Physically-Enhanced Training of Neural Networks for Hydraulic Modelling of Rivers and Flood Events

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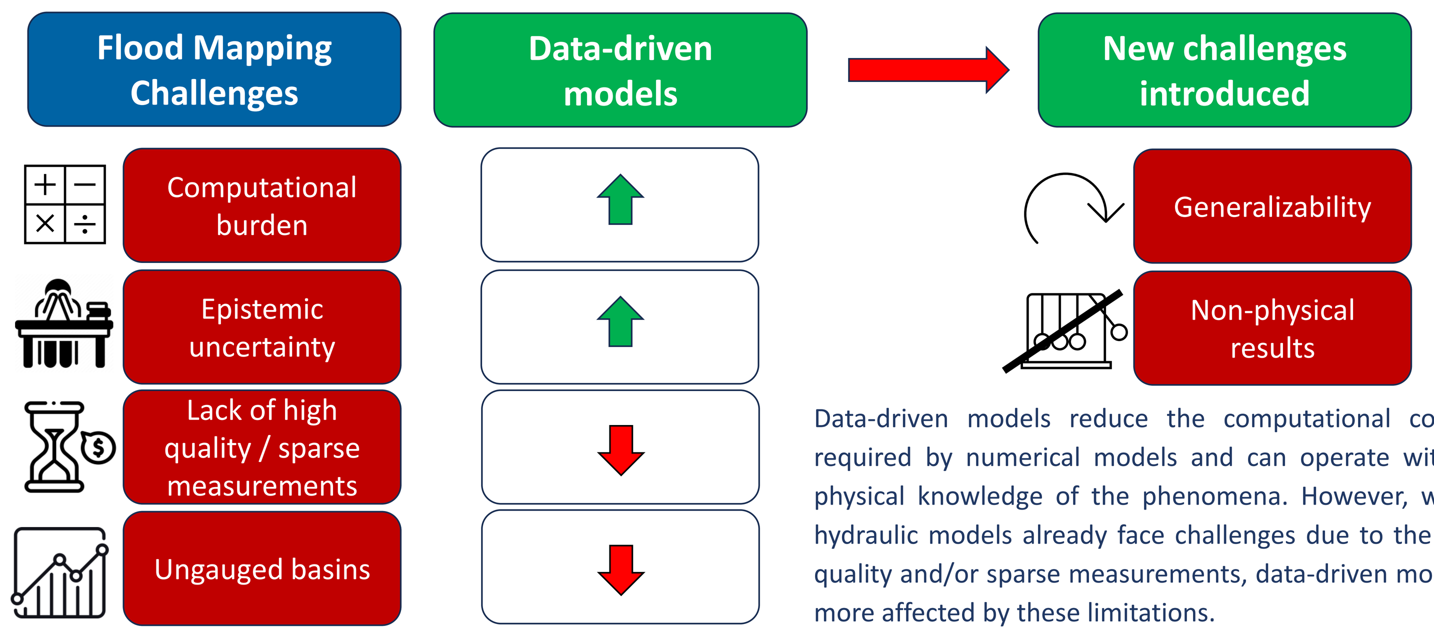
1 Introduction

Machine Learning is gaining increasing attention from the scientific community in hydrological and hydraulic research. Data-driven models can help address some of the **most relevant challenges** in flood mapping.



Data-driven models reduce the computational cost and time required by numerical models and can operate without explicit physical knowledge of the phenomena. However, while classical hydraulic models already face challenges due to the lack of high-quality and/or sparse measurements, data-driven models are even more affected by these limitations.

Despite their advantages, data-driven approaches suffer from **poor generalization capabilities** (i.e., difficulty in predicting new, unseen scenarios). Furthermore, their results are often **non-physical**.

2 Methodology

We propose **introducing physical information**, relying on **user expertise**, into the training phase of **data-driven models** in the form of a **regularization term** of the **loss function** $\mathcal{L}$. The similarity with the PINNs approach is limited to the formulation of the modified loss function.

$$\mathcal{L} = \lambda \cdot \mathcal{L}_{DD}(y, \hat{y}) + (1-\lambda) \cdot \mathcal{L}_P(x, y, \hat{y})$$

- $\mathcal{L}_{DD}$ is the **data-driven error metric** (e.g. MSE), depending on the true and predicted outputs $(y, \hat{y})$;
- $\mathcal{L}_P$ is a **physical loss term** employing physical principles, laws, and quantities, which are not explicitly formulated in the original dataset, and it can depend also on the inputs x;
- λ is a weighting hyperparameter.

The physical loss term $\mathcal{L}_P$ enriches the information content of the dataset and, in this sense, we can note its similarity to **data augmentation**.

$\mathcal{L}_P$ does not necessarily resort to PDEs, making it suitable for scenarios with **significant epistemic uncertainties**, such as river hydraulics. The method appears **highly versatile**.

Why physics in data-driven models?

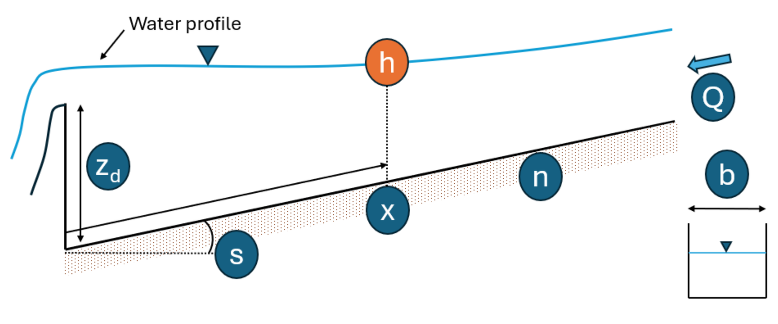
- The intersection between physically-based methods and deep learning for modeling complex physics systems is a cutting-edge research field.
- Research on artificial intelligence is moving towards solutions where physics is incorporated into the machine learning training process.

Why PINNs show limited practical uses in the river hydraulic context?

- PINNs are designed as Neural Solvers for differential problems governed by PDEs.
- Every change in the domain requires training a new PINN.
- In case of significant epistemic uncertainty, the governing equations may not be fully known or explicitly available.

3 1D Experiment: Varied Flows in river

A **highly controllable and informative experiment** has been carried out for a synthetic, 1D hydraulic problem: the reconstruction of a steady-state, one-dimensional water surface profile in a rectangular channel.



Water profile reconstruction: inputs and outputs are depicted as blue and orange circles, respectively. Three different approaches and architectures have been used (see the Reference for further details)

Governing equation:

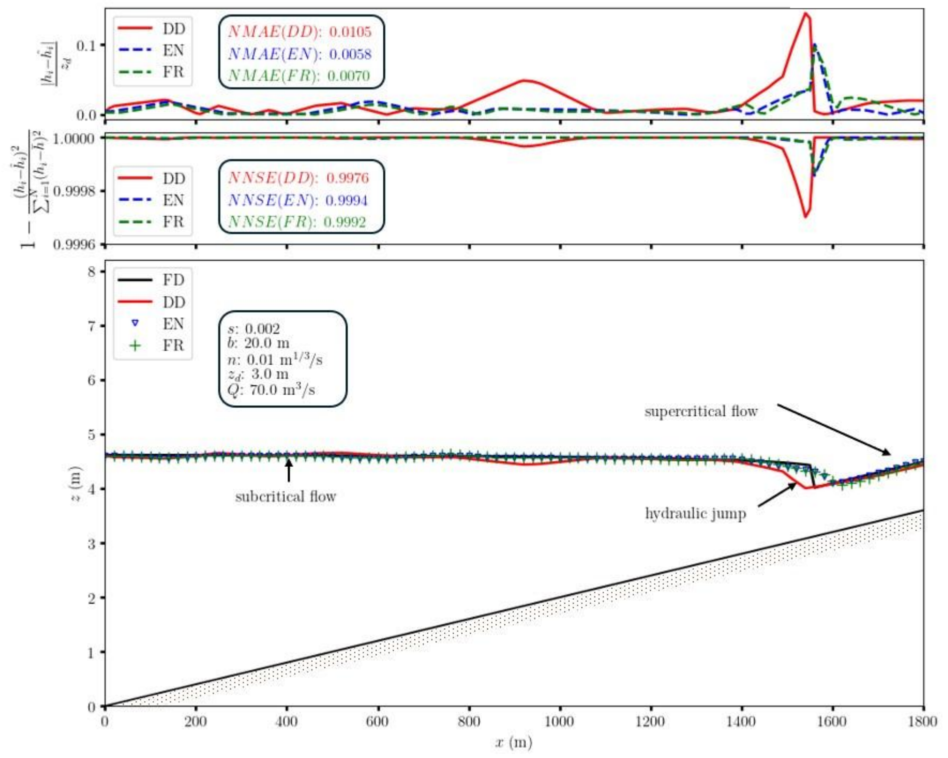
Specific Energy equation $\frac{dE}{dx} = s - J$

Additional complexity:

Possible presence of a **hydraulic jump** (mixed flow)

DEEP LEARNING ARCHITECTURE: FFNN

The **physical training strategies** consist in exploiting the local values of the:



- Specific energy (EN)

$$\mathcal{L}_P = \frac{\sum_{i=1}^{N}(E(h_i) - E(\bar{h}_i))^2}{N}$$

- Froude number (FR)

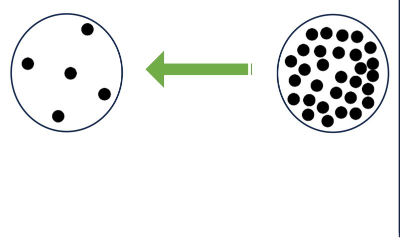
$$\mathcal{L}_P = \frac{\sum_{i=1}^{N}(Fr(h_i) - Fr(\bar{h}_i))^2}{N}$$

which are used as conveyors of physical information in the Loss.

Typical outcome of the comparison between the employed models (DD, EN, and FR), and the reference solution (FD).

Paralleling challenges often encountered in flood mapping applications, we tested the model:

- reducing the training data size
- in extrapolation

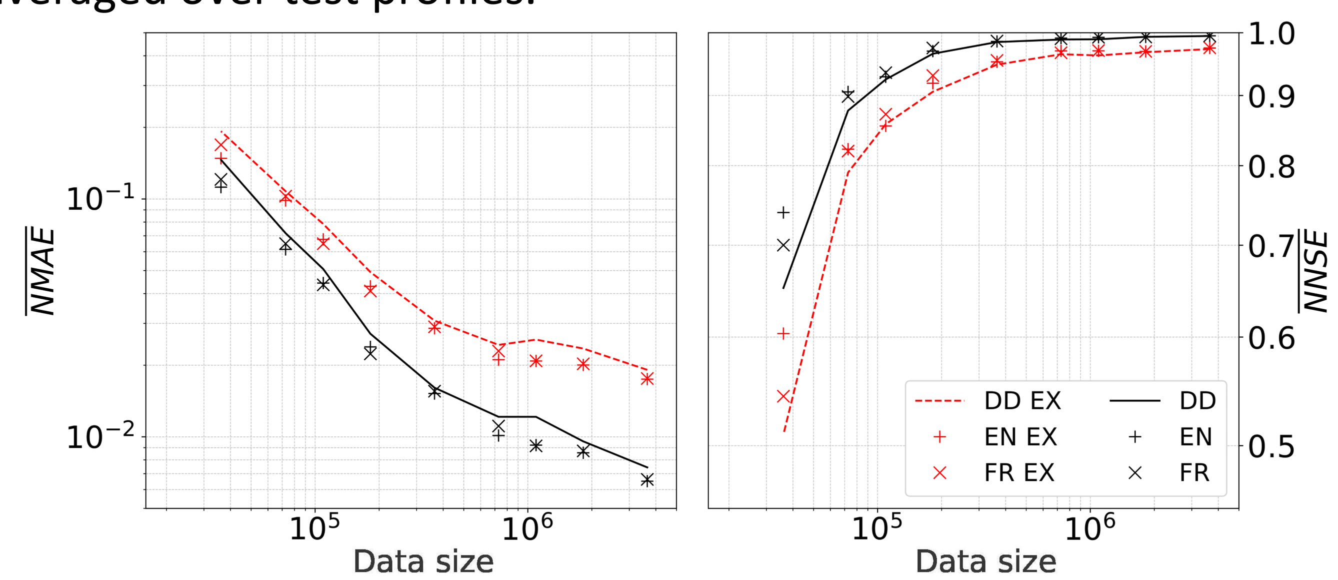


Why this kind of assessment ?

It is of great relevance to the application of NNs to flood mapping, where small datasets are available and cases featuring values of the observed quantities falling out of the range of the recorded series need to be predicted.

RESULTS

We compare data-driven and physically-trained models using metrics averaged over test profiles.

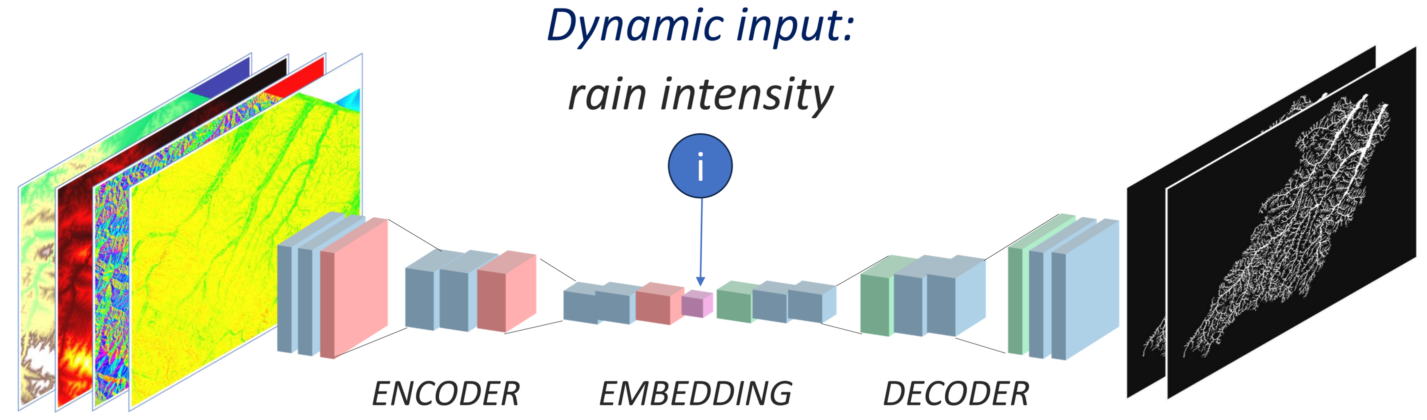


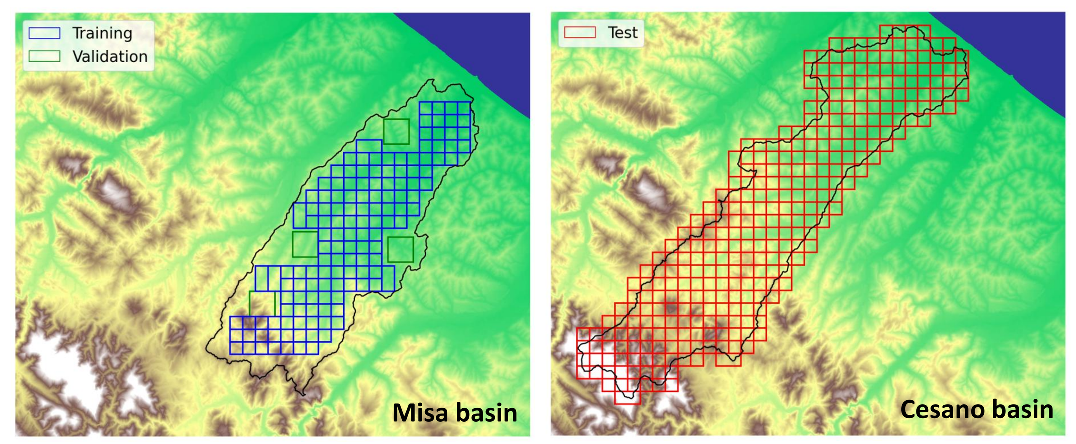
Mean values of two evaluation metrics (NMAE and NNSE) on the test set against the size of the training dataset. Black traces and markers represent model's results on the test dataset fully contained in the range of the training one; red ones regard the test dataset containing values out of the range of the training dataset (extrapolation, EX series). Although performance is lower for extrapolated scenarios, the beneficial effect of physical information remains evident.

4 2D Experiment: Catchment Generalizability

We investigate whether incorporating **physics-based training strategies** can enhance **generalization to unseen catchments without resorting to model retraining**. This task remains a significant challenge for ML-based flood models.

DEEP LEARNING ARCHITECTURE: CNN ENCODER-DECODER





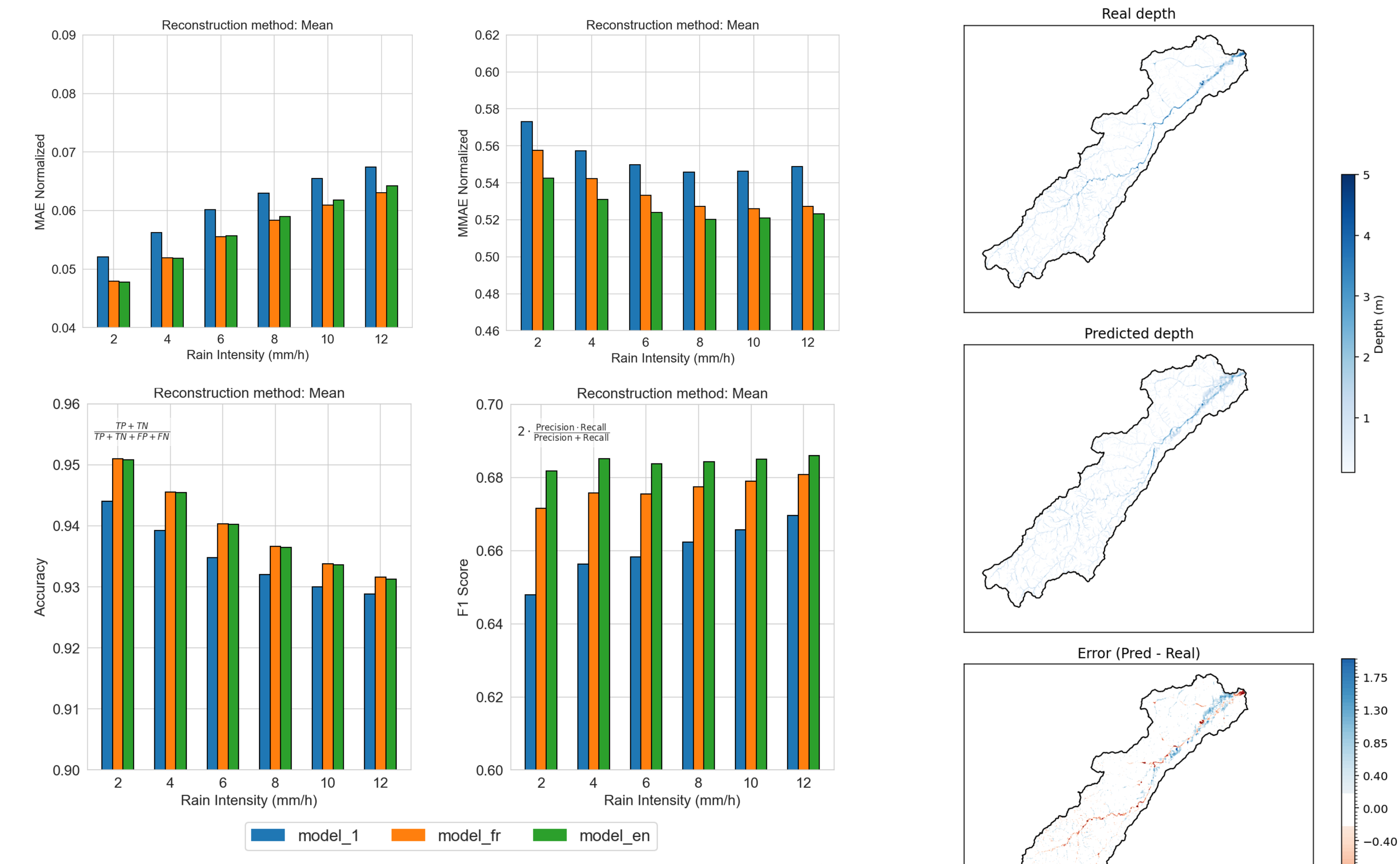
Training and validation patches are extracted from the Misa basin (left panel), while the Cesano basin is divided in test patches (right panel)

How is the dataset structured?

Two basins located in the Marche region of Italy are considered: the Misa basin is used for training and validation, while the Cesano basin is used for testing. Given the deep learning architecture, both topographic features and outputs are processed as patches. For the Misa basin, four validation zones are selected, and overlapping training patches are generated around them. In the Cesano basin, overlapping patches are also extracted for testing.

Ground-truth flood maps are generated with HEC-RAS simulations for ten rainfall intensities, each run until **steady-state conditions** are reached.

RESULTS



Regression and classification metrics are used to compare the models (shown here using the mean reconstruction method). The right panels display predictions and errors for the unseen basin under a single rainfall intensity.

DEVELOPMENTS

Future developments will include **performance evaluation** under **varying geometric differences** between training and test basin. Additionally, the models will be applied at **large scale for rapid hydraulic hazard assessment**, with a focus in **ungauged catchments**.

Reference:
Guglielmo, G., Montessori, A., Tucny, J. M., La Rocca, M., & Prestininzi, P. (2025). A priori physical information to aid generalization capabilities of neural networks for hydraulic modeling. *Frontiers in Complex Systems*, *2*, 1508091.

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