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Informed Neural Networks for Flood Forecasting with Limited Amount of Training Data

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Abstract

This study presents a novel approach to improving the accuracy of flood forecast models with limited training data.
Flood forecast information is crucial for early evacuation planning.
However, the probability of flooding caused by continuous heavy rainfall is increasing, even in areas where we have not installed flood forecasts.
New methods exist to provide flood forecasts, but they require long-term observations and regular updating of extensive data on the basin.
Existing methods of providing new flood forecast information require long-term observations and regular updates of extensive data on the watershed.
These requirements are related to the construction time and cost of providing flood forecasts.
To address this issue, we propose Informed Neural Networks (INN) that integrate existing domain knowledge of river engineering to enhance the performance of flood forecasts with a limited amount of training data.
We evaluated the performance of our proposed method with Japanese real-world river water levels and compared it to conventional methods such as artificial neural networks (ANN).
Our results demonstrate that the INN can significantly improve forecasting accuracy with only a small amount of training data, comparable to conventional methods trained with eight times the amount of flood data.
This study highlights the potential of INN as a novel approach for accurate and efficient flood forecasting with limited training data.

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Key Points:

- We developed a methodology to improve the precision of flood forecasting technology, specifically when working with limited amounts of data.
- The methodology incorporates a domain-specific knowledge into the architecture and training procedure of Neural Networks (NN).
- Proposed method has demonstrated superior accuracy compared to conventional methods, even under conditions of data scarcity.

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Abstract

This study presents a novel approach to improving the accuracy of flood forecast models even if training data is limited. Flood forecast information is crucial for early evacuation planning. However, the probability of flooding caused by continuous heavy rainfall is increasing, even in areas for which floods have not been anticipated. While methods exist to provide flood forecasts, they require long-term observations, and regular updating of extensive data on the catchment basin. These requirements impact the construction time and cost of providing flood forecasts. To address this issue, we propose the Informed Neural Network (INN); it draws on existing domain knowledge of river engineering to enhance the performance of flood forecasts with limited amounts of training data. We evaluate the performance of our proposed method by assessing Japanese real-world river water levels and compare the results to those of conventional methods such as artificial neural networks (ANNs). Our results demonstrate that INN can significantly improve forecast accuracy with only a small amount of training data, comparable to conventional methods trained with three times the amount of flood data with three hours forecast. This study highlights the potential of INN as a novel approach for accurate and efficient flood forecasting with limited training data.

Plain Language Summary

This study introduces a new method called the informed neural network to enhance the accuracy of flood forecasting models when the training data is limited. Accurate flood forecasts are crucial for early evacuations, as the risk of flooding due to heavy rainfall is increasing even in areas without existing flood risk. Traditional methods for generating flood forecasts require extensive data and continuous updates, making the process time-consuming and costly. In contrast, the INN approach incorporates existing knowledge of river engineering to improve forecasting performance with a just a small amount of training data. We evaluate the INN method with real-world river water level data from Japan, and compared it to conventional methods such as artificial neural networks. The results demonstrate that the INN approach significantly improves forecast accuracy, even with limited training data, to match conventional methods trained with eight three more flood data with three hours forecast. This study highlights the potential of INN as an innovative and efficient approach for accurate flood forecasting, particularly in situations with limited training data.

1 Introduction

Flood forecast information can enable municipalities to plan proactively and residents to safely evacuate in the event of a flood. Consequently, accurate flood forecasting is crucial in areas susceptible to flooding. Recently, Japan has observed an increase in heavy rainfall compared to the past (Kawase et al., 2020; Hirockawa et al., 2020) Kawase et al. (2020) showed central and western regions experiencing record-breaking total precipitation of 48- and 72-hours at approximately 1,300 precipitation stations in 2018. Weather officials continue to observe such unprecedented heavy rains. Some studies predict that these changes are due to climate change and that the rainfall trend will continue(Kusunoki et al., 2006; Kitoh & Uchiyama, 2006; Duan et al., 2015; Osakada & Nakakita, 2018; Takemi & Unuma, 2020). As a result, such an increase in unexperienced heavy rain cause the risk of flooding in areas previously unaffected by it. There are 30,000 rivers in Japan, of which only 393 provide forecast information. Climate change has increased the risk of thousands of rivers for which flood forecasts are not provided. Therefore, it is necessary to provide flood forecasts at more new locations. The cost of the forecasting system is essential when providing flood forecast information to many new locations.

There are two approaches for flood forecasting: rainfall-runoff-based approach and data-driven-based approach. The rainfall-runoff-based approach requires various data types, such as basin characteristics distribution. However, these data require high quality(Hapuarachchi et al., 2011), making it challenging to acquire and continuously update the data. In contrast, the data-driven approach requires only rainfall and river water level data but the need for measurements over a more extended period. Based on existing literature, a training dataset spanning at least five years and containing at least 15 flood events for data-driven methods (Mukerji et al., 2009; Noymanee & Theeramunkong, 2019). Such requirements for long-term data measurements make providing flood forecast information for new sites difficult. Therefore, a method to achieve flood forecasting with a few types and a limited amount of training data is an essential issue for flood forecasting.

In the field of data-driven methods, one potential solution to address the issue of limited training data is to incorporate prior information into the learning process of NN. This approach is known as Informed Machine Learning (IML), and many groups have applied IML to various domains(Von Rueden et al., 2021). IML can improve model performance by applying various types of prior knowledge, such as knowledge graphs and equations, to the learning process. Many IMLs use NNs as a building block, especially called Informed Neural Networks (INN). INN has achieved improved model performance in many areas. Despite these advancements, identifying practical prior knowledge and corresponding Informed Machine Learning methods for flood forecasting remains challenging.

This study introduces a novel method to implement INN for flood forecasting, suitable for limited training data scenarios. The proposed approach incorporates prior knowledge about the "rainfall-runoff-river water level relationship" and "tank model" derived from river engineering knowledge into a NN. We evaluated the performance of INN, To evaluate the INN's performance, We conducted a comparative analysis between the proposed and conventional methods using flood data from a river in the Kyushu region of southwestern Japan. The results indicated that the proposed INN method performed as well as the conventional method when sufficient training data was available. Moreover, the proposed method retained its accuracy even when the training data was limited. In contrast, when training data was limited, the conventional ANN showed a more significant Root Mean Squared Error (RMSE) up to 8 times higher than the proposed INN method. These results suggest that the INN approach is a promising alternative for accurate flood forecasting when limited training data is available. Overall, the proposed method offers an effective solution for improving the accuracy of flood forecasting with limited training data, and its potential applicability to other domains where data availability is restricted warrants further exploration.

2 Related works

There are two kinds of approaches to flood forecasting. One is a rainfall-runoff-based approach, and another is a data-driven approach. Methods based on the rainfall-runoff approach determine the amount of water runoff from the basin and then determine river water levels. Methods based on the data-driven approach often predict river water levels directly.

Many methods were proposed related to the rainfall-runoff-based approach. This method has some parameters, such as precipitation, discharge, and basin characteristics. Especially, to account for the spatial bias of rainfall and the distribution of land features, the rainfall-runoff method often requires dividing the basin into subregions, and it has been called the distributed rainfall-runoff approach (Brocca et al., 2011). Rainfall-runoff approach has parameters related to catchment characteristics. Basin characteristics include terrain, soil, geology, land cover, and more (Cole et al., 2006). Such parameters are not always available, and even when they are, they are often of poor quality and require improvement (Hapuarachchi et al., 2011). Therefore, they cannot always be the best approach to provide flood forecasting for many rivers in a short period and maintain it in the future.

A typical model in the data-driven approach is the statistical model. The autoregressive moving average (ARMA) (Valipour et al., 2012) and autoregressive integrated moving average (ARIMA) (Valipour et al., 2013) are representative and basic models in this area. A statistical model related to ARMA and ARIMA is reported to be more efficient regarding computational cost and generalization compared to the rainfall-runoff approach (Aziz et al., 2014). In the statistical model, several methods treat floods as stochastic processes and predict probability distributions from historical data(Kroll & Vogel, 2002). However, even the more advanced models need improvement in terms of the accuracy of short-term forecasts and the complexity of their applicationa(Mosavi et al., 2018). The machine learning (ML) model is another data-driven approach. ML models for flood forecasting include a variety of algorithms such as neural networks (NN) (Le et al., 2019; Elsafi, 2014; F.-J. Chang et al., 2007), neuro-fuzzy(Mukerji et al., 2009; Chen et al., 2006; Roodsari et al., 2019), and support vector machines(Han et al., 2007; Yan et al., 2018). ML models also include algorithms such as NNs that can deal with nonlinearities in the rainfall-runoff process. ML models are reported to have better performance and less complexity than physical models (Abbot & Marohasy, 2014). The issue with these data-driven approaches is the long-term measurement data. Several literatures have reported 15 to 45 flood data events or 5 to 20 years of measurements to build ML models (Song et al., 2019; Mukerji et al., 2009; Nguyen & Chen, 2020; Noymanee & Theeramunkong, 2019) .

To address the issue of long-term measurement data, Researchers attempt to integrate prior knowledge into the ML models pipeline that has been made in the fields of physical and natural phenomena. These attempts are called informed machine learning (IML) The main goal of this endeavor is to improve accuracy and challenge the problem of limited training data volume. These efforts are based on the taxonomy proposed by Von Rueden et al. (2021) and are divided into several methods depending on the representation of prior knowledge. In particular, for problems involving natural phenomena and physical systems, the type of existing knowledge that describes the system includes algebraic equations. One idea in an attempt to integrate this algebraic equation into the machine learning pipeline is loss function modification. Karpatne et al. (2017) achieved accuracy beyond conventional techniques by adding the equation relating water temperature and density to the loss function for the lake temperature modeling using NNs. Loss function modification by differential equations, another option, is also a subset of Algebraic equations. Zhu et al. (2019) has achieved higher accuracy than conventional methods for the problem of surrogate modeling of systems described by differential equations using NNs, without using training data, by using the equation as a loss function. These improvements show the possibility of INN for a limited amount of data by changing the loss function based on the algebraic equation. The next category of possible prior knowledge is knowledge graphs, which represent the relationships among the elements of the system. M. B. Chang et al. (2016) applies a network structure of NNs that dynamically changes from scene to scene to predict the motion of multiple rigid bodies that affect each other. It achieves improved accuracy over conventional static network structures. This result indicates the possibility of a network structure of NNs suitable for the target system. In flood forecasting by IML, Qian et al. (2019) use simulation results by the finite volume method as training data to speed up the two-dimensional flood simulation by the shallow water wave equation and train the neural network. As a result, they achieved 50,000 times faster than the simulation. Accelerating prediction using such existing simulation results is called surrogation and is one of the applications of IML. Bhasme et al. (2021) used IML to improve annual water balance prediction accuracy. In this research, they define the relationship between the variables of the physical model that predicts runoff by learning with ML models. Mahesh et al. (2022) used IML to predict spatiotemporal floods on one-dimensional channels. IML was realized by setting the loss function of NNs based on the Saint Venant equation. When compared with ML models, IML showed higher performance. In IML, although there are many studies on physics and natural phenomena, there are still few studies on hydrology, and there needs to be knowledge about the problem of a limited amount of training data for flood forecasting. Therefore, we set the following questions to obtain new knowledge about the applicability of IML, especially INN, in flood forecasting. The overall research question this paper tries to answer is, "Can INN be applied to flood forecasting when flood data are limited?" Consequently, the following two questions about INN is needed to be answered.

1. Can INNs perform as other conventional flood forecasting methods in the condition of a sufficient amount of training data?
2. Can INN maintain the performance rather than conventional methods in the condition of a limited amount of training data?

3 Materials and Methods

3.1 Study Area and Data Acquisition

The study area in this study is shown in 1. Oyodo River is located in the Kyushu region of southwestern Japan, with a basin area of $2,230\ km^2$ and a length of $107\ km$. The source of the Oyodo River is Nakadake, and the river's main channel passes through the Miyakonojo Basin, mountainous areas, and the Miyazaki Plain. The river has caused damage from flooding 12 times between 1936 and 2005 due to rainfall during the rainy season. The predicted flood site, Hiwatashi, is located in the middle reaches of the Oyodo River, $52\ km$ from the source, and has a basin area of $861\ km^2$. At Hiwatashi, the government set the river water level of $6\ m$ as the flood warning level and $9.2\ m$ as the flood hazard level to warn of flooding. We constructed the data used for study validation from the river water level history of the Oyodo River, following the work of (Hitokoto et al., 2017). Extract flood events exceeding $6\ m$ from the river water level and precipitation data. One event should be from 72 hours before to 48 hours after the river water level peak. From 1990 to 2014, we have constructed 23 flood events, of which four flood events (1990, 1993, 2004, and 2005) had river water levels exceeding $9.2\ m$. We use fourteen rainfall stations and four river water level stations around and upstream of the basin to obtain data for the same period. We obtained all data from the Water Information System database of the Ministry of Land, Infrastructure, Transport, and Tourism in Japan(Ministory of Land, Infrastructure, Transport, and Tourism in Japan, 2021).

3.2 Conventional ANN for flood forecasting

This section describes the conventional ANN based on the work of Hitokoto et al. (2017). A schematic diagram illustrating flood forecasting with an ANN is presented in Figure 2. The model takes three kinds of input data: river water levels at the forecast location, the river water level at the upstream location, precipitation in the basin, and outputs predicted river water levels. The river water level data for in-

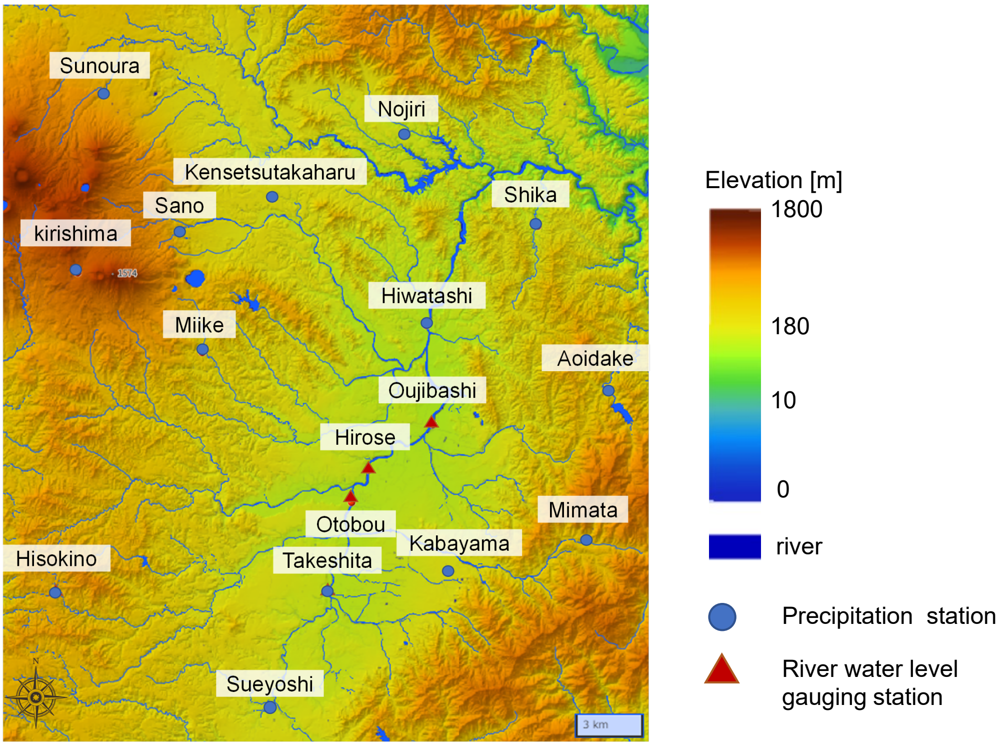

Figure 1. Location of the Hiwatashi gauging station,related rivers and near by stations.This map uses the data from standard elevation map published by Geospatial Information Authority of Japan and edited by NTT Advanced Technology Corporation.

put is hourly data for a certain period for the location of the flood forecast and its upstream locations. The input rainfall is the observed and predicted rainfall at multiple locations in the basin. The ANN model comprises three fully connected layers, with ReLu activation functions applied to the first and second layers. We trained the ANN in two stages. As a pre-training step, the middle layers are optimized as denoising autoencoders. The denoising autoencoders have the same number of output variables as inputs, and it is trained to regenerate input from noise-added input. Next, the learning process is performed using the parameters optimized as denoising autoencoders as the initial values. In this learning process, the river water level and rainfall data are used as input data and river water level data are used as training data. The river water level data is hourly data for a certain period at the flood forecasting location and upstream. The precipitation data are also hourly for a certain period at multiple locations around the basin. This ANN is optimized to minimize the mean squared error between the predicted and actual river water levels. Adam optimizer was used to update parameters. Dropouts were applied to avoid over-fitting. Learning stops after a predetermined number of epochs. The number of neurons in the middle layer, batch size, learning rate, dropout rate, and number of epochs are subject to hyperparameter tuning.

3.3 Prior knowledge and proposed INN architecture

We propose an INN integrating two prior knowledge into an ANN to prevent performance degradation on limited training data. The first knowledge is the rainfall-runoff and water level relationship. The rainfall refers to precipitation, especially in the basin to be forecasted, and runoff refers to the water moving over and un-

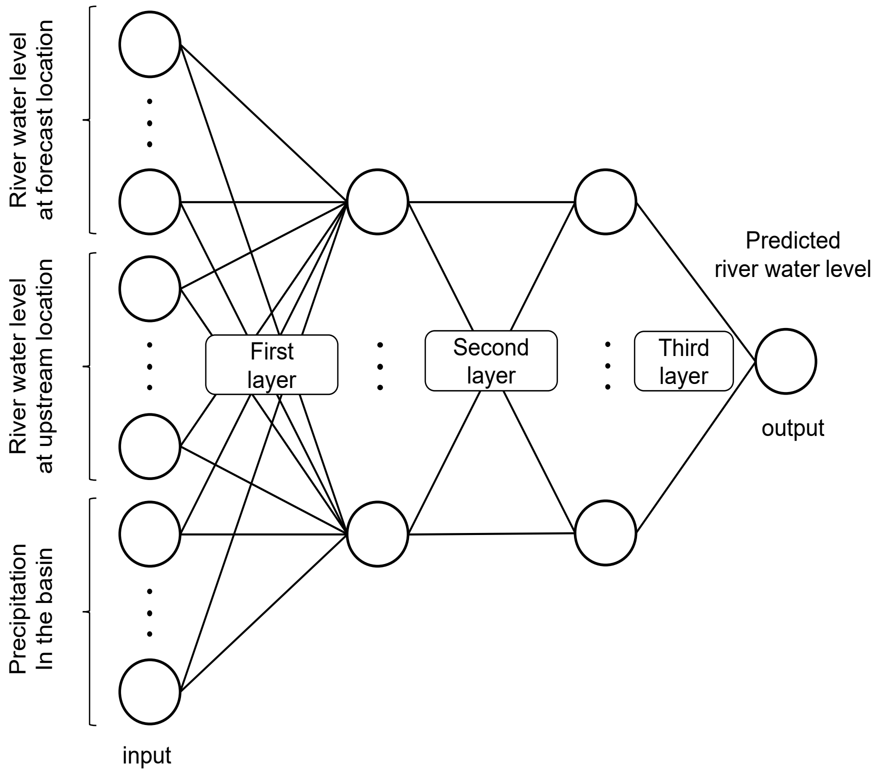

Figure 2. Architecture of conventional ANN. It has three middle leyar and with multiple inputs and one output. The input includes river water level at forecast location, river level at upstream location and precipitation in the basin.

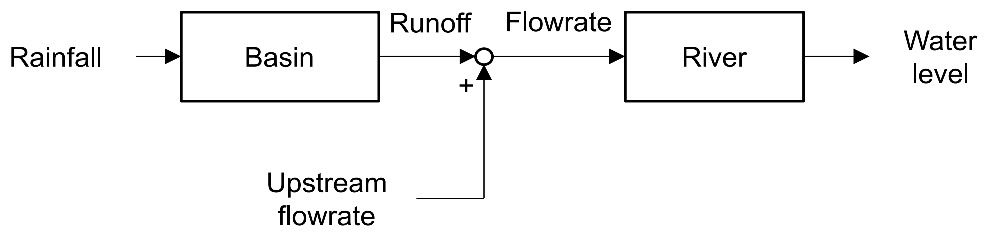

Figure 3. A block diagram showing the relationship between rainfall-runoff and water levels. Rainfall flows into the basin, merges with the upstream flow of the river, and affects water levels.

der the surface of the land in the basin area. Understanding this relationship and deriving flow rate into rivers is one of the significant interests of river engineering. Then, the rainfall-runoff and water level relationship can be understood as shown in the block diagram in Figure 3. First, rain falls on the basin, and the water flows upstream through various pathways. Next, the volume of water from the river upstream is combined to form the river. This flow rate and physical shape define the water level at a point of the river. Integrating this prior knowledge into the ANN is performed by modifying the structure of the NN as shown in figure 4 to mimic the block diagram in figure 3. First, the network is divided into two parts. Part 1 is a NN that converts rainfall in a watershed to river flow. Part 2 is a NN that converts the amount of water from the basin to the river and the flow rate from upstream to the predicted water level. The inputs are the precipitation in the basin to Part 1 and the river level upstream to Part 2. Part1 outputs three kinds of vector named ΔS, R, Q, and ΔS is the input to Part2. This network architecture modification aims to create a model that suits the task of flood forecasting.

The second piece of prior knowledge is the tank model. As mentioned above, the rainfall-runoff relationship is a significant issue in river engineering, and many models have been proposed to explain its behavior. The tank model simulates a basin as a tank and models the relationship between rainfall, basin storage, and runoff. In the tank model, rainfall is fed into the tank, some of it accumulates, and some water flows out as runoff. This model is one of the simplest rainfall-runoff models, and this tank model was chosen for its simplicity of integration into the INN. The tank model is composed of three variables, as follows:

$$\Delta S(t) = R(t - \tau) + Q(t) \tag{1}$$

t is the time each value was observed. τ is the time delay between rainfall-runoff. $\Delta S(t)$ is water strage change in the tank(basin). $R(t - \tau)$ is precipitation with time delay. Q is the runoff flow rate. Equation 1 represents the relationship between rainfall with time delay and conservation of tank storage and runoff. The integration of the tank model into the ANN is done in the following procedure. The output of Part 1, which is responsible for rainfall-runoff, is divided into the tank model variables: rainfall R, tank storage change ΔS, and runoff Q. Next, add the penalty term $loss_{penalty}$ shown below to the loss function.

$$loss_{penalty} = \sum_{i \in n} |\Delta S_i(t) - R_i(t - \tau) - Q_i(t)| \tag{2}$$

n is a predefined number of elements in each vector output from part 1. This is the just transition of the term $R(t - \tau)$ and $Q(t)$ in Equation 1 and when $loss_{penalty} = 0$ Equation 2 is equivalent to Equation 1. And each outputs ΔS, R, Q in 4 are corresoponding to $\Delta S_i(t)$, $R_i(t - \tau)$, $Q_i(t)$ in Equation 2. Since this penalty term is

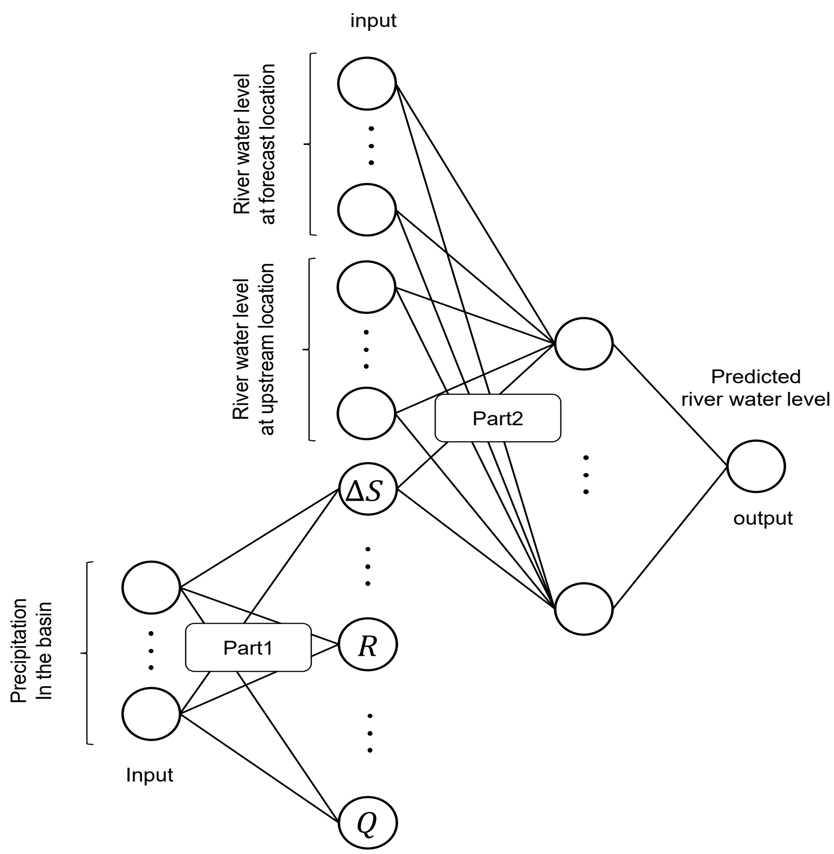

Figure 4. The proposed INN architecture. It is designed to simulate the relationship between rainfall-runoff and water levels. This architecture has two parts: Part1 and Part2. Part1 has precipitation input, and Part2 has Part1 output and water level input.

optimized to be zero during the learning process, it is expected that Part 1 will be optimized to mimic the behavior of the tank model. Moreover, since $\Delta S(t)$ is defined as having a linear relationship with the amount of runoff to the river, $\Delta S(t)$ of Part 1 in Figure 4 is input to Part 2. Note that these two changes are not mathematically complete constraints that satisfy the tank model and rainfall-runoff relationship. Thus the output of Part 1 need not match the values of each variable when the tank model is built for the same basin. Same as conventional ANN, the number of neurons in the middle layer, batch size, learning rate, dropout rate, and number of epochs are subject to hyperparameter tuning.

3.4 Model Development

The same gauging and perception data are used for the ANN and the development of the proposed INN. ANN and INN were optimized to minimize the mean squared error of training data. The model is trained with the water level at time $t+n$, n hours ahead of the Hiwatashi gauging station at time t, as the objective value. The inputs to the model are the water level at Hiwatashi gauging station at time t and one hour ahead at time $t-1$, the water level upstream at time $t, t-1, t-2$ and the hourly rainfall from $t+n-1$ to $t+n-5$ at the precipitation gauging location. Note that the actual rainfall values are used to train and test even if the rainfall values are in the future from time t. The Adam optimizer was used in the training process for each model. Hyperparameter tuning is performed by grid search for the number of training epochs, the number of neurons in the middle layer, the learning rate, and the dropout rate. The data used for development is divided into training data and validation data for hyperparameter tuning, which are separated from test data.

4 Result

Two comparisons were conducted to compare the INN and some conventional methods. The results were evaluated in terms of RMSE. The RMSE is obtained by the following,

$$RMSE = \sqrt{\frac{1}{N}\Sigma_t \left(L(t) - L_{prediction}(t)\right)^2} \tag{3}$$

N is the number of water level samples. $L(t)$ is the water level at time t, $L_{prediction}$ is the predicted water level at time t.

4.1 Comparison with conventional methods for a sufficient amount of training data

The result of the conventional ANN and the proposed method forecast for the Hiwatashi gauging station is shown in Figure 5 and Figure 6 The prediction results follow the transition of the ground truth. During periods of water level over three meters (between two gray dashed lines), the predictions are more consistent with the ground truth than the results of ANN in case of the year 2004 and 2005. Both the ANN and the INN predictions are unstable in the year 1990 and 1993. These unstable predictions may be due to noise in the input observed variables in these test sets.

The RMSE of the flood forecast results at the Hiwatashi gauging station is shown in Figure 7. Conventional methods are ANN, a hybrid of ANN and distributed runoff model (hybrid), distributed runoff model (runoff), embedding, and the proposed method. In addition, ANN1 is the result traced from Hitokoto et al. (2017), and ANN2 is the result of in-house code. The difference between ANN1 and ANN2

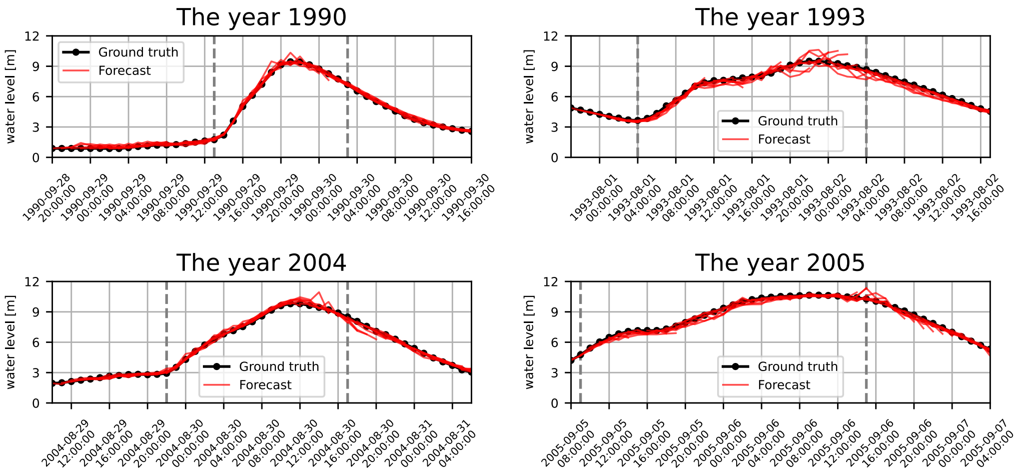

Figure 5. Forecast for the Hiwatashi gauging station in the year 1990, 1993, 2004, and 2005 by conventional ANN2 model. The black points with black lines denote the observed river level as ground truth, and the red solid line shows the forecast river level up to 6 hours ahead. The area between the two gray dotted lines displays the range of data over which the RMSE was evaluated.

is that it uses a framework for implementation, and hyperparameter tuning is performed on a test set and a separate validation set. Figure 7 -(a), (b), (c), and (d) show the results for 1990, 1993, 2004, and 2005. The RMSE for ANN1, hybrid, runoff, and embedding is traced from Hitokoto et al. (2017) and Okuno et al. (2021). Each figure shows the RMSE of the predicted and actual values for the 1 to 6 hourly forecast horizons. Each method's RMSE is distributed in the 0.04 m to 1.2 m range. In the case of the proposed method, the values are distributed in the range of 0.038 m to 0.85 m, and it was never the worst accuracy in all cases. In case (a)Year 1990, the RMSE proposed becomes large when forecasting 5 hours, but in all other years, the RMSE is about the same compared to other methods. Unlike other results, the proposed method and ANN2 are hyperparameter-tuned with a test set and a completely isolated validation set. Considering this difference in experimental conditions, the proposed method has sufficient performance. Based on this result, the domain knowledge which was combined with INN does not cause performance degradation even in the condition of not limited training data.

4.2 Sensitivity analysis about the number on the flood data in the training data

The proposed method should maintain high performance even under conditions where there is not a sufficient amount of data. To verify the performance of INN under such conditions, we performed a sensitivity analysis. The RMSE at the Hiwatashi gauging station with different test data is shown in Figure 8 and Figure 9. We compared the conventional method (ANN2) and the proposed method in this study. Each figure shows the result for 1993 and 2004. In Figure 8, for (a)1 hour forecast and (b)3 hours forecast, the RMSE of INN does not increase as the number of flood events in the training data decreases. On the other hand, in conventional ANN2, the RMSE tends to rise rapidly as the number of flood data becomes smaller. The RMSE value of Proposed is smaller than that of ANN2 when the training set has less number of flood data (6 >). In the (c)6 hours forecast, the magnitude of

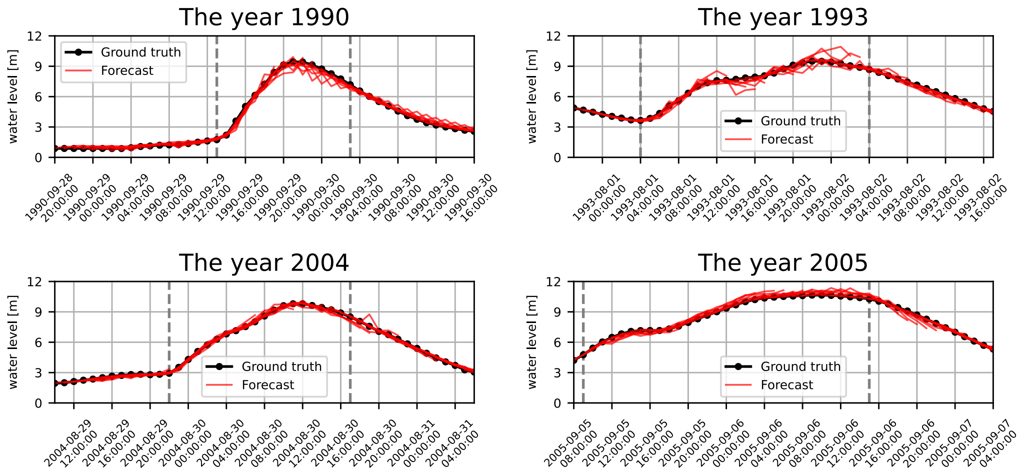

Figure 6. Forecast for the Hiwatashi gauging station in the year 1990, 1993, 2004, and 2005 by proposed INN model. The black points with black lines denote the observed river level as ground truth, and the red solid line shows the forecast river level up to 6 hours ahead. The area between the two gray dotted lines displays the range of data over which the RMSE was evaluated.

Proposed RMSE changes more than in (a) and (b) for the number of flood data. Under conditions where the number of flood data is five or less, three-quarters of the cases have a smaller RMSE than ANN2. The result in Figure 9 has the same trend as in Figure 8. The RMSE value of Proposed is smaller than that of ANN2 when the training set has less number of flood data (5 >). In the (c)6 hours forecast, the magnitude of Proposed RMSE changes more than in (a) and (b) for the number of flood data. Same as Figure 8, under conditions where the number of flood data is five or less, three-quarters of the cases have a smaller RMSE than ANN2.

5 Disscusion and Conclusion

In this study, we proposed a novel approach to flood forecasting methods with NNs. The proposed method is an INN that integrates existing knowledge of rainfall-runoff, river-level relationships, and the tank model in river engineering with conventional ANNs. Integrating the existing knowledge into the INN was performed by modifying the network architecture and adding a penalty term. These two changes aim to improve the initial conditions and the learning process of NNs. We applied the proposed INN to a real-world river in Japan to test its performance. Under conditions where there was sufficient training data, the proposed INN was performed, as well as several critical conventional methods. When the training data was limited, it significantly outperformed the conventional ANN. This difference tended to increase as the forecast horizon became small. The improvement in results is due to changes in the network architecture based on existing knowledge and the addition of a penalty term. This change is assumed to be due to the initial learning conditions and the optimizer's contribution to improving the learning process. These results are a new contribution that shows a practical way to improve the accuracy of INNs with a limited amount of training data. The proposed INN will enable the provision of flood forecasting systems with a short development time in areas where flood forecasting has not been installed, thereby reducing the risk to life during floods. INN

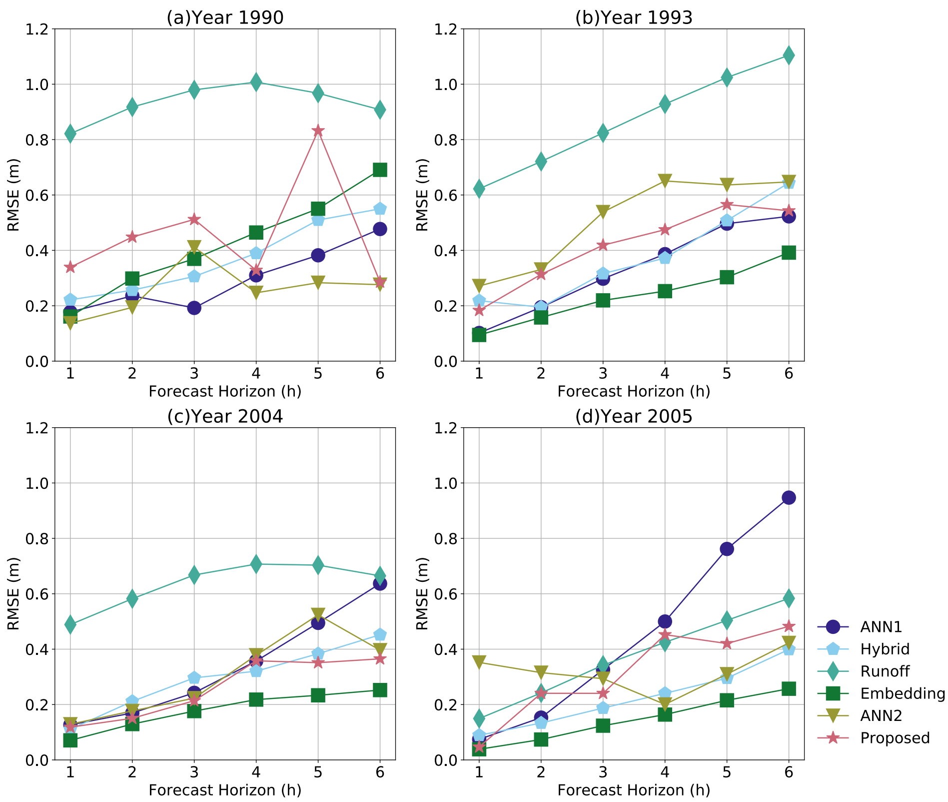

Figure 7. RMSEs of 1 to 6-hour forecasts for 4 test cases (a)year 1990,(b) year 1993,(c)year 2004, and (d)year 2005. We compared the performance of the proposed method with that of ANNs from the literature (ANN1), the distributed runoff-rainfall model (runoff), the hybrid model of ANN and runoff (hybrid), predictions based on dynamical system theory (embedding), and the performance of ANNs based on in-house experimental codes (ANN2). Note that the results for ANN1, runoff, hybrid, and embedding were scanned for values from Hitokoto et al. (2017) and Okuno et al. (2021)

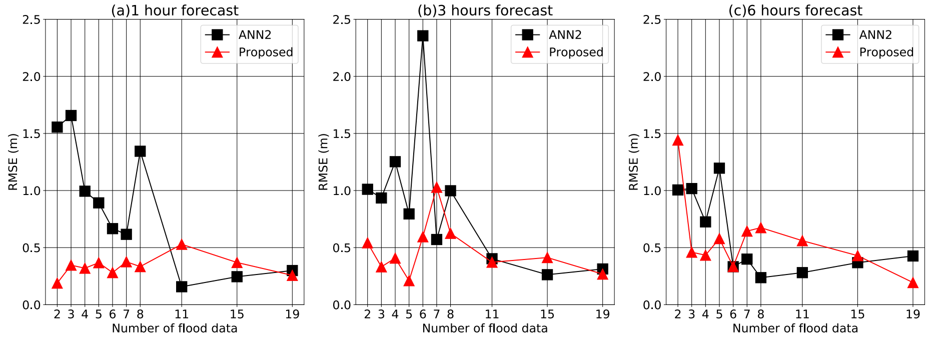

Figure 8. RMSE for 1993 test data versus the number of flood data in the training data set. The red line is the proposed method, and the black line is the conventional ANN with in house implementation (ANN2).

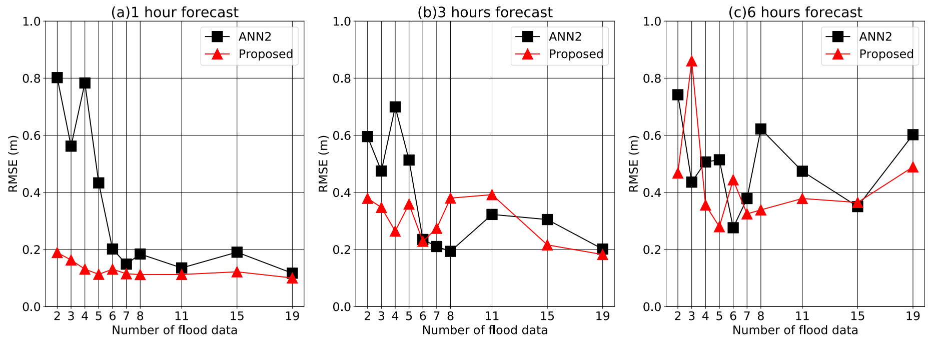

Figure 9. RMSE for 2004 test data versus the number of flood data in the training data set. The red line is the proposed method, and the black line is the conventional ANN with in house implementation (ANN2).

will help to cope with heavy rainfall in unprecedented areas due to recent climate change. Overall, we obtained favorable results for the questions set in section 2.

The future work of this research is the following two. First, the INN proposed in this study was designed to integrate two simple pieces of existing knowledge for ease of implementation. Therefore, the performance when other existing knowledge is integrated has yet to be discovered, and what kind of existing knowledge is more suitable for integration is an important question. Second, the river tested in this study is the only one in Japan, and its performance in other Japanese rivers and rivers around the world with larger basins is still being determined. So, evaluation of the proposed INN on more diverse rivers is necessary. In addition, the performance of the proposed technology for more complex phenomena where factors other than rainfall affect floods is also the subject of future research.

6 Open Research Section

The rainfall and river water level data used in this study are freely available at (Ministory of Land, Infrastructure, Transport, and Tourism in Japan, 2021)(http://www1.river.go.jp/). The data is freely accessible, but you must select a location and time period. Related metadata (location name and time period) is listed in (Hitokoto et al., 2017). The elevation map data is freely available at (Geospatial Information Authority of Japan, 2020)(https://maps.gsi.go.jp/vector/#7).

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