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Spatially-distributed Deep Learning for rainfall-runoff modelling and system understanding

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The prediction of streamflow from precipitation data is one of the traditional disciplines of hydrological modelling and has major societal implications such as flood forecasting, efficient use of hydro-power and urban and regional planning. Recently, data-driven approaches have been applied successfully for rainfall-runoff modelling, often outperforming equivalent physical modeling approaches. However, these studies have almost exclusively focused on temporal data and have neglected data on the spatial distribution of the inputs.

To close this gap, we trained convolutional long-short-term-memory (ConvLSTM) models on daily temperature and precipitation maps of the catchment area to predict the streamflow of the Elbe river. This supervised deep learning method combines convolutional and recurrent neural networks to extract useful features in the spatio-temporal input maps to predict the river's streamflow. We embedded the model into a Bayesian framework to deliver estimates of prediction uncertainty along with the predictions. Moreover, we derived saliency maps that highlight the most relevant patterns in precipitation and temperature for the Elbe's major flood events.

Comparison with physical simulations show that our Bayesian ConvLSTM approach (1) performs on par with results from physical modeling while requiring only input data on temperature and precipitation, (2) provides useful uncertainty estimates, and (3) is able to generate interpretable saliency maps of flooding events.

In conclusion, this study showcases the applicability of deep learning methods for rainfall-runoff modelling as well as the methods' potential to gain spatial insight into the hydrological system.