R&D item

2. DNN for Weather

Progress until FY2023

1. Outline of the project

During FY2023, we conducted foundational studies through surveys and preliminary experiments on data-driven weather forecasting models. We outlined detailed prototypes and milestones for development in the upcoming fiscal years. Specifically, we decided to develop a proxy model based on the Vision Transformer due to its anticipated forecasting accuracy, the volume of training data, and the available computing resources (parallel GPU computers). Preliminary experiments using an existing model as a baseline informed our decision to explore extending the model. This extension will consider the trade-off between model weight reduction and prediction accuracy as a guideline for further development. Additionally, we reviewed and prepared the benchmark data necessary for model training and shared it across several related projects.

2. Outcome so far

From 21 related papers published since 2020, we systematically surveyed the elemental technologies used in each model, the employed datasets, evaluation metrics, and computing resources to understand current research trends. Based on this analysis, we determined the policy for developing several prototype models. As shown in Table 1, we selected a Vision Transformer and convolutional neural network with an attention mechanism. We decided on an autoregressive model using only the eight main physical quantities from atmospheric reanalysis data for one time step as input and output values.

Additionally, we studied variable compression at the time of input and conducted preliminary experiments. Specifically, in contrast to the existing model (ClimaX), which compresses all input variables into a single representative variable, we proposed a method to explicitly compress variables into multiple representative variables, as shown in Fig. 1. Preliminary experiments using a small-scale model demonstrated that the proposed method improved forecasting accuracy while reducing the number of model parameters by about 50% compared to the existing method.

Furthermore, we prepared a dataset of downscaled atmospheric reanalysis data (DSJRA-55) as a common benchmark for model development, in addition to the mesoscale model MSM, which is currently used in weather forecasting.

3. Future plans

Based on the results of preliminary studies and experiments, we will continue developing forecast models specifically for predicting heavy rainfall phenomena in the areas surrounding Japan. In particular, we will promote the integration of forecast models with different temporal resolutions (e.g., 1-hour, 3-hour, 6-hour, and 12-hour) and the development of forecast models that seamlessly link global to regional scales. Additionally, we will develop fundamental technology for lightweight and highly accurate data-driven prediction models.

In addition to benchmark data, we will choose benchmark events (i.e., July 2018 heavy rain) using data-driven prediction models to advance our research.

Table 1: Machine learning methods, elemental technologies and training data for prototype development.

Component	Detail
ML architecture	**CNN** (Attention R2U-Net), **Vision Transformer** (Swin Transformer)
Loss function	Latitude-Weighted MSE, Pressure-weighed loss, **MAE**, CRPS
Preprocessing	**Z-score normalization** for each 2D data
Input variables	3D: **U**, **V**, **T**, **Q**, RH, **Z** 2D: **U10m**, **V10m**, **T2m**, MSLP, Total precipitation (TP), OLR Fixed: **Sea/land**, **Geopotential height**
Output variables	**Same as input** (excluding fixed variables) **-> Precipitation**
Pressure level	13 level
Temporal resolution	**1 h**, 3 h, **6 h**, 24 h
Forecasting approach	Direct forecasting, Continuous forecasting, Iterative forecasting
Training data	GPV-MSM, DSJRA55
Training approach	**Base model** + Fine-tuning (precipitation)

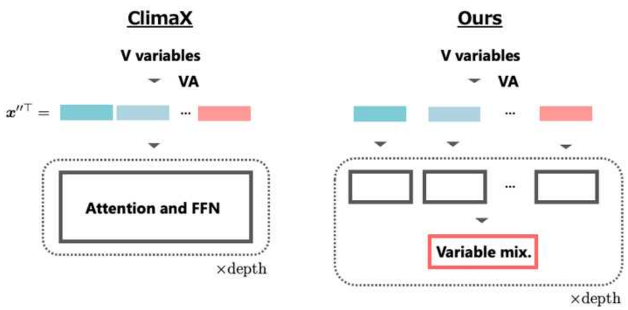

Fig. 1: Comparison of input variable handling between the existing model (ClimaX) and the proposed method.