Comparison of projected rice blast epidemics in the Korean Peninsula between the CMIP5 and CMIP6 scenarios

Kyoung-Tae Lee1 · Hye-Won Jeon2 · Sook-Young Park3 · Jaepil Cho2 · Kwang-Hyung Kim1

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Abstract
Recently, the International Panel for Climate Change released the 6th Coupled Model Intercomparison Project (CMIP6) climate change scenarios with shared socioeconomic pathways (SSPs). The SSP scenarios result in significant changes to climate variables in climate projections compared to their predecessor, the representative concentration pathways from the CMIP5. Therefore, it is necessary to examine whether the CMIP6 scenarios differentially impact plant–disease ecosystems compared to the CMIP5 scenarios. In this study, we used the EPIRICE-LB model to simulate and compare projected rice blast disease epidemics in the Korean Peninsula using five selected family global climate models (GCMs) of the CMIP5 and CMIP6 for two forcing scenarios. We found a similar decrease in rice blast epidemics in both CMIP scenarios; however, this decrease was greater in the CMIP6 scenarios. In addition, distinctive epidemic trends were found in North Korea, where the rice blast epidemics increase until the mid-2040s but decrease thereafter until 2100, with different spatial patterns of varying magnitudes. Controlling devastating rice blast diseases will remain important during the next decades in North Korea, where appropriate chemical controls are unavailable due to chronic economic and political issues. Overall, our analyses using the new CMIP6 scenarios reemphasized the importance of developing effective control measures against rice blast for specific high-risk areas and the need for a universal impact and vulnerability assessment platform for plant–disease ecosystems that can be used with new climate change scenarios in the future.

Keywords Shared socioeconomic pathway · Representative concentration pathway · Plant–disease ecosystem · Rice blast · Disease epidemic

Kwang-Hyung Kim
sospicy77@snu.ac.kr

1 Department of Agricultural Biotechnology, Seoul National University, Seoul 08826, Korea
2 Convergence Center for Watershed Management, Integrated Watershed Management Institute, 16489 Suwon, Korea
3 Department of Plant Medicine, Sunchon National University, Suncheon 57922, Korea
1 Introduction

Climate change has impacted plant–disease ecosystems in recent decades, and the frequency and intensity of deviations from typical plant–disease ecosystems are increasing. Massive crop losses can occur when weather conditions are conducive to disease development. Thus, the International Plant Protection Convention (IPPC) proposed “Strengthening Pest Outbreak Alert and Response Systems” as a Development Agenda item for the IPPC Strategic Framework 2020–2030 (FAO 2019), with the goal of building a global pest alert system with mechanisms to evaluate and communicate emerging pest risks. Furthermore, with a changing climate, invasions of new pathogens or increases in the aggressiveness and/or infectivity of existing pathogens can cause sudden outbreaks of plant disease in areas where climate change favors the pathogen. In particular, the frequently reported possibility of temperature adaptation, either through genetic change or phenotypic plasticity, may increase concerns about the geographic expansion of plant pathogens by emergence or reemergence (Burdon and Zhan 2020).

To understand the possible impacts of climate change on plant–disease ecosystems, various modeling approaches and disease models (mechanistic and empirical/statistical) have been adopted, which use multiple combinations of inputs and outputs, such as the number of global climate models (GCMs) and emission scenarios, environmental and agronomic variables, spatial and temporal resolution, and disease risk parameters (e.g., epidemic area, infection risk, and yield loss) (Juroszek and von Tiedemann 2015). The representative concentration pathway (RCP) scenarios of the 5th Coupled Model Intercomparison Project (CMIP5) from more than 40 GCMs have been used in many previous impact studies and have produced valuable projections for policymakers and the scientific community (Kim and Cho 2016; Kim and Koh 2019; Viswanath et al. 2017). The RCP4.5 scenario assumes that greenhouse gas emissions will stabilize anthropogenic radiative forcing at 4.5 W m\(^{-2}\) in the year 2100 without ever exceeding that value, whereas the RCP8.5 scenario corresponds to a nominal anthropogenic forcing of 8.5 W m\(^{-2}\) by 2100 (Riahi et al. 2015). The recent 6th Coupled Model Intercomparison Project (CMIP6) represents climate features better by including recent experiments on global climate modeling. The GCMs in CMIP6 generally have finer resolutions with improved dynamic processes, and the shared socioeconomic pathway (SSP) scenarios of the CMIP6 include new social and economic factors along with the RCP (O’Neill et al. 2017). The SSP scenarios also allow estimations of future energy and land use changes based on adaptation and mitigation intensity levels (O’Neill et al. 2016; Wang et al. 2018). SSP2-4.5 and SSP5-8.5 of the CMIP6 have similar emission levels to RCP4.5 and RCP8.5, respectively.

Understanding the differences in the behavior of the CMIP5 and CMIP6 models is essential because of their critical role in evaluating climate change impacts. For the Korean Peninsula, several studies have analyzed the differences or uncertainties in climate variables, including extreme climatic risks. Song et al. (2021a) examined the model reproducibility and uncertainty in the projections using the reliability ensemble average method. They reported that the CMIP6 showed improved historical climate simulation versus the CMIP5, and the uncertainty in the precipitation projections was higher for the SSPs than for the RCPs and vice versa for the temperature projections. Kim et al. (2020) assessed the simulation efficiency of the CMIP5 and CMIP6 models for simulating summer heatwaves in Korea and concluded that the CMIP6 models were better overall for simulating heatwaves than the CMIP5 models. The precipitation simulations were also compared using one family GCM (INM-CM4 of CMIP5 and INM-CM5 of CMIP6); the uncertainties,
quantified using standard deviations and interquartile ranges, in the CMIP6 model were smaller than those in the CMIP5 model (Song et al. 2021b). However, there are currently no studies demonstrating the simulation efficiency of the CMIP6 models concerning the impacts of different climate change scenarios on plant–disease ecosystems.

In our previous study (Kim and Cho 2016), we assessed changes in rice blast probabilities using multi-model ensembles (MMEs), constructed by running 11 GCMs of CMIP5, to emphasize the uncertainties in climate change scenarios resulting from varied initial conditions and structural differences in the GCMs. Although the study did not assess the rice blast probability in North Korea, the projected rice blast risks remained relatively high in the northern part of South Korea that indicated that rice blast may also be a serious issue in North Korea under climate change. In addition, due to current unpredictable climate variability, the incidence of rice blast is increasing in South Korea (from the National Crop Pest Management System of the Rural Development Administration of South Korea; URL = “https://ncpms.rda.go.kr/npms”). Field observations showed irregular but severe occurrences of panicle blast depending on weather conditions from 1999 to 2008 (Lee et al. 2010). Chung et al. (2022) recently reported severe rice blast outbreaks occurred nationwide in 2020 in South Korea. Not only in South Korea, rice blast is also a major endemic yield reducer in rice production in North Korea, as inferred from many previous studies (Chen et al. 2014; Chung et al. 2019; Guo et al. 2018; Kim 1999). Moreover, Onaga et al. (2017) showed that temperature elevation could favor rice blast infection by compromising plant resistance and accelerating pathogen colonization of plant tissue. Kobayashi et al. (2007) also observed that elevated CO2 concentration made rice plants more susceptible to the infection of rice blast via their free-air CO2 enrichment (FACE) experiment. Overall, rice blast will remain an important threat in the future, thus necessitating continuous assessment of the impacts of climate change on it.

The purpose of our study was to simulate and compare future rice blast epidemics in the Korean Peninsula using five family GCMs of the CMIP5 and CMIP6 for two forcing scenarios (RCP4.5 and 8.5). We directly compared individual GCMs from both scenarios and MME of all five corresponding GCMs to understand the changes between the CMIP6 and CMIP5 in terms of plant–disease ecosystem perspectives. Although recent studies have attempted to understand the differences in the behavior of these models in various climatic aspects, this is the first study that has examined the distinctive and comparative features of both scenarios from the perspective of plant disease impacts and risk assessment. In addition, our study covered the entire Korean Peninsula to understand the impacts of climate change on plant–disease ecosystems over the nine degrees of latitudinal distribution (approximately 1000 km) comprising the diverse agro-ecological zones throughout the Peninsula.

## 2 Data and methods

### 2.1 Study area and data

The Korean Peninsula, including both North and South Korea (34° N–43° N and 124.5° E–131° E), was selected for this study (Fig. S1). The spatial variability in climate is strongly influenced by the East Asian monsoon. The major land cover categories are forest (57.4%) and croplands (35.1%); thus, the topography also affects the spatial variability in climate. The climatic characteristics also differ by latitude (Sung et al. 2017). The annual
mean temperature is approximately 11 °C in North Korea and 14 °C in South Korea. North Korea, with an average annual precipitation of 596.3 mm, is drier than South Korea (1196.4 mm).

Among the GCMs, this study identified all family GCMs that participated in both the CMIP5 and CMIP6 scenarios and subsequently selected family GCMs that provided all weather variables (temperature, precipitation, and relative humidity) on a daily scale, as required for the EPIRICE-LB. Some family GCMs were removed, as they do not have complete data sets for all historical (1981–2010) and future (2011–2100) data without missing or erroneous data. In addition, only one GCM from a model provider was selected to represent broader modeling physics. Finally, five family GCMs for both CMIP scenarios were selected, and the names of the GCMs, modeling centers, and resolutions are listed in Table S1. Our previous study indicated that the five GCMs for CMIP5 showed reasonably good reproducibility for the mean values of temperature, precipitation, and relative humidity for 100 days of EPIRICE-LB simulation during the historical period, as shown in Fig. 4 of Kim and Cho (2016).

The CMIP data are available from the Earth System Grid Federation (Williams et al. 2016). Two pairs of forcing scenarios, RCP4.5 and RCP8.5 for CMIP5 and SSP2-4.5 and SSP5-8.5 for CMIP6 models, were considered as future climate change scenarios. Each pair presented the same end of the century forcing (4.5 and 8.5 W m$^{-2}$). The RCP4.5 assumes that greenhouse gas emissions will stabilize anthropogenic radiative forcing at 4.5 W m$^{-2}$ in the year 2100 by employment of a range of technologies and strategies for reducing greenhouse gas emissions, whereas the RCP8.5 corresponds to a nominal anthropogenic forcing of 8.5 W m$^{-2}$ by 2100, which reflects the continuously increasing trend of greenhouse gas emission in the face of limited global/national policy intervention (Olivier et al. 2017). As current emissions are tracking close to the RCP8.5 pathway (Schwalm et al. 2020), these two scenarios have been the most realistic and relevant scenarios for policy makers to develop policy interventions for climate change in Korea.

We obtained the daily maximum air temperature (°C), minimum air temperature (°C), precipitation (mm), and relative humidity (%) observation data from 87 weather stations of the Korea Meteorological Administration from 1981 to 2010. We also used these same variables in the CMIP scenarios to represent the simulated weather data. For the historical simulations, data from 1981 to 2010 were used. CMIP data for 2011 to 2040 were used for the very near future, 2041–2070 for the near future, and 2071–2100 for the distant future. Unfortunately, the historical data for the CMIP5 scenario were not available after 2005 because the historical simulation ended. Thus, future simulations for 2006 to 2010 were used as the historical data for CMIP5. As some CMIP5 GCMs do not have weather data for 2100, we used the data for 2071–2099 from the GCMs for the distant future period.

2.2 Methods

2.2.1 Bias correction and downscaling of the CMIP climate change scenarios

The simulated weather data of the GCMs often show large deviations compared to observed data and thus cannot be directly applied to the impact assessment studies (Ines and Hansen 2006; Teng et al. 2015). The difference between the simulated and observed weather data, or the bias, can be corrected using various bias correction methods. In this study, we used simple quantile mapping (SQM), one of the most commonly used bias correction methods (Cannon et al. 2015; Koenker and Schorfheide, 1994; Ringard et al. 2017;
Song et al. (2021a). SQM was developed using the fitQmapQUANT function based on comparison of the empirical cumulative distribution instead of the theoretical cumulative distribution function (CDF) among the R-based “qmap” packages (Cho et al., 2018; Gudmundsson, 2016). SQM is a non-parametric method that uses empirical quantile mapping to estimate the bias between the observed data for each quantile and the GCM data; therefore, it can minimize the overestimation that may be caused by the CDF equation.

The selected five family GCMs were bias-corrected and spatially downscaled to 87 weather station points for all periods using the SQM (Cho et al. 2020). Thirty years of observed data obtained from the stations were used as a reference for the SQM method.

Three sequential steps were used to conduct the SQM, as follows:

Step 1: For each month in the 1981–2010 data, the daily observation data for each grid and the corresponding daily GCM data were sorted by magnitude. By comparing observation and GCM data, the bias for each quantile was calculated using a ratio.

Step 2: For each grid point, the daily data for each month, extracted from the GCM for a selected future period, were sorted by magnitude. The bias was corrected by applying the ratio for each quantile calculated from step 1 to the same quantile for the future periods. After bias correction, the bias-corrected data was restored to its original order.

Step 3: Steps 1 and 2 were repeated for all 12 months and all four periods (historical, very near future, near future, and distant future).

2.2.2 EPIRICE-LB model simulation

We used the EPIRICE-LB model to simulate rice blast risks in the Korean Peninsula using in situ observations (the observed data) from 87 weather stations and climate change scenarios (the simulated data) from the CMIP models. Daily weather variables such as average air temperature, total precipitation, and average relative humidity were used as input data for the model simulation. The original EPIRICE by Savary et al. (2012) was adopted and modified to reflect the rice paddy and climate characteristics of South Korea through parameterizations, calibrations, and the addition of new modules, resulting in the EPIRICE-LB (Kim et al. 2015). The EPIRICE-LB consists of two main modules: an SEIR (Susceptible, Exposed, Infectious, Recovered) infection module and a host site growth and senescence module (Fig. S2). The SEIR model has been widely used to model epidemics in plants, animals, and humans. A central element of this model is the rate of infection, which is affected by temperature, leaf wetness, plant age, and cultivar susceptibility input variables. The model outputs are a disease progress curve and disease severity data, providing information about the dynamics of disease development and an assessment of disease intensity, respectively.

In our previous study (Kim et al. 2015), the EPIRICE-LB model was successfully validated against observed disease incidence data for rice blast in Korea. Statistical equivalence and quantitative envelope of acceptance tests were applied on the deviations of the model outputs from the observed disease incidences to evaluate whether the EPIRICE-LB is sufficiently accurate for its intended purpose of climate change impact assessment. As a result, we presented that the level of agreement between the observed and simulated epidemics for the past years was high, and concluded that the model was found to be valid according to the model performance criteria we applied. For further details about model modification process and performance of the EPIRICE-LB, we refer the reader to the study by Kim et al. (2015).
For each CMIP scenario, daily site-specific climate scenarios were generated and used by the EPIRICE-LB to compute the rice blast risks in the form of the area under the disease progress curve. Since the CMIP scenarios are just projections or best possible scientific guess of climate for the future periods, we did not use any results for a specific day, season, or year from the EPIRICE-LB simulation. Rather, we looked at the projected trends or magnitudes over 30 years in the study. In brief, EPIRICE-LB was run for the 87 weather stations across the Korean Peninsula using the daily climate data for each year of the historical (1981–2010), very near future (2011–2040), near future (2041–2070), and distant future (2071–2100) periods. For the simulations, we used a neutrally resistant cultivar to represent the cultivars with various resistance levels (Chung et al. 2019; Roh et al. 2007). It is impossible to predict which cultivars will be planted in the future; thus, we also used this neutrally resistant cultivar for the future simulations.

The optimum rice transplanting dates for all stations and periods were determined using the accumulated temperature method to estimate the heading date and, from that, estimate the transplanting date (Lee et al. 2011; Yoon and Choi 2020). Briefly, the heading date was estimated to occur when the average temperature within 40 days after heading became 22.5 °C. In this study, the most popular mid- to late-maturing rice cultivar was selected, and the optimal transplanting date was calculated as the date at which the sum of the average temperatures above the base temperature (10 °C) of rice becomes 2100°, accumulated back from the estimated heading date. For the EPIRICE-LB simulations, the average transplanting dates for each period were used in the comparisons between the rice blast risks from the simulated data of individual CMIP scenarios and those from the observed weather data.

All EPIRICE-LB simulations were run for 100 days from the transplanting date, and annual rice blast risks were calculated from the maximum disease severity during each simulation. Rice blast risks were summarized by computing the 30-year mean simulated severity for each period.

2.2.3 Model evaluation using the historical simulations

In this study, we used two evaluation methods to compare the simulation efficiency of both CMIP scenarios on historical rice blast risks, using the EPIRICE-LB simulations with in situ observations from the 87 weather stations, which represented the observed rice blast risks. For this model evaluation, the bias-corrected CMIP scenario data and the observed weather data, both for the historical period (1981–2010), are used as input for the EPIRICE-LB.

First, we evaluated the spatial reproducibility of both CMIP scenarios, versus the observed weather data, by generating risk maps for average rice blast epidemics over the Korean Peninsula. For graphical comparison, we created MME for both CMIP5 and CMIP6 for the historical period. They generated results as follows. For a given GCM at each station, the average rice blast risks over the 30-year EPIRICE-LB simulations were calculated, resulting in one average value per GCM, which were then averaged for the five GCMs for CMIP5 and CMIP6 to calculate the MME means. These were then visualized on the maps by spatially interpolating the point values over the Korean Peninsula using the kriging method (Nelson et al. 1999).

Second, the relative error (RE) was used to examine the mean error for the simulated data from each CMIP compared to the observed weather data (Eq. 1).
where $X$ indicates the climatological mean of $X$, the rice blast risk scores, calculated either using the CMIP-simulated ($m$) or the observed ($o$) weather data. RE values closer to zero indicate that the simulations are similar to the observations. The RE can explain the similarity between the observed rice blast risks and those from the CMIP.

The behavior of individual GCMs was evaluated by comparing rice blast epidemics from each family GCM and the MME for both CMIP5 and CMIP6. A box plot was created to present the disease impact. The box plot illustrates the range of uncertainty in the rice blast risk estimations, resulting from uncertainty in each GCM, and provides a good means of model comparison. To evaluate the simulation efficiency of individual GCMs over distinct climatic conditions and topography in the Korean Peninsula, we divided the rice blast risks from the weather stations into North and South Korean regions, and analyzed the average rice blast risks in both regions.

### 2.2.4 Climate change impacts on rice blast and the CMIP comparisons for the future periods

Using a similar method to that of the historical period, MME for rice blast risks over the future periods were generated for the 87 weather stations based on two emission scenarios (RCP4.5 and 8.5) for each CMIP model. In this study, we analyzed the projections of rice blast risks for all three future periods (2011–2040, 2041–2070, and 2071–2100). To calculate the percent changes in blast severity over the future periods, EPIRICE-LB simulations with the CMIP scenario data for the historical period (1981–2010) were compared with the ones with the CMIP scenario data for each future period (2011–2040, 2041–2070, or 2071–2100). The CMIP scenario data that are bias-corrected using SQM were used in the simulations. The percent changes in blast severity during the future periods, depicting the climate change impacts on rice blast, were spatially interpolated and visualized on maps using the kriging method.

The behavior of individual GCMs during the future periods was evaluated by comparing the yearly time series of projected changes in rice blast risks to that of the historical period. MME simulations from the five GCMs were also derived with the mean and variance of the model projections. We used the simulated rice blast risks under RCP4.5 and RCP8.5 for all five family GCMs of CMIP5 and CMIP6. To understand the effects of distinct climatic conditions and topography on the GCMs and rice blast risks, we generated separate time series graphs of North and South Korea. In addition, to set a baseline and depict gradual long-term changes in the rice blast risk, we calculated a 30-year moving window average including the simulated risks for the previous 29 years. For example, to calculate the change in average risk in 2011, we averaged the risk from 1982 to 2011 and calculated the percent change compared to the historical period.

To investigate whether the differences in the simulated risks from CMIP5 and CMIP6 were related to projected changes in climate, we calculated the mean temperature, precipitation, and relative humidity for the 100 days of the EPIRICE-LB simulation period for each year. These weather conditions were considered critical factors that determine the final output of the EPIRICE-LB. We conducted this analysis for all 87 weather stations and the near-future period. To calculate the changes in climate between the historical period and the near future period, we subtracted all averages of the historical period from those
of the near future period and subsequently divided them into North and South regions. The results were box-plotted to show the distribution of the projected changes in each variable from each CMIP scenario.

3 Results

3.1 Evaluation of the simulation efficiency of CMIP5 and CMIP6 scenarios

The simulation efficiency of the CMIP5 and CMIP6 scenarios was evaluated using the historical period EPIRICE-LB simulations for rice blast epidemics over the Korean Peninsula. Risk maps of average rice blast epidemics using the observed weather data (observed epidemics) were compared to those with the simulated weather data (simulated epidemics) from the family GCMs to evaluate the spatial reproducibility of the CMIP5 and CMIP6 scenarios (Fig. 1). Although the spatial patterns for the observed and simulated epidemics were similar, their estimated severity differed significantly in some regions. For instance, in the Jeonnam province of South Korea, the largest rice cultivation area with the highest production in the Korean Peninsula as of 2021, the CMIP scenarios underestimated the epidemic risks by more than 50% in comparison to the observations, as shown in the RE maps of both scenarios. Moreover, the CMIP scenarios tend to underestimate the epidemics throughout the Korean Peninsula; however, the CMIP6 scenario showed better REs (near zero) in the Hambuk province in North Korea. Overall, there were negligible differences between CMIP5 and CMIP6 in the spatial distribution of REs, indicating that CMIP6 inherited the spatial distributions from CMIP5 and showed no significant improvement in the spatial reproducibility for the epidemics.

The spatial pattern of rice blast epidemics, simulated using the observed weather data, varied over the Korean Peninsula during the historical period. The southernmost areas, mostly the Jeonnam and Gyeongnam, showed relatively high risks of rice blast, indicating that the climate during rice cropping seasons over the last 30 years was conducive to rice blast disease in those regions. Some provinces, such as Gangwon and Ryanggang, showed higher epidemic risks in portions of the province, where both scenarios showed very similar spatial patterns. Although there was a significant underestimation in Jeonnam province, our findings indicate that both CMIP scenarios show relatively good spatial reproducibility over the Korean Peninsula, compared to the observed data.

The behavior of individual GCMs was evaluated by comparing rice blast epidemics from each family GCM and the MME for both CMIP5 and CMIP6 scenarios with those from the observed weather data (Fig. S3). Among individual GCMs, variations in the medians and dispersion width of epidemic risks were larger in South Korea than in North Korea, due to the distinct climatic conditions and topography of the Korean Peninsula. The GCMs with the highest reproducibility and similar medians and variances to the observed epidemics include the inmcm4 of CMIP5 in North Korea and the GFDL-ESM2M of CMIP5 and INM-CM5-0 of CMIP6 in South Korea. Nevertheless, we confirmed that MME generally results in better and more stable simulation efficiency than individual models, as shown in Figure S3. Additionally, more near-optimum areas for rice blast epidemics occurred in South Korea, as shown by the higher severity ranges in the box plots. This spatial difference between the North and South was similarly observed in the epidemic risk maps in Fig. 1. In addition, the individual family GCMs in both CMIP scenarios consistently underestimated the epidemics in North...
Korea, while estimations varied significantly among GCMs in South Korea. As a result, the MME of both CMIP scenarios showed similar underestimation in North Korea; however, that of CMIP6 in South Korea showed better reproducibility and was comparable to the observed data. Overall, our findings indicate that the simulation efficiency of

Fig. 1 Risk maps of the average rice blast epidemics by administrative area in the Korean Peninsula for the historical period (1981–2010), simulated by EPIRICE-LB using a weather observations from 87 stations and the simulated weather data from five family GCMs of the b CMIP5 and d CMIP6. Relative errors (REs) between the epidemic scores from the observed and the simulated weather data for the c CMIP5 and e CMIP6 models were also calculated.
individual family GCMs from both CMIP scenarios varied with no further improvement regarding the ability to reproduce the epidemics from the historical period.

3.2 Future changes in rice blast epidemics in both CMIP5 and CMIP6 scenarios

The rice blast epidemic risks from individual family GCMs and MME from both CMIP scenarios during the future periods, from 2011 to 2100, were generated for the 87 stations based on the RCP4.5 (Fig. 2) and RCP8.5 (Fig. 3) emission scenarios. The yearly time series percent change in rice blast severity compared to the historical period from individual GCMs projected a broad range of possible climate change impacts on the epidemics and showed distinctive temporal trends between North and South Korea (Figs. 2a and 3a). Under RCP4.5, both CMIP scenarios projected consistently decreasing impacts on average in South Korea with a narrow uncertainty range (±1 standard deviation, colored area in Figs. 2a and 3a); however, in North Korea, they showed increasing epidemics over the next 30 years, which remain until the 2070s. Moreover, the CMIP scenarios exhibited different temporal patterns in North Korea. The magnitude of the increase (medians of both CMIP scenarios) was significantly higher in CMIP5 than in CMIP6, and the changes were maintained for longer in CMIP5, until 2100. These yearly time series are graphically represented in the percent change risk maps from the MMEs for both CMIP scenarios (Fig. 2b). The positive percent changes in epidemics in North Korea were significant over most of the region during the very near future, and gradually decreased over the near and distant future. Additionally, this decrease was faster in CMIP6 than in CMIP5, indicating that the climatic conditions in the CMIP6 scenario deviated very quickly from the optimum conditions for rice blast epidemics, likely due to faster climate change in CMIP6 over time.

For the rice blast risks under RCP8.5, where climate change is rapid, the CMIP scenarios projected more consistent and rapidly decreasing impacts on average in South Korea (Fig. 3). However, CMIP6 showed a broader uncertainty range than CMIP5 in South Korea, as depicted by the colored area in Fig. 3a, indicating that the variations among the individual GCMs in CMIP6 were larger than those in CMIP5. For North Korea under RCP8.5, the positive percent changes were similar to those under RCP4.5 but relatively shorter and dramatically increasing, with the CMIP5 reaching the peak severity earlier than CMIP6. In addition, the positive percent changes under RCP8.5 were maintained for a shorter period, decreasing steeply from the 2030s onwards in both scenarios. The percent change risk maps show the spatial patterns of rice blast epidemics over the future periods (Fig. 3b) and confirm the yearly time series graphs for both regions. Similar to the RCP4.5, we found that the rate of the decrease in epidemics was faster in CMIP6 than in CMIP5. Overall, both the CMIP and RCP scenarios showed a consensus of significantly increasing epidemics in North Korea until the near future and consistently decreasing epidemics in South Korea.
Fig. 3  Same as Fig. 2, except the RCP8.5 scenarios were used instead
3.3 Dissecting the future changes in rice blast epidemics from contributing weather variables

Figure 4 shows the relative contributions of specific weather variables to the projected changes in rice blast epidemics for the near future period (2041–2070), in both North and South Korea. During rice-growing seasons, temperature and precipitation increased in all scenarios, whereas relative humidity increased or decreased depending on the scenario. Additionally, the magnitude of these changes varied depending on the scenario. Compared to the historical period, the CMIP6-8.5 and CMIP5-8.5 showed the largest temperature increases (4.2 °C and 4.6 °C) in North and South Korea, respectively. The CMIP6 scenarios showed larger temperature increases than the CMIP5 scenarios in North Korea, but vice versa in South Korea. SSP2-4.5 and SSP5-8.5 of the CMIP6 have similar emission levels to RCP4.5 and RCP8.5, respectively. In the case of precipitation, the CMIP5 scenarios showed greater increases in both North and South Korea. However, CMIP6 was greater for relative humidity. These results indicate that the five family GCMs from each CMIP scenario project distinctive climatic conditions for the Korean Peninsula.

Box plots showing the projected changes in rice blast epidemics and weather variables indicated that temperature, precipitation, and relative humidity were the combinatory factors affecting the epidemics in the Korean Peninsula. For North Korea, the percent change in epidemic severity in CMIP5 under RCP4.5 (CMIP5-4.5), with 3.3 °C higher temperature, 150 mm more rainfall, and similar relative humidity, was greater than 35%. Comparing the CMIP6-4.5 and CMIP5-8.5 scenarios, similar temperature, slightly less rainfall, and approximately 2% higher relative humidity increased epidemics by approximately 10%.
These results indicate that temperature and relative humidity were the prominent driving factors for the projected changes in the North Korean region. Interestingly, the temperature in the CMIP6-4.5 was comparable to that in the CMIP5-8.5 during simulated rice-cropping seasons, which partially explains the accelerated warming in CMIP6 under the same emission scenarios. In South Korea, all the scenarios during the near future period suggest a considerable reduction in epidemics compared to the historical period, with various intensities among scenarios. Notably, the temperature increases in South Korea exceeded the optimum temperature range for rice blast epidemics. Comparing the CMIP5-8.5 and CMIP6-8.5 scenarios, the CMIP5-8.5, irrespective of slightly higher temperature and lower relative humidity, showed less reduction in epidemics than the CMIP6-8.5; the CMIP5-4.5 and CMIP6-4.5 also showed this pattern. These observations might be caused by the noticeable differences in rainfall between the two scenarios. Overall, among the three weather variables, it can be assumed that temperature was the major factor that determined the projected changes in epidemics under climate change, followed by relative humidity and rainfall amount in the South Korean region. In conclusion, these results indicate that climate change is projected to cause significant changes in weather in the Korean Peninsula, and the combinatorial changes in the weather variables may result in different levels of rice blast epidemics.

4 Discussion

In this study, we compared the simulation efficiency of CMIP5 and CMIP6 scenarios based on simulated rice blast epidemics to the historical period over the Korean Peninsula. The CMIP scenarios underestimated the rice blast epidemic risks by more than 50% in comparison to the observed epidemics in the Jeonnam province of South Korea (Fig. 1). Strong underestimation occurred mostly in Gwangju, a metropolitan city of Jeonnam province, indicating that the urban heat island (UHI) effect might have caused higher epidemic risks. Moreover, the downscaled CMIP scenarios using SQM might have failed to reflect the specific UHI effects formed in the city and thus simulated lower epidemics. Since the GCMs almost universally lack representation for urban areas (Zhao et al. 2021), it was necessary to correct the air temperature bias using statistical bias correction methods such as the SQM. However, SQM cannot correct all biases, resulting in errors in many CMIP scenarios (Burgstall et al. 2021; Cho et al. 2020; Hatchett et al. 2016). Further analysis of the errors from SQM over the Jeonnam province could address the strong underestimation in this study.

The RE maps of both CMIP scenarios showed zero to 30% underestimation of rice blast epidemics throughout the Korean Peninsula. In the RE map of CMIP5 for South Korea, the REs tended to increase towards southern South Korea. Our previous study, which projected potential epidemics of rice blast using 11 GCMs of CMIP5, showed the same results, where the MME in northern South Korea showed the best simulation efficiency with epidemics comparable to the observed ones, and the MME in the southern area showed the worst simulation efficiency, as shown in Figure 2 of Kim and Cho (2016). Rice blast epidemics are dependent on location-specific weather conditions that are significantly affected by the temporal dynamics of weather variables, which are recorded in observed weather data (Kim et al. 2015). However, owing to fundamental variations in initial conditions and structural differences in the GCMs, there are inherent uncertainties in simulating the actual weather dynamics using GCMs. To overcome or quantify the uncertainties in individual
GCMs, multiple GCMs should be used (Kim and Cho 2016). However, due to the reasons mentioned in the methodology, we only used five family GCMs, which might have led to the overall underestimation tendency (Semenov and Stratonovitch 2010). Nevertheless, both CMIP scenarios showed relatively good spatial reproducibility compared to the observed weather data, and the overall REs were acceptable for the primary purposes of this study.

Although the variations in epidemic risks among individual GCMs were larger for South Korea than for North Korea, the MME of CMIP6 in South Korea was comparable to the observed weather data (Fig. S3). This confirms previous findings that MME generally results in better and more stable simulation efficiency over individual GCMs. Although the CMIP6 could be considered to show better reproducibility than CMIP5, we cannot rule out the possibility of random effects of accidently obtaining a similar median value. To reduce this concern, more GCMs are needed to calculate MME values; the proper number of GCMs depends on multiple criteria. For instance, various measures to evaluate the model simulation efficiency can be used to select or assign weights to GCMs (Gleckler et al. 2008; Lee and Kim, 2018; Maxino et al. 2008; Moore et al. 2010; Werner 2011). Furthermore, if GCM projections are viewed as spatially and temporally consistent sets of plausible future climate conditions, there is no need to favor some over others, indicating that we can use as many available GCMs as possible. As more family GCMs in both CMIP5 and CMIP6 become available, it will be interesting to examine whether more GCMs will result in similar results to those shown in Figure S3.

The yearly time series of projected risk changes from individual GCMs showed distinctive temporal trends between North and South Korea (Figs. 2a and 3a) under both RCP4.5 and 8.5 scenarios. The present analyses showed that the decreasing trend in epidemics from our previous studies of the CMIP5 scenarios was maintained (Kim et al. 2015), but the magnitude of this decrease was greater in the CMIP6 scenarios. Comparing the percent changes in rice blast epidemics and the changes in weather variables (Fig. 4) revealed that temperature, with combinatory effects of precipitation and relative humidity, was the prominent driver that influenced the projected epidemic trends and the differences between North and South Korea during the near future period (2041–2070). Although precipitation and relative humidity did not dramatically change compared to the historical period, greater epidemic risks of rice blast were observed when the temperature reaches a predefined optimum range and both the rainfall and relative humidity increase, similar with our previous study (Kim and Jung, 2020). Moreover, during our experiments, the EPIRICE-LB outputs were highly dependent on the interannual variability in weather parameters in the scenarios generated by the GCM models, although these variabilities and the model outputs were offset by averaging them for a 30-year period.

Focusing only on temperature changes in Fig. 4, we observed that the average temperatures in North Korea ranged from 24 to 25.1 °C, which spans the upper limits of the optimum temperature range for rice blast infection in the EPIRICE-LB (Kim et al. 2015). In contrast, average temperatures in South Korea ranged from 27.3 to 28.3 °C, for which less than 40% of the relative infection risk is calculated by the model. Furthermore, in our previous study, we observed dramatic fluctuations in rice blast epidemics when the average temperatures exceeded the lower or upper limits of the optimal temperature range (Kim et al. 2015). Therefore, the gradual average temperature increases in North Korea (21–26 °C) explain the increasing epidemics until the near future period, which is followed by a sharp decrease toward 2100, whereas the continuous decrease in rice blast epidemics in South Korea are expected due to the marginally optimum average temperatures during the historical period. Our analysis also revealed that CMIP5 and CMIP6 scenarios showed...
contrasting changes of average temperature: Compared to CMIP5, CMIP6 showed faster temperature increases in North Korea, but more decreases were observed in South Korea. This difference might be in line with the fact that the SSP scenarios for CMIP6 allow estimations of future energy and land use changes based on adaptation and mitigation intensity levels, thus involving a rapid growth energy-intensive pathway with higher emissions (O’Neill et al. 2016). It can be inferred that the different social and economic pathways, reflected in the SSP scenarios, for North and South Korea might result in the different speed of climate changes for two countries on the Korean Peninsula.

The daily infection rate \( (R_c) \) of EPIRICE-LB is determined by leaf wetness, which is estimated from the relative humidity, precipitation, and temperature; when the maximum daily relative humidity is higher than 90%, or when daily rainfall exceeds 5 mm, some leaf wetness is assumed to occur (Kim et al. 2015; Savary et al. 2012). Our results from the comparison between the CMIP6-4.5 and the CMIP5-8.5 scenarios in North Korea (Fig. 4), where approximately 2% higher relative humidity, similar temperature, and slightly less rainfall led to a 10% epidemic increase, coincides with the EPIRICE-LB algorithm for leaf wetness. In addition, the rainfall differences in all CMIP scenarios resulted in some differences in epidemics in South Korea (Fig. 4). Considering that the leaf wetness algorithm of EPIRICE-LB depends more on the frequency of rainfall greater than 5 mm rainfall and less on the rainfall amount, rainfall differences of 80–100 mm during the cropping season might not affect the epidemics. Because the climatic conditions in South Korea during the near future period were not favorable to the epidemics, a general epidemiological principle may apply, which states that under marginal climatic conditions, any limiting factors, even those with minor influence, can act as a determining factor for plant diseases. Therefore, we identified that temperature was the major factor that determined the projected changes in rice blast epidemics under climate change, followed by relative humidity and rainfall amount.

As we observed in the yearly time series of rice blast risks in Figs. 2a and 3a, the large variation in rice blast epidemics from individual GCMs provides very important information concerning the level of uncertainty that decision makers should consider when developing policies or plans to cope with the projected impacts. As mentioned previously, an appropriate number of GCMs are required to determine the acceptable range of uncertainty that represents the limitations of the climate change scenarios due to the variations in initial conditions and the structural differences in the GCMs. Nevertheless, our results from five GCMs can be used to understand the likely magnitude of changes in rice blast risk in the Korean Peninsula and thus help proactively prepare effective and efficient adaptive measures for the coming decades, especially in North Korea. The projected epidemics in North Korea showed distinct spatio-temporal patterns with a broad range of magnitudes based on combinations of CMIP and RCP scenarios. If the combinations of different scenarios represent the uncertainty in future climate change, decision makers must utilize the consensus in impacts from all scenarios for less regret in adaptation while still preparing for the extreme conditions from each scenario.

In North Korea, rice blast is a major endemic yield reducer, recurring every year with different magnitudes depending on weather conditions (Chung et al. 2019; Kim 1999), due to the chronic shortage of agricultural inputs such as fertilizers and fungicides resulting from strong economic sanctions. Although related literature on the historical occurrences of rice blast in North Korea is scarce due to their information blocking policy, news articles regarding the outbreak of rice blast in North Korea are frequently found (articles not shown). Alternatively, we can estimate the possible occurrence level in North Korea, especially in the northern areas bordering China, from the literature of Chinese scientists.
In fact, Chen et al. (2014) and Guo et al. (2018) showed that the rice-producing areas of China that border North Korea are classified as moderate-risk regions based on the intensity and acreage of rice blast occurrences from 2000 to 2014, indicating that the rice paddies of North Korea near the border might have similar risks during these periods. This partly explains our simulation results for the historical period (Fig. 1).

Overall rice production in North Korea has decreased as imports of fertilizers, herbicides, pest control materials, and agricultural machinery and parts have decreased because of the economic sanctions against North Korea and recent border closures due to the novel coronavirus infection (COVID-19). Considering the studies by Kobayashi et al. (2006) and Onaga et al. (2017), elevated CO₂ and temperature under climate change will likely increase the rice blast epidemics in North Korea. Although there is less risk of blast epidemics from the overuse of nitrogen application, poor nutrition might cause negative impact by decreasing the innate immunity of rice plant to diseases (Bonman and Garrity 1992; Hoffland et al. 1999). A recent study identified North Korea as one of the most food-insecure countries in the world, with more than 59% of the population suffering from food insecurity in 2020 (Baquedano et al. 2020). This also indicates that no control measures are available, even during serious rice blast outbreaks due to variable climates, now and in the future. Climate change will introduce a series of stressors to North Korean agriculture, including possible crop losses due to disease outbreaks, which could upset its fragile governance and resource base and lead to instability or conflict. As we projected potentially increasing rice blast epidemics in North Korea over the next 30 years, proper adaptive measures must be designed for the country, such as global humanitarian efforts to relieve tensions from food insecurity by aiding agricultural inputs and introducing disease early warnings with anticipatory action plans.

5 Conclusion

Since our primary objective in the study was to compare rice blast epidemics simulated from climate change projections reported by CMIP5 and CMIP6 scenarios, we remind the reader that the skill of GCM projected daily climate variables has not been verified by comparing them with daily observed weather data for establishing their usability in rice blast predictions using the EPIRICE-LB model. Future evaluation of the efficiency of the GCM scenarios in representing essential weather parameters, required for the use of EPIRICE-LB model, will increase the practical applicability of the findings from this study (Koutroulis et al., 2016). In this study, we used the EPIRICE-LB model to simulate and compare the rice blast disease epidemics over the Korean Peninsula in future periods using five selected family GCMs in both CMIP5 and CMIP6 for two forcing scenarios (4.5 and 8.5). We confirmed the decreasing trend in rice blast epidemics found in the CMIP5 scenarios in our previous studies (Kim et al. 2015), but the magnitude of the decrease was greater in the CMIP6 scenarios. In addition, we found distinctive epidemic trends in North Korea, where the rice blast epidemics increase until the mid-2040s but decrease thereafter, with different spatial patterns of various magnitudes. Therefore, controlling rice blast diseases will remain important over the next several decades in North Korea, where appropriate chemical controls are not available due to chronic economic and political issues. Overall, our analyses using the new CMIP6 scenarios reemphasized the importance of developing effective control measures against rice blast for specific high-risk areas. In addition, we suggest that a universal impact and vulnerability assessment platform
for plant–disease ecosystems should be developed. As more realistic and accurate climate change scenarios are developed in the coming decades, we will need a universal impact and vulnerability assessment platform that can interchangeably accept different versions of the scenarios for comparison.

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**Data availability** The datasets are available from the corresponding author on reasonable request.

**Declarations**

**Ethical approval** Not applicable.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Conflict of interest** The authors declare no competing interests.

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