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Physics-informed graph neural networks for operational flood modelling

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Abstract: Flooding is a major global hazard, causing severe economic losses and public health risks. Climate change is expected to intensify the hydrological cycle, leading to more frequent and extreme flood events. Addressing these challenges requires accurate risk assessment and rapid emergency response, both of which depend on understanding the spatiotemporal evolution of floods. Hydrodynamic models are essential for this purpose, as they simulate inundation extent, flood depth, and flow dynamics.

Physics-based numerical models provide accurate flood simulations but are too computationally demanding for real-time use. Deep learning methods offer faster predictions but often lack physical interpretability and struggle with irregular domains. Graph neural networks (GNNs) circumvent these issues by representing unstructured spatial domains as graphs, enabling processing without any complex transformations. Moreover, their flexible architectures make it possible to embed physics-informed constraints, improving stability, interpretability, and generalizability.

We propose a novel physics-informed GNN that predicts water volumes at nodes and flows along edges simultaneously, unlike existing models that focus only on node predictions, by using information from neighbouring nodes. A dual attention mechanism is incorporated to focus learning on the most relevant spatial and temporal interactions, enhancing robustness and performance. Training incorporates a custom loss function that integrates physical knowledge at two scales: (i) constraints to preserve global mass balance, and (ii) node-level constraints to preserve local mass balance to better reflect shallow-water flow dynamics. To improve prediction stability, the model is trained in an autoregressive manner through a multi-step-ahead loss function that accumulates errors across multiple inference steps. This allows the model to correct noisy input from its own predictions, leading to a more accurate multi-step rollout.

The model is evaluated using flood scenarios generated with the HEC-RAS numerical solver (U.S. Army Corps of Engineers, 2021). As a surrogate to 2D hydrodynamic models, the accuracy of the GNN is inherently bounded by the accuracy of the numerical solver, which serves as the ground truth in surrogate model building. Hence, the model is validated only against synthetic flood simulations. Results show that our model outperforms standard GNN baselines across multiple benchmarks, providing more accurate predictions of both water volumes and flows. Importantly, it demonstrates strong generalization to unseen flood events, attributed to its embedded physics constraints that enable learning of fundamental flow mechanics rather than solely statistical mappings. It retains the significant computational advantages of deep learning approaches, achieving speed-ups suitable for real-time operational forecasting.

Overall, this study advances data-driven flood modelling by combining hydrodynamic accuracy with computational efficiency. By jointly predicting nodal and edge variables, embedding multiple physics-informed components, and mitigating roll-out instability, the proposed framework represents a step forward for operational flood forecasting. Future work will focus on extending the approach to large-scale graph domains and validating its performance against historical flood observations, paving the way for wider adoption in disaster risk management and climate resilience planning.

REFERENCES

U.S. Army Corps of Engineers, Hydrologic Engineering Centre (2021) HEC-RAS hydraulic reference manual (version 6.0). Institute for Water Resources, Davis, CA.

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