DSAIE project: Spatio-temporal flood modelling with deep learning

Contact person: Roberto Bentivoglio (R.Bentivoglio@tudelft.nl)

Department of Water Management/ Department of Hydraulic Engineering

1 Introduction

Flooding is one of the most dangerous and recurrent natural hazards, accounting for significant human and economic losses every year. To address this issue, we require the development of flood models to facilitate proactive measures and mitigation strategies. Numerical modelling is a reliable approach for simulating floods, but it comes with the drawback of high computational costs. In the recent years, researchers have explored data-driven methodologies based on neural networks to overcome this limitation [Bentivoglio et al., 2022]. However, most models are used only for a specific case study and disregard the dynamic evolution of the flood wave. This limits their generalizability to topographies that the model was not trained on and in time-dependent applications.

Within this project, you are asked to develop a deep learning model that can predict the spatio-temporal evolution of a flood over unseen topographies. As a possible scheme, the model can look something like Figure 1 in which the outputs of the model for each time step are auto-regressively fed as new inputs into the model. But you are also free to explore different strategies as long as you can provide the spatio-temporal evolution of the flood. For example, your model could predict all of the time steps at the same time.

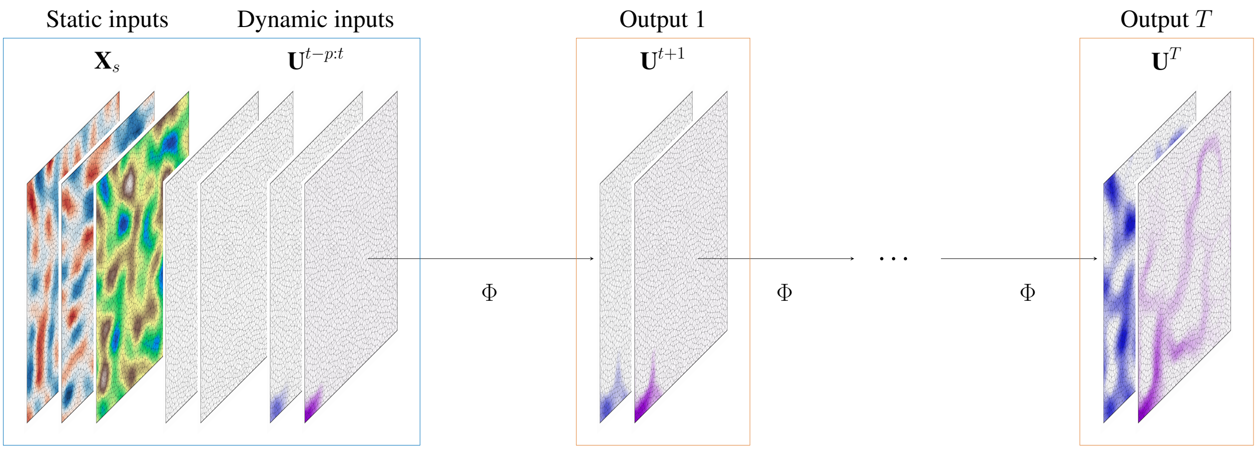

Figure 1: Schematics of the spatio-temporal flood model. Your model should take topographical and hydraulic inputs to produce the evolution at different time steps of the hydraulic variables.

2 Background knowledge

2.1 Flood modelling

When assuming negligible vertical accelerations, floods can be modelled via the shallow waters equations (SWE). These are a system of hyperbolic partial differential equations that describe the behaviour of shallow flows by enforcing mass and momentum conservation. Since they are analytically intractable, they are commonly solved via numerical discretizations, such as the finite volume method. Because of stability constraints, numerical methods can become very slow.

2.2 Deep learning

We recommend to tackle the project using either convolutional neural networks (week 2.4) or graph neural networks (advanced topics), as they were already proven to be successful models for this kind of task [Bentivoglio et al., 2023].

If you are curious or motivated you can also explore other models such as Fourier Neural Operators that also provide good results in similar fields [Li et al., 2020].

3 Data and Resources

3.1 Dataset

To validate your model, you will use a dataset of dike-breach flood simulations that can be found at `https://dx.doi.org/10.5281/zenodo.7764418`. This repository contains three different datasets, as described in the corresponding README file. Each simulation has a different topography, as the main objective is to assess the generalizability of your model to unseen case studies. Datasets 2 and 3 also have further complications. Thus, **for this project it is sufficient to use the first dataset**, in which the location of the boundary condition does not change.

4 Project task

Develop a deep learning model that predicts the spatio-temporal evolution of floods over unseen topographies. You should validate it using the provided dataset.

If you want to increase difficulty and prove that your model is really good, you can use datasets 2 and 3 as test cases.

References

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