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Uncertainty quantification of rainfall runoff predictions using Gaussian process models

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This study presents an application of Gaussian process models (GPMs) as a surrogate of complex Monte Carlo simulations for the quantification of input and parameter uncertainty of rainfall runoff predictions of the physically based spatially distributed rainfall runoff model WaSim (ETH). In this work we provide an operational approach to the computational problems of comprehensive Monte Carlo simulations arising when observations (i.e. measurements of rainfall and discharge) and calibrated parameters are sources of uncertainty.
Gaussian processes are typically used to approximate the deterministic model and their associated uncertainties by a random function comprised of a linear combination of kernel functions and a specified covariance function. Radial basis functions and squared exponential covariance function is used for the GPM in this study.
GPM have been used to estimate and compare parameter and input uncertainty related to flood prediction in the fast responding Rietholzbach catchment in Switzerland. To model the input uncertainty multiple (24) measured rainfall events have been selected which have led to major floods in the Rietholzbach catchment. For each event 150 new realizations have been simulated based on the turning bands method. To model parameter uncertainty the MO-ROPE algorithm was used for multi-criteria calibrations resulting in a set of 100 robust model parameter sets with comparable model performance.
Two independent training and validation data sets related to parameter uncertainty and input uncertainty, respectively, were generated and used in the training of the GPM and two other neural architectures (multi-layer perceptrons, MLP and support vector machines, SVM). In the application the GPM showed a superior performance in the prediction of mean and uncertainties compared to the two other neural archietectures MLP and SVM.