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RESEARCH ARTICLE

Potential Impacts on Climate Change on Paddy Rice Yield in Mountainous Highland Terrains

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Abstract

Crop models are suitable tools to assess the potential impacts of climate change on crop productivity. While the associated assessment reports have been focused on major rice production regions, there is little information on how climate change will impact the future rice crop production in mountainous highland regions. This study investigated effects of climate change on yield of paddy rice (*Oryza sativa*) in mountainous highland terrains of Korea using the CERES-Rice 4.0 crop model. The model was first calibrated and validated based on observed data and then applied to simulations for the future projections of rice yield in a typical mountainous terrain which borders North and South Korea, the Haean Basin in Kangwon Province, Republic of Korea. Rice yield in the highland terrain was projected to increase by 2050 and 2100 primarily due to elevated CO_2 concentration. This effect of CO_2 fertilization on yield (+10.9% in 2050 and +20.0% in 2100) was also responsible for increases in water-use efficiency and nitrogen-use efficiency. With management options, such as planting date shift and increasing nitrogen application, additional yield gains were predicted in response to the future climate in this area. We also found that improving genetic traits should be another option to get further yield increases. All in all, climate change in mountainous highland areas should positively influence on paddy rice productivity.

Key words: climate change, highland, rice, simulation, yield

Introduction

Global CO_2 emissions which account for 77% of anthropogenic Green House Gasses (GHGs) are projected to increase by 40 to 110% between 2000 and 2030 due to fossil fuel use alone (IPCC 2007). A warming of up to 0.2°C per decade is expected during the next two decades according to the IPCC Special Report on Emission Scenarios (SRES). The possible doubling of atmospheric CO_2 and its associated warming in this century may have significant impacts on agricultural production through changes in evapotranspiration, plant growth rates, plant litter composition, and the nitrogen-carbon cycle (Long et al. 2006). However, the effect at different locations globally will vary depending on the magnitude and seasonal characteristics of climate change in the given region, as well as on the specific responses of crops, forage, or livestock species, and location-specific management. To prepare proactive measures to minimize possible decreases in crop production resulting from climate change, it is essential to study the impacts of projected increases in anthropogenic GHGs and potential climate change on crops and cropping systems of interest under different physical settings (e.g. regional climate conditions in highlands vs. lowlands, etc.).

Among numerous crops to consider, rice is one of the most important, since it is a stable food in at least 95 coun-

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tries and for a significant portion of the world's population (Coats 2003; IRRI 2002). Rice production should provide 2,000 million metric tons by the year 2030 due to population growth over this century (FAO 2002). Thus, significant improvements in rice production will be required. Rice is produced primarily in Asia, which accounts for ~ 94% of the total world production and one of the hot spots for rice production is monsoonal Asia. Mountainous highlands are also of interest for resilient rice production in the future. Nevertheless, little information currently exists to indicate how climate change will impact the future rice crop production in the highlands of Asia.

In an agricultural system, plant growth and development are determined by the integrated response of multiple ecophysiological processes to interacting environmental variables (temperature, atmospheric CO_2 concentration, nutrient and water availability, and agronomic management). It is both necessary and challenging to identify the most important factors that will influence production under climate change, and clarify climate interactive effects on production in field experiments. On this basis, agricultural system models may be correctly calibrated and validated. Validated system models can be employed to explore how temperature increases and precipitation changes associated with elevated CO_2 concentration will influence the response of crops in terms of productivity and nitrogen-use efficiencies (Ahuja et al. 2000; Kirschbaum 2000).

Many studies have already been carried out to understand rice productivity in a changing climate (Ainsworth 2008; Hatfield et al. 2011; Iizumi et al. 2011; Kim et al. 2013; Matthews et al. 1997). Some of these efforts were based on experimental field studies (e.g. Kim et al. 2011), but most have exclusively employed crop simulation approaches (e.g. Iizumi et al. 2011; Kim et al. 2013). While most reports have been focused on dominant rice production regions, there is little information on how climate change will affect the future rice production in mountainous highland regions. While genetic potentials and cultivation techniques of for higher production should be improved in order to feed the world with resilient rice production in the future, appropriate production acreages should be guaranteed as well. Those in mountainous highlands would be of interest to achieve these requirements. Our objectives of this study were: (1) to investigate the potential impacts of climate change on paddy rice yield in a typical mountainous highland terrain of the Korean Peninsula using the validated CERES-Rice 4.0 model and (2) to find out adaptive approaches of the future field management and cultivar improvement options to changing climate in the mountainous highland.

Materials and Methods

DSSAT4.0-CERES-Rice model

The DSSAT4.0-CERES crop model (Jones et al. 2003) was used to simulate rice productivity. The model simulates net biomass production based on the radiation-use efficiency (RUE) approach. The effects of CO_2 on RUE are empirically determined using curvilinear multipliers (Allen et al. 1987; Peart et al. 1989). A y-intercept term in a modified Michaelis-Menten equation is used to fit responses of the biomass production to CO_2 concentration:

$$RUE = \frac{R_m \cdot CO_2}{CO_2 + K_m} + R_i \qquad [1]$$

where R_m is the asymptotic response limit of ($R - R_i$) at high CO_2 concentration, Ri is the intercept on the y-axis, and K_m is the value of the substrate concentration (i.e. CO_2), at which ($R - R_i$) = 0.5 R_m. Similar approaches were used in previous studies simulating CO_2 effects on cropping systems with the EPIC (Williams et al. 1989), APSIM (along with nitrogen-use efficiency and water-use efficiency) (Reyenga et al. 1999), and Sirius (Jamieson et al. 2000) models.

Model parameterization and calibration

CERES-Rice 4.0 was calibrated and validated for the observed data of climate change effects on paddy rice, and then used to project future rice productivity under changing climate conditions such as elevated CO_2, precipitation, and temperature. Field experimental data from the temperature gradient field chamber (TGFC) with CO_2 enrichment system (Kim et al. 2011) provided a basis to simulate the projected shifts in atmospheric CO_2 concentration and air temperature based on the A1B scenario (IPCC 2007). The experiment was conducted at Chonnam National University (35° 10' N, 126° 53' E, 33 m above sea level) in Gwangju, Republic of Korea (ROK). The experimental treatments included two CO_2 levels (ambient CO_2, 371 ppm, and elevated CO_2, 622 ppm) and three temperature levels (ambient temperature and +1°C and +2°C elevated temperatures). The experiment was performed as a series of studies to investigate the effect of the simultaneous increases of atmospheric CO_2 and air temperature on temperate rice cultivars (*Oryza sativa* subsp. Japonica cv. NamPyeong, SaeGyeHwa, and UnKwang) grown in a paddy using TGFC. Using the 2009 - 2010 data, CERES-Rice 4.0 was evaluated for its performance in reproducing the field behavioral responses of paddy rice production to the altered climate conditions. The model simulated the measured values reasonably well, resulting in comparable significant differences within the CO_2, temperature, and cultivar regimes in both calibration and validation (Fig. 1). Further details can be found from the report by Kim et al. (2013).

The validated CERES-Rice 4.0 model was then used to simulate the recent decadal yield of paddy rice in a typical mountainous terrain which borders North and South Korea, the Haean Basin (38° 14 - 19´ N, 128° 5 - 10´ E) in Kangwon Province, ROK (Fig. 2). The model was recalibrated for the Haean rice cultivating conditions with the parameters (Table 1), which were derived as described below.

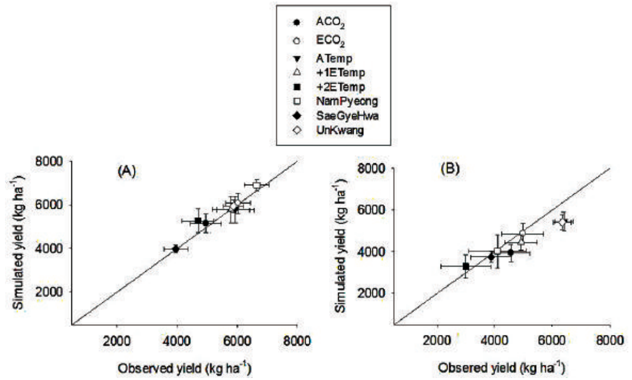

Fig. 1. Comparisons between simulated and measured rice grain yields for (A) calibration obtained in 2009 and (B) validation obtained in 2010 with the different treatments of CO_2, temperature, and cultivar. The measurement data were obtained from a temperature gradient field chamber (TGFC) with CO_2 enrichment experiment installed at Chonnam National University, Gwangju, ROK. Vertical and horizontal bars represent $\pm$1 SE for simulated and measured mean values, respectively. Symbols used for the treatments: ACO_2 = ambient CO_2 concentration (371 ppm); ECO_2 = elevated CO_2 concentration (622 ppm); ATemp = ambient temperature; +1ETemp = +1°C elevated from the ambient temperature; +2 ETemp = +2°C elevated from the ambient temperature; NamPyeong, SaeGyeHwa, and UnKwang = rice variety names.

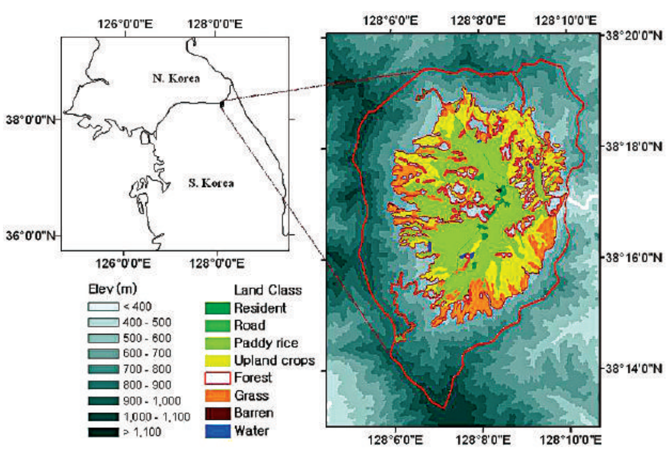

Fig. 2. Map and location of the research site for model applications in the highland Haean Basin in Kangwon, ROK. Elevation ranges from 400 to 1,100 m. The average annual air temperature is ~10.5°C at valley sites and ~7.5°C at the northern ridge line. Average precipitation is estimated at 1,200 mm with 50% falling during the summer monsoon.

The minimum driving variables for the model are as follows: (1) daily weather data of daily solar radiation, maximum and minimum temperatures, and daily precipitation; (2) soil chemical and physical information including soil physical and hydraulic properties, soil texture, and initial soil nitrogen and soil water status; and (3) typical crop management data such as planting dates, planting depth, row spacing plant population, and the amount and method of irrigation and fertilizer applications are also used. To determine genetic coefficients for simulations of the rice cultivars using the crop model, an iterative approach (Godwin et al. 1989) was employed through trial-and-error to match the measured yields with simulated values for the regions of application, respectively. The combination of cultivar parameters that give the minimum root mean square difference (RMSD), Eq. [4], is selected for further validations of the model.

Table 1. Generic coefficients developed for simulation of the paddy rice cultivar Odae using the CERES-Rice 4.0 model

No.	Coefficient: definition	Value
1	P1: Time period (expressed as growing degree days [GDD] in C above a base temperature of 9°C) from seedling emergence during which the rice plant is not responsive to changes in photoperiod.	200.0
2	P2O: Critical photoperiod or the longest day length (in hours) at which the development occurs at a maximum rate.	12.0
3	P2R: Extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in C) for each hour increase in photoperiod above P20.	35.0
4	P5: Time period (expressed as GDD in C) from beginning of grain filling (3 to 4 days after flowering) to physiological maturity with a base temperature of 9°C.	530.0
5	G1: Potential spikelet number coefficient as estimated from the number of spikelets per g of main culm dry weight (less lead blades and sheaths plus spikes) at anthesis.	70.0
6	G2: Single grain weight (g) under ideal growing conditions, i.e. non-limiting light, water, nutrients, and absence of pests and diseases.	0.210
7	G3: Tillering coefficient (scaler value) relative to IR64 cultivar under ideal conditions.	1.2
8	G4: Temperature tolerance coefficient.	1.0

Application of the validated model to projections of future rice production

CERES-Rice 4.0 was applied to simulate the projected effects of future climate on crop production in the Haean-myun area for 10-year periods centered on 2050 (2045 - 2054) and 2100 (2095 - 2104) with results from the A1B GHG emission scenario (IPCC 2007) applied in four GCMs (Table 2). Thus, temperature and precipitation projections for Haean were obtained with increased radiative forcing by 550 ppm (for the 2050 period) and 750 ppm (for the 2100 period) in atmospheric CO_2 concentration.

The GCM projected shifts in climate variables (Table 2) were then used over the 10-year (2001 - 2010) baseline of historical climate data (weather station in Haean, Kangwon of the Korea Meteorological Administration) as daily increases in minimum and maximum temperatures, in precipitation and solar radiation to approximate conditions in the later 21st century.

Table 2. Global circulation models (GCMs) used for climate change projections

No	Model ID, vintage	Host center institution	Atmospheric resolution (lat, long, °)
1	GFDL_CM2.0, 2005	Geophysical Fluid Dynamics Laboratory, USA	2.0 x 2.5
2	GFDL_CM2.1, 2005	Geophysical Fluid Dynamics Laboratory, USA	2.0 x 2.5
3	CCSM3, 2005	National Center for Atmospheric Research, USA	1.4 x 1.4
4	UKMO_HadGEM1, 2004	Hadley Centre for Climate Prediction and Research/Met-Office, UK	1.3 x 1.9

Table 3. Changes in temperature, precipitation, and solar radiation for the years centered on 2050 (2045 - 2054) and 2100 (2095 - 2104) as simulated with four-selected general circulation models (GCM) and based on the A1B scenario of IPCC. The changes were then averaged to obtain ensemble values, indicating the average shifts in climate compared to the mean values in the 10-year (2001 - 2010) baseline for Haean, ROK

Year	GCM	Temperature (°C)	Precipitation (mm day^{-1})	Solar radiation (MJ m^{-1} day^{-1})
2050	GFDL_CM2.0	+2.82	+0.51	-0.49
	GFDL_CM2.1	+2.42	-0.14	+0.50
	CCSM3	+1.81	+0.06	+0.60
	UKMO_HadGEM1	+2.09	-0.39	+0.30
	Ensemble	+2.28	+0.01	+0.23
2100	GFDL_CM2.0	+3.71	+0.86	-1.13
	GFDL_CM2.1	+2.88	+0.78	-1.04
	CCSM3	+2.36	+0.65	+0.28
	UKMO_HadGEM1	+3.70	-0.56	+0.95
	Ensemble	+3.16	+0.43	-0.24
10-year baseline		8.89	4.61	13.25

Responses to CO_2 and temperature

Sensitivity of CERES-Rice 4.0 to changes in atmospheric CO_2 and temperature inputs was examined based on the model fits to crop production data and validation for Haean. Simulations were conducted using 10 years of measured climate data as the reference upon which stepwise changes in CO_2 and temperature as single factors were superimposed. Thus, inter-annual variability is averaged into the apparent single factor response. The CO_2 concentration was increased from 200 to 1,200 µmol mol^{-1} in 100 µmol mol^{-1} steps. Temperature sensitivities were examined by increasing or decreasing the measured daily maximum and minimum temperatures by -3 to + 7°C in steps of 1°C.

Nitrogen-use efficiency (NUE) and water-use efficiency (WUE) were quantified using simulated grain yield in association with nitrogen absorbed (N_a), Eq. [2], and transpiration (T), Eq. [3], respectively:

$$NUE = \frac{Yield}{N_a} \qquad [2]$$

where yield is in kg ha^{-1} and N_a is in kg ha^{-1} at the time of harvest.

$$WUE = \frac{Yield}{T} \qquad [3]$$

where yield is in kg ha^{-1} and T is in mm determined over the crop growing season.

Statistical evaluations

Goodness-of-fit estimators used were P value from the paired t-test and correlation coefficient (r). In addition, two statistics were used to evaluate the model performance: model efficiency (ME) (Nash and Sutcliffe 1970), Eq. [4] and RMSD, Eq. [5].

$$ME = 1 - \frac{\sum_{i=1}^{n}(S_i - M_i)^2}{\sum_{i=1}^{n}(M_i - M_{avg})^2} \qquad [4]$$

$$RMSD = \left[\frac{1}{N}\sum_{i=1}^{n}(S_i - M_i)^2\right]^{1/2} \qquad [5]$$

where Si is the i^{th} simulated value, Mi is the i^{th} measured value, M_{avg} is the averaged measured value, and n is the number of data pairs. ME values are equivalent to the coefficient of determination (R^2), if the values fall around a 1:1 line of simulated versus measured data, but E is generally lower than R^2 and can be negative when the predictions are very biased.

The mean values of cumulative distribution functions (CDFs) for different projection periods were tested for significance of differences from the mean of baseline CDF using the Duncan's Multiple Range Test (DMRT, Duncan 1995) using PROC GLM (SAS version 9.2, Cary, NC). Kolmogorov-Smirnov (K-S) test using PROC NPAR1WAY was also performed for the data between the baseline CDF and each of the projection year's CDF. For this purpose, it was assumed that the year-to-year values within a CDF were statistically independent, because each year's data were separately simulated (not in a continuous simulation for all years) to minimize the temporal dependence. In all significant tests including DMRT and K-S test, a 95% confidence threshold was applied.

Results

Model parameterization and validation

Applying the model to the Haean environment, we could generally reproduce the observed rice yields of the last 10 years (2001 - 2010), simulated separately for calibration using 2006 - 2010 data and validation using 2001 - 2005 data (Fig. 3). Statistical analyses (e.g. in paired t-tests, P = 0.363 for calibration and P = 0.834 for validation) indicate, however, that there was no significant agreement between simulation and measurement, which we believe is attributable to the small sample size. Nevertheless, simulated and measured mean values lined up on the one-to-one line within ±1 SE both in calibration and validation. Assuming the current yield simulation acceptably agreed with the yield report, we applied the validated model to simulate effects of climate change on paddy rice production.

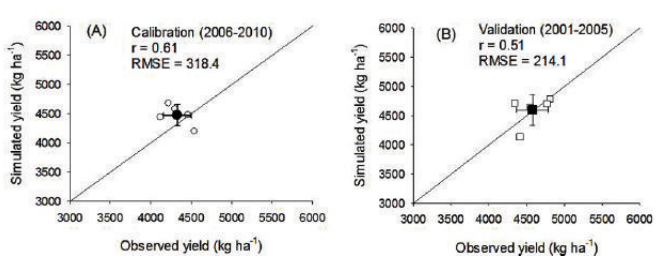

Fig. 3. Comparisons between simulated and observed rice grain yields for (A) in calibration and (B) validation using the data obtained at Haean-myon, Kangwon province for the recent 10-year period (2001 - 2010). Open circles and squares represent all the data points while the closed symbols represent the mean values. Vertical and horizontal bars represent ±1 SE for simulated and measured mean values, respectively.

Table 4. Statistical analysis of the independent effects of CO_2, precipitation and temperature, and the combined effects of CO_2, temperature, solar radiation, and precipitation on paddy rice yield, evapotranspiration (ET), and nitrogen absorbed (N_a) from the simulation data (Fig. 3)

Treatment	Year[1]	Yield		ET		N_a	
		K-S test[2]	CDF mean[3] (kg ha^{-1})	K-S test	CDF mean (mm)	K-S test	CDF mean (kg ha^{-1})
CO_2	Baseline	-	4,530^c	-	445.3^a	-	113.9^b
	2050	0.003	5,024^b	0.759	428.4^a	0.759	119.0^a
	2100	< 0.001	5,438^a	0.401	412.0^a	0.401	122.5^a
Precip.	Baseline	-	4,530^a	-	445.3^a	-	113.9^a
	2050	0.988	4,499^a	1.000	445.3^a	0.100	113.9^a
	2100	0.759	4,480^a	0.759	458.6^a	0.100	112.1^a
Temp.	Baseline	-	4,530^a	-	445.3^a	-	113.9^a
	2050	0.401	4,568^a	0.015	359.7^b	0.759	113.7^a
	2100	0.759	4,387^a	0.015	348.8^b	0.759	114.4^a
Comb.	Baseline	-	4,530^c	-	445.3^a	-	113.9^b
	2050	0.001	5,416^b	0.015	351.0^b	0.401	122.4^{ab}
	2100	< 0.001	6,000^a	0.015	338.0^b	0.055	131.0^a

[1] 2050 and 2100 represent the 10-year centers for 2045 - 2054 and 2095 - 2104, respectively.
[2] K-S refers to Kolmogorov-Smirnov test. The numbers in the column represent P-values at 95% confidence intervals.
[3] CDF represents cumulative distribution function. The values followed by the same lower-case letters (e.g., a, b, and c) within each column for each treatment are not significantly different based on the Duncan's Multiple Range Test (DMRT) at 95% confidence intervals.

Projected changes in rice yield in 2050 and 2100

Cumulative distribution functions (CDF) for simulated yields for the 10 baseline years (BL: 2001 - 2010) are compared with the projections [CO_2 (A - C), temperature (D - F), precipitation (G - I), and three factors combined (J - L)] for 2050 and 2100 in Fig. 4. A cumulative probability curve was preferentially used to present the results, because when a probability curve was used it differentiated well one from another (e.g. the projections in comparison with the BL). With increasing CO_2 concentration (i.e. 550 ppm for 2050 and 750 ppm for 2100), yield (Fig. 4A), and nitrogen absorption (Fig. 4C) increased with significant differences according to the DMRT at 95 % confidence intervals (Table 4). ET (Fig. 4B) decreased but it was not statistically significant. With precipitation change scenarios, yield (Fig. 4D), ET (Fig. 4E), and nitrogen absorption (Fig. 4F) neither increased nor decreased according to the statistical analyses (Table 4). With increasing temperatures, yield (Fig. 4G) exhibited at optimum in 2050 at higher CDF (> 0.5) but a continual decrease at lower CDF. Nitrogen absorption (Fig. 4I) showed an opposite pattern to the yield while ET (Fig. 4H) significantly decreased. With all three factors-combined for 2050 and 2100, yield (Fig. 4J) and nitrogen absorption (Fig. 4L) increased but ET (Fig. 4K) decreased according to the DMRT at 95% confidence intervals (Table 4).

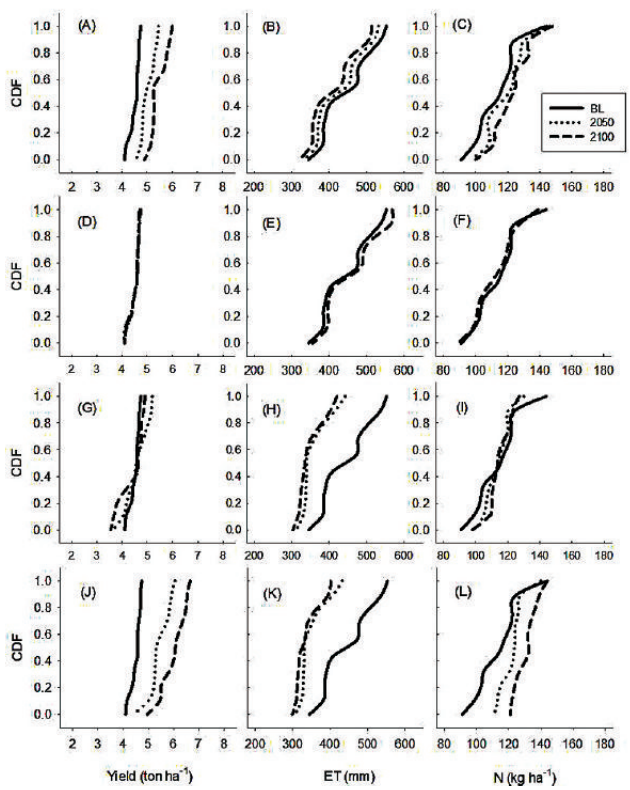

Fig. 4. Cumulative distribution function (CDF) of rice grain yield, evapotranspiration (ET), and nitrogen absorbed (N_a) for the cultivated rice in the Haean basin for the 2050s (2045 - 2054) and 2100s (2095 - 2104) relative to the simulated yield for the 10 baseline years (2001 - 2010). Each panel represents the projection results for effects of only CO_2 on (A) yield, (B) ET, (C) N_a; effects of precipitation on (D) yield, (E) ET, (F) N_a; effects of temperature on (G) yield, (H) ET, (I) N_a; and effects of all three factors-combined on (J) yield, (K) ET, (L) N_a, respectively.

Water-use efficiency (WUE) and nitrogen-use efficiency (NUE) showed an upward trend with increasing CO_2 concentrations and with the combined climate change scenarios for years 2050 and 2075 (Fig. 5). However, both WUE and NUE maintained constant with only precipitation change scenarios while WUE was higher under the elevated temperatures than the current (baseline) temperature.

Sensitivity of crop production-related components to CO_2 and temperature

Simulated yield, evapotranspiration, crop nitrogen uptake, water-use efficiency, and nitrogen-use efficiency generally

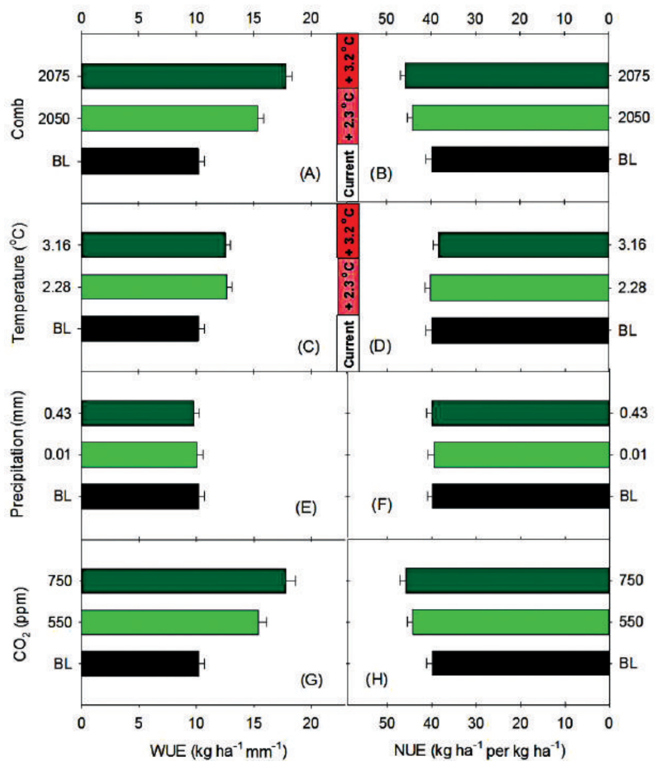

Fig. 5. Water-use efficiency (WUE) and nitrogen-use efficiency (NUE) for the baseline and future projections centered on 2050 (2045 - 2054) and 2100 (2095 - 2104) in relation to CO_2, precipitation, temperature independently, and the combined effect (Comb).

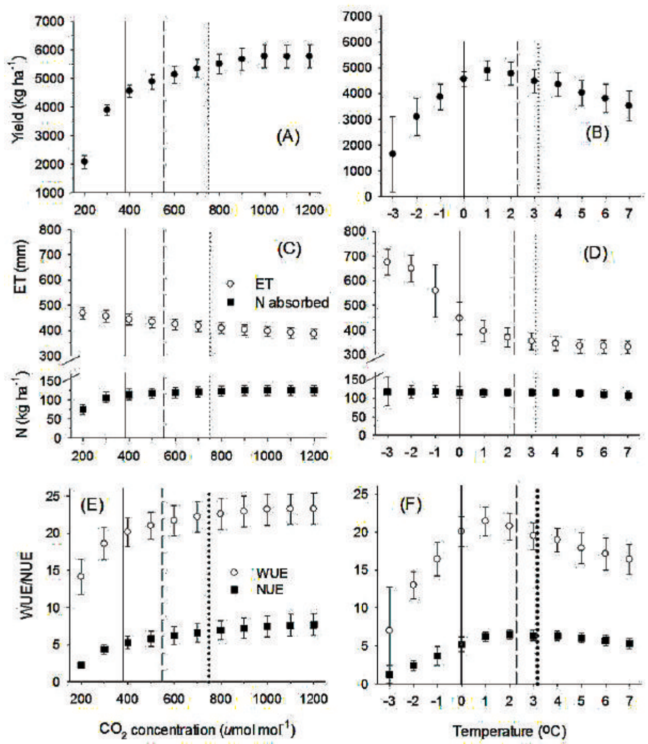

Fig. 6. (A and B) Projected responses of grain yields, (C and D) evapotranspiration, ET, and nitrogen taken up into biomass, and (E and F) nitrogen-use efficiency, NUE, and water-use efficiency, WUE, to changing CO_2 concentration and temperature, respectively. Solid, dashed, and dotted lines represent the current, years 2050 and 2100 status variables, respectively. Vertical bars of the data points represent $\pm$1 SE (n =75). WUE (kg ha^{-1} mm^{-1}) = yield/ET; NUE = yield/N (kg ha^{-1} per kg ha^{-1}).

exhibited curvilinear dependencies with respect to CO_2 concentration and temperature (Fig. 6). Simulations were carried out with 10 years of climate data and the results averaged and presented. Grain yield (Fig. 6A) increased in response to CO_2 concentration in a parabolic pattern, increasing rapidly to the current level of CO_2 (~ 385 ppm) and apparently saturating at ~1,000 ppm. ET (Fig. 6C) gradually decreased in response to the increasing CO_2 concentration. Nitrogen uptake (Fig. 6C), WUE, and NUE (Fig. 6E) rapidly increased until the current CO_2 conditions with only small further increments as CO_2 increased above ambient.

Grain yield response to temperature changes (Fig. 6B) exhibited a maximum in the 1°C change scenario from the current temperature, and a slow linear decrease with greater temperature increments. ET (Fig. 6D) decreased rapidly until the current temperature with the rate of decrease growing smaller as temperature increased above the current conditions. Nitrogen uptake (Fig. 6D) changed only a little in response to temperature. Both WUE and NUE (Fig. 6F) reached maxima with the +1°C change from the current temperature and linearly decreased with larger temperature increases. According to these results, temperature appears to be currently below the optimum for the rice cultivar under the environmental conditions of the mountainous terrain.

Adaptation strategies in response to climate changes

Rice yields under the 'combined influences of temperature, precipitation, solar radiation, and CO_2' were simulated to identify the optimal planting and nitrogen application windows that would further improve the possible effects of climate change on paddy rice (Figs. 7A and B). We repeated all the above simulations with the rice planted at 20 and 10 days before, and also 10 and 20 days after, their actual planting dates, as well as with extra nitrogen application amounts of 50, 100, and 150 kg ha^{-1}, in order to see whether these simulated management changes would increase crop yields. We also made an adaptation strategy using the cultivar parameters (see Table 1) to explore a potentially adaptable optimum trait of each cultivar for the changing climate conditions (Figs. 7C - F). Four parameters of interest (i.e. P1, P2R, P5, and G1) were selected and simulations were performed at -10, +10, +20, and +30 GDD (in cases of P1, P2R, and P5), and coefficient (in case of G1) from the parameterized base values to see adaptabilities to the elevated temperatures predominantly.

Yields as a function of the 10 day-early planting scheme increased by 8.6% in the climate change scenario of year 2050 (Fig. 7A). Yields as a function of the additional N application schemes increased by 4.4 ~ 6.9% with additions greater than 50 kg ha^{-1} (Fig. 7B). Meanwhile, yields increased by up to 6.4, 11.0, 0.6, and 10.3% with increasing the genetic parameter values of P1, P2R, P5, and G1, respectively (Figs. 7C - F). For both management and genetic trait adjustment schemes, it appears that additional yield gains can be

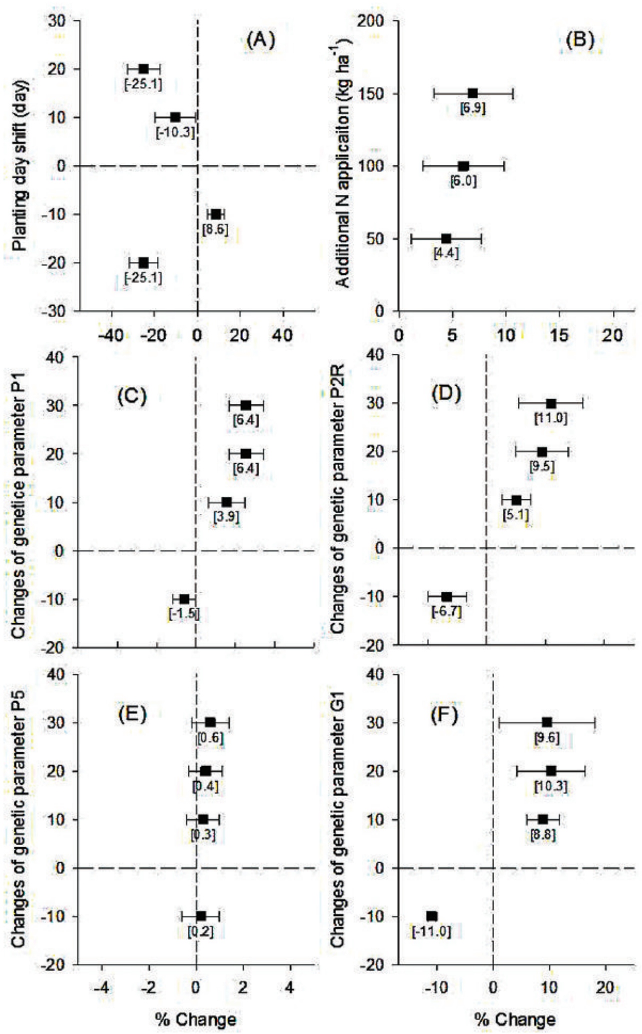

Fig. 7. Percent changes in paddy rice yield in response to adjustment in management practices for (A) planting date and (B) nitrogen application as well as cultivar parameter changes of (C) P1, (D) P2R, (E) P5, and (F) G1, i.e. increase and decreases in cultivar parameter vs. base parameter values (0) for the 2050s (2045 - 2054) as described in the text. Vertical and horizontal dashed lines, and horizontal bars represent the current conditions of managements and grain yields, and ± SE (n = 10) for the mean of each change value, respectively.

achieved under changing climate in comparison to the baseline (BL).

Discussion

The recent report by Kim et al. (2013) showed that simulation could reproduce the field measurement of paddy rice under the CO_2, temperature, and cultivar regimes. Similar to previous findings by other studies which concluded that models are capable of simulating CO_2 effects on wheat crop yield (Asseng et al. 2004; Ko et al. 2010; Tubiello et al. 1999), they demonstrated this with CERES-Rice 4.0 using the paddy rice data obtained from the temperature gradient field chamber (TGFC) and with CO_2 enrichment system. While the model seems applicable in the current study, it still must be improved to answer more sophisticated research questions about field crop physiology of scientific interest, such as related to detailed crop development, growth performance, and plant-water-soil-nutrient interactions.

Adams et al. (1990) reported that future changes in temperature and precipitation can lead to increases in crop water demands and reductions in yield, while increased CO_2 is predicted to enhance crop yield in the US. Our results suggest that the CO_2 fertilization effects would dominate over the climate change impacts of other factors on future paddy rice production in this highland mountain region. This finding is consistent with the report by Saseendran et al. (2000) who concluded that a yield increase in rice under rain-fed conditions is possible under the projected future climate. The yield increases in our study were estimated to be 19.6% in 2050 and 32.5% in 2100, which have a reasonable agreement to the report by Horie et al. (1995). They projected yield increases at higher latitude regions such as Sapporo at +16.6% using a modified SIMRIW crop model simulated under the CO_2 concentration of 700 ppm with the GISS model-predicted climate. Our demonstrative simulation study for various mountainous terrains (Fig. 8) shows yield increases of 5.5, 8.6, and 21.7% in 2050, and 17.5, 20.6, and 32.8% in 2100 at 236 m (Sinnam), 352 m (Shinrim), and 540 m (Jinbu), respectively. These yield increases are mainly attributable to positive impacts of the elevated CO_2 concentrations.

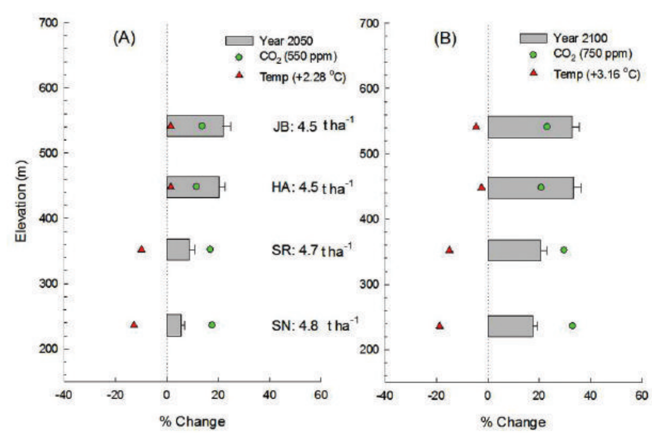

Fig. 8. Percent changes of paddy rice yield in response to climate change in (A) 2050 and (B) 2100 at the different elevated areas (JB = Jinbu, HA = Haean, SR = Shinrim, and SN = Sinnam) of the mountainous terrains. Vertical dashed lines and horizontal bars represent the current conditions of grain yields and ± SE (n = 10) for the mean of each change value, respectively.

The elevated temperatures are projected to influence negatively from lower elevations than about 400 m. We also found that CO_2 fertilization effect would dominate over the other climate change scenarios in WUE and NUE in relation to the combined climate change scenarios in the mountainous regions (see Fig. 5).

While the present results show a general agreement with those of Adams et al. (1990) and Hatfield et al. (2011), different climate change projections with maximum and minimum temperature variability might provide different results. The results may also be influenced by different atmospheric resolutions as well as origins of the GCMs (see Table 1). Evaluation of the GCM models was not a scope of this study, and we hypothesized that all the projections are probable. In addition, there are still questions whether current crop models are suitable for future conditions; we cannot be entirely sure that this is guaranteed by validations that utilize current climate conditions. Therefore, further studies should be undertaken to address these issues with more advanced climate change projections and with better process-based models of the agricultural system. More advanced crop models could provide better quantification of possible interactions of CO_2 effects with climate and other environment factors such as temperature, soil water, and nitrogen.

The sensitivity responses to CO_2 concentration and temperature from simulations are qualitatively similar to those reported for rice cultivation conditions of temperate climate by Kim et al. (2013) as well as tropical humid climate by Saseendran et al. (2000). In addition, our results are comparable with reports for wheat in a Mediterranean environment of Australia (Lugwig and Asseng 2006) and in a semi-arid environment of the United States (Ko et al. 2010). The sensitivity results imply that under future climate conditions (IPCC 2007), yield should be increased by CO_2 fertilization effects (see Fig. 6A), but potentially being leveled in 2050 and slightly decreased in 2100 (see Fig. 6B) in comparison with the current conditions due to the influence of temperature increases. Given the results obtained with other grain crops, it is our opinion that these conclusions on sensitivity to climate change variables are generally applicable for describing responses of rice yield, ET, nitrogen absorption, WUE, and NUE to CO_2 and temperature.

Future crop production is possibly adapted to climate change by employing alternative management practices and new crop genotypes adapted to projected future climate conditions (Dhungana et al. 2006). The changes in crop yield under both management and genetic trait adjustment scenarios in response to climate change should be attributable to the dominant effects of temperature and CO_2 affecting yield. Suitable cultivar selection to adapt to warming conditions is achievable only with sufficient plasticity in photoperiod and vernalization requirements of crops (Masle et al. 1989). In our simulation study (see Fig. 7), such characteristics are taken into account to provide an additional adaptation strategy.

Conclusions

The validated CERES-Rice 4.0 model shows that the rice yield at Haean-myun in Kangwon Province of Korea, which is a typical mountainous highland area used for paddy rice production in monsoonal East Asia, should increase during the remainder of this century mainly due to an increase of CO_2. We also examined the sensitivity of rice to individual climate change variables for future model applications as well as additional adaptation options to the potential climate change impact on yield. The simulations are comparable with some complex model simulations of photosynthetic carbon uptake in reproducing the dynamics of whole plant level crop growth (Tubiello and Ewert 2002). A validated model is a good tool for analyzing the possible impacts of climate change on rice production in the region. The CERES-Rice 4.0 model responded satisfactorily to the climate change-deriving factors including CO_2 and temperature. We found that CO_2 fertilization effects would dominate over the climate change impacts for the rice yield in this highland terrain. We also found that additional yield gains would be allowed with practicing management options as well as improving genetic traits in response to future climate. The results from the model demonstrate the promise of the model for simulating climate change impacts on rice production with variable climate from a local to regional scale under monsoon climate systems.

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References

Adams RM, Rosenzweig C, Peart RM, Ritchie JT, McCarl BA, Glyer JD, Curry RB, Jones JW, Boote KJ, Allen LH. 1990. Global climate change and US agriculture. Nature 345: 219-224

Ahuja LR, Rojas KW, Hanson JD, Shafer MJ, Ma L. 2000. Root zone water quality model-Modeling management effects on water quality and crop production. Water resources publications, LLC, CO, USA, pp 372

Ainsworth E. 2008. Rice production in a changing climate: a meta-analysis of responses to elevated carbon dioxide and elevated ozone concentration. Global Change Biol. 14: 1642-1650

Allen LH, Boote KJ, Jones JW, Valle RR, Acock B, Rogers HH, Dahlman RC. 1987. Response of vegetation to rising carbon dioxide: photosynthesis, biomass, and seed yield of soybean. Global Biochem. Cycles 1: 1-14

Asseng S, Jamieson PD, Kimball B, Pinter P, Sayre K., Bowden JW, Howden SM. 2004. Simulated wheat growth affected by rising temperature, increased water deficit and elevated atmospheric CO_2. Field Crops Res. 85: 85-102

Coats B. 2003. Global rice production. In CW Smith, RH Dilday, eds, Rice origin, history, technology and production, Wiley, Hoboken, NJ, USA, pp 247-470

Dhungana P, Eskridge KM, Weiss A, Baenziger PS. 2006. Designing crop technology for a future climate: an example using response surface methodology and the CERES-Wheat model. Agric. Syst. 87: 63-79

FAO. 2002. World Agriculture: Towards 2015/2030

Summary Report. FAO, Rome, Italy
Godwin DC, Ritchie JT, Singh U, Hunt LA. 1989. A user's guide to CERES-wheat – v2.10. International fertilizer development center, Muscle Shoals, pp 89
Hatfield J, Boot K, Kimball B, Ziska L, Izaurralde R, Ort D, Thomson A, Wolfe D. 2011. Climate impacts on agriculture: implications for crop production. Agron. J. 103: 351-370
Horie T, Kropff MJ, Centeno HG, Nakagawa H, Nakano J, Kim HY, Ohnishi M. 1995. Effect of anticipated change in global environment on rice yields in Japan, In S Peng et al., eds, Climate change and rice, Springer-Verlag. Berlin, Germany, pp 291-302
Iizumi T, Yokozawa M, Nishimori M. 2011. Probability evaluation of climate impacts on paddy rice productivity in Japan. Climatic Change 107: 394-415
IPCC 2007. Summary for Policymakers. In B Metz, OR Davidson, PR Bosch, R Dave, LA Meyer et al., eds, Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Review, Cambridge, United Kingdom and New York, NY, USA
IRRI. 2002. Rice Almanac: Source book for the most important economic activity on earth, Ed 3, CABI Publishing, Oxon, UK
Jamieson PD, Berntsen J, Ewert F, Kimball BA, Olesen JE, Pinter PJ, Porter JR, Semenov MA. 2000. Modeling CO_2 effects on wheat with varying nitrogen supplies. Agric. Ecosyst. Environ 82: 27-37
Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ, Ritchie JT. 2003. The DSSAT cropping system model. Eur. J. Agron. 18: 235-265
Kim H, Ko J, Kang S, Tenhunen J. 2013. Impacts of climate change on paddy rice yield in a temperate climate. Global Change Biol. 19: 548-562
Kim H, Lim S, Kwak J, Lee D, Lee S, Ro H, Choi W. 2011. Dry matter and nitrogen accumulation and partitioning in rice (Oryza sativa L.) exposed to experimental warming with elevated CO_2. Plant Soil 32: 59-71
Kirschbaum MUF. 2000. Forest growth and species distribution in a changing climate. Tree Physiol. 20: 209-322
Ko J, Ahuja L, Kimball R, Anapalli S, Ma L, Green TR, Ruane AC, Wall G, Pinter P, Bader DA. 2010. Simulation of free CO_2 enriched wheat growth and interactions with water, nitrogen, and temperature. Agric. For. Meteorol. 150: 1331-1346
Long SP, Ainsworth EA, Leakey ADB, Nosberger J, Ort DR. 2006. Food for thought: Lower-than-expected crop yield stimulation with rising CO_2 concentrations. Science 312: 1918-1921
Lugwig F, Asseng S. 2006. Climate change impacts on wheat production in a Mediterranean environment in Western Australia. Agric. Syst. 90: 159-179
Masle J, Doussinault G, Sun B. 1989. Responses of wheat genotypes to temperature and photoperiod in natural conditions. Crop Sci. 29: 712-721
Matthews R, Kropff M, Horie T, Bachelet D. 1997. Simulating the impact of climate change on rice production in Asia and evaluating options for adaption. Agric. Syst. 54: 399-425
Nash JE, Sutcliffe JV. 1970. River flow forecasting through conceptual models: Part I. A discussion of principles. J. Hydrol. 10(3): 282-290
Peart RM, Jones RB, Curry K, Boote KJ, Allen LH. 1989. Impacts of climate change on crop yield in the Southern U.S.A. In JB Smith, DA Tirpak, eds, The potential effects of global climate change on the United States, Report to Congress, U.S. Environmental Protection Agency, EPA-230-05-89-050, Washington D.C., Appendix C
Reyenga PJ, Howden SM, Meinke H, McKeon GM. 1999. Modeling global climate change impacts on wheat cropping in south-east Queensland. Environ Model & Software 14(4): 297-306
Saseendran SA, Singh KK, Rathore LS, Singh SV, Sinha SK. 2000. Effects of climate change on rice production in the tropical humid climate of Kerala, India. Climatic Change 44: 495-514
Tubiello FN, Ewert F. 2002. Simulating the effects of elevated CO_2 on crops: approaches and applications for climate change. Eur. J. Agron. 18: 57-74
Tubiello FN, Rosenzweig C, Kimball BA, Pinter PJ, Wall GW, Hunsaker DJ, LaMorte RL, Garcia RL. 1999. Testing CERES-wheat with Free-Air Carbon Dioxide Enrichment (FACE) experiment data: CO_2 and water interactions. Agron. J. 91: 247-255
Williams JR, Jones CA, Kiniry JR, Spanel DA. 1989. The EPIC crop growth model. Transaction of ASAE 32(2): 497-511