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Introducing a fully differentiable, fully distributed Rainfall-Runoff Model

Fedor Scholz, Manuel Traub, Thomas Scholten, Christiane Zarfl, and Martin Butz
University of Tuebingen, Germany (fedor.scholz@uni-tuebingen.de)

Traditional hydrology simulates rainfall-runoff dynamics by means of process-based models (PBMs), which are derived from physical laws. The models exhibit realistic behavior. Their internal states can by directly interpreted, because they reflect the modeled current state of the hydrological dynamics. Natural processes in general are very complex, though, such that is is simply impossible to model every aspect in detail. In the case of hydrology, for example, anthropological influences, such as the exact influence of the sewer system, as well as natural factors, such as soil and rock types and structures, are extremely hard to model in all their details. As a result, high uncertainty remains about the models' necessary components and their parameterizations, leaving room for improvement Sit et al. [2020], Nearing et al. [2021]. Data-driven approaches, like deep neural networks (DNNs), offer an alternative. They are trained on large amounts of data by gradient descent via automatic differentiation. This enables them to automatically discover relationships in the training data, which often leads to superior performance Kratzert et al. [2018], Shen [2018]. Due to the DNNs' complexity, however, these relationships are hard to investigate and often fail to respect physical laws. Hybrid modeling combines both approaches in order to benefit from their respective advantages. In this work, we present a physics-inspired, fully differentiable and fully distributed rainfall-runoff model to predict river discharge from precipitation. Our DNN architecture consists of a land module and a river module. The land module receives RADOLAN-based precipitation data and propagates runoff laterally over a regular grid (1km2 grid size) taking land surface structure information into account. Runoff is then captured as input to the river module, which mimics the actual river network by means of a graph neural network. Due to the involved, physically motivated inductive biases, our model can be trained end-to-end from the RADOLAN data as the main input and sparse discharge data as output. We showcase our model on the Neckar river catchment in South Germany, achieving NSE values of 0.88 and 0.84 when we predict 1 and 10 days into the future, respectively. In contrast, persistence yields NSE values of 0.5 and 0.06 for the corresponding forecast horizons. Due to our model's differentiability we expect to be able to infer the origin of measured discharge or turbidity—and thus erosion—in the near future. We thus hope that this information could be used to create policies

that mitigate both the danger of floods and extreme erosion.