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Improved flood predictions by combining satellite observations, topographic information and rainfall spatial data using deep learning

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Flood warning systems are needed to plan mitigation measures and inform response strategies. The extent and dynamics of floods are typically predicted using physics-based hydrological models, which are computationally expensive and data assimilation is difficult. Deep-learning models can overcome these limitations, enabling fast predictions informed by multiple sources of data. Studies show this can be achieved while retaining or improving the level of detail and accuracy previously attainable. We, therefore, propose a deep-learning flood forecasting tool that combines multiple sources of readily available data to quickly generate flood extent maps, which can inform warnings.

We train a neural network with U-NET architecture consisting of encoder and decoder convolutional modules. In the encoder module, features are extracted from the input and the data is downsampled to reduce complexity. Subsequently, the data is upsampled back to the original dimension in the decoder module and each 10 by 10 m pixel of the output image represents a flood prediction. The input to the neural network includes radar rainfall observations, LIDAR topographic scans, soil type and land use maps, groundwater depth simulations and previous inundation maps. All inputs are individually normalized and pre-processed. The rainfall observations are temporally aggregated to various intervals, hydrological features are highlighted in the topographic scans, and soil types and uses are grouped into categories.

The model is trained and evaluated against a set of maps of surface water extent derived from Synthetic Aperture Radar (SAR) satellite observations. The predictions are scored against the target images by computing the critical success index (CSI), which measures the percentage of correct predictions among the total predicted of observed flooded areas. Permanent water bodies and areas where flooding is not captured by the satellite images (e.g. in forests) are masked out during both training and evaluation. The model is trained on a set of flooding events that occurred between 2018 and 2020 within the Jammerbugt Municipality in northern Denmark, which extends for about 850 km^2. The model is validated on spatially independent data and tested on temporally independent events from the same study area.

The proposed model yielded up to ~60% CSI with the test dataset, which is comparable to existing flood screening approaches. The test data included both fluvial and pluvial flooding as well as observed surface water in coastal areas. Large flooded areas were correctly predicted, while false negatives were frequently obtained for smaller areas. The overall performance of the proposed method is expected to improve by further tuning the model hyperparameters and by treating separately flood processes with different dynamics (e.g. pluvial vs. fluvial vs. coastal). These tradeoffs are compensated by the minimal computational time required to generate predictions once the model has been trained. Also, it is expected that the model can easily be transferred to other locations since it relies on local topographic information. The additional advantage of using a deep-learning approach is the ability to easily integrate alternative and additional data sources, which enables, for example, longer-term flood warnings driven by rainfall forecasts instead of observations.