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Physics-Informed Neural Networks for Statistical Emulation of Hydrodynamical Numerical Models

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The application of numerical models for flood and inundation modelling has become widespread in the past decades as a result of significant improvements in computational capabilities. Computational approaches to flood forecasting have significant benefits compared to empirical approaches which estimate statistical patterns of hydrological variables from observed data. However, there is still a significant computational cost associated with numerical flood modelling at high spatio-temporal resolutions. This limitation of numerical modelling has led to the development of statistical emulator models, machine learning (ML) models designed to learn the underlying generating process of the numerical model. The data-driven approach to ML involves relying entirely upon a set of training data to inform decisions about model selection and parameterisations. Deep learning models have leveraged data-driven learning methods with improvements in hardware and an increasing abundance of data to obtain breakthroughs in various fields such as computer vision, natural language processing and autonomous driving. In many scientific and engineering problems however, the cost of obtaining data is high and so there is a need for ML models that are able to generalise in the 'small-data' regime common to many complex problems. In this study, to overcome extrapolation and over-fitting issues of data-driven emulators, a Physics-Informed Neural Network model is adopted for the emulation of all two-dimensional hydrodynamic models which model fluid according the shallow water equations. This study introduces a novel approach to encoding the conservation of mass into a deep learning model, with additional terms included in the optimisation criterion, acting to regularise the model, avoid over-fitting and produce more physically consistent predictions by the emulator.