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Applications of convolutional neural networks and remote sensing data to predict flood extents

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Abstract: Observing and interpreting the flood predictions from a hydrodynamic model provides the most reliable results for connectivity analysis. However, the application of physically-based models is limited due to the complexity of their calibration, computation, and validation processes, especially when applying them to large and remote catchments with scarce temporal and spatial data. Deep learning (DL), especially Convolutional Neural Networks (CNNs), is an attractive alternative to hydrodynamic modelling. DL models can use the training data from remote sensing data to produce the results with comparably high accuracy. The DL models using remote sensing data can avoid the complicated process of setting up a hydrodynamic model, which is extremely expensive and time-consuming, especially for remote catchments.

We propose an approach to manipulate the CNN models to produce a daily time series of flood extents using training data from the DEA Water Observation (https://www.dea.ga.gov.au/products/dea-water-observations) and Sentinel-2 images. The northern part of the Narran River catchment, located in the Condamine-Balonne River floodplain in New South Wales, Australia, is the showcase for this method. One-dimensional (1D) CNN (using only discharge data) and two-dimensional (2D) CNN (using discharge data and either a Digital Elevation Model or a Flood Occurrence Map) are applied. In total, for both DEA Water Observation and Sentinel-2 images, there are 440 images for training and 127 images for testing, in 21 flood events from 20/12/1987 to 31/12/2020. We conduct a detailed comparison between the two CNN structures. The 1D CNN and 2D U-Net models yielded results comparable to the satellite images with Hit Rate values of 0.853 and 0.873, respectively. The 1D CNN structure is straightforward and only requires the discharge as an input, leading to shorter computational times. The 2D CNN models allow the combination of the 2D geographic data and the spatial climate data (e.g., precipitation) in training. Therefore, the 2D CNN models result in a better prediction of flood extents.

Preparing training datasets from remote sensing images for the CNN models requires fewer resources than preparing inputs for a hydrodynamic model. No bathymetric data, initial and boundary conditions are required except for the gauged flow data at the inlet at Wilby Wilby (GS.422016, http://www.bom.gov.au/waterdata/). The CNN models in this study are much faster than hydrodynamic models in predicting flood extent. It only took approximately 7 hours to train a 2D CNN model and less than 11 seconds to predict a 308-day flood event (daily time step), while a 2D hydraulic model can take 6-7 days to run for a similar flood event at the same catchment. The models were run on the Multi-modal Australian ScienceS Imaging and Visualisation Environment (MASSIVE) computing facility with 2 K80 GPUs and 117 GB RAM (https://www.monash.edu/research/infrastructure/platforms-pages/massive). However, there are certain limitations in using DL models for flood prediction. DL models require a sufficiently large amount of data covering various flood conditions. DL models cannot deal with the changes in the catchment topography and require to be retrained for those cases. This limits the applications of the DL models to be used for some purposes, such as testing flood mitigation options and efficiency.

Our analysis suggests that the accuracy of the CNN models highly depends on the quality and quantity of the training data. The complexity and errors in the DEM at the Narran River catchment significantly affect the prediction of the flood extents. Hence, improving the quality and quantity of the training data is recommended before using the models for real-time flood forecasting.

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