第 II 部門

Convolutional Neural Network with Multiple Atmospheric Variables to Emulate Dynamic Downscaling Process of RCM

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1．Background of the study General circulation models (GCMs) are powerful tools widely used in hydrological prediction, however their coarse grids make them unsuitable for regional analysis, therefore, a downscaling method is required to utilize the GCM output in regional scale assessment. Dynamical downscaling (DDS) considers physical background and recalculates the GCM output as boundary conditions to obtain higher resolution information in a smaller domain. However, DDS requires many computational resources. As one of the downscaling methods that do not require significant computational resources, convolutional neural network (CNN)-based downscaling has been proposed in recent years. The aim of this study is to emulate the process of DDS using CNNs by applying GCM output as input data and regional climate model (RCM) output as label data.

2． Data and Objective Area The data used in this experiment is output from an AGCM, a model developed by the Japan Meteorological Agency (JMA) and the Meteorological Research Institute (MRI) under the project of Kakushin (2007-2011) and Sousei (2012-2016). In this study, d4PDF global data was utilized as an input, and regional downscaled data of d4PDF around Japan (119.63 ° to 149.44 ° longitude and 24.83 ° to 47.13 ° latitude) were utilized as an output. Here, the global data (coarse resolution) provides 60 km or 133 km resolution, and regional data provide 20 km resolution. The variables and resolution of the data available in this experiment are summarized in Table.1. As for the period covered in the experiment, only August of each year from 1980 to 2000 were used.

Table. 1 Variables in d4PDF

Data type		Variables
Label	20km	Precipitation
		Surface air temperature
Input	60km	Precipitation
		Surface air temperature
		Surface air humidity
		Total cloud content
		Sea-level pressure
	133km (500hPa, 850hPa)	Temperature
		Geopotential
		Cloud water content
		Vertical pressure velocity

Table. 2 Hyperparameter setting

Hyper parameter	Setting
Filter size	3×3
Number of layers and units	5 levels (28 Conv) 64 - 128 - 256 - 512 – 1024
Activation function	ReLU
Pooling	Max Pooling
Batch size	31
Epoch	300
Learning rate	0.0002

3．Experimental Design U-Net is one type of CNN model which has Encoder-Decoder structure proposed by Ronneberger et. al.[1] (2015) and its structure is shown in Fig.1. Three experiments are conducted, which investigate the effect of input dataset, hyperparameters, and label dataset respectively. Basic hyperparameter settings of the model are shown in Table.2.

In experiment 1, the label data is 20km precipitation, and input datasets are changed for four conditions. Exp.1-A contains all 5 input from variables in 60km while Exp.1-B contains the same input as Exp.1-A except for precipitation. Exp.1-C contains 9 input (all 8 variables in 133km, and precipitation) while Exp.1-D contain the same input as Exp.1-C except for precipitation.

In experiment 2, input dataset and label dataset are the same as Exp.1-C because its condition is considered as the closest to

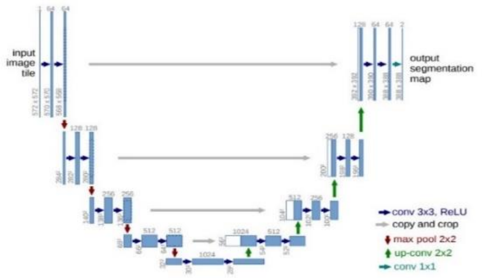

Fig. 1 The structure of U-Net

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that of RCM, and hyperparameters are changed four five conditions. Exp.2-3L and Exp.2-7L changes the number of convolutional layers to 3 and 7 levels respectively. Exp.2-F5 changes the filter size to 5 × 5. Exp.2-FRL changes the activation function to FReLU which is proposed by Ma et. al.[2] (2020) and is specialized for image recognition. Exp.2-NP replaces pooling layers to convolutional layers.

In experiment 3, input dataset and hyperparameters are the same as Exp.1-C and label dataset is changed for three conditions. Exp.3-3P contains three consecutive precipitation information with 6hours interval (t_{-1}, t_0, t_{+1}), while Exp.3-5P contains five (t_{-2}, t_{-1}, t_0, t_{+1}, t_{+2}). Exp.3-TP contains precipitation and temperature. The outputs from each model are averaged over month for analysis. We analyze the data both qualitatively and quantitatively. Qualitatively, we obtain image, and quantitatively, we calculate RMSE and Modified RMSE which only considers the values higher than threshold (1.0).

4. Result and Discussion The result of three experiments are shown in Fig.2. In experiment 1, the focus is 1) the cases with and without precipitation, 2) the cases with 2D and 3D information. For the first comparison, the value of Exp.1-B is significantly smaller than that of Exp.1-A. These results indicate that the coarse information of precipitation might even prevent more accurate prediction. For the second comparison, the result of Exp.1-B was significantly smaller than that of Exp.1-D. Between Exp.1-A and Exp.1-C, there is no

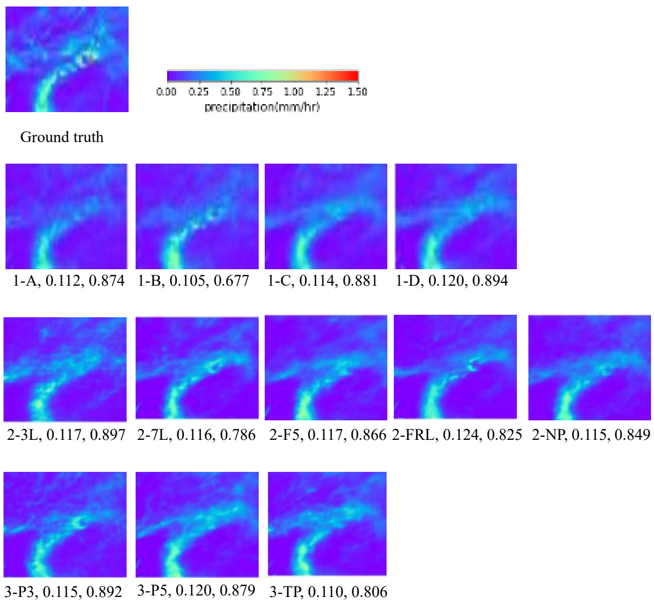

Fig. 2 Result of monthly average

(Experiment condition, RMSE [mm/h], Modified RMSE [mm/h])

significant difference quantitatively but qualitatively Exp.1-A is more consistent with the ground truth than Exp.1-C. These results indicate that the two-dimensional data are more accurate than the three-dimensional data, regardless of the presence or absence of precipitation.

In experiment 2, the value of Exp.2-3L is larger than that of Exp.1-C in terms of Modified RMSE while the value of Exp.2-7L is lower. For Exp.2-F5, which has the largest receptive field[3] of all model, there is no significant difference between Exp.1-C. Also, Exp.2-FRL and Exp.2-NP have lower value, which are considered as models that substantially increase the number of convolution process by changing activation function and pooling layer respectively. These results indicate that the number of convolution process have significant effect on the prediction accuracy.

In experiment 3, for Exp.3-P3 and Exp.3-P5, there is no significant difference between Exp.1-C. For Exp.3-TP, it has lower value both in terms of RMSE and Modified RMSE. These results indicate that the accuracy is higher when the label dataset includes not only precipitation but also temperature in comparison to when only precipitation is included.

5. Conclusion In this study, experiments were conducted to emulate the DDS process of the RCM using CNNs. As a particular result, the experiment 1 indicates that input dataset without precipitation might be better than that with precipitation, and the experiment 3 indicates not only the possibility to predict multiple variables at one time but also the possibility that the multi variables in label dataset might help the prediction each other. Though further investigation is required for the application, this paper can contribute to the development of efficient downscaling method with CNNs.

Reference

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[3] Khaled Koutini, Hamid Eghbal-zadeh, Matthias Dorfer, Gerhard Widmer (2019). The receptive field as a regularizer in deep convolutional neural networks for acoustic scene classification. arXiv:1907.01803v1