

Sensitivity analysis of the hyperparameters of CNN for precipitation downscaling

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I. Introduction

Nowadays, a convolutional neural network (CNN), which is a kind of deep neural network has been shown to have high applicability to precipitation downscaling in previous studies[1-2]. CNN has various hyperparameters, which greatly affect the estimation accuracy. In the field of computer science, researches on hyperparameter settings have been conducted, especially for image recognition. However, there are few studies that investigated the sensitivity analysis of hyperparameters on precipitation downscaling by means of CNN. Therefore, this study conducted a sensitivity analysis of the hyperparameters of CNN for precipitation downscaling. For this study, atmospheric reanalysis data were used as the inputs for precipitation downscaling by means of CNN, and daily average precipitation at the basin level were used as the target data. Then, this study focused on the hyperparameters of CNN that have a great influence on the feature extraction of input data (such as kernel size, number of output channels in the convolutional layer, etc.). Considering that the learning process of CNN has randomness, CNN was trained 100 times for the setting conditions of each hyperparameter and evaluated the estimation accuracy.

II. Methodology

CNN is basically composed of convolutional layer, pooling layer, and fully-connected layer. Convolution layer extracts features from the inputs by means of kernel.

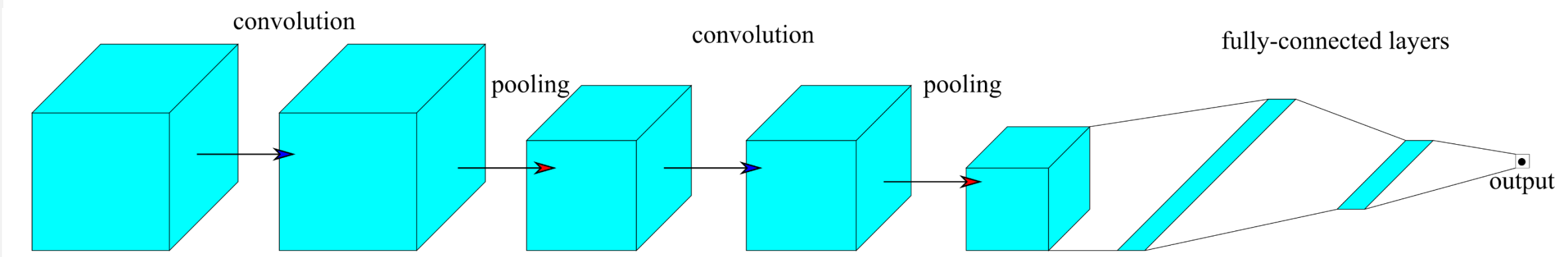


Figure 1. CNN structure

III. Study Area and DataSet

Study Area

- The Shira River Basin (SRB), Kyushu region, Japan was selected as the study area (Fig.1).
- The Shira River Basin (SRB) was selected as the study area.
- The length of the Shira River is 74 km.
- The area size of the SRB is 480 km².

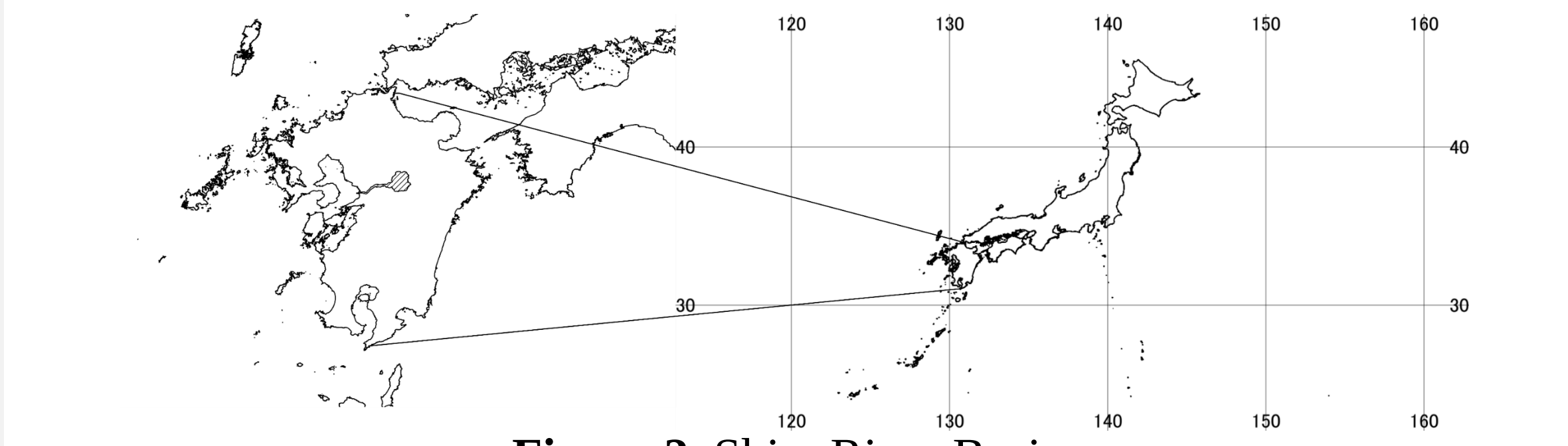


Figure 2. Shira River Basin

Dataset

To train, validate, and test for LSTM rain-runoff modeling, this study uses observed daily flow discharge and daily observed precipitation data.

Input data: APHRODITE [3]

- It is gridded daily precipitation data based on gauging observation data.
- It covers the entire Japan spatially with a resolution of 0.05-degree x 0.05-degree (about 5 km), and the 112 years from 1900 to 2015 temporally.
- This study calculated basin-average values at the study watershed from APHRODITE.

Target data: ERA-interim (atmospheric reanalysis data)

- It spatially covers the entire world, and temporally ranges from 1 January 1979 to August 2019.
- It provides various three-dimensional atmospheric variables on 37 pressure levels from 1 hPa to 1000 hPa.
- The horizontal resolution is 0.75-degree x 0.75-degree (about 80 km), and the temporal resolution is 6 hourly: 0:00, 6:00, 12:00, and 18:00r UTC.

IV. Model Implementation

- 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.
- The dataset is divided into three datasets: the training dataset (1980-2005), the validation dataset (2006-2010), and the test dataset (2011-2015).
- For the evaluation of model accuracy this study selected the Nash-Sutcliffe efficiency (NSE)[4],
- The combination of precipitation data at the integration intervals shown in the table was used as input data.
- The training processes of CNN have randomness. Therefore, the training processes with the training and validation datasets are repeatedly conducted 100 times.
- This study compared the estimation accuracy of 100 learning results using a box plot.

$$NSE = 1 - \frac{\sum_{t=1}^T (P_{obs}^t - P_{sim}^t)^2}{\sum_{t=1}^T (P_{obs}^t - \overline{P_{obs}})^2}$$

* T denotes the calculation time, P_{obs}^t and P_{sim}^t denote the observed precipitation and estimated flow rate at time t , respectively, and $\overline{P_{obs}}$ denotes the average value of the observed flow rate.

Table 1. Variables
Variable
specific humidity (q)
meridional wind speed (u)
zonal wind speed (v)
vertical wind speed (w)

Table 2. The configurations used for the comparisons of kernel size.			
Case	Kernel Size	Channel	Structure
K1	3	64	2L
K2	4		
K3	3		3L
K4	4		

Table 3. The configurations used for the comparisons of number of Channels.

Case	Channel	Structure
C1	16	2L
C2		3L
C3		2L
C4	32	3L
C5		2L
C6	64	3L

V. Results

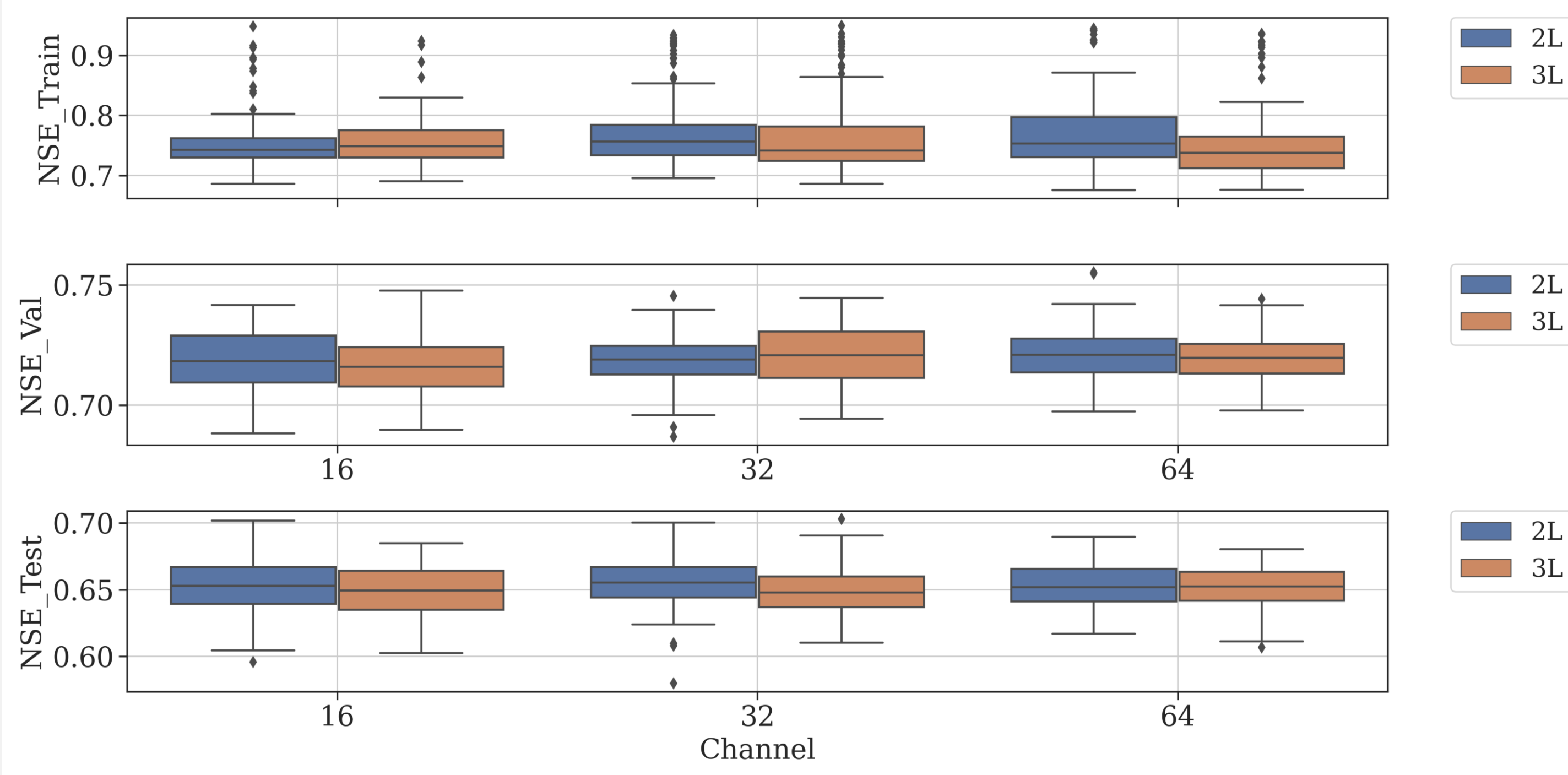


Figure 3. The effect of the number of channels and CNN structure.

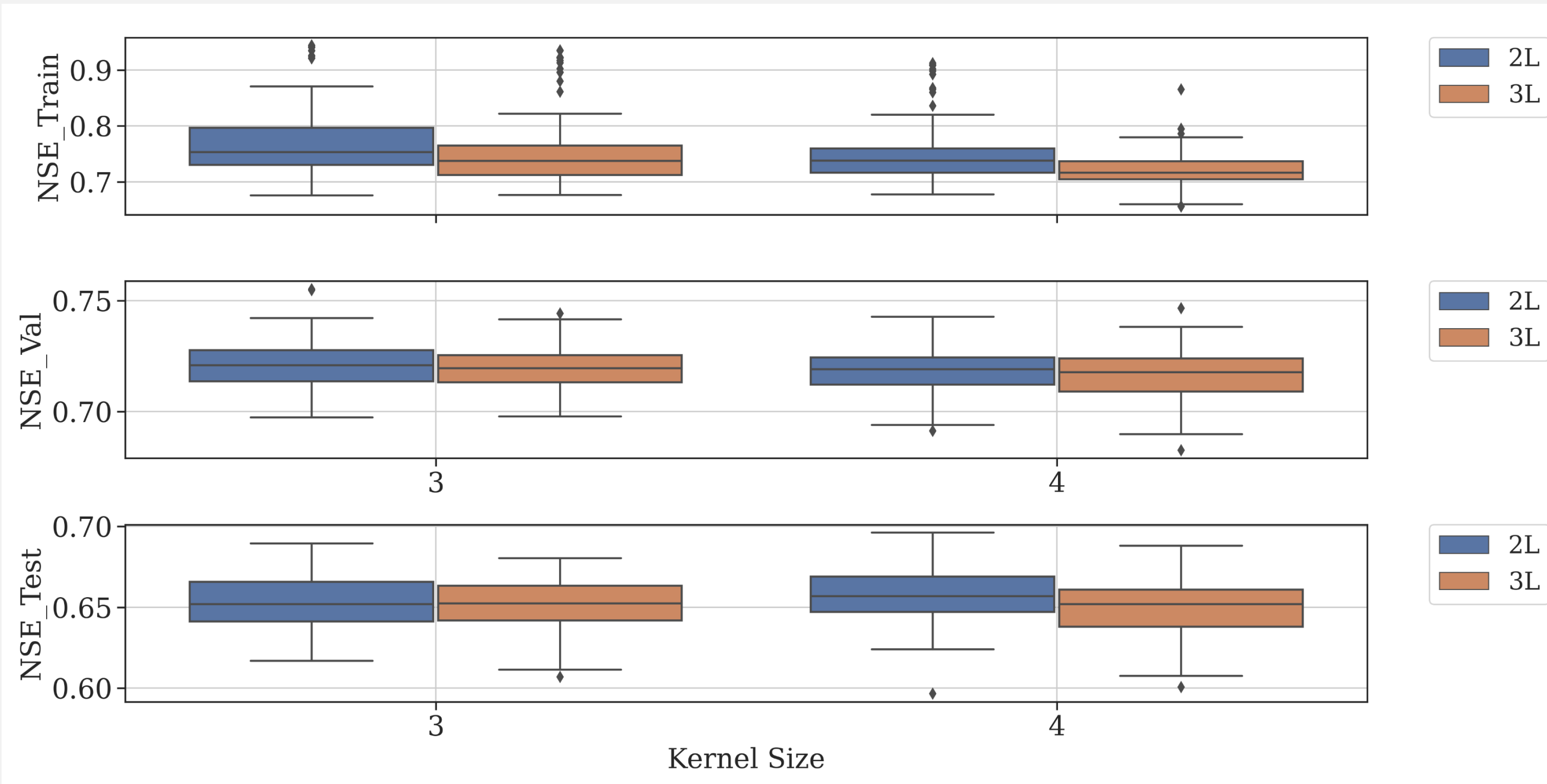


Figure 4. The effect of kernel size.

VIII. Discussion

- 2L was more accurate than 3L in many cases. Therefore, it was shown that the estimation accuracy does not always increase even if the structure of the CNN is deep.
- Case 1 had the highest estimation accuracy during the test period.
- The estimation accuracy did not improve clearly even if the number of channels was increased.
- When the CNN structure was 2L, increasing the kernel size showed a slight decrease in accuracy during the training period. On the other hand, the accuracy improved slightly during the validation/test period.
- As the results, it was shown that the estimation accuracy fluctuates greatly even if the hyperparameter settings are the same. This is thought to be due to the initial value of the weight and batch selection.

VII. Conclusions

This study conducted a sensitivity analysis of the hyperparameters of CNN for precipitation downscaling. Atmospheric reanalysis data were used as the inputs for precipitation downscaling by means of CNN, and daily average precipitation at the basin level were used as the target data. This study focused on the hyperparameters of CNN that have a great influence on the feature extraction of input data (such as kernel size, number of output channels in the convolutional layer, etc.).

As the results of detailed sensitivity analysis, it was shown that the estimation accuracy may not be improved even if the structure of CNN deeper. Contrarily, It was also shown that initial conditions such as batch selection and bias in the CNN learning process may have relatively large effects on the learning results.

References

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