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Predicting potential epidemics of rice leaf blast and sheath blight in South Korea under the RCP 4.5 and RCP 8.5 climate change scenarios using a rice disease epidemiology model, EPIRICE

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ABSTRACT

Rice diseases, responsible for about 8% of annual yield losses of rice production in South Korea, are likely to be affected by meteorological changes resulting from global climate change. No critical evaluation has yet been made of the potential impacts of climate change on rice diseases in South Korea. This study involved a quantitative analysis of two rice diseases that result in the greatest damages, leaf blast and sheath blight, using the generic epidemiological model, EPIRICE. The goals of the study were to evaluate the EPIRICE model using historical rice disease incidence data and fine-scale weather data for 2002–2010 in South Korea, and then to assess likely changes in national disease probabilities under climate change scenarios to allow for more robust planning. EPIRICE was calibrated and validated against observed disease incidence data for leaf blast and sheath blight. Observed and simulated epidemics for both diseases were compared using disease progress curves and the area under the disease progress curve. Statistical equivalence and quantitative envelope of acceptance tests were applied on the deviations of the model outputs to evaluate whether EPIRICE was sufficiently accurate for its intended purpose. The level of agreement between the observed and simulated epidemics was high and the model was found to be valid according to the performance criteria. Predicted daily climate data based on the Intergovernmental Panel on Climate Change (IPCC) Representative Concentration Pathways (RCP) 8.5 and 4.5 scenarios were used as inputs into the EPIRICE model. Outputs from the model runs were displayed using geographic information systems (GIS) to show future changes in potential epidemics for both rice diseases. Overall, the incidence of epidemics for both diseases was simulated to gradually decrease toward 2100. These results can be used to interpret the likely magnitude of changes in disease risk in regions of South Korea and to estimate climate change impacts on disease losses and disease control.

1. Introduction

A number of rice disease simulation models have been developed to understand, predict, and manage rice diseases (Hashimoto et al., 1984; Kobayashi et al., 1995; Teng and Savary, 1992). In South Korea, three rice diseases have been the focus of epidemiological modeling: leaf blast and sheath blight caused by fungal pathogens, and bacterial grain rot by a bacterial pathogen (Cha et al., 2001; Do, 1998; Kim, 2001). These models incorporate varying degrees of detail regarding the biology of rice diseases. The modeling approaches used for these different pathosystems differ greatly because of profound differences in the details of the mechanisms underpinning their epidemiological dynamics. To predict disease incidence more precisely, the models generally try to incorporate all major environmental and cultural factors into the model simulation. Thus, a successfully developed model may not be widely adaptable to other areas where cultivars, cultural practices, and environments are quite different. In addition, due to structural complexities and temporal and spatial restrictions of their input requirements, it is difficult to link these models to other applications such as GIS and global climate model (GCM)-generated climate data at various temporal and spatial resolutions. Although some models can potentially be converted to use lower resolution input data such as daily or monthly weather variables, most disease models use hourly weather variables (Sparks et al., 2011). To consider as many factors affecting disease development as possible, many rice disease models need cultivation-related information such as the rice cultivar, transplanting date, and even daily trapped

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airborne fungal spore numbers as input variables. A broad range of weather variables is also used for the modeling, including air temperature, relative humidity, rainfall, solar radiation, wind speed, and others. Furthermore, some of the models were validated for only one or a few field-level sites (Do, 1998; Kim, 2001), limiting their application to specific regions.

EPIRICE is a generic epidemiological model that can be parameterized to address any specific rice disease (Savary et al., 2012). It was recently developed as a general model framework for fungal, viral, and bacterial diseases at different levels of hierarchy in a crop canopy (leaves, sheaths, entire plants) depending on the nature of the disease. Thus, its structure was designed to be as simple as possible, involving a few state variables and a limited number of core parameters and weather variables. Due to its generality and structural simplicity, EPIRICE can be used to address different biological interactions of rice plants caused by various pathogens, can easily be linked with other applications such as climate data in GIS, and can be expanded spatially from the field level to a regional or global level.

Savary et al. (2012) developed EPIRICE to evaluate the potential importance of plant diseases in rice and their intensity and distribution at a global scale, at which very limited actual field data on disease epidemics exist across different locations and years. Given its original scope, EPIRICE was evaluated only by comparing its simulated epidemics with a set of observed epidemics reported in the literature. Therefore, there are a number of limitations that need to be resolved before EPIRICE can be used for other locations at a higher spatial resolution such as the field scale. First, several core parameters need to be modified to reflect local region-specific cultural practices and growing conditions, including fertilization, irrigation systems, and local climate. Second, the simplified model structure prevents all critical factors associated with disease epidemiology from being considered, thus, limiting more accurate prediction of disease. For instance, the basic infection rate R_c was considered a constant for all rice cultivars in the original study, while experimental data indicate that the infection rate is actually highly dependent on the resistance level of each rice cultivar. Adding additional parameters reflecting cultivar resistance should increase its accuracy, particularly in areas like the Korean Peninsula where a high diversity of rice cultivars are planted each year.

EPIRICE was originally parameterized for five major rice diseases (brown spot, leaf blast, bacterial blight, sheath blight, and tungro) that frequently occur in tropical Asia. Among these, we selected rice leaf blast and sheath blight for application of the EPIRICE model in South Korea in this study. Rice blast disease, caused by *Magnaporthe oryzae*, is of major economic importance and it is reported to occur in 60 countries (Parthasarathy and Ou, 1965). Rice blast epidemics caused a major food crisis in South Korea in the 1970s, with yield losses of 10–50 percent (Mew et al., 2004). Sheath blight, caused by *Rhizoctonia solani*, is a major rice disease, second, only to rice blast in reducing both grain yield and quality (Lee and Rush, 1983; Ou, 1985). Rice leaf blast and sheath blight remain the most destructive rice diseases in South Korea, with a 15% and 60% annual incidence in rice paddy fields, respectively (RDA, 2010b). More than three agrochemical sprays are usually conducted during a crop growing season for these diseases in South Korea. Without chemical control, these diseases together are estimated to account for nearly 7% of yield loss out of a total 8.27% yield loss caused by all rice diseases combined.

Climate change effects on rice diseases and pests have been carefully studied for a few pathosystems (Luo et al., 1995; Teng et al., 1996; Webb et al., 2010). Often, the results indicated increased epidemics but sometimes the opposite effect manifests, depending on the type of pathosystem and modeling environment. Many of these studies have focused on specific diseases, aimed at analyzing the effects of climate change components on specific disease cycle phases in particular pathosystems (Kobayashi et al., 2006) or on modeling the effects of climate change on risk probability (epidemics) or risk magnitude (yield losses). Projected changes in the Korean climate could either increase or decrease disease prevalence, depending on several interacting factors. For example, under elevated CO_2 concentrations, the potential risks of infection with rice leaf blast and epidemics of rice sheath blight have been reported to increase (Kobayashi et al., 2006). Luo et al. (1998) predicted that elevated temperatures would result in less severe blast epidemics in most locations in Korea. In addition, sheath blight is a typical tropical rice disease favored by high temperature and high relative humidity (Lee and Rush, 1983). Based on the coupled model intercomparison project phase 5 (CMIP5) climate models, the projected climate of the Korean Peninsula showed increased temperature with enhanced precipitation toward 2100 (Ahn and Hong, 2013). Thus, it is anticipated that sheath blight will remain to be one of the rice diseases to be favored by a climate change regime.

To obtain reasonably accurate scientific predictions, we investigated the potential effects of climate change on the risk probabilities of these two major rice diseases in South Korea using the EPIRICE model. The goal of the modeling was to use the estimates as a guideline to make recommendations to national risk management programs such as rice breeding with respect to disease resistance or research prioritization for the disease control. We began by modifying the EPIRICE model to improve its performance at the field scale, so that the model could be used to simulate disease potential in South Korea. Local region-specific parameterization was conducted and additional functions were incorporated into the model. Using historic rice disease incidence

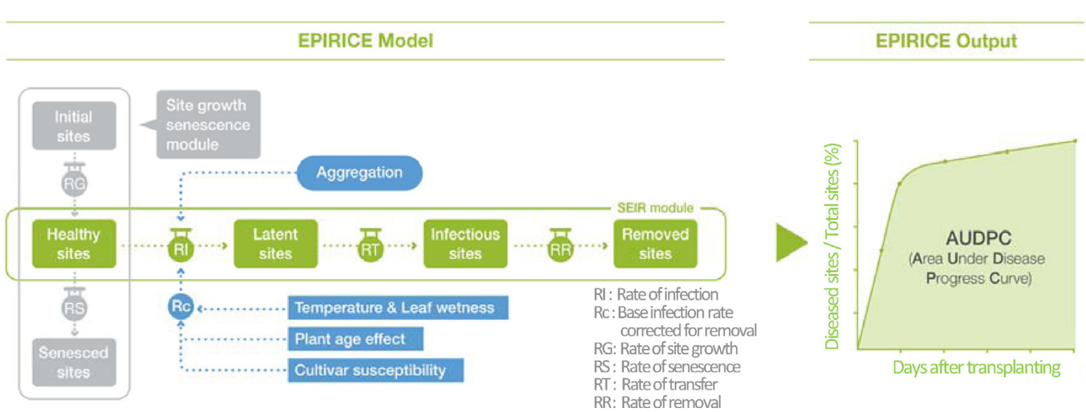


Fig. 1. EPIRICE model structure and output.

Table 1
Parameterization and references for EPIRICE-LB (leaf blast) and EPIRICE-SB (sheath blight).

Attribute	Parameter	EPIRICE-LB			EPIRICE-SB		
		Original study	Current study	Ref.[a]	Original study	Current study	Ref.[a]
Sites	Site size	45 mm^2 of a leaf	44 mm^2 of a leaf	1, 2	1 tiller	1 tiller	–
	Sx (max no.of sites)	30,000	90,000	3,4	800	800	–
	Initial sites	600	600	–	75	90	12
Crop growth	RRG (relative rate of growth)	0.1	Slight decrease with aging, rapid decline right after heading stage	3,4,5	0.1	Starts with high growth rate, rapid decline after max tillering stage	12, 13
	RRS (relative rate of senescence)	0.01	0.005	3,4,5	0.01	0.005	12, 13
Epidemic onset	Date	15	15	–	30	30	–
Residence times	p (duration of latent period)	5	4	6,7,8	3	4	14, 15
	i (duration of infectious period)	20	20	–	120	65	Surveys
Infection rate	$r_l = \ln(x_2/x_1)/(t_2-t_1)$	0.28	0.28	–	0.23	0.23	–
	$R_c = r_l/\{\exp(-r_l p)-\exp(-r_l[p+i])\}$	1.14	0.86	–	0.46	0.58	–
Age effect	A	(Strong) decrease with plant age	Rapid decline after max tillering stage	9, 10	(Slight) Increase over age	Increase until max tillering, decrease after heading stage	14,16,17
Temperatureeffect	T	Optimum: 25 °C	Optimum: 19–24 °C	2, 11	Optimum: 28 °C	Optimum: 23–27 °C	16,18
Wetness effect	W	1 if canopy wet, 0 otherwise	Change with leaf wetness duration	2	1 if canopy wet,0 otherwise	Change with leaf wetness duration	16,18
Aggregation	a	1	1	–	2.8	2.8	–

[a] Ref. (References): 1: Kim (2001); 2: Choi et al. (1987); 3: Lee et al. (1997); 4, Park et al. (2004); 5: Kim et al. (2010); 6: Roumen and De Boef (1993); 7: Lee (1978); 8: Ra et al. (1997); 9: Koh et al. (1987); 10: Hwang et al. (1987); 11: Yoshino (1979); 12: RDA (2010a); 13: Hong (2002); 14: Rodrigues et al. (2003); 15: Kim et al. (1985); 6: Kim (2009); 17: Kim and Lee (1989); 18: Do (1998).

Table 2
R_c values based on rice cultivar resistance to leaf blast.

R_c	Resistance level	Rice cultivars[a]
0.55	Resistant	Namcheon, Unbong, Jinbu, Taeseong, Nongbaek
0.69	Moderately resistant	Ilmi, Unkwang, Sambaek, Dongan, Dongjin #1, Odae, Sangju, Sangmi
0.86	Neutral	Dongjin, Chucheong, Dobong, Olchal, Nampyeong, Junam, Saechucheong, Hwayeong, Daean, Sindongjin, Hopum, Onnuri, Samkwang, Dobong, Sura
1.03	Moderately susceptible	Ilpum, Hwasung, Jinheung, Juan
1.28	Susceptible	Palkeum, Nakdong, Jinju

[a] All cultivars except for Onnuri are generally named with a suffix "-byeo" such as "Namcheon-byeo", but in this study they will be written without it for the sake of simplicity.

data and fine-scale (1-km) weather data for 2002–2010, validation of the modified EPIRICE model was conducted. Subsequently, we applied the validated model to generate maps simulating potential epidemics (represented as the area under disease progress curve; AUDPC) for rice leaf blast and sheath blight under two climate change scenarios, Representative Concentration Pathways 8.5 (RCP 8.5) and 4.5 (RCP4.5) (Riahi et al., 2011; Thomson et al., 2011), for 2011–2100.

2. Data and methods

2.1. Research workflow

This study consisted of three steps: EPIRICE parameterization and calibration, EPIRICE validation, and application of EPIRICE to climate change scenarios. Because EPIRICE was originally developed to be used regionally or globally to estimate potential epidemics, parameterization, calibration, and validation were needed before applying it directly to South Korea, particularly at the field scale.

2.2. Parameterization of the EPIRICE model

The original EPIRICE model translated to the *R* language (v 2.11.1; http://www.r-project.org) was available on R-Forge: https://r-forge.r-project.org/projects/cropsim/. Fig. 1 shows the structure of the EPIRICE model with its input variables and the model output. The model consists of two main modules: a susceptible-exposed-infectious-removed (SEIR) infection module and a host site growth and senescence module. The SEIR model has been widely used to model epidemics of infectious diseases of plants, as well as of animals and humans. A central element of this model is the rate of infection (RI), which is written as: $\mathrm{RI} = dL/dt = R_c I C^a$, where the rate of change in infected-latent sites L with time t (dL/dt) is proportional to (i) the number of infectious sites I, (ii) a power function of the proportion C of sites that are healthy relative to the total number of sites in the system, and (iii) R_c, the basic infection rate corrected for removals (Van Der Plank, 1963). The value of the exponential parameter a is ≥ 1 depending on the level of disease aggregation. Growth and senescence of the host population was added to the model structure in a very simple logistic manner to describe the increase or decrease in the number of healthy sites over time. To describe the effects of host aging and weather variables on the host-pathogen interaction, three modifiers, A, T, and W, that reflect the effects of plant age, temperature, and leaf wetness, respectively, were incorporated into the model as $R_c = R_c\mathrm{Opt} \times A \times T \times W$, where R_cOpt refers to a reference potential value of the basic infection rate corrected for removals. For more details, refer to Savary et al. (2012).

Model parameters for both leaf blast and sheath blight diseases were initially adopted from the original EPIRICE study, in which most of the parameters were derived from the literature. Among these, slight or complete modifications of certain parameters were conducted based on cultural practices and disease epidemic patterns specific to South Korea; the resulting parameters are given in Table 1. The modified parameters included site size, the maximum and initial number of sites, site growth and senescence rate, duration of latent and infectious periods, crop age, temperature, wetness effects on infection rate, and epidemic onset (days after crop establishment; DACE).

Parameters for the modified EPIRICE were primarily derived from the scientific literature on rice crops in South Korea and through review of the annual crop yield test reports and annual crop pests & diseases forecast control reports published annually by the Korean Rural Development Administration (RDA). References for each parameter are indicated in Table 1. Parameters related to "sites" were revised due to different agricultural practices and rice growth patterns between South Korea and other Asian regions for which the original EPIRICE was parameterized. The system considered is 1 m^2 of a rice crop stand. Thus, the number of sites represents how many sites are within the 1 m^2 of a rice crop stand. For leaf blast, the average size of typical leaf symptoms is 44 mm^2; thus this is defined as a site (Choi et al., 1987; Kim, 2001). For sheath blight, a tiller is defined as a site. Leaf area index growth in rice paddies in South Korea formed the basis for calculating the maximum number of sites (Sx) for leaf blast (Lee et al., 1997; Park et al., 2004). The relative rates of growth and senescence were determined by reviewing patterns of change in the leaf area index and number of tillers for leaf blast and sheath blight, respectively, recorded in South Korea. For R_c, the approaches used in the original paper were adopted. Briefly, the apparent rate of disease increase was initially calculated in the early stage of an epidemic: $r_l = \ln(x_2/x_1)/(t_2 - t_1)$, where x_1 and x_2 are the diseased fractions at two successive dates t_1 and t_2. R_c can then be estimated as $R_c = r_l/\{\exp(-r_l p) - \exp(-r_l[p+i])\}$. As the duration of the latent period (p), 4 days was derived from the literature review, replacing the original values of 5 days for leaf blast and 3 days for sheath blight. In the original study, the infectious period i for sheath blight was prolonged to its maximum possible duration, 120 days. However, the duration was changed to 65 days for sheath blight in this study. In South Korea, formal disease surveys of sheath blight are conducted by extension agents based on an official disease survey manual, which indicates that diseased tillers should not be counted after the heading stage if it does not carry ears. Therefore, their infectious duration should be determined as the number of days from disease onset (15 DACE) to the heading date (normally 80 DACE), from which an infectious period of 65 days was estimated for sheath blight. Temperature effects (T) on the disease infection rate were modified by reviewing studies published based on experiments or field tests done in South Korea. As a result, broader ranges of the optimum infection temperatures were applied for leaf blast and sheath blight. As shown in Fig. 2, the temperature range in which more than 90% of the relative infection risk is expected was designated the optimum temperature range for each disease and incorporated into each model. The parameterized models for leaf blast and sheath blight were named EPIRICE-LB and EPIRICE-SB, respectively. LB stands for leaf blast and SB for sheath blight.

One additional parameter was introduced as a host parameter for the leaf blast model. This parameter was a multiplication factor defining five general degrees of host resistance to leaf blast disease: susceptible, moderately susceptible, neutral, moderately resistant, and resistant. Categorization of the host resistance level was based on reported results of upland blast nursery tests conducted by the RDA from 2001 to 2010 in different regions of South Korea. Each rice cultivar shown in Table 2 has a designated R_c value of 0.55, 0.69, 0.86, 1.03, or 1.28 corresponding to rice cultivar resistance levels of resistant, moderately resistant, neutral, moderately susceptible, or susceptible, respectively. In the model, this value replaced the default basic infection rate corrected for removals (R_cOpt) of 0.86 (Table 1).

2.3. Quality control of the observed field data for rice disease incidence

Field data to be used for EPIRICE validation was subjected to a series of quality control (QC) evaluations. Field data for both diseases were recorded every 10 days consisting of at least 6 data points, with each disease survey beginning on different dates. Data for the observed epidemics were initially selected based on whether they exhibited a normal disease progress curve for the disease, indicating the disease survey was conducted in a proper way following the official manual (RDA, 2010b). For example, leaf blast is normally characterized by a unimodal bell-shaped disease curve showing a rapid but gradual increase followed by a gradual decrease; a normal sigmoidal disease curve is also expected for a sheath blight epidemic. Applying this gradual increase/decrease concept, we established a QC criterion that there should be at least one intermediate score recorded between the starting point and the maximum peak score for the epidemic and also between the peak score and the ending point. Field data with no intermediate scores were filtered out. For sheath blight QC, we discarded all abnormal data showing an incomplete or non-sigmoidal curve. In addition, there were some sheath blight data showing $a > 20\%$ drop in disease severity immediately after the maximum peak score. These data were removed, as we assumed that there can be no actual recovery of diseased tillers within the survey period; thus, $a > 20\%$ decline is not possible in a real situation. The second QC criterion was the disease onset date, which should be no more than 60 DACE for leaf blast and 70 DACE for sheath blight. This was determined considering the model simulation periods, which are over a 77-day period for EPIRICE-LB and an 88-day period for EPIRICE-SB. When comparing with the model simulation results, the field data with disease onset after the above-mentioned QC criterion were determined ineligible for a normal disease progress curve. In addition, disease onset of no more than 60 DACE for leaf blast and 70 DACE for sheath blight were not reported on most disease records in the literature (Hwang et al., 1987; Kim, 2001; Kobayashi et al., 2006; Lee and Rush, 1983; Savary et al., 2001). The final QC criterion was a minimum threshold for the maximum peak score in a disease progress curve, particularly for leaf blast. The purpose of this criterion was to rule out low quality field data. For leaf blast, 0.5% disease severity was established as the minimum cut-off value, because it was the lowest score given by extension agents during disease surveys in the field. Field data with less than 0.5% of maximum peak score were considered as unreliable data (personal comm., multiple respondents).

2.4. Model calibration, validation, and sensitivity testing

Calibration of the EPIRICE models to fine-tune the parameters for each disease was conducted using observed epidemics obtained directly from the RDA or reported in the literature. The RDA test plot data for sheath blight in Hwaseong (2002) was used for EPIRICE-SB calibration. When there was no available or insufficient ground truth data, the calibration was conducted by comparing the simulated epidemics with an available set of observed epidemics in South Korea reported in the literature. This was the case for EPIRICE-LB calibration, where disease curves of leaf blast for 8 rice cultivars with different levels of blast resistance were derived from Hwang et al. (1987). Calibration also included modification of site growth and senescence rates based on changes in the leaf area index or number of tillers during the rice growing period for EPIRICE-LB or EPIRICE-SB, respectively.

The model was subsequently validated using historic rice disease incidence data and weather data from 2002 to 2010. Annual crop pests & diseases forecast control reports and annual crop yield reports from the RDA were collected to extract historic data for rice disease incidence, rice cultivars planted, and transplanting dates for each county. Most disease incidence data used for validation were obtained directly from the RDA. A telephone survey was conducted to identify the rice cultivars for counties in which cultivar information could not be derived from the RDA reports.

The Korea Meteorological Administration (KMA, http://www.kma.go.kr) provided 1-km-scale weather data for 2000–2010 generated by the parameter-elevation regression on independent slopes model (PRISM) from historic weather data collected from 76 automatic synoptic observation system (ASOS) and 462 automatic weather system (AWS) observations over South Korea (Kim et al., 2012). Because the PRISM weather data included only temperature and precipitation data, we derived relative humidity data from the closest ASOS observations among 76 stations. All simulations were run over a 77-day period for EPIRICE-LB and an 88-day period for EPIRICE-SB. Daily weather variables were used as input data for the model simulations.

The model validation was based on whether there was good agreement between the observed historic data and the potential epidemics simulated by the EPIRICE models. Simulated outputs for disease epidemics were based on changes in disease severity with time (daily percentage of the total lesion area over the whole leaf area) and the AUDPC. The AUDPC was calculated by accumulating the daily disease severity for the entire growing season, providing information about the dynamics of disease development

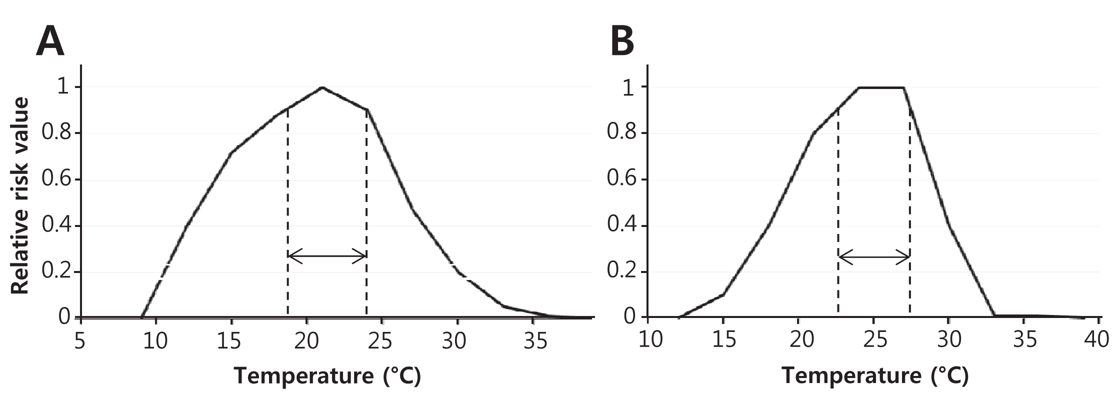


Fig. 2. Response of the infection rate index (shown here as the relative risk value) to temperature used in (A) EPIRICE-LB (leaf blast) and (B) EPIRICE-SB (sheath blight). Each graph was drawn based on the temperature effect parameter shown in Table 1. The dotted lines indicate the optimum daily temperature range within which more than 90% of the relative infection risk is expected.

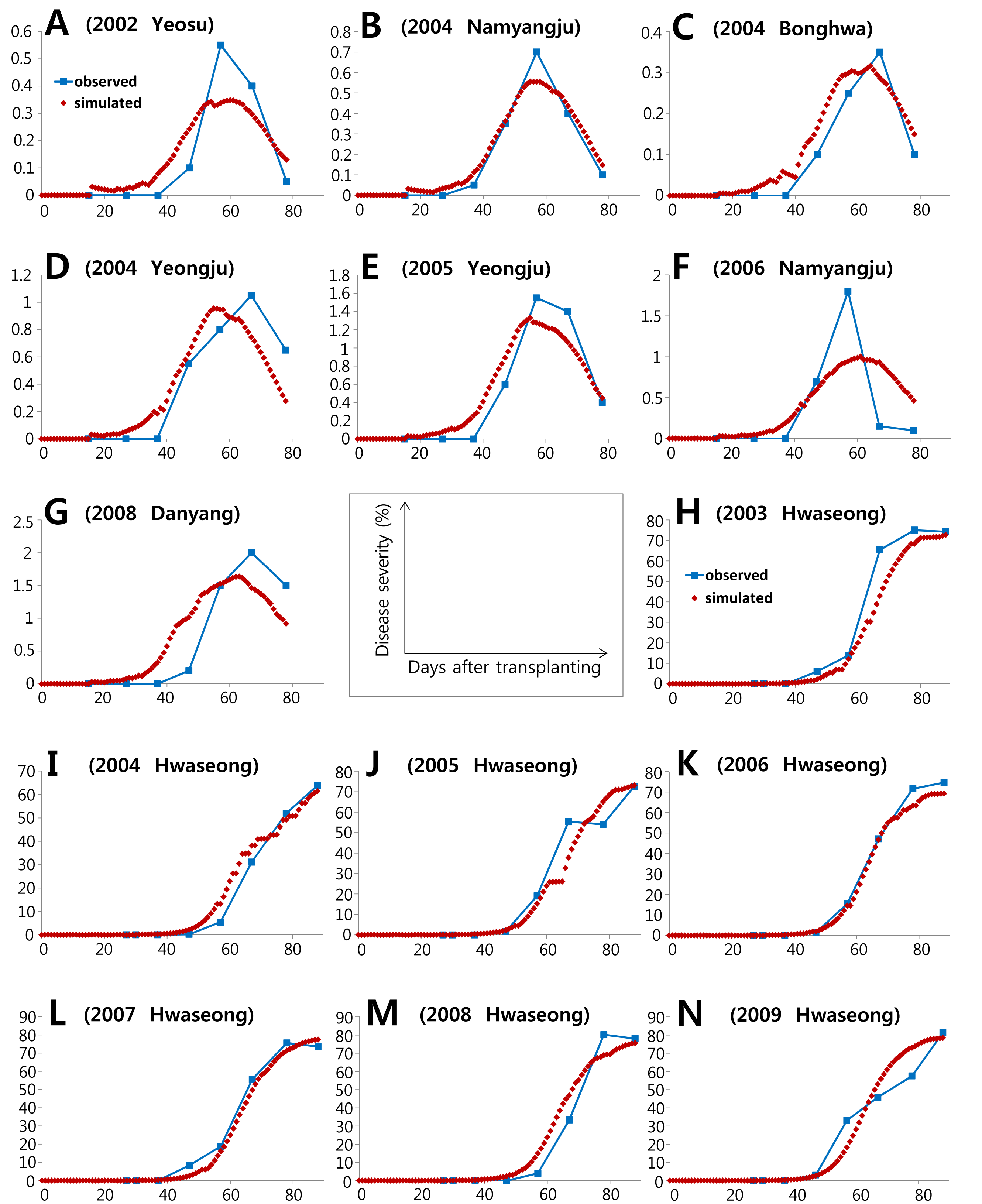


Fig. 3. Graphic comparisons of observed (blue line) and simulated (red dots) disease progress curves for (A–G) rice leaf blast and (H–N) sheath blight epidemics. Simulations were run over a 77-day period for EPIRICE-LB (leaf blast) and an 88-day period for EPIRICE-SB (sheath blight), based on observed periods for each disease. Daily weather variables were used as input data for the simulations.

Table 3
AUDPC (% days) comparisons between observed and simulated epidemics for EPIRICE-LB (leaf blast).

Year	2002	2004	2004	2004	2005	2006	2008
City	Yeosu	Namyangju	Bonghwa	Yeongju	Yeongju	Namyangju	Danyang
Cultivar[b]	Ilmi	Odae	Dongjin	Odae	Odae	Odae	Chucheong
R_c [c]	0.69	0.69	0.86	0.69	0.69	0.69	0.86
sim.audpc	11.06	16.44	47.39	28.46	39.85	30.74	52.35
obs.audpc	10.98	15.75	38.63	28.10	38.40	27.13	46.25
AUDPC deviation[a]	0.09	0.69	8.76	0.36	1.45	3.61	6.10

[a] AUDPC deviation: sim.audpc–obs.audpc.
[b] EPIRICE-LB analysis includes additional cultivar information.
[c] EPIRICE-LB analysis includes additional R_c information corresponding to each cultivar.

and an assessment of disease intensity. Graphic comparisons were made by plotting the observed and simulated disease progress curves together. This technique was used to subjectively evaluate the goodness of fit and whether EPIRICE was sufficiently accurate for its intended purpose. Statistical comparisons were conducted using AUDPC. This value could be used because the observed and simulated epidemics had the same duration. Statistical equivalence tests on AUDPC deviations were applied (Andrade-Piedra et al., 2005; Garrett, 1997). Equivalence tests are designed to test a null hypothesis of unequal means rather than that of equal means as in the standard hypothesis framework. Thus, they are appropriate for model validation in which observed and simulated values are compared and the desired result is that both are equivalent. The following approach was used: (i) AUDPC values for the simulated epidemics were normalized to the maximum sim.audpc and then the corresponding obs.audpc values were also normalized by the same normalization ratio that was used for the corresponding sim.audpc normalization; (ii) the AUDPC deviations (sim.audpc–obs.audpc) were calculated; (iii) the 95% confidence interval on the mean of the AUDPC deviations was determined based on a t distribution; (iv) a tolerance range for AUDPC deviations, i.e., the interval within which the mean of the deviations is considered acceptable, was defined; and (v) the 95% confidence interval was compared with the tolerance range. The null hypothesis "the mean of the AUDPC deviations is greater than the tolerance range" was rejected with a type I error of 5% when the confidence interval of the mean of the deviations fell within the tolerance range. The performance criterion for considering the model valid was rejection of this null hypothesis.

The tolerance range was determined based on the accuracy of the measurements of leaf blast and sheath blight severity, which is directly related to the AUDPC. Based on surveys of agricultural extension agents and RDA personnel, it was determined that evaluation of leaf blast and sheath blight severity in the field using a percentage scale suffers from an inaccuracy of approximately 10–20%, depending on the circumstances. It would be unreasonable to expect the model to perform as well as this, but a somewhat strict tolerance range of 15% of the mean of obs.audpc was used for both diseases considering the strict QC criteria applied for field data.

Deviations in AUDPC were also analyzed using the method described by Willocquet et al. (2012). This is a graphic yet quantitative method. In contrast to the equivalence test, in which the mean of the AUDPC deviations was compared with a predefined tolerance range, in this case, each AUDPC deviation was compared with an envelope of acceptance. The envelope of acceptance was constructed by multiplying sim.audpc by the tolerance range described above (0.15). An indicator called the envelope of acceptance test (EAT) was defined as the percentage of epidemics for which the deviations fell within the limits of the tolerance range (the envelope of acceptance). Therefore, the value of EAT varied from 0 to 100%. The performance criterion for considering the model valid was that the AUDPC deviations fell within the envelope of acceptance for at least 75% of the epidemics.

Sensitivity tests were conducted using 1-km-scale weather data obtained from the KMA and the closest ASOS stations. Daily temperature, precipitation, and relative humidity data were extracted for rice paddy fields in Danyang in 2008 and Hwaseong in 2003 as reference data for leaf blast and sheath blight, respectively. The reference data of the selected locations were compared with those for entire regions of South Korea to determine whether their agreement was within a predefined variation of ±5%. It was shown that the average temperature, precipitation, and relative humidity of the two reference locations represent an average weather condition of South Korea for each selected year. For EPIRICE-LB, field data with neutral levels of cultivar resistance were selected as reference data, because different levels of cultivar resistance were to be examined in the sensitivity test. The sensitivities of EPIRICE-LB and EPIRICE-SB were analyzed for 4–5 variables, including daily mean temperature and relative humidity, daily precipitation, transplanting date, and/or rice cultivar resistance level to leaf blast. By changing the values of a variable in the model with the other variables held the same as the reference condition, the responses of the model were analyzed. The levels of each variable were determined based on observed and anticipated changes in each variable over the past and future 50 years, respectively. Information for the past was derived from historic weather data obtained from ASOS stations and RDA reports for transplanting date, and for the future from the KMA-generated climate change scenario (RCP 8.5) over South Korea. The levels for the test were determined based on the overall range of each variable observed or estimated for the past and future periods. As a result, 6 levels of temperature deviations, ±1, ±2, and ±3 °C from daily mean temperatures, were compared with the reference variable. Five levels of relative humidity and precipitation corresponding to deviations of 0, ±5, and ±10% relative to normal daily relative humidity and daily precipitation were applied. In addition, transplanting dates within 10-day-intervals of 5 May, 15 May, 25 May, 4 June, and 14 June and the 5 levels of

Table 4
AUDPC (% days) comparisons between observed and simulated epidemics for EPIRICE-SB (sheath blight).

Year	2003	2004	2005	2006	2007	2008	2009
City	Hwaseong	Hwaseong	Hwaseong	Hwaseong	Hwaseong	Hwaseong	Hwaseong
sim.audpc	1726.02	1403.28	1657.20	1702.12	1881.02	1817.31	1970.86
obs.audpc	2045.45	1247.53	1718.93	1789.58	2017.58	1622.25	1853.13
AUDPC deviation[a]	−319.43	155.75	−61.73	−87.46	−136.55	195.06	117.73

[a] AUDPC deviation: sim.audpc–obs.audpc.

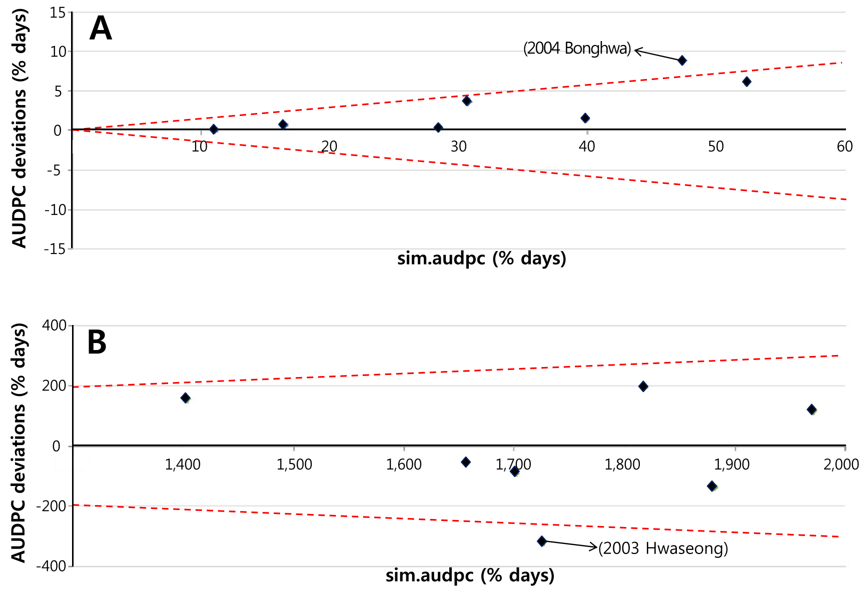


Fig. 4. Envelope of acceptance tests for (A) EPIRICE-LB (leaf blast) and (B) EPIRICE-SB (sheath blight). Deviations in the AUDPC (difference between the mean simulated AUDPC (sim.audpc) and the mean observed AUDPC (obs.audpc)) and the envelope of acceptance (sim.audpc × 0.15, dotted red lines) were plotted against sim.audpc. Each data point (rhombus) represents an (A) leaf blast or (B) sheath blight epidemic in a certain location and year.

cultivar resistance (Table 2) were used as input variables for the sensitivity tests.

2.5. Climate data, EPIRICE runs, and mapping potential epidemics using GIS with climate data

Both EPIRICE-LB and EPIRICE-SB were run for each 1-km grid cell for the regions of South Korea using daily climate data (daily maximum, minimum, and average temperature, precipitation, and relative humidity) annually for 2000–2100. Briefly, simulation target grids were selected by overlaying the 1-km grid cells for South Korea with a land-use GIS map of rice paddies obtained from the Korea Ministry of Environment, resulting in 7378 grids. The output of the Hadley Center climate model (HadGEM2-AO) was downscaled using HadGEM3-RA by the Korea Meteorological Research Institute (METRI) to produce a high-resolution (12.5-km) regional scenario based on the RCP 8.5 and RCP 4.5 scenarios. The temperature and precipitation data were further downscaled to a 1-km scale to enhance the resolution of the regional scenarios using the PRIsm-based downscaling estimation (PRIDE) model for South Korea (Kim et al., 2012).

The KMA provided daily maximum, minimum, and average temperature and precipitation data at 1-km resolution for each year from 2000 to 2100, including a recent period (2000–2010). The relative humidity variable was generated through a series of bias corrections of the 12.5-km regional scenario data (RCP 4.5 and RCP 8.5) using a quantile mapping method based on 30 years of historic data from 76 ASOSs (Jaepil Cho unpublished data). The reliability of the climate change scenario dataset used in this study was examined by comparing two consecutive model runs using both observed weather data and the scenario data (RCP 8.5) for a specific location for each disease over 2000–2010. For both EPIRICE-LB and EPIRICE-SB, good agreement (±10%) was obtained between the observed data and scenario simulations for the 11-year mean AUDPC (data not shown).

The EPIRICE models were run using predetermined transplanting dates, rice cultivars, and daily climate data for each year. For the two scenarios and the entire period from 2000 to 2100, it was assumed that the transplanting dates were the same as the average transplanting date (25 May) for 2000–2010 and a moderately resistant rice cultivar was planted, as this represents the majority of cultivars currently planted in South Korea. All simulations were run for a 100-day period for both models. Annual simulated potential epidemics (represented as the AUDPC) for the leaf blast and sheath blight diseases were outputs from the models. The resulting maps of AUDPC were presented using ArcGIS 10.0. The 101 years of climate data resulted in 101 outputs for each disease. Each 10 years of data was summarized by computing the 10-year mean of the potential AUDPC for each cell, resulting in 9 consecutive sets of 10-year interval disease potential maps, including an additional historic map for 2000–2010. The maps show a measure of the potential disease intensity for a particular disease throughout a cropping season.

3. Results

3.1. Parameterization and calibration of EPIRICE

Parameterization and calibration of the original EPIRICE model developed by Savary et al. (2012) were conducted for leaf blast and sheath blight simulations for South Korea. The revised parameters for site size, maximum and initial number of sites, site growth and senescence rate, duration of latent and infectious periods, crop age, temperature, wetness effects on the infection rate, and epidemic onset used in this study are shown in Table 1, in comparison to those of the original model. Additionally, 5 levels of R_c were developed and used to characterize major rice cultivars based on their resistance to leaf blast disease in multiyear upland rice blast nursery tests and were incorporated into EPIRICE-LB (Table 2).

3.2. EPIRICE validation

The objective of validation was to determine whether the model was reasonably accurate within its domain of applicability and consistent with its intended application. The domain of applicability was South Korea, as we used only data from this region. The intended application of the model was for estimating potential epidemics of major rice diseases under two climate change scenarios. In this study, we used field data from South Korea to assess the reliability of EPIRICE for research, particularly climate change impact analysis. The first step was to assess the suitability of the field data using a series of QC criteria to determine their usability and ensure that there were no obvious errors. We then compared the epidemics simulated by the two EPIRICE models with those observed in the field using graphic and statistical tests. The level of agreement between the model output and the observed data was assessed by comparison with subjective and objective performance criteria.

The EPIRICE models met the predefined performance criteria for all graphic and statistical tests. The disease progress curves generated by each EPIRICE model were a reasonably accurate fit to the data observed in the field (Fig. 3). Both models were able to predict the effects of environmental conditions and, in case of leaf blast, of host resistance. In many cases, the model predictions slightly overestimated or underestimated the observed epidemics, but these deviations were judged to be minor. Notably all simulated disease progress curves for rice leaf blast epidemic exhibited lower maxima than that of the observed ones (Fig. 3A–G).

To quantitatively evaluate the model performance, we compared the model outputs in terms of AUDPC (% days) with the observed data (Tables 3 and 4). Using the resulting deviations between the simulated and observed AUDPCs, graphic and quantitative EAT tests were conducted (Fig. 4). The EAT test for EPIRICE-LB indicated that 6 of the 7 AUDPC deviations fell within the predefined envelope of acceptance, giving a mean EAT value of 83%, higher than the predefined performance criterion of 75%. The AUDPC deviation for the 2004 Bonghwa data fell outside the envelope of acceptance. The EAT test for EPIRICE-SB resulted in similar performance, giving a mean EAT value of 83%. In this case, the AUDPC deviation for the 2003 Hwaseong data fell outside the envelope of acceptance.

In the equivalence test (Fig. 5), the 95% confidence intervals of the mean of the AUDPC deviations for EPIRICE-LB (1.46, 6.29) fell within the predefined tolerance range (±7.27). Therefore, the null hypothesis "the mean of the AUDPC deviations is greater than the tolerance range" was rejected at $\alpha = 0.05$, indicating that the differences between sim.audpc and obs.audpc were acceptable. Similarly, the differences between sim.audpc and obs.audpc for the EPIRICE-SB were acceptable, because the 95% confidence interval of the mean of the AUDPC deviations (−167.03, 128.61) fell within the predefined tolerance range (±298.51).

3.3. Sensitivity of EPIRICE-LB and EPIRICE-SB

Sensitivity analyses of the two EPIRICE models highlighted the effects of changing weather variables on model outputs. The reference weather conditions for both leaf blast and sheath blight monitored at rice paddy fields in Danyang in 2008 and Hwaseong in 2003, respectively, are shown in Fig. 10. Both climates exhibited a typical monsoon season with frequent precipitation from the end of June to the end of July. The average temperatures were 23.5 °C for Danyang in 2008 and 23.0 °C for Hwaseong in 2003, within the normal range of each year's average temperatures (Refer to Fig. 9).

Responses of the EPIRICE models to temperature, transplanting date, relative humidity, and/or cultivar resistance to leaf blast were plotted and compared with the response to the reference conditions: 0 °C for temperature; 25 May for transplanting date; ×1 for relative humidity; and 0.86 for cultivar resistance (Fig. 6). Temperature changes proportionately affected the EPIRICE-LB output (Fig. 6A), indicating that the model is sensitive to temperature changes from the reference condition. A temperature increase of 1 °C significantly decreased blast infection risk, while decreases in temperature resulted in a significant increase in disease intensity compared to the normal response (0 °C). Similar responses to transplanting date and relative humidity were observed, but of a different magnitude. In EPIRICE-LB, the basic infection rate (R_c) exponentially increased as the cultivar resistance level decreased (Fig. 6D), reflecting the significant impact of rice cultivar resistance on disease intensity. The EPIRICE-SB run was sensitive to changes in weather conditions and transplanting date. Notably, both a decrease and increase in temperature compared to the reference condition (0 °C) resulted in decreased sheath blight infection risk. While the magnitudes of the responses to temperature and transplanting date were not as dramatic as for EPIRICE-SB, greater changes were observed in response to 5% (×0.95) and 10% (×0.9) decreases in relative humidity (Fig. 6G). The responses of both EPIRICE models to varying amounts of rainfall were investigated, but no clear differences were found for either model. This is likely because the rainfall effect on leaf wetness duration was compounded by the effect of already high relative humidity (data not shown). These sensitivity tests indicated that all of the weather variables except rainfall, as well as the transplanting date and cultivar resistance, are important input factors for the EPIRICE-LB model, although EPIRICE-SB responded less sensitively to the given ranges of input variables.

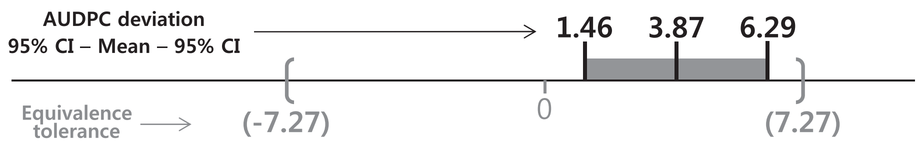
3.4. Potential epidemics of rice leaf blast and sheath blight in South Korea

The geographic distribution maps for potential epidemics of leaf blast and sheath blight under the future RCP 4.5 and RCP 8.5 climate change scenarios showed decreasing risk probabilities compared with the climatological normal for 2000–2010. Declines under the RCP 8.5 scenario (Fig. 7), were greater than those under the RCP 4.5 scenario (Fig. 8). Both scenarios show low levels of epidemics during the period of 2090–2100 for both leaf blast and sheath blight. This indicates that the future weather conditions are not predicted to favor rice leaf blast or sheath blight. Thus, climate change may result in these diseases becoming less of a concern over the long term. Over the next 10–20 years, however, these diseases could potentially intensify or at least maintain their historic or present levels of intensity, according to the EPIRICE runs. For leaf blast, the mean predicted AUDPCs for 2020–2030 under both scenarios showed slight increases in disease risk in some parts of the country, mainly in coastal Chungcheong Province, compared to those for 2000–2010 (Figs. 7 and 8). However, sheath blight risk was predicted to be nearly the same in 2020–2030 as in 2000–2010 and afterwards, was also predicted to show a continual decline toward 2100, similar to leaf blast.

To investigate whether these interesting behaviors for both disease epidemics were related to future weather conditions, we calculated the annual mean AUDPC values for the rice paddy regions of South Korea from 2000 to 2100 and displayed the mean AUDPCs together with the yearly mean values for temperature and relative humidity for the 100-day EPIRICE simulation period. Leaf blast and sheath blight simulations (Fig. 9) were plotted with mean temperature and relative humidity values. Notably, the AUDPCs for leaf blast had high interannual variation from 2000 until the mid-2020s ranging from 7 to >60% days. Variations in temperature and relative humidity during the same period were similar to other periods, except for the projected abnormally hot year of 2017. After the mid-2020s, the AUDPCs began to stabilize with smaller fluctuations and continued to decrease toward 2100. The yearly mean temperature for the corresponding period showed a prominent increasing trend from 24 to 30 °C, whereas a slight decrease in the relative humidity with relatively high interannual variations was predicted. Similar to leaf blast, sheath blight AUDPCs decreased overall towards 2100. However, a distinct trend from that for leaf blast was observed (Fig. 9). A somewhat steady increase in the annual mean AUDPC was initially predicted until 2040, while dramatic AUDPC fluctuations ranging from 700 to >2,600% days followed during 2040–2070. During this highly variable period, the temperature was predicted to increase from 26 to 28 °C, likely indicating that this specific tem-

A

Year	2002	2004	2004	2004	2005	2006	2008
City	Yeosu	Namyangju	Bonghwa	Yeongju	Yeongju	Namyangju	Danyang
sim.audpc	52.35	52.35	52.35	52.35	52.35	52.35	52.35
obs.audpc	51.93	50.15	42.67	51.68	50.44	46.20	46.25
AUDPC deviation	0.42	2.20	9.68	0.67	1.90	6.15	6.10



B

Year	2003	2004	2005	2006	2007	2008	2009
City	Hwaseong	Hwaseong	Hwaseong	Hwaseong	Hwaseong	Hwaseong	Hwaseong
sim.audpc	1970.86	1970.86	1970.86	1970.86	1970.86	1970.86	1970.86
obs.audpc	2335.60	1752.11	2044.27	2072.12	2113.93	1759.32	1853.13
AUDPC deviation	-364.74	218.75	-73.41	-101.26	-143.07	211.54	117.73

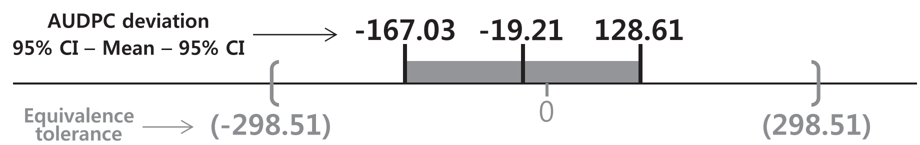


Fig. 5. Equivalence tests using the AUDPC deviation between the observed and simulated epidemics for (A) EPIRICE-LB (leaf blast) and (B) EPIRICE-SB (sheath blight). For each test, the upper table shows obs.audpc values normalized to the maximum value of sim.audpc and AUDPC deviations (sim.audpc–obs.audpc) for each epidemic. The lower panel shows the equivalence test results for the AUDPC deviations, with brackets indicating the equivalence tolerance limits around 0 and the shaded region indicating the 95% confidence interval (95% CI) around the observed difference in the mean AUDPC deviations (Mean). The tolerance range was determined as 15% of the mean of obs.audpc for each epidemic.

perature range with large AUDPC fluctuations may be critical for sheath blight epidemics.

4. Discussion

This study consisted of a set of general model-building processes for mechanistic disease models. The target model here was EPIRICE, developed as a global-scale model for various rice diseases as a general model framework. In this study, the potential performance and generality of the model was verified with respect to whether it was able to address rice diseases at different spatial scale. Specific levels of host resistance to leaf blast were also incorporated in the model for more realistic estimation. The newly parameterized EPIRICE was successfully applied to field-level epidemics for both leaf blast and sheath blight diseases in South Korea. This approach of addressing major diseases with a general model framework such as EPIRICE is simpler compared to other approaches that manipulate various individual disease models to evaluate climate change impacts on rice disease epidemics.

EPIRICE can be used as a research tool to illustrate concepts of impact analysis and to estimate relative epidemic potentials based on host resistance and future changes in the environment. Our method of predicting disease intensity is limited because other factors are not taken into account. The existence and amount of initial inoculum, the amount of fertilizer, and other possible extreme weather conditions that could make hosts vulnerable are among the critical factors affecting development of a disease. The distribution and available number of virulent pathogen races is also an important factor affecting the magnitude of disease intensity. For example, some three-quarters of the rice-producing land in the 1970s in South Korea were planted with the Tongil rice cultivar. In 1978, there was a sudden outbreak of blast disease that affected almost 20% of Korean rice paddies due to an emergence of new pathogen races to which Tongil rice proved highly susceptible (Lee et al., 1976). The onset of disease also needs to be determined depending on the weather and the amount of available inoculum. However, because the availability of inoculum was not considered in our study, constant disease onset dates derived from the literature and reports were applied. Field studies to determine inoculum loads and their effect on the onset of epidemics would be useful, particularly if such work could be incorporated into the present EPIRICE model to more accurately estimate disease onset. Considering these limitations, major conclusions based on simulation analyses should be conceptually applied as the risk probability resulting only from projected weather conditions.

EPIRICE was validated through two key principles. First, we applied a set of QC criteria to rule out any abnormal disease records among the field data. For validation purposes, this procedure was required because EPIRICE was designed to generate potential epidemics under given weather conditions and for selected cultivars. However the potential epidemics do not always occur in the field due to unexpected factors that are critical for diseases progress, as mentioned before. Focusing on the disease risk probability, rather than accurate, realistic disease consequences, we determined somewhat subjective but reasonable rules for which data to use for validation. Second, we defined performance criteria to determine whether the level of agreement between the model output and field data was acceptable. To our knowledge, there is no scientific consensus regarding the criteria that a plant disease model must meet to be considered operationally valid. Thus, we proposed a set of criteria by referencing suggestions by other researchers in the literature or based on advice from agricultural extension agents in the field. The criteria for judging whether the performance of the model was acceptable for each epidemic were based on the estimated variability of the field data.

Developing these principles was important for the validation process. As Rykiel (1996) stated, a model cannot be expected to generate results more accurate and precise than data for the actual

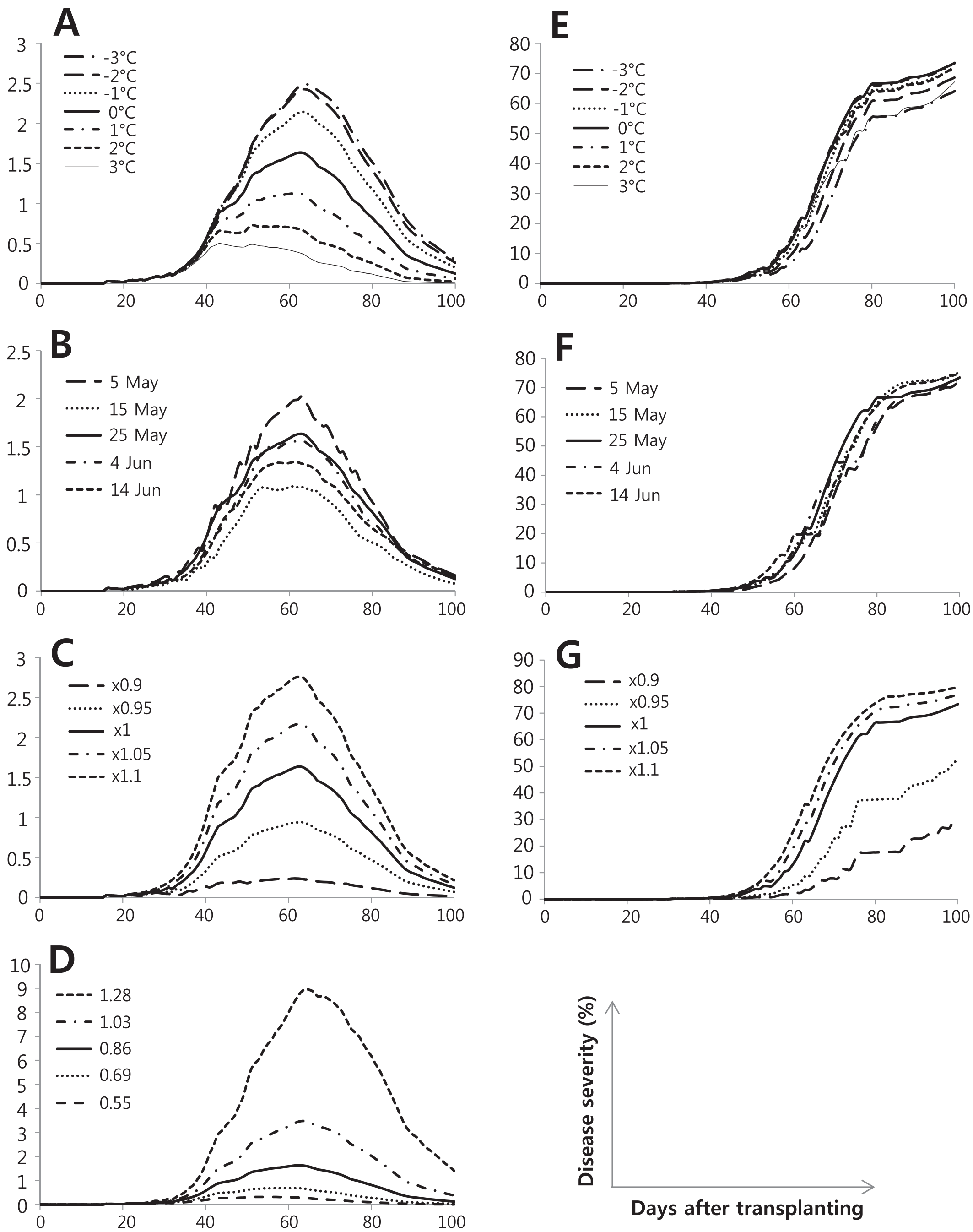


Fig. 6. Sensitivity tests for (A–D) EPIRICE-LB (leaf blast) and (E–G) EPIRICE-SB (sheath blight). Reference weather conditions for EPIRICE-LB and EPIRICE-SB were derived from the RDA test plots in Danyang in 2008 and Hwaseong in 2003, respectively. Sensitivity to (A, E) temperature, (B, F) transplanting date, (C, G) relative humidity, and (D) cultivar resistance level were examined.

system. In other words, the testability of a model is defined by the accuracy and precision of the ground truth data. Therefore, we needed to determine the reliability of the ground truth data first and then filter out any possible errors through a series of QC criteria. These QC criteria are primarily focused on accounting for artificial errors introduced during disease survey. All of the remaining data were subjected to our validation tests. By defining these performance criteria, operational validation could be defined as a yes-or-no proposition, i.e., the model either does or does not meet the specified performance criteria. Once again, our conclusion regarding the validity of EPIRICE was based on the level of agreement between the model output and the field data being acceptable according to predefined subjective and objective performance criteria.

Sensitivity testing characterizes the response of model outputs to input variation. Based on the sensitivity test, the responses of the EPIRICE models to several input variables were determined. EPIRICE-LB was very sensitive to variations in the transplanting date, likely resulting solely from the change in the weather, as the transplanting date determines the cropping season and each cropping season experiences different weather conditions. In contrast, the model responses to different ranges of rainfall were not significantly different from the reference condition. The intensity of rainfall may not have much effect on the model output, because

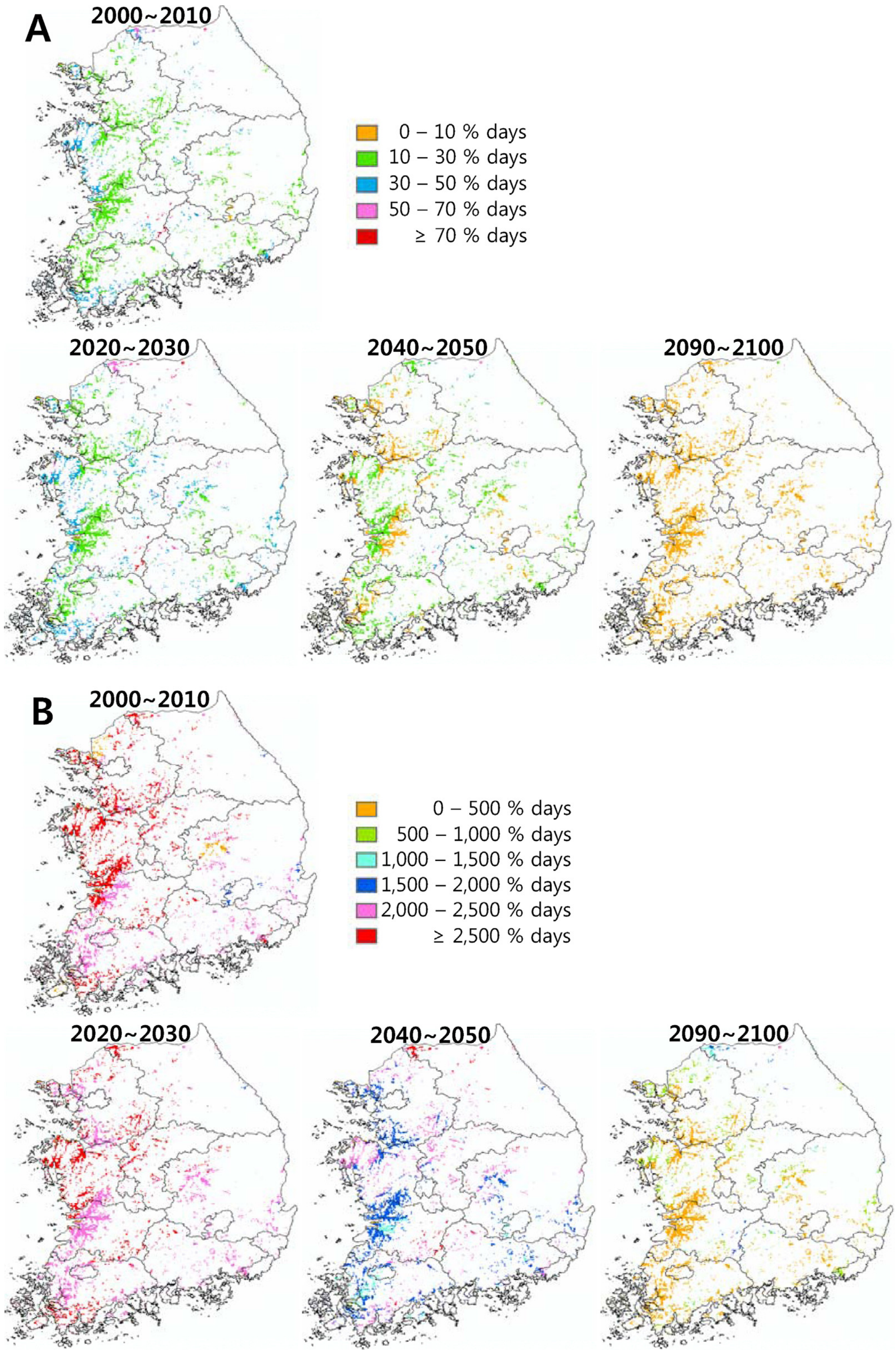


Fig. 7. Potential epidemics of (A) leaf blast and (B) sheath blight simulated by EPIRICE-LB and EPIRICE-SB, respectively, using the RCP 8.5 climate change scenario. Simulated outputs for each disease epidemic were represented as the area under disease progress curves, AUDPC (% days). The AUDPC values were displayed on selected 7378 rice paddy (1-km) grids on the map.

EPIRICE estimates leaf wetness using a very simple algorithm in terms of daily rainfall amount. Therefore, if the frequency rather than the intensity of the rainfall was applied in the sensitivity test, the model may have responded more sensitively to rainfall variations. An alternative explanation may be that the already-high relative humidity of the reference condition may have compounded the effect of rainfall on leaf wetness duration. Unlike variations in rainfall, EPIRICE was sensitive to other weather variables such as temperature and relative humidity. However, EPIRICE-LB showed more sensitive responses than EPRICE-SB, especially to changes in

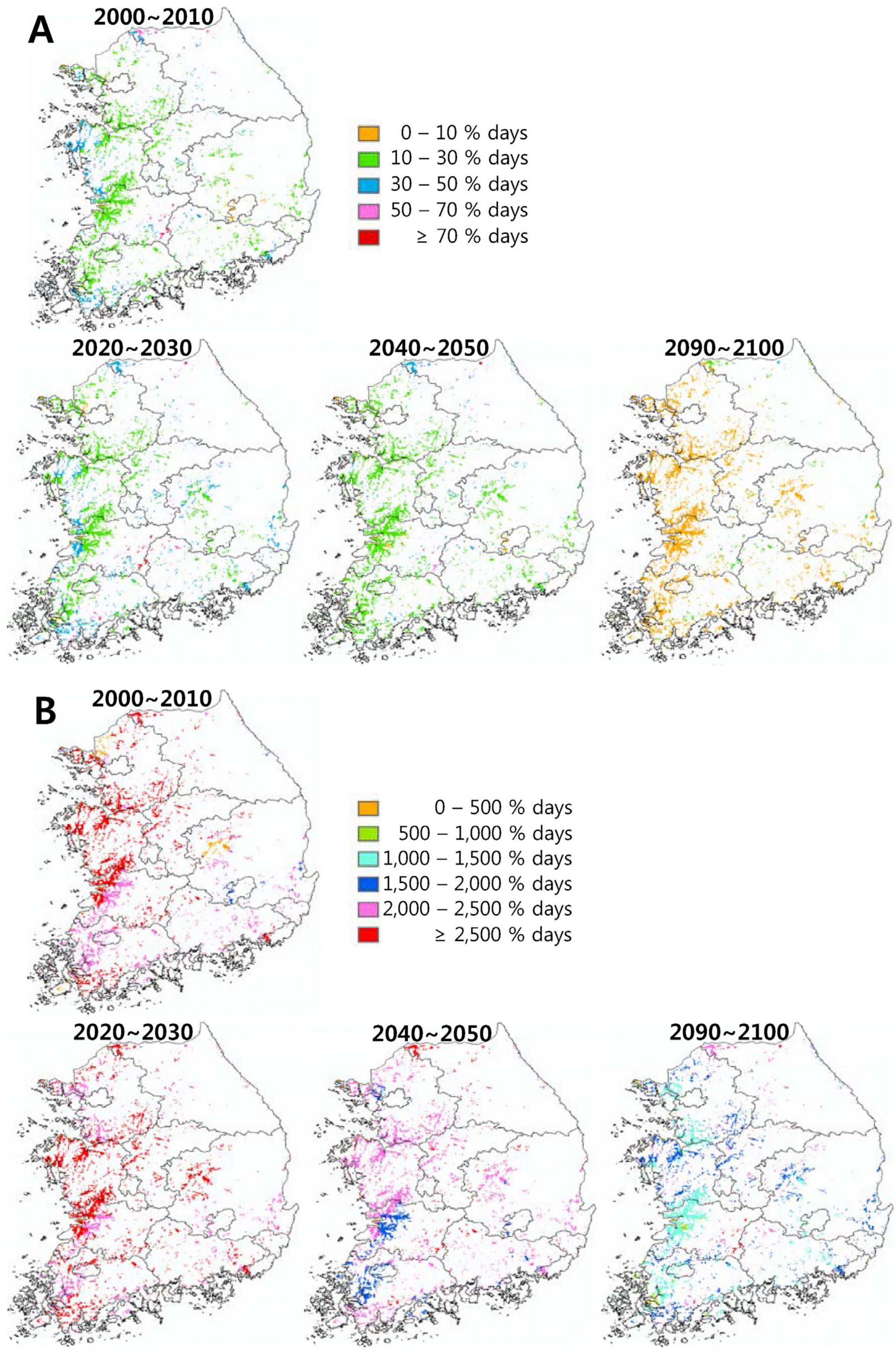


Fig. 8. Potential epidemics of (A) leaf blast and (B) sheath blight simulated by EPIRICE-LB and EPIRICE-SB, respectively, using the RCP 4.5 climate change scenario. Simulated outputs for each disease epidemic were represented as the area under disease progress curves, AUDPC (% days). The AUDPC values were displayed on selected 7378 rice paddy (1-km) grids on the map.

temperature. This lower sensitivity of EPIRICE-SB may be attributed to different tolerances of the leaf blast and sheath blight to environmental stresses. For example, compared to leaf blast, which is mostly restricted to temperate and subtropical areas, sheath blight occurs over broader climatic regions such as temperate, subtropical, and tropical; thus it is essentially endemic in all rice production areas (Banniza and Holderness, 2001). This may indicate that sheath blight is more tolerant to environmental stresses than leaf blast. However, we should be cautious in concluding which model is more sensitive than the other, because these conclusions are strongly

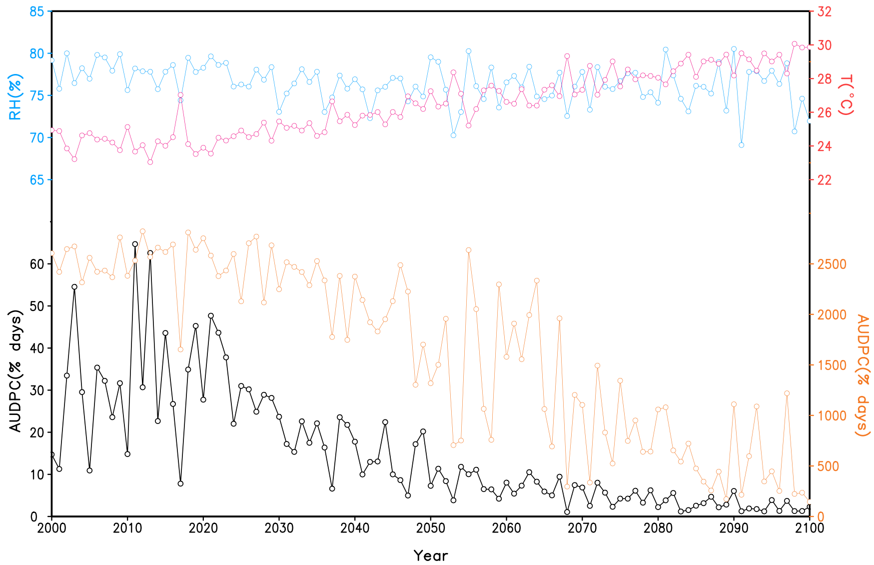


Fig. 9. Yearly mean AUDPC (% days) values for the simulated leaf blast (black line) and sheath blight (orange line) epidemics over the rice paddy area of South Korea, with the average values of temperature (°C, red line) and relative humidity (%, blue line) for the 100-day period of the EPIRICE simulations from 2000 to 2100 under the RCP 8.5 scenario.

influenced by the levels of the variables used in the sensitivity test. Variables that have a broader distribution of peak scores will appear less sensitive to change than variables that have a narrower distribution of peak scores (Vonk Noordegraaf et al., 2003). This is a weakness of sensitivity analysis and, therefore, carefully selecting the variables and their representative ranges is important.

Regarding the risk maps of potential epidemics of rice diseases for the present and future periods, our results suggest that for both RCP 4.5 and RCP 8.5 scenarios there will be a decreasing trend in disease intensity. This was somewhat expected due to the predicted temperature increase of 6 °C under the RCP 8.5 scenario by the end of the 21st century. Far higher than optimal infection temperatures are not favorable to either leaf blast or sheath blight pathogens. Overall, the predicted decline in leaf blast in the future is in agreement with Luo et al. (1998), who stated that further temperature elevations compared to current climate are associated with significantly less severe blast epidemics. They also found that changes in the amount of rainfall were not predicted to affect the occurrence of epidemics due to having little effect on the leaf wetting period (Luo et al., 1995). The potential role of challenges for water management under climate change in changing disease risk can also be included in the modeling approaches for more realistic prediction (Savary et al., 2006). Focusing only on present-day-rice paddies, we, in this study, did not account for the possibility that farmers may adapt to climate change by expanding into and cultivating new areas for rice paddies. Thus, the future rice cultivation

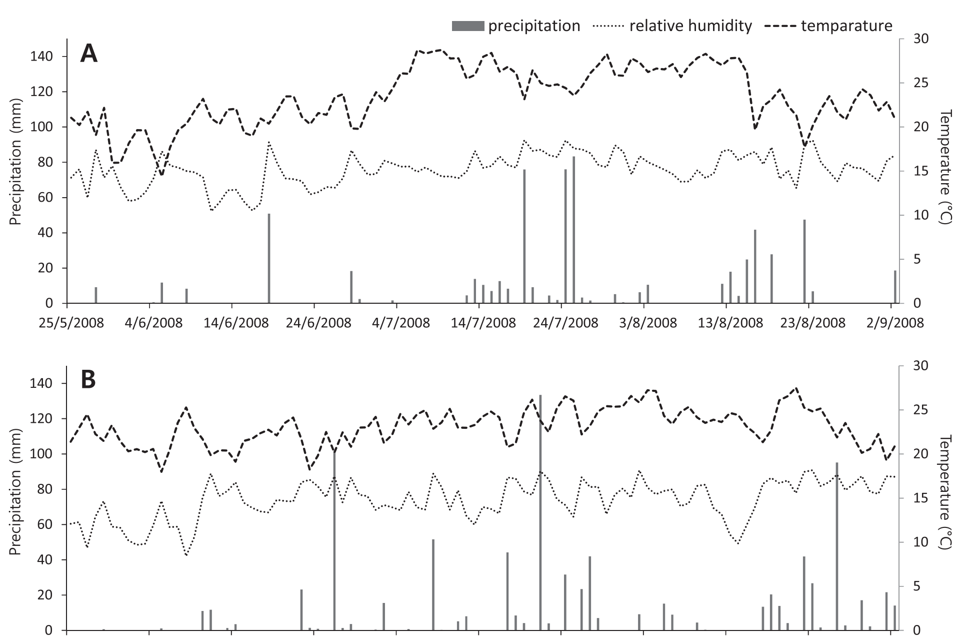


Fig. 10. Daily mean temperature, relative humidity, and precipitation at the rice paddy test plots monitoring leaf blast and sheath blight diseases for (A) Danyang in 2008 and (B) Hwaseong in 2003, respectively, used as the reference weather conditions for the respective sensitivity tests.

area may not be the same as the present area that was modeled, suggesting that potential epidemics in more mountainous areas such as Gangwon Province might need to be considered. This could produce entirely different disease risk maps in the coming years. Another adaptation to climate change is to select rice cultivars that can resist potential flooding, drought, salinity stress, and various pathogens and pests (Matthews et al., 1997; Wassmann et al., 2009). For the future epidemic runs, we chose to use only a moderately resistant cultivar, since the majority of rice cultivars planted at present belong to this category. Incorporating different cultivar-specific traits into the model and using the most representative cultivars for future years may provide more a realistic estimation of future epidemics. However, it will also make the model more complicated than we initially intended and make it more challenging to link with other applications. Furthermore, we do not know yet what cultivars will be planted even in the very near future. There are many uncertain factors that determine the choice of cultivar, such as changes in the preferences of consumers, socio-economic or political decisions affecting rice cultivation, and further expansion of free trade with other countries. In the original EPIRICE study, the optimum rice transplanting date was derived from a crop model simulation (Savary et al., 2012). However, we did not repeat that process. Instead we used the same transplanting date for the future simulations, assuming there will be no major change in the transplanting date. It may be inappropriate to determine specific transplanting dates with a crop growth model simulation, because transplanting in a region often takes place over extended periods that are influenced not only by actual weather conditions but also socio-economic considerations and cultural practices such as rice cultivar selection. Furthermore, for transplanting date optimization to be meaningful, precipitation and water availability in the future should be considered, which are uncertain. Recognizing these limitations and making the overall process simple but as representative of the actual conditions as possible, we have obtained a preview of long-term climate change impacts on two rice diseases through the present modeling work.

Results of leaf blast and sheath blight simulations were simultaneously presented with the yearly change of mean temperature and relative humidity variables. There were transient fluctuations in the interannual AUDPCs observed for both diseases within specific temperature ranges, i.e., 23–25 °C for leaf blast and 26–28 °C for sheath blight. Combining this observation with the optimal ranges of infection temperatures for both diseases (Fig. 2), we infer that there were dramatic fluctuations whenever the temperature exceeded the lower or upper limits of the optimal infection temperature. Even slight variations in temperature at these limits affected the rate of infection by 50%, increasing in magnitude when the temperature crossed the upper limit (Fig. 2). The AUDPCs were also sensitive to interannual variations in relative humidity. It was common to see similar up-and-down patterns, but with opposite directions, of the temperature and relative humidity variables. This somewhat synchronized variation in the weather variables generated the expected model responses. For instance, greater epidemic risks are generally anticipated when temperature decreases and relative humidity increases based on model algorithms. In other words, the model outputs were highly dependent on interannual variabilities of weather parameters in the scenarios generated by the GCM model. Therefore, it might be interesting to see whether the interannual variability of the model outputs is offset by using multiple GCM ensemble scenarios.

Simultaneous presentation of the AUDPC, temperature, and relative humidity in Fig. 9 also illustrated why EPIRICE-LB was more sensitive to the weather variables than EPIRICE-SB in the sensitivity tests. The key question here was the reference condition for each model. The reference conditions for EPIRICE-LB and EPIRICE-SB were in 2008 and 2003, respectively. In 2008, EPIRICE-LB showed substantial fluctuations in its outputs, most likely because the mean temperature in 2008 was reaching the upper limit of the optimal infection temperature of the model. In contrast, the interannual variations in the EPIRICE-SB outputs were relatively stable for that time period, indicating that the reference condition may have been within the wide range of optimal infection temperatures (Fig. 2B). Accordingly, the sensitivity tests may have been affected by the reference conditions chosen for the tests. Thus, it may be possible to obtain more sensitive responses to weather variables if the reference condition for EPIRICE-SB were chosen from 2040–2070, a period for which large fluctuations in AUDPCs were predicted.

Climate change will certainly affect the development of rice diseases. Because the magnitude and range of these changes is very uncertain, however, prediction of climate change effects on these pathosystems is difficult and speculative. Although speculative, published data has suggested potential problems that may occur under a modified climate. Experimental research on a diverse range of disease systems has improved our comprehension of potential climate change impacts. Modeling approaches have been adopted more frequently for impact assessment, given the multitude of atmospheric and climatic factors, the possible changes in scenarios, and the number of disease systems. As noted, the forecasts made by EPIRICE models were based on only one set of GCM-generated climate data and thus, are expressed in a non-probabilistic format. The KMA has generated the 1-km scale scenario data from a GCM (HadGEM2-AO) model. So this climate data was the only one available to use for this study. Therefore, predictions from this study may not accurately reflect the true state of knowledge concerning potential future conditions affecting rice diseases. An alternative way to solve this problem is to use climate forecasts expressed in terms of probabilities to accommodate the uncertainty inherent in the forecasting process using multiple GCM models. Probabilistic disease predictions using probabilistic climate data will enable end users to make the best possible decisions. Indeed, probability forecasts have been demonstrated to have superior benefits in some agricultural applications that make use of meteorological and climatological information (Cantelaube and Terres, 2005; Challinor et al., 2005).

5. Conclusions

The present study involved two main components: (1) modification of EPIRICE and (2) linking of EPIRICE to climate change data to generate disease risk maps. The first component entailed adaptation of an existing simulation model, EPIRICE. The use of EPIRICE for widely different diseases is possible due to the generality of the model, which was designed to model epidemics caused by various pathogens such as fungi, bacteria, and viruses. There are lessons learned in terms of adapting a more general EPIRICE model to a national analysis such as climate change impact analysis for South Korea. National adaptation of a global model requires national specificities incorporated for host crop cultivation practices such as irrigation, fertilization, and cultivars, disease management, and local climate variability. Spatial downscaling of the model follows with more detailed functionality of the model, for example adding additional modules and elaborating existing modules or algorithms. More local ground truth data will be needed for the model calibration and validation.

As a successfully verified generic model for potential plant disease epidemics, the adapted EPIRICE will possibly be applied to prioritizing research on crop health management in South Korea. For example, maps of potential epidemics of rice leaf blast and sheath blight under different climate change scenarios (RCP 4.5 and RCP 8.5) provided strategic information on where and what intensity of epidemics may occur, their temporal patterns over the years, and therefore guidance with respect to the assessment of disease risk probability. This enabled development of basic methodological components that could be used in a subsequent risk management process such as linking with agrochemical applications or applying rice cultivar profiles with respect to disease resistance. The resulting maps can also be used as basic information allowing stakeholders to carry out more robust planning concerning long-term national food supply and food security. A good example of such planning would be the national program for rice breeding, in which diseases with greater epidemic potential in the future are prioritized for breeding research.

The potential risk maps for the rice disease epidemics predicted a decreasing trend in disease intensity. Nevertheless, there were transient but significant year-to-year variations from 2000 until the mid-2020s for leaf blast and in 2040–2070 for sheath blight. These are critical periods during which we will need to monitor any sudden epidemics annually and if possible, be prepared for any forecasted high disease risks by establishing an effective risk management system. Furthermore, increased frequency and intensity of climate extremes with greater climate variability are expected and may lead not only to significant reductions in crop yields but altered dynamics of plant diseases and pests, which may also exacerbate yield reductions. Therefore, we suggest devising a disease management system for rice diseases by utilizing integrated management technologies involving the EPIRICE-based disease forecasting system.

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