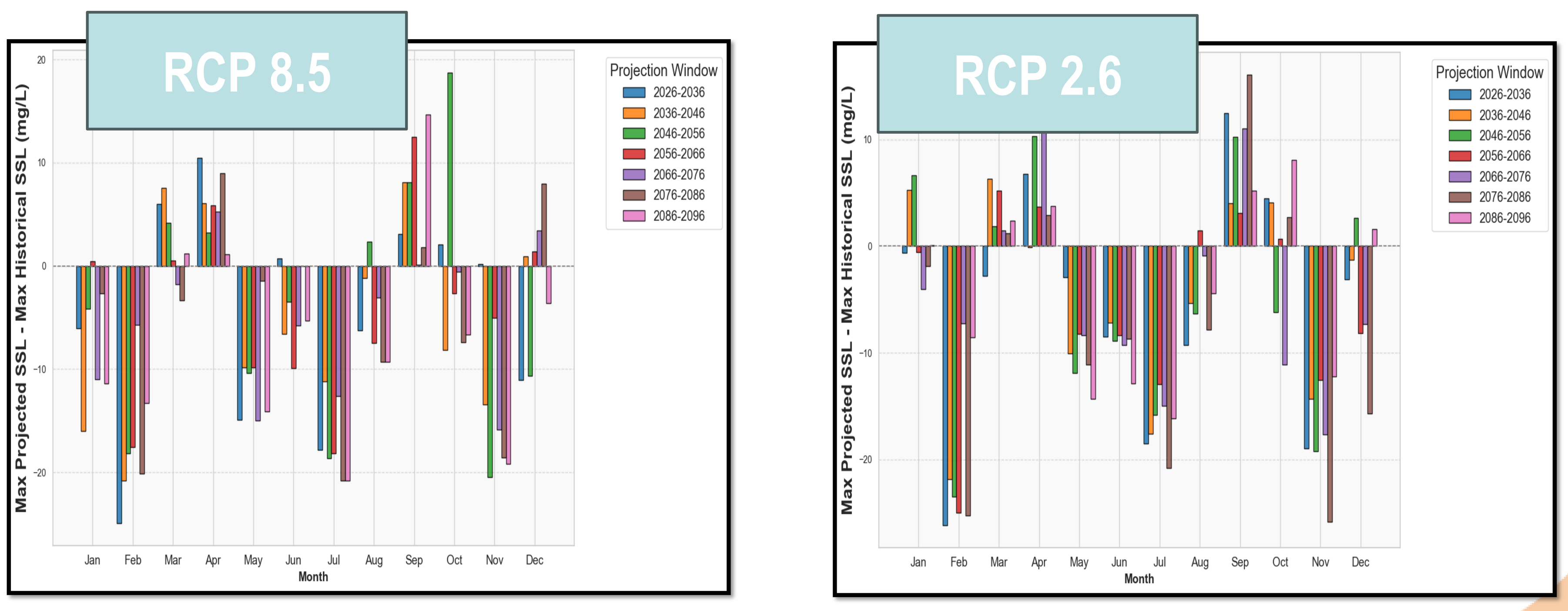

Figure 6: Maximum difference between historical and projected SSL across two scenarios