Thesis for the Degree of Master of Science

Study on a Temporal Adaptative High Resolution Long-term Prediction System for Agrometeorological Outlook Service

by

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(농업기상 예측 서비스를 위한 시간 흐름을 따라가는 고해상도 장기예보 시스템에 관한 연구)

Advisor: Prof. Jai-Ho Oh

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Kyung-min Choi

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최 경 민

부 경 대 학 교 대 학 원 환 경 대 기 과 학 과

요 약

1년 작물 생산량은 국가 식량생산 계획, 농산물 가격안정, 농업정책 수행 등을 위한 기초자료를 산정하는 가장 기본적인 단위의 통계자료이다. 또한 한 해 작물 생산량을 예측함으로써 농작물의 생산성을 높이기 위한 농업적 연구가 가능하다. 우리나라에서도 작물 생산량 예측을 위해 다양한 작물 모델들을 이용한 연구가 진행되어왔다. 그러나 대부분의 연구들이 기후변화 시나리오에 따른 한반도 작물 생산량 변화에 초점이 맞추어져 온 실정이며 다른 작물 모델들의 연구에서 한해 작물 생산량 예측을 위한 고해상도 농업기상 예측자료에 대한 연구가 매우 드물다.

작물모델을 이용하여 한반도 작물 생산량 예측을 위해 필요한 농업기상 자료는 다음과 같은 사항들을 고려해야 한다. 첫째, 작물 생산량 산정을 위해 사용되는 작물 모델이 필요로 하는 일 자료 형태의 기상 변수가 요구되며, 둘째, 한 해 작물 생산량 예측을 위해서는 파종기부터 수확기까지의 장기예측 농업기상 자료가 필요하다. 셋째, 한반도의 지역별 작물 생산량을 정확하게 예측하기 위해서는 고해상도 농업기상 자료가 필요하다. 마지막으로, 농업기상 자료의 예측성을 높이기 위해 예측자료는 파종기부터 수확기까지 시간이 지남에 따라 새로운 예측이 이루어져야 하고, 과거기간에 대해 관측자료 기반의 고해상도로 복원된 자료가 대체되어 한해 생산량 예측에 이용되어야 한다. 이 모든 것을 고려하여 본 연구에서는 ‘농업기상 예측 서비스를 위한 시간 흐름을 따라가는 고해상도 장기예측자료 생산 시스템’을 제안하고자 하였다.

본 연구에서는 한반도 지역을 대상으로 독일 기상청에서 사용하는 대기대순환모델(Atmospheric General Circulation Model, AGCM)인 GME를 사용하여 40km의 수평 해상도를 갖는 일 단위의 농업기상 장기예측자료를 생산하고, 정량적 기온/강수 진단 모델(Quantitative Temperature/Precipitation Model, QTM/QPM)을 이용하여 기온과 강수 변수에 대하여 1km 수평 해상도를 갖는 고해상도 예측자료를 생산하였다. GME와 QTM/QPM을 이용한 고해상도 장기예측은 2015~2016년에 대하여 매달 수행되어 시간이 흐름에 따라 새로운 예측자료가 대체되도록 하였고, 지나간 과거에 대하여는 관측자료 기반의 1km 고해상도 복원 자료가 대체되도록 하여 시간 흐름에 따라 적절한 타입의 자료가 제공되는 농업기상 장기예측 시스템을 구축하였다. 이는 농업분야에서 각종 작물의 한 해 생산량 예측과 수확량 분석에 유용한 농업기상자료가 될 것으로 사료된다.

I Introduction

1. Background and purpose of research

The annual crop yields is the most basic unit of statistical data as fundamental data for national food production, agricultural price stabilization, and agricultural policy execution. Agricultural research is possible to increase the productivity of crops by predicting annual crop yields. The vegetation distribution of crops depends on the climatic conditions of the plantation, but the growth of crops depends on the environment of the plantation. Since the growth of crops is influenced by meteorological factors such as temperature, precipitation, and radiation flux, agricultural weather information is fundamental and essential material for predicting crop yields.

A variety of methods have been tried to predict crop yields for a long time. Recently, research is active using crop models that enable quantitative analysis based on the growth model of crops by soil, weather conditions, and variety of crops. Crop models are computer programs that mimic the growth or development of crops. Models simulate or mimic the actual crop behavior by predicting the growth of components such as leaves, roots, stems, or grains. In a brief look at the history of crop modeling, in the 1960s, there was a first attempt to make photosynthetic rates model of crop canopies (de Wit, 1965). This model was used to estimate potential food production in some areas and to provide indications for crop cultivation and management. This model led to the structure of the Elementary Crop growth Simulator (ELCROS) which has basic statistical photosynthetic models and crop growth simulation structures, including crop respiration by de Wit et al. in 1970. After then, a functional equilibrium between shoot growth and root, micrometeorology, and canopy resistance quantification to gas exchanges were added to this model which developed into the Basic Crop growth Simulator (BACROS) in 1978. In 1982, there was the development of model by International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) to help resource poor farmers. The major product of IBSNAT was the Decision Support System for Agro-Technology Transfer (DSSAT) which is widely being used as a research tool until now (Oteng-Darko, P. et al., 2013). Similarly, major crop models were developed through the process of projects in various institutions throughout the world.

Crop models are classified into different types depending upon the each purpose for which it is designed. There are empirical models, mechanistic models, static models, dynamic models, deterministic models, stochastic models, simulation models, and optimizing models and so on. Among these models, the most commonly used models are simulation models. Because these are designed to simulate the system at short time intervals (daily time-step), these address the aspects of variability associated with daily changes in weather and soil conditions. This short time step simulation requires large input data to run the model, such as climate parameters, soil characteristics, and crop parameters. Around 40 years ago, various crop models have developed and used for various purposes. In particular, it is mainly used to analyze the yield of various agricultural crops, or to predict future crop yields.

In Korea, studies have been conducted to predict crop yields according to weather conditions using several crop models such as CERES (Crop Environment Resource Synthesis), ORYZA 2000, and EPIC (Jo and Yun, 1999; Yun and Jo, 2001; Lee et al., 2005; Lim et al., 2015). However, these studies mostly use Korean environment variables as the input data of crop models developed abroad to estimate the production volumes of domestic rice crops and compare them with actual yield. And these studies were conducted based on historical weather data only. On the other hand, most studies on predicting crop yields are concentrated in studies on changes in domestic crop yields due to climate change scenarios (Chung et al., 2006; Chung, 2010; Sim et al., 2011; Lee et al., 2012; Nam et al., 2012). The utilization of the climate change scenarios using these GCM is the threshold for using a single result of the GCM model. Shin and Lee (2014) used the ensemble seasonal prediction weather data to predict crop yields, and there were some limitations about large spatial resolution and converting monthly data into daily data because of utilizing several kinds of global meteorological forecast data. Korea has various regional climate patterns because it consists of small but complex terrain. This is because the nation's territory is geographically small but consists of complex terrain, which has a diverse regional climate. Chun et al. (2012) proposed the 100m resolution agrometeorological information analysis system based on the observational data using LAPS (Local Analysis and Prediction System), but only short-term predictions are possible because of using the regional forecast results which has 10 km resolution and 6 hours intervals as a input data of LAPS.

All the take together, the agrometeorological data should take into account the following to predict crop yields using crop models. First, to predict the annual crop yields, long-term agrometeorological prediction is required from seeding season to harvest season, and secondly, it requires a weather parameter as the daily data for crop models that are used for crop yields. Third, to predict regional crop yields accurately on the Korean Peninsula, high resolution agrometeorological prediction data are needed. Finally, to increase the predictability of agrometeorological data, predictions must be made again over time from seeding season to harvest season, and the observation-based high resolution synthetic data should be replaced for the past time, which should be used to predict the annual crop yields. In light of all this, this study has established 'A temporal adaptative high resolution long-term prediction system for agrometeorological outlook services'.

In the chapter 1, the background and purpose of research are introduced. The description of Temporal adaptative high resolution long-term prediction system and its important advantages are introduced in detail. In the chapter 2, the methods to calculate observation-based synthetic data and long-term prediction data are described. In the chapter 3, agrometeorological variables for crop models or pest models, observation-based synthetic temperature and precipitation, final high resolution prediction data, and time series at station point are described. Finally in the chapter 5, this study is closed by conclusion.

2. Temporal adaptative high resolution long-term prediction system introduction

Utilization of crop models for estimating the annual crop yields and pest models in agricultural fields can ultimately contribute significantly to improving the annual crop productivity. Since agrometeorological information is essential in agriculture, it is important to provide a one-year agrometeorological prediction for annual crop yields production. The system proposed in this study have a large aim to provide sustainable data for crop yields prediction and analysis in Korea. The major advantage is, firstly, to produce long-term agrometeorological prediction data from seeding season to harvest season. Second, these data are calculated as the daily data to enable input materials for crop models and pest models. Third, the prediction data is high-resolution to predict crop yields by small region in the Korean Peninsula with complex terrain. And finally, significant advantage in this system is to update the data as the new prediction data for the future and to replace the data with the observation-based high resolution synthetic data for the past. As time goes by, it provides the proper type data for continuous prediction of annual crop yields from seeding season to harvest season. Two methods have been applied to enhance the predictability of long-term agrometeorological data in this system. One is to update the prediction data as the new every month. Another is ensemble prediction method. Further details of method are described in the next chapter.

In this study, long-term agrometeorological prediction data for crop seeding and harvest time in Korea. Most of the domestic studies about crop models were mostly applied to rice varieties and corn in some cases. In case of rice that is main crop in Korea, seeding season is different from region to region, but usually from early April to middle part of April and harvest season is last part of September. Corn is sown in middle part of April and harvested from late July to early August. However, prediction periods has set up from March to October to provide agrometeorological data in this system for various crop varieties.

The Structure diagram of 'Temporal Adaptative High Resolution Long-term Prediction System' is shown in Fig. 1. If the present point of view is the beginning of 2016, observation data can be used for the analysis of crops in past years. To predict an annual crop yields in 2016, long-term prediction data are needed from seeding season to harvest season. In January, it provides long-term prediction data from March to October using GCM (General Circulation Model) except February, the spin-up time of model simulation. When it comes to February, the new prediction data are updated to the new prediction from April to October except the spin-up time, March. For the March, previous prediction data which was carried out in January is still used for estimating an annual crop yields. Then becoming March, the prediction data are replaced with the new, from May to October. With this lapse of time, new predictions are carried out every month, and updated to new prediction. Becoming April, it is able to get observation data on March. The prediction data are replaced by observation-based synthetic data for temperature and precipitation which are the most important factors in crop models and pest models. The new year begins after the crop harvest season and the new long-term prediction is carried out again for the new year. This time-traveling agrometeorological data provision system is 'Temporal Adaptative High Resolution Long-term Prediction System'.

The experimental design is shown in Fig. 2 for this system. To produce high resolution observation-based data and prediction data which have 1 km × 1 km resolution, the observation data and prediction data from AGCM (Atmospheric General Circulation Model) are used as the input data for quantitative model. Using quantitative temperature/precipitation models, high resolution synthetic and prediction data are produced. Domain is the Korean Peninsula and period is March to October for two years (2015, 2016).

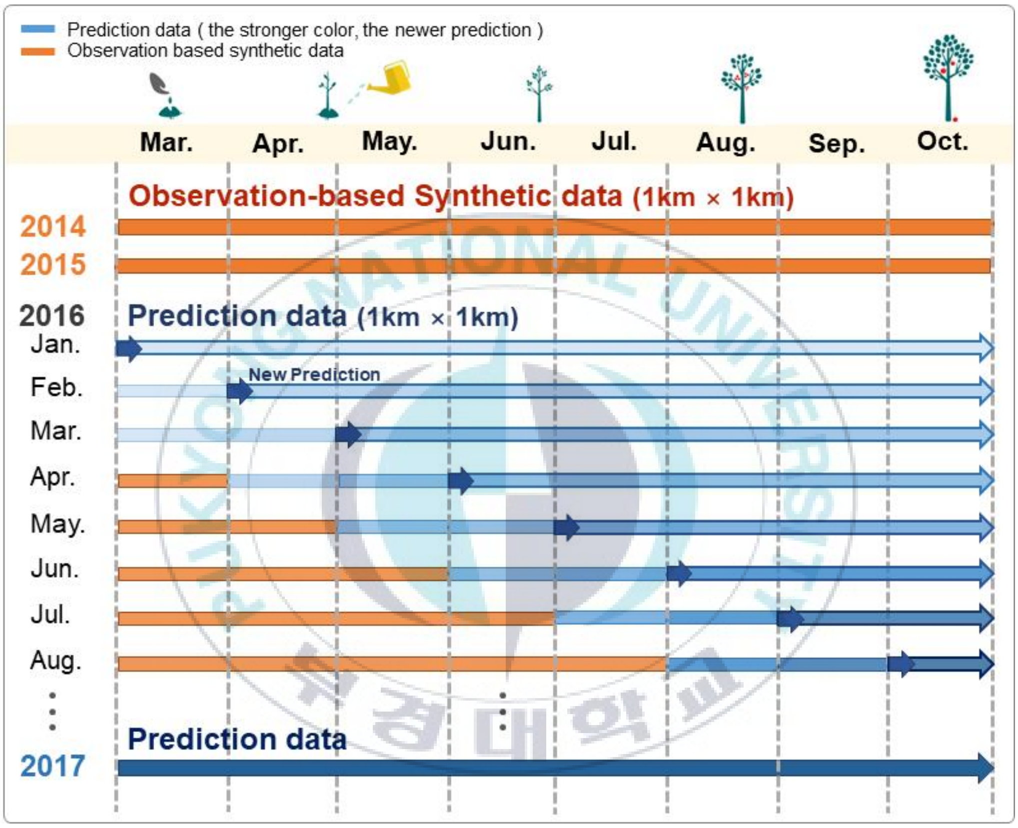

Figure 2. Structure diagram of Temporal Adaptative High Resolution Long-term Prediction System

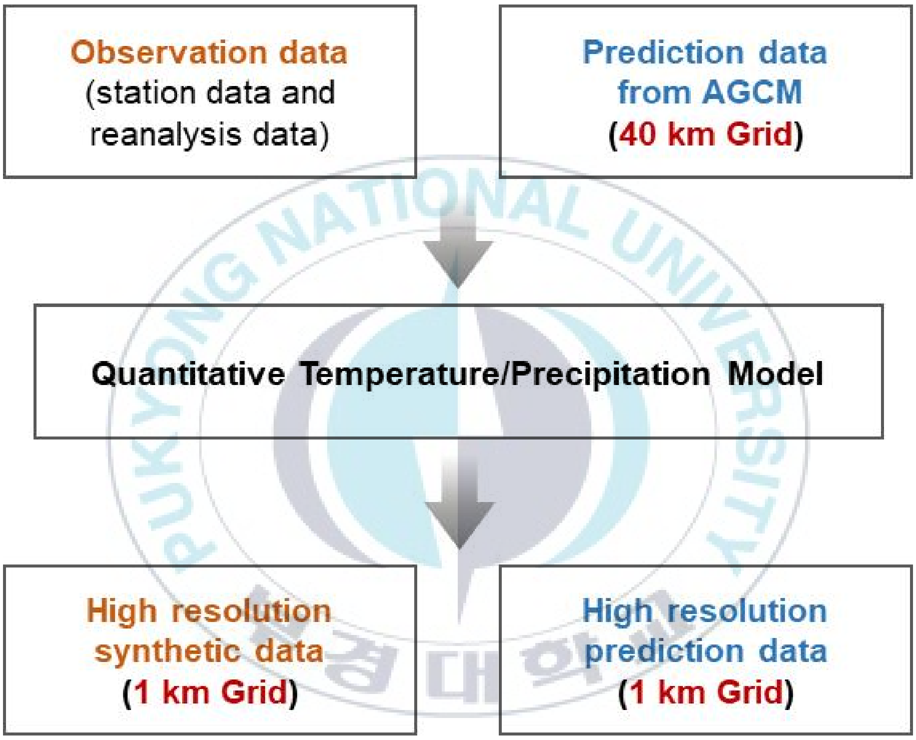

Figure 3. The experimental design for the system

Ⅱ Method

1. Calculating method for synthetic data

The diagnostic models QTM (Quantitative Temperature Model) and QPM (Quantitative Precipitation Model) consider the small-scale topography effect, which is not treated in the mesoscale resolution. In this study, to calculate to high resolution temperature and precipitation data, the diagnostic models have been used as the downscaling method which was used Kim and Oh (2010), Bae (2015) and Kang (2017). As the small-scale topography, DEM (Digital Elevation Model) data which have 1 km resolution, from Consortium for Spatial Information.

A. Quantitative Temperature Model (QTM)

QTM calculates the temperature using the high resolution topography data. The method of calculating detailed regional temperatures using QTM is to consider the detailed terrain effects that are not addressed in mesoscale resolution. The high resolution temperature is calculated by add and subtraction as much as the temperature lapse rate which is occurred by difference of altitude between the mesoscale topography and high resolution topography at each point. The temperature lapse rate parameter (Γ) considered in QTM is calculated at of each point, rather than the environmental lapse rate which has the value of 6.5 ℃/km (Eq. 1).

$$\Gamma_{L1-L2} = \frac{dT}{dZ} = -\frac{T_{L1} - T_{L2}}{Z_{L1} - Z_{L2}} \quad (1)$$

Where Γ_{L1-L2} is the temperature lapse rate in layer between $L1$ and $L2$ isobaric surfaces. T_{L1} and T_{L2} are the temperatures in the $L1$ and $L2$ isobaric surfaces from the observation data or mesoscale model data for prediction. Z_{L1} and Z_{L2} are the geopotential height in the $L1$ and $L2$, respectively. This method was introduced in Kang (2017). Using the temperature in the five vertical levels (1000 hPa, 850 hPa, 700 hPa, 500 hPa and 300 hPa), the temperature lapse rate for four layers is calculated at each point, every time interval of data. For calculating the temperature by topography effect, mesoscale or observation temperature is calculated to 1000 hPa level value using the eq. 2.

$$T_{1000hPa} = T_{obs.} + \Gamma \times H_{meso.} \qquad (2)$$

Where T_{obs} is the observation which can be mesoscale model temperature as well, Γ is the temperature lapse rate which was calculated from input dat of QTM, and $H_{meso.}$ is the topography which has mesoscale resolution. Then, the 1000 hPa temperature is interpolated to 1 km resolution using bilinear interpolation method. Finally, the temperature is calaulated with small-scale topography effects using DEM topography data and temperature lapse rate for each point (Eq. 3).

$$T_{qtm} = T_{intp.} - \Gamma \times H_{DEM} \qquad (3)$$

Where T_{qtm} is final temperature which has 1 km resolution, $T_{intp.}$ is the interpolated temperature from $T_{1000hPa}$, and H_{DEM} is DEM topography data.

B. Quantitative Precipitation Model (QPM)

QPM calculates precipitation in detailed region considering small-scale topography effect. QPM was used many studies(Bell, 1978; Misumi et al., 2001; Kim and Oh, 2010; Bae, 2015). It has the advantages of saving computing resources using numerical model to calculate the small-scale precipitation intensity.

The following description is the simple progress of QPM calculating to small-scale precipitation. The mixing ratio of rainfall can be presented as the mass of rainfall containing dry mass of unit mass with condensation rate and evaporation rate of rainfall. Eq 4 is shown the continuity equation (Kessler, 1996).

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

Where x, y and z are horizontal and vertical coordinates, t is time, u, v and w are horizontal and vertical wind components, ρ is air density, Q_r is mixing ratio of rainfall, V_r is falling speed of rainfall, P_1 is condensation rate, and E_1 is evaporation rate.

The continuity equation of raindrop mixing ratio can be separated to mesoscale field and small-scale perturbation field as given Eq. 5.

$$\frac{\partial(\overline{Q_r}+Q_r{}')}{\partial t} = -\overline{u}\frac{\partial(\overline{Q_r}+Q')}{\partial x} - \overline{v}\frac{\partial(\overline{Q_r}+Q')}{\partial y} - \overline{w}\frac{\partial(\overline{Q_r}+Q')}{\partial z}$$
$$+\frac{1}{\rho}\frac{\partial}{\partial z}[\overline{\rho}V_r(\overline{Q_r}+Q_r{}')] + (\overline{P_1}+P_1{}') - (\overline{E_1}+E_1{}') \tag{5}$$

There are some assumptions. First, the atmosphere is steady state. Second, variations of rainfall mixing ratio are consistent over time in steady state. And third, wind components ($\overline{u}$, $\overline{v}$, $\overline{w}$) and air density ($\overline{\rho}$) are approximated to the values from the mesoscale data. The perturbation of rainfall mixing ratio ($Q_r{}'$) is difference of rainfall mixing ratio from additional condensation ($P_1{}'$) and evaporation ($E_1{}'$) according to the small-scale topography effect. In the terrain-following coordinate system, $Q_r{}'$ is calculated through the parameterization process. Finally, precipitation intensity is calculated from changes of the rainfall between the water vapor due to the influence of the terrain (Eq. 6).

$$I = V_r(\overline{Q_r}+Q_r{}') \tag{6}$$

C. Data

To produce observation-based synthetic temperature and precipitation in the Korean Peninsula, following data that used as the input of QTM and QPM is described in Table 1. The observation data are obtained from Automatic Weather System (AWS) and the Automatic Synoptic Observation System (ASOS) which has 1 hour interval. The 3 hours interval observation data are used for calculating synthetic temperature and precipitation in South Korea. These observation data are from the Korea Meteorological Administration (KMA). KMA performs their own quality control. The number of AWS station points is 494 and the number of ASOS station points are 93 (Fig. 3).

The MERRA 2 reanalysis data are used as the vertical data in the Korean Peninsula and the surface data in North Korea. Because it is almost impossible to get the observation data in North Korea, reanalysis data which processed from global observation data are used for producing observation-based synthetic data. Kang (2017) set this dataset for QTM and QPM in his study. Additionally MERRA data are updated with MERRA 2 in this study because the National Aeronautics and Space Administration (NASA) provides new dataset. And the reanalysis data points are added more points for accuracy precipitation data compared to Kang's study. Kang (2017) produced the observation-based synthetic climate data of temperature and precipitation for 15 years (2000-2014). But the new climate data calculated again in this study using the updated method.

Table 1. Information of AWS & ASOS observation data used in QPM, QTM

Data	Time interval	Number of station or resolution
AWS / ASOS (KMA)	3 hours	494 / 93
MERRA 2 (NASA)	vertical data: 3 hours	$1.25^{\circ} \times 1.25^{\circ}$, 72 levels
	surface data: 3 hours	$0.667^{\circ} \times 0.5^{\circ}$

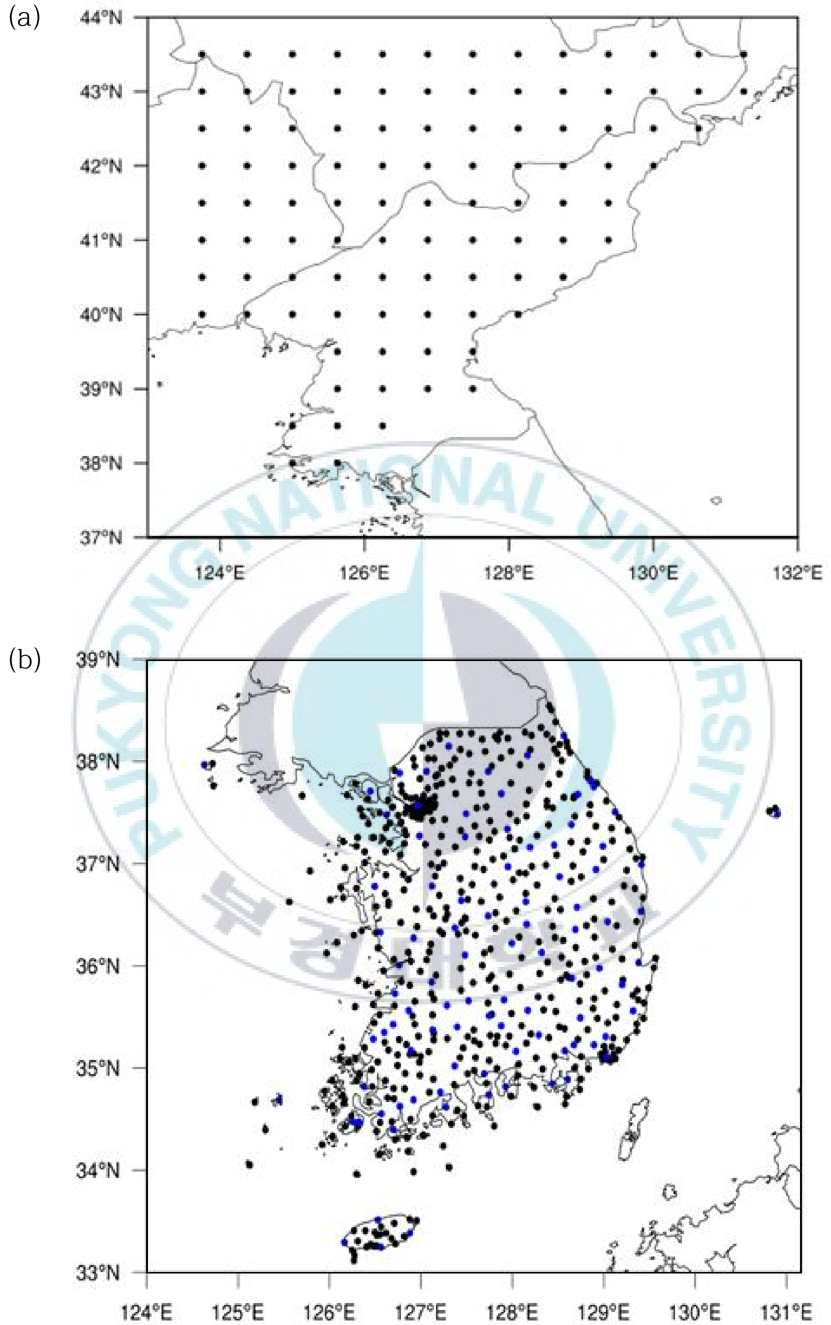

Figure 3. Data points distribution of (a) MERRA 2 reanalysis data and (b) AWS (black points) & ASOS (blue points) sites

2. High resolution prediction method

A. Prediction model and data description

In this study the agrometeorological data are produced for 2015, 2016 according to the concept of 'Temporal adaptative high resolution long-term prediction system'. To predict the meteorological variables, global model GME (Operational Global Model (GM) and the regional model for central Europe) has been used. GME is hydrostatic model that is developed by DWD (Deutscher Wetterdienst). Because it has icosahedral-hexagonal grid, there are several advantages. A major advantage of this grid makes it to avoid the pole problem by CFL (Courant-Frierich-Lewy) condition that exists in Cartesian grid coordinate system. It is also easy condition to increase the resolution of prediction. Grid has consists of the equilateral triangles (Fig. 4). This model increases resolution by creating a new triangle to connect the middle points of the same triangle grid. It can be divided to equal interval of grid and be used less computing resource to increase resolution (Majewski, et al., 2002).

In this study, long-term prediction has carried out using GME version 3.0. Because the GME model is AGCM, boundary condition data is used to consider the ocean condition (Table 2). The SST (Sea Surface Temperature) data have got from NOAA OI (National Oceanic and Atmospheric Administration Optimum Interpolation) and sea ice data have got from ECMWF (European Centre for Medium Range

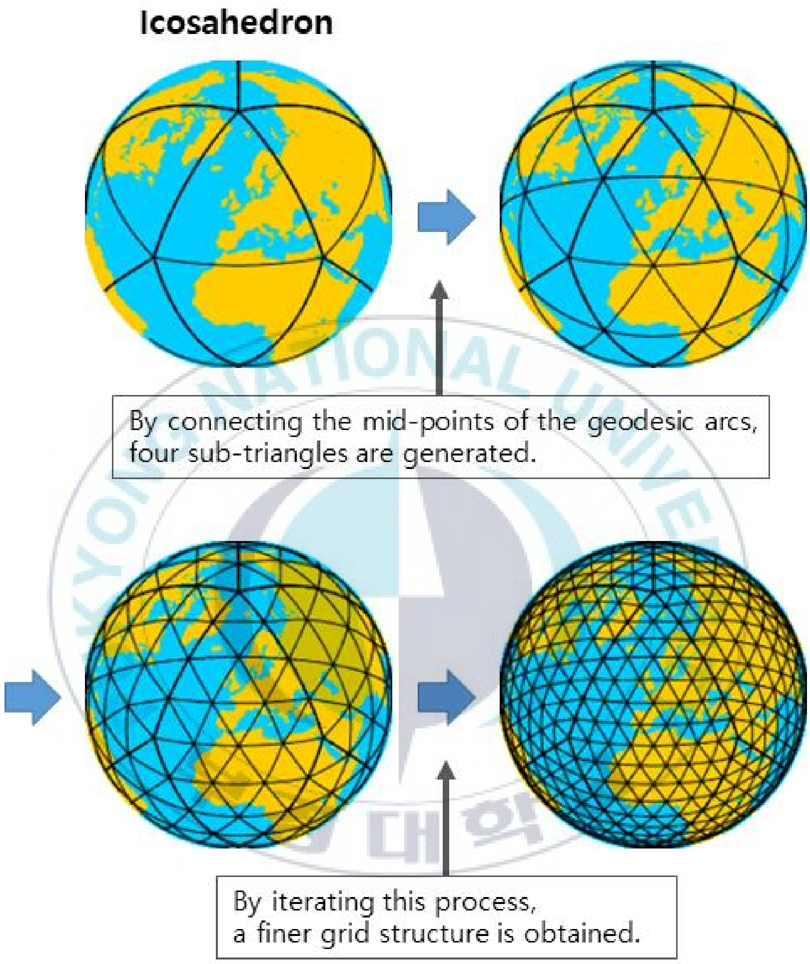

Figure 4. Process of increasing resolution grid structure in the icosahedral-hexagonal grid

Weather Forecasts). Present SST and sea ice changes compared with climatological data are considered whether consistent or not. Then final boundary data are used as the input of GME model. AGCM is calculates the future weather condition using several equations. Therefore, the initial data is also required to present the start points atmospheric condition. ECA (The European Climate Assessment) reanalysis dataset which has gaussian grid is used as the initial data for GME. This data has got from ECMWF. After the initial data are horizontally re-gridding to GME model grid, it used to run the model.

The time-lagged ensemble method is used to reduce the uncertainty of prediction by the longer model running time. This time-lagged ensemble method is one of prediction method carrying out several predictions. It is proposal the statistical probability of prediction results through many model simulations rather than a deterministic outcome. In this study, 10 ensemble predictions have carried out from seeding season to harvest season in every month.

Finally, the agrometeorological long-term prediction data which has 40 km resolution have been produced for 2015, 2016.

Table 2. Details of SST and sea ice boundary data

Variable	SST (Sea Surface Temperature)	Sea ice
Grid Number (Lon/Lat)	360×180	144×73
File Format	NetCDF	NetCDF
Time Period	1971-2000 Daily Data	1971-2000 Daily Data
Data Source	NOAA OI (National Oceanic and Atmospheric Administration Optimum Interpolation)	ECMWF (European Centre for Medium Range Weather Forecasts)

Table 3. Details of ECMWF reanalysis data grid and resolution information

Spectral	Gaussian	Lat/Lon	Grid Number
T511	N256	0.351	1024×512

B. Calculation the high resolution prediction data

To calculate high resolution (1 km × 1 km) prediction data from mesoscale (40 km × 40 km) prediction output, QTM and QPM have used. It can be denominated as 'GME-QTM' and 'GME-QPM' in this study. The method is same with to calculate observation-based synthetic data except the use of model topography data and model data. The high resolution prediction temperature and precipitation data are produced considered the small-scale topography effect which are not be treated in mesoscale topography. The comparison topography data is shown in Fig. 5 which have different resolutions.

In this study the long-term prediction data are calculated to high resolution in 2015, 2016 and AMIP (Atmospheric Model Intercomparison Project) type model climatology for 30 years (1979-2008) is calculated as well.

Final high resolution data obtained from difference between mean of ensemble prediction and model climatology added to present climatology (Fig. 6).

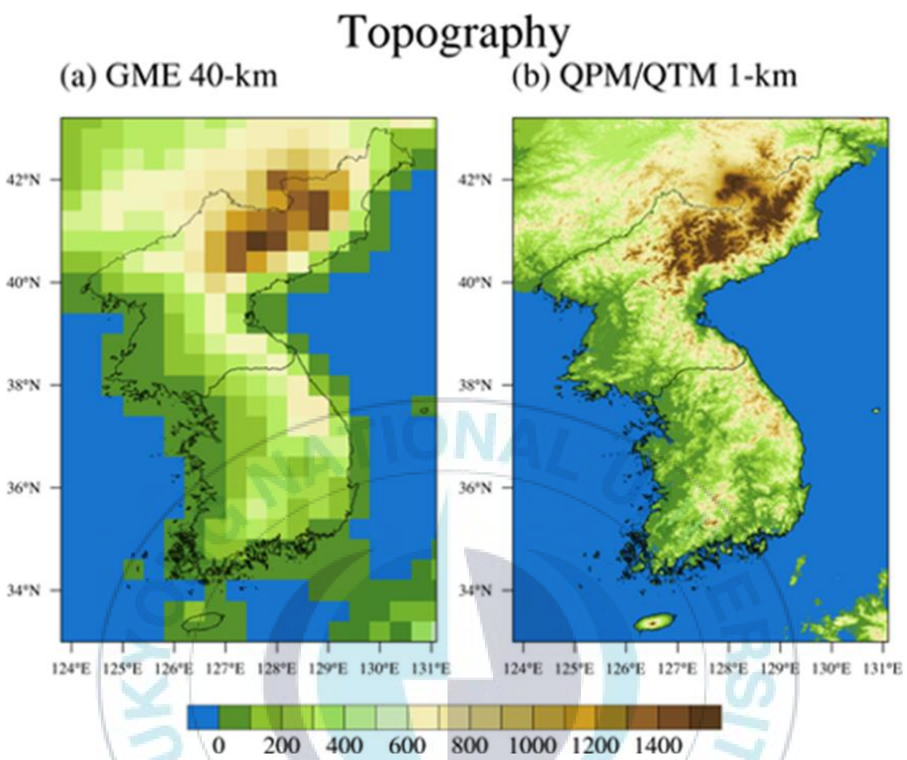

Figure 5. Comparison topography data between (a) GME model topography and (b) DEM topography which is used in QPM and QTM

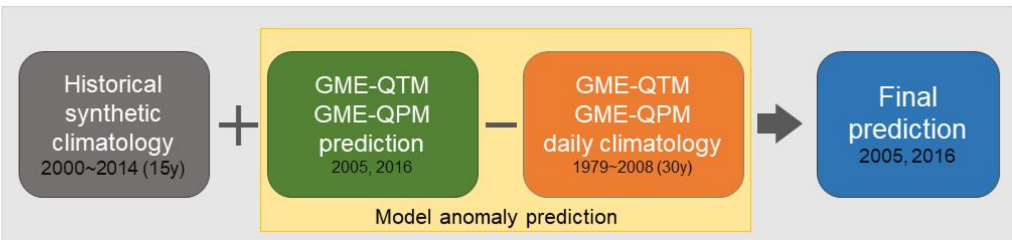

Figure 6. Process to calculate the final prediction

Ⅲ Results

1. Result of agrometeorological variables prediction dataset

The essential agrometeorological variables are different by what kind of crop models is used. Song et al. (2014) reviewed 14 crop models to estimate possibility of application to Korean for prediction the crop yields. For the major agrometeorological input data for crop model are temperature, precipitation and radiation. However the other meteorological variables are still used even that have consist value.

Several variables of prediction data of GME model which are possible to be input data of crop models and pest models have been set (Table 4 and Fig. 7). These 22 variables can be combined to the other variables. For example, using zonal wind (U_10M) and meridional wind (V_10M), wind speed can be created by calculating. The variables of input data can be selected depending on the kind of crop models. The list of variables is enable to run any crop model as the meteorological input data of crop model or pest model. These are calculated to daily data what is required common data type for crop models.

The ensemble prediction results of GME have 40 km resolution. Those are presented in Fig. 7 for the sample period in May, 2016. For visualization the monthly averaged value are plotted.

Table 4. Prediction variables list from GME model for crop models

GME Variable name		Element (Unit)
Temperature	T_2M	temperature 2m above ground (K)
	TMIN_2M	minimum of temperature 2m above ground (K)
	TMAX_2M	maximum of temperature 2m above ground (K)
	T_M	temperature at a depth of ~ 8 - 10 cm of the old 2-layer soil model (K)
	T_SO	soil temperature (K)
Water contents	TOT_PREC	Total precipitation (kg/m2)
	RUNOFF_S	surface water run-off (kg/m2)
	RUNOFF_G	ground water run-off (kg/m2)
	W_I	water content of interception storage (mmH2O)
	W_G1	water content of upper soil layer (0 - 10 cm) of the old 2-layer soil model (mmH2O)
	W_G2	water content of lower soil layer (10 - 100 cm) of the old soil model (mmH2O)
Humidity	QV_S	specific humidity at the surface; over water, this corresponds to 100% relative humidity. (kg/kg)
	QV_2M	specific humidity 2m above ground (kg/kg)
Cloud cover	CLCT	total cloud cover (%)
	CLCH	high cloud cover (0 - 400 hPa) (%)
	CLCM	medium cloud cover (400 - 800 hPa) (%)
	CLCL	low cloud cover (800 hPa - surface) (%)
Radiation	ASOB_S	solar radiation balance at the surface (W/m2)
	ALB_RAD	(solar) shortwave albedo at the surface (%)
Wind	U_10M	zonal wind 10m above ground (m/s)
	V_10M	meridional wind 10m above ground (m/s)
Pressure	PS	surface pressure on model orography (Pa)

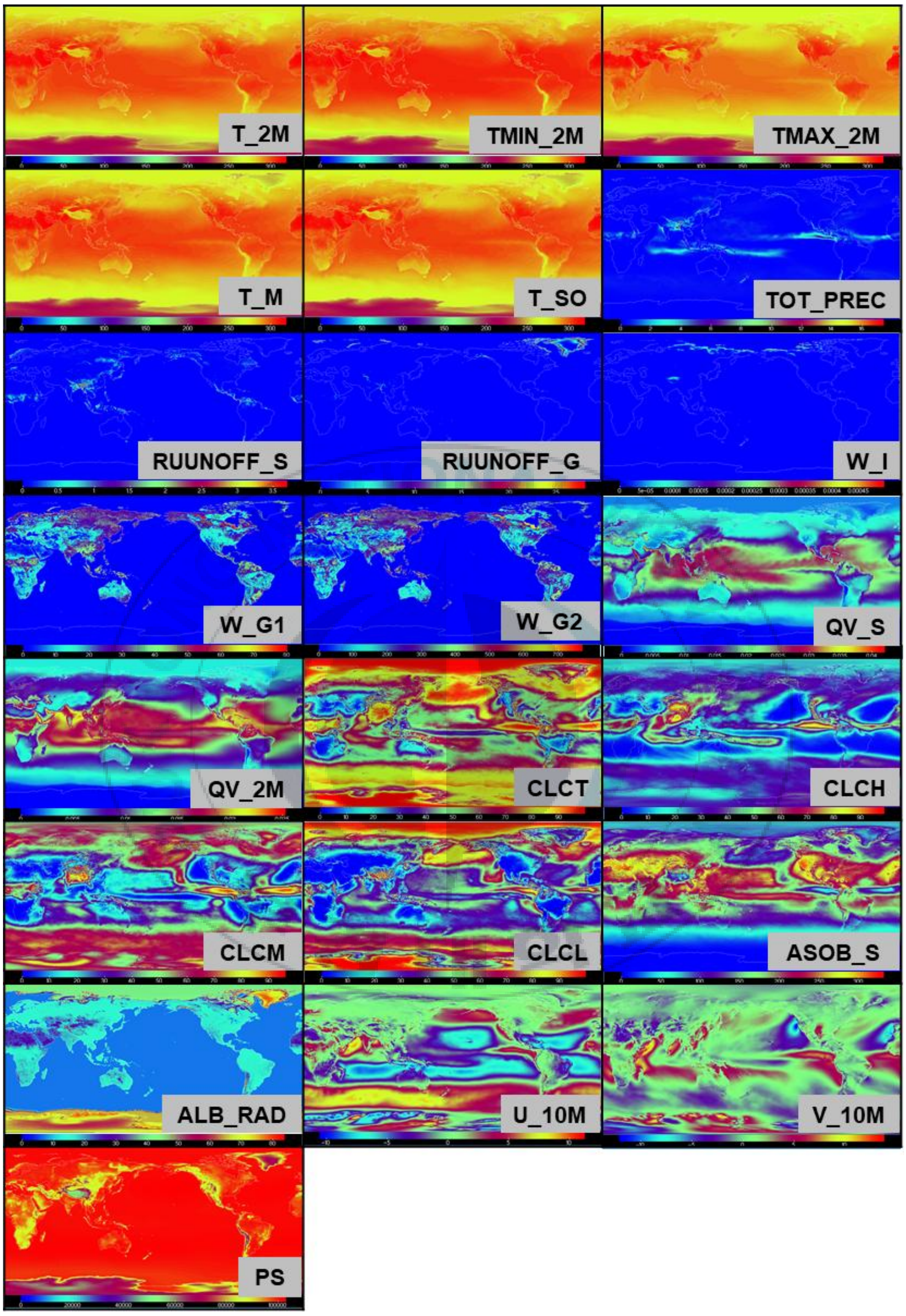

Figure 7. Prediction variables of ensemble prediction sample for crop models that have same orders with Table 4. (visualization period of samples: May, 2016 / initial date: May 21-30, 2016.)

2. Observation-based synthetic temperature/precipitation

To calculate the observation-based synthetic temperature and precipitation, the observation (AWS, ASOS, and MERRA 2) data have been used to QPM and QTM.

In this study, the observation temperature and precipitation have been calculated to 1 km high resolution data in two kinds of period for different purposes. First purpose is to produce the observation-based high resolution data as the past data which replace prediction data for the past time. The simulation period is March to October for 2 years (2015, 2016) by experiment design of this study. The results of high resolution synthetic temperature and precipitation as the historical data which replaces prediction data is shown in Fig. 8 and 7 respectively. And second purpose is to obtain the present climatology data. This present climate data is required to calculate final high resolution prediction. In the process to calculate the high resolution final prediction, model anomaly prediction data are added to historical synthetic climatology (Fig. 6). This historical synthetic climatology from observation data indicates the present climatology in The Korean Peninsula. It would be the standard data compared with future wether conditions. Therefore, by adding model anomaly prediction which indicates future climate changes compared to present climate, final high resolution prediction can be obtained. For the present climatology, 15 years observation data have been calculated using QTM and QPM. The period is from 2000 to 2014. After calculating to detailed data in every for 15 years, the data have been averaged to daily data.

For the QPM and QTM results using observation data are described in the previous studies (Kim and Oh, 2010; Bae, 2015; Kang, 2017).

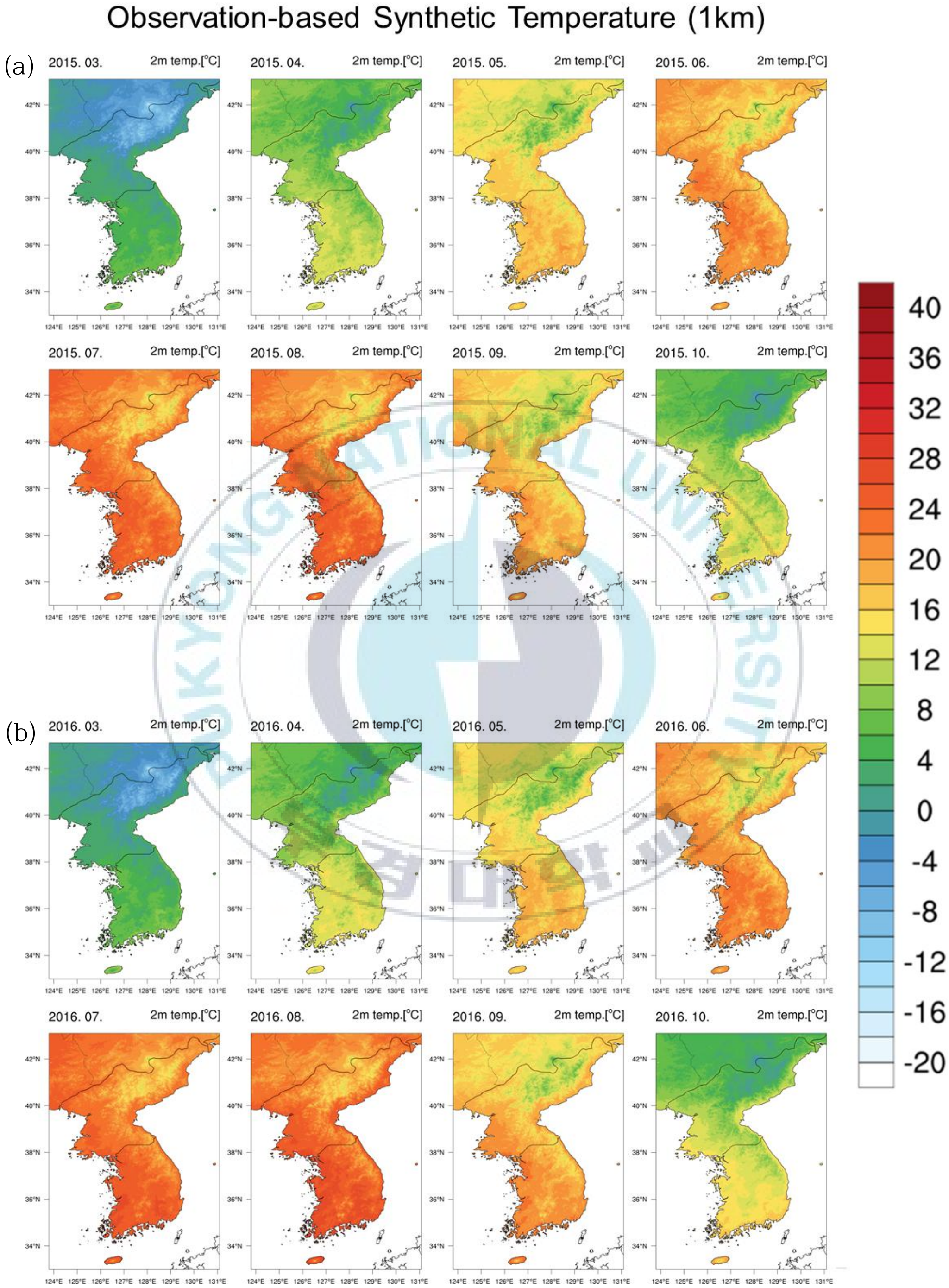

Figure 8. Observation-based synthetic temperature over the Korean Peninsula in March to October (a) 2015 and (b) 2016

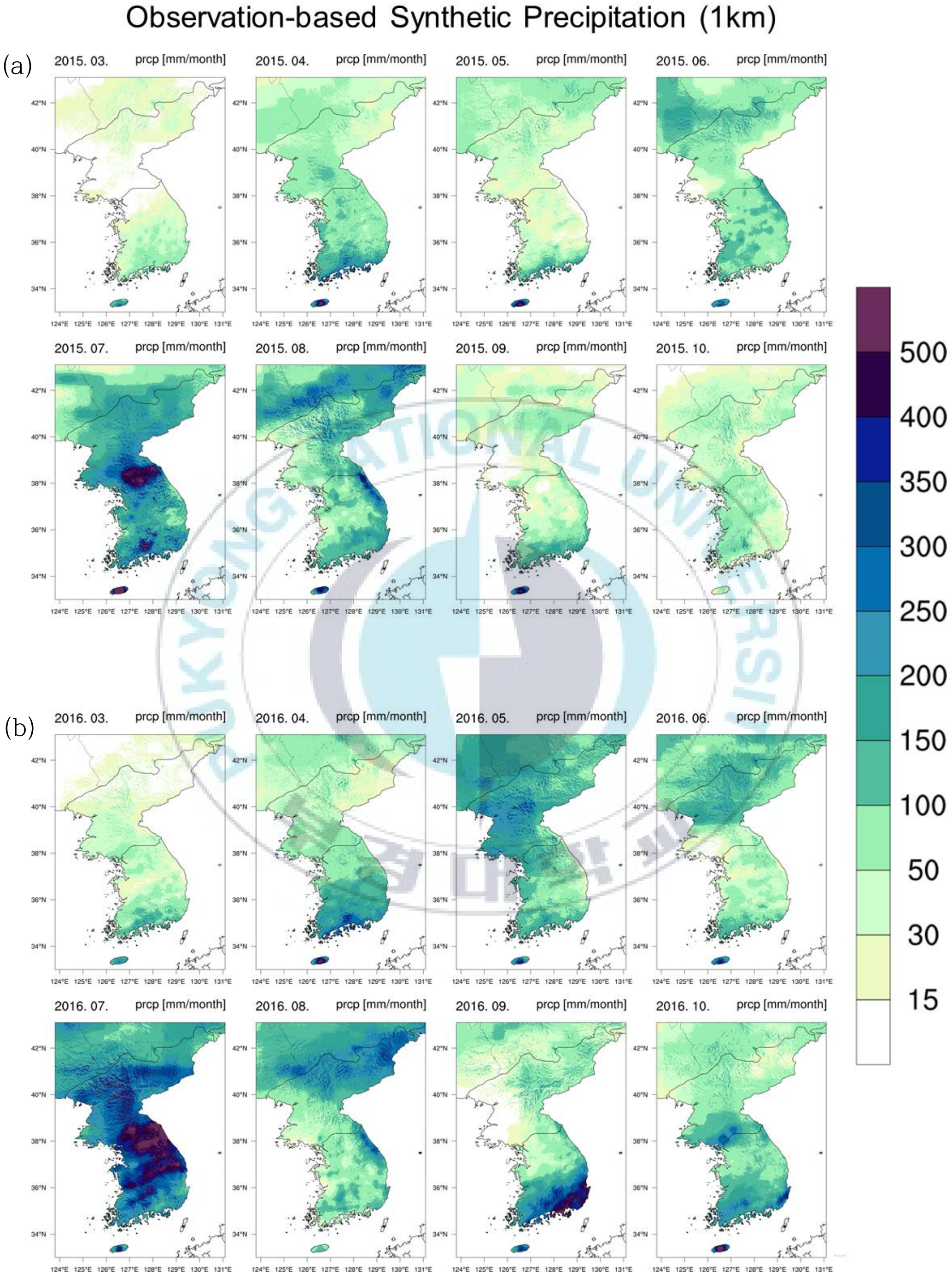

Figure 9. Observation-based synthetic precipitation over the Korean Peninsula in March to October (a) 2015 and (b) 2016

3. Final high resolution long-term prediction data

To obtain the high resolution long-term temperature and precipitation prediction, the GME-QTM and GME-QPM process have been carried out. Using GME prediction results, the temperature and precipitation have been calculated to 1 km high resolution data by QPM and QTM.

There are two kinds of high resolution prediction data through their different purpose of usages. From January to August in 2015 and 2016, 10 times simulation have performed every month for ensemble prediction. Total simulation number is 160. Each simulations have been calculated to detailed data using QTM and QTM. Then the 1 km high resolution data are averaged to ensemble mean. Another calculating the GME simulation is to obtain the high resolution model climatology. The period of GME model climatology is 1979 to 2008, 30 years by AMIP (Atmospheric Model Intercomparison Project). The GME climatology has been calculated to 1 km high resolution data for 30 years. Then the high resolution climatology data have been averaged to daily data.

Finally, the high resolution long-term prediction data have been obtained by the model anomaly prediction data added to historical synthetic climatology (Fig. 6). The results of final prediction is shown in Fig. 10. For visualization sample date has been selected. Initial date of this ensemble prediction is 21-30 January in 2015.

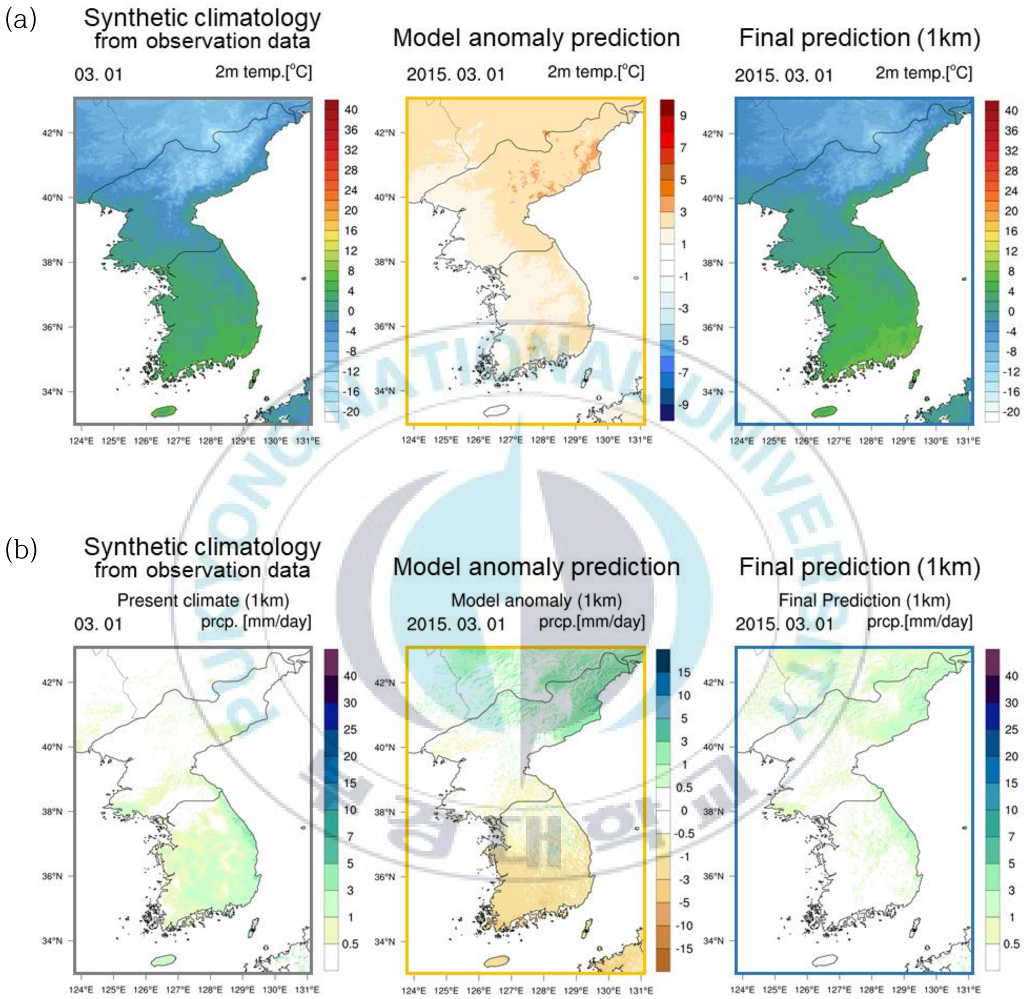

Figure 10. Process of final high resolution (a) temperature and (b) precipitation prediction which obtained by the model anomaly prediction data added to historical synthetic climatology

4. Time series at station point

The 16 ASOS station points have been selected to indicate the results of temporal adaptative prediction system. 2 station points in each district are where produce large crop yields in Korea. The details of station are described in Table 5. The distribution of stations are pointed in Fig. 11. The stations are evenly spread.

The meaning of 'temporal adaptative' is that the data is changed as time goes by. The temporal adaptative temperature data are shown in Fig. 12. The temperature data is at the Seosan station which is the largest rice crop yields region in Korea. Each name of 11 plots means the month when the data is provided. In JAN 2015, there is prediction data only. In Feb 2015, there are the new prediction data and previous prediction data for the period of March which occurred by model spin-up time. In APR, the prediction on March that the past time becomes observation-based synthetic temperature. The same as thes way, data are changed to their proper type. In the same way, precipitation dataset is shown in Fig. 13. This figure is also Seosan station data. As time goes by, precipitation data are changed by more observation-based synthetic data. Because of the prediction is ensemble prediction data and the final prediction is obtained by model anomaly prediction added to synthetic present climatology, for the precipitation, it is tend to have number of precipitation days more than observation data with less amount. The time series graph at the other stations, are not shown here at all. But the results indicate the temporal adaptative dataset in the same way. On each month, temperature and precipitation data are can be used for the prediction the annual crop yields using crop model and for the prediction vermination using the pest models.

Table 5. The information of 16 ASOS stations where produced large crop yields in South Korea

District	Station name	Station number	Latitude of station	Longitude of station
Gyeonggi-do	Icheon	203	37.264	127.4842
	Paju	99	37.8859	126.7665
Gangwon-do	Cheorwon	95	38.1479	127.3042
	Wonju	114	37.3376	127.9466
Chungcheongbuk-do	Cheongju	131	36.6392	127.4407
	Chungju	127	36.9704	127.9527
Chungcheongnam-do	Buyeo	236	36.2724	126.9208
	Seosan	129	36.7766	126.4939
Jeollabuk-do	Buan	243	35.7295	126.7166
	Jeongeup	245	35.5632	126.8661
Jeollanam-do	Goheung	262	34.6182	127.2757
	Haenam	261	34.5536	126.569
Gyeongsangbuk-do	Sangju	137	36.4084	128.1574
	Gyeongju	283	35.8175	129.2009
Gyeongsangnam-do	Hapcheon	285	35.565	128.1699
	Miryang	288	35.4915	128.7441

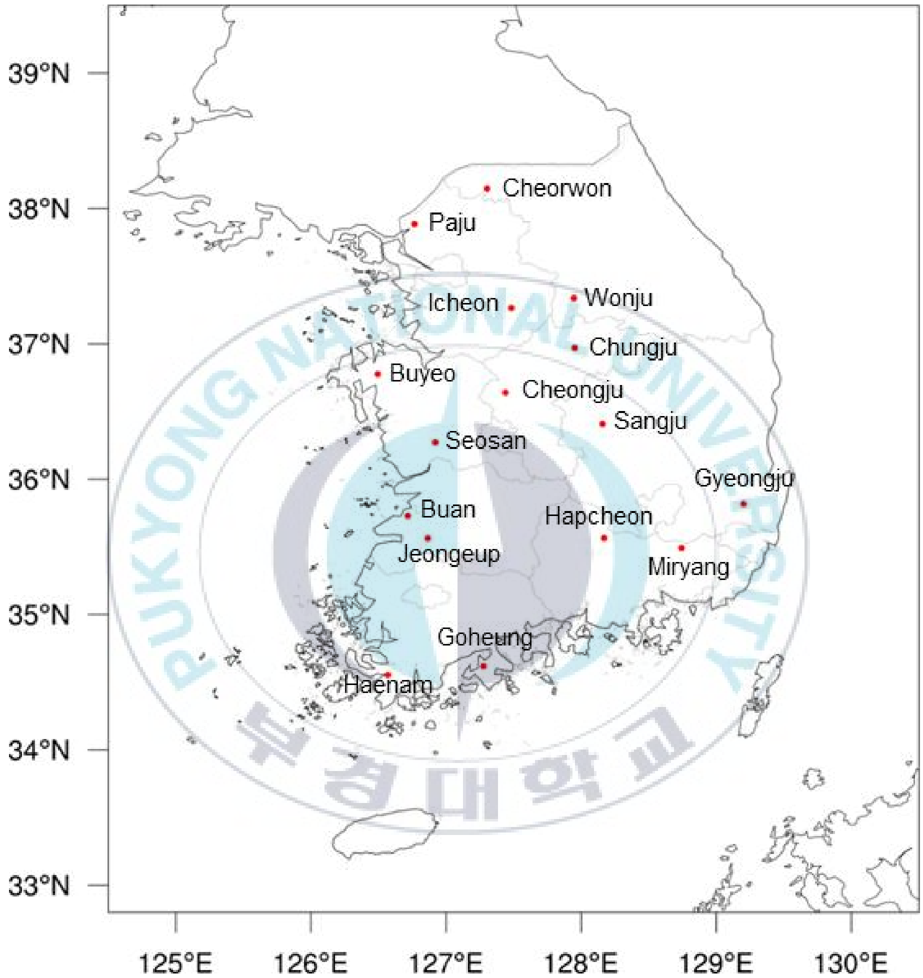

Figure 11. Distribution of 16 station points

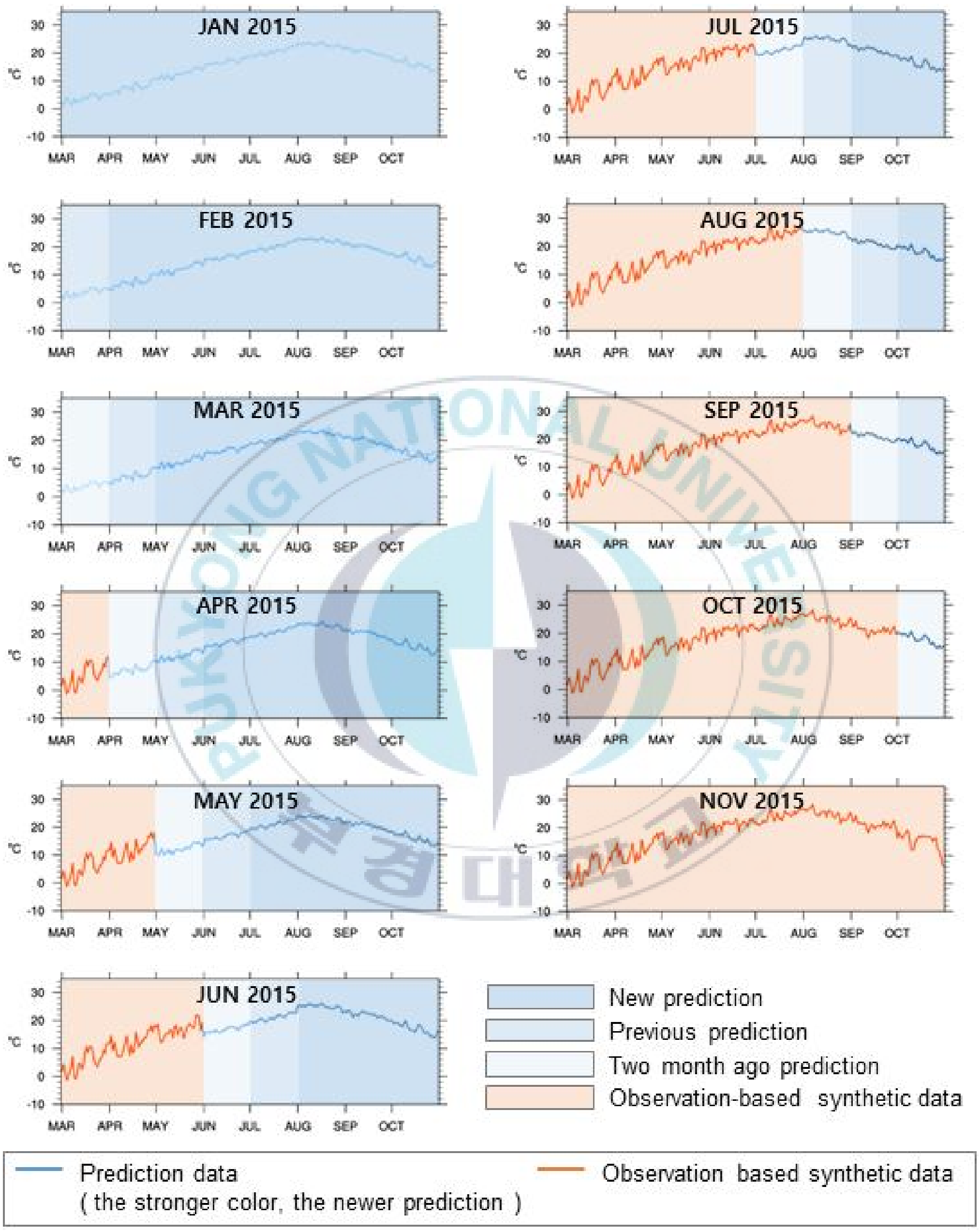

Figure 12. Temporal adaptative daily temperature data with combination of observation-based synthetic data and prediction data at Seosan station

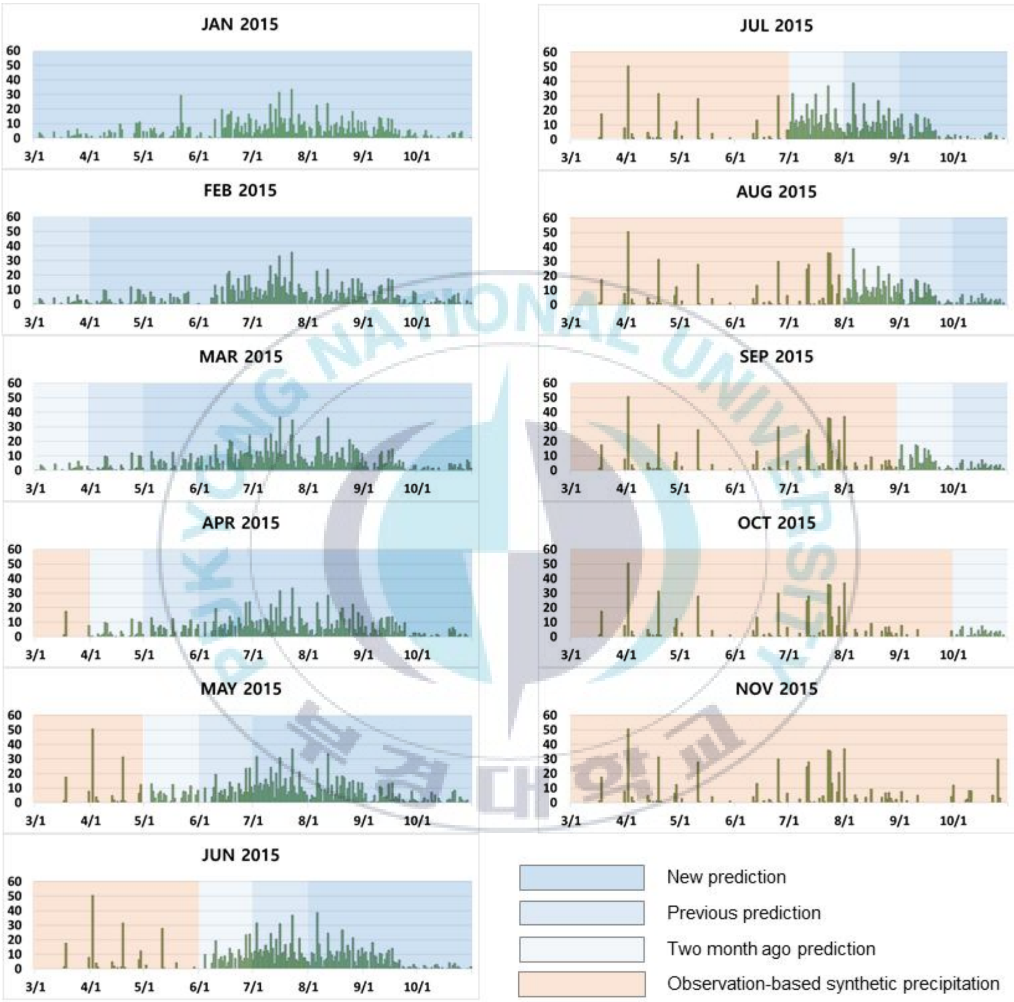

Figure 13. Temporal adaptative daily precipitation data with combination of observation-based synthetic data and prediction data at Seosan station

Ⅳ Conclusion

This study has established ‘A temporal adaptative high resolution long-term prediction system for agrometeorological outlook services’. This agrometeorological data provision system considers four significances to predict crop yields using crop models. First, to predict the annual crop yields, long-term agrometeorological prediction is required from seeding season to harvest season, and secondly, it requires a weather parameter as the daily data for crop models that are used for crop yields. Third, to predict regional crop yields accurately on the Korean Peninsula, high resolution agrometeorological prediction data are needed. Finally, to increase the predictability of agrometeorological data, predictions must be made again over time from seeding season to harvest season, and the observation-based high resolution synthetic data should be replaced for the past time, which should be used to predict the annual crop yields.

To produce high resolution observation-based data and prediction data which have 1 km × 1 km resolution, the observation data and prediction data from AGCM are used as the input data for quantitative model. Using QTM and QPM, high resolution synthetic and prediction data are produced. The diagnostic model, QTM and QPM, consider the small-scale topography effect, which is not treated in the mesoscale resolution. Domain is Korean peninsula and period is March to October for two years(2015, 2016).

As a results, 3 kinds of data are obtained. First is 22 variables of prediction data of GME model which are possible to be input data of crop models and pest models. This data has 40 km resolution. Second results is high resolution observation-based data To produce high resolution observation-based, using QTM and QPM with AWS, ASOS and MERRA 2 observation or reanalysis data. Two kinds of observation-based synthetic data are calculated. Those are the synthetic data for the past data for 2 years (2015-2016) through the experiment design and the present climatology data for 15 years (2000-2014) which are used for prediction data. And third is the final prediction data which have 1 km high resolution. To obtained the final prediction data, the model climatology for 30 years (1979-2008) and long-term prediction data for 2 years (2015-2016) have been calculated to detailed data. Then the high resolution long-term prediction data have been obtained by the model anomaly prediction data added to historical synthetic climatology. Additionally the time series at the 16 station data have been analysis to indicate the temporal adaptative system.

Through the concept of temporal adaptative high resolution long-term prediction system, the high resolution temperature and precipitation data is provided for the future, and the new prediction data is updated every month, on the other hand, the observation-based synthetic data is replaced the prediction data for the past. This changeable dataset would be useful data for prediction and analysis annual crop yields using crop models and pest models.

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