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Rice Growth and Yield Responses to Climate Variabilities and Scenarios

Le Huu Phuoc[1], Irfan Suliansyah[2], Feri Arlius[3], Irawati Chaniago[2], Nguyen Thi Thanh Xuan[1], Nguyen Tran Nhan Tanh[4] and Pham Van Quang[1,*]

[1]*Faculty of Agriculture and Natural Resources, An Giang University, Vietnam National University, An Giang, Vietnam*
[2]*Faculty of Agriculture, Andalas University, West Sumatra, Indonesia*
[3]*Faculty of Agricultural Technology, Andalas University, West Sumatra, Indonesia*
[4]*Faculty of Engineering - Technology - Environment, An Giang University, Vietnam National University, An Giang, Vietnam*

([*]Corresponding author's e-mail: pvquang@agu.edu.vn)

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Abstract

Rice is the essential food crop of An Giang Province. Vietnam and the whole world are facing several problems hindering climate change, such as increased temperature and CO_2 concentration that many manufacturers' companies and managers need to estimate output to make production plans or adjust policies. In this study, the model known as SIMPLE was applied to simulate the biomass and yield of rice in 2 crop seasons Autumn - Winter 2020 (AW) and Winter - Spring 2020 - 2021 (WS), in Cho Moi district, An Giang province, Vietnam (10° 23' 47"N, 105° 27' 41"E) and analyzed the effects of climate variabilities and scenarios on simulation results. Heat stress showed a relatively negative impact on the growth and development of rice in AW more seriously than WS due to climate variabilities. Climate change scenario RCP8.5 (RCP - Representative Concentration Pathway) has predicted that atmosphere temperature may increase above 4 °C and CO_2 concentration to reach 900 ppm by the end of the 21st century. As a result, from the model, for every 100 ppm CO_2 concentration increase, the cumulative rice biomass increased by 8 and 10 % in AW and WS, respectively. Moreover, conditions assumed from the model that increased 5 °C caused a decrease in cumulative biomass up to 7.2 % in AW season compared to 3.1 % in WS season. However, with responses of 5 °C increasing in the model, rice yield decreased relatively rapidly from 8.5 % in AW and 7 % WS.

Keywords: Biomass, Climate change, Crop modeling, CO_2, Rice, Temperature, Yield

Introduction

Rice (*Oryza sativa* Linnaeus) is an essential food crop in Vietnam, Southeast Asia, and many countries worldwide. Vietnam has 7.2 million hectares of rice (grown with 2 to 3 crops a year), of which the Mekong Delta accounts for 13 % of the area but accounts for over 50 % of the country's rice-growing area. Annually exporting 6 - 6.5 million tons of rice [1]. Mekong Delta has been heavily affected by climate change and sea level rise [2].

According to the annual assessment of the countries most affected by extreme weather events in the period 1997 - 2016, Vietnam ranked 5th in the Global Climate Risk Index in 2018 and 8th in the Global Climate Risk Index in long-term climate risk (CRI) [3]. Besides the influence of irregular and extreme rain and sunlight, such as too much rain or sunshine in a too short period, and lack of irrigating water, the other effect seems to be extreme temperatures following the annual warming trend [4]. Compared with the temperature background from 1986 - 2005, the annual average temperature in An Giang province (a southwestern province of the Mekong Delta) increased by 0.8 °C (0.4 - 1.2 °C) in 2016 - 2035, increased by 1.4 °C (1.0 - 2.0 °C) in 2046 - 2065 with RCP4.5. With the current trend, the increase in temperature would likely go faster. Under the RCP8.5 scenario, the temperature would rise by 0.9 °C (0.6 - 1.3 °C) in 2016 - 2035 and increase by 1.9 °C (1.4 - 2.6 °C) 2046 - 2065. The highest temperature could reach 42.5 °C in 2020; 43 °C in 2050, and 44 °C in 2100 [5]. Increased night temperature negatively affects the reproductive stage of rice, reducing the effect of increased atmospheric CO_2 concentration, dry matter accumulation, and yield reduction [6]. According Betts *et al.* [7], CO_2 concentrations by the end of this century would be 750 ppm on average (from 520 to 930 ppm). Increased CO_2 concentration improves dry matter accumulation and yield increases, but nutrition may reduce [8].

Applying digital transformation and high technology to agriculture in An Giang province is still in its infancy and receiving attention from An Giang province and the agricultural management agency. Managers, rice production companies, and cooperatives need a tool to plan and make decisions in advance, estimate their productivity to be exported or the amount of straw after each crop to be used for other purposes. Therefore, biomass and yield simulation have been identified as a quick and economical solution to meet the demand for commercial rice production and the need for agricultural management of the provinces for the present and future under climate change conditions. More and more simulation modeling-based are being developed in rice production for planning and decision-making, especially concerning the changing climate. For essential crops like wheat, several agricultural simulation models like EPIC, DSSAT, APSIM, CropSyst, AquaCrop have been created to date [9]. However, they require a large number of data and parameters [10], but data are usually not readily available or are wait consume time to analyze in laboratories because of complicated parameters. For example, the widely used model is the DSSAT, which requires many genotype-specific parameters to define a new crop [11]. The EPIC model [12] needs 22 parameters, the AquaCrop model [13] needs 29 parameters, while SIMPLE only needs 13 parameters [14]. In this study, simulations were utilized by applying a modeling known as SIMPLE, which had not been studied before in Vietnam, to predict biomass and yield in rice in framing and climate change scenarios. This model overcomes the limitations of the previous models as it is relatively more uncomplicated, has fewer parameters, is fast and economical. An advantage of this model is that it is possible to add more models such as fertilizer soil nutrition, and to use for many plants like oil and fiber crops, vegetables, and fruits, agricultural food, and feed.

This study's primary goal is to evaluate rice biomass and yield by applying a standard dynamic crop modeling known as SIMPLE. The model is based on recognized crop physiology principles. The objectives were to (i) execute SIMPLE model using the field-grown rice cultivar with readily available experimental data; (ii) perform a sensitivity analysis to examine the effects of temperature changes and CO_2 concentration on biomass and yield.

Methods and materials

Experiment site

Two experiments were carried out in 2 typical rice crops in the Mekong Delta (AW 2020 and WS 2020 - 2021) at Hoa Binh Commune, Cho Moi district, An Giang province, Vietnam (10° 23' 47"N, 105° 27' 41"E). The soil was a clay loam with an organic matter content of 1.6 %. The summarized weather conditions of Autumn - Winter 2020 (AW) and Winter - Spring 2020 - 2021 (WS) are presented in **Table 1**.

Table 1 Summary of the climatic features of the experiment site for the 2 seasons.

Climatic features	AW	WS
Total rainfall (mm)	874.1	89.1
Number of rainy days	62.0	38.0
Mean temperature (°C)*	30.5 ± 2.1	29.0 ± 1.9
Mean Radiation (MJ $m^{-2}d^{-1}$)**	15.8 ± 4.5	19.7 ± 3.3

*recorded by Thermo Recorder TR-72Ui (T&D Corp, Japan)
**data from the Agroclimatology Community of the POWER Data Access Viewer

Experiment method

The experiment field was divided into 3 equal areas (repeated 3 times). The aim is to average the crop parameters needed to be in the model. Rice seed was sown directly on an area of 2,000 m^2 of 3 rice crops field. The crop management, soil, and weather parameters were also collected and calculated during the experiments to input data.

The density of rice sowing was 15 kg of rice seedling per ha, fertilized with the formula 116-45-30, divided 3 times as the farming technique in the area 1) first fertilizer (10 days after sowing [DAS] 30 % N - 50 % P_2O_5 - 50 % K_2O, 2) second fertilizer (22 DAS) 40 % N - 50 % P_2O_5, and 3) third fertilizer (44 DAS) 30 % N - 50 % K_2O.

Crop parameters recorded during cultivation: Total vegetative biomass every 10 days (above ground)

Experiment parameters

Time variable

Time of sowing, maturity, harvest

Crop management

1) Seed name, seeding date, harvest date (days of the year).
2) Total vegetative biomass every 10 days (above ground), total dry matter, harvest index, grain yield.

Soil parameters

Name of soil type, Available Water Content - AWC, Runoff Curve Number - RCN, Deep drainage coefficient - DDC, Root zone depth - RZD (mm).

Weather parameters

Daily air temperature (°C); annual rainfall (mm/day); daily solar radiation - SRAD (MJ m^{-2} day^{-1}); concentration of CO_2 in the atmosphere (ppm).

Method of measurement

Soil factors

Sampling: at each place, take 5 points (4 points at 4 corners and 1 in the middle) with a depth of 0-20cm, mixing them into a sample (about 01 kg, analyzed at the laboratory at An Giang University).

Table 2 Some analysis methods of soil parameters were used in the research.

Soil parameters	Analysis methods
pH	Water extraction: soil ratio of 5:1, measured by pH meter
EC	Water extraction: soil ratio of 5:1, measured by EC machine
N total	Modified Kjeldahl method (TCVN[1] 6498[2]:1999)
P_2O_5 total	Indicator value of total phosphorus content in soil (TCVN 7374: 2004). Spectrophotometric method for determination of phosphorus dissolved in sodium hydroxide solution
Potassium exchange	Method of determining potassium exchange (TCVN 8662:2011). Using 1.0 mol/l ammonium acetate (pH = 7.0) dissolved available potassium in the soil. Determination of potassium content in the soil sample, extracted by emission spectroscopy method
Organic matter (%)	Determination of total organic carbon by Walkley - Black method (TCVN 9294: 2012)
Porosity (%)	Bulk density = weight of dry soil (105 °C) in sampling ring of 98,125cm^3 and particle density ratio = 2.65 d/cm^3 to calculate porosity (%) = 100 (1-bulk density / 2.65)
Deep drainage coefficient-DDC	It is the amount of deep drainage water divided by the total amount of input water (rainfall + irrigation), determined by the water balance equation: $D = P + I - ET_a - \Delta S$, where D is the amount of drainage water from the bottom of the soil layer; P, I, and Et_a is rainfall, irrigation, and the amount of actual evaporation; and ΔS: Change the amount of water stored in the soil. Use the Lysimeter method
Root zone depth-RZD (mm)	Field survey by digging or drilling
Available Water Content (AWC) - the amount of water available to plants	Determined based on pF curve, through the formula: $\theta_{AWC} = \theta_{FC} - \theta_{WP}$; θ_{FC}: Soil water content at field capacity and θ_{WP}: Permanent wilting point.
Soil water retention curve (pF curve)	The soil water characteristic curve (pF curve) is analyzed by sandboxes system and pressure plate apparatus with 8 value of pF: pF0.4, pF1.0, pF1.5, pF1.7, pF2, pF2.5, pF3.1, and pF4.2. Then soil water retention curve is developed by fitting the model of van Genuchten (1980) to the pressure-soil moisture content data. Soil samples taken by the method specified in the standard TCVN 6651:2000, including undisturbed samples, soil samples will be saturated in water for 48 hours, then using the sandbox system for soil water pressure head from 0 to 0.1 bar (pF: 0 to 2) and pressure plates for pressure heads from 0.3 to 15 bar (pF: 2.5 to 4.2).

[1] *TCVN: Vietnam Standard*
[2] *6498: Number of a decision in Vietnam*

Weather parameters:

Using day-to-day measuring devices at the experiment site

The rice cultivar used in the experiment was a high-yielding variety (IR50404) with a growing period of 90 to 95 days. The details of soil properties and management for the experiments are shown in **Table 3**.

Table 3 Soil properties at the research site.

Items	Characteristics
Soil texture percentages	
Sand	30
Silt	42
Clay	28
Soil	
Total nitrogen (%)	0.17
Total phosphorus (%P_2O_5)	0.03
Exchangeable potassium (cmol kg^{-1})	0.23
Field capacity (cm^3 cm^{-3})	0.18
Available water capacity [AWC (cm^3 cm^{-3})]	0.14
Runoff curve number (RCN)	84
Deep drainage coefficient (DDC)	0.18
Root zone (RZD - mm)	329
Groundwater level (cm)	35.8
Fertilizer applies (kg ha^{-1})	
N	90
P_2O_5	52
K_2O	45

Model description

In SIMPLE model, the crop yield is calculated as the product of the harvest index (HI) and the fraction of the above-ground cumulative biomass from sowing to maturity as follows:

$$Yield = Biomass\_cum \times HI \tag{1}$$

here, HI is the harvest index, calculated as the ratio of grain to total dry matter, and Biomass_cum is calculated by:

$$Biomass\_cum_{i+1} = Biomass\_cum_i + Biomass\_rate \tag{2}$$

Biomass_rate is the daily biomass growth rate of the current day, and $Biomass\_cum_i$ is the cumulative biomass until the current day. Biomass_rate is determined as Eq. (3). This is based on the idea of radiation use efficiency - RUE of which plant canopy intercepts daily photosynthesis active radiation (PAR) and converts to crop biomass [15]. The daily variation in crop biomass is influenced by stress variables such as high temperature, drought, and atmospheric CO_2 concentration [16].

$$Biomass_{rate} = \begin{matrix} Radiation * fSolar * RUE * 〚fCO〛\_2 * f(Temp) \\ * \min((f(Heat), f(Water)) \end{matrix} \tag{3}$$

where fsolar is the fraction of the solar radiation intercepted by the crop canopy based on Beer-Lambert's law of light attenuation", fCO_2 is the CO_2 impact, f(Heat) is the heat stress, and f(Water) is the water stress [16,17].

fSolar for leaf growth and senescence period is calculated as follows:

$$Solar = \begin{cases} \frac{f_{Solar\_max}}{1+e^{-0.01(TT-I_{50A})}}, & \text{leaf growth period} \\ \frac{f_{Solar\_max}}{1+e^{-0.01(TT-(T_{sum}-I_{50B}))}}, & \text{leaf senescence period} \end{cases} \tag{4}$$

where I50A is the cumulative temperature needed for leaf area development to intercept 50 % of solar energy during canopy closure; I50B is the cumulative temperature needed from maturity to intercept 50 % of radiation during canopy senescence; fSolar-max is the maximum of radiation that a crop intercept.

TT is the cumulative mean temperature which is calculated as follows:

$$\Delta TT = \begin{cases} T - T_{base}, & T > T_{base} \\ 0, & T \leq T_{base} \end{cases} \tag{5}$$

$$TT_{i+1} = TT_i + \Delta TT \tag{6}$$

Here, TT_i: The cumulative mean of the temperature of day i, ΔTT: The daily added mean temperature; T: The daily average temperature $(T_{MAX} + T_{MIN})/2$; and T_{base}: The base temperature for plant phenological development [16,17].

Temperature stress, heat stress, drought stress, water stress, and CO_2 impact are calculated by Eqs. (7) - (12), referred to as cited in Zhao *et al.* [14]; Asseng *et al.* [18]; Bindi *et al.* [19], Ewert *et al.* [20]; Priestley and Taylor [21]; Ritchie *et al.* [22]; Ittersum *et al.* [23]; and Woli *et al.* [24].

$$f(Temp) = \begin{cases} 0, & T < T_{base} \\ \frac{T-T_{base}}{T_{opt}-T_{base}}, & T_{base} \leq T < T_{opt} \\ 1, & T \geq T_{opt} \end{cases} \tag{7}$$

T_{base} and T_{opt}: The base and optimal temperature for crop growth, respectively of a particular specie.

$$f(Heat) = \begin{cases} 1, & T_{max} \leq T_{heat} \\ 1 - \frac{T-T_{base}}{T_{opt}-T_{base}}, & T_{heat} < T_{max} \leq T_{extreme} \\ 0, & T_{max} > T_{extreme} \end{cases} \tag{8}$$

With T_{heat}: Threshold temperature of biomass growth rate begins to be reduced by heat stress, and $T_{extreme}$: the extreme temperature threshold of biomass growth rate reaches 0 because of heat stress.

$$f(CO_2) = \begin{cases} 1 + S_{CO_2}(CO_2 - 350), & 350ppm \leq CO_2 < 700ppm \\ 1 + 350.S_{CO_2}, & CO_2 > 700ppm \end{cases} \tag{9}$$

Here, S_{CO2}: Relative increase of RUE of every 1 ppm to elevated CO_2 from atmospheric CO_2 concentration.

$$f(water) = 1 - S_{water} \times ARID \tag{10}$$

ARID: standardized index: $ARID = 1 - \frac{\min(ETo,\ 0.096PAW)}{ETo}$ (11)

PAW: Plant-available water content in the soil texture [24]. ETo: the reference evapotranspiration, computed by Priestley and Taylor [25]. The radiation interception is affected when the drought stress becomes severe enough, and the calculation is similar to the AquaCrop model [26].

$$fSolar\_water = \begin{cases} 0.9 + f(Water), & f(Water) \leq 0.1 \\ 1, & f(Water) > 0.1 \end{cases} \tag{12}$$

Model parameters and input data

There are 13 parameters used to run a SIMPLE model, as shown in **Table 4**, with 4 for cultivar characteristics. Tsum, I50A, and I50B were determined from the observations of experiment data and the air temperature data. The HI was calculated as described in Wnuk *et al.* [27]. The remaining parameters were from the literature.

Table 4 Parameter literature values of the rice model.

Name	Description	Value	Note
Cultivars parameters			
T_{sum}	Thermal time requirement from sowing to maturity in daily mean (°C days)		*
HI	Harvest index		*
I50A	Thermal time requirement after sowing fraction of light interception to reach 50 % (°C days)		*
I50B	Represents natural senescence. Thermal time requirement from maturity backward for a light interception to reach 50 % (°C days)		*
Species parameters			
T_base	Base temperature (daily mean T) for phenology development and growth (°C)	10	[28]
T_opt	Optimal temperature (daily mean T) for biomass growth (°C)	30	[14]
RUE	Radiation use efficiency (above ground biomass + below ground, if the harvestable product is below ground) (g $MJ^{-1}m^{-2}$)	1.24	[14]
I50maxH	The maximum daily increase in I50B due to heat stress (°C d)	100	[14]
I50maxW	The maximum daily increase in I50B due to water stress (°C d)	10	[14]
MaxT	The threshold for daily Tmax to start accelerating senescence due to heat stress (°C)	34	[14]
Extreme_T	Daily Tmax threshold when RUE becomes 0 due to heat stress (°C)	50	[14]
CO2_RUE	The relative increase in RUE per 1 ppm elevated CO_2 above 350 ppm	0.08	[14]
S_Water	Sensitivity of RUE to drought stress (ARID index)	1.0	[14]

*Adjusted or calibrated to suit the conditions where the experiment was performed.

Data calibration and validation of the model were implemented by doing several simulations using cultivar parameter sets within a reasonable range (excluding keeping soil parameters the same for all the trials). In both experiments, the biomass was measured periodically every 10 days from sowing to maturity. The observed data were used to validate the simulation outputs. Tsum (cumulative daily mean temperature) was set so that the canopy cover at the harvest date was about 80 %. After each model run, I50A and I50B were recalibrated based on daily mean temperature above T_{base} and iterative simulation until good fits to experimental results. Then the best-fit set of cultivar parameters was used to test sensitivity analysis.

Input variables required to run the SIMPLE model include weather (daily maximum/minimum temperature, rainfall, and solar radiation), atmospheric CO_2 concentration, sowing/harvesting date, irrigation, initial variables, and four variables characterizing the soil (**Tables 3 and 4**), including fraction of plant available water-holding capacity (AWC; one number for entire soil profile, limited by rooting depth), runoff curve number (RCN), deep drainage coefficient (DDC), and root zone depth (RZD, a fixed maximum depth) (**Table 5**).

Table 5 Input variables needed to run SIMPLE model.

Input variables	Description	Unit
Weather	Daily maximum temperature (TMAX)	°C
	Daily minimum temperature (TMIN)	°C
	Daily rainfall amount (RAIN)	mm
	Daily solar radiation (SRAD)	MJ m^{-2} day^{-1}
Soil characteristics	Atmospheric CO_2 concentration	ppm
	Soil water holding capacity (AWC)	-
	Runoff curve number (RCN)	-
	Deep drainage coefficient (DDC)	-
	Root zone depth (RZD)	mm
Crop management	Sowing date (SowingDate)	-
	Harvesting date (HarvestDate)	-
Initial	Biomass (InitialBio)	Kg
	Cumulative temperature (InitialTT)	°C day
	Solar radiation interception (InitialFsolar)	-

Notes: The daily solar radiation (MJ m^{-2} day^{-1}) was collected from the Agroclimatology Community of the POWER Data Access Viewer (NASA Langley Research Center (LaRC) POWER Project funded through the NASA Earth Science/Applied Science Program (https://power.larc.nasa.gov/data-access-viewer/) for a period of 2 years from 2020 to 2021 at the experiment location. The air temperature was recorded by Thermo Recorder TR-72Ui (T&D Corp, Japan). Point data collected for study location (10° 23' 47"N, 105° 27' 41"E).

Sensitivity analysis

Sensitivity analysis uses the methods of Morris [29] and FAST (Fourier Amplitude Sensitivity Test) [30]. In this study, the Moris method is the method in which the parameters would be selected and discretized in the same standard space, covering the entire volume of space in which they can transform. This method allows for determining the most critical parameters among the parameters of a complex model. At the same time, it allows determining whether the effects of the parameter are insignificant, linear, nonlinear, or interactive with other parameters. This arrangement will be based on the concept of the primary effect (EE) of a given parameter. The evaluation will be done by computing r iterations (r orbitals), at r different points in the input, then the averages will be determined, standard deviation from which to draw conclusions about the sensitivity of each input parameter.

$$\mathrm{EE}_i = \frac{f(x_1,.....x_{i-1,},x_i+\Delta I,x_{i+1},...x_n)-f(X)}{\Delta i} \tag{13}$$

here f(X) and $f(x_1,.....x_{i-1,},x_i+\Delta I,x_{i+1},...x_n)$ are the model's response to the variation of 1 interval A of the variable x. This interval A depends on p (the number of expected values of the variable x) in real space.

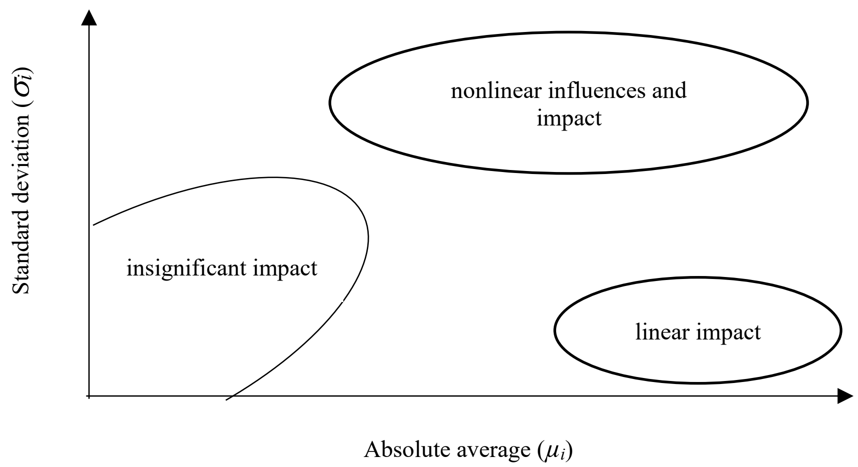

Figure 1 Classify the influence of input parameters by the Morris method [31].

Morris method is a screening method for influencing factors. This method will determine the fluctuations of each parameter through the mean (μ), and standard deviation (σ) of each parameter. When analyzing sensitivity using the Morris method, the number of run models can be set, giving the mean and standard deviation of the input parameters data. The larger the mean (μ) and the standard deviation (σ) reflect that the more significant the effect of that parameter on yield or biomass will be and the stronger the interaction with other parameters. In other words, the sensitivity of those parameters in the model is higher.

The set of parameters that gave the best fit between simulation and observation was used as a control treatment to test the sensitivity for a better understanding of the impact of future climate change on agricultural production. Sensitivity analysis was implemented with incremental changes in mean temperature change: +1, +2, +3, +4, +5 °C, and atmospheric CO_2 concentration change: +50, +100, +150, +200, and +250 ppm.

In FAST method, the nonlinear influence parameters have high sensitivity and intense interaction with other parameters, which will significantly impact the input results. Parameters with different mean and standard deviation are screened by Morris method, but it is unknown which parameter has the primary sensitivity and by what percentage influence. The FAST method will help to quantitatively evaluate each parameter (FAST refers to the influence scale from 0 - 1).

Model calibration and validation

Calibration was performed using the measured data sets, and the model was validated using metric data sets of the cropping seasons of the rice seasons AW 2020 and WS 2020-2021. Due to the simulated (S_i) and observed (O_i) data, the model validation was conducted using the relative root mean square of error (RRMSE) criterion Eq. (14).

$$RRMSE = \left[\frac{1}{n} \sum_{i=1}^{n} (S_i - O_i \right]^{1/2} \tag{14}$$

where n is the sample number, Oi and Si are the observed and observed values of the ith observation (i = 1 to n)

For RRMSE, values closer to zero imply a good fit between observed and simulated yields [32]. A zero value for RRMSE means that the model accurately predicts the observations.

After building the simulation yield model and the actual yield, the model will be tested. Evaluating the accuracy of the crop yield simulation, the efficiency coefficient (Nash Sutcliffe Efficiency - NSE) would be used to compare the values between observed and crop modeling.

$$NSE = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - O_{mean})} \tag{15}$$

This coefficient is proposed by Nash-Sutcliffe (1970) [33]. NSE ranges from negative infinity to 1. A value of NSE equal to 1 represents a perfect model fit, and negative NSE values indicate that the mean observed value is a better predictor than the simulated value.

Results and discussions

Weather and growth characteristics

Both the Autumn - Winter 2020 (AW) and Winter - Spring 2020 - 2021 (WS) crops were grown with the same IR50404 rice variety. The characteristics of temperature and rainfall in An Giang province, Vietnam have quite distinct seasons (wet and dry seasons). The AW crop was sown on August 3rd, 2020, in the last months of the rainy season. Meanwhile, the WS crop was planted in early December of 2020, the month with the lowest temperature of the year (**Figure 2**). **Figure 2** shows that the average, minimum and maximum temperatures of the WS crop were lower than AW. The time from sowing to maturity of the AW crops was 86 days, and the WS was 92 days. The lower temperature tends to prolong the growing period of the plant.

Rainfall was uniformly distributed in the AW season, while in the WS crop, it is almost concentrated about 30 days after sowing (**Figure 3(a)**). Daily solar radiation in AW and WS were shown in **Figure 3(b)**, and the variation depends on the amount of cloud cover. However, the total solar radiation in the AW is lower than that in the WS (17.24 and 18.47 MJ m^{-2} day$^{-1,}$ respectively). Usually, in the study area, the yield of WS crops is higher because the temperature is suitable, and the flowering time does not fall on rainy days, which can reduce the quality of pollination.

Generally, weather patterns differed between the AW and WS crops, especially rainfall and temperature regime (**Figures 2** and **3**). This may affect the growth, development, and yield of rice crops. The total biomass of the WS growing season was 11,985 t ha^{-1}, slightly higher than the AW (10,640). The yield of WS was 5,233 t ha^{-1}, also higher than that of AW crop (5,040 t ha^{-1}).

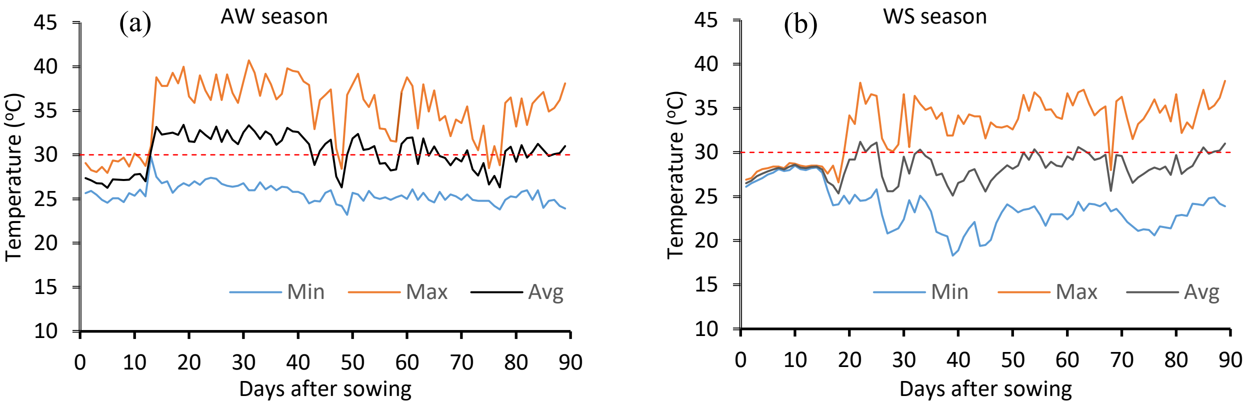

Figure 2 Daily minimum, maximum and average temperature for (a) AW2020, and (b) WS2020-2021.

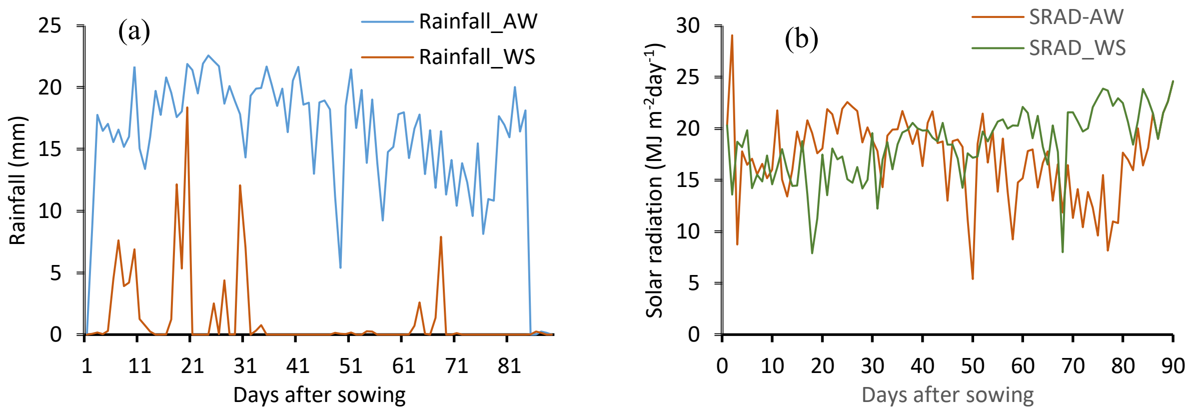

Figure 3 (a) Daily rainfall and (b) daily solar radiation of 2 rice seasons.

Model estimation and validation

Simulated and observed patterns of total vegetative biomass for rice in both seasonal crops are shown in **Figure 5**. The observed biomass dynamics were generally well simulated with the SIMPLE model. The model also described the differences between both seasons. The RRMSE for the final grain yield obtained between the observed and simulated results was relatively low, 4.2 to 5.5 % (**Table 6**). This means that the model could be suitable for the application. The model also evaluates the crucial responses to environmental growing conditions, such as f(solar), f(temp) (**Figure 6**).

Table 6 Observed and simulated.

Rice season	Observation (kg ha^{-1})		Simulation (kg ha^{-1})		RRMSE (%)
	Biomass	Yield	Biomass	Yield	
Autum - Winter	10640	5040	11045	4762	5.5
Winter - Spring	11985	5233	11598	5451	4.2

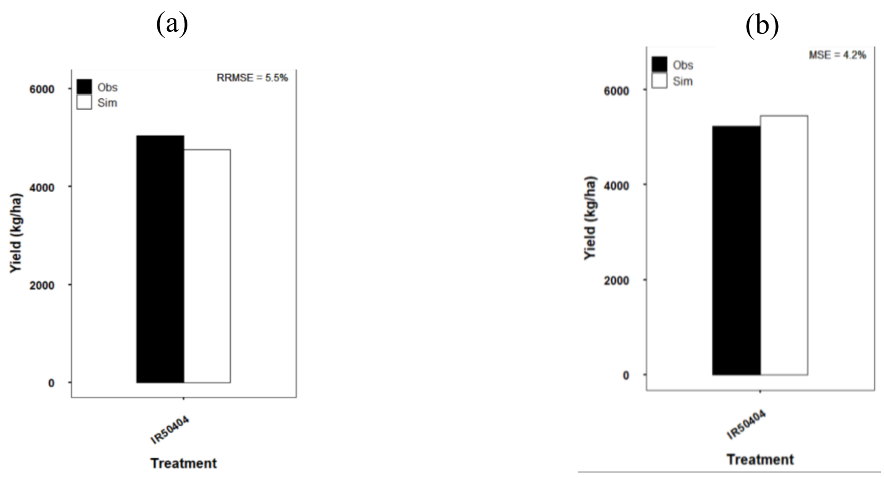

Figure 4 Simulated (white column) and Observed (black column) yield of (a) AW and (b) WS, simulated and drawn by Rstudio.

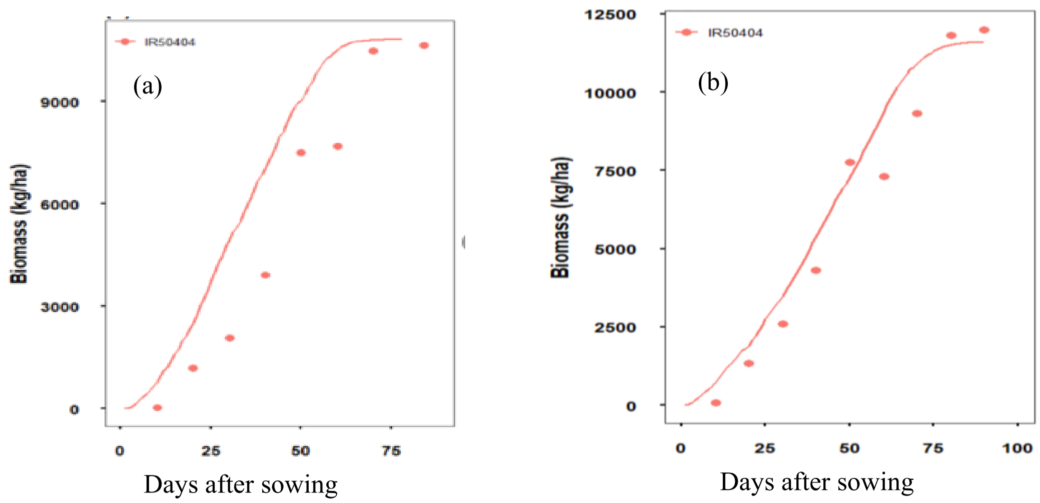

Figure 5 Simulated (red line) and Observed (red symbol) biomass of (a) AW and (b) WS, simulated and drawn by Rstudio.

To assess the suitability of a crop model, the NSE index was used for both the mean level and the variability of the measured biomass changes [34]. The observed biomass changes are satisfactorily reproduced by all models for all aggregated scales (measured by the Nash-Sutcliffe efficiency). The NSE is a composite parameter for the mean model bias and variability [35]. It is particularly suitable for out-of-sample cross-validations [36]. The NSE index in the two experimental crops in the field ranged from 0.87 to 0.90, showing the appropriateness of the model. NSE $\geq$ 0.75 has been considered a model that has been operating with good simulation [37].

Table 7 NSE index for 2 rice crops in An Giang province, Vietnam.

AW crop				WS crop			
DAP	**Biomass-Obs (kg ha^{-1})**	**Biomass-Sim (kg ha^{-1})**	**NSE**	**DAP**	**Biomass-Obs (kg ha^{-1})**	**Biomass-Sim (kg ha^{-1})**	**NSE**
10	33	779	0.98	10	78	710	0.99
20	1,198	2,491	0.93	20	1,341	1,819	0.99
30	2,083	4,960	0.49	30	2,592	3,343	0.95
40	6,870	7,031	0.96	40	4,300	5,161	0.73
50	7,977	9,017	0.69	50	7,750	7,012	0.83
60	9,564	10,514	0.92	60	8,565	9,002	0.97
70	10,483	10,804	0.99	70	9,317	10,490	0.88
86	10,640	11,069	0.99	80	9,600	11,069	0.84
				92	9,950	11,152	0.91
O_{mean}	**6106.00**				**5943.667**		
Average			**0.87**				**0.90**
SD			0.18				0.08

Heat stress

In the AW crop, there were more periods with f(temp) approaching value 1.0 that having temperature $T > T_{opt}$ of rice (> 30 °C) than in the WS crop (**Figure 8**). In the AW season, it rains more. However, there were many episodes of hot weather in 15 - 42 DAP and 50 - 55 DAP periods. In contrast, f(temp) value in the WS, there were many times when it was low at 18 - 20 DAP and 40 - 45 DAP. This contributes to the lower biomass rate of the AW than the WS (Eq. (3)).

For heat stress, in optimal conditions without the impact of heat, f(heat) will be equal 1.0. When $T_{max} > T_{extreme}$, f(heat) gets smaller. When f(heat) approaches the value 0, the vegetative biomass (straw) approaches 0. **Figure 7** shows AW crop had many days with f(heat) less than 0.8 in the pre-flowering stage, but WS crop f(heat) value was higher than AW. It means that the effect of heat on biomass in WS crops was lower than AW. In this model, heat stress accelerates canopy senescence by increasing I50B, which shortens the maturity date and reduces AW yield.

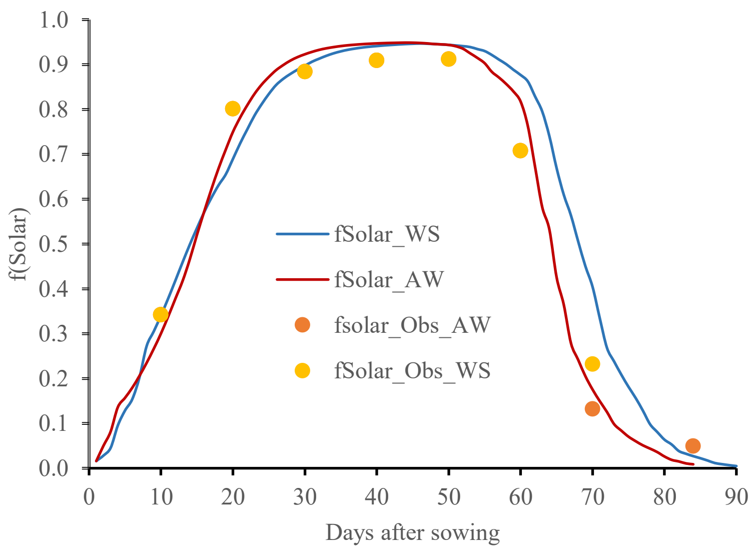

Figure 6 Dynamics of a fraction of radiation interception (fSolar) intercepted by a crop canopy of AW and WS. Simulated (lines) and observed (symbols).

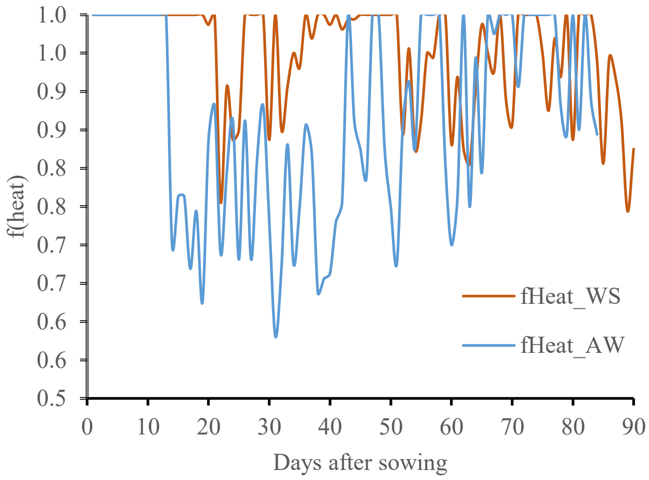

Figure 6 Heat stress impacted.

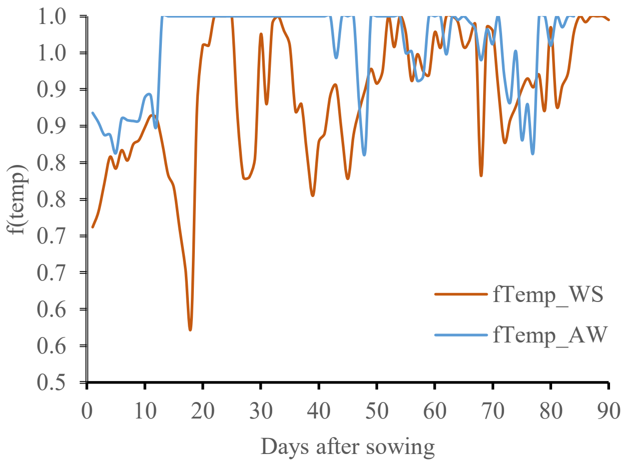

Figure 7 Temperature, heat, and solar radiation impact.

Further discussion with farming conditions in Cho Moi district, An Giang, Vietnam that considering heat stress on rice alone, WS crop would be more affected by biomass and grain yield. However, the weather in WS crops was more favorable for farming than AW due to strong wind and rain. That caused more falls in the AW crop at the time of harvest. The pollination stage was affected by severe wind and rain, producing higher unfilled grain rates [38].

Besides, the customary farming conditions of farmers in the Mekong Delta is to irrigate water almost the growth time, so f(water) = 1, which means the water stress is absent. For the cases of upland rice, drought stress is still expressed and calculated by this model [14].

Sensitivity analysis

The research issue was to analyze the volatility of 10 parameters that affect rice yield. Based on the formula of Morris method, which is a screening method for influencing factors, this method will determine the fluctuations of each parameter through the absolute mean (μ), deviation standard (σ) of each parameter in two seasons AW, WS in Cho Moi district, An Giang province, Vietnam. Through the assessment, it was found that in both crops, there were 2 parameters with high sensitivity affecting rice yield, specifically RUE and T_{base} (**Figure 9**). According to the effect classification chart of the parameters, the effect of RUE was a nonlinear and highly sensitive impact, strongly interacting with other parameters and having an essential effect on the input results. The T_{base} parameter had a small mean but a significant standard deviation, so the effect of this parameter was also a nonlinear influence. The remaining eight parameters have a much smaller impact (**Figure 9**).

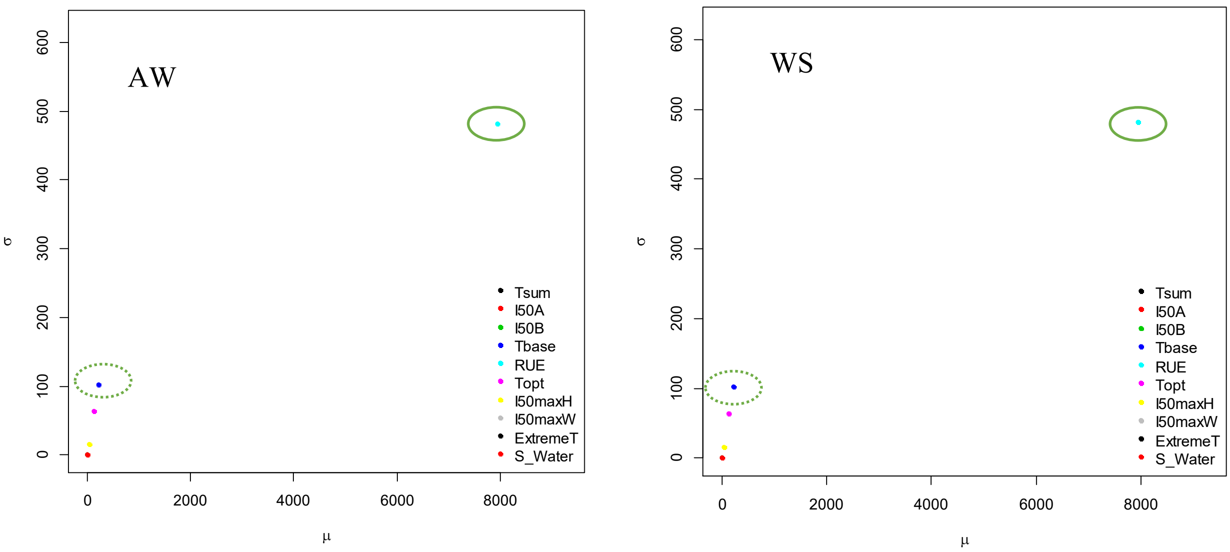

Figure 8 Assessing sensibility by Morris.

Once only screening input parameters means we cannot know which parameter has the primary sensitivity and ratio of impact to final yield. Therefore, the FAST method will help to evaluate each parameter quantitatively. When comparing parameters with nonlinear impact, high sensitivity, intense interactions with other parameters, and meaningful impact on input, the results showed that these parameters had different mean and standard deviation. The analysis results (**Figure 10**) showed that RUE and T_{base} were 2 parameters with significant impact, in which RUE was the parameter having the primary influence on productivity. If the total sensitivity of 10 parameters is 100 %, then the sensitivity of RUE accounts for 99 % and the sensitivity of T_{base} accounts for 1 %, and the remaining parameters have non-significant value. The research has also been consistent with the studies of Confalonieri *et al.* [39], Paleari and Confalonieri [40] when published research results showed that RUE parameter had a significant influence. In addition, other parameters such as LAI (Leaf Area Index), T_{opt} (optimum temperature) were also essential depending on the specific farming conditions, climate characteristics, and soil properties of rice [42,43].

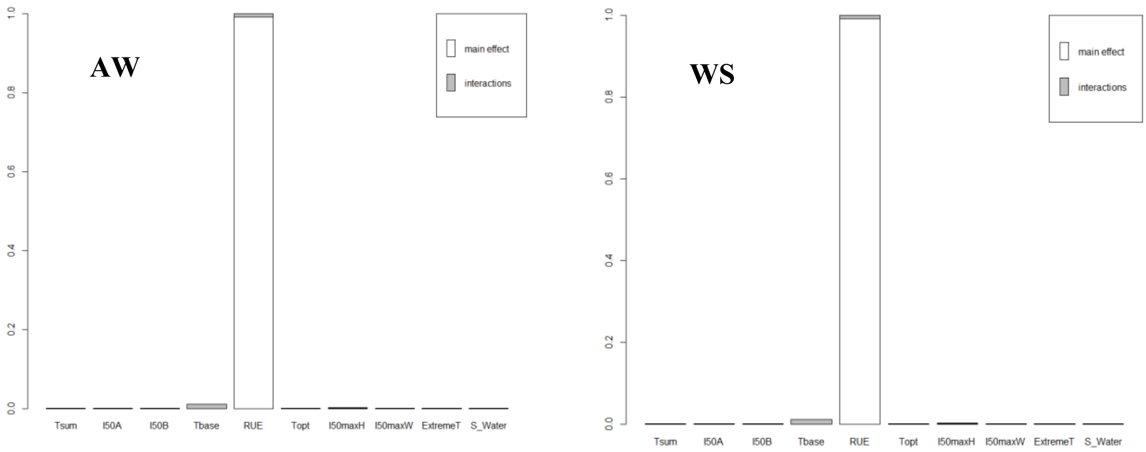

Figure 10 Impacts assessment by FAST.

Biomass responses in higher temperature and CO_2 concentration

Total simulated biomass dynamics for the two crop seasons is shown in **Figure 11**. The results from the model showed that increasing 5 °C caused a decline in final cumulative biomass by about 7.2 % in AW season compared to 3.1 % in WS season. The biomass increased earlier in the AW season before flowering (50 DAP was more than 9,100 kg ha^{-1} compared to 7,600 kg ha^{-1} in the WS crop), but in the end, it was roughly the same mass.

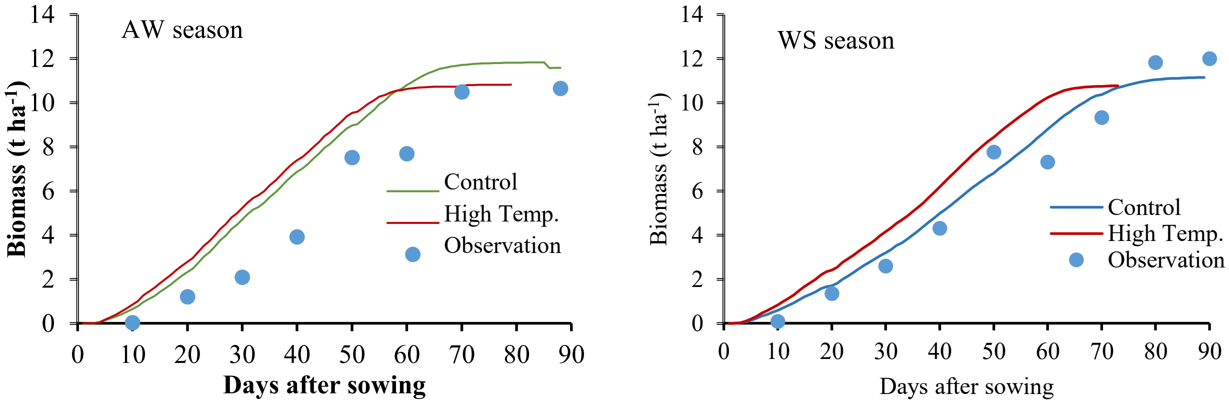

Figure 9 Total above-ground biomass under different atmospheric temperatures for the control and high temperature (+5 °C). Observed and controlled data from this experiment. Simulated (lines) and observed (symbols).

Figure 12 shows simulated total biomass from a free-air CO_2 enrichment for the control (400 ppm) and high CO_2 (600 ppm). With an increase in CO_2 concentration, yield increased cumulative biomass in AW and WS were 1.6 and 2.2 t ha^{-1}, corresponding to an increase in biomass from 15.3 to 20.0 %. For every 100-ppm increase, the cumulative biomass increased by 8 and 10 %, respectively (**Figure 12**). Research conducted by Hao *et al.* [41] also indicated that with a free-air CO_2 enrichment at an elevates of 320 ppm, rice grain yield increased 30.7 % by Oryza1 model.

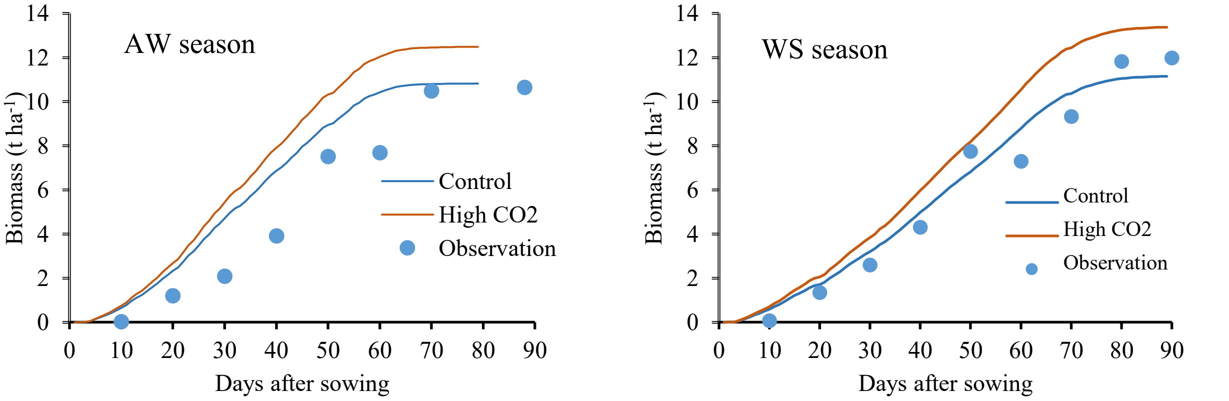

Figure 10 Total above-ground biomass under different atmospheric CO_2 concentrations for the control (400 ppm) and high CO_2 (600 ppm) observed total biomass from the experiment site. Simulated (lines) and observed (symbols).

Relative yield responses in higher temperature and CO_2 concentration

Relative yield changes simulated with increasing temperature and CO_2 concentration are shown in **Figure. 8**. Responses of the model to the assumption of 5 °C growing, rice yield decreased rapidly in the AW with about 8.5, and 7 % in WS (**Figure 13**). With an increase in CO_2 concentration, the yield increased about 14 and 16 % per 100 ppm for the AW and WS respectively (**Figure 13**).

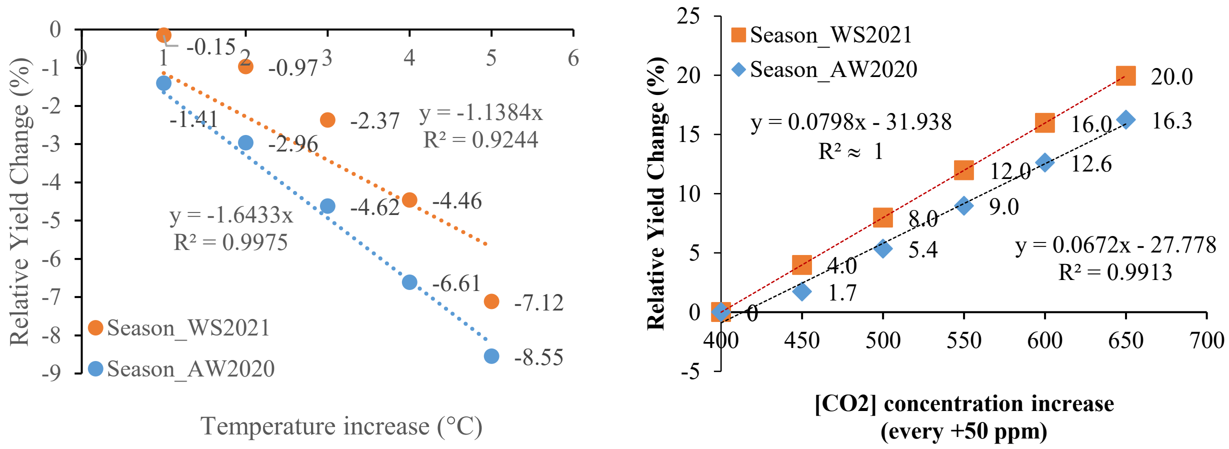

Figure 13 Simulated yields for rice with (a) increasing temperature and (b) elevated atmospheric CO2 concentration. Trendline (dotted lines) and observed (symbols).

Overall, model calibration and evaluation results showed that the SIMPLE model could predict the biomass and grain yield of rice in both AW and WS crop seasons in An Giang province, Viet Nam. Significant positive relationships were found between observed and simulated rice yields for the AW (**Figure 10(a)**) and WS (**Figure 10(b)**). The comparison with observations indicates that the simulations were reasonable for yield (RRMSE was 5.5 % for the AW and 4.2 % for the WS). However, the simulated yield underestimates AW yields and overestimates the WS. This may probably arise due to uncertainties in input parametrization.

Elevated temperatures beyond those required for rice would reduce final grain yield. The treatment at ambient temperature produced the maximum grain production of 6.2 t/ha, followed by 5.3 t/ha at 2 °C increase and 4.7 t/ha at 4 °C level [28]. The yield loss caused by high temperatures was attributed to sterile florets and shorter crop growth [42].

According to the global climate change scenario of the temperature increase in East Asia, in the period 3 (2080 - 2099), the predicted average temperature according to RCP 2.6, RCP 24.5, RCP 6.0, RCP 8.5 would increase by times 0.98, 1.89, 2.47, and 4.06 °C, respectively [43]. RCP8.5 scenario would raise the temperature at the end of this century by more than 4 °C, and the yield response from this model will decrease by only 6.61 % on average. However, it is also just the contribution of the temperature factor to the model. The future estimation must also be checked for the input data to other parameters in the model. RUE parameter changes in a decreasing direction would strongly affect yield because RUE is highly sensitive to input parameters (**Figures 9** and **10**).

In the combined effect of biotic and abiotic factors that may reduce grain yield more seriously, yield can be reduced by up to 4.7 % in WS season when every 1 °C increases for irrigated rice [44]. A GIS simulation study by Yuliawan and Handoko [45] on the effects of increased temperature using Shierary Rice Model in Karawang, Indonesia, showed that the yield of rained rice decreased by 11.1 % for each °C. When using the ORYZA model to simulate rice yield, Krishnan *et al.* [46] predicted a yield decrease of 7.63 % when the temperature increased 4 °C compared to ambient. He attributed the decline in yield mainly to the sterility of rice spikelets at higher temperatures.

Research conducted by Hao *et al.* [41] also indicated that a free-air CO_2 enrichment increased rice grain yield by 30.7 % at 320 ppm elevated by Oryza1 model. In addition to increased CO_2 concentration, there are positive effects on rice yield, but more importantly, other extreme effects (maximum temperature and increased night temperature [47]) brought a more substantial impact on yield. According to the trend of climate change, the parameters in input data may show negatively affect productivity, such as RUE (decreasing), I50A, and I50B (increasing, 50maxH (increasing), T_{max} (rising). In addition, the RCP scenarios also emphasize that the extreme heat events are not uniform throughout the day and during the month, accompanied by an increase in continuous rain during pollination days, which reduces the number of spikelets per unit area [48]. In addition, the biological factors of rice to cope with sudden changes in solar radiation, rainfall, and high temperature at the vulnerable time or stage that negatively affect rice yield have not been fully modeled enough. For example, pests increase the damage to the rice field, and farmers must spray more pesticides, growth regulators, or occurring rain that floods deep water at the seedling stage, inhibiting growth. Regarding models, the uncertainties in predicting rice yield by current crop models are influenced by various climatic conditions [49].

Conclusions

Rice grown in the AW season showed a tendency to shorten the growing season compared to that grown in the WS season in Cho Moi, An Giang, Vietnam.

The SIMPLE model can be used to predict rice biomass and yield under different weather conditions. Assumed conditions and global climate change scenarios with increasing mean temperature and CO_2 concentration indicated a decrease in rice yield in both seasons regardless of whether increased CO_2 concentration.

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