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Improving operational flood forecasting through data assimilation

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Accurate flood forecasts have been a challenging topic in hydrology for decades. Uncertainty in hydrological forecasts is due to errors in initial state (e.g. forcing errors in historical mode), errors in model structure and parameters and last but not least the errors in model forcings (weather forecasts) during the forecast mode. More accurate flood forecasts can be obtained through data assimilation by merging observations with model simulations. This enables to identify the sources of uncertainties in the flood forecasting system. Our aim is to assess the different sources of error that affect the initial state and to investigate how they propagate through hydrological models with different levels of spatial variation, starting from lumped models. The knowledge thus obtained can then be used in a data assimilation scheme to improve the flood forecasts.

This study presents the first results of this framework and focuses on quantifying precipitation errors and its effect on discharge simulations within the Ourthe catchment (1600 km^2), which is situated in the Belgian Ardennes and is one of the larger subbasins of the Meuse River. Inside the catchment, hourly rain gauge information from 10 different locations is available over a period of 15 years. Based on these time series, the bootstrap method has been applied to generate precipitation ensembles. These were then used to simulate the catchment's discharges at the outlet. The corresponding streamflow ensembles were further assimilated with observed river discharges to update the model states of lumped hydrological models (R-PDM, HBV) through Residual Resampling. This particle filtering technique is a sequential data assimilation method and takes no prior assumption of the probability density function for the model states, which in contrast to the Ensemble Kalman filter does not have to be Gaussian. Our further research will be aimed at quantifying and reducing the sources of uncertainty that affect the initial state in distributed models and will assess the added value of spatially measured data.