Effects of the spatial and temporal resolution of meteorological data on the accuracy of precipitation estimation by means of CNN

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Abstract. Future climate projections are valuable datasets to investigate the impacts of future climate changes on natural disasters such as intense precipitation, severe flood, and drought. However, they are too coarse depending on the purpose, and downscaling is required in such a case. There is nowadays a downscaling technique using deep learning such as CNN. Atmospheric information can be used as an input for precipitation downscaling by means of Convolutional Neural Network (CNN). For such precipitation downscaling, the spatial and temporal resolution of the atmospheric information may be important. This study obtained atmospheric information from a coarser reanalysis dataset and a finer reanalysis dataset as input for precipitation downscaling. As a coarser reanalysis dataset, ERA-Interim was selected. As a finer reanalysis dataset, ERA5 was utilized. Then, this study investigated the effect of spatial and temporal resolution of input data on the estimation accuracy of precipitation downscaling by CNN. For simplification, daily average precipitation at a watershed was used as the target data. The results show advantage of the use of a higher resolution as input can improve the model accuracy.

1. Introduction
In recent years, meteorological disasters have become more frequent and severe in the world. Global warming is considered to be a cause. There is a possibility that the magnitude and frequency of meteorological disasters will increase due to global warming in the future. Under such circumstances, it is very important to predict future precipitation in consideration of global warming to reduce damage caused by meteorological disasters such as floods and droughts.

Future climate projections are often used to predict future precipitation. Basically, future climate projections are obtained by numerical simulation using a general circulation model based on future prediction scenarios. Hence, future climate projections are valuable to assess the impacts of climate change.
However, resolutions of future climate projections data are generally too low for regional or watershed scale assessments. Downscaling is necessary for attaining high-resolution data from future climate projections. Dynamic downscaling and statistical downscaling have mostly been utilized as downscaling methods. In addition to these methods, nowadays, deep learning is used for downscaling. In the field of hydrology, many studies have been conducted on the applicability of various types of deep learning methods. There are various types of deep learning methods, and in recent years Long Short-Term Memory (LSTM) network, Convolutional Neural Network (CNN), and Convolutional LSTM Network (ConvLSTM) have been mainly applied in the field of hydrology. PAN et al. (2019) [1] estimated precipitation by utilizing CNN. The GPH and PW field data are used as inputs. The results showed CNN has applicable to precipitation estimation. Sadeghi et al. (2019) [2] proposed Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks CNN (PERSIANN-CNN). In the study, CNN was trained with bispectral satellite imagery (infrared and water vapor) as input data and precipitation rate as target data. The study showed that CNN outperforms the baseline model. Kratzert et al. (2018) [3] successfully utilized LSTM for rain-runoff modeling. SHI et al (2015) [4] proposed the ConvLSTM for precipitation nowcasting. The ConvLSTM used the radar echo data (it recorded every 6 minutes) used as input data and predicted 15 frames ahead. All in all, the high applicability of deep learning methods to the field of hydrology has been shown. Compared to these deep learning methods, ConvLSTM requires a huge calculation cost. As for LSTM, it is good at analyzing time-series data. However, LSTM cannot reflect spatially information in input data. Hence, LSTM is not very suitable for downscaling where the input data is two-dimensional. Then, CNNs are thought to be able to extract spatial features efficiently. Therefore, CNNs are more suitable for downscaling among deep learning methods.

The applicability of CNN to downscaling precipitation was investigated in many previous studies. In precipitation downscaling by means of CNN, in general, precipitation distribution is used as input and spatial information is refined, or precipitation is estimated from atmospheric variables. Regarding the latter, Miao et al. (2019) [5], implemented 2D CNN for precipitation downscaling and showed the high possibility of application because of its high estimation accuracy. Nagasato et al. (2020) [6] investigated the characteristics of precipitation downscaling using 2D CNN. Additionally, they revealed that CNN can estimate precipitation at basin levels with high accuracy. These results of the studies show that CNNs have a large potential to estimate time-series precipitation with high accuracy. Nagasato et al. (2020) suggest that the estimation accuracy may change when the horizontal resolution of the input data changes. In recent years, ERA5, which has a higher spatiotemporal resolution are available although the previous studies used ERA-interim. The temporal resolution and spatial resolution of ERAI are 6 hours and 0.75 degrees, respectively. On the other hand, ERA5 has 6 times higher temporal resolution and 3 times higher spatial resolution than ERAI. It may be possible to improve the results of precipitation estimation by using ERA5 as input.

Therefore, this study investigated the effect of spatiotemporal resolution of input data on estimation accuracy in precipitation downscaling by CNN. CNN was implemented with the atmospheric variables extracted from ERA5 and ERA-Interim. As the target data, the daily average precipitation at the basin level was used. Similarly, this study implemented a CNN that uses atmospheric variables extracted from ERA-interim as input and made a detailed comparison between the two. Regarding the comparison between the two, detailed comparisons and examinations were conducted under various structural and hyperparameter setting conditions.

2. Methodology

2.1. Convolutional Neural Network
Convolutional Neural Network (CNN) which is a kind of deep Neural Network has been successfully applied to image recognition. CNN is composed of several types of layers such as convolutional layers, pooling layers, and fully connected layers. Generally, CNN has a structure in which convolution layers and pooling layers are connected alternately. The most characteristic algorithm of
CNN is the processing in the convolutional layer. In the convolution layer, the filter is slid into the input data and the feature is extracted by performing the product-sum operation (convolution operation). In the pooling layer, a filter is applied to the data output from the convolution layer to reduce the spatial size of the input data. A pooling layer is also used to accommodate changes in the position of features in the feature map. Hereafter, the filters used for input/output data and feature extraction in the convolution layer are called feature maps and kernels, respectively. In the fully connected layer, feature maps are formed into output shape. The kernel at the convolutional layer, bias, and weights at the fully connected layer are trained with the gradient descent procedure.

3. Study area
As the study area, Shira River Basin (SRB) was selected as the study area (Figure 1). SRB is located in the northern part of the Kyushu region of Japan. The length of the Shira River is 74 km. The area size of the SRB is 480 km$^2$. The upstream of Shira River is located in Aso caldera. In addition, there is a raised riverbed downstream of Shira River.

4. Dataset
This study uses atmospheric reanalysis data as input, and uses observed precipitation data as target data. The daily watershed-scale precipitation was calculated from observed daily precipitation data. The observation precipitation data were obtained from the Asian Precipitation-Highly-Resolved Observational Data Integration Towards Evaluation Data of Water Resources (APHRODITE) [7]. APHRODITE is continental-scale daily precipitation grid data based on rain gauge observation data with a resolution of 0.05-degree x 0.05-degree (about 5km). It covers the entire Japan spatially, and the 112 years from 1900 to 2015 temporally. In this study, the daily average precipitation in the target basin was calculated from APHRODITE.

Atmospheric variables were obtained from ERA-interim (ERAI) and ERA5 atmospheric reanalysis data, from the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA-interim and ERA5 are atmospheric reanalysis dataset. ERAI covers the entire world and from 1 January 1979 to 31 August 2019. ERA5 covers the entire world and from 1 January 1979 to the present. The spatial resolution of ERAI is 0.75-degree x 0.75-degree (about 80km) and the temporal resolution is 6 hourly. On the one hand, the spatial resolutions and temporal resolution of ERA5 are 0.25-degree x 0.25-degree and hourly. ERA-Interim and ERA5 contain three-dimensional atmospheric variables on 37 pressure levels from 1 hPa to 1000 hPa. From ERA-interim and ERA5, this study obtained various atmospheric variables at 300/500/700/800/850/925/1000 hPa (Table.1). Regarding variables, U component of wind, V component of wind, W component of wind, specific humidity were selected based on the research results of Nagasato et al. (2020).

Figure 1. Shira River Basin, Kyushu region, Japan.
5. Model Implementation

This study employed PyTorch which is a framework of deep learning in Python. As the loss function, the Mean Square Error (MSE) is selected. Adam [8] is used as the optimizer. Epoch is set to 200. As a pooling method, Max-pooling was selected for pooling layers to emphasize the edges in the input data. The softplus function [9] is set as the activation function so that precipitation is not estimated to be a negative value. The mini-batch gradient descent method was used to save cost in the calculation. The number of data contained in the subset is called the batch size and was set to 512 in this study. The basic architecture of CNN is illustrated in Figure 2.

As aforementioned, the horizontal resolution is different between ERAI and ERA5. The horizontal resolution of ERA5 is three times finer than that of ERAI. This study obtained variables from two horizontal ranges: 6x6 and 8x8 grids for ERAI, and 16x16 and 22x22 for ERA5. These smaller and larger grid areas of each reanalysis dataset cover the same areas, respectively. The temporal resolution is also different between ERAI and ERA5. The temporal resolution of ERAI is 6 hourly. There are four time steps of 3:00, 9:00, 15:00, and 21:00 within a day in Japan Standard Time. The temporal resolution of ERA5 is hourly. There are 24 time steps within a day. To estimate daily basin-average precipitation at the study watershed, this study uses six time steps of ERAI. In addition to the above four time steps within the day, two time steps (21:00 on the previous day and 3:00 on the next day) are utilized.

With these input data, the model accuracy is compared with ERAI and ERA5. For the comparisons, several configurations are tried to increase the reliability of the comparison results. First, two and three sets of the layers (the convolutional layer, the batch normalization layer, and the max pooling layer) are tried, which are referred to be as 2L and 3L. In addition, the number of the output channel of the first convolutional layer is set to be 16, 32, or 64. As described above, two different sizes of the grid area are utilized. Then, to investigate the effects of the spatial and temporal resolution separately, this study utilizes not only 24 steps within a day from ERA5, but also extracted the same six time steps from ERA5 as ERAI. The configurations used for the comparisons are shown in Table 1-2.

With each configuration, CNN is trained with the training dataset during the period 1980-2005, is validated with the validation dataset during 2006-2010, and is tested with the test dataset during 2011-2015. During the validation period, it is confirmed whether overfitting has occurred, and during the test period, the estimation accuracy of the model is evaluated. The learning process of CNN has randomness depending on the initial conditions and batch selection. Hence, in this study, learning is performed 50 times with each configuration. Among the 50 trained results, the best model is selected, and then it is tested with the test dataset. To evaluate model estimation accuracy, this study utilizes the root mean square error (RMSE), the correlation coefficient (R), and the Nash-Sutcliffe efficiency (NSE).

![Figure 2. Basic architecture of CNN.](image-url)
Table 1. The configurations used for the comparisons of spatial resolution.

| Case | S1 | S2 | S3 | S4 | S5 | S6 |
|------|----|----|----|----|----|----|
| data | S1-1 | S2-3 | S3-5 | S4-9 | S5-11 | S6-13 |
| Channel | ERA-interim | ERA-interim | ERA-interim | ERA-interim | ERA-interim | ERA-interim |
| Grid size | 6 x 6 | 6 x 6 | 8 x 8 | 6 x 6 | 8 x 8 | 6 x 6 |
| Structure | 2L | 3L | 2L | 3L | 2L | 3L |

Table 2. The configurations used for the comparisons of temporal resolution.

| Case | T1 | T2 |
|------|----|----|
| Time range | T-1 | T-3 |
| Structure | 2L | 3L |
| Grid size | 6 | 16 x 16 |

6. Results and Discussion
First, ERAI and ERA5 were compared with the three numbers of output channels and with 2L and 3L. In these cases, only six time steps were utilized from ERA5 in order to investigate the effects of the spatial resolution of the model. Meanwhile, 6x6 and 16x16 of the grid size were utilized for ERAI and ERA5, respectively. Table 3-4 shows the three statistics (RMSE, R, RMSE) for the test period. Except in S5, ERA5 show better statistical values compared to ERAI. For instance, in S2, the use of ERA5 improved the NSE value by 0.011-0.073, the RMSE value by 0.21-1.098 mm, and the R value by 0.002-0.044. Figure 3 shows the NSE values for the two periods: the training period, the validation period. Because there are 100 trained results with each reanalysis dataset with each configuration, the results are illustrated by boxplots. These boxplots more clearly show the advantage of ERA5. For instance, the median values of NSE obtained with ERA5 are higher than those with ERAI in all the cases. The median values were improved by 0.087-0.132 for the training period and 0.001-0.012 for the validation period by using ERA5.

The same comparisons are conducted with 8x8 and 16x16 of grid size for ERAI and ERA5, respectively. These results (S3-6 and S3-8, and S6-14 and S6-16) are also shown in Table 3 and Figure
3. Basically, the increase in the grid size does not clearly increase the model accuracy with ERAI and ERA5. For the training period, the three statistical values with 2L were worsened by the larger grid size for both of the reanalysis dataset. They were improved with 3L. However, the NSE values were generally worsen for the validation period (Figure 3). Consequently, the use of ERA5 has still advantage over ERAI in these cases, too.

**Table 3. NSE values for the test period (Effects of the spatial resolution of input data on the accuracy).**

| Case | Training | Validation | Test |
|------|----------|------------|------|
|      | NSE_max | NSE_median | NSE_max | NSE_median | NSE | RMSE | R   |
| S1   | 0.948   | 0.743      | 0.742   | 0.718       | 0.675 | 11.8 | 0.827 |
| S1-2 | 0.956   | 0.851      | 0.764   | 0.719       | 0.686 | 11.6 | 0.829 |
| S2   | 0.934   | 0.757      | 0.745   | 0.719       | 0.642 | 12.4 | 0.805 |
| S2-4 | 0.941   | 0.861      | 0.766   | 0.727       | 0.715 | 11.0 | 0.849 |
| S3   | 0.944   | 0.753      | 0.755   | 0.721       | 0.675 | 11.8 | 0.827 |
| S3-6 | 0.955   | 0.765      | 0.755   | 0.717       | 0.644 | 12.3 | 0.804 |
| S3-7 | 0.947   | 0.840      | 0.753   | 0.727       | 0.722 | 10.9 | 0.854 |
| S3-8 | 0.954   | 0.855      | 0.752   | 0.723       | 0.669 | 11.9 | 0.820 |
| S4   | 0.924   | 0.749      | 0.748   | 0.716       | 0.659 | 12.1 | 0.815 |
| S4-9 | 0.952   | 0.880      | 0.756   | 0.727       | 0.703 | 11.3 | 0.841 |
| S5   | 0.949   | 0.742      | 0.745   | 0.721       | 0.703 | 11.3 | 0.848 |
| S5-11| 0.958   | 0.870      | 0.768   | 0.732       | 0.684 | 11.6 | 0.833 |
| S5-12| 0.935   | 0.738      | 0.744   | 0.720       | 0.631 | 12.6 | 0.807 |
| S6   | 0.940   | 0.740      | 0.744   | 0.715       | 0.693 | 11.5 | 0.836 |
| S6-15| 0.946   | 0.854      | 0.764   | 0.732       | 0.693 | 11.5 | 0.835 |
| S6-16| 0.965   | 0.852      | 0.752   | 0.727       | 0.715 | 11.0 | 0.856 |

**Figure 3. NSE values for the training and validation periods (Effects of the spatial resolution of input data on the accuracy).**


The effects of the used time steps of ERA5 were also investigated as shown in Table 4 and Figure 4. The use of the hourly time steps (24 hours within a day) improved the model accuracy compared to the use of the six-hourly time steps. For the test period, the NSE, RMSE, and R values were improved by 0.041, 0.84 mm, and 0.021, respectively, with 2L. They were improved by 0.019, 0.36 mm, and 0.010, respectively, with 3L. There are some reductions in the NSE values for the training period by using the hourly time steps. However, generally NSE value for the training period is clearly higher than for the other two periods. The results may indicate that the use of the hourly time steps mitigates overfitting to the training dataset and improve the results for the other periods.

Table 4. NSE values for the test period (Effects of the temporal resolution of input data on the accuracy).

| Case | Training | Validation | Test |
|------|----------|------------|------|
|      | NSE_max  | NSE_median | NSE_max | NSE_median | NSE | RMSE | R   |
| T1   |          |            |        |            |     |      |     |
| T-1  | 0.947    | 0.840      | 0.753  | 0.727      | 0.722| 10.9 | 0.854|
| T-2  | 0.928    | 0.775      | 0.771  | 0.742      | 0.763| 10.1 | 0.875|
| T2   |          |            |        |            |     |      |     |
| T-3  | 0.946    | 0.854      | 0.764  | 0.732      | 0.693| 11.5 | 0.835|
| T-4  | 0.948    | 0.785      | 0.772  | 0.745      | 0.712| 11.1 | 0.845|

Figure 4. NSE values for the training and validation periods (Effects of the temporal resolution of input data on the accuracy).

7. Conclusion
This study investigated effects of the spatial and temporal resolution of meteorological data on the accuracy of precipitation estimation by means of CNN. For the purpose, the two reanalysis dataset with different spatial and temporal resolutions, ERAI and ERA5, were utilized. The results show advantage of the use of a finer resolution as input can improve the model accuracy. Not only the spatial resolution of the meteorological data, but also their temporal resolution affects the model accuracy. The goal of the series of this study is to develop the methodology to accurately downscale precipitation from coarse resolution data because future climate projections are generally coarse. Increase in resolution of future climate projections them may be valuable.
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