DEEP LEARNING APPROACH FOR PREDICTION OF WATER LEVEL IN RIVERS

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ABSTRACT

In recent years, climate change has been responsible for many flood disasters. It is essential that protective measures should be developed against these. One of these measures is a flood forecasting system in which rising water-levels in rivers are predicted ahead of time. Although several researchers have applied artificial intelligence, and especially deep learning technology, to flood prediction, there is a lack of clarity regarding which deep learning approach is most effective in flood prediction. This study aimed to investigate the prediction of floods from water-level data by using a deep learning approach with data collected from the Kinu River. We adopted the LSTM (long short-term memory) algorithm, which is a type of recurrent neural network that readily reflects time-series data. In this study, we collected water-level data from five stations on the Kinu River, a branch of the Tone River, Japan. The results indicate that it is possible to utilize water-levels to predict flood events with a high level of accuracy.

Keywords: flood prediction, water-level, deep learning, recurrent neural network, LSTM

1. INTRODUCTION

In recent years, enormously heavy rains have caused huge flood disasters around the world. The increased frequency and intensity of these heavy rains are mainly due to climate change. It is urgently necessary to take effective measures against flood disasters to reduce loss of life and damage to property. One of these measures is the development of a flood forecasting system to predict rising water levels in rivers. Previous studies on flood prediction were mainly based on physical models using data-assimilation approaches (*e.g.*, Noh et al., 2013; Kashiwada and Nihei, 2018). Although these approaches are useful for reproducing current water-level profiles along rivers, there are significant issues relating to the prediction of rising water levels a few hours ahead. A possible solution may be found through artificial intelligence, and especially through deep learning technology, which has now been applied to various engineering fields, including hydraulic engineering. Although several researchers have applied artificial intelligence to flood prediction (*e.g.*, Maier and Dandy, 2000; Hitokoto et al., 2017), there is a lack of clarity regarding which deep learning technology approach is most suitable for flood prediction.

This study aims to investigate flood prediction from water levels using a deep learning approach with water-level data obtained previously. For this, we adopted an LSTM (long short-term memory) algorithm, which is a kind of recurrent neural network. The field site chosen for the study was the Kinu River, a branch of the Tone River in Japan. This study is a part of Ito et al. (2019).

2. OUTLINE

2.1 Model of deep learning for flood prediction

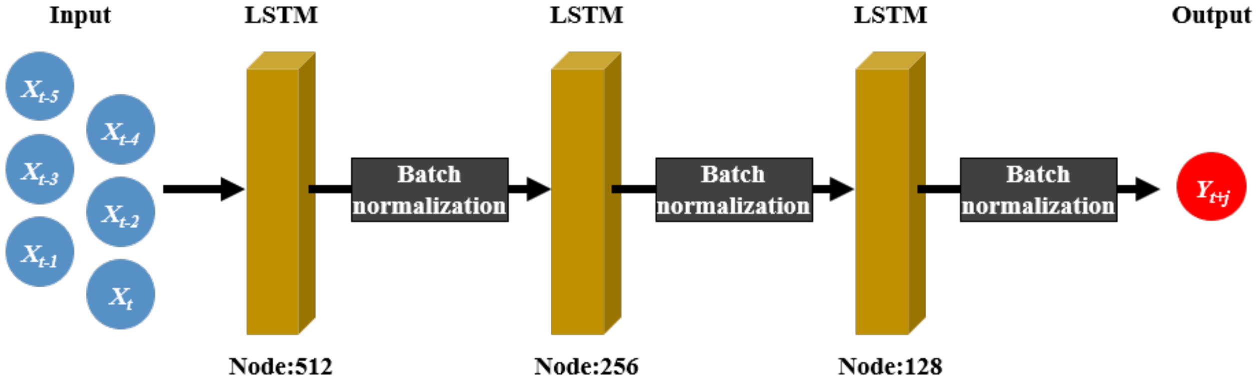

Figure 1. Conceptual diagram of the present model that predicts from time "*t*" to "*j*" hours later

Table 1. List of hyperparameters in this model.

Hyperparameter	Value
Epoch	50
Batch size	128
Optimizer	Adam
Loss function	Mean Square Error
Dropout	20%
Recurrent dropout	20%

For the present study, we used an LSTM algorithm (Hochreiter and Schmidhuber, 1997), which can reflect time series data as a deep learning approach. The stacked LSTM used in this study connects multiple layers, as shown in **Fig. 1,** to express the complex time correlation of the target dataset. We here selected three LSTM layers and set the node numbers of each layer to 512, 256 and 128, respectively, as shown in **Fig. 1**. In addition, batch normalization (Ioffe and Szegedy, 2015) was introduced after processing each LSTM layer to improve the

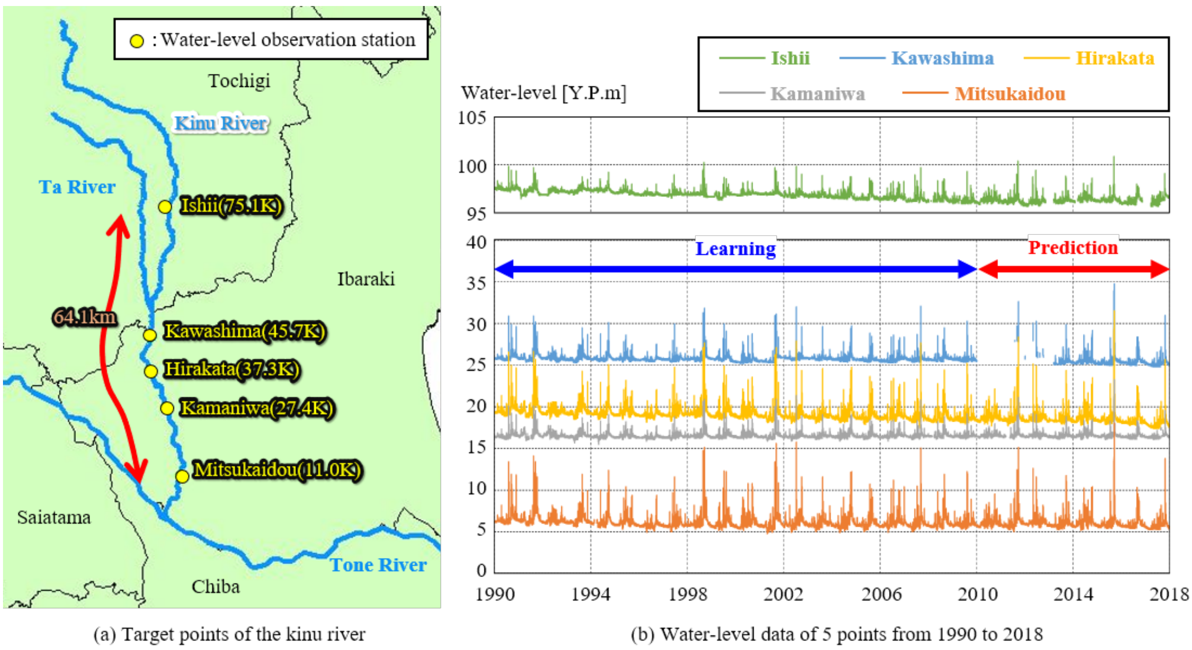

Figure 2 Study sites in the Kinu River **(a)** and time series of water-level data at five stations from 1990 to 2017 **(b)**.

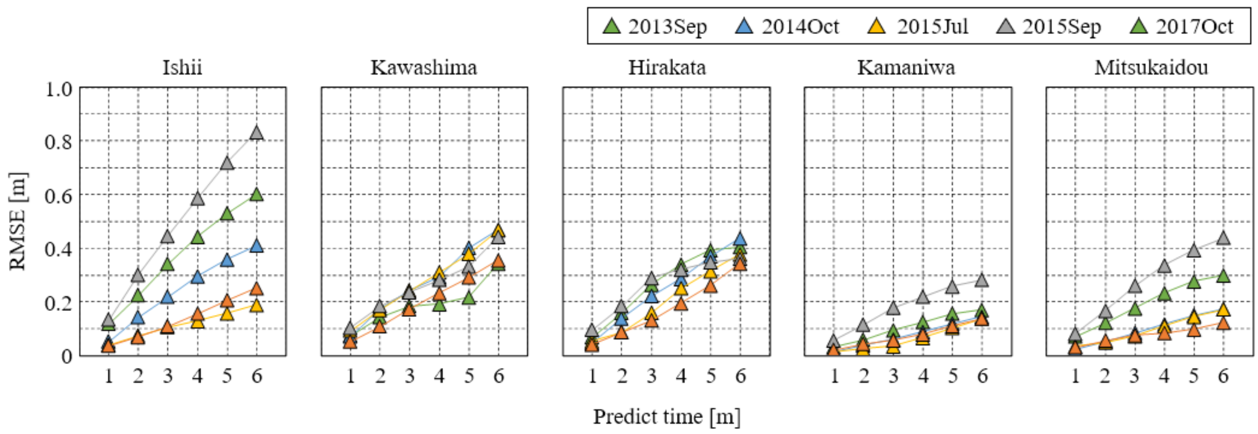

Figure 3. RMSE (root mean square error) values between the observed and predicted water levels at each prediction time.

learning efficiency. This model was constructed to output the objective variable Y_{t+j} at j hours (j=1 - 6) after time t using the input data which are the explanatory variables X_{t-i} from i hours ago to the current time t (i=0 - 5). The explanatory and objective variables are hourly water-level differences. We aimed to predict the water level up to six hours later, and so prepared six prediction models for each prediction hour. By using this model, the hourly water level differences from one hour to six hours later were predicted, and we calculated the water level at each prediction time by adding the water-level at the current time to these difference values. Other hyper-parameter settings are shown in **Table 1**. It should be noted that the dropout and recurrent dropout were set at 20% for each layer to prevent over-fitting in the model.

2.2 Data

We applied this model to flood prediction for the Kinu River, Japan. For this river, we selected five stations for water-level observation: Ishii (75.1 km upstream from the Tone River), Kawashima (45.7 km upstream), Hirakata (37.3 km upstream), Kamaniwa (27.4 km upstream), and Mitsukaidou (11.0 km upstream) as shown in **Fig. 2(a)**. The data used for learning and prediction were the hourly water-level differences at these five points. **Fig. 2(b)** shows the water-level data for the five points from 1990 to 2017. For this study, we used the water levels from 1990 to 2009 as the learning data and the water levels from 2010 to 2017 as the prediction data. For the analysis, we ideally needed continuous water-level data with none missing, however some data were missing from the observed water-levels. To compensate for this, a linear interpolation was applied to data missing from the learning data. Where data were missing from the prediction data, those measurements were excluded from the analysis. From the water-level database, we identified 20 flood events in the learning data and five flood events in the prediction data.

3. RESULTS AND DISCUSSION

Fig. 3. shows the numerical accuracy of the flood prediction in the present model. The values for the RMSE (root mean square error) between the observed and the predicted water levels are indicated for five flood events. The horizontal axis in the figure indicates the prediction time *i,* which is *i* hours ahead from the current time *t*. The results indicate that the RMSE values at the Ishii station were relatively large, and the maximum RMSE value was more than 0.8 m for the flood event in September, 2015, which was the largest in the Kinu River during the measurement period. Since the Ishii station is located at the point furthest upstream in the analysis, as shown in **Fig. 2(a)**, the predicted data at the Ishii station was not affected by the water level further upstream from the Ishii station. This may be the cause of the large RMSE values at the Ishii station. In contrast, the RMSE values at the other four stations were less than 0.5 m, even for the largest event in September, 2015. This indicates that the present model with its deep learning maintained a high level of accuracy in its prediction of the water level in a flood event when the upstream water level data were included.

4. CONCLUSION

We developed a neural network model with a stacked LSTM algorithm in order to predict water levels in a river up to six hours ahead. The results show that, by using water-level data from multiple points, the model can predict what the water level will be six hours later.

ACKNOWLEDGMENTS

Financial support for this study was provided by JSPS (Japan Society for the Promotion of Science) KAKENHI, grant number JP16H02365.

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