RESEARCH REPORT 2015-20

APEC CLIMATE CENTER

# Linking APCC Seasonal Climate Forecasts to a Rice-Yield Model for South Korea

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# Preface

The multi-model ensemble (MME) technique was designed around the start of this century to quantify uncertainties in forecasts associated with model formulation and has been considered as an effective means of improving weather and climate forecasts. As a result, various MME prediction systems are currently utilized at several operational centers (e.g., the European Centre for Medium-Range Weather Forecasts (ECMWF), the International Research Institute for Climate and Society (IRI), National Center for Environmental Prediction (NCEP), Meteorological Service of Canada (MSC), World Meteorological Organization Lead Center (WMO LC), and the North American Multimodel Ensemble (NMME) that routinely provide MME seasonal forecasts.

Since its inception in 2005, The Asia-Pacific Economic Cooperation (APEC) Climate Center (APCC) has devoted considerable effort to developing a MME prediction system for producing improved and well-validated seasonal and regional forecasts in both deterministic and probabilistic frameworks for research and operational purposes. Currently, the APCC operates the largest ensembles in the world and has obtained essential experience in developing and assessing multi-model predictions. Along with seasonal forecasts, their verification information of retrospective forecasts (hindcast) is now also available online via their website. However, verification of real-time forecasts is not yet operational, although it is a very important issue from an operational perspective to investigate the ability of the APCC MME prediction system in presenting seasonal temperature and precipitation for real-time forecasts in a timely manner.

Motivated by this, a real-time verification system has been developed to assess the quality of the single-model and multi-model predictions in the APCC operational environment. Along with this, we have improved the current verification system for hindcasts considering the recent improvements of the APCC operational prediction system. The present report also provides a preliminary documentation of the seasonal forecasts issued by the APCC operational multi-model forecasts, with a large set of predictions currently available in an operational context, particularly focusing on real-time predictions of temperature and precipitation. The developed real-time verification system has been successfully employed by the APCC as an operational tool and internally provided their information every month. All verification information of the hindcast and real-time forecasts will be available online beginning in 2015.

The APCC will continue to improve the accuracy of its long-range climate prediction information. The new service will bring us one step closer to meeting users' expectations as the public gains awareness on how climate affects their lives, and also strives to promote our mutual interests and scholarly exchange with the climate forecasting centers and institutes within the APEC region and beyond. Finally, I extend my thanks to you and I hope you enjoy this 2014 Research Report.

**Dr. Chin-Seung Chung**

Director / APEC Climate Center

March. 2015

## ABSTRACT

The WGEN, SIMMETEO, and LARS-WC stochastic weather generators are widely used in a range of studies, including agricultural crop simulations to determine the potential impact on crop growth, development, and yield. To assess the potential and limitations of weather generators, their climate simulation performance should be evaluated when applied over a new region, or linked with crop models. The Asia-Pacific Economic Cooperation Climate Center (APCC) recently developed a 6-month lead multi-model ensemble (MME) prediction system. Weather generators could link APCC seasonal climate predictions to crop models to generate daily weather data and provide real-time simulation of crop growth and assessment of crop productivity. The objectives of this study are to evaluate the three generators for 63 weather station sites over South Korea, and determine the potential for translating APCC's seasonal climate outlook into predictions of rice yield using the CERES-Rice model. The study concludes that the performances of the generators are accurate in simulating maximum and minimum mean temperatures, and solar radiation; however, they have difficulty in reproducing precipitation. The performances vary from site to site. The LARS-WG matches the observed data closer than the WGEN and SIMMETEO. In general, rice yields simulated using synthetic weather data generated with and without bias correction are similar to the yields stimulated using observed weather date. Simulated rice yields of different cultivar responses to weather data are different. Unkwang is less sensitive to variation of weather factors than Nampyeong and Saegyewha. The APCC climate outlook has the potential to forecast rice yields over Korea. However, the accuracy and reliability of yield forecasting may vary considerably from year to year and site to site.

# Contents

## Linking APCC seasonal climate forecasts to a rice-yield model for South Korea

# 1. INTRODUCTION

## 1.1 Paddy Rice in Korea

Rice is the staple food of Korea and one of the country's most important agricultural commodities for those involved in rice farming. Approximately half of the agricultural land is comprised of rice paddies. Rice yields show strong interannual variation as a result of climate variations. For example, in the mountainous regions of Korea, rice plants can suffer from low temperatures at any stage. In 1980, a spell of low temperatures started in late July and continued until late August; all rice-cultivated areas were susceptible to the cold temperatures at the reproductive stage, and 783,000 ha of rice field was damaged with grain yields declining by up to 26% compared with the national average of the previous 5 years (Lee 2001).

The Korean peninsula is located in the Far East, between 33° 06′ and 43°01′ N latitude and 124° and 131°53′ E longitude, in the northern temperate climatic zone, characterized as warm subhumid/subtropical with summer rainfall. The Korean Peninsula has a continental weather pattern with hot and humid summers and severely cold winters. Rice is a summer crop, grown between April and October. Droughts, floods, high and low temperatures and winds are major meteorological disasters for rice farming. Shim et al. (2003) reported that the total number of meteorological disasters from 1981-2000 were 23, 49, and 69 by drought, high temperature, and low temperature, respectively. Although droughts occur extremely frequently, severe damage is minimized in most areas due to the availability of the irrigation system.

The Korean peninsula has two main agricultural regions near the Taebaek Mountains. Except for the southwestern part of the country, most paddy rice is cultivated in valleys between mountains with steep slopes (Figure 1A). Five agroecological zones (AEZs) (Figure 2A) are determined mainly by elevation and latitude, although soil characteristics and wind from the Pacific Ocean in the east coastal areas are also important (Shin et al. 1995). During the rice-growing season, the mean monthly air temperatures range from 11°C in April to 25°C in August. However, the variations of air temperatures are very strong according to the region and year. The rice calendar in each AEZ can be different in terms of sowing date and transplanting date, as shown in Table 1.


**Figure 1.** Paddy fields (green color) in South Korea

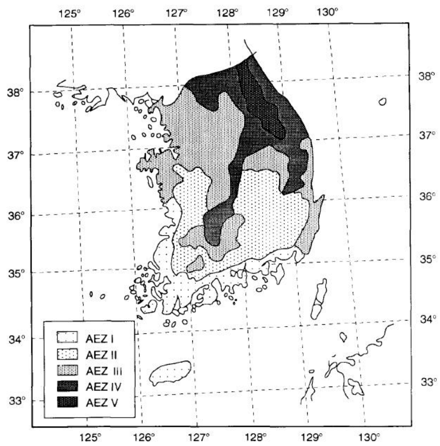


**Figure 2.** Agroecological zones (AEZ) in South Korea (Adapted from Shin et al., 1995)

**Table 1.** Paddy rice sowing date and transplanting date in each AEZ in South Korea (Adapted from Shin et al. 1995)

| | Sowing | | | Transplanting | | | |
|---|---|---|---|---|---|---|---|
| AEZ | Early limit | Optimum | Late limit | Early limit | Optimum | Late limit | Early limit |
| I | 1 Apr | 20 Apr | 30 Apr | 27 Apr | 30 May | 15 Jun | 2 Jul |
| II | 1 Apr | 20 Apr | 30 Apr | 27 Apr | 30 May | 15 Jun | 2 Jul |
| III | 1 Apr | 15 Apr | 20 Apr | 10 Apr | 25 May | 5 Jun | 12 Jul |
| IV | 1 Apr | 5 Apr | 15 Apr | 15 May | 20 May | 25 May | 24 Jul |
| V | 1 Apr | 5 Apr | 10 Apr | 18 May | 20 May | 25 May | 21 Jul |

### 1.2 Rice modeling and decision making

One of the greatest potential applications of crop modeling is yield forecasting. Timely and accurate crop yield forecasting is important for decision makers to have time to take any appropriate action. If the production is higher than originally planned, it may require the transportation of grain to deficit areas. On the other hand, with lower production, early warnings of poor crop harvest can allow policy makers to take necessary actions to ameliorate the effects of food shortages. For example, it might be necessary to import grain from the international market. To achieve a high yield for a crop, the farmer could adjust management practices accordingly. For example, with extreme temperatures higher or lower than optimal temperature, the planting date may be advanced or delayed, respectively. In addition, a different fertilizer supply and supplementary irrigation can also be changed accordingly.

### 1.3 Weather and crop modeling

Global Climate Models or General Circulation Models (GCMs) are a computer-based version of the Earth system to simulate the climate system and the interactions between the system components (Dibike and Coulibaly 2005). GCMs simulate the future climate in a horizontal global grid with horizontal resolutions of $2^{o}$ to $48^{o}$ latitude and longitude and are generally issued as averages in time. They are presently considered to be the most reliable source of climate information at continental and hemispherical scales. However, GCMs are unable to represent sub grid and local scale features and dynamics (Carter et al. 1994) because of the effect of spatial and temporal averaging on the random noise resulting from the chaotic nature of the atmosphere, and computational capacity limitations.

Weather is a key determinant in agricultural production. Crop yield is a function of dynamic, nonlinear interactions between weather, soil-water and nutrient dynamics, management practices, and crop physiology and phenology. Crops do not respond to average conditions for the growing season, but to dynamic interactions between weather, other environmental factors, and crop characteristics. A range of interacting weather variables mediate many aspects of crop growth and development. To capture the dynamic nonlinear interactions between weather, soil-water and nutrient dynamics, and crop physiology and phenology, process-oriented crop simulation models, such the DSSAT, typically operate on a daily time step and a spatial scale with a homogeneous plot.

Daily weather data are normally required for the application of crop simulation models. These include maximum and minimum air temperatures, total solar radiation, and total precipitation for most of these studies (Hoogenboom 2000). The usefulness of crop model estimates is largely dependent on the quality of the weather input data (Meinke et al. 1995). High-quality weather data are therefore required to obtain reliable simulations.

GCM output cannot be used directly for crop modeling due to the mismatch in the spatial and temporal resolution between the GCMs and crop models. Many applications, such as crop modeling, require the equivalent of point climate observations and are highly sensitive to field scale climate variations.

### 1.4 APCC climate outlook

The Asia-Pacific Economic Cooperation Climate Center (APCC) launched a 6-month-lead in seasonal climate prediction using six operational coupled GCM models through cooperation with six research institutes (Table 2). The forecasts are issued every month expressed as monthly mean and spatially averaged at the grid cell scale of 2.5° × 2.5°.

**Table 2.** Acronyms and description of GCMs used in the APCC seasonal forecasts (adapted from Kang et al. 2014)

| Model acronym | Institution(country) | Model resolution | Ensemble size | References |
|---|---|---|---|---|
| APCC | APEC Climate Center (Korea) | T85L26 | 5 | Jeong *et al.* (2008) |
| NCEP | NCEP Climate Prediction Center (USA) | T62L64 | 15 | Saha *et al.* (2006) |
| PNU | Pusan National University (Korea) | T42L18 | 5 | Sun and Ahn (2011) |
| POAMA | Bureau of Meteorology Research Centre (Australia) | T47L17 | 10 | Zhao and Hendom (2009) |
| SNU | Seoul National University (Korea) | T42L21 | 6 | Ham and Kang (2011) |
| UH | University of Hawaii (USA) | T31L19 | 10 | Fu and Wang (2004) |

## 1.5 Downscaling

There are several approaches for linking seasonal climate predictors and crop models as a solution to the scale mismatch between the GCM output and the crop modeling required at a field scale (Hansen and Indeje 2004; Hansen et al. 2006). Downscaling techniques have been widely used. There are two fundamental approaches for the downscaling of large-scale GCM output to a finer resolution: dynamic downscaling and statistical downscaling. In dynamic downscaling, GCM output are fed into regional climate models as boundary conditions to enable the prediction of the regional climate at a spatial scale of tens of kilometers. This procedure is based on the complex physics of atmospheric processes and involves considerable computational resources. In dynamic downscaling techniques, it is assumed that the parameterization schemes selected for past climates are also valid for the climate in the future. Dynamic downscaling produces responses in physically consistent ways with climate models. In addition, dynamic downscaling techniques are highly dependent on the boundary conditions provided by the GCMs. As compared to the use of GCM output, dynamic downscaling has more accurate downscaled results. However, the downscaling spatial scale of tens of kilometers is still too large for many crop models.

### 1.5.1 Statistical downscaling

Statistical downscaling relies on the empirical quantitative relationships derived between the large-scale GCM output (predictors) and the local surface variables (predictands), such as precipitation, air temperature, and solar radiation. The major assumption is that the relationships derived between the GCM output and the local weather variables for the past-observed climate are equally valid for the future. The most common form is the predictand as a function of the predictor(s), but other types of relationships have been used; for example, the relationship between the predictors and the statistical distribution parameters of the predictand (Pfizenmayer and von Storch 2001) and the frequencies of extremes of the predictand (Katz et al. 2002). Unlike dynamic downscaling, statistical downscaling does not involve complex atmospheric physics, and hence, is computationally less expensive (Sachindra et al. 2012).

In statistical downscaling, for the establishment of relationships between the GCM output and the input weather variables of agricultural models, preferably long records of observed weather data are required. This is because a long record of observations could possibly contain the full variability of the observed climate and hence allow the downscaling models to better model climate changes.

Statistical downscaling techniques can be grouped into three categories: weather classification, regression models, and weather generators (Wilby et al. 2004). Statistical downscaling is advantageous because it is comparatively cheap and computationally efficient, can provide point-scale climatic variables from GCM-scale output, can be used to derive variables not available from RCMs, is easily transferable to other regions, is based on standard and accepted statistical procedures, and is able to directly incorporate observations into the method. However, it requires a long and reliable observed historical data series for calibration, and is dependent upon the choice of predictors, non-stationarity in the predictor-predictand relationship, does not include climate system feedbacks, and is dependent on GCM boundary forcing and affected by biases in the underlying GCM.

In weather classification methods, large-scale weather patterns are grouped under a finite number of discrete states or weather types (Anandhi 2010) according to their similarity with 'nearest neighbors' or reference sets. Then the links between the predictand and the prevailing weather state of large-scale weather patterns are identified, and the corresponding field scale weather can be replicated by considering the large-scale weather patterns at any given time by resampling or using regression functions. The analogue approaches (Lorenz 1969; Timbal et al. 2009; Charles et al. 2013; Shao and Li 2013) and recursive partitioning (Schnur and Lettenmaier 1998) are examples of the weather classification techniques.

Regression techniques develop the simple means for either linear or nonlinear regression equations (transfer function) between the GCM output and the predictands. Widely applied methods include the linear regression technique (Marzban et al. 2006), multi-linear regression (Murphy 1999; Chu et al. 2010), artificial neural networks (Tisseuil et al. 2010), and gene expression programming (Hashmi et al. 2011). Regression-based downscaling methods are the most commonly used statistical downscaling techniques (Nasseri et al. 2013) mainly due to their simplicity and effectiveness. However, a major issue of under prediction of daily precipitation variance is often associated with regression approaches because of the relatively low predictability of local amounts by large-scale forcing alone (Wilby et al. 2004).

### 1.5.2 Weather generators

Weather generators are mathematical models that produce the statistical attributes of a local weather variable (such as the mean and variance) by scaling their parameters according to the corresponding historical climate variable or changes characterized in the GCM output. These techniques possess the advantage of generating observed statistical characteristics of daily weather variables at a particular site. In addition, the stochastic weather generators could generate any desired length of time with similar statistical properties as the observed climate. Weather generators traditionally used for filling missing data and interpolating or extrapolating the data to indefinite lengths by using the statistical properties of the observed historical data have become a very popular tool for downscaling (Dibike and Coulibaly 2005). In addition, stochastic weather generators can be used for risk assessment studies by generating a large number of different climate scenarios.

There are two fundamental types of weather generators, based on the approach to model daily precipitation occurrence: the Markov chain approach (Hughes et al 1999) and the spell-length approach (Wilks 1999) or alternating renewal processes. The Markov approach is a random process that is constructed, which determines whether a location as rainy or dry, conditional upon the state of the previous day, following given probabilities. The combination of Markov chains and the two-parameter Gamma distribution is commonly used in this type of weather generator (Richardson 1981), in which Markov chains are used to predict the occurrences of wet days and the Gamma distribution is used to determine the corresponding amounts of rain, such as the WGEN (Richardson and Wright 1984), SIMMETEO (Geng et al. 1986, 1988; Soltani and Hoogenboom 2003; Hashmi et al.

2003) and MARKSIM (Jones and Thornton 2000). In the spell-length approach, instead of simulating rainfall occurrences day by day, the model operates by fitting a probability distribution to observed relative frequencies of wet and dry spell lengths, such as the Long Ashton Research Station Weather Generator (LARS-WG, Semenov and Barrow 1997). A comprehensive review of the theory behind weather generators and their evolution over time as well as their use for different purposes can be found in Wilks and Wilby (1999).

The most obvious disadvantages of weather generators are models using local climate relationships that may be not directly applicable in other local climates, even though the extent to which this limits their usefulness has not been fully tested. They also tend to underestimate inter-annual variability (Fowler et al. 2007).

Generated daily weather data may be used in a variety of applications in crop modeling to complete or replace the long-term series of historical data, especially if some data sets are missing or contain erroneous data (Hoogenboom 2000). Generated weather data can provide various combinations of weather realizations for risk-analysis studies (Mavromatis and Hansen 2001), where the probability distribution of the simulated outcomes is important for understanding the system, or for decision-making (Thornton and Hoogenboom 1994). Generated weather can also be used in various types of agricultural management models to assess the risks associated with different alternatives (Larsen and Pense 1982). In a real-time model, the generated data can be used as future sequences in crop-simulation models for yield forecasting (Thornton et al. 1997; Bannayan and Crout 1999; Georgiev and Hoogenboom 1999). In recent years, weather generator data have been used extensively in climate change and variability studies to determine the potential impact on agricultural production (Mearns et al. 1996; Riha et al. 1996; Semenov and Barrow 1998).

There are two approaches to link climate forecasts to crop models using a weather generator. One is to condition the parameters of a generator for a given forecast, i.e., to adjust the parameters of a weather generator according to the climate forecasts. This is the most common method for generating weather forecasts (e.g., Wilks 1989, 2002; Zhang et al. 2004; Semenov and Doblas-Reyes, 2007) and for climate change impact studies (e.g., Mearns et al. 1997; Semenov and Barrow 1997). An alternative approach is to constrain the generated daily sequences to match predicted monthly or seasonal means and other statistical properties. This is accomplished by sampling generated sequences until they reach approximate target values. Details of the second and third approach can be found in Hansen et al. (2006) and Hansen and Ines (2005).

### 1.6 Bias corrections

Although GCMs are regarded as the best tools available for future climate projections, there are biases in GCM output. GCM bias is simply explained as the deviation of GCM output from the observations (Salvi et al. 2011). According to Ojha et al. (2012), GCMs often incorrectly estimate the occurrence and intensities of precipitation. The main causes of GCM bias are the limited understanding of the atmosphere and the simplified representation of the atmospheric processes in GCMs (Li et al. 2010).

Bias correction is performed in two distinct ways: (1) the correction of bias in GCM outputs and (2) the correction of bias in the predictands (e.g. precipitation), which were downscaled from the GCM output. There are number of different widely used bias-correction techniques. Johnson and Sharma (2012) used nested bias correction in monthly precipitation output of GCMs over Australia. Ojha et al. (2012) applied monthly bias-correction for removing the bias in precipitation output of number of GCMs over India. The assumption behind these two methods is that the biases in the GCM output for past climates will remain the same for future climate (Johnson and Sharma 2012). Wood et al. (2004) used the quantile mapping technique for bias correction of the monthly precipitation and temperature output of a GCM. Piani et al. (2010) employed the gamma distribution-based quantile mapping technique for bias correction of daily precipitation over Europe. Li et al. (2010) introduced the equidistant quantile mapping techniques. Kharin and Zwiers (2002) applied a regression-based bias correction for the removal of bias from precipitation outputs of a GCM. Lafon et al. (2013) applied four bias-correction techniques of linear scaling, nonlinear scaling, gamma distribution-based quantile mapping and empirical distribution-based quantile mapping to correct the bias in daily precipitation over the UK. They suggested that all bias-correction techniques were able to correct the average. Sachindra et al. (2014) used three techniques of equidistant quantile mapping, monthly bias correction, and nested bias correction to correct bias against the observed precipitation pertaining to the period of 1950–1999. They reported that all of these bias-correction techniques were able to adequately correct the statistics of downscaled precipitation.

### 1.7 Applications of weather generators

WGEN has been evaluated in a number of studies (e.g., Meinke et al. 1995; Semenov et al. 1998; Puche and Silva 2001; Hartkamp et al. 2003). Richardson (1981) applied WGEN in the United States. To properly apply the model, Richardson (1981) discovered that the model required at least a 20 years of measured precipitation data and between 10-15 years of observed temperature data. His research concludes that the model successfully reproduced rainfall and air temperature weather series. WGEN has often been applied by many researchers from various disciplines, such as hydrology and natural resource management. For instance, Katz (1996) applied the model to simulate climatic change scenarios and Mearns et al. (1996) for wheat simulation purposes. Meinke et al. (1995) showed that simulated yields obtained using generated data by WGEN were not significantly different from those obtained using actual data. Sentelhas et al. (2001) and Hartkamp et al. (2003) compared WGEN and SIMMETEO for the climate conditions of the Brazilian tropics and sub-tropics and the Mexican sub-tropics, respectively. Soltani and Hoogenboom (2003) compared WGEN and SIMMETEO and concluded that when daily weather data are available, WGEN is preferable. However, when only monthly averages are available, SIMMETEO should be used.

Semenov et al. (1998) applied the LARS weather generator in United States and Europe. Their research findings revealed that the weather generator performed well in distributing the wet and dry series because of its built-in alternating renewal process. They reported that the LARS-WG tended to match the observed data more closely than WGEN. LARS-WG has frequently been used in climate change studies at different geographical locations under different climatic conditions; for example, Bae et al. (2008), Haris et al. (2010), Semenov and Stratonovitch (2010), Qian et al. (2011), Zarghami et al. (2011) and Lashkari et al. (2012). Chen and Brissette (2014) tested five weather generators (WGEN, CLIMGEN, CLIGEN, WeaGETS, and LARS-WG) and found that LARS-WG is better at simulating daily rainfall amounts.

LARS-WG has been used in Korea for various studies. Bae et al. (2007) used LARS-WG to generate climate scenarios for evaluating climate change impacts on water resources in Korea. They reported that the data generated by LARS-WG reflect the regional climate characteristics very well. Hong et al. (2009) estimated rice evapotranspiration for 9 different regions in Korea under climate change scenarios for 90 years from 2011-2100. The future weather data were forecasted using LARS-WG. They concluded that rice evapotranspiration will increase due to warmer temperatures in the future. Shin et al. (2010) analyzed future temperature and precipitation of 8 scattered meteorological stations in South Korea by applying the LARS-WG downscaling method. Park et al. (2012) compared watershed streamflow using GCM data and observed historical weather data for a watershed located in the northeastern part of Korea. The GCM data were prepared using bias correction and LARG-WG downscaling.

The weather data generated by stochastic weather generators are only synthetic weather data, i.e., random values that mimic the observed historical weather data, and only reflect the climate of the time period when the observed historical climate data were used to calibrate weather generator parameters and the forecasted monthly mean values, rather than the actual future weather. Discrepancies between the observed historical weather data and the synthetic weather data are almost unavoidable. Therefore, the output of a weather generator should be tested to ensure its representation of a given climate and/or intended application. One method of testing is a statistical comparison, which compares the synthetic weather data with the observed historical weather data; the synthetic data could be generated by only observed historical weather data, observed historical weather data and hindcast data, or observed historical weather data and forecasted data. Another method is to compare the yields simulated by crop model as input with observed historical weather data and with synthetic weather data to determine if the simulation crop yields are sensitive to the discrepancies. Furthermore, comparisons may be used as an evaluation of the stochastic weather generator from the application prospect and provide useful information for improving stochastic weather generation algorithms and for selecting bias correction methods.

The uncertainty in crop yield related to weather is associated with particular management strategies that can be estimated through repeated simulations using a crop model (Bannayan and Crout 1999). For example, the frequency distributions of possible yield can be obtained by multiple model runs with possible weather inputs for a given growing season. Many studies have been conducted using this procedure to forecast crop yield. Arkin and Dugas (1981) forecasted sorghum yield and Duchon (1986) predicted maize yield by updating the crop model with the growing season. Semenov and Porter (1995) proposed linking a LARS-WG weather generator to a crop model to provide real-time simulation of crop growth and assessment of crop productivity. Bannayan and Crout (1999) used the SUCROS dynamic simulation crop model and SIMMETEO weather generator (Geng et al. 1986) to provide a pre-harvest forecast of crop biomass and grain yield for winter wheat in the form of a frequency distribution by updating the model from early within the growing season (vegetative phase) up to the milky grain stage (reproductive phase). Hansen and Indeje (2004) proposed linking the CERES-Maize models with dynamic seasonal climate forecasts from the WGEN weather generator. They demonstrated that the WGEN weather generator had potential for translating seasonal climate forecasts into predictions of crop responses. Apipattanavis et al. (2010) coupled the DSSAT/CERES-Maize with daily synthetic weather series generated by WEGN and a semi-parametric weather generator (Apipattanavis et al. 2007) consistent with historical climate data and two different scenarios of predicted seasonal climate. They concluded that the linkage of stochastic weather generators and crop simulation models is useful to translate raw climate information into distributions of yield for agricultural risk assessment and management. Presenting expected yield in terms of crop yield distributions is more important to stakeholders than raw climate information.

### 1.8 Objectives

The objectives of this study are to evaluate three generators for 63 weather station sites over South Korea, representing different climates and regions, to select a weather generator for the CERES-Rice model, and to determine the potential for translating the APCC seasonal climate outlook into predictions of rice yield using the CERES-Rice model.

## 2. MATERIALS AND METHODS

### 2.1 Weather Generators

The weather generators used in this study were adaptations of WGEN (Richardson and Wright 1984), SIMMETEO (Geng et al. 1986, 1988) and LARS-WG (Racsko et al. 1991; Semenov and Barrow 1997). WGEN and SIMMETEO are implemented in the weather data manager WeatherMan (Pickering et al. 1994), an application program that is part of the Decision Support System for Agrotechnology Transfer (DSSAT) software (Tsuji et al. 1994; Hoogenboom et al. 1999). These three weather generators are well known and widely used stochastic weather generators that require a number of local parameters as input to be able to generate a weather series for a specific site. DSSAT is a suite of crop models and computer programs integrated into a single software package to facilitate the application of crop-simulation models in research and decision-making.

There are statistical correlations and dependencies between weather variables. For example, compared to wet days, maximum temperature and solar radiation are likely to be higher on dry days (Richardson and Wright 1984). The weather generators consist of three sequential steps, the determination of precipitation occurrence, the generation of daily precipitation amount and the generation of daily maximum and minimum temperature. In general, daily precipitation occurrence, i.e., distinguishing either dry or wet days (Wilks and Wilby 1999), can be generated by different models, such as a two-state first-order Markov chain dependent on transition probabilities (Richardson and Wright 1984), alternating renewal processes (Green 1964), discrete autoregressive moving models (Chang et al. 1984), Poisson models (Duckstein et al. 1972), and point process models (Smith and Karr 1983; Kavvas and Delleur 1981). Precipitation intensity is generated using probability density functions, such as a gamma distribution and a mixed-exponential distribution (Richardson 1981). The values of maximum and minimum temperature are generated using autoregressive techniques based on the wet or dry day (Lall et al. 1996; Rajagopalan and Lall 1999). The daily standard deviations and means used by the autoregressive process are dependent on the precipitation events, i.e., wet and dry days (Richardson and Wright 1984; Wilks and Wilby 1999).

For the purpose of this study, only the Markov chain and alternating renewal processes will be described in detail since they are frequently used by weather generators to generate daily precipitation and temperature for crop modeling.

### 2.1.1 Markov chain model

Markov chain models have been used successfully in many weather generators (e.g. Green 1964; Katz 1977; Stern and Coe 1984; Richardson 1981; Richardson and Wright

1984; Wilks 1989; Katz and Parlange 1998). The order of the Markov Chain indicates the number of time steps in previous states used to determine the probability distribution of the current state. The simplest and most common approach for modeling wet- or dry-day occurrence is a first-order Markov chain, in which each current state is dependent on the previous state (Fitzpatrick and Krishnan 1967; Sahin and Sen 2001), even though second-order (e.g. Mason, 2004) and higher-order (e.g. Dubrovsky et al. 2004) Markov chain models have been developed (Wilks 1989; Stern and Coe 1984; Jones and Thornton 1993). For example, the probability of a wet or dry day on a given day is conditioned on whether the previous day was wet or dry. The two-state, first-order Markov chain uses the conditional probabilities described by Mimikou (1983), Richardson and Wright (1984), and Skiles and Richardson (1998), and is given by

$$P_i(W/D) = w \tag{1}$$

$$P_i(D/D) = 1 - w \tag{2}$$

$$P_i(D/W) = d \tag{3}$$

$$P_i(W/W) = 1 - d \tag{4}$$

where $P_i(W/D)$ is the probability of a wet day on day i, given a previous dry day; $P_i(D/D)$ is the probability of dry day on day i, given a previous dry day; $P_i(D/W)$ is the probability of dry day on day i, given a previous wet day; $P_i(W/W)$ is the probability of wet day on day i, given a previous wet day; w is the probability of a wet day following a dry day; d is the probability of a dry day following a wet day.

Markov chain transition probabilities in equations 2.1 to 2.4 can use a Fourier series or quadratic spline function to interpolate monthly and seasonal values for the probability of a wet or dry day in order to maintain consistency in the periodic variation (Semenov et al. 1998).

### 2.1.2 Alternating renewal process

An alternating renewal process (Racsko et al. 1991) model is a stochastic approach that uses spell length models to generate precipitation occurrence. The rainfall data are described as a sequence of alternating dry and wet spells of different length. A new spell length is only determined when a run of consecutive dry or wet days ends (Wilks and Wilby 1999). Unlike the Markov chain model, the model does not simulate precipitation occurrence day by day. The precipitation occurrence is determined by fitting a probability distribution to the relative frequencies of dry and wet spell lengths. The probability distributions used in the alternating renewal process can be the modified logarithmic series (Green 1964), the binomial distribution (Buishand 1978), the semi-empirical distribution (Racsko et al. 1991) and the geometric distribution (Roldan and Woolhiser 1982). The alternating renewal process can simulate better for the length of dry and wet spells compared to the Markov chain model. However, it cannot determine a season (Srikanthan and McMahon 2001).

### 2.1.3 Daily precipitation amount

There are several distributions that are used by weather generators to simulate the precipitation amount when a wet day is generated, such as a gamma distribution (Woolhiser and Pegram 1979), semi-empirical distribution (Racsko et al. 1991), exponential distribution (Buishand 1978), lognormal distribution, and mixed-exponential distribution (Richardson 1981). Only the two widely used methods, the gamma distribution and the semi-empirical distribution, are briefly described in this study.

The gamma distribution has been widely used by many researches and has become a popular choice for fitting probability distributions to rainfall totals because its shape is similar to that of the histograms of the rainfall data. The probability density function of two-parameter gamma distribution is given by

(5)

where β (β > 0) is a scale parameter, α (α > 0) is the shape parameter, and χ is a random variable of the daily precipitation amount in mm. The parameters α and β are calculated on a monthly basis (Kuchar 2004; Taulis and Milke 2005).

The two-parameter gamma distribution has been used by many weather generators, such as WGEN, SIMMETEO and MARKSIM, because it is easy and flexible to use (Richardson 1981; Jones and Thornton 1993; Soltani and Hoogenboom 2003). However, the gamma distribution can underestimate the precipitation amount of the monthly mean and variances (Katz and Parlange 1998; Zheng and Katz 2008).

A semi-empirical precipitation distribution in LARS-WG is defined as the cumulative probability distribution function (Semenov and Stratonovitch 2010). The number of intervals used in version 5.5 is 23, which offers a more accurate representation of the observed distribution compared with the original version that used 10. The precipitation amount, $v_i$, corresponding to the probability, *pi*, is calculated as

$$v_i = \min\{v{:}P(v_{obs} \leq v) \geq p_i\} \quad i = 0, \ldots , 23 \tag{6}$$

where P() denotes the probability based on the observed data {vobs}. Three values close to 1 are fixed: $p_{n-1}$=0.999, $p_{n-2}$=0.995, and $p_{n-3}$=0.985, along with the corresponding values of $v_o = \min\{v_{obs}\}$ and $v_n = \max\{v_{obs}\}$.

### 2.1.4 Daily maximum and minimum temperature

The maximum and minimum temperatures are largely dependent on the precipitation status of the day (Soltani and Hoogenboom 2003), since precipitation and temperature are inter-dependent. The maximum and minimum temperatures on wet days are low and high on dry days. The weather generators simulate temperature based on the precipitation occurrence (Semenov et al. 1998; Rajagopalan and Lall 1999; Birt et al. 2010). Two components of a stochastic weather simulator are used to model daily maximum and minimum temperature (Matalas 1967; Richardson 1981; Johnson et al. 1996; Semenov et al. 1998). These are the multivariate autoregressive process and semi-empirical distributions.

The Multivariate Autoregressive Process was developed by Matalas (1967) and is calculated by

$$x_i(r) = Ax_{i-1}(r) + B\varepsilon_i(r) \tag{7}$$

where $x_i(r)$ and $x_{i-1}(r)$ are 2×1 matrices of residual elements for days $i$ and $i$-1, respectively; ($r$ = 1) represents maximum temperature and ($r$ = 2) represents minimum temperature. $A$ and $B$ are 2×2 matrices derived from serial and cross correlation between minimum and maximum temperatures (Richardson 1981; Hanson et al. 1994; Johnson et al. 1996).

In the LARS-WG version 5.5, the maximum and minimum temperatures for dry and wet days are approximated by semi-empirical distributions calculated for each month, with auto- and cross-correlations calculated monthly. In the original version, only annual auto- and cross-correlation coefficients were used. Auto- and cross-correlation between climatic variables were modeled by applying the multivariate autoregressive model to the normalized residuals.

## 2.2 Weather generators

### 2.2. 1 WGEN

The WGEN weather generator was developed by the Agricultural Research Services of the United States Department of Agriculture (USDA), and is primarily based on the procedure described by Richardson (1981). WGEN generates estimates of daily precipitation, maximum and minimum temperatures, and solar radiation, and is designed to preserve interdependence between variables as well as persistence and seasonal characteristics at a given location (Richardson and Wright 1984). In WGEN, the occurrence of wet or dry days is generated with a first-order Markov chain model in which the probability of rain on a given day is conditioned on whether the previous day was wet or dry. When a wet day is generated, the two-parameter gamma distribution is used to generate the precipitation amount. For generating daily values of maximum and minimum temperature and solar radiation, the residual of the three variables are generated using a multivariate normal generation procedure that preserves the serial correlation and cross correlation of the variables. The final values of the three variables are determined by adding the seasonal means and standard deviations to the generated residual elements. The procedure used for generating solar radiation and temperature is based on the assumption that these are weakly stationary processes. A one-term Fourier series is used to model the seasonal variation in both temperature and solar radiation. Distributions of solar radiation are truncated at 16 and 85% of extraterrestrial irradiance. Lag-1 auto- and cross-correlations among maximum and minimum temperatures and solar radiation are maintained by sampling random normal deviates from a tri-variate autoregressive model. WGEN requires long records of daily weather data to estimate parameters. For more details, refer to Richardson (1981, 1984), Richardson and Wright (1984), Semenov et al. (1998), and Mavromatis and Hansen (2001).

The major adaptations of WGEN relate to how WeatherMan handles input parameters. All parameters are estimated on a calendar-monthly basis. Daily values are computed internally, using linear interpolation. WeatherMan replaces coefficients of variation (CV) with standard deviations to avoid instability problems when temperatures approach 0°C (Mavromatis and Hansen 2001).

#### 2.2.2 SIMMETEO

The principle of SIMMETEO of WeatherMan is the same as in the WGEN generator, but uses different input data (Table 3). The main difference between SIMMETEO and WGEN is that the generation parameters for SIMMETEO can be estimated from monthly climatic summaries, whereas WGEN requires daily data for estimating the input parameters. The modified SIMMETEO model uses monthly means of the number of wet days, precipitation, solar radiation, maximum temperature and minimum temperature, and regression equations to compute conditional means, standard deviations and precipitation parameters (Geng et al. 1986, 1988; Pickering et al. 1994).

Monthly means of solar radiation and maximum temperature for dry and wet days and their standard deviations are also required for weather generation. All of these parameters are estimated for each month using first-order Fourier series. Annual average solar radiation for dry and wet days are computed from the solar radiation difference. Standard deviations of solar radiation on dry and wet days are calculated from their means and coefficients of variation. Annual average coefficients of variation of 0.24 (0.48) for standard deviations of solar radiation on dry (wet) days and amplitudes of 0.08 (0.13) for standard deviations of solar radiation on dry (wet) days are considered for the Fourier equation. Mean annual maximum temperatures for dry and wet days are calculated from the temperature difference. For each month, standard deviations of the maximum and minimum temperatures on dry and wet days are calculated from their monthly means.

#### 2.2.3 LARS-WG

The first version of the LARS-WG weather generator was developed in 1991 (Racsko et al. 1991), using an improved Makov chain model of precipitation. LARS-WG uses a semi-empirical distribution to approximate probability distributions of dry and wet series, daily precipitation, minimum and maximum temperatures and solar radiation. The length of each series is chosen randomly from the wet or dry semi-empirical distribution for the month. For a wet day, the precipitation value is generated for the particular month, independent of the length of the wet series or the amount of precipitation on the previous days. Daily minimum and maximum temperatures are considered as stochastic processes, with daily means and daily standard deviations conditioned on the wet or dry status of the day. The solar radiation distribution, which varies significantly on wet and dry days, is modeled independently of temperature using separate semi-empirical distributions that describe wet and dry days differently (Semenov and Barrow 2002). By perturbing parameters of distributions for a site with the predicted changes of climate derived from global or regional climate models, a daily climate scenario for this site could be generated and used in conjunction with a process based impact model for assessment of impacts.

**Table 3.** Summary of the main features of three generators.

| Weather generator | Precipitation | | Temperature | | Solar radiation | Correlation |
|---|---|---|---|---|---|---|
| | Occurrence | Intensity | Maximum | Minimum | | |
| WGEN and SIMME-TEO | Transition probabilities of a first-rder, two-state Markov chain | Gamma distribution | Conditional normal distribution | Unconditional normal distribution | Conditional truncated normal distribution | Tri-variate ($T_{max}$, $T_{min}$, $R_s$) autoregressive constant |
| LARS-WG | Alternating renewal with semi-empirical distribution | Semi-empirical distribution | Conditional normal distribution | Conditional normal distribution | Semi-empirical distribution | Bi-variate ($T_{max}$, $T_{min}$) autoregressive constant |

## 2.4 CERES-Rice Model

The CERES-Rice (Crop Estimation through Resource and Environment Synthesis-Rice) model (Ritchie et al. 1986; Singh et al. 1993), a physiologically based rice model designed at Michigan State University, included in the Decision Support System for Agrotechnology Transfer (DSSAT), was developed by the International Benchmark Systems Network for Agrotechnology Transfer (IBSNAT). DSSAT/CERES-Rice is a useful tool for simulating rice growth, development, and yield of different cultivars on a uniform area of land under all agroclimatic conditions. It is widely used as a decision support system (Jones et al. 2003; Timsina and Humphreys 2006). The model represents the integrated responses to environmental factors, such as solar radiation, maximum and minimum air temperatures, precipitation, day-length variation, soil properties, and soil water conditions, cultivar genetics, and management practices. Other limiting factors, such as weeds, diseases, and insects, which are also important in the rice production process, are not considered in the model. The model inputs are summarized below:

Modeling location: latitude, longitude, elevation, slope, aspect, water table depth.

Daily weather: daily maximum and minimum air temperatures, global solar radiation, rainfall.

Soil: classification using the local system and (to a family level) the USDA-NRCS taxonomic system, root growth factor, drainage coefficient. Soil properties, including depths of layers; percentages of sand, silt, and clay, and bulk density at various depths; moisture content at the lower limit, drained upper limit, and at saturation for various depths, N and organic matter content.

Initial conditions: C:N ratio and weight of root and shoot residues of previous crops incorporated or retained in the field; date and depth of residue incorporation; soil water, and $NO_3$ and $NH_4$ at each depth.

Management practices: rice cultivar, plant density (number of plants for direct-seeded rice, number of seedlings per hill for transplant rice), sowing depth, planting date, age of transplants, irrigation (dates and amount), and N fertilization (dates, type, and amount).

### 2.4.1 Growth stages

The growth stages are numbered 1 through 9; 1 through 5 represent the active aboveground growing stages, and 6 through 9 describe other events in the crop cycle. Growth stages and their corresponding descriptions are summarized in Table 4.

**Table 4.** Growth stages simulated by the DSSAT/CERES-Rice model (adapted from Ritchie et al. 1987)

| Stage no. | Event | Plant parts growing |
|---|---|---|
| 7 | Fallow or presowing | |
| 8 | Sowing to germination | |
| 9 | Germination to emergence | Roots, coleoptile |
| 1 | Juvenile | Roots, leaves |
| 2 | Floral induction | Roots, leaves, stems |
| 3 | End of leaf growth and heading | Roots, leaves, stems, panicle |
| 4 | Anthesis or flowering | Roots, stems, panicle |
| 5 | Grain filling | Grain |
| 6 | Physiological maturity to harvest | |

The CERES-Rice model assumes that development rates are directly proportionate to temperatures between 9 and 32°C. When minimum and maximum daily air temperatures are within this range, daily thermal time (DTT) is used to describe the process of rice development. DTT is calculated as the average between the minimum and maximum temperatures, with a base temperature of 9°C. If the maximum and minimum temperatures are outside the given range, thermal time is calculated using a different set of relationships. DTTs for different growth stages vary by cultivar. A photosensitivity variety directly affects the thermal time requirement during the induction stage (stage 2). A photoperiod-sensitivity variety has a longer DTT requirement when day length is longer than the optimum photoperiod. The phenology component also varies with the water or N deficit at different growth stages (Singh et al. 1999).

### 2.4.2 Genetic Coefficients

The genetic coefficients used in the DSSAT/CERES-Rice phenology and growth simulation are shown in Table 5. The coefficients P1, P2R, and P2O are associated with DTT. The vegetative growth period is completed when the accumulation of DTT reaches a threshold (P1); the reproductive growth stage is completed when the accumulation of DTT reaches a threshold (P5).

Table 5. Genetic Coefficients for the DSSAT/CERES-Rice model (adapted from Singh et al. 2002)

| | |
|---|---|
| P1 | Time period in growing degree days (base 9°C) from emergence to end of juvenile phase |
| P2R | Photoperiod sensitivity (degree day delay per hour increase in daylength) |
| P2O | Critical photoperiod or longest daylength (h) at which development occurs at maximum rate. At values higher than P2O the development rate is slowed (depending on P2R) |
| P5 | Degree days (base 9°C) from beginning of grain-filling (3-4 d after flowering) to physiological maturity |
| G1 | Potential spikelet number coefficient as estimated from number of spikelets per g main culm + spike dry weight at anthesis (#/g) |
| G2 | Single dry grain weight (g) under nonlimiting growing conditions |
| G3 | Tillering coefficient (scalar value) relative to IR64. A higher tillering cultivar will have values greater than 1 |
| G4 | Temperature tolerance coefficient. Usually 1.0 for cultivars grown in normal environment. G4 for japonica type rice grown in warmer environments would be > 1.0. Tropical rice grown in cooler environments or season will have G4 < 1.0 |

### 2.4.3 Rice Yield

The DSSAT/CERES-Rice assumes that the mean value of 1,000-rice weight is very stable for each cultivar. In the CERES-Rice model, grain weight is the product of the grain growth rate and the filling duration. A genetic coefficient (G2, Table 2) is the single grain weight rate under optimum growing conditions. In the model, the rice yield is directly proportionate to panicle weight, which is influenced by the environment and plant conditions.

## 2.5 Input Data

### 2.5.1 Spatial downscaled weather data

The forecast datasets for downscaling using a weather generator included in this study include the APCC raw data of each grid cell, and their anomalies (GRID). The monthly forecasts are expressed as monthly mean and spatially averaged with a lead time of 6 months and at a grid cell scale of 2.5°×2.5°.The second forecast dataset includes the data for each station (RW); this is simply interpolated from the cell data to each station. The third dataset is the SDMME-Sm (SM), which estimates the multi-model ensemble

(MME) mean using data downscaled from the single-model ensemble (SME) means of the coupled GCMs, SDMME-Ae (AE) is a dataset calculated from the MME means by simply averaging all model ensembles applied to statistical downscaling. Lastly, the newly designed SDMME-We (WE) uses a weighted ensemble scheme for the MME mean. Details about these methods can be found in Kang et al. (2014).

### 2.5.2 Observed weather data

As many as 63 weather stations with long-term and reliable daily weather data were selected for the study to assess the three generators (unconditional scenarios) to represent a large geographical area and several climatic zones in South Korea (Table 6 and Figure 3). For each location, 23 years (1983–2005) of daily data for precipitation and maximum and minimum temperatures, and solar radiation were available, as provided by the Korea Meteorological Administration. Six weather stations inside the grid cell between 22°45’ to 36°15’ E and between 126°15’ and 128°45’ N (one grid cell for the APCC forecast) are randomly selected for rice modeling to represent different AEZs inside the grid cell.

**Table 6.** Locations and elevations of 63 weather stations. The station numbers with * are used for rice yield simulation

| Station | Name | Lat. | Long. | Elev (m) | Station | Name | Lat. | Long. | Elev (m) |
|---|---|---|---|---|---|---|---|---|---|
| 90 | Sokcho | 38°15′ | 128°33′ | 18.1 | 202 | Yangpyeong | 37°29′ | 127°29′ | 48 |
| 100 | Daegwally-eong | 37°40′ | 128°43′ | 772.6 | 203 | Icheon | 37°15′ | 127°29′ | 78 |
| 101 | Chuncheon | 37°54′ | 127°44′ | 77.7 | 211 | Inje | 38°03′ | 128°10′ | 200.2 |
| 105 | Gangneung | 37°45′ | 128°53′ | 26 | 212 | Hongcheon | 37°41′ | 127°52′ | 140.9 |
| 108 | Seoul | 37°34′ | 126°57′ | 85.8 | 221 | Jecheon | 37°09′ | 128°11′ | 263.6 |
| 112 | Incheon | 37°28′ | 126°37′ | 68.2 | 226 | Boeun | 36°29′ | 127°44′ | 175 |
| 114 | Wonju | 37°20′ | 127°56′ | 148.6 | 232 | Cheonan | 36°46′ | 127°07′ | 21.3 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 115 | Ulleungdo | 37°28′ | 130°53′ | 222.8 | 235 | Boryeong | 36°19′ | 126°33′ | 15.5 |
| 119 | Suwon | 37°16′ | 126°59′ | 34.1 | 236 | Buyeo | 36°16′ | 126°55′ | 11.3 |
| 127 | Chungju | 36°58′ | 127°57′ | 115.1 | 238 | Geumsan | 36°06′ | 127°28′ | 170.4 |
| 129 | Seosan | 36°46′ | 126°29′ | 28.9 | 243 | Buan | 35°43′ | 126°42′ | 12 |
| 130 | Uljin | 36°59′ | 129°24′ | 50 | 244 | Imsil | 35°36′ | 127°17′ | 247.9 |
| 131 | Cheongju | 36°38′ | 127°26′ | 57.2 | 245 | Jeongeup | 35°33′ | 126°51′ | 44.6 |
| 133 | Daejeon | 36°22′ | 127°22′ | 68.9 | 247 | Namwon | 35°24′ | 127°19′ | 90.3 |
| 135* | Chupung-nyeong | 36°13′ | 127°59′ | 244.7 | 256 | null | 35°04′ | 127°14′ | 74.6 |
| 136 | Andong | 36°34′ | 128°42′ | 140.1 | 260 | Jangheung | 34°41′ | 126°55′ | 45 |
| 138 | Pohang | 36°01′ | 129°22′ | 2.3 | 261* | Haenam | 34°33′ | 126°34′ | 13 |
| 140* | Gunsan | 36°00′ | 126°45′ | 23.2 | 262 | Goheung | 34°37′ | 127°16′ | 53.1 |
| 143 | Daegu | 35°53′ | 128°37′ | 64.1 | 271 | Bongwhoa | 36°56′ | 128°54′ | 319.8 |
| 146 | Jeonju | 35°49′ | 127°09′ | 53.4 | 272 | Yeongju | 36°52′ | 128°31′ | 210.8 |
| 152 | Ulsan | 35°33′ | 129°19′ | 34.6 | 273 | Mungyeong | 36°37′ | 128°08′ | 170.6 |
| 155 | Changwon | 35°10′ | 128°34′ | 37.2 | 277 | Yeongdeok | 36°31′ | 129°24′ | 42.1 |
| 159 | Busan | 35°06′ | 129°01′ | 69.6 | 278 | Uiseong | 36°21′ | 128°41′ | 81.8 |
| 162 | Tongyeong | 34°50′ | 128°26′ | 32.7 | 279 | Gumi | 36°07′ | 128°19′ | 48.9 |
| 165 | Mokpo | 34°49′ | 126°22′ | 38 | 281 | Yeongcheon | 35°58′ | 128°57′ | 93.6 |
| 168 | Yoesu | 34°44′ | 127°44′ | 64.6 | 284* | Geochang | 35°40′ | 127°54′ | 221 |
| 170 | Wando | 34°23′ | 126°42′ | 35.2 | 285 | Hapcheon | 35°33′ | 128°10′ | 33.1 |
| 184 | Jeju | 33°30′ | 126°31′ | 20.4 | 288 | Miryang | 35°29′ | 128°44′ | 11.2 |
| 188 | Seongsan | 33°23′ | 126°52′ | 17.8 | 289* | Sancheong | 35°24′ | 127°52′ | 138.1 |
| 189 | Seogwipo | 33°14′ | 126°33′ | 49 | 294* | Geoje | 34°53′ | 128°36′ | 46.3 |
| 192 | Jinju | 35°09′ | 128°02′ | 30.2 | 295 | Namhae | 34°48′ | 127°55′ | 45 |
| 201 | Ganghwa | 37°42′ | 126°26′ | 47 | | | | | |

**Figure 3.** Locations of weather stations in South Korea. The black square indicates the grid cell between 22°45’ to 36°15’ E and between 126°15’ and 128°45’ N, in which 6 weather stations are randomly selected for rice modeling.

### 2.5.3 Parameters estimations in LSRS-WG

To test the impacts of bias correction on crop models, synthetic daily weather data are generated with and without bias correction. Monthly bias-correction (MBC) is used in this study. MBC is a relatively simple bias-correction method (Johnson and Sharma 2012). In this study, this method is employed to correct the mean rainfall and mean temperature spatially downscaled with the APCC climate outlook against corresponding observed weather data. For precipitation, it is assumed that the ratio of observed precipitation to the hindcast data is unchanged.

$$P_i = (\overline{P_{o,i}}/\overline{P_{h,i}}) \tag{10}$$

In the above equation, P is precipitation, i is the month, the over bar indicates the monthly mean, and subscripts o and h are observed values and hindcast values for a given month.

For temperature, it is assumed that the difference between the observed and hindcast remains constant for a given month:

$$T_i = (\overline{T_{o,i}} - \overline{T_{h,i}}) \tag{11}$$

where T is air temperature.

Applying equations 11 and 12 to LARS-WG, when the forecasts are in absolute value, the bias corrected parameters in the field scenario are estimated by

$$P_i = P_{f,i}/\overline{P_{f,i}} \tag{12}$$

$$T_i = T_{f,i} - \overline{T_{f,i}} \tag{13}$$

The parameters without bias correction in the field scenario are obtained by

$$P_i = P_{f,i}/\overline{P_{o,i}} \tag{14}$$

$$T_i = T_{f,i} - \overline{T_{o,i}} \tag{15}$$

When the forecasts are anomalous, i.e., in terms of the APCC raw data for grid cell, the average anomalies for the hindcast period is equal to zero, and the equations for calculating parameters in field scenario in LARS-WG are the same both with and without bias correction;

$$P_i = 1 + P_{fa,i}/\overline{P_{o,i}} \tag{16}$$

$$T_i = T_{fa,i} \tag{17}$$

where fa indicates an anomalous forecast.

### 2.5.4 The soil data

GIS format data are extracted using QGIS software. Each rice paddy area located near a weather station is selected for simulation.

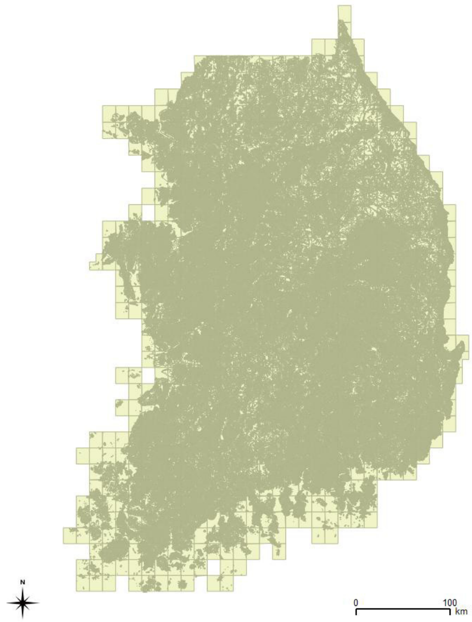


**Figure 4.** GIS soil map of South Korea

### 2.5.5 Cultivar genetic coefficients

Three different cultivars (*Oryza sativa* L. subsp. Japonica cv. Nampyeong, Saegyehwa, and Unkwang) are selected for this study. Nampyeong, Saegkyewha, and Unkwang are common japonica rice cultivars and represent the late-, mid- and early-season cultivar, respectively. Nampyone is a high quality cultivar, adaptable to low nitrogen fertilizer cultivation. The heading date of Nampyeong is in the middle of August for the ordinary season cultivation. Saegyehwa is produced in Korea, and is a relatively low-yield rice. Unkwang was developed in 2004 in South Korea. This cultivar has short grains and a growth duration of approximately 113 days from transplant to harvest. Unkwang has high grain quality and cold tolerance. It is adaptable in the northern plains, and the mid- and southern mountainous areas of South Korea.

Kim et al. (2002) listed genetic coefficients for 19 rice cultivars in Korea. Kim et al. (2012) reported genetic coefficients for three rice cultivars. It is worth noting that the genetic coefficients for a cultivar estimated by different studies can be different. For example, Jeong et al. (2011), Shim et al. (2010) and Jeong (2014) reported different values for the cultivar Chucheongbyeo. The rice genetic coefficients for simulations using the CERES-Rice model are adapted from Kim et al. (2013) (Table 7).

The detailed information about experimental design and calculation of rice genetic coefficients can be found in Kim et al. (2013). A brief description is presented here. The rice crop data used for calibration and validation of the CERES-Rice were obtained from the experiments conducted in 2009 and 2010 in the temperature gradient field chamber (TGFC) with a $CO_2$ enrichment system located at Chonnam National University (35° 10' N, 126° 53'E, 33 m above the sea level), Gwangju, Korea. The TGFCs were arranged with a split-plot design, encompassing two $CO_2$ levels (ambient $CO_2$ and elevated $CO_2$ of 650 ppm) assigned as main plots, and with three temperature levels (ambient temperature and elevated temperatures, 1°C and 2°C above the ambient) assigned as subplots. An iterative approach was employed to develop genetic coefficients for the CERES-rice model through trial-and-error to match the measured phenology and yields with the simulated values. Simulated rice grain yield values were reasonably consistent with the empirically measured yields in calibration for all cultivars using the 2009 data. Simulated yields corresponded well with the empirically measured yield values validated by the 2010 data.

**Table 7.** Genetic coefficients for three rice cultivars using the CERES-Rice model (adapted from Kim et al. 2013).

| No. | Coefficient: definition | Nampyeong | Saegyewha | Unkwang |
|---|---|---|---|---|
| 1 | P1: Time period (expressed as growing degree days [GDD] in C above a base temperature of 9 °C) from seedling emergence during which the rice plant is not responsive to changes in photoperiod | 490.0 | 200.0 | 320.0 |
| 2 | P20: Critical photoperiod or the longest day length (in hours) at which the development occurs at a maximum rate | 12.0 | 12.0 | 12.0 |
| 3 | P2R: extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in C) for each hour increase in photoperiod above P20 | 20.0 | 90.0 | 10.0 |
| 4 | P5: Time period (expressed as GDD in C) from beginning of grain filling (3–4 days after flowering) to physiological maturity with a base temperature of 9 °C | 690.0 | 530.0 | 700.0 |
| 5 | G1: Potential spikelet number coefficient as estimated from the number of spikelets per g of main culm dry weight (less lead blades and sheaths plus spikes) at anthesis | 99.0 | 55.0 | 99.0 |
| 6 | G2: Single grain weight (g) under ideal growing conditions, i.e., nonlimiting light, water, nutrients, and absence of pests and diseases | 0.024 | 0.021 | 0.022 |
| 7 | G3: Tillering coefficient (scalar value) relative to IR64 cultivar under ideal conditions | 1.2 | 1.3 | 1.2 |
| 8 | G4: Temperature tolerance coefficient | 1.2 | 1.0 | 1.0 |

### 2.5.6 Management practices

Table 1 shows the rice-cropping calendar of different AEZs in Korea. The seedlings are transplanted with 15 × 30 cm hill spacing (Jeong et al. 2014) and 3 seedlings per hill (Yang et al. 2013). The fertilizers are applied according to the standard fertilizer rate (kg/ha) three times: pre-plant (N:P:K=55:45:40), tilling ((N:P:K=44:0:0) and panicle (N:P:K=33:0:17). Auto-irrigation management is the selected form of irrigation in the simulation since most of rice fields are well irrigated in Korea.

## 2.6 Generation of synthetic weather data

The general downscaling procedures are described in Figure 5, in which a total of 10 datasets are available. In this study, 9 datasets are available after bias correction: (1) SDMME-Ae with bias correction, AE-BC, (2) SDMME-Ae-without bias correction, AE-NBC, (3) Grid cell anomalies, GRID, (4) Raw with bias correction, RW-BC, (5) Raw without bias correction RW-NBC, (6) SDMME-Sm with bias correction, SM-BC, (7) SDMME-SM without bias correction, SM-NBC, (8) SDMME-We with bias correction, WE-BC, and (9) SDMME–We without bias correction, WE-NBC. The 23 time series of synthetic weather data are annually generated for each site.

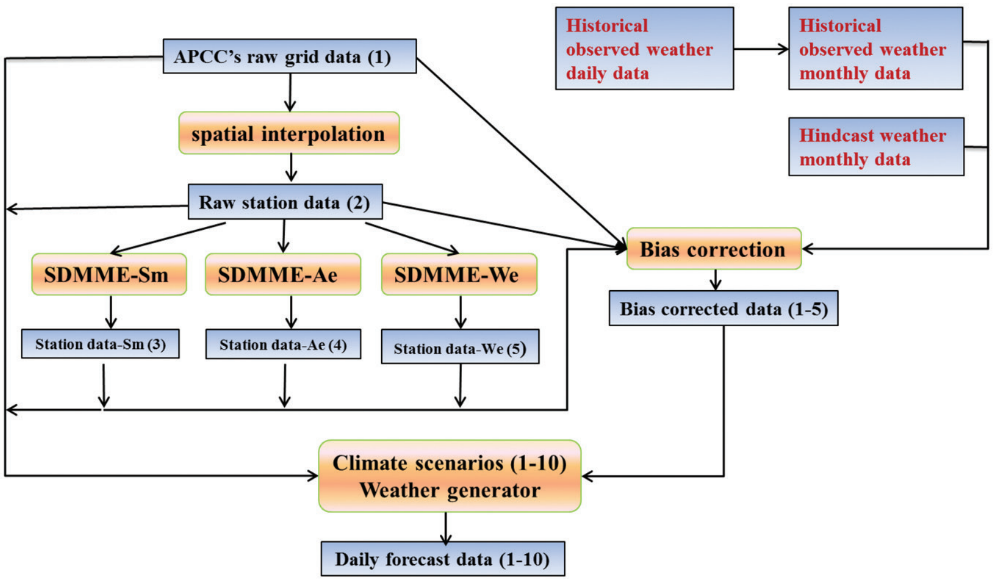


**Figure 5.** Downscaling procedures.

# 3. RESULTS

### 3.1 Rice yield simulated using observed weather data

Table 8 shows the cultivar Nampyeong yields simulated using 23 years of observed weather data from 1983-2005. The highest average yield in 23 years is 8394 kg/ha with standard deviation of 1022 kg/ha near station 289. The lowest average yield is 7602 kg/ha with a standard deviation of 766 kg/ha near station 135. The yield variations for each station are similar except for the yields in 2001, in which the yield is lowest near station 261, but highest near station 289, suggesting that the yields of Nampyeong show similar trends in most years. The high standard deviations indicate that the yields are sensitive to weather conditions.

**Table 8.** Simulated rice yield (kg/ha) for cultivar Nampyeong using observed weather data for station 135, 140, 261, 284, 289, 294 from 1983-2005. There are missing yields since at least one observed solar radiation was equal to zero in the growth period which ends the simulation.

| Sation | 135 | 140 | 261 | 284 | 289 | 294 |
|---|---|---|---|---|---|---|
| 1983 | | 8677 | 7100 | 8198 | 7419 | 7041 |
| 1984 | 7137 | 7880 | 7965 | 8237 | 6523 | 8130 |
| 1985 | 8534 | 7983 | 8666 | 9055 | 9245 | 8339 |
| 1986 | | 8801 | 9229 | 8780 | 7994 | 8887 |
| 1987 | 7467 | 7861 | 7929 | 8093 | 9326 | 8195 |
| 1988 | 8156 | 7611 | 8318 | 8871 | 7511 | 8401 |
| 1989 | 8771 | 7747 | 8037 | 8477 | 8906 | 8419 |
| 1990 | 7092 | 8357 | 6470 | 7331 | 7573 | 5856 |
| 1991 | 7741 | 7965 | 8877 | 8853 | 9307 | 8215 |
| 1992 | 8364 | 6767 | 7629 | 6326 | 8700 | 7866 |
| 1993 | | 8970 | 8065 | 9002 | 8244 | 8833 |
| 1994 | | 6469 | 8181 | 7259 | 7728 | 7835 |
| 1995 | | 7365 | 7742 | 6637 | 6970 | 6228 |
| 1996 | 6708 | 9165 | 7195 | 7023 | 7027 | 7684 |
| 1997 | 7423 | 8499 | 7832 | 8406 | 8684 | 8525 |
| 1998 | 6516 | 8270 | 8674 | 8769 | 9839 | 8583 |
| 1999 | 7902 | 7726 | 8020 | 8544 | 8376 | 8715 |
| 2000 | 8234 | 8517 | 8357 | 8513 | 8900 | 8393 |
| 2001 | 6380 | 8680 | 6310 | 8510 | 10147 | 8354 |
| 2002 | | 8109 | 8677 | 8849 | 9181 | 8849 |
| 2003 | | 7976 | 9076 | 9509 | 9972 | 8728 |
| 2004 | | 8711 | 6799 | 7209 | 8158 | 8069 |
| 2005 | | 8465 | 7992 | 9031 | 7348 | 8318 |

**Table 9.** Simulated rice yield (kg/ha) for cultivar Saegyewha using observed weather data for station 135, 140, 261, 284, 289, 294 from 1983-2005. There are missing yields since at least one observed solar radiation was equal to zero in the growth period which ends the simulation.

| Sation | 135 | 140 | 261 | 284 | 289 | 294 |
|---|---|---|---|---|---|---|
| 1983 | | 4990 | 4563 | 4665 | 5035 | 4013 |
| 1984 | 4180 | 4650 | 4538 | 4700 | 4658 | 3944 |
| 1985 | 4282 | 4855 | 5733 | 4759 | 5020 | 5121 |
| 1986 | 4325 | 4786 | 4805 | 4893 | 5161 | 4662 |
| 1987 | 4161 | 4725 | 4321 | 4627 | 4788 | 4198 |
| 1988 | 4405 | 4438 | 4637 | 4633 | 4901 | 4225 |
| 1989 | 4916 | 4614 | 4417 | 4886 | 4859 | 4563 |
| 1990 | 4380 | 4413 | 4351 | 4828 | 4927 | 4099 |
| 1991 | 4485 | 4626 | 4752 | 4929 | 4795 | 4200 |
| 1992 | 4539 | 4465 | 4460 | 3544 | 5262 | 4533 |
| 1993 | | 4612 | 4581 | 4437 | 4712 | 4432 |
| 1994 | | 4525 | 4974 | 5073 | 5000 | 4849 |
| 1995 | | 5115 | 4353 | 4677 | 5189 | 3995 |
| 1996 | 4082 | 4514 | 4695 | 4774 | 4984 | 4316 |
| 1997 | 4312 | 4425 | 4957 | 4839 | 4722 | 5043 |
| 1998 | 3319 | 4254 | 4362 | 4821 | 4923 | 4648 |
| 1999 | 3792 | 4784 | 4462 | 4437 | 4791 | 4008 |
| 2000 | 4633 | 4495 | 4924 | 4797 | 5288 | 4464 |
| 2001 | 4475 | 3942 | 4666 | 4687 | 4924 | 4260 |
| 2002 | | 4891 | 4724 | 4668 | 4740 | 5376 |
| 2003 | 5014 | 5495 | 4924 | 5367 | 5270 | 5456 |
| 2004 | | 5034 | 4578 | 4748 | 4741 | 5186 |
| 2005 | | 4698 | 4737 | 4827 | 5026 | 4695 |

The yields of the cultivar Saegyewha simulated using 23 years of observed weather data from 1983-2005 (Table 9) are much lower than the yields of Nampyeong. The highest average yield is 4944 kg/ha with a standard deviation of 321 kg/ha near station 289. The lowest average yield is 4331 kg/ha with a standard deviation of 402 kg/ha near station 135. The yield variations for each station are similar except for the yields in 1992, in which the yield declines to the lowest value near station 261, but reaches its highest value near station 289. Most standard deviations are lower than 10% of the average yields, indicating that the yields of Saegywha are relatively stable and not very sensitive to weather conditions.

The simulated yields of the cultivar Unkwang using 23 years of observed weather data from 1983-2005 (Table 10) are much higher than the yields of Saegyewha, and lower than the yields of Nampyeong. The highest average yield is 7028 kg/ha with a standard deviation of 332 kg/ha near station 289. The lowest average yield is 6705 kg/ha with a standard deviation of 711 kg/ha near station 140. The yield variations for each station are similar with a few exceptions. Most standard deviations are lower than 7% of the average yields, indicating that the yields of Unkwang are not very sensitive to weather conditions.

In general, the responses of the three cultivar yields are different. The late maturity cultivar, Nampyeong, is sensitive to weather conditions, whereas the early maturity cultivar, Unkwang, is less sensitive to weather conditions, suggesting the importance of weather forecast is different for different rice cultivars. Rice yields for three cultivars near the same location usually have similar trends, but with exceptions, implying that weather conditions in a given year can favor a specific cultivar.

**Table 10.** Simulated rice yield (kg/ha) for cultivar Unkwang using observed weather data for station 135, 140, 261, 284, 289, 294 from 1983-2005. There are missing yields since at least one observed solar radiation was equal to zero in the growth period which ends the simulation.

| Sation | 135 | 140 | 261 | 284 | 289 | 294 |
|---|---|---|---|---|---|---|
| 1983 | | 6772 | 6771 | 6929 | 6402 | 6434 |
| 1984 | 6223 | 7091 | 6820 | 6588 | 6910 | 6662 |
| 1985 | 6783 | 6492 | 8011 | 6524 | 6908 | 7416 |
| 1986 | 7114 | 7287 | 7064 | 7144 | 7020 | 7067 |
| 1987 | 6175 | 7016 | 6795 | 6603 | 7228 | 6879 |
| 1988 | 6373 | 5796 | 6869 | 6907 | 7386 | 6851 |
| 1989 | 7456 | 7338 | 7231 | 6985 | 6888 | 6920 |
| 1990 | 6481 | 6911 | 6237 | 6957 | 6835 | 6845 |
| 1991 | 6777 | 6885 | 7083 | 7060 | 7408 | 7003 |
| 1992 | 6700 | 4717 | 6719 | 5461 | 6944 | 6511 |
| 1993 | | 6822 | 7120 | 7099 | 7439 | 7733 |
| 1994 | | 6841 | 6700 | 6389 | 6869 | 6354 |
| 1995 | | 5621 | 6972 | 6791 | 7476 | 6387 |
| 1996 | 6410 | 6757 | 7101 | 7020 | 7418 | 7071 |
| 1997 | 6567 | 6681 | 6927 | 6425 | 7096 | 7217 |
| 1998 | 6277 | 5982 | 6586 | 6874 | 6022 | 7248 |
| 1999 | 6283 | 7024 | 6674 | 6882 | 7164 | 6822 |
| 2000 | 6988 | 7097 | 7013 | 6832 | 7041 | 6854 |
| 2001 | 7239 | 6029 | 6780 | 7130 | 6900 | 7001 |
| 2002 | | 7440 | 7171 | 6741 | 7098 | 7703 |
| 2003 | 7500 | 8122 | 7955 | 6786 | 7134 | 7558 |
| 2004 | | 7110 | 6629 | 6497 | 6952 | 7602 |
| 2005 | | 6399 | 6623 | 6529 | 7116 | 7431 |

## 3.2 Quality of unconditional weather series

### 3.2.1 Precipitation amount

WGEN and SIMMETEO use a gamma distribution function to model the precipitation amount when a wet day is generated, whereas LARS-WG uses a semi-empirical distribution. Three models generate synthetic values to 1 decimal place, which is the same as required by the CERES-Rice model. Figure 6 (left) shows the comparison of daily mean precipitation of observed values against generated values. Overall, three generators can generate the daily mean of precipitation with linear regression equations of y=1.01x for LARS-WG and SIMMETEO and y=0.97x for WGEN. However, if excluding the extreme heavy rainfall station 295 (mean value of 5.2 mm/day), we can see that the WGEN slightly underestimates precipitation. LARS-WG and SIMMETEO can capture the annual variation of precipitation as indicated in Figure 6 (right).

Figure 7 shows the comparison of monthly mean rainfall generated by the three generators and observed data in six locations. Overall, the three models reproduce the monthly mean precipitation reasonably well, with some differences from site to site. For example, at weather station 140, the generated mean precipitation from LARS-WG in July and August is less than the observed values. At weather station 261, the generated rainfall from WGEN in July is greater than the observed value. For weather station 284, the generated monthly rainfall from SIMMETEO in July is greater than the observed value.

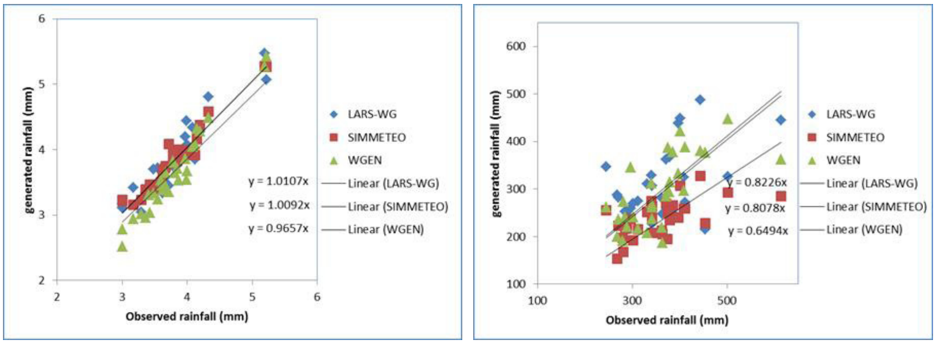


**Figure 6.** Mean of daily rainfall (left) and standard deviation of annual rainfall (right) of observed versus generated values from three weather generators (WGEN, SIMMETEO, and LARS-WG) for 62 weather stations

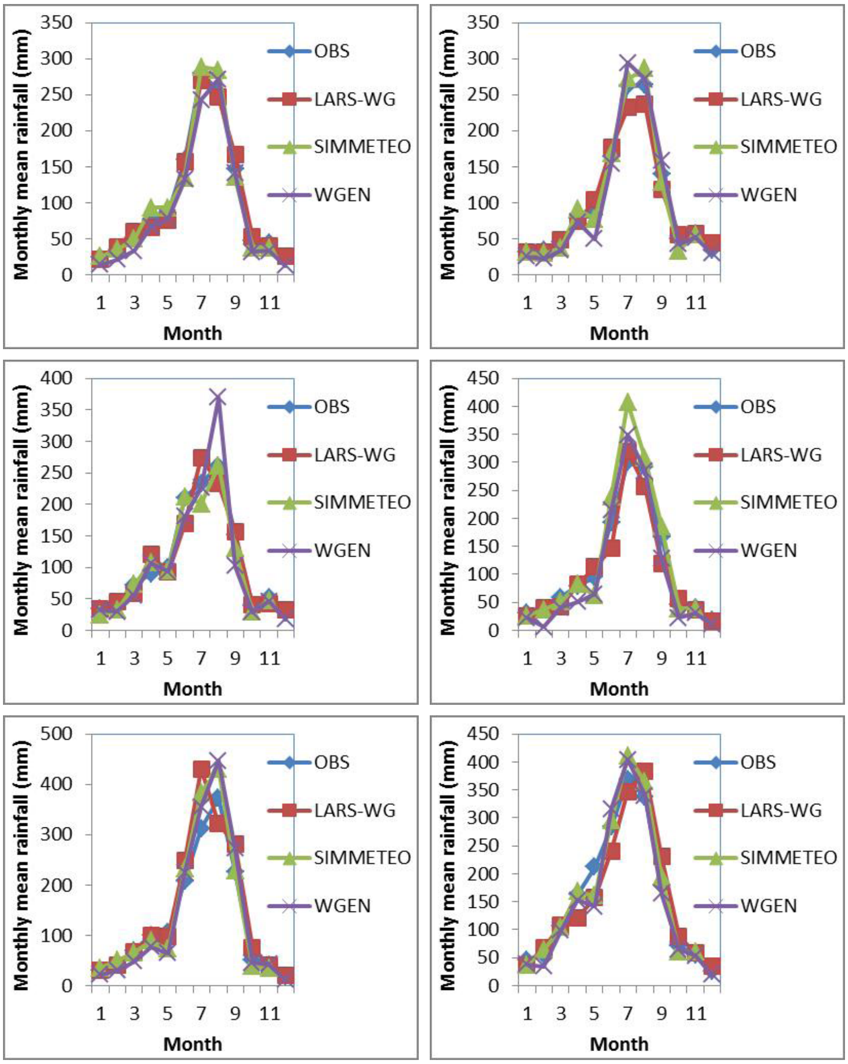


**Figure 7.** Comparison of monthly mean rainfall for observed data and synthetic data generated by WGEN, SIMMETEO, and LARS-WG for weather stations 135 (top left), 140 (top right), 261 (middle left), 284 (middle right), 289 (bottom left) and 294 (bottom right).

### 3.2.2 Minimum temperature

The three models use very similar techniques to generate daily maximum and minimum temperature. The mean and variances are conditioned on the wet and dry day occurrence and the temperatures are reduced to normalized residuals. The seasonal cycles of the mean and variance are modeled by a finite Fourier series, with three harmonics in LARS-WG and two harmonics in WGEN and SIMMETEO. However, LARS-WG uses a pre-set cross-correlation instead of estimating the cross-correlation from the observed residuals in WGEN and SIMMETEO. Three weather generators accurately reproduce the daily mean value of minimum temperature, as shown in Figure 8 (left) for the comparison of the annual mean minimum of observed and generated temperature. However, SIMMETERO and WGEN slightly overestimate, and LARGS-WG slightly underestimates the variation of daily minimum temperature, respectively (Figure 8, right).

The minimum temperatures generated by LARS-WG are closer to observed values than the values generated by WGEN, and both LARS-WG and WGEN perform better than SIMMETEO, as shown in Figure 8. For example, the observed maximum temperature was 20.1°C in July at weather station 294, and the generated values are 19.9, 20.4, 20.7°C by LARS-WG, WGEN and SIMMETEO, respectively.

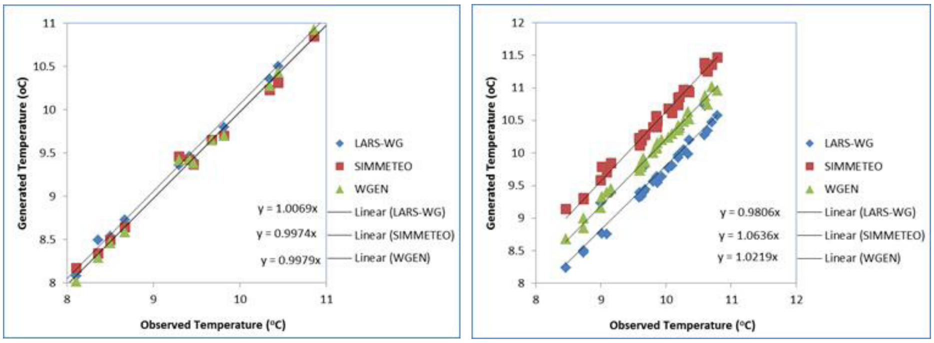


**Figure 8.** Mean of daily minimum temperature (left) and standard deviation of daily minimum temperature (right) of observed versus generated values from three weather generators (WGEN, SIMMETEO, and LARS-WG) for 63 weather stations.

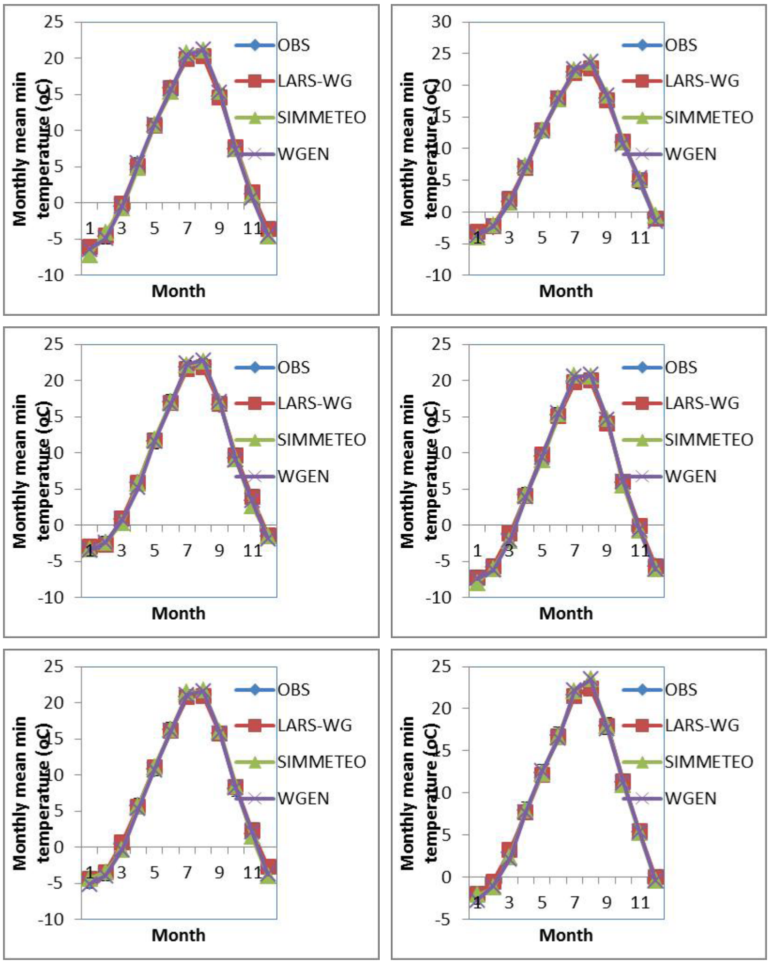


**Figure 9.** Comparison of monthly mean minimum temperature for observed data and synthetic data generated by WGEN, SIMMETEO, and LARS-WG for weather stations 135 (top left), 140 (top right), 261 (middle left), 284 (middle right), 289 (bottom left) and 294 (bottom right).

One of the most potentially useful features of a weather generator is the capability to provide an indication of minima temperature, since low temperature damage of rice is an important factor in rice production (Lee 2001). The performances of LARS-WG and SIMETTO are the best and worst, respectively, for generating daily minima temperature as compared with observed values (Figure 10). For example, in January at weather station 294, the generated minima temperatures are -16.3, -12.3, -18.6°C by LARS-WG, WGEN and SIMMETEO, respectively; the observed value was -14.7°C. In August, the generated minima temperatures are 14.9 and 12.3°C by WGEN and SIMMETEO, respectively; the observed value and the generated value by LARS-WG were the same at 12.3°C

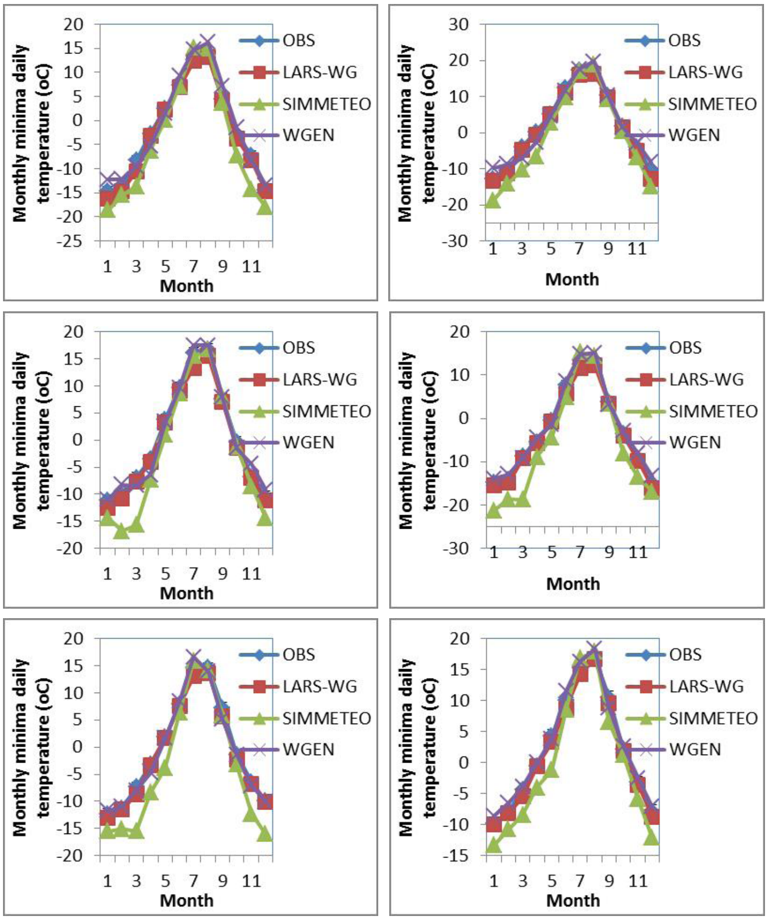


**Figure 10.** Comparison of monthly minima daily temperature for observed data and synthetic data generated by WGEN, SIMMETEO, and LARS-WG for weather stations 135 (top left), 140 (top right), 261 (middle left), 284 (middle right), 289 (bottom left) and 294 (bottom right).

### 3.2.3 Maximum temperature

The theory for generating maximum temperature is the same for generating minimum temperature. As shown in Figure 11, the LARS-WG generated data match the observed values more closely than WGEN, and SIMMETEO. For example, in the rice-growing season in July, at weather station 294, the mean value of the maximum temperature generated by SIMMETEO is 1.8°C higher than the observed value, whereas the generated data by LARS-WG and WGEN are very close to the observed value.

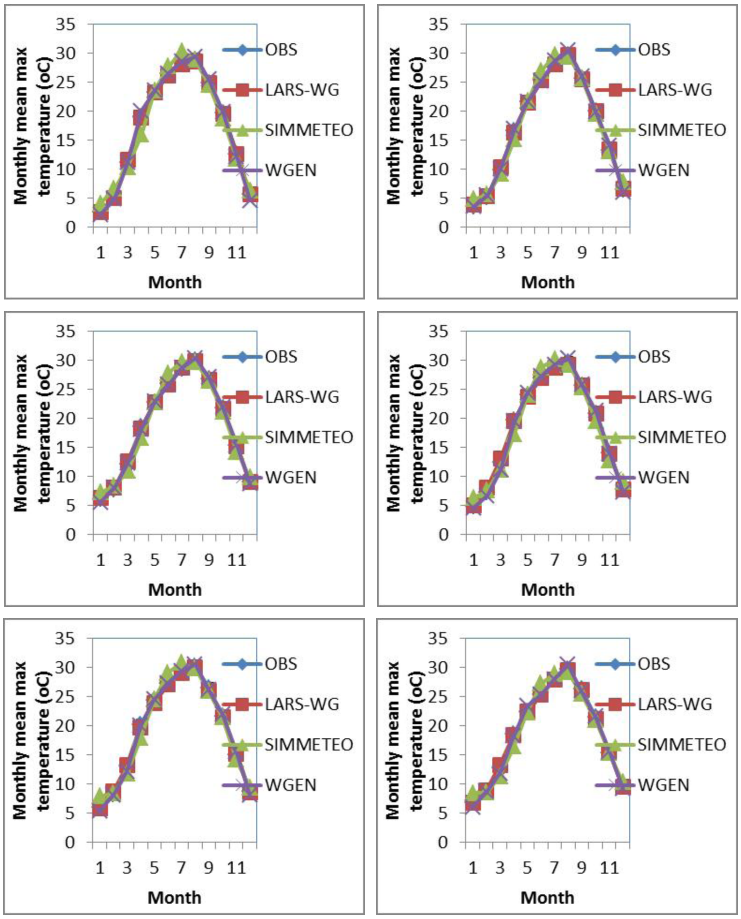


**Figure 11.** Comparison of monthly mean maximum temperature for observed data and synthetic data generated by WGEN, SIMMETEO, and LARS-WG for weather stations 135 (top left), 140 (top right), 261 (middle left), 284 (middle right), 289 (bottom left) and 294 (bottom right).

### 3.2.4 Daily maximum temperature

The maximum daily temperature is one of the most important factors affecting rice yield. With global warming, rice production is facing more frequent damage due to hot temperatures. The three generators perform very well at simulating mean daily maximum temperature as shown in the left panel of Figure 12. SIMMETEO and WGEN produce similar but slightly larger standard deviations of daily maximum temperature. LARGS-WG slightly underestimates the standard deviation of daily maximum temperature (Figure 12, right).

The three weather generators show similar performances in reproducing mean maximum temperature, as shown in Figure 10. The generated data from LARS-WG matches the observed values more closely than WGEN, and both LARS-WG and WGEN perform better than SIMMETEO.

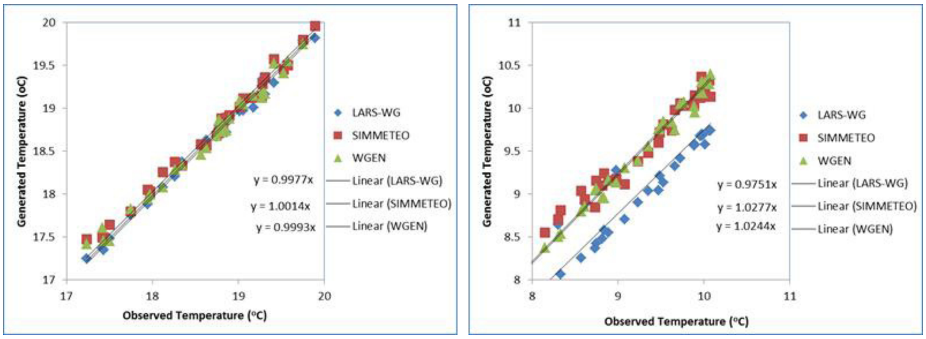


**Figure 12.** Mean of daily maximum temperature (left) and standard deviation of daily maximum temperature (right) of observed versus generated values from three weather generators (WGEN, SIMMETEO, and LARS-WG) for 63 weather stations.

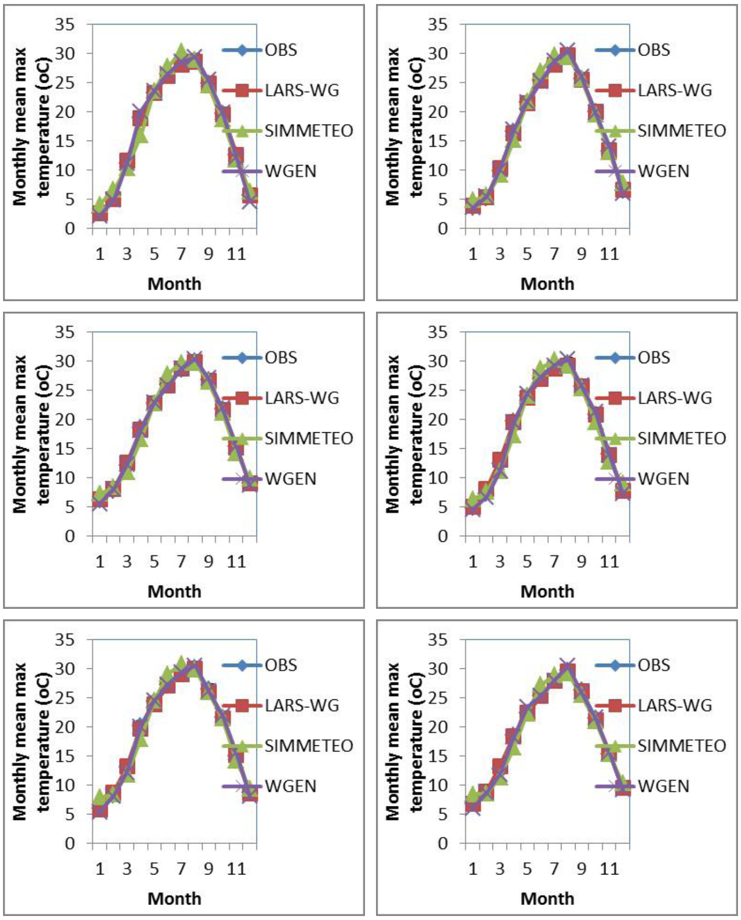


**Figure 13.** Comparison of monthly maxima daily temperature for observed data and synthetic data generated by WGEN, SIMMETEO, and LARS-WG for weather stations 135 (top left), 140 (top right), 261 (middle left), 284 (middle right), 289 (bottom left) and 294 (bottom right).

### 3.2.5 Radiation

LARS-WG uses a semi-empirical distribution to model solar radiation, whereas WGEN and SIMMETEO use normal distributions. Overall, the three generators perform very well in simulating daily total solar radiation, as shown in the left panel of Figure 14, with little scatter for low solar radiation in the SIMMETERO simulations. The slopes of the three regression lines are very close to 1. LARS-WG can accurately reproduce the standard deviation of daily solar radiation. However, SIMMETERO and WGEN slightly underestimate the standard deviation of daily solar radiation (Figure 14, right).

LARS-WG can reproduce the monthly mean solar radiation, but WGEN and SIMMETEO perform poorly, as shown in Figure 15, which shows the comparison of data generated by the three generators and the observed values.

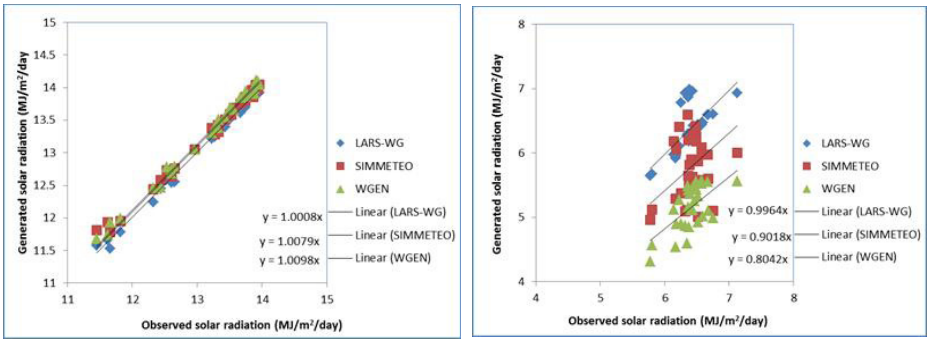


**Figure 14.** Mean of daily (left) and standard deviation of total daily solar radiation (right) of observed versus generated values from the three weather generators (WGEN, SIMMETEO, and LARS-WG) for 63 weather stations

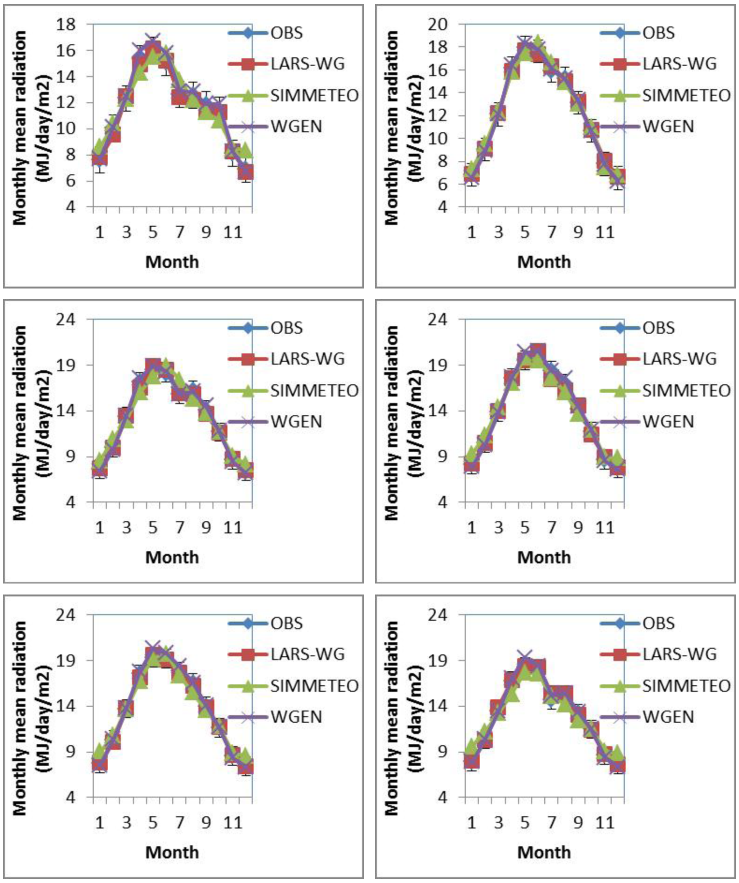


**Figure 15.** Comparison of monthly mean radiation for observed data and synthetic data generated by WGEN, SIMMETEO, and LARS-WG for weather stations 135 (top left), 140 (top right), 261 (middle left), 284 (middle right), 289 (bottom left) and 294 (bottom right).

### 3.3 Rice yield

Figures 16-21 and Table 11-16 summarize results of the various rice-yield hindcast scenarios. The standard deviations of yields simulated using observed weather data are larger than that using different generated weather data. This is because the yields simulated using generated weather data are average values from 23 replications of weather data for each year. Since the average value usually masks the variation of individual values, the standard deviations of yields simulated using 23 series weather data for each year are small. For weather station 135, as shown in Table 11, the 23-year average yield of the cultivar Nampyeong simulated using observations is close to the average value of rice yield simulated using different climate scenarios, except by RW-NBC. For the cultivar Saegyewha, the average yields simulated using synthetic data underestimate the yield simulated using observed weather data. For the cultivar Unkwang, the average yields simulated using synthetic data are similar to the observed values. All of the standard deviations of the three cultivars from simulations using generated weather data by different scenarios are much smaller than those using observed values, suggesting that the yearly variations for rice yields are much less than the observed values, as shown in Figure 16.

Figure 16 shows the comparison of the average simulated rice yields of the three cultivars using generated forecast weather data in each year with the corresponding observed yields. At weather station 135, the rice yields simulated using observed weather data are considerably different from the average yields simulated using generated forecast weather data.

**Table 11.** Mean and standard deviation of rice yield (kg/ha) for 23 years simulated by observed weather data and synthetic weather data generated by LARS-WG with a combination of different spatial downscaling data and different bias correction methods for station 135 from 1983 to 2005. The bias correction methods are AE-BC, AE-NBC, GRID, RW-BC, RW-NBC, SM-BC, SM-NBC, WE-BC and WE-NBC. The standard deviation of rice yield simulated using synthetic weather data is calculated using the average value of each year.

| Cultivar | Value | OBS | AE-BC | AE-NBC | GRID | RW-BC | RW-NBC | SM-BC | SM-NBC | WE-BC | WE-NBC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Namp-yeong | Mean | 8107 | 8414 | 8443 | 8413 | 8311 | 8307 | 8423 | 8453 | 8416 | 8442 |
| | Stdev | 779 | 20 | 28 | 30 | 27 | 26 | 24 | 38 | 26 | 27 |
| Saegye-wha | Mean | 4534 | 3756 | 3837 | 3773 | 3935 | 3869 | 3772 | 3880 | 3727 | 3806 |
| | Stdev | 456 | 141 | 141 | 156 | 237 | 167 | 160 | 234 | 137 | 121 |
| Unkwang | Mean | 7025 | 7027 | 7057 | 7027 | 7135 | 7133 | 7032 | 7060 | 7031 | 7056 |
| | Stdev | 413 | 14 | 15 | 22 | 71 | 70 | 24 | 23 | 22 | 23 |

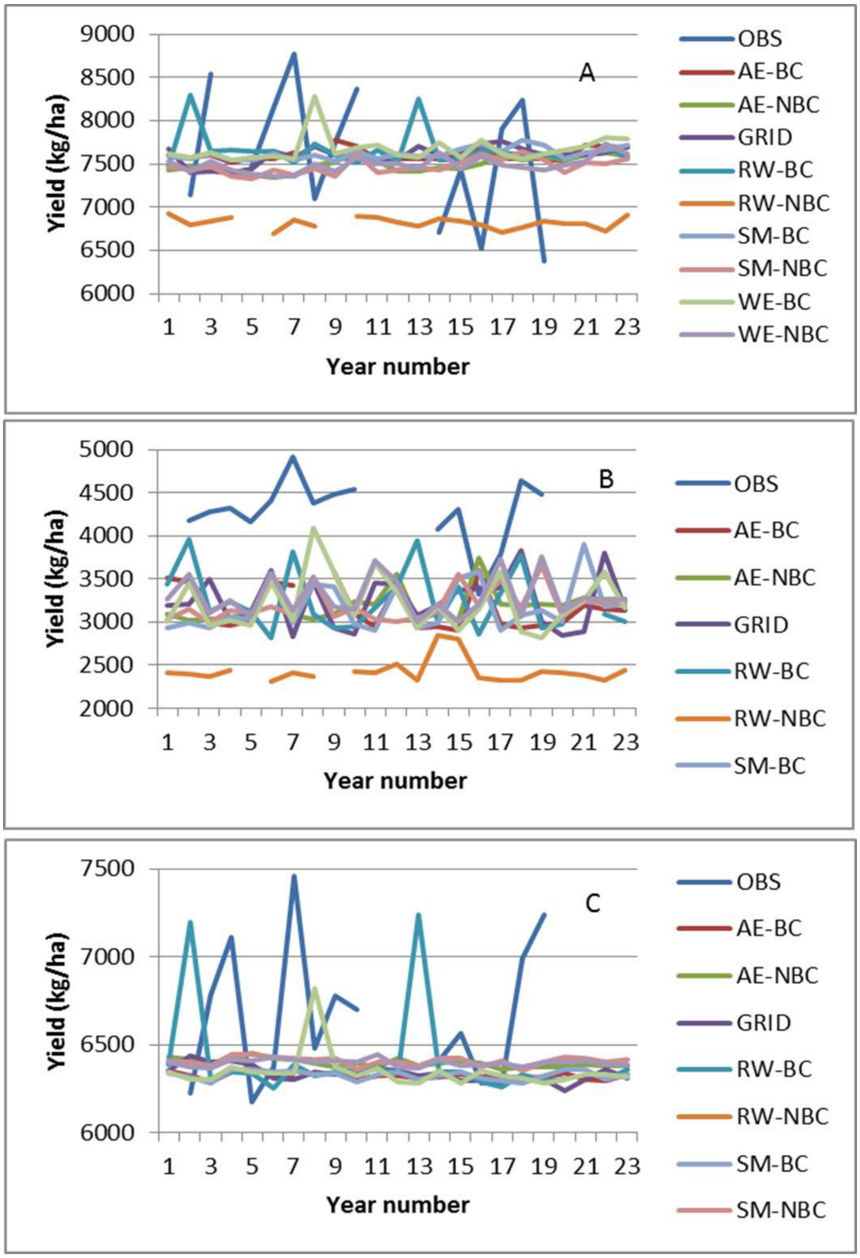


**Figure 16.** Rice yield simulated using observed weather data and mean rice yield for station 135 (same conditions as in Table 11).

For weather station 140, as shown in Table 12, the 23 year average yield of the cultivar Nampyeong simulated using observed weather data is close to the average value of rice yield simulated using different climate scenarios, except by SM-NBC. For cultivar the Saegyewha, the average yields simulated using synthetic data are less than the observed yield. For the cultivar Unkwang, the average yields simulated using synthetic forecast data are similar to the observed value. All of the standard deviations of Nampyeong and Unkwang from simulations using generated forecasts by different scenarios are much smaller than the observed values, suggesting that the yearly variations of the rice yields for these two cultivars are much less than observed values, which are shown in Figure 17. However, for the cultivar Saegyewha, the standard deviations from using forecasts and observations are similar.

Figure 17 shows the yearly trend of average simulated rice yields of three cultivars using generated forecasts with the corresponding observed yields. For a given year at weather station 140, the rice yields simulated using observed weather data can be similar to or different from the corresponding average yields simulated using generated forecast weather data.

**Table 12.** Mean and standard deviation of rice yield (kg/ha) for station 140 (same conditions as in Table 11)

| Cultivar | Value | OBS | AE-BC | AE-NBC | GRID | RW-BC | RW-NBC | SM-BC | SM-NBC | WE-BC | WE-NBC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Namp-yeong | Mean | 8112 | 7945 | 7995 | 7948 | 7953 | 8347 | 7955 | 6518 | 7964 | 7980 |
| | Stdev | 661 | 35 | 37 | 47 | 48 | 110 | 60 | 655 | 71 | 69 |
| Saegye-wha | Mean | 4667 | 3371 | 3578 | 3349 | 3418 | 3779 | 3482 | 2896 | 3376 | 3423 |
| | Stdev | 319 | 207 | 394 | 204 | 282 | 252 | 334 | 336 | 255 | 109 |
| Unkwang | Mean | 6706 | 6863 | 6898 | 6869 | 6868 | 6924 | 6870 | 6685 | 6869 | 6900 |
| | Stdev | 712 | 10 | 11 | 17 | 13 | 35 | 12 | 122 | 18 | 20 |

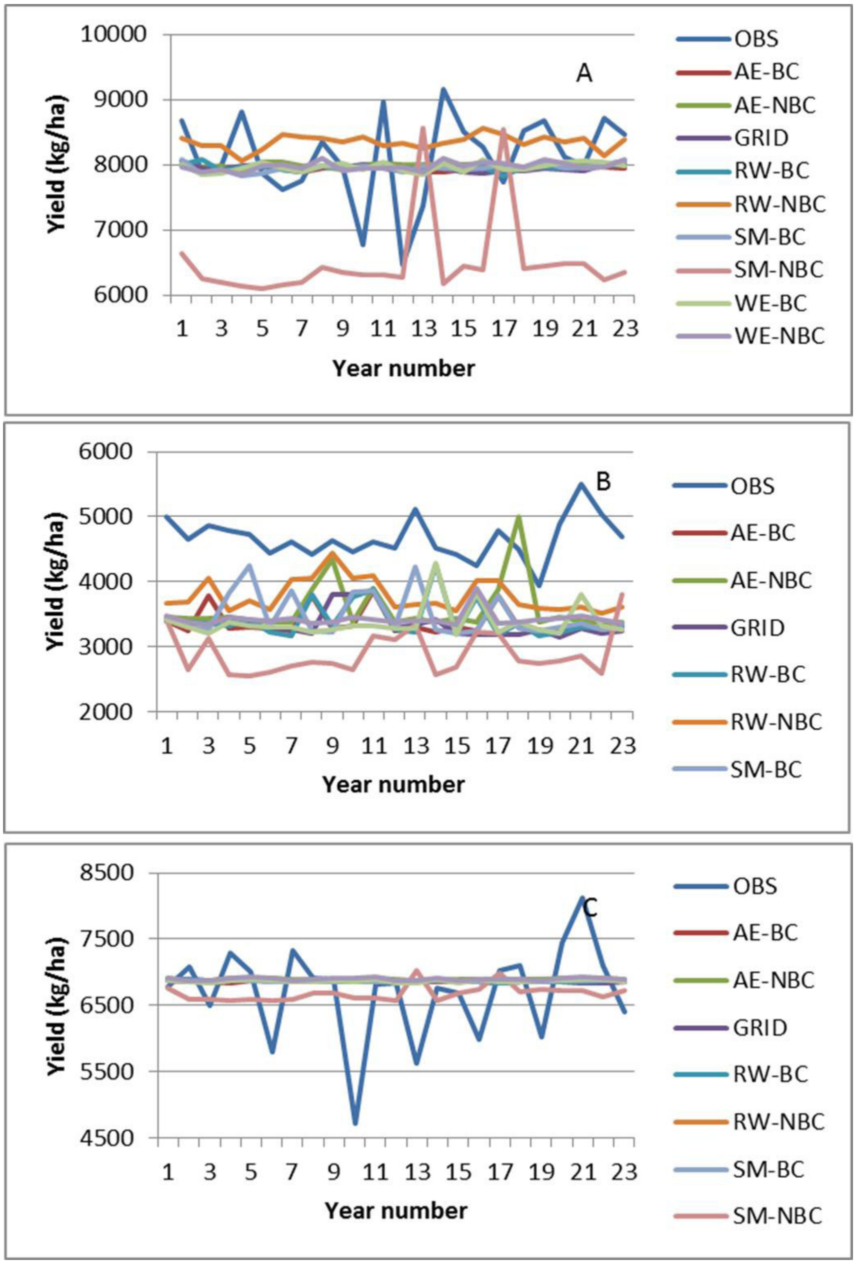


**Figure 17.** Rice yield (kg/ha) simulated using observed weather data and mean rice yield at station 140 (same conditions as in Table 11)

For weather station 261, Table 13 shows that the 23-year average yields of Nampyeong and Unkwang simulated using observed weather data are similar to the corresponding average values of rice yields simulated using different climate scenarios. All of the standard deviations of Nampyeong and Unkwang from simulations using generated forecasts by different scenarios are much smaller than the observed values. For Saegyewha, the average yields simulated using synthetic data underestimate the observed yield. However, for Saegyewha, the standard deviations from using forecasts and observations are similar.

Figure 18 shows the yearly trend of average simulated rice yields of three cultivars using generated forecasts with the corresponding observed yields. For a given year at weather station 261, the rice yields simulated using observed weather data can be similar to or different from the corresponding average yields simulated using generated forecast weather data. For Unkwang, the individual rice yield simulated using generated forecasts are close to the corresponding yield using observed weather data from 1986 to 2002.

**Table 13.** Mean and standard deviation of rice yield (kg/ha) 261 (same conditions as in Table 11).

| Cultivar | Value | OBS | AE-BC | AE-NBC | GRID | RW-BC | RW-NBC | SM-BC | SM-NBC | WE-BC | WE-NBC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Namp-yeong | Mean | 7963 | 8183 | 8192 | 8170 | 8167 | 7988 | 8181 | 8204 | 8182 | 8205 |
| | Stdev | 779 | 27 | 17 | 37 | 41 | 32 | 39 | 36 | 27 | 26 |
| Saegye-wha | Mean | 4675 | 3838 | 3814 | 3839 | 3751 | 3920 | 3818 | 3896 | 3840 | 3900 |
| | Stdev | 308 | 228 | 131 | 195 | 163 | 171 | 234 | 186 | 189 | 175 |
| Unkwang | Mean | 6950 | 6888 | 6926 | 6890 | 6881 | 6941 | 6882 | 6924 | 6882 | 6926 |
| | Stdev | 399 | 35 | 26 | 25 | 28 | 28 | 27 | 25 | 25 | 32 |

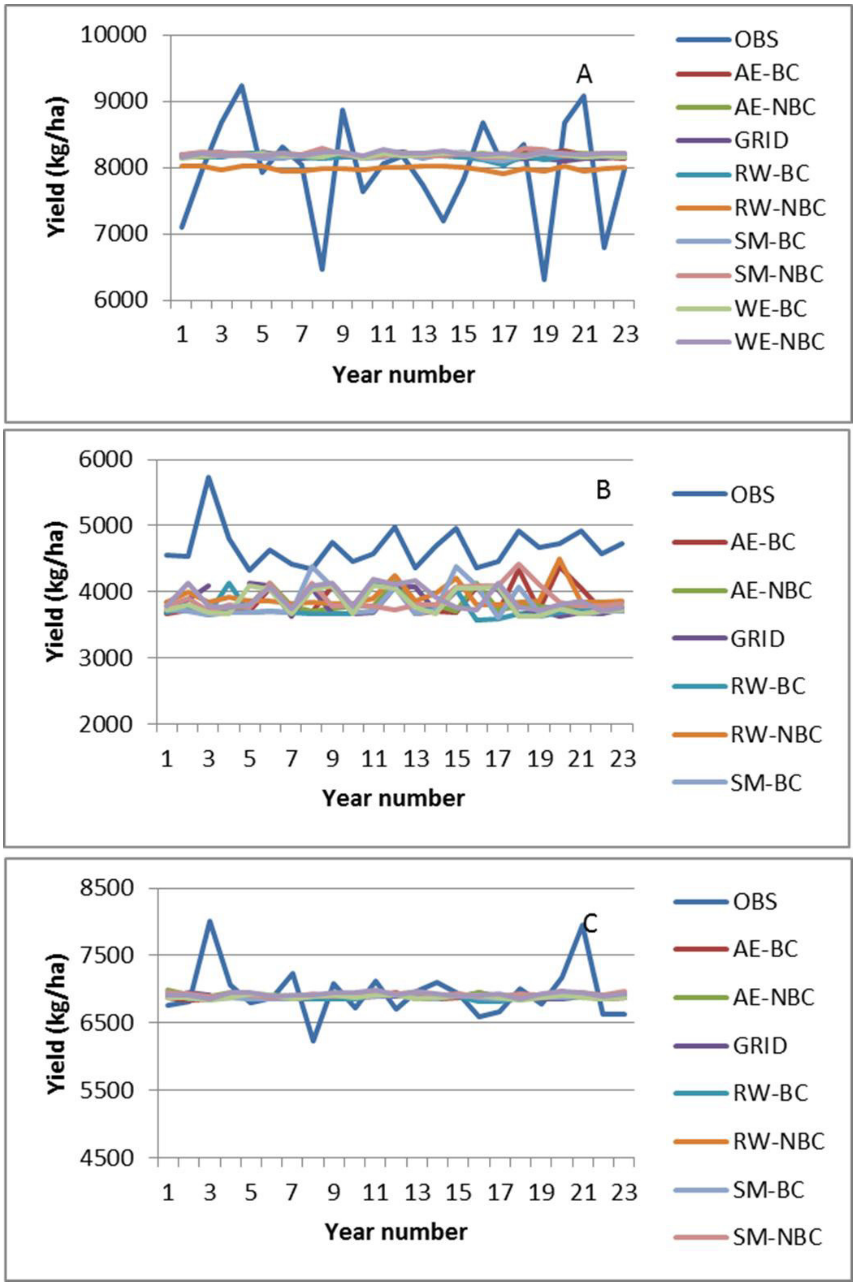


**Figure 18.** Rice yield (kg/ha) for station 261 (same conditions as in Table 11).

For weather station 284, the 23-year average yields of Nampyeong simulated using observed weather data are similar to the corresponding average values of rice yields simulated using different climate scenarios. All of the standard deviations of Nampyeong from simulations using generated forecasts by different scenarios are much smaller than the observed values (Table 14). For Unkwang, the yield simulated using observations are similar to the yields simulated using forecasts with different scenarios, except for the GRID data. For Saegyewha, the average yields simulated using synthetic data underestimate the observed yield. However, for Saegyewha, the standard deviations from using forecasts and observations are similar.

Figure 19 shows the yearly trend of average simulated rice yields of three cultivars using generated forecasts with the corresponding observed yields. For a given year at weather station 261, the rice yields simulated using observed weather data can be similar to or different from the corresponding average yields simulated using generated forecast weather data. For cultivar Unkwang, the individual rice yield simulated using generated forecasts are close to the corresponding yield using observed weather data from 1983 to 2001.

**Table 14.** Mean and standard deviation of rice yield (kg/ha) at station 284 (same conditions as in Table 11).

| Cultivar | Value | OBS | AE-BC | AE-NBC | GRID | RW-BC | RW-NBC | SM-BC | SM-NBC | WE-BC | WE-NBC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Namp-yeong | Mean | 8238 | 8444 | 8435 | 8102 | 8443 | 8285 | 8443 | 8428 | 8440 | 8455 |
| | Stdev | 856 | 25 | 23 | 48 | 21 | 35 | 27 | 29 | 33 | 72 |
| Saegye-wha | Mean | 4722 | 4170 | 4138 | 3758 | 4091 | 4182 | 4097 | 4158 | 4095 | 4134 |
| | Stdev | 321 | 164 | 107 | 173 | 107 | 148 | 84 | 139 | 117 | 101 |
| Unkwang | Mean | 6798 | 6860 | 6922 | 6561 | 6862 | 6949 | 6868 | 6930 | 6861 | 6935 |
| | Stdev | 446 | 15 | 12 | 45 | 22 | 27 | 29 | 28 | 29 | 36 |

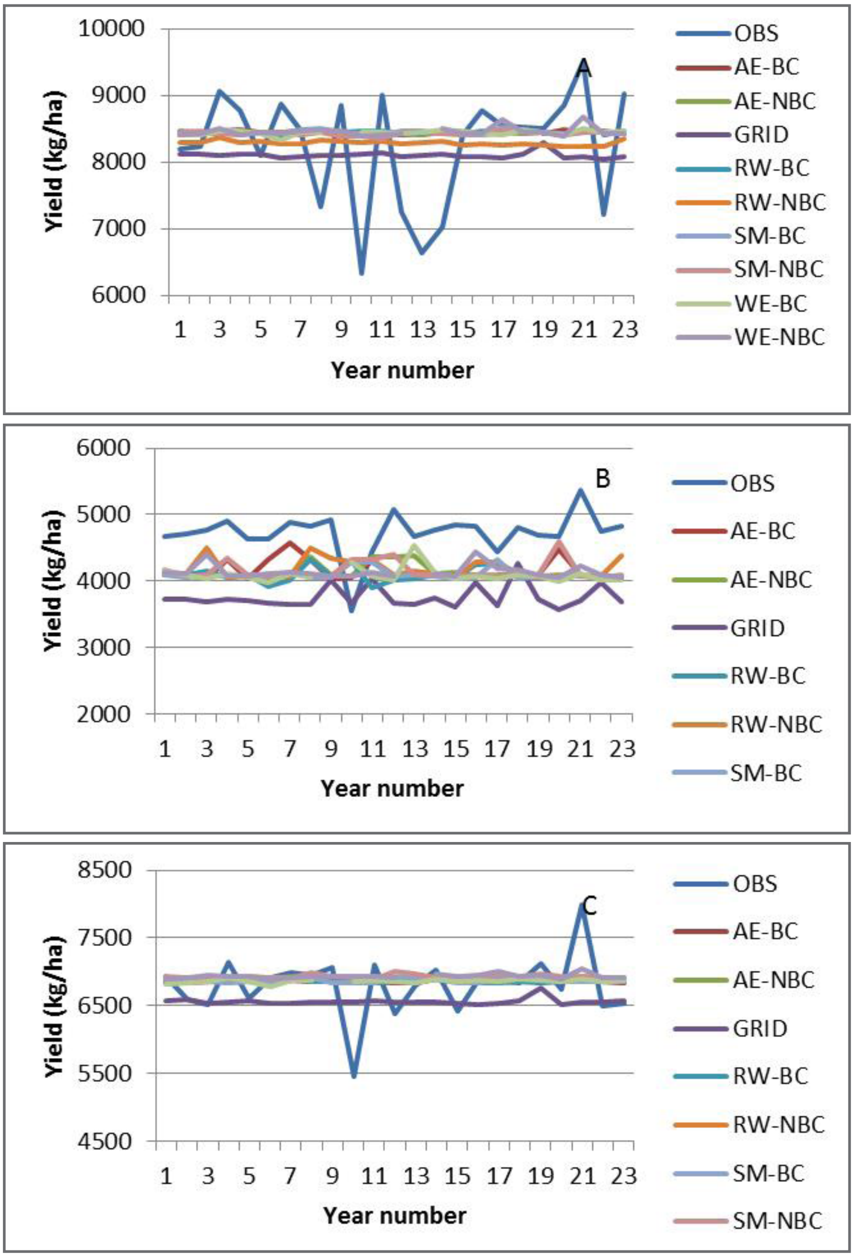


**Figure 19.** Rice yield simulated for station 284 (same conditions as in Table 11).

For weather station 289, the 23-year average yields of Nampyeong an Unkwang simulated using observed weather data are similar to the corresponding average values of rice yields simulated using different climate scenarios. All of the standard deviations of Nampyeong and Unkwang from simulations using generated forecasts by different scenarios are much smaller than the observed values (Table 14). For Saegyewha, the average yields simulated using synthetic data underestimate the observed yield. However, for Saegyewha, the standard deviations from using forecasts and observations are similar.

Figure 16 shows the yearly trend of average simulated rice yields of three cultivars using generated forecasts with the corresponding observed yields. For a given year at weather station 289, the rice yields simulated using observed weather data can be similar to or different from the corresponding average yields simulated using generated forecast weather data. For Unkwang, the individual rice yield simulated using generated forecasts are close to the corresponding yield using observed weather data from 1983 to 2005, except in 1998.

**Table 15.** Mean and standard deviation of rice yield at station 289 (same conditions as in Table 11).

| Cultivar | Val-ue | OBS | AE-BC | AE-NBC | GRID | RW-BC | RW-NBC | SM-BC | SM-NBC | WE-BC | WE-NBC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Nampy-eong | Mean | 8395 | 8849 | 8827 | 8852 | 8853 | 8857 | 8863 | 8850 | 8863 | 8856 |
| | Stdev | 1022 | 42 | 158 | 56 | 54 | 85 | 64 | 102 | 111 | 88 |
| Saegye-wha | Mean | 4944 | 3877 | 4037 | 4030 | 3904 | 4174 | 3973 | 4172 | 4094 | 4142 |
| | Stdev | 191 | 168 | 208 | 261 | 187 | 144 | 220 | 317 | 310 | 271 |
| Unkwang | Mean | 7028 | 6989 | 7021 | 6987 | 6987 | 7090 | 7013 | 7034 | 7006 | 7036 |
| | Stdev | 332 | 28 | 57 | 38 | 32 | 55 | 65 | 69 | 71 | 67 |

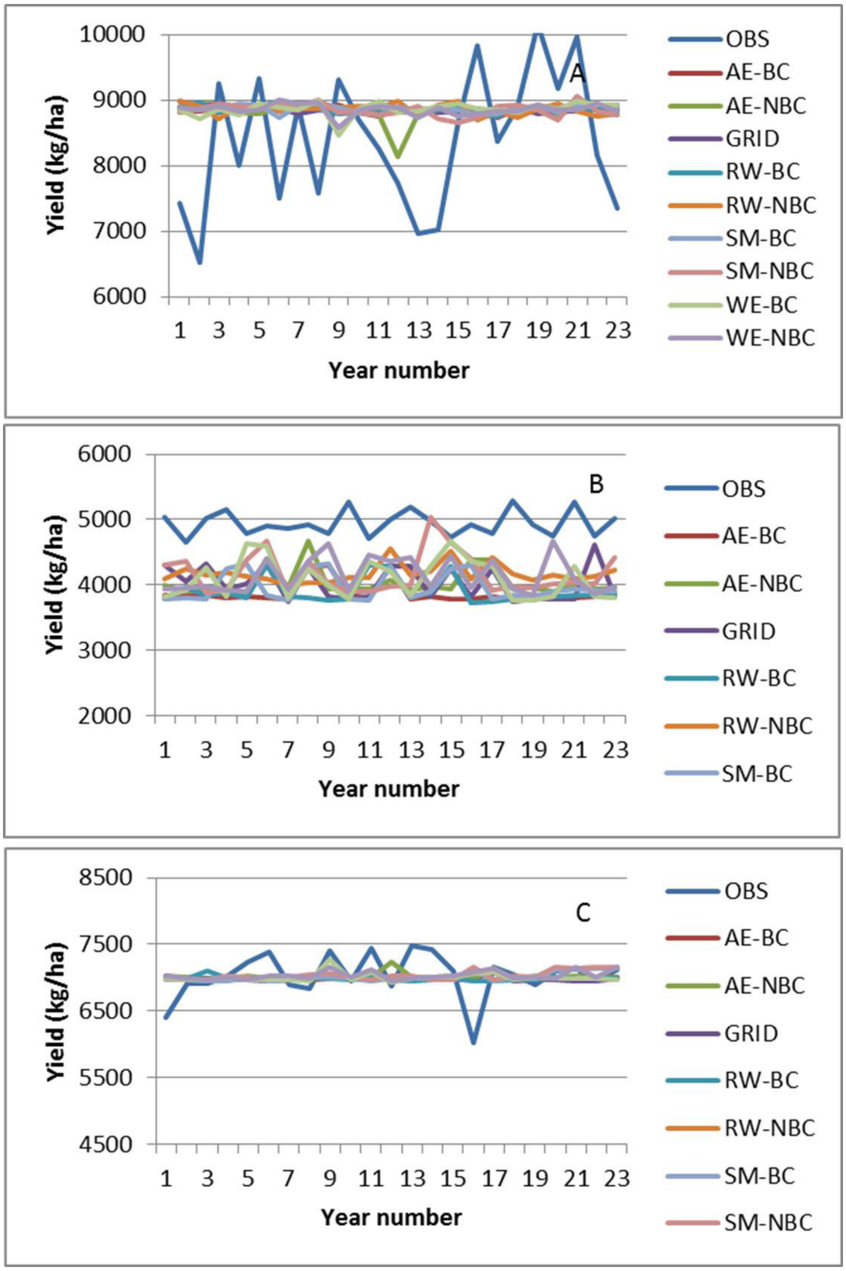


**Figure 20.** Rice yield simulated at station 289 (same conditions as in Table 11).

For weather station 294, the 23-year average yields of Nampyeong an Unkwang simulated using observed weather data are similar to the corresponding average values of rice yields simulated using different climate scenarios. All of the standard deviations of Nampyeong and Unkwang from simulations using generated forecasts by different scenarios are much smaller than the observed values (Table 16). For Saegyewha, the average yields simulated using synthetic data underestimate the observed yield. However, for Saegyewha, the standard deviations from using forecasts and observations are similar.

Figure 21 shows the yearly trend of average simulated rice yields of three cultivars using generated forecasts with the corresponding observed yields. For a given year at weather station 294, the rice yields simulated using observed weather data can be similar to or different from the corresponding average yields simulated using generated forecast weather data. For Unkwang, the individual rice yield simulated using generated forecasts are close to the corresponding yield using observed weather data from 1984 to 2005, except for missing data in 1994, 1995, 2002, 2004 and 2005.

**Table 16.** Mean and standard deviation of rice yield (kg/ha) for 23 years simulated by observed weather data and synthetic weather data generated by LARS-WG with a combination of different spatial downscaling data and different bias correction methods for station 294 from 1983 to 2005. The bias correction methods are AE-BC, AE-NBC, GRID, RW-BC, RW-NBC, SM-BC, SM-NBC, WE-BC and WE-NBC. The standard deviation of rice yield simulated using synthetic weather data is calculated using the average value of each year.

| Cultivar | Value | OBS | AE-BC | AE-NBC | GRID | RW-BC | RW-NBC | SM-BC | SM-NBC | WE-BC | WE-NBC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Nampyeong | Mean | 8107 | 8414 | 8443 | 8413 | 8311 | 8307 | 8423 | 8453 | 8416 | 8442 |
| | Stdev | 779 | 20 | 28 | 30 | 27 | 26 | 24 | 38 | 26 | 27 |
| Saegyewha | Mean | 4534 | 3756 | 3837 | 3773 | 3935 | 3869 | 3772 | 3880 | 3727 | 3806 |
| | Stdev | 456 | 141 | 141 | 156 | 237 | 167 | 160 | 234 | 137 | 121 |
| Unkwang | Mean | 7025 | 7027 | 7057 | 7027 | 7135 | 7133 | 7032 | 7060 | 7031 | 7056 |
| | Stdev | 413 | 14 | 15 | 22 | 71 | 70 | 24 | 23 | 22 | 23 |

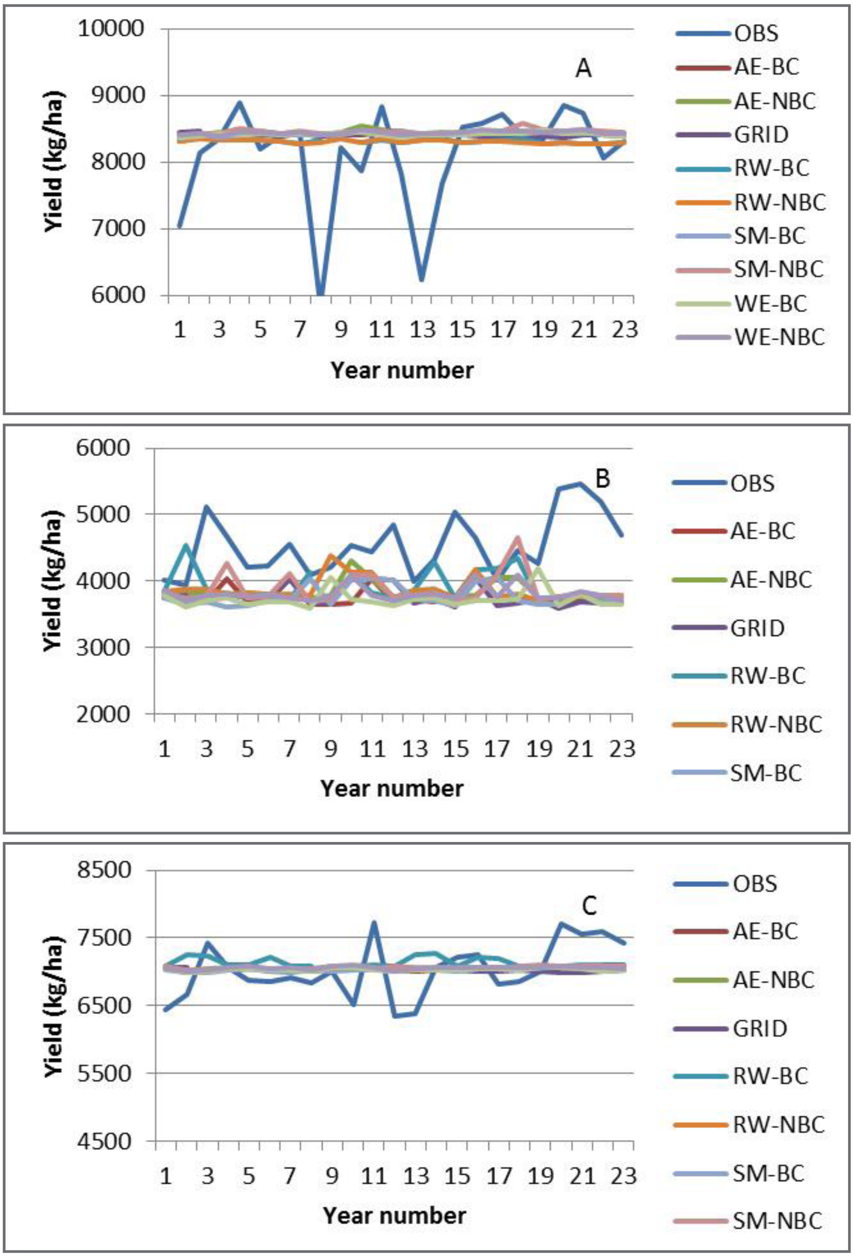


**Figure 21.** Rice yield (kg/ha) simulated using observed weather data and mean rice yield simulated using synthetic weather data generated by LARS-WG with a combination of different spatial downscaling data and different bias correction methods for station 294 from 1983-2005. The bias correction methods are AE-BC, AE-NBC, GRID, RW-BC, RW-NBC, SM-BC, SM-NBC, WE-BC and WE-NBC. A is for Nampyeong, B is for Saegyewha and C is for Unkwang.

The averages and standard deviations of rice yields simulated by synthetic forecasts generated by LARS-WG with a combination of different spatial downscaling data and different bias correction methods for stations 135, 140, 261, 284, 289 and 294 in each single year from 1983 to 2005 are calculated (data not shown). The bias correction methods are AE-BC, AE-NBC, GRID, RW-BC, RW-NBC, SM-BC, SM-NBC, WE-BC and WE-NBC. Overall, for Nampyeong, the mean yields simulated using different scenarios can be similar, but have some exceptions without bias correction; for example, at station 135 in 1983, the yields simulated using scenario RW-NBC is considerably lower than that simulated using other scenarios. For Unkwang, the mean yields simulated using different scenarios are similar For Saegyewha, the mean rice yields can be similar or have large differences among the different scenarios.

The cumulative distribution functions of rice yields simulated using synthetic weather forecasts generated by LARS-WG with a combination of different spatial downscaling data and different bias correction methods show that the yields of Unkwang simulated using different scenarios are similar, and most yields of Nampyeong are similar with a few exceptions. However, for Saegyewha, the yields modeled using different scenarios vary (data not shown).

# CONCLUSIONS

The three generators LARS-WG, WGEN and SIMMETERO are widely used for linking climate forecasts to crop models. They use observed weather data to fit parameters for the daily weather distributions of minimum and maximum temperature, precipitation and solar radiation, which are usually required as input data for crop modeling. The three generators analyze dry and wet days separately and therefore include a mechanism for selecting the wet and dry status of each day in the generated weather data. The main difference of the three generators is in the choice of the daily distributions used. WGEN and SIMMETERO use simple standard distributions, whereas LARS-WG uses more flexible semi-empirical distributions.

The results demonstrate the performances of the three generators are accurate in simulating maximum, minimum and mean temperature, and solar radiation; however, they have difficulty in reproducing precipitation. The performances vary from site to site. Weather data modeled by LARS-WG matches the observed data closer than that by WGEN and SIMMETEO. SIMMETEO is only used if there is not daily historical data available but monthly means are available. It is important to validate the weather generators by examining the output at each site before the generated data are used in crop modeling.

In general, rice yields simulated using synthetic weather data generated with bias correction are closer to the yields simulated using observed weather data than those without bias correction. The 26-year average rice yields of the cultivars Nampyeong and Unkwang are similar to the simulations using observations, with a few exceptions. The yields of the cultivar Saegyewha simulated using generated forecasts are usually overestimated. For a given year, the rice yields simulated using synthetic forecasts can be similar to or substantially different from the yields simulated using observations, indicating that the APCC climate outlook has the potential to forecast rice yields over Korea. However, the accuracy and reliability of yield forecasting using the APCC climate outlook may vary considerably from year to year and site to site with some periods and sites having high skill and other periods or regions having less skill. Other factors, such as the use of generated weather data, reliability of genetic parameters adopted from other studies, and inherent model errors in the CERES-Rice model could affect the accuracy of the simulation.

Further studies are required in terms of more model calibration, monthly updates of yield simulation, and more testing of climate scenarios.

The CERES-Rice model can only provide the potential yield under optimal environmental conditions, which assumes that there are no pests or disease, and the crops are free from weed stress and wind damage. This study does not validate by comparing with observed field rice yield since yield data for the three cultivars under optimal conditions are not available. Further validation may be needed in further studies. It is also possible for the CERES-Rice model to couple with a pest and disease model to simulate rice yield closer to the real field conditions.

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**RESEARCH REPORT** 2015-20

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