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A Study on Ultra-high Resolution Season Prediction System for a Practical Usage to Agricultural Community

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I. Introduction

Agriculture is influenced by weather condition rather than other environmental factors. Many studies about the impact of weather or climate conditions to the output of agricultural products have been done (Burhan and Handan, 2002; Chen *et al.*, 2004). Menza and Silva (2009) mentioned that meteorological variables affect resource availability and fundamental processes associated with crop growth and development. Yield of crop can be also determined by weather or climate conditions such as the amount of rainfall, seasonal trend, and meteorological disaster.

However, the future weather condition cannot be controlled, hence agrometeorological forecasting service is very important to help most of the cultivations. Ministry of Agriculture and Forestry (2001) conducted the development of regional climate prediction and application system for agriculture. Subsequently, Shin and Lee (2014) suggested the practical use of information on seasonal prediction to forecast agricultural productivity. Efforts have been vested towards advanced research pertaining to application of seasonal prediction for agricultural productivity.

For a practical usage to agricultural community, daily prediction data is used in crop model. Moreover, ultra-high resolution prediction data is also useful especially over regions that are deprived of observational data. Therefore, considering the needs of agricultural community, we constructed ultra-high resolution seasonal prediction system using GME atmospheric general circulation model (GCM) and diagnostic quantitative temperature and precipitation model (QTM and QPM).

II. Data and Method

2.1. Seasonal prediction

In this study, the seasonal prediction data has been produced using GME, which is

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an operational Global Model (GM) and a regional model (EM) for central Europe of Deutscher Wetterdienst (DWD). Since, GME model is an Atmospheric General Circulation Model (AGCM), observed sea surface temperature (SST) and sea ice cover data (Table 1) are needed to prescribe boundary condition. Further, seasonal prediction is simulated based on the prescribed boundary condition. Yet another dataset, which is necessary for providing initial condition, is ECMWF reanalysis data with a gaussian grid of T511. To construct the ensemble prediction, time-lagged method is applied with initial conditions from different dates. Finally, the ensemble mean is used for seasonal prediction.

Table 1. Boundary data used in seasonal prediction

Variable	**SST**		**Sea Ice**	
Data	Present data	Climatology	Present data	Climatology
Grid Number (Lon.×Lat.)	360×180	360×180	1024×512	144×73
Time Interval	Weekly averaged Data	Daily Data (1971~2000)	Hourly Data	Daily Data (1971~2000)
Data Source	National Oceanic and Atmospheric Administration Optimum Interpolation (NOAA OI)		European Centre for Medium Range Weather Forecasts (ECMWF)	

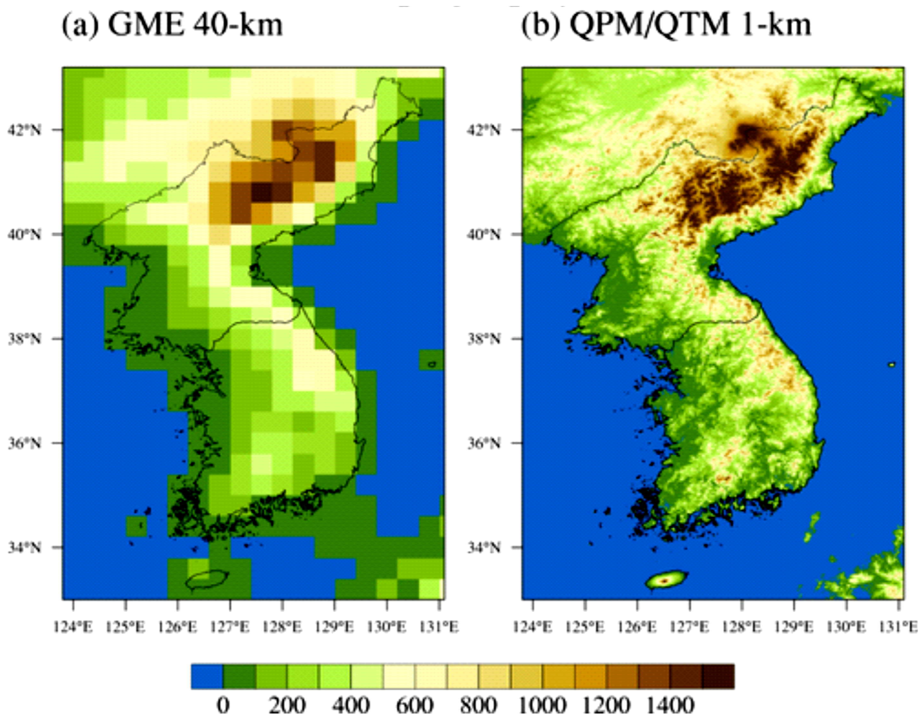

Fig. 1. Topography data of GME model and DEM; (a) GME 40 km, (b) QPM/QTM 1 km.

2.2. Downscaling

The diagnostic models QTM and QPM consider the small-scale topography effect, which is not treated in the mesoscale model. Due to the difference in spatial resolution of GME model and Digital Elevation Model (DEM) topography, new datasets of temperature and precipitation are calculated by considering the orographic effect. As shown in Fig. 1, the domain size selected is 31.8~44.4˚N, 123.8~131.2˚E.

We use the following process of QTM to generate ultra-high resolution temperature data. At first, temperature at 2 m above ground is calculated at sea-level pressure using lapse rate.

$$T_{slp} = T_{gme} + \Gamma \times H_{gme} \tag{1}$$

Then, the temperature is interpolated to 1 km × 1 km spatial grid resolution.

$$T_{slp} \rightarrow T_{intp} \tag{2}$$

Next, the orographic effect is incorporated by recalculating the temperature using the altitude data of DEM.

$$T_{qtm} = T_{intp} - \Gamma \times H_{dem} \quad (3)$$

We use the following process of QPM to generate ultra-high resolution precipitation data.

The continuity equation of raindrop mixing ratio Q_r following Kessler (1969) is given below:

$$\frac{\partial Q_r}{\partial t} = -u\frac{\partial Q_r}{\partial x} - v\frac{\partial Q_r}{\partial y} - w\frac{\partial Q_r}{\partial z} + \frac{1}{\rho}\frac{\partial}{\partial z}(\rho V_r Q_r) + P_1 - E_1 \quad (4)$$

(where x, y, and z represent coordinate system; t is time; u, v, and w are wind components; ρ is density of air; V_r is fall speed of raindrop; P_1 is condensation and E_1 is evaporation.)

The continuity equation of raindrop mixing ratio can be separated to mesoscale field and small-scale perturbation field as given below:

$$\frac{\partial(\overline{Q_r} + Q'_r)}{\partial t} = -\bar{u}\frac{(\overline{Q_r} + Q'_r)}{\partial x} - \bar{v}\frac{\partial(\overline{Q_r} + Q'_r)}{\partial y} - \bar{w}\frac{\partial(\overline{Q_r} + Q'_r)}{\partial z} + \frac{1}{\bar{\rho}}\frac{\partial}{\partial z}(\bar{\rho} V_r(\overline{Q_r} + Q'_r)) + (\overline{P_1} + P'_1) - (\overline{E_1} + E'_1) \quad (5)$$

Using the topography effect, the small-scale perturbation is calculated in algorithm of QPM (Kim, and Oh, 2010). Finally, rainfall intensity is calculated.

$$I = V_r(\overline{Q_r} + Q'_r) \quad (6)$$

III. Conclusion

The results of this study provide two kinds of data. First one is daily prediction data for the crop model. The set of variables is flexibly selected according to user’s needs. The second one is an ultra-high resolution precipitation and temperature data.

The results of model simulation are provided for not only seasonal prediction but also for input data of crop model. The data disseminated to the agricultural community will comprise of mean of daily ensembles of predicted data along with GME’s climatology data.

We will also provide ultra-high resolution agrometeorological data generated from QTM and QPM. These downscaling methods calculate the temperature and rainfall at a spatial resolution of 1 km × 1 km by considering the effect of small-scale topography, which is not treated in the mesoscale model. The results provided are highly useful in seasonal prediction, particularly in data sparse regions.

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