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Reduced-Order Flood Modeling Using Uncertainty-Aware Deep Neural Networks

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While impressive results have been achieved in the well-known fields where Deep Learning allowed for breakthroughs such as computer vision, language modeling, or content generation [1], its impact on different, older fields is still vastly unexplored. In computational fluid dynamics and especially in Flood Modeling, many phenomena are very high-dimensional, and predictions require the use of finite element or volume methods, which can be, while very robust and tested, computational-heavy and may not prove useful in the context of real-time predictions. This led to various attempts at developing Reduced-Order Modeling techniques, both intrusive and non-intrusive. One late relevant addition was a combination of Proper Orthogonal Decomposition with Deep Neural Networks (POD-NN) [2]. Yet, to our knowledge, in this example and more generally in the field, little work has been conducted on quantifying uncertainties through the surrogate model.
In this work, we aim at comparing different novel methods addressing uncertainty quantification in reduced-order models, pushing forward the POD-NN concept with ensembles, latent-variable models, as well as encoder-decoder models. These are tested on benchmark problems, and then applied to a real-life application: flooding predictions in the Mille-Iles river in Laval, QC, Canada.
For the flood modeling application, our setup involves a set of input parameters resulting from onsite measures. High-fidelity solutions are then generated using our own finite-volume code CuteFlow, which is solving the highly nonlinear Shallow Water Equations. The goal is then to build a non-intrusive surrogate model, that's able to *know what it knows*, and more importantly, *know when it doesn't*, which is still an open research area as far as neural networks are concerned [3].

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