FLOOD FORECAST BASED ON DEEP LEARNING USING DISTRIBUTION MAP OF PRECIPITATION

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ABSTRACT

When flooding is expected at a river construction site, workers are able to evacuate to a place of safety within a few hours. If heavy machinery and materials are present, several hours are required to ensure safety. One responsibility of the construction manager is to make a judgement as to whether evacuation is necessary. Recently, a flood forecast system has been developed and applied to river work; based on forecast water levels, the man-ager can make a judgement based on personal experience. However, this system has some problems: 1) tuning of system parameters and the collection and selection of data takes a lot of time; 2) to secure the robustness, water levels are predicted by multiple methods and the manager’s judgement may be affected if there are discrepancies among the predictions. In this paper, a new forecasting technique for judging whether water levels will exceed a ‘flood’ threshold or not is developed using deep learning based on weather forecast rain distribution maps. The input data are the center of gravity of rainfall and the amount of rainfall. The method is applied to the Abukuma River in Fukushima prefecture and is able to judge flooding in excess of the threshold value, giving a correct evaluation rate of 60%. The precision of the judgement can be improved by selecting the learning data. This technique is suitable for application to safety management during river construction work.

Keywords: river construction, safety management, flood prediction, neural network, rain distribution maps

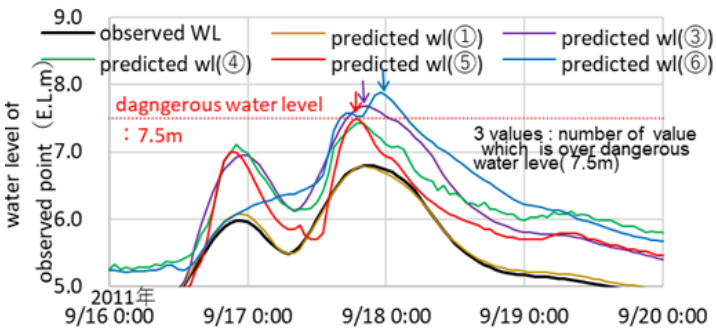
1. INTRODUCTION

Extreme natural phenomena such as heavy downpours and extremely hot days are becoming more frequent as a result of global warming. For example, if we focus on rainfall, there were about 238 annual occurrences of precipitation reaching at least 50 mm per hour between 2008 and 2018 (a 10-year period). This is about 1.4 times the average annual frequency between 1976 and 1985 [1)]. More than 10 fatal disasters induced by heavy rain, including land-slides and river flooding, have occurred since 2011 as a result of severe weather fronts and typhoons [2)]. Erosion control dams and embankments have been constructed to mitigate disasters caused by torrential downpours. However, it is also very important to ensure that torrential downpours do not compromise safety during the construction of such infrastructure. In particular, when doing river work, it is necessary not only to protect the lives of workers in the case of river flooding during the construction period, but also to evacuate construction materials and equipment (construction assets) such as heavy machinery. In our company, therefore, the water level at the construction site of the river is predicted in advance, and when the predicted water level reaches a ‘dangerous’ level set by the constructor, a flood warning system distributes alerts to the parties concerned by e-mail or the Web. Currently, this system is in use for river construction sites[3) 4)]. It combines several prediction methods, including a regression model, a numerical model, and a cumulative rainfall model. The regression model predicts the water level at 10 or 30 minute intervals based on measured water levels upstream from the prediction point. The numerical model and cumulative rainfall model are based on from 24 to 72 hours, determined by location, of analysis data (measured values) and forecast values for six hours ahead. One of the characteristics of this system is its robustness. For instance, even if one of the prediction methods fails due to problems such as the transmission of input data, the system continues to operate with the other methods. In applying this system to actual river work, there are found to be discrepancies in predicted flood times and water levels, but the system does give advance warning that the water level will exceed the critical water level. The system has contributed to safety management during construction[3) 4)].

One drawback of the system is that it takes some time and labor to prepare measured values such as water level, flow rate and rainfall for use in construction and for the tuning of prediction methods. Further, in some cases there may be no observation points for water level and rainfall close to prediction point, or observation stations may be closed or under inspection, making measured values unavailable. Even if predictions are available, the person in charge of construction needs to determine the propriety and timing of flood control measures at least from 5 to 10 hours in advance based on the outputs of the system and his/her own experience. However, predicted water levels vary with the prediction method, so when predictions are close to the danger level, he/she may suffer hesitation as to whether or not to proceed with flood control measures (Figure 1).

In this paper, a deep learning technique to predict flood occurrence using only precipitation distribution maps is presented, taking the Abukuma River as a case study of a first class river which is classified in Japan designated by the River Law. Predictions made using the technique are compared with observed values; see Fig. 1 for an example. Using this technique, flood occurrence can be reliably predicted with easily acquired data up to several tens of hours ahead. Distribution maps of precipitation are easy to obtain for any region and can be compared with actual water level and rainfall observations for the river. Here, analytical rainfall maps provided by the Japan Meteorological Agency are used. The maps include the spatial distribution of rainfall intensity (GPV data; grid point values data). Maps offered by private weather companies could also be used to this method, however the accuracy of such forecasts is not considered here.

Figure 1.Example of water level prediction results for actual river



2. OVERVIEW OF DEEP LEARNING

Deep learning (DL) is an extension of the neural network (NN) method. While NN has only one intermediate layer, DL has more than two intermediate layers. Both NN and DL use combinations of input and output layers (learning data) to determine weighting factors. When new data is presented to the input layer, DL is able to obtain results from the output layer (Figure 2). Each layer contains nodes simulating neurons, and the number of nodes corresponds to the number of input/output data points stored in the input and output layers, respectively. The number of nodes to be set optionally is stored in the intermediate layer. Each node in a layer is coupled with all nodes in the neighboring layer (nodes of the input layer are coupled with those of the first intermediate layer; the first intermediate layer with the adjacent intermediate layer; the most behind intermediate layer with the output layer), and the strength of the coupling is determined by the weighting factor. The node values of the intermediate layers and the output layer are calculated using the weighting factors, which are obtained from an activation function. The activation function simulates transmission of information from one neuron to another. The weighting factors are determined by updating a set number of times (the number of learning cycles) such that the difference between the node value of the output layer obtained by the calculation and the node value (original value) is minimized. The optimum number of learning cycles differs de-pending on the details and conditions of the calculation. But with increasing number of learning cycles, the weighting factor is optimized and the calculation result improves[8) 9)]. The greater the number of intermediate layers in DL, the more the weighting factor and the calculation time increases. But the node value of the intermediate layer can consolidate features of the input layer and output layer numerically and, as a result, the output result often becomes better. In this study, we use the zigmoid function as the activation function and the Adam method for updating the weightings[8) 9)].

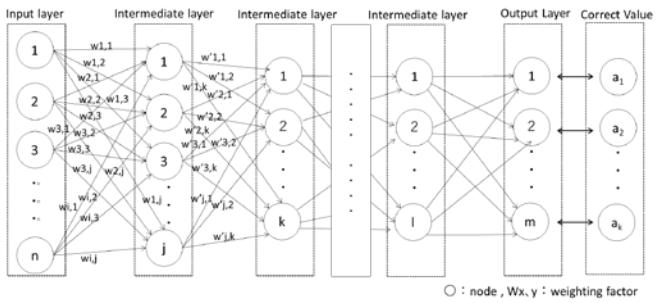


Figure 2. Overview of deep learning

The study parameters are the total number of intermediate layers (2 and 3), the number of nodes (the same number of nodes, 40, as in the input layer and twice that number, or 80 nodes), and the number of learning cycles (2,500, 5,000, 7,500 and 10,000) (Table 1). The response rate (percentage of correct answers) was obtained by comparing prediction results with measured values.

Table 2. Calculation conditions for deep learning

Intermediate Layer Number	Node Number	Learning cycles
2・3	40・80	2,500・5,000・7,500・10,000

(Total 32 Case)

3. PREDICTION OF FLOOD OCCURRENCE BY DEEP LEARNING

3.1 forecasting procedure

3.1.1 Selection of Prediction Point and Establishment of Catchment Area

The first step is to select the location of the prediction point and establish the catchment basin for this point. In this study, the Ejiri Observatory (Figure 3), which is well downstream on the Abukuma River flowing through Miyagi and Fukushima Prefectures, was selected as the prediction point. The catchment of the river at the Ejiri Observatory is approximately 4,400 km^2. Figure 4 shows the water level history at the Ejiri Observatory from 2007 to 2018. These water levels are based on hourly observations obtained from the Ministry of Land, Infrastructure, Transport and Tourism's hydrological water quality database[10]. In this study, when water level exceeds critical water level, T.P. + 8.0 m and the water level is rising compared to 1 hour ago and 2 hours ago, we call it 'flood'. On the other hand, the water level does not exceed the critical level, we call 'no flood'(Figure 5). Using this judgement method, there were 37 flood events at the Ejiri Observatory over the 12 years from 2007 to 2018. Here water level from March to May were excluded because there were increasing of water level by melt snowy which was caused by temperature. The catchment basin is the upper catchment area including Ejiri Observatory, as obtained from "watershed boundary and non-catchment data" (Ministry of Land, Infrastructure and Transport) [11](Figure 3).

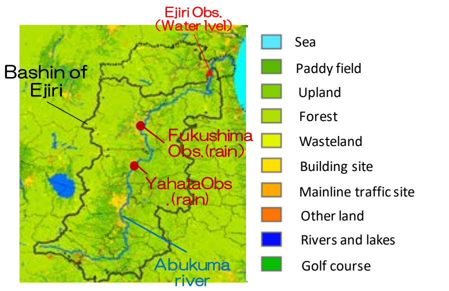


Figure 3. Abukuma River and station location

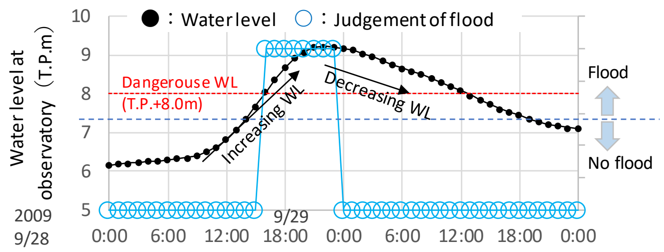


Figure 5 Flood Judgement

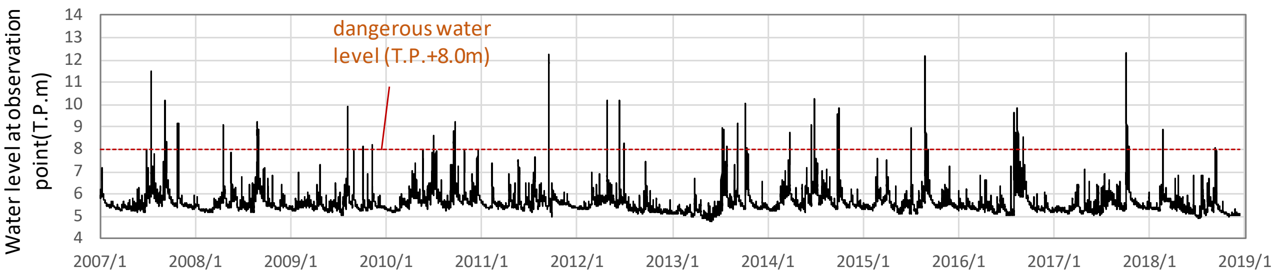


Figure 4. Water level history at Ejiri Observatory

3.1.2 Grayscale Rain Distribution Maps and Obtaining Center of Gravity and Precipitation

The distribution maps of precipitation indicating actual rainfall intensity were created using rainfall data (on a 1 km grid) for 12 years (2007-2018) from the Japan Meteorological Agency (leftmost map in Figure 6). Rainfall intensity coloring is based on Radar Nowcast[12]. Next, the Ejiri Observatory catchment was extracted from this map (center map in Figure 6). For use in DL, it is necessary to digitize distribution maps, so in this work the RGB levels of the maps were converted to luminance (0-255 grayscale) (rightmost map in Fig. 6). We considered the use of these obtained grayscale values as DL learning data, but the amount of information per map is very large. (For example, a 200 x 200 pixel image has 40,000 data points.) It was considered that convergence of the weighting factors would take too long when rain distribution maps covering several years are to be learned. So not only a high-specification computer and parallel computing but also long calculation time would be required, but in actual, it will be hard to apply this method for some construction site because . Therefore, to express the features of the rain distribution maps with a small amount of data, center of gravity information from the catchment basin map was used as representative values for DL. This center of gravity information consists of the coordinates of the center of gravity of the rain distribution maps(X, Y), the distance from the prediction point to those coordinates (L), and the amount of rainfall (R). The coordinates represent distance from the origin, with the lower left corner of the grayscale image as the origin (Fig. 6). The distance to the center of gravity is defined as the squared sum of the barycentric coordinates X and Y. Rainfall is the sum of the gray values. The gravity information was created for every hour over the 12 years from 2007 to 2018 at the same time points as the water level observations.

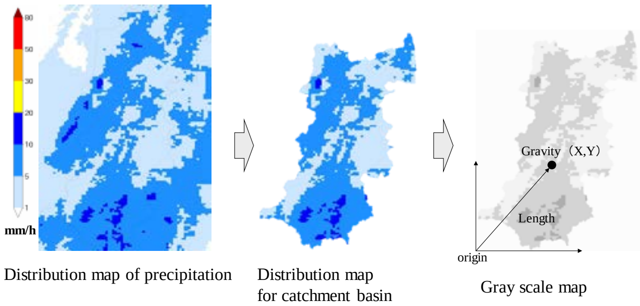


Figure 6 Center of gravity calculation

3.1.3 *Creating Learning and Test Data*

The full set of data for DL was prepared by combining the occurrence of 'flood' water levels determined by the method in Fig. 5 with the center of gravity information for the 5~14 hours before the water level observation time point. Learning data and data used for prediction (test data) were prepared from this full data set. The prediction of flood by this method is every 1 year, and the test data used for the predictions was extracted from the full data set. The learning data is obtained by removing the test data from the full data set. Based on the full data set, the test data and learning data were classified. In preparing the data for DL, any missing observations by the Ejiri observatory were excluded; the timing of missed observations differed by year. After data preparation, the total number of data points was 105,195. The test data accounted for 8,183 to 8,770 points, and the learning data was 94,555 to 95,142 points. The number of 'flood' data points was 359, accounting for 0.35% of the total. The accumulation time of the center of gravity information (from 5 to 14 hours in advance of a time 'flood' occurred) was determined from water levels at the Ejiri observatory[10)] and precipitation at two points (the Fukushima Observatory and the Yawata Observatory (Fig. 3))[10)]. The time delay between the start of rainfall, peak rainfall and the time point at which the Ejiri Observatory water level exceeded the dangerous level (T.P. + 8 m) was examined for all 37 flood events (Fig. 7). The average of these time de-lays was 14 hours and 5 hours, and this determined the accumulation time of 5?14 hours before (a period of 10 hours). This also means that by using center of gravity information from 5~14 hours ago, upcoming water levels can be predicted 5 hours ahead from the time of the latest rain distribution maps.

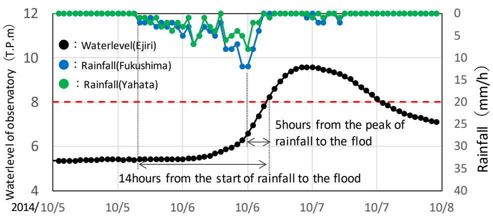
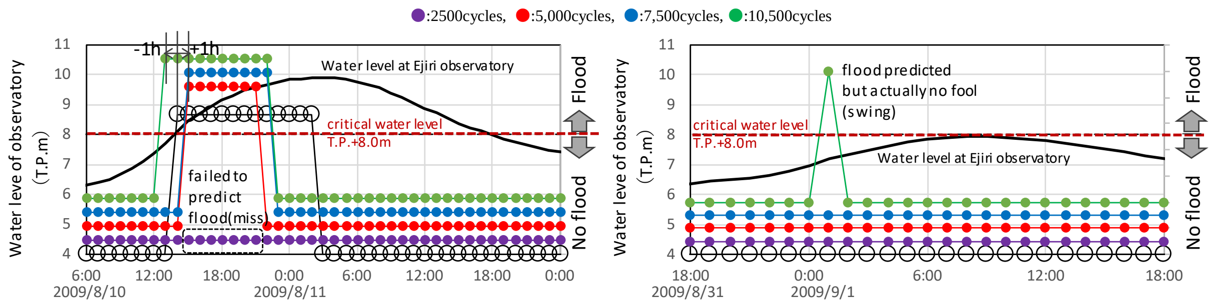


Figure 7 Rainfall and water level at Ejiri Observatory

3.1.4 *Prediction of flood occurrence and compilation of results*

The weighting factors for DL were calculated from the learning data, and then the occurrence of flooding in each year from 2007 to 2018 was predicted. In compiling the results, the time discrepancy between the predicted time of 'flood' and the actual time of a 'flood' observation was examined in the range of up to 24 hours and totaled. An example of the results is shown in Fig. 8 (a). Here, the actual 'flood' period began at 14:00, but the predictions made after 5000 and 7500 learning cycles indicate 'flood' at 15:00, which is an hour late. In the case of 10,000 learning cycles, the predicted time was 13:00, one hour early. With 2,500 learning cycles, the prediction failed (because water level exceeded critical level called 'flood', but the method predicted 'no flood'). In this study, this results was called 'Miss'. Figure 8 (b) shows an example of a 'Swing', in which no flood actually occurred but the technique predicted 'flood'.



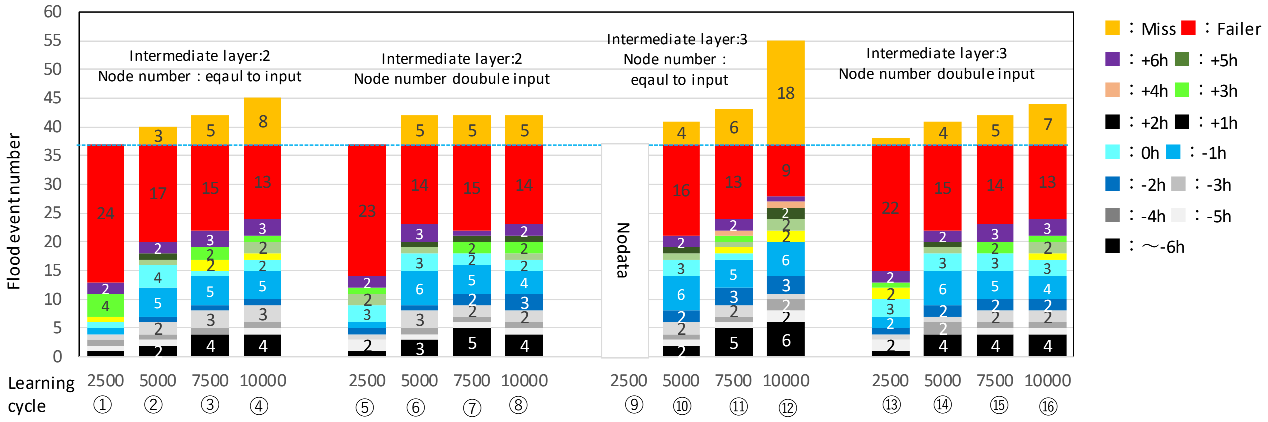
(a) Flood predictions and failure to predict (b) Flood predicted but not occur

Figure 8 Examples of prediction results

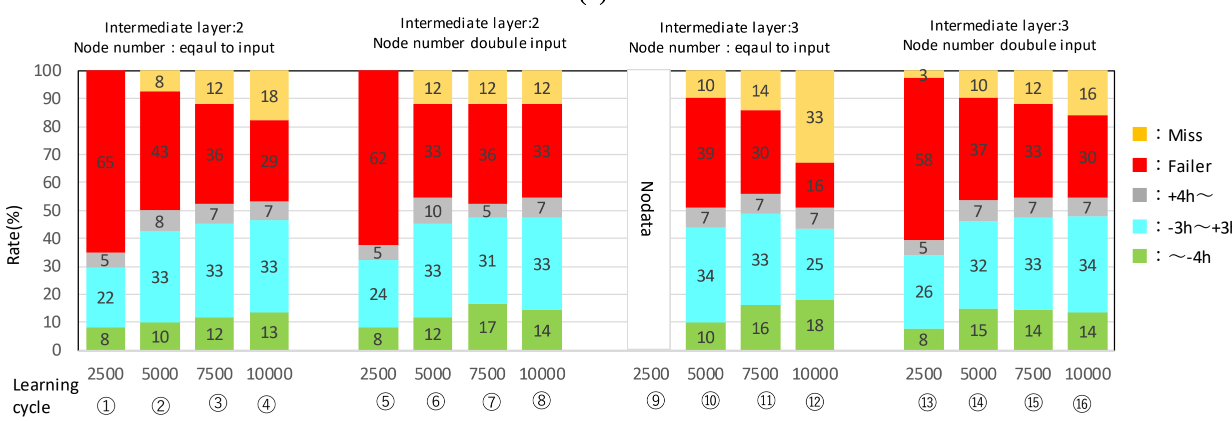
3.2 prediction result

Figure 9 shows the time discrepancy results and learning frequency for prediction failure, ‘swing’ and ‘flood’. Here, ±0 h means predicted and actual times were the same, the minus sign (-) means the prediction was earlier than the actual flood time, and the plus sign (+) indicates the prediction was later than the actual flood. Figure 9(a) is a number of predicted result and (b) shows rate of (a).

With increasing learning cycles, number of intermediate layers, and number of nodes, the number of prediction failures ‘miss’ decreased while ‘flood’ and ‘swing’ results increased. This is thought to be because the weighting factors are optimized with more learning and the sensitivity to test data increases. A time discrepancy of 0h to ±3h for a ‘flood’ occurred in 22-34% of cases(Figure 9 (a)①⑩⑯). If time discrepancy is disregarded, ‘flood’ was predicted correctly in 35-56% of cases(Figure 9 (a)①⑪). Moreover, the percentage of ‘swing’ increased and the percentage of failure to predict decreased. The combined percentage of these two results was 36-65%(Figure 9 (a)①⑧).



(a) Numbers

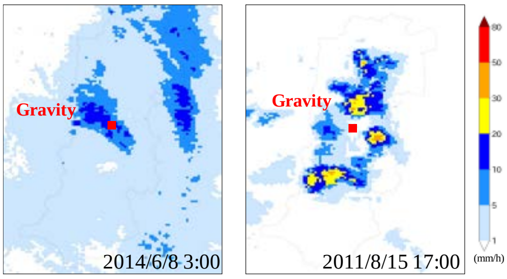


(b) Rate

Figure 9 Aggregation results

As to the reasons for obtaining 50% failure and ‘swing’ results even as the number of learning cycles increased, one explanation is that the center of gravity information would be identical even for different rainfall distributions. For example, Fig. 10 shows uniform rainfall occurred over the entire catchment area (Fig. 10 (a)) and localized torrential rain occurred in the catchment (Fig. 10 (b)). The position of the center of gravity, the distance to the center of gravity, and the amount of precipitation are almost the same in the two cases. When very heavy local rainfall occurs, it may exceed the soil's recharge capacity and rainwater rapidly flows over the surface into rivers, causing water levels to rise and an increased discharge. Therefore, it was suspected that the test data at the time of flooding was similar to the learning data of "no flood " and predicted that "miss".

In order to consider the rainfall distribution with method, the map was segmented using a grid for calculation of center of gravity. Learning data and test data were created by combining center of gravity information for each segmented area.



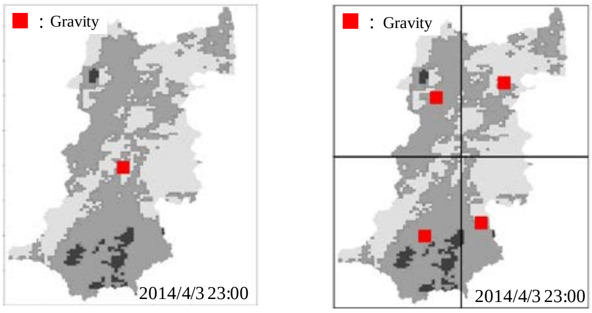
(a) uniform rainfall (b) localized torrential rain

Figure 10 Rainfall patterns and center of gravity

3.3 prediction by image segmentation

3.3.1 Summary

The distribution maps of precipitation were segmented into four parts (Fig. 11). The prediction method is as described in section 3(1) above. Since the number of nodes in the input layer has been increased by segmentation, the number of nodes in the intermediate layers was also increased to 160, which is equal to the number of nodes in the input layer, and doubled to 320 nodes.



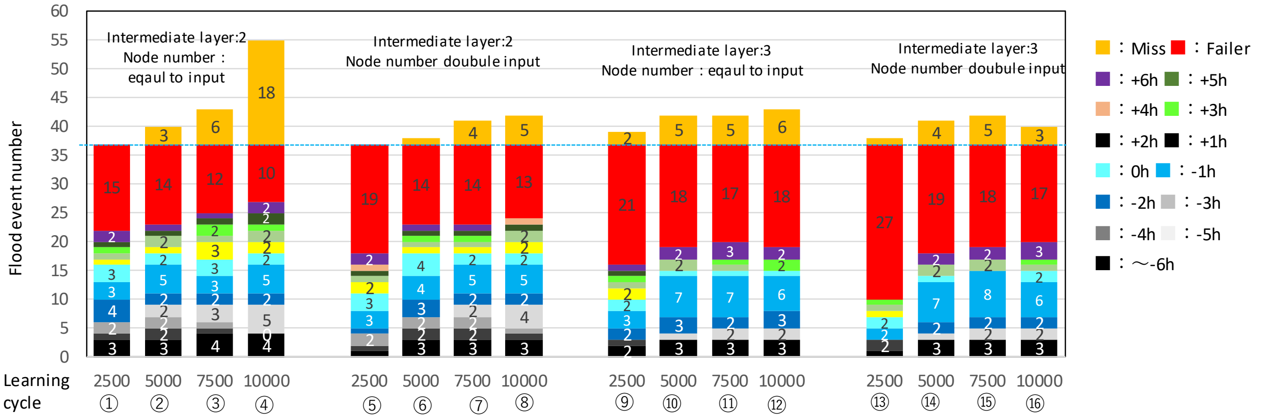
(a) no segmentation (b) 4 segments

Figure 11 Center of gravity

3.3.2 Prediction Result

Figure 12 shows the aggregated predictions. Compared with Figure 9. Predicted results 'flood' with intermediate layer 2 are increased(①〜⑧). For a given number of learning cycles, the number of failures to predict a flood is fewer. It can be said that image segmentation with intermediate layer 2 has improved prediction accuracy. The percentage of correctly predicted 'flood' events 27% (Figure 12 (b) ⑤) to 40% (Figure 12 (a) ③⑧) with a 0h to ±3h time discrepancy, and 51% (Figure 12 (b) ④) to 60% (Figure 12 (a) ⑥) regardless of the time discrepancy, suggesting that it was equivalent to the not segmented case (Figure 9). But with intermediate layer 3, 'flood' results are decreased(⑨〜⑯) compared to not segmented case. Especially, in the case of 2500 cycles with intermediate layer 3 and node number double input, number of failures has increased. This is because the amount of learning data increased 4 times and the weighting coefficients failed to optimize. In addition, the number of nodes and the number of weights increased because the number of intermediate layers was increased from two to three.

The results that could not be predicted were common to the seven events. Therefore, it was predicted excluding these seven events with intermediate layer 2 of not segments case. As a result, the prediction results improved and 'flood' results are increased(Figure 13 (a)(b)). The percentage of 'flood' events over 65% with a 0h to ±3h time discrepancy(Figure 13 (b)). From this, it was thought that prediction accuracy has decreased due to unlearned learning and the prediction result improved by increasing the learning data.



(a) Numbers

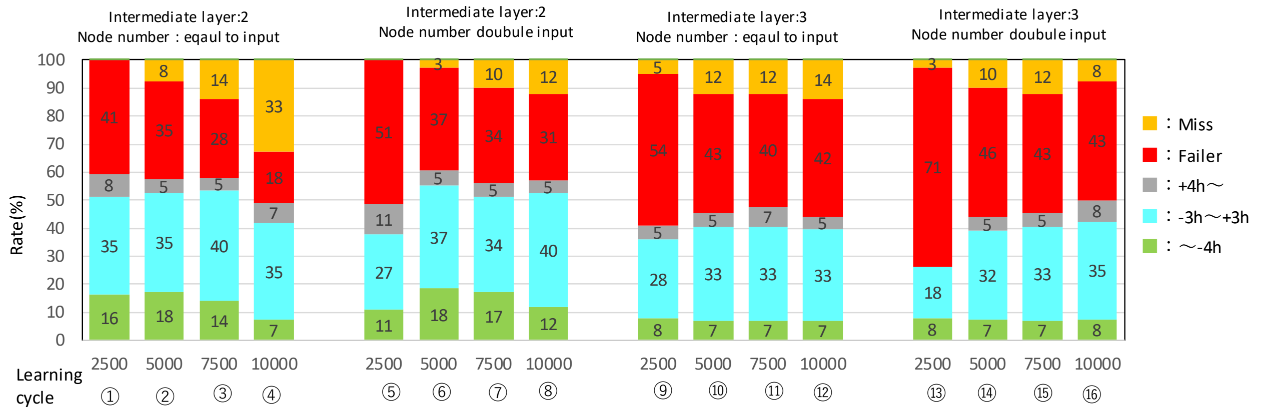
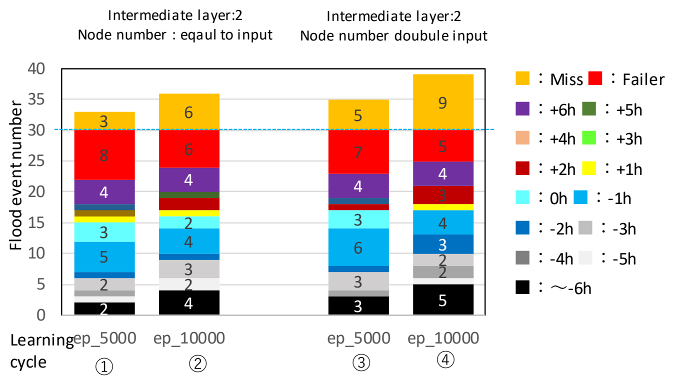
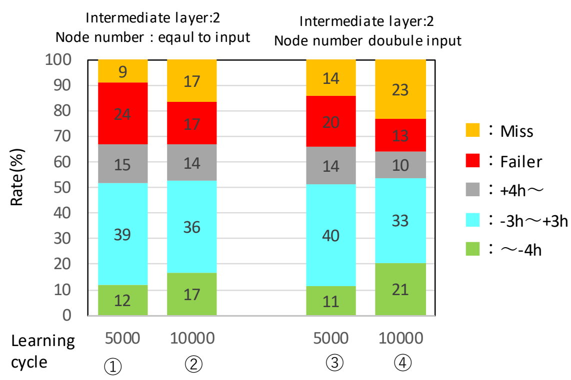


Figure 12 Aggregation results(4 segments)



(a) Numbers



(b) Rate

Figure 13 Aggregation results(not segments and excluding 7 events)

4. EFFECTIVENESS WHEN APPLIED TO RIVER WORKS

First, since predictions of ‘flood’ and ‘no flood’ can be derived using only distribution maps of precipitation, this method is available after only a short preparation period. Using results as shown in Fig. 1, there is no hesitation in deciding whether or not to take countermeasures against inundation.

Second, there is a possibility that any result other than a failed prediction can be used for safety management. A ‘flood’ result can be reliably obtained using rain distribution maps prepared from weather forecasts 12 to 3 hours ahead with segmentation into four divisions and 5,000 learning cycles (Fig. 14). The occurrence or non-occurrence of flooding can be predicted 17 hours ahead of the present time, while the time discrepancy between actual flooding and the prediction is -8 to + 15 hours when the map is segmented into four and there are 1,000 learning cycles. Therefore, even if flooding were to occur 8 hours earlier than the predicted time (-8 hours), this is still 9 hours ahead of the time when the prediction is made. This early prediction of ‘flood’ is effective for alerting construction workers. In fact, the time difference of ± 0 ~ 3 hours is considered to be within the allowable range when the person in charge judges the propriety of flood control measures. A ‘swing’ result serves as a reminder when water levels rise close to the dangerous level, but a ‘swing’ when there is no water level rise means a failed prediction. However, for example, even if there are 3 ‘swing’ events over a 12 year period, the annual average is 0.25. Even if flood control measures taken in response are in vain, this may be considered acceptable given the number of times that flooding causes human and property damage. Based on the above, it is possible to consider that maximum60% (Figure 12 (b)⑥) is valid when only ‘flood’ is allowed, and maximum63% (Figure 12 (a) (4)) is valid when only ‘flood’ and ‘swing’ are allowed, depending on the approach taken when introducing this method. Further, using this method in combination with other prediction methods may allow the efficient and effective imposition of safety measures. For example, minimum flood countermeasures may be put in place when this method predicts ‘flood’ and then choosing other countermeasures according to the scale of flooding indicated by other water level predictions.

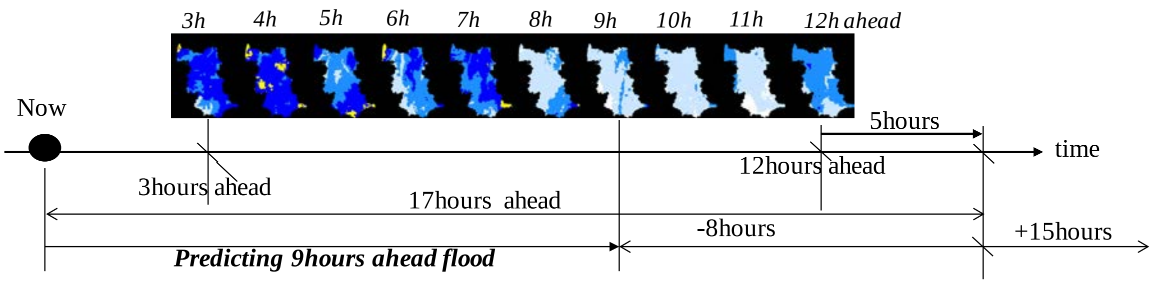


Figure 14 Prediction using weather forecast 12 hours ahead

5. CONCLUSIONS

Deep learning was used to predict the occurrence of flooding along the Abukuma River using only spatial distribution maps of precipitation. The predictions were compared with measured values of water levels. The maps were converted into a grey scale according to luminous and the center of gravity of the luminous was obtained both for the whole map and for the map segmented into four. Learning data was obtained by combining this with the amount of rainfall and observed ‘flood’ or ‘not food’ occurrences. Flood events for the river were then predicted and the results com-pared with the 37 actual observed floods. With increasing map segmentation, learning cycles and intermediate layers, prediction accuracy improved. With sufficient learning cycles, a high percentage of ‘flood’ events was correctly predicted. And it was indicated to decrease frailer when learning data are increased. Using this method, predictions can be made a considerable time in advance from rain distribution maps from weather forecasts, contributing to the management of safety during river works.

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