Reconstruction of groundwater level at Kumamoto, Japan by means of deep learning to evaluate its increase by the 2016 earthquake

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Abstract. Groundwater is a very important water resource at Kumamoto City. Kumamoto City is the capital city of Kumamoto Prefecture, which is located in the Kyushu region, Japan. All domestic water is obtained from groundwater in Kumamoto City. Modeling groundwater is a difficult issue. Conditions under the ground are complex, and difficult to be obtained. Even the delineation of a groundwater basin is frequently unknown. Nowadays, deep learning is a hot topic in many research fields including geoscience. A recurrent neural network (RNN) is a type of deep learning that is suitable for time series modeling. Then, it has been successfully applied for groundwater modeling. Therefore, this study utilized a new type of RNN, Long and Short-Term Memory (LSTM) network, to model groundwater level at a monitoring well within Kumamoto City. The results in this study showed good agreement with the observed groundwater. In addition, it is known that severe earthquakes in April 2016 affected the groundwater level around Kumamoto City. The groundwater level model by LSTM was also utilized to estimate the effects of the severe earthquakes on the groundwater level. The results indicated that the earthquakes may have increased the groundwater level at Kumamoto City by more than 3 m.

1. Introduction
Groundwater is a very important water resource at Kumamoto City. Kumamoto City is the capital city of Kumamoto Prefecture, which is located in the Kyushu region, Japan (Figure 1). The population of the Kumamoto Prefecture is approximately 1.74 million. The population of Kumamoto City is approximately 0.73 million. Approximately 42% of the population in Kumamoto Prefecture is in Kumamoto City. Meanwhile, Kumamoto City is the third-largest city in the Kyushu region. Then, approximately 80% of domestic water is obtained from groundwater in Kumamoto Prefecture. All domestic water is obtained from groundwater in Kumamoto City. Also, groundwater is utilized not only for domestic water but also for agricultural and industrial water. It is very important to investigate the conditions of groundwater around Kumamoto City.
Severe earthquakes hit Kumamoto Prefecture in 2016. The first huge earthquake hit at 21:26 (JST) on April 14. The magnitude of the earthquake was 6.5. The second huge earthquake hit at 1:25 (JST) on April 16. The magnitude of the second one was 7.3. Besides, many earthquakes occurred around Kumamoto Prefecture. 1,223 earthquakes were recorded on April 16, 2016. The series of earthquakes caused not only property losses but also human loss. According to the report of Kumamoto Prefecture, 1,665,588 houses were damaged or lost, 93 people were killed, and 2,346 people were injured by the earthquakes. It is also known that these severe earthquakes affected the groundwater.

It is not easy to model groundwater. Groundwater can be modeled with physically-based models, conceptual models, or black-box models. A physically-based model such as ModFlow [1] is based on the governing equations of groundwater. It has several important features. It is literally consistent with the physical processes of groundwater. It can also describe the behavior of groundwater flow. However, it is generally very computationally intensive. Meanwhile, it requires a lot of information under the ground. When it is difficult to obtain sufficient information under the ground, it is difficult to model groundwater properly. A conceptual model is between a physically-based model and a black-box model. A well-known conceptual model may be a tank model. A tank model was applied for modeling groundwater around Kumamoto City [2]. However, a conceptual model generally requires knowledge and experience to properly set up its structure, and it may also require some information of the study area although it will be much less than that required by a physically-based model.

When there is not sufficient information about the study area, it may be a good option to use a black-box model for groundwater modeling. Also, it may be possible to sufficiently supplement the data required for rainfall runoff modeling by using the reanalysis data. Nowadays, machine learning is a hot topic in many research fields, which is known as deep learning. Deep learning was originally developed mainly in the computer science field. However, it has recently been applied or developed in other research fields. There is a type of deep learning that is suitable for time series modeling. The type of deep learning is called Recurrent Neural Network (RNN). Especially, it is known that a new type of RNN, Long and Short-Term Memory (LSTM) network, has the potential to accurately model time series. Therefore, LSTM has been utilized for time series modeling in various research fields including natural science. For instance, LSTM has been utilized for river discharge modeling [3], river

Figure 1. Study area.
discharge forecasting [4–9], precipitation estimation [10–12], reservoir operation modeling [13], lake water level forecasting [14,15], sea surface level modeling [16] and so on. Besides, it has been also employed for some applications of groundwater modeling or forecasting, and these studies were very successful [17–20].

In this context, this study tries LSTM for groundwater modeling at a monitoring well within Kumamoto City and then investigates its applicability by checking the model accuracy. Also, the developed model is utilized to reconstruct groundwater level after the earthquakes. After that, the reconstructed groundwater level is compared with the observation in order to try to quantify the effects of the earthquakes on the groundwater level at Kumamoto City.

2. Study area and Data
This study focuses on groundwater level at a monitoring well within Kumamoto City. The location of the gauging station is non-public because of the regulation. The groundwater level data are available at the daily temporal-scale from April 2011 to December 2019. This station was selected because of the data availability (longer period and fewer missing parts). The groundwater level has yearly fluctuation. Meanwhile, there is some gap in the groundwater level between the periods before and after April 2016. As aforementioned, severe earthquakes happen in the middle of April 2016. Just after the earthquakes, the groundwater around Kumamoto City clearly increased, which was caused by water release due to ruptures at the surrounding mountain aquifers accordint to Hosono et al. (2020) [21].

Daily precipitation and daily mean air temperature data are used as input for the groundwater level modeling in this study. It is expected that a deep learning method can reflect effects of air temperature on the groundwater level thorough evapotranspiration. These data were obtained at the Kumamoto meteorological station from a website operated Japan Meteorological Agency (https://www.jma.go.jp/jma/). The Kumamoto meteorological station is also located in Kumamoto City. The meteorological data are available from 1891 to the present.

3. Methods
3.1. Long and Short-Term Memory network
The Long and Short-Term Memory (LSTM) network is a kind of recurrent neural network (RNN). RNN is a type of neural network, which is categorized into deep learning. RNN has a recurrent block or multiple recurrent blocks. A recurrent block contains learnable parameters such as weights and biases, similar to a traditional neural network.

![Figure 2. LSTM block.](image-url)
Then the learnable parameters of the recurrent block(s) are trained with a set of input data and target data. When RNN receives time series data as input, the recurrent block is literally utilized recurrently. Because of this feature of RNN, RNN can work well with sequential data including time. However, a traditional RNN has a serious problem in its structure. Sometimes a traditional RNN cannot learn long-term dependencies between input data and target data. In general, a deep learning method including RNN is trained with a gradient descent method. During its training process with a gradient descent method, the learnable parameters cannot sometimes be updated properly.

To solve this issue, LSTM was developed by Hochreiter and Schmidhuber (1997) [22] and Gers et al. (2000) [23]. LSTM has several additional functions compared to a traditional RNN. A typical recurrent block of LSTM, which is referred to be as an LSTM block, consists of a cell state and four gates. A cell state works as an internal memory which is considered to keep information during a long-term period. The four gates are called the cell gate, the input gate, the output gate, and the forget gate. The structure of LSTM is illustrated in Figure 2. When using time series data as input, an LSTM block receives input data at a time step. The input data are given to the four gates; the cell gate, the input gate, the output gate, and the forget gate. The information passing through the input gate and the cell gate are integrated. The cell state at the previous step passes through the forget gate. These two kinds of information are kept as the cell state (memory) at the current time step. Then, the information of the memory goes through the output gate. The information out from the output gate is called a hidden state. The hidden state at the current time step is utilized at the next time step together with the input data at the next step. Finally, the hidden state is transformed by the Affine transformation to the shape of the target data, which becomes the output of LSTM. A LSTM block is recurrently used along the time of input time series as shown in Figure 3. After the learnable parameters of RNN are trained, the trained parameters are the same along time.

### 3.2. Application and model configuration

This study implemented a daily groundwater level model at a single point within Kumamoto City utilizing LSTM with daily precipitation data and daily mean air temperature data as inputs. Similar to other deep learning methods, LSTM has several model options, which are called hyper-parameters. This study set the input data length (IDL) as 365 (days). The hidden state length is set to be 50. The aforementioned LSTM block can be multi-layered. This study tried one, two, and four LSTM layers. LSTM is trained with a mini-batch gradient descent method. The batch size is set to be 512. The shuffling batch selection method is utilized to extract batches from the dataset. As the loss function, the mean square error (MSE) is utilized. To adjust the learning rate of the gradient descent method, the Adam optimization algorithm [24] is employed. The activation function is the linear function in this study.

The dataset before the severe earthquakes is utilized to train and verify the model. The dataset before the severe earthquakes is divided into three parts: the training dataset from April 2011 to March 2014, the validation dataset from April 2014 to March 2015, and the test dataset from April 2015 to March 2016. The training dataset and the validation dataset are utilized for the training process. The learnable parameters are updated with the training dataset. The overfitting is checked with the validation dataset.

This training process is conducted with a single LSTM layer, two LSTM layers, and four LSTM layers, respectively. There is some randomness in the training process such as the initial conditions of the learnable parameters. In consideration of the randomness, the training process is conducted 100
times with each configuration. Then, the best result with respect to the loss for the validation dataset is selected as the final trained model for each configuration. Finally, the test dataset is utilized to check the accuracy of the final trained model.

After testing the model, the trained model is also run with the dataset for the period from April 2016 to March 2019, which is the period after the severe earthquakes. Then, the simulated groundwater level is compared with the corresponding observations.

4. Results and Discussions

Table 1 shows the goodness-of-fit test for the test dataset that was obtained by LSTM with different numbers of layers. The correlation coefficient (R), the Nash-Sutcliffe efficiency (NSE), and the room mean square error (RMSE) obtained by LSTM with a single layer are 0.737, 0.271, and 2.361 m, respectively. Those with the two layers are 0.949, 0.850, and 1.070 m, respectively. Then, these statistical values with the four layers are 0.948, 0.858, and 1.042 m, respectively. LSTM with the four layers showed the best accuracy with respect to NSE and RMSE. Contrarily, R is the largest with the two layers. A larger number of layers of LSTM increases the number of learnable parameters (weights and biases). This study set the hidden state length the same among the three configurations. The number of learnable parameters with two layers is double that with a single layer. An increase in the learnable parameters helps LSTM to properly learn the fluctuation of groundwater level.

Figure 4 shows the time series obtained by LSTM with a single layer. LSTM with a single layer clearly underestimates the groundwater level except for the validation period, compared to the corresponding observations. For instance, the maximum groundwater level during the training period (April 2011- March 2014) is 27.7 m in the observation while it is 22.9 m in the simulated results. Figures 5 and 6 show the time series of the groundwater level obtained by LSTM with two layers and with four layers. Both of the simulated results show good agreement with the corresponding observation for all three periods. These results indicate that LSTM has a high potential to model groundwater level at the daily temporal scale.

This study utilized daily precipitation and daily mean air temperature only at a single meteorological station as input to the model. The recharge areas of groundwater around Kumamoto City are much wider. Meanwhile, precipitation generally does not evenly fall. If using two-dimensional precipitation field data as input may improve the model accuracy. On the other hand, it is known that the groundwater at Kumamoto City is also affected by precipitation fall around the city. Precipitation distribution is heterogeneity. However, this study shows high accuracy even though precipitation was obtained from a single point. It may indicate that the flexibility of LSTM for time series modeling.

Table 1. R, NSE, RMSE for the test period obtained by LSTM with each number of layers.

| Layers | R    | NSE  | RMSE |
|--------|------|------|------|
| 1      | 0.845| 0.903| 0.878|
| 2      | 0.847| 0.841| 0.850|
| 4      | 0.837| 0.912| 0.909|
Finally, the trained model with the four layers was run for the period from April 2016 to quantify the increase in the groundwater level after the severe earthquakes. The difference in the groundwater level between the simulated results and the corresponding observations is 0.206 m during the period from April 2015 to March 2016 on average. Contrarily, it suddenly becomes large just after April 2016 as shown in Figure 7. The difference is 3.29 m from April 2016 to March 2017, 3.36 m from April 2017 to March 2018, and 1.81 m from April 2018 to March 2019. The observed groundwater level is more than 3 m larger than simulated results for two years. Then the difference reduces in 2018. Because the trained model accurately models the groundwater level before the severe earthquakes, it may be able to be considered that the gap between the simulated results and the corresponding observations is caused by the severe earthquakes.

5. Conclusions
This study utilized a deep learning method, LSTM, to model groundwater level at a single point within Kumamoto City, Japan. The results show that LSTM is capable to model groundwater level in the study area. Meanwhile, the trained model is utilized to quantify the increase in the groundwater by the severe earthquakes that occurred in April 2016. The results in this study indicate that severe earthquakes increase the groundwater level at the study point by more than 3 m.

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