Seasonal precipitation forecast model in wet and dry seasons using global monthly surface temperature by deep learning

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In recent years, the number of extreme weather events has increased around the world, it has caused disasters such as drought and flood. Water management in Thailand has been very difficult because of conflicting extreme disasters such as drought and flood has occurred continuously in the same area. A typical method of predicting precipitation was a numerical prediction model based on physical equations. However, the accuracy of long-term precipitation prediction using numerical prediction model has not yet reached a level applicable to practical use. In this paper, seasonal forecast of monthly precipitation model in Bangkok, Thailand was made using deep learning and global surface temperature.

The used data were the global monthly surface temperature and monthly precipitation. The analysis period was from January 1958 to August 2017. The training phase was from January 1958 to December 2007, and the test period was from January 2008 to August 2017. Used data within training phase was divided into study data and validation data. Natural observation data had the characteristic that the number of occurrences decreased as the intensity increased. In order to eliminate the variation in precipitation intensity between the training data and the validation data, used data within training phase was rearranged them in the order of precipitation intensity and separated.

In this study, a seasonal precipitation forecast model was developed using convolutional neural network. Convolutional neural network algorithms excel in image processing. First, an ensemble forecast of precipitation was performed using random elements from machine learning. As a result, the forecasted precipitation was underestimated when the precipitation by JRA55 was large, and the forecasted precipitation was overestimated when the precipitation by JRA55 was small. It was difficult to predict monthly precipitation such as the past maximum. The range of predicted precipitation was different depending on whether or not the monthly precipitation by JRA55 exceeds 200 mm. As a cause of this, it was considered that the influence of the monthly surface temperature was different between the low intensity precipitation phenomenon and the high intensity precipitation phenomenon. For this reason, in this paper, as an initial study, the used data was divided into a dry season (November to April) and a rainy season (May to October). Precipitation forecast models in each period was developed.

Case 0 was a precipitation forecast model created using all the data of the training phase regardless of the season, and Case 1 was a precipitation forecast model created by dividing the used data into the dry season and the rainy season.

According to the validation data results, in Case0, the MAE was 55.3 mm and the RMSE was 74.2 mm. In Case 1, the MAE was 56.1 mm and the RMSE was 73.7 mm. Comparing the results of the dry season between Case0 and Case1, MAE was 2.7mm smaller and RMSE was 7mm smaller in Case1 value than in Case0 value. Comparing the results of the rainy season between Case0 and Case1, MAE was 4.5mm bigger and RMSE was 4.9mm bigger in Case1 value than in Case0 value.

According to the test data results, in Case0, the MAE was 49.1 mm and the RMSE was 66.2 mm. In Case 1, the MAE was 54.6 mm and the RMSE was 70.3 mm. Comparing the results of the dry season between

Case0 and Case1, MAE was 3.0mm smaller and RMSE was 3.8mm smaller in Case1 value than in Case0 value. Comparing the results of the rainy season between Case0 and Case1, MAE was 13.8mm bigger and RMSE was 9.1mm bigger in Case1 value than in Case0 value. The prediction accuracy of the dry season was higher, but the prediction accuracy of the rainy season was lower when the models were created for the two seasons-the dry season and the rainy season.