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Uncertainty of Simulated Paddy Rice Yield using LARS-WG Derived Climate Data in the Geumho River Basin, Korea

LARS-WG 기후자료를 이용한 금호강 유역 모의발생 벼 생산량의 불확실성

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ABSTRACT

This study investigates the trends and uncertainty of the impacts of climate change on paddy rice production in the Geumho river basin. The Long Ashton Research Station stochastic Weather Generator (LARS-WG) was used to derive future climate data for the Geumho river basin from 15 General Circulation models (GCMs) for 3 Special Report on Emissions Scenarios (SRES) (A2, A1B and B1) included in the Intergovernmental Panel on Climate Change (IPCC) 4th assessment report. The Food and Agricultural Organization (FAO) AquaCrop, a water-driven crop model, was statistically calibrated for the 1982 to 2010 climate. The index of agreement (IoA), prediction efficiency (R^2), percent bias (PBIAS), root mean square error (RMSE) and a visual technique were used to evaluate the adjusted AquaCrop simulated yield values. The adjusted simulated yields showed RMSE, NSE, IoA and PBIAS of 0.40, 0.26, 0.76 and 0.59 respectively. The 5, 9 and 15 year central moving averages showed R^2 of 0.78, 0.90 and 0.96 respectively after adjustment. AquaCrop was run for the 2020s (2011-2030), 2050s (2046-2065) and 2090s (2080-2099). Climate change projections for Geumho river basin generally indicate a hotter and wetter future climate with maximum increase in the annual temperature of 4.5 °C in the 2090s A1B, as well as maximum increase in the rainfall of 45 % in the 2090s A2. The means (and ranges) of paddy rice yields are projected to increase by 21 % (17-25 %), 34 % (27-42 %) and 43 % (31-54 %) for the 2020s, 2050s and 2090s, respectively. The A1B shows the largest rice yield uncertainty in all time slices with standard deviation of 0.148, 0.189 and 0.173 $t \cdot ha^{-1}$ for the 2020s, 2050s and 2090s, respectively.

Keywords: GCM; AquaCrop; climate change; paddy rice; uncertainty; yield

I. Introduction

Rice (*Oryza sativa*) is grown in a wide range of climatic conditions, from river deltas to mountainous regions across the world (Seck et al., 2012). The optimum temperature for the normal development of rice ranges from 27 to 32 °C and it is widely accepted that climate change affects global agriculture through rising temperatures (Kumar et al., 2012). Impacts of changing precipitation regimes and increased atmospheric carbon dioxide (CO_2) levels on rice yields vary across spatial and temporal scales (Ye et al., 2013). The effects of climate change on rice production are of particular concern in most of Asia because it is the staple food (Zhang et al., 2010). The capacity to make regional yield prediction before harvest is important in many aspects of agricultural decision-making (Wang et al., 2010). Most crop-weather models are applicable to individual plots but can be broadly applied to larger scales based on their capability to interpret the impacts of weather variability on crop status and the projected yield at a regional basis (Yun, 2003). Crop models including AquaCrop (Raes et al., 2011), can be used to evaluate the future impacts of climate change on crop development, growth and yield by combining future climate conditions obtained from GCMs (Nkomozepi and Chung, 2011).

In models, phenological crop development is controlled by the cumulative daily mean temperature above a minimum threshold value and higher temperatures shorten the length

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of successive rice crop stages and consequently the total rice crop cycle (Supit, 2012). The AquaCrop model is preferable because a less complex structure is assumed and the number of input parameters is reduced by the use of a linear relation between biomass growth rate and transpiration through a water productivity parameter (Abedinpour et al., 2012). AquaCrop growth simulation model is therefore one of the most useful tools used to assess the impact of environment, crop management, genetics and breeding strategies, as well as climate change and variability on growth and yield (Craufurd et al., 2013). The simplicity of AquaCrop lies in the readily available input data and graphic user interface that makes it user-friendly (Singh et al., 2013).

Yun (2003) was able to project the rice production of each county in Korea with reasonable agreement about a month earlier than the actual harvest date. However, the crop model predictions of responses of plant-processes to the climate possess some degree of uncertainty generated through process and parameter systematic and random errors (Dono et al., 2013). For example in Gwangju, rice yields have been estimated to be reduced by 22.1 and 35.0 % and conversely, to be increased by 12.6 and 22.0 % in a different emissions scenario by the end of the 21st century (Kim et al., 2013). The quantification of uncertainty is required to assess the forecast accuracy and aide in climate change adoption and mitigation management decisions (Nkomozepi and Chung, 2012). In a previous study, the paddy irrigation water requirement was predicted to increase by between 1.1 to 7.9 % as a result of climate change in the Geumho river basin (Chung and Nkomozepi, 2012). The objective of this study was to extend the previous study and to assess the trends and uncertainty of rice yield predictions given by multiple GCMs for the Geumho river basin.

II. Material and Methods

1. Study Area

The field data are representative of various experiments conducted in paddy fields near Daegu, the Republic of Korea (35° 45' N, 128° 45' E) which lies in the Geumho

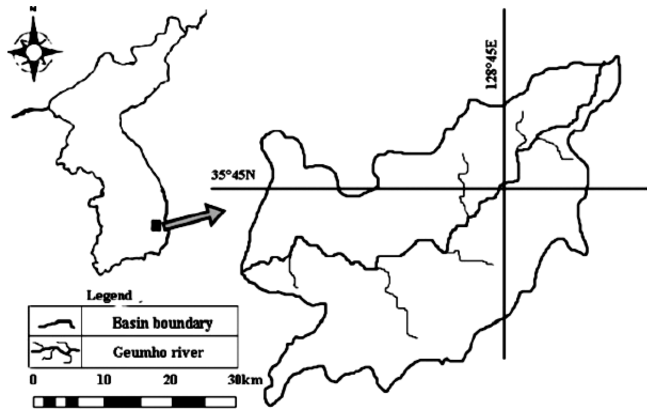

Fig. 1 Geumho River basin location map (Chung and Nkomozepi, 2012)

river basin (Fig. 1). The Geumho river basin is under the Asian monsoon climate with an annual mean temperature and precipitation of 14.1 °C and 1,064 mm, respectively, for the years 1982 to 2010. The average gross duty of paddy irrigation water per unit area in the Geumho river basin was reported to be 12,300 m^3 ha^{-1} excluding effective rainfall of 3,300 m^3 ha^{-1}, and the average rice yield before milling was 6.01 ton ha^{-1} for the same period (Chung and Nkomozepi, 2012, Korean Statistical Office).

2. Climate Data

The change factor statistical adjustment and downscaling technique has previously been applied in related studies (Chung, 2010; Chung and Nkomozepi, 2012). The change factor method involves obtaining future weather variables by applying relative or absolute change factors to a predefined baseline range of weather variables. The LARS-WG was used in this study and is a better approach in that it considers the changes in both the mean and variability in the future. The observed monthly climate data i.e. daily temperatures, rainfall, wind speed, relative humidity and sunshine hours for Daegu and Yeongchon were obtained from the Korean Meteorological Administration (KMA) and the 1975s (1961-1990) were adopted as the baseline period.

The observed weather data is used to determine the parameters that specify the probability distributions of weather variables and their correlation coefficients used in LARS-WG. Future climate data were then generated stochastically by perturbing the baseline climate with the outputs from the GCMs using LARS-WG. The LARS-WG model simulates precipitation occurrence using a two-state, first order Markov chain: precipitation amounts on wet days using a gamma distribution; temperature and radiation components using first-order tri-variate auto-regression that is conditional on precipitation occurrence (Semenov and Barrow, 1997). 15 GCM (listed in Table 3) simulation results for 3 Special Report on Emissions Scenarios (SRES) scenarios (A2, A1B and B1) included in the IPCC 4th assessment report were used in this study. The greenhouse gas emissions scenarios are a reflection of the uncertainty of the future and GCMs striving to represent complex natural systems (Nkomozepi and Chung, 2012). In general, the A2, A1B, and B1 scenarios represent future scenarios of continuously increasing population, new and efficient technologies, and ecologically friendly, respectively. The annual mean atmospheric CO_2 concentration is estimated to reach 856, 717, and 549 ppm by 2100 for A2, A1B, and B1, respectively (IPCC, 2007). Brief descriptions of the 15 GCMs utilized in this study including their resolutions and the organizations and countries in which they were developed are available on http://www.rothamsted.ac.uk/mas-models/larswg/GCMs.htm. Climate data for the 2020s (2011-2030), 2050s (2046-2065) and 2090s (2080-2099) time slices were used in this study. These three time horizons also correspond to the different requirements of different stakeholders.

3. AquaCrop Model

AquaCrop model has a structure that overarches the soil-plant-atmosphere continuum. It includes the soil, with its water balance; the plant, with its development, growth and yield processes; and the atmosphere, with its thermal regime, rainfall, irrigation, evaporative demand and carbon dioxide concentration. Additionally, some management aspects are explicitly considered, as they will affect the soil water balance, crop development and therefore crop yield. The functional relationships between the different model components are depicted in Fig. 2 and detailed descriptions can be found in Raes et al. (2011).

Input parameters for the AquaCrop model include crop, soil, irrigation and cultural management. Soil properties

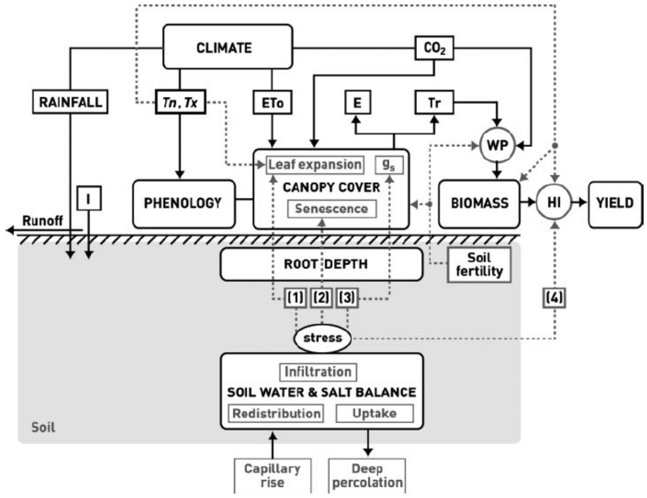

Fig. 2 Schematics of AquaCrop showing the main components of the soil-plant-atmosphere continuum (Raes et al., 2011).

Table 1 Symptoms of heat stress in rice plants (Shah et al., 2011)

Growth Stage	Threshold temperature (℃)	Symptoms
Emergence	40	Delay and decrease in emergence
Seedling	35	Poor growth of the seedling
Tillering	32	Reduced tillering and height
Anthesis	34	Poor anther dehiscence and sterility
Flowering	35	Floret sterility
Grain formation	34	Yield reduction
Grain ripening	29	Reduced grain filling

such as texture and rootable soil depth were investigated by experiments. A review by Shah et al. (2011) summarized the recent research findings on the responses of rice to high temperature, and reported the symptoms of heat stress as shown in Table 1. The temperatures shown here were considered in the crop parameters input file. Output includes crop growth, soil water balance, and yield and water productivity. In this study, rice yields are not affected by rainfall because simulations were for full irrigated conditions.

4. AquaCrop Model Output Adjustment and Evaluation

Despite the lack of consensus and comprehensive guidance to facilitate AquaCrop model evaluation in terms of the accuracy, model results are used for assessment on different temporal and spatial scales. Model calibration and validation is required and generally involves the alteration of parameters to compare simulated values with observed values (Tragoolram et al., 2011). The AquaCrop model, when calibrated and validated is suited for studies of future climate change because of its descriptive realism and reasonably good predictive power shown in various environments (Nkomozepi and Chung, 2011). In this study, AquaCrop simulated yield values were first adjusted for 1982-2000 and then evaluated for 2000 to 2010. Observed yield (Y_a) values for the evaluation period were obtained from the Korean Statistical Information Service (KOSIS). AquaCrop simulated rice yields (Y_{AC}) for the study area were generated by AquaCrop using the best possible available input data for each year from 1982 to 2010 representative of the Geumho river basin. It was assumed that the Y_a and Y_{AC} could be fitted to second order polynomial equations as a function of time and were related by a factor K, also a function of time (year) as shown in equation 1. An iterative procedure was carried out to derive K and transform Y_{AC} to be closer to Y_a.

$$Y_a = KY_{AC};\ K = f(year) \tag{1}$$

where Y_a is the actual yield, Y_{AC} is the simulated yield, K is a transformation function of year.

A function derived for K for 1982-2000 was validated for 2001-2010 and the process repeated until a satisfactory function which would be applied in the future simulated data were obtained. The final K adjusts Y_{AC} to Y_s, which would be used in the assessment of future rice yields in the study area. While it is known that a good performance at simulating the Y_a does not guarantee that future simulations will be accurate, the calibration, evaluation or simple adjustment processes increase the likelihood that the future simulation values will be accurate and reliable. Commonly used statistics such as the index of agreement (IoA), prediction efficiency (R^2), percent bias (PBIAS), root mean square error (RMSE) and a visual technique were used to evaluate the adjusted AquaCrop simulated yield values (Equations 2 to 5).

$$RMSE = \left[n^{-1} \sum_{i=1}^{n} \left(Y_{s_i} - Y_{a_i} \right)^2 \right]^{0.5} \tag{2}$$

$$PBLAS = \left[\frac{\sum_{i=1}^{n} \left(Y_{a_i} - Y_{s_i} \right) \times 100}{\sum_{i=1}^{n} Y_{a_i}} \right] \tag{3}$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n} \left(Y_{a_i} - Y_{s_i} \right)^2}{\sum_{i=1}^{n} \left(Y_{a_i} - \overline{Y}_a \right)^2} \right] \tag{4}$$

$$IoA = 1 - \left[\frac{\sum_{i=1}^{n} \left(Y_{s_i} - Y_{a_i} \right)^2}{\sum_{i=1}^{n} \left(|Y'_{s_i}| + |Y'_{a_i}| \right)^2} \right] \tag{5}$$

where n is the number of pairs of observed (Y_a) and adjusted simulated (Y_s) rice yield data, Y'_s and Y'_a are the respective residuals.

III. Results and Discussion

1. Future Climate Change

Climate change projections for Geumho river basin generally indicate a hotter and wetter future climate as shown by the box and whisker plots in Fig. 3. The results indicate a maximum annual temperature increase of 4.5 ℃ in the 2090s A1B, as well as a maximum rainfall increase of 45 % in the 2090s A2. Nevertheless, some models predicted decreases in rainfall of up to 14 % in the 2020s A2. As a result of the assumed higher CO_2 emissions the A2 generally shows higher changes in temperatures and rainfall. It can also be noted that the changes shown in Fig. 3 will not elevate mean temperatures above the threshold temperatures shown in Table 1 but could drive daily or shorter span temperature above thresholds. In one study, exposure to 41 ℃ for 4 hours at the flowering stage caused irreversible damage and plants became completely sterile (Shah et al., 2011).

2. AquaCrop Model Output Adjustment and Evaluation

The results reveal an increasing trend in both the actual and AquaCrop simulated rice yields for the period 1982-

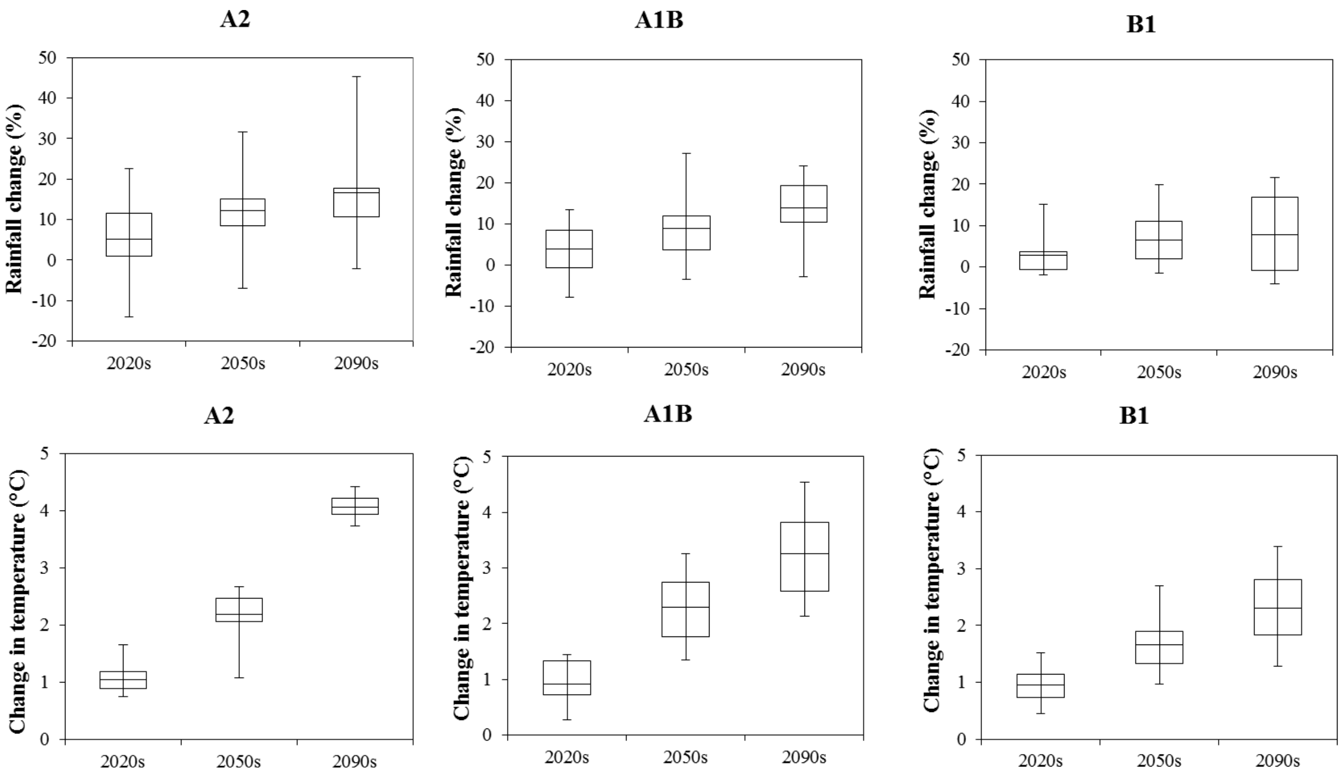

Fig. 3 The GCM predicted changes in rainfall and mean temperature

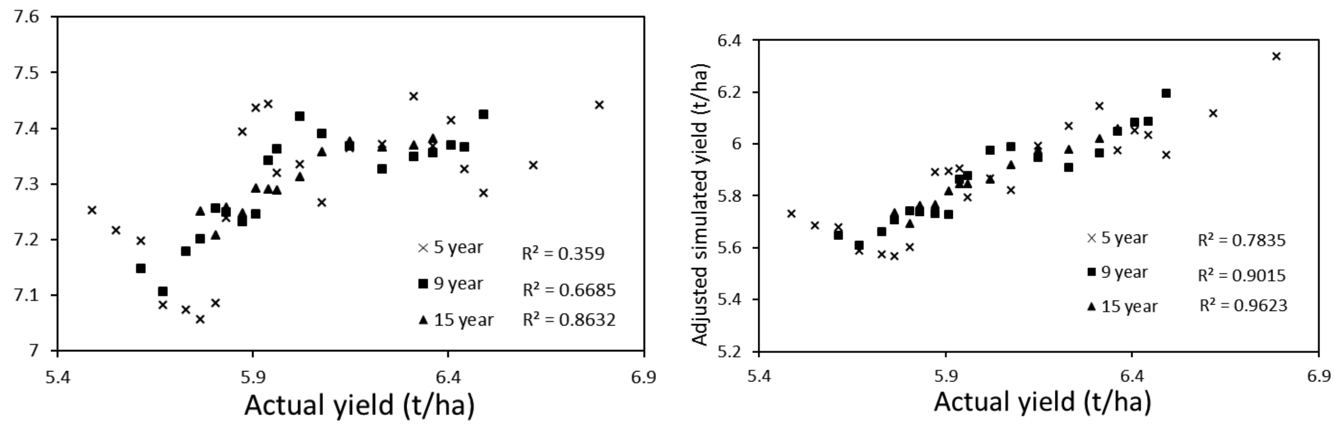

Fig. 4 AquaCrop model evaluation, (a) before adjustment and (b) After adjustment

2010. While a linear approach that assumes a constant rate of increase would be applicable, a second order polynomial approximation of the yield was used to account for the latest enhanced warming. The actual yield and the simulated yield values are shown in Fig. 4 (a). There are discrepancies between the two data sets in trend and variability. The actual and simulated yields transformed by the adjustment and evaluation process are shown in Fig. 4 (b). The iterative process was used to account for the uncertainty that arises as a result of the increase from field to larger catchment scale (e.g planting dates, cultivars and management practices etc that are distributed continuously throughout the Geumho river basin).

The adjusted simulated yields showed RMSE, NSE, IoA and PBIAS of 0.40, 0.26, 0.76 and 0.59 respectively. These values show that the adjusted simulated rice yield values are improved. IoA is a descriptive parameter that varies between 0 and 1, with the value of 1.0 indicating excellent agreement (Todorovic et al., 2009). NSE ranges between $-\infty$ and 1.0 and values between 0.0 and 1.0 are viewed as acceptable levels of performance. Values less than 0 indicate that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance (Moriasi et al., 2006). The PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts and the results of this study shows that the simulated values are slightly larger than observed values. The 5, 9 and 15 year central moving averages showed prediction efficiency (R^2) of 0.36, 0.67 and 0.86 respectively before adjustment and 0.78, 0.90 and 0.96 respectively after adjustment (Fig. 4). Longer period mean values were almost identical.

3. Rice Yield and Water Productivity

There is strong agreement between the 15 GCMs on the future rice yield as shown in Table 2 and Fig. 5. Rice yields will increase in the future with the CO_2 fertilization and increased temperatures. The A2 Scenario shows the highest increases in yield of up to 54 % in the 2090s and the least increases in the 2020s B1. The means (and ranges) of paddy rice yields are projected to increase by 21 % (17-25 %), 34 % (27-42%) and 43 % (31-54 %) for the 2020s, 2050s and 2090s, respectively. The interquartile range magnitude ranges from 2-4 % meaning there is little variability in the simulated yield. This is because models can show small differences in temperature but still be within the stipulated optimum temperatures. Large changes in yield are encountered when temperature go below 10 ℃ and beyond 35 ℃.

Table 2 Predicted changes in the rice yield compared to the baseline (%)

GCM*	2020s			2050s			2090s		
	A2	A1B	B1	A2	A1B	B1	A2	A1B	B1
BCM2	-	22	19	-	36	32	-	47	34
CGMR	-	19	-	-	35	-	-	48	-
CNCM3	21	-	-	35	-	-	49	-	-
CSKMK3	-	21	21	-	39	33	-	48	35
FGOALS	-	24	22	-	39	33	-	50	37
GFCM21	22	25	20	38	35	31	53	46	35
GIAOM	-	22	19	-	42	30	-	48	35
HADCM3	20	18	19	35	33	28	50	42	31
HADGEM	20	21	-	35	34	-	-	-	-
INMCM3	19	19	18	35	35	30	53	48	34
IPCM4	21	21	18	34	34	28	49	43	31
MIHR	-	20	17		34	27	-	43	32
MPEH5	22	24	21	39	35	31	54	47	32
NCCCSM	19	-	-	35	-	-	52	-	-
NCPCM	21	23	-	38	38	-	-	-	-
Average (range)	21 (17-25)			34 (27-42)			43 (31-54)		

* Bjerknes Centre for Climate Research (BCM2), Canadian Centre for Climate Modeling and Analysis (CGMR), Centre National de Recherches Meteorologiques (CNCM3), Australia's Commonwealth Scientific and Industrial Research Organization (CSKMK3), Institute of Atmospheric Physics (FGOALS), Geophysical Fluid Dynamics Laboratory (GFCM21), Goddard Institute for Space Studies (GIAOM), UK Meteorological Office (HADCM3 and HADGEM), Institute for Numerical Mathematics (INMCM3), Institute Pierre Simon Laplace (IPCM4), National Institute for Environmental Studies (MIHR), Max-Planck Institute for Meteorology (MPEH5), National Centre for Atmospheric Research (NCCCSM and NCPCM).

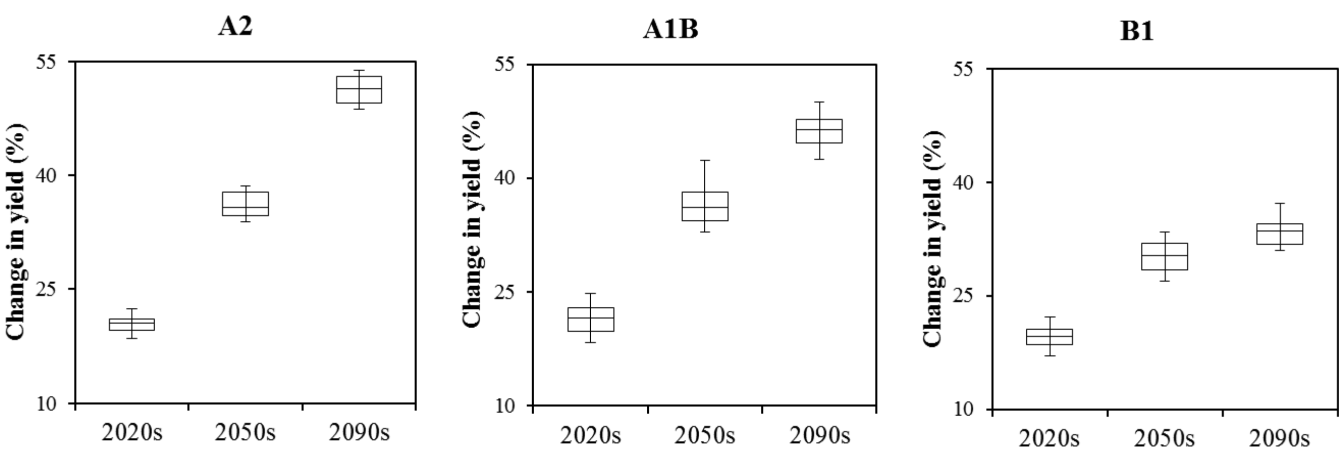

Fig. 5 Simulated changes in rice yield from the baseline (%)

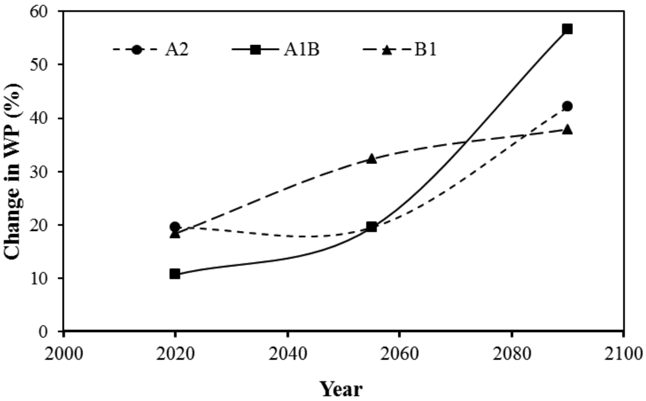

Fig. 6 Simulated changes in the water productivity (WP)

The water productivity (WP) (Kg m^{-3}) is defined by Kassam and Smith (2001) as the ratio of the rice yield to the water consumption by evapotranspiration. There was little variation in changes in the WP across the GCMs and it was also predicted to increase in the future (Fig. 6). Generally WP is impacted by the changes in crop water requirements and simulated marketable yield. The highest increase was in 2090s A1B (57 %) and the lowest increase was 2020s A1B (11 %). This is beneficial because to meet the food requirement, crop management must adapt to climate variability, for example, by using crops that produce more biomass per amount of water used at the plant and the ecosystem levels (Tallec et al., 2013).

4. Uncertainty in the Predicted Rice Yield

The mean and standard deviation (SD) of the simulated future paddy rice yield are shown in Table 3. As pointed out in the previous section, the yield was predicted to increase in the future. The SD, an indicator of variability and uncertainty, was predicted to increase in the future within each emissions scenario. The A1B shows the largest uncertainty in all time slices with SD of 0.148, 0.189 and 0.173 t ha^{-1} for the 2020s, 2050s and 2090s, respectively. However, when the yields from all scenarios are compared, the standard deviation is shown to decrease although it is still much greater than the intra-scenario standard deviation.

Due to time and computational limitations, monthly values were used in this study and therefore extreme values in future climate scenarios are leveled off. The difficulty in accurate prediction of the potential impacts of climate change to yields further adds to the uncertainty. This study only considers climate change impacts on rice yields and further research should address how adaptation strategies such changing planting dates, other crop varieties etc., affect crop yield.

Table 3 Mean and standard deviation of the baseline and future paddy rice yield (unit: t ha^{-1})

Scenario	Baseline	2030s		2050s		2090 s	
		Mean	SD	Mean	SD	Mean	SD
A2	6.95	8.38	0.091	9.44	0.122	10.52	0.142
A1B		8.45	0.148	9.46	0.189	10.18	0.173
B1		8.31	0.109	9.06	0.153	9.29	0.139
Total		8.34	0.132	9.33	0.243	9.95	0.540

IV. Conclusion

This study presented predictions of the impact of climate change on rice yields using climate data generated by 15 GCMs. The AquaCrop model was successfully statistically calibrated (adjusted) for the 1982 to 2010 climate. In general, regardless of the SRES scenario the rice crop was predicted to benefit from the increasing temperature and atmospheric CO_2 concentration. There is strong agreement between the 15 GCMs on the future rice yield and the average projected increase in the rice yields is 21 %, 34 % and 43 % for the 2020s, 2050s and 2090s, respectively from the baseline of 6.95 t ha^{-1}. The A1B shows the largest yield uncertainty in all time slices with standard deviation of 0.148, 0.189 and 0.173 t ha^{-1} for the 2020s, 2050s and 2090s, respectively. By the end of the 21st century rice yields could increase by up to 51 % and water productivity by up to 57 %. Although the research has reached its aims, there were some unavoidable limitations which were addressed by the assumptions of uniform variety and management practices in all farms in the study area and in the future. The study focuses solely on the impact of climate change therefore further research should address other factors affecting crop yield.

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