Production of Fine-resolution Agrometeorological Data Using Climate Model

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ABSTRACT

A system for fine-resolution long-range weather forecast is introduced in this study. The system is basically consisted of a global-scale coupled general circulation model (CGCM) and Weather Research and Forecast (WRF) regional model. The system makes use of a data assimilation method in order to reduce the initial shock or drift that occurs at the beginning of coupling due to imbalance between model dynamics and observed initial condition. The long-range predictions are produced in the system based on a non-linear ensemble method. At the same time, the model bias are eliminated by estimating the difference between hindcast model climate and observation. In this research, the predictability of the forecast system is studied, and it is illustrated that the system can be effectively used for the high resolution long-term weather prediction. Also, using the system, fine-resolution climatological data has been produced with high degree of accuracy. It is proved that the production of agrometeorological variables that are not intensively observed are also possible.

Key words : Dynamical downscaling, Hindcast, Predictability, Regional model, Long-range forecast

I. INTRODUCTION

Due to many reasons, long-term forecast ranging from a week to several months has very low predictability. Among the reasons, improper initial condition given to weather forecast model and our poor understanding in physical processes involved in nature hinder our forecast skill. The continuously changing boundary conditions such as variations of ocean surface temperature and land surface moisture and temperature also make our forecast difficult (IPCC, 2007).

Since atmosphere strongly interacts with biosphere, hydrosphere, lithosphere and cryosphere, for the proper simulation and forecast of future weather and climate, such interactions should be considered in the dynamic prediction models (Meehl, 1995). Also, a type of initial data initializations such as data assimilation method should be applied for the generation of proper initial condition suitable for the model integration (Kalnay, 2003).

Nowadays a new technique called ensemble prediction method has been introduced for weather and climate prediction (Krishnamurti, 2000). According to their studies the ensemble method increases the predictability by reducing the uncertainties that a model can have due to its bias.

In this research, we developed a new fine-resolution long-range weather forecast system by considering above mentioned shortages that limit our forecast skill. The system developed in this research is unique in many respects. First of all, it uses a coupled general circulation model for the weather and climate prediction. Secondly a data assimilation method is applied to reduce the initial shock or drift occurred due to the imbalance between model dynamics and observation. Thirdly, the predictions are produced based on an ensemble method.

II. PREDICTION SYSTEM: MODELS AND EXPERIMENTS

2.1. CGCM and hindcast

The CGCM used in the long-range weather prediction system is so called Pusan National University CGCM (PNU CGCM), which basically consists of 4 models and a coupler: CCM3 Atmospheric GCM, MOM3 Oceanic GCM, LSM land surface model, EVP sea-ice model and a OASIS coupler. In the model, atmosphere, ocean, land surface, sea-ice and are allowed to interact with each other through the coupler. Any kinds of flux-adjustment or flux-correction methods are not applied so that the model can have full degree of freedom in determining its future states.

Using the CGCM, 12-month lead hindcasts integrated at middle of each months (1.5 months ahead for the prediction) of each year for the period 1981-2011 have been made. For the hindcast of March 2010-Feburary 2011, as an example, model uses initial condition of middle of January 2010 and starts the integration. The hindcasted sets of data are used not only for global-scale prediction but also initial conditions of regional dynamical downscaling.

2.2. Regional Model and dynamic downscaling

The regional model in the weather prediction system is WRF model still used as a operational model of Korea Meteorology Administration (KMA). From the model integration, variables such as surface air temperature, maximum and minimum temperature, dew point temperature, precipitation, humidity, wind speed and direction, surface pressure, net solar radiation, radiation duration time, albedo, surface heat flux, moisture flux, and soil temperature and soil moisture at 5, 25, 70, 150 cm depth are stored at every one hour interval.

The regional model can be applied to any domains we have interest. Fig. 1 shows a schematic diagram showing a dynamical regional downscaling for the regions of Asia and Mongol, as an example. The initial and boundary conditions of the regional model are given by PNU CGCM, which also produces all kind of model output on hourly basis, for the regional hindcast and simulation. In order to produce high resolution climatology, meanwhile, the initial and boundary conditions obtained from global-scale observation data are also used.

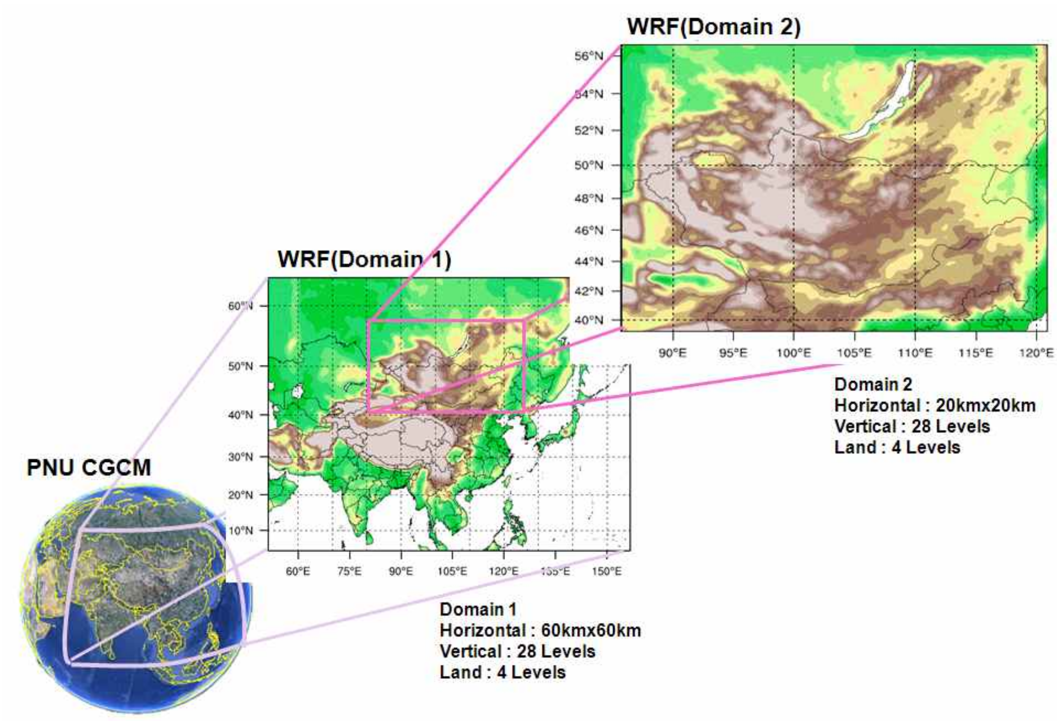

Fig. 1 Schematic diagram showing a dynamical regional downscaling for the regions of Asia and Mongol.

2.3. Data Assimilation

Unlike the atmosphere, ocean has long thermal inertia. Thus the memory contained in ocean remains several weeks to thousands years influencing global climate. Therefore it is very important for the ocean to have correct thermal inertia at the time of integration begins. A variational method with a filter (VAF) is used for the system to generate dynamically and thermally balanced initial oceanic condition (Huang, 2000; Ahn *et al*., 2005).

2.4. Ensemble Prediction

According to recent studies (e.g., Krishnamurti, 2000), ensemble prediction enables us to have better forecast skill. The ensemble method is one of technique to make forecast more skillful by fulfilling prediction several times. Each of the prediction has slightly different initial condition. The aim of the method is to reduce an uncertainty that exists in the model prediction, as explained in the chaos theory. For our prediction system, we adapted Self-Organizing Map (SOM) method, which is a kind of artificial neural network (ANN) methods, for the ensemble prediction. The non-linear self-organizing statistical method is found to be the most efficient method for our system.

2.5. Model Bias correction

As already mentioned in chapter 1, all of the physically-based dynamic weather model has their own bias in the model output, so far. Thus, in the study, the model bias is removed using the model climatology obtained from the hindcast. By comparing the climatology of model and observation, the bias is estimated. Also, several linear and nonlinear bias correction methods can be applied for the removal of model bias.

III. RESULTS

3.1. CGCM hindcast results

Fig. 2 shows the temporal correlation coefficients of the Spring surface air temperature hindcasted at middle of January (1.5 months ahead) of each year over 31-year from 1981-2011, as an example. In the figure, CGCM hindcast (Fig. (b)) are compared with Atmospheric GCM (AGCM) case (Fig. (a)). As we can see, the correlation coefficients of CGCM hindcast are better than those of AGCM. Although the coefficients of other important variables are not shown here, CGCM hindcasts are always better than AGCM hindcast. It implies that the CGCM which allows interactions between atmosphere and other subsystems such as biosphere and hydrosphere is better than the atmosphere-only model results.

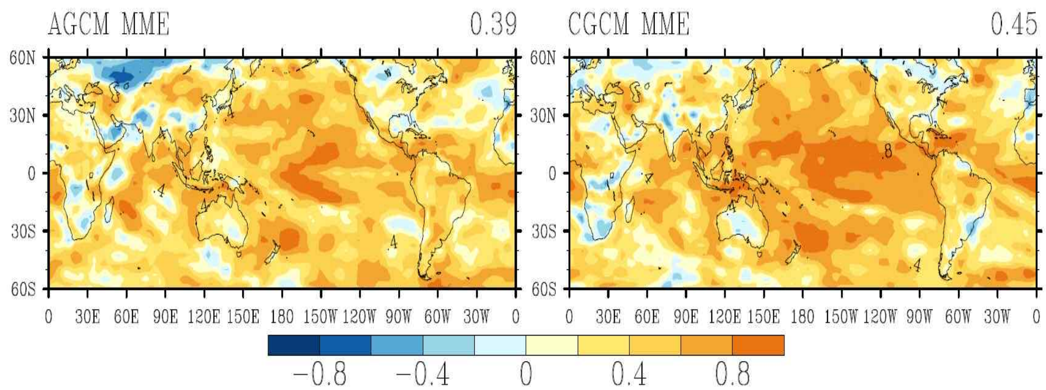

Fig. 2 Temporal correlation coefficients of the Spring surface air temperature hindcasted at middle of January (1.5 months ahead) of each year over 31-year from 1981-2011 for AGCM (left) and CGCM(right).

3.2. Regional downscaling for climate data production

Fig. 3 shows the Spring precipitation climatology produced by downscaling over North American region with 30km x 30km (the first nested domain) and 10km x10km (the second nested domain) resolution, respectively, using our system, as an example. The model bias-corrected results (c) and (f) are compared with observation (a) and (d), and uncorrected raw model data (b) and (e). It should be noted that the average distance between the observational sites for the region is over 60 km. As we can see from the figure, the bias corrected model climatology is similar to the observation depicting general pattern of precipitation distribution over the region. Moreover, it shows more detailed structure of regional precipitation than observation. Since the average distance between the observational station is more than the model resolution, even the observation cannot capture the detailed structure of precipitation better than bias-corrected model (Im and Ahn, 2011). On the other hand, the uncorrected model result shows large bias.

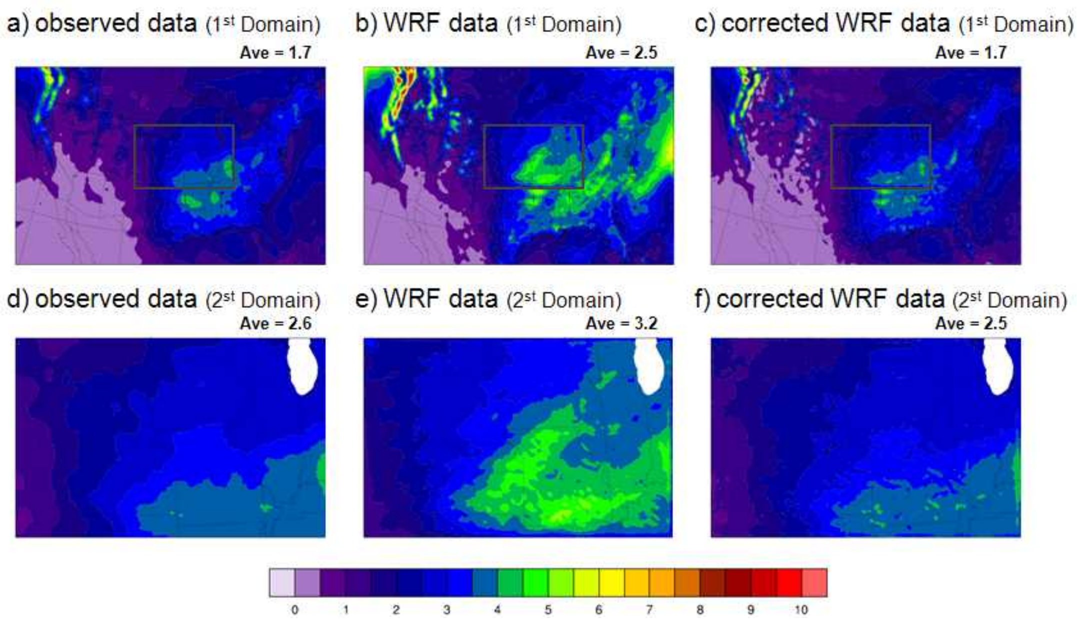

Fig. 3 Spring precipitation climatology over North America obtained by (a), (c) observation and regionally downscaled (b), (d) uncorrected result and (c), (f) bias-corrected result with resolution of 10km x10km. Unit is mm/day. Upper and lower figures are for North America (30km x 30km) and the central north region (10km x10km), respectively.

Climatology of South Korea is also produced by using dynamical downscaling and model bias-correction. Fig. 4 shows the April temperature climatology produced by downscaling over South Korea with a 3km x 3km nested domain, as an example. The model bias-corrected results (d) is compared with observation (a) and (b), and uncorrected raw model data (c). In the figure, (a) is obtained from the conventional observation sites (ASOS), and (b) from ASOS and AWS operated by KMA. The average distance between the observational sites for (a) and (b) are more than 20km and 10km, respectively. Not only the bias corrected model climatology is also similar to the observation in depicting general pattern of temperature distribution over the region, but also it shows more detailed structure of regional temperature than observation. Meanwhile the average distances between the observational stations in ASOS and ASOS+AWS are too coarse to show the details.

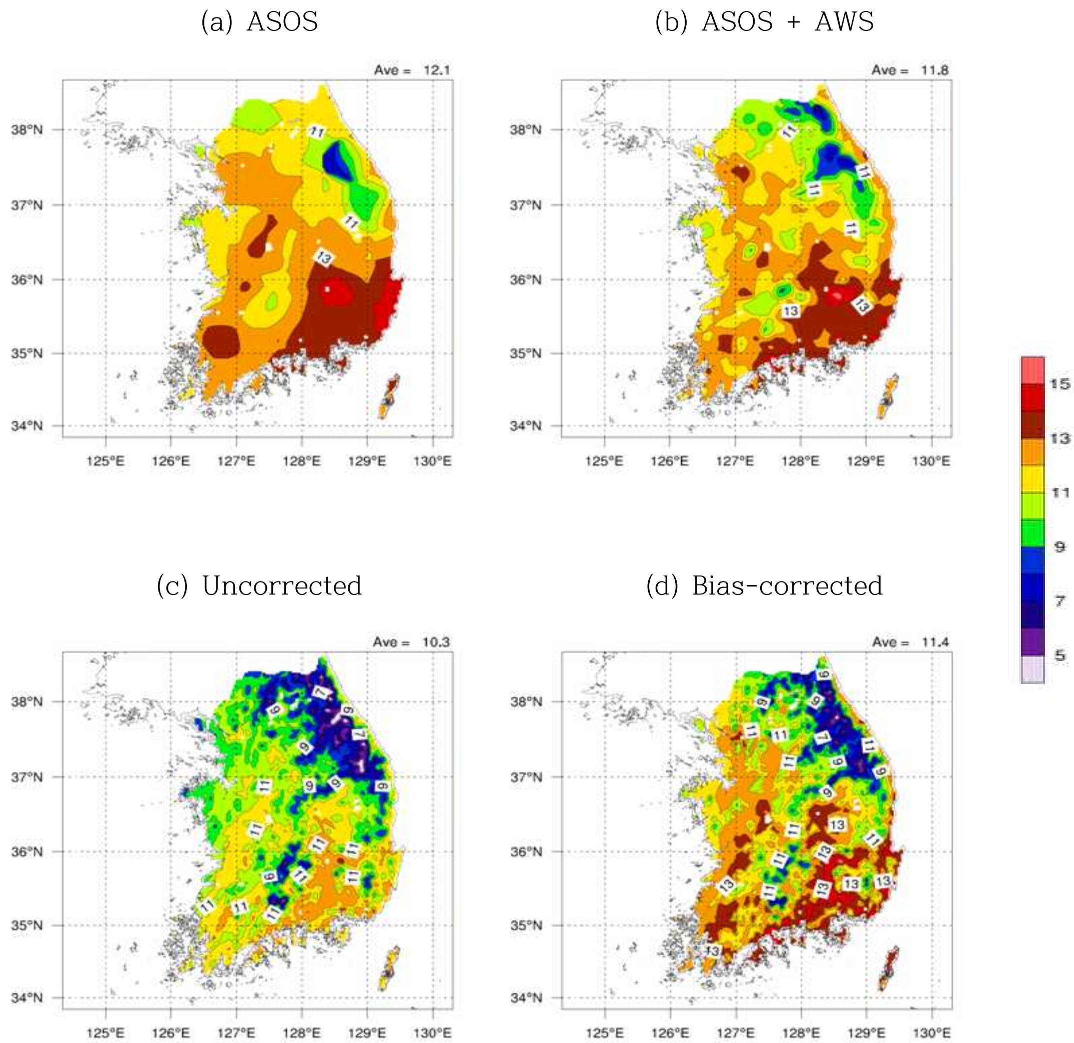

Fig. 4 April temperature climatology over South Korea obtained by (a) ASOS observation, (b) ASOS and AWS observation, (c) bias-uncorrected model climatology and (d) bias-corrected model climatology (Unit: ^{o}C). Model resolution is 3km x 3km.

3.3. Regional downscaling for long-term ensemble prediction

Fig. 5 shows the temporal correlation coefficients of Winter surface air temperature hindcasted at middle of October (1.5 months ahead) of each year for the period 1981-2011 (31-year) over Asia region, as an example. In the figure, 8-ensemble member hindcasts (Fig.

5(b) and (c)) are compared with a single member experiment (Fig. 5(a)). Fig. 5(b) and (c) are, respectively, linear simple composite method (SCM) and non-linear SOM method. As we can see, the correlation coefficients of the ensemble hindcasts are better than that of single member hindcast. Although, not all of variables are presented in this paper, the ensemble hindcasts are always better than that of single member hindcast in many respects. The prediction skill of ensemble also depends on the methods of ensemble. Many ensemble techniques are compared with each other to find out the best method of ensemble (e.g. Ahn *et al.,* 2011.). The figure illustrates that the non-linear SOM method shows better predictability than the linear conventional SCM method, as studied by Ahn *et al.* (2011).

(a) Non-ensemble (b) Ensemble-SCM (c) Ensemble-SOM

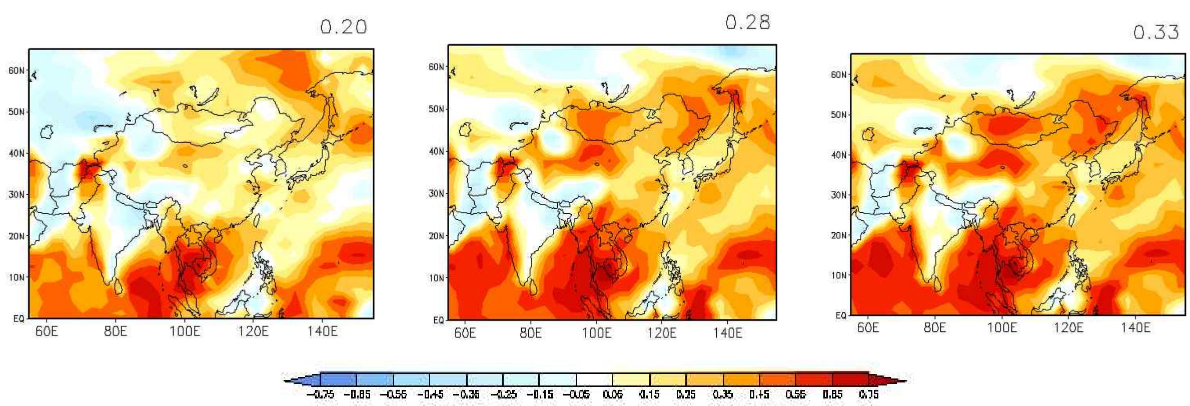

Fig. 5 Temporal correlation coefficients of Winter surface air temperature hindcasted at middle of October (1.5 months ahead) of each year for the period 1981-2011 (31-year) over Asia region.

IV. DISCUSSION AND SUMMARYY

A new fine-resolution long-range weather forecast system is introduced in this research. PNU CGCM is used to give more degree of freedom for the model in determining its own future weather and climate states. Also, VAF data assimilation method is applied to the system in order to reduce the initial shock or drift that occurs at the beginning of coupling due to imbalance between model dynamics and observed initial condition. At the same time, the predictions are produced in the system based on an non-linear SOM ensemble method. All the model bias are eliminated by estimating the difference between hindcast model climate and observation.

It is illustrated that the system can be effectively used for the high resolution long-term weather prediction. Also it is proved that the production of climate variables with fine resolution are possible, even for the variables that are not intensively observed such as ground temperature and wetness, and solar and terrestrial radiations.

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