Geophysical Research Abstracts
Vol. 18, EGU2016-11262-1, 2016
EGU General Assembly 2016

A hybrid deep neural network and physically based distributed model for river stage prediction

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We developed the real-time river stage prediction model, using the hybrid deep neural network and physically based distributed model.
As the basic model, 4 layer feed-forward artificial neural network (ANN) was used. As a network training method, the deep learning technique was applied. To optimize the network weight, the stochastic gradient descent method based on the back propagation method was used. As a pre-training method, the denoising autoencoder was used. Input of the ANN model is hourly change of water level and hourly rainfall, output data is water level of downstream station.

In general, the desirable input of the ANN has strong correlation with the output. In conceptual hydrological model such as tank model and storage-function model, river discharge is governed by the catchment storage. Therefore, the change of the catchment storage, downstream discharge subtracted from rainfall, can be the potent input candidate of the ANN model instead of rainfall.
From this point of view, the hybrid deep neural network and physically based distributed model was developed. The prediction procedure of the hybrid model is as follows; first, downstream discharge was calculated by the distributed model, and then estimates the hourly change of catchment storage form rainfall and calculated discharge as the input of the ANN model, and finally the ANN model was calculated. In the training phase, hourly change of catchment storage can be calculated by the observed rainfall and discharge data.

The developed model was applied to the one catchment of the OOYODO River, one of the first-grade river in Japan. The modeled catchment is 695 square km. For the training data, 5 water level gauging station and 14 rain-gauge station in the catchment was used. The training floods, superior 24 events, were selected during the period of 2005-2014. Prediction was made up to 6 hours, and 6 models were developed for each prediction time.
To set the proper learning parameters and network architecture of the ANN model, sensitivity analysis was done by the case study approach. The prediction result was evaluated by the superior 4 flood events by the leave-one-out cross validation. The prediction result of the basic 4 layer ANN was better than the conventional 3 layer ANN model. However, the result did not reproduce well the biggest flood event, supposedly because the lack of the sufficient high-water level flood event in the training data. The result of the hybrid model outperforms the basic ANN model and distributed model, especially improved the performance of the basic ANN model in the biggest flood event.