https://doi.org/10.48048/tis.2024.7490

Simulation of Maize Biomass and Yield in An Giang, Vietnam, under Climate Variabilities

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Received: 9 September 2023, Revised: 8 October 2023, Accepted: 15 October 2023, Published: 30 January 2024

Abstract

In this study, the SIMPLECrop model was applied to simulate maize biomass and yield 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). The research aimed to analyze the effects of climate variabilities, particularly increased temperature, on maize growth and yield.

The growth period for the Winter - Spring 2020 - 2021 season was 67 days, which was 1 day longer than the AW season (Autumn - Winter 2020). Four cultivar parameters, namely Tsum, HI, I50A, and I50B, were employed for the calibration process to fine-tune the model. Sensitivity analysis using Morris and FAST methods revealed that RUE and Tbase had the highest sensitivity and significant impact on the SIMPLECrop model. These 2 parameters showed strong interactions and played a crucial role in influencing model outcomes. The evaluation of the model's performance resulted in RRMSE values ranging from 4.8 to 6.3 % and NSE values between 0.86 and 0.93, indicating good agreement between model predictions and observed data.

Regarding the impact of temperature increase, a 5 °C temperature rise led to a reduction in stover biomass ranging from 5.2 % (Autumn - Winter 2020) to 19.3 % (Winter - Spring 2020 - 2021) and a decrease in yield by 11.3 % (Autumn - Winter 2020) and 27.0 % (Winter - Spring 2020 - 2021). Simulating an increase in CO_2 concentration alone, varying from 50, 100, 150, 200 to 250 ppm, resulted in increased biomass and yield for maize. The most substantial increases were observed at 250 ppm CO_2, with approximately 2.5 % higher biomass and 7.7 to 9.1 % greater yield. However, under more severe heat stress (5 °C increase), the positive effects of elevated CO_2 were mitigated, resulting in a reduced increase in biomass and yield, approximately 3 - 5 %. These findings highlight the importance of considering temperature and CO_2 interactions when assessing crop responses to climate variability.

Keywords: Climate variabilities, Elevated CO_2, High temperature effect, Maize, Simulation biomass, Simulation yield

Introduction

Maize, scientifically known as *Zea mays*, plays a crucial role in global food security, serving as a staple crop in many countries [1]. In Vietnam, maize is a vital food source, particularly in An Giang Province (a province in southern Vietnam). However, the production of maize, like many other crops, is vulnerable to the adverse effects of climate change, including rising temperatures and increasing levels of atmospheric carbon dioxide (CO_2) [2]. An Giang Province, situated in the Mekong Delta of Vietnam, boasts a strategic advantage for cultivating maize, with its favorable soil characteristics and suitable climate conditions. However, the province, like the rest of the world, faces the challenges posed by climate change, which can have adverse effects on crop yields. Temperature increases, variations in rainfall patterns [3] such as fluctuations in the distribution, timing, intensity, and frequency of rainfall in a particular region over time, and shifts in CO_2 concentrations [4] can all disrupt maize growth and development, ultimately affecting its productivity

The Representative Concentration Pathway (RCP) scenarios are a set of standardized greenhouse gas concentration trajectories used in climate modeling and research to project future climate change. These scenarios represent various potential future pathways for the concentration of greenhouse gases like carbon dioxide in the Earth's atmosphere. The estimates for Vietnam's climate change scenario are primarily based on the Representative Concentration Pathway (RCP) scenarios developed by the IPCC [5]. These scenarios outline potential future greenhouse gas emissions and their corresponding effects on global temperature. In the case of Vietnam, RCP scenarios highlight the likelihood of temperature increases ranging from 1 to 4 °C by the end of the 21st century [4]. Additionally, CO_2 concentrations are predicted to reach levels well above the pre-industrial era (period before the significant industrialization and widespread use of fossil fuels, which started in the late 18th century), potentially exceeding 900 ppm [6]. Higher temperatures and elevated CO_2 levels can lead to several potential impacts on maize cultivation. These include increased heat stress on plants during critical growth stages, changes in precipitation patterns leading to drought or excessive rainfall, altered pest and disease dynamics, and shifts in the geographic suitability for maize cultivation. These combined effects can threaten crop yields and food security, making it crucial for agricultural practices and policies to adapt to the changing climate conditions to ensure a stable maize production in the face of such challenges. These changes in temperature and CO_2 concentration have profound implications for the country's agriculture, particularly staple crops like maize.

The consequences of elevated temperature and CO_2 concentration on crop productivity are of paramount concern to both researchers and policymakers. Rising temperatures can induce heat stress, alter growing seasons, and impact the overall development of crops [7-9]. Meanwhile, elevated CO_2 concentrations, on the other hand, can influence photosynthesis rates and water use efficiency [10].

Crop modeling is an indispensable tool in modern agriculture, providing a systematic approach to assess how different factors affect crop growth and yield [11]. By integrating data on climate, soil, and crop-specific parameters, these models offer a powerful means to simulate and predict crop behavior under various scenarios [12]. Crop models are instrumental in decision-making processes for farmers, policymakers, and researchers alike.

There are several models available for simulating maize yields, such as the DSSAT (Decision Support System for Agrotechnology Transfer) and APSIM (Agricultural Production Systems sIMulator). However, a large amount of data and parameters are required by these models [13], and acquiring such data is often challenging or time-consuming due to the complexity of the parameters involved. For instance, the widely used DSSAT model necessitates numerous genotype-specific parameters for defining a new crop [14]. In contrast, the SIMPLECrop model only requires 13 parameters and a few input variables, such as irrigation, rainfall, weather, and soil properties (which will be introduced in the methods section), to specify the model [15]. The SIMPLECrop model stands out from other crop models in several key aspects. Firstly, in terms of scope and focus, SIMPLECrop adopts a minimalist approach, aiming for ease of use and quick simulations. It provides basic estimates of crop growth and yield and is suitable for scenarios where detailed data or computational resources are limited. Secondly, when it comes to complexity, SIMPLECrop lives up to its name by maintaining simplicity. It intentionally keeps the complexity low, making it accessible to users with limited modeling experience. On the other hand, more comprehensive models like DSSAT are known for their complexity, as they encompass detailed representations of crop physiology, genetics, and intricate environmental interactions. Lastly, the applications of these models differ significantly. SIMPLECrop is best suited for quick, rough estimates of crop performance and is commonly used in educational settings or when a basic assessment suffices. In summary, while SIMPLECrop offers simplicity and accessibility, other crop models vary in scope, complexity, data requirements, and applications, catering to diverse research needs and scenarios in the field of agriculture and crop science.

The SIMPLECrop model was utilized in this study to simulate maize yield and biomass under various climate scenarios. Valuable insights into the potential impacts of climate change on maize cultivation in Vietnam were sought, along with evidence-based recommendations for sustainable agricultural practices. The investigation was conducted across 2 maize crop seasons, Autumn - Winter (AW) and Winter - Spring 2020 - 2021 (WS), resulting in the collection of observation data for inputting into the crop model. Furthermore, the model, once calibrated and evaluated, proved to be effective in simulating maize biomass and yield under diverse weather conditions.

Accurate predictions of maize yield and biomass in An Giang Province are essential for sustainable agricultural planning and management. Farmers, agribusinesses, and local agricultural authorities require reliable information to make informed decisions about planting, harvesting, and resource allocation. Additionally, anticipating changes in maize production due to climate variability is crucial for ensuring food security in the region.

To address these concerns, this study applied the SIMPLECrop model to simulate maize yield and biomass in An Giang Province, Vietnam. The model considers multiple factors, including temperature, CO_2 concentration, and various stressors, to provide a comprehensive assessment of maize growth under changing climatic conditions.

Methods and materials

Field experiments

The objective of this study was to obtain average crop parameters required for model input (as observational data), calibrate the model, and assess its performance. Two experiments were conducted on 2 typical maize crops in the Mekong Delta region, the Autumn - Winter 2020 and Winter - Spring 2020 - 2021 seasons, at Hoa Binh Commune, Cho Moi District, An Giang Province, Vietnam (at 10°23'47"N, 105°27'41"E). The experimental soil characteristics consisted of clay loam soil with an organic matter content of 1.6 %. Both experiments were conducted on a 500 m^2 plot using the Gold 58 F1 variety. Data input involved the systematic collection and calculation of crop management, soil, and meteorological parameters throughout the experiments.

The fertilizer application rate was 190 N - 90 P_2O_5 - 190 K_2O kg/ha and the planting density was 75×25 cm^2. All data were recorded and averaged based on the 4 replications. Vegetative biomass (above-ground biomass) was measured every 10 days. Drying at 70 °C for 48 h in a drying chamber was conducted until a constant weight was achieved to determine dry matter. This process ensured the complete removal of moisture from the samples.

The parameters related to soil at the research site have been analyzed or measured, and the results were as follows in **Table 1**.

Table 1 Soil parameters analyzed in 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

Model description

In the SIMPLECrop model [15], crop yield resulted from multiplying the harvest index (HI) by the cumulative above-ground biomass from sowing to maturity, as expressed in Eq. (1);

$$Yield = Biomass_{cum} \times HI \quad (1)$$

Here, HI represents the harvest index, computed as the grain-to-total dry matter ratio, while Biomass cum is derived as follows;

$$Biomass\_cum_{i+1} = Biomass\_cum_i + Biomass\_rate \quad (2)$$

Biomass_rate denotes the daily growth rate of biomass for the current day, and $Biomass\_cum_i$ represents the cumulative biomass up to the current day. Biomass_rate was determined by Eq. (3), based on the concept of radiation use efficiency (RUE), where the plant canopy captures daily photosynthetically active radiation (PAR) and converts it into crop biomass [16]. Daily variations in crop biomass were influenced by stress factors like high temperature, drought, and atmospheric CO_2 concentration.

$$Biomass_{rate} = Radiation * fSolar * RUE * f(CO2) * f(Temp) * \min((f(Heat), f(Water)) \tag{3}$$

Here, fsolar signifies the fraction of solar radiation intercepted by the crop canopy, following Beer-Lambert's law of light attenuation. F (CO_2) represents the CO_2 impact, f (Heat) was heat stress, and f (Water) was water stress.

fSolar for leaf growth and senescence period was computed 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 represented the cumulative temperature required for leaf area development to intercept 50 % of solar energy during canopy closure, I50B was the cumulative temperature needed from maturity to intercept 50 % of radiation during canopy senescence, and fSolar-max is the maximum radiation intercepted by a crop.

TT was the cumulative mean temperature which was 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 represented the cumulative mean temperature on day i, ΔTT was the daily added mean temperature, T was the daily average temperature (TMAX+TMIN)/2, and Tbase signified the base temperature for plant phenological development.

Temperature stress, heat stress, drought stress, water stress, and CO_2 impact are calculated by Eqs. (7) - (12), referred to [15], Asseng, Foster [17], Bindi, Fibbi [18], Ewert, Rodriguez [19], Priestley and Taylor [20], Ritchie, Godwin [21], Van Ittersum, Howden [22], and Woli, Jones [23], as cited in Zhao, Liu [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.

Model parameters and input data

There were 13 parameters used to run a SIMPLECrop model

Cultivar parameters: Tsum, I50A, and I50B, HI (harvest index)

Species parameters: T_{base}, T_{opt}, RUE, I_{50maxH}, I_{50maxW}, T_{max}, T_{ext}, S_{CO2}, S_{water}

Input variables required to run the SIMPLECrop model include weather (daily maximum/minimum temperature, rainfall, and solar radiation), atmospheric CO_2 concentration, sowing/harvesting date, irrigation, initial variables, and 4 variables characterizing the soil (**Table 2**).

Table 2 Input variables to run SIMPLECrop 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}
	Atmospheric CO_2 concentration	ppm
Soil characteristics	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.

Sensitivity analysis

The sensitivity analysis in this study employed the Morris [25] method as well as the FAST (Fourier Amplitude Sensitivity Test) method [26]. Specifically, the Morris method was utilized to select and discretize parameters within a standardized space, encompassing the entire parameter space. The Morris method serves as a screening technique for identifying influential factors. It quantifies the variations in each parameter by examining their means (μ) and standard deviations (σ). A higher mean (μ) and standard deviation (σ) indicate a more substantial impact of that parameter on yield or biomass and a stronger interaction with other parameters. Within the FAST method, parameters with non-linear influences demonstrated high sensitivity and robust interactions with other parameters, significantly influencing the input results.

The sensitivity analysis involved incremental changes in mean temperature (+1, +2, +3, +4 and +5 °C) and atmospheric CO_2 concentration (+50, +100, +150, +200 and +250 ppm).

Model calibration, validation, and evaluation

Cultivar parameters were calibrated. The models calibrated the parameters of the cultivars within a fair range (but kept the cultivar parameter constant for the same cultivar when grown in different seasons). This calibration referred to the specific data sets of aboveground dry matter accumulation (calibrated T_{sum}), a fraction of radiation interception (calibrated I50A and I50B), and final yield (dry grain) (calibrated HI).

In this study, 2 key metrics, Root Relative Mean Square Error (RRMSE) and Nash-Sutcliffe Efficiency (NSE), were employed to assess the model's performance. A lower RRMSE value indicates a closer fit to the observed data, while a higher NSE value signifies a better alignment with the real-world data.

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

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

where n was the sample number, Oi and Si were the observed and observed values of the ith observation (i = 1 ton)

Results and discussions

Weather characteristics

The minimum, maximum, and average daily temperatures collected at the study site of maize plants during the 2 seasons, Autumn - Winter 2020 (AW) and Winter - Spring 2020 - 2021 (WS) were shown in **Figures 1** and **2**. The WS crop had an average temperature lower than the Autumn - Winter 2020 crop, from 1.5 to 2.5 °C. Rainfall was uniformly distributed in the AW season. The rainfall recorded in the Autumn - Winter 2020 crop was 7.05 times higher than in the WS crop, 457.1 and 64.8 mm/crop, respectively. Significantly higher rainfall was observed in the AW maize crop area, typically ranging from 4 - 15 mm/day, especially on days when rainfall approached 50 mm/day.

Daily solar radiation in Autumn - Winter 2020 and Winter - Spring 2020 - 2021 was shown in **Figure 2**. However, the total solar radiation in the AW was lower than that in the WS (average 17.24 and 18.47 MJ/m^2/day, respectively). Regularly, in the study area, the yield of WS crops was higher because the temperature was suitable, and the flowering time did not fall on rainy days, which can reduce the quality of pollination.

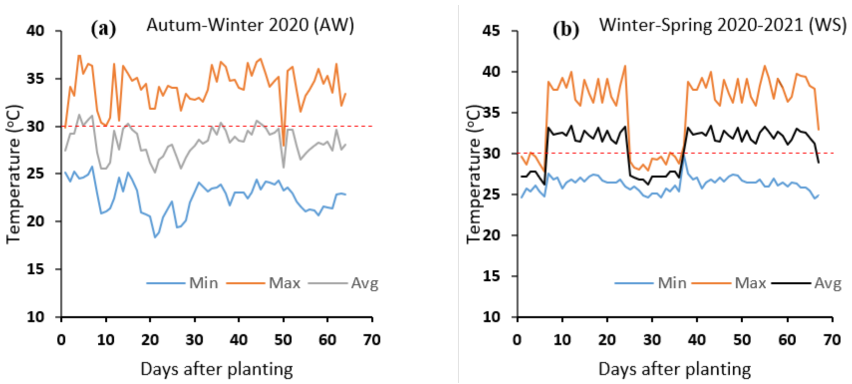

Figure 1 Daily minimum, maximum and average temperature of 2 maize seasons; (a) Autum - Winter 2020 (AW) and (b) Winter - Spring 2020 - 2021 (WS).

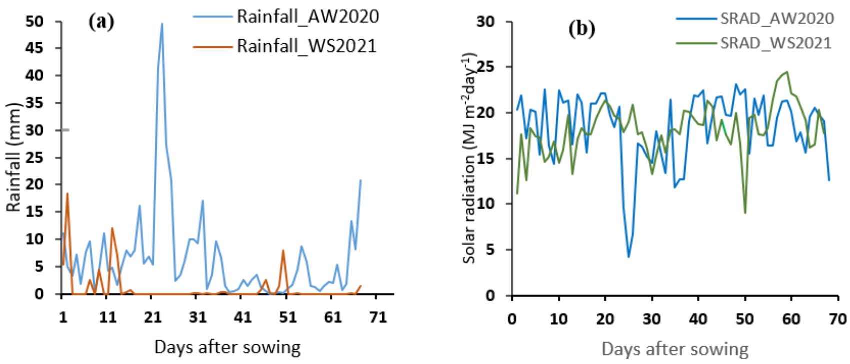

Figure 2 (a) Daily rainfall and (b) daily solar radiation of 2 maize seasons.

Agroinformatics data for crop modeling inputs

Growth time

Maize is typically harvested when it reaches physiological maturity. At this stage, the kernels have achieved their maximum dry weight and moisture content has decreased to an optimal level for storage. The kernels have a mature color, which is often a combination of yellow, brown, or orange, depending on the variety. They should also feel hard and not easily dented with a fingernail.

The results of the field experiments indicated that the growth duration of maize in the WS season was 1 day longer compared to the Autumn - Winter 2020 season (**Table 3**).

Table 3 Planted and harvest time.

Autumn - Winter 2020 (AW)			Winter - Spring 2020 - 2021 (WS)		
Planted	**Harvest**	**Growth time (day)**	**Planted**	**Harvest**	**Growth time (day)**
10 Jul. 2020	14 Sep. 2020	66	24 Dec. 2020	25 Feb. 2021	67

Results in **Table 4** showed that the height of maize increased gradually from 10 to 30 days after planting (DAP) and increased rapidly during the 30 to 40 DAP period, increasing 58 and 50 cm, respectively, in Autumn - Winter 2020 (AW) and Winter - Spring 2020 - 2021 (WS) crops. By 60 DAP, the height of maize was 223.5 cm in the AW season and 224.9 cm in the WS crop.

The biomass of fresh stalks between the WS crop and the Autumn - Winter 2020 crop was illustrated in **Table 4**. The leaf biomass peaked at approximately 50 DAP and gradually declined until harvest. The leaves and stems gradually decreased weight at the near-harvest stage (R5 stage), and the plant exhibited a more yellowish appearance. Furthermore, the husks progressively lightened, and the grain and cobs became drier. The highest biomass at 50 DAP was 47.6 tons/ha in Autumn - Winter 2020 and 52.4 tons/ha in WS.

Overall, the statistical analysis indicates that there were significant differences in Plant height, Fresh biomass, and Dry biomass between the 2 treatments at various time points. Treatment effects were markedly pronounced in Fresh biomass and Dry biomass, with Treatment WS generally outperforming Treatment AW. However, for Plant height, the differences were most prominent at earlier stages (10 and 20 DAP), leveling off at later stages (30 to 60 DAP).

The maize kernel yield in the Autumn - Winter 2020 (AW) and Winter - Spring 2020 - 2021 (WS) crops was recorded at 8.9 and 9.5 tons/ha, respectively. Furthermore, the harvest index for the AW and WS crops reached 0.45 and 0.51, indicating a higher proportion of yield in relation to the total biomass for the WS crop compared to the AW crop.

These yield figures indicate that the WS crop outperformed the AW crop in terms of maize kernel production. The increase in yield from the AW to the WS crop suggests that factors such as growing conditions, weather had a positive impact on the crop's overall productivity. The WS crop, being a more favorable planting season, typically exhibits higher productivity in An Giang Province, southern of Vietnam. Additionally, the study analyzed the harvest index, which was a crucial indicator of resource-use efficiency in agriculture. The harvest index for the AW crop was 0.45, whereas the WS crop exhibited a higher harvest index of 0.51. This difference in harvest index values indicates that a greater proportion of the total biomass produced in the WS crop was allocated to maize kernel yield compared to the AW crop. These findings suggest that the WS crop not only yielded more maize kernels but also utilized resources more efficiently to achieve this higher yield. This information can be valuable for farmers and researchers seeking to enhance maize production and resource-use efficiency in similar agricultural contexts.

Table 4 Plant height, biomass of maize, Cho Moi district, An Giang province.

Day after planting (DAP)	Plant height (cm)		P	Fresh biomass (kg/ha)		P	Dry biomass (kg/ha)		P
	AW2020	**WS2020 - 2021**		**AW2020**	**WS2020 - 2021**		**AW2020**	**WS2020 - 2021**	
10	43.2b	46.5a	*	413b	677a	*	67	67	ns
20	61.8b	67.1a	*	10,501	10,603	ns	756a	120b	*
30	95.5a	101.3	ns	32,667b	38,333a	*	1,989	1,909	ns

Day after planting (DAP)	Plant height (cm)		P	Fresh biomass (kg/ha)		P	Dry biomass (kg/ha)		P
	AW2020	WS2020 - 2021		AW2020	WS2020 - 2021		AW2020	WS2020 - 2021	
40	153.1	151.8	ns	44,500b	48,332a	*	4,005b	5,894a	*
50	188.3	192.2	ns	47,600b	52,442a	*	5,412b	7,700a	*
60	223.5	224.9	ns	45,215b	49,800a	*	7,596b	8,100a	*

AW2020: Autum - Winter 2020
WS2020-2021: Winter Spring 2020 - 2021
Fresh biomass: includes the leaves, stems, cobs (above the ground)
Dry biomass: refers to the total weight of the plant material of maize after it has been harvested and thoroughly dried to remove all moisture content.
In the statistical analysis, the Duncan's test (at a significance level of 5 %) was employed to compare the mean values of AW and WS, for each of criteria: Plant height, Fresh biomass, and Dry biomass at 10, 20, 30, 60 days after planting.

Model validation, calibration, and evaluation

Once the model ran without errors, the simulated values of interest were contrasted with actual data, leading to the computation of validation metrics. Following this, the simulation typically necessitates adjusting certain parameters and assessing the model's performance, often gauged using the RRMSE value. If unsatisfactory, a return to the previous stage for recalibrating parameters within reasonable bounds may be required. Within the research, 4 cultivar parameters (Tsum, HI, I50A, I50B) were employed for the calibration process. The results of the parameters used for calibrating the maize crops were presented in **Table 5**.

Table 5 Model parameters in the SIMPLECrop model.

Name	Description	Range	Note
Tsum	Thermal time requirement from sowing to maturity in daily mean (°C days)	1816 - 1974	*
HI	Harvest index	0.41 - 0.43	*
I50A	Thermal time requirement after sowing fraction of light interception to reach 50 % (°C days)	347 - 364.6	*
I50B	Represents natural senescence. Thermal time requirement from maturity backwards for the light interception to reach 50 % (°C days)	85.3 - 84	*
Tbase	Base temperature (daily mean T) for phenology development and growth (°C)	10	[27]
Topt	Optimal temperature (daily mean T) for biomass growth (°C)	30	[28]
RUE	Radiation use efficiency (above ground biomass + below ground, if the harvestable product is below ground) (g MJ/m^2)	2.1	[15]
I50maxH	The maximum daily increase in I50B due to heat stress (°C days)	100	[15]
I50maxW	The maximum daily increase in I50B due to water stress (°C days)	12	[15]
MaxT	Threshold for daily Tmax to start accelerating senescence due to heat stress (°C)	34	[15]
ExtremeT	Daily Tmax threshold when RUE becomes 0 due to heat stress (°C)	50	[15]
CO2_RUE	A relative increase in RUE per 1ppm elevated CO_2 above 350 ppm	0.01	[15]
S_Water	Sensitivity of RUE to drought stress (ARID index)	1.5	[15]

Cultivar parameters used to calibrate
*Calibrated to suit the conditions where the experiment was performed.

Sensitivity analysis

Morris analysis

The analysis aimed to assess the variability of ten parameters impacting maize yield. Utilizing the Morris method, recognized as a screening technique for influential factors, this approach examined the fluctuations in each parameter by calculating their mean (μ) and standard deviation (σ) across 2 seasons, Autumn - Winter 2020 and Winter - Spring 2020 - 2021, in Cho Moi district, An Giang province. The evaluation identified 2 highly sensitive parameters affecting maize yield in both cropping seasons: RUE and Tbase (**Figure 3**). In terms of parameter impact classification, RUE exhibited a non-linear, highly sensitive influence with strong interactions among other parameters, significantly affecting input outcomes. Although the Tbase parameter had a small mean value, it exhibited substantial standard deviation, resulting in a non-linear influence. The remaining 8 parameters had notably lower impacts (**Figure 3**).

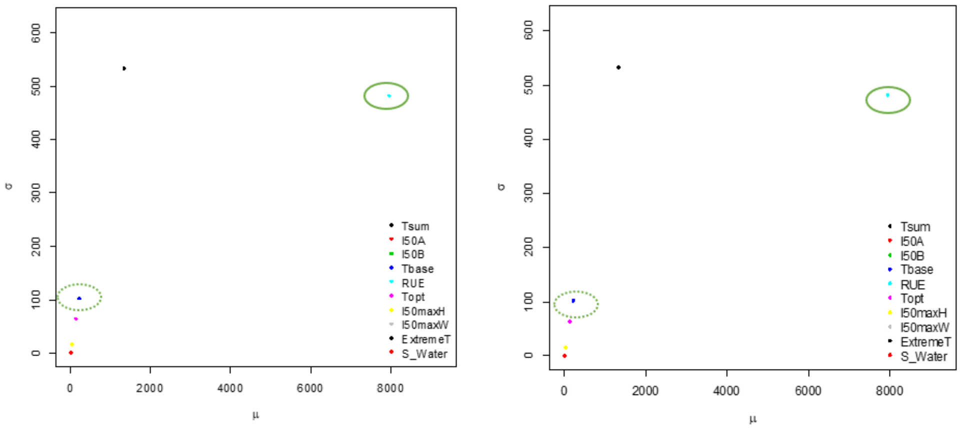

Figure 3 Assessing sensitivity by Morris.

FAST analysis

The screening of input parameters alone did not reveal the primary sensitivity or their contribution to the final yield. Quantitative evaluation of each parameter could be achieved through the FAST method. When comparing parameters characterized by nonlinear impact, high sensitivity, strong interactions with other parameters, and a substantial impact on input, the results indicate variations in mean and standard deviation. In the analysis results (**Figure 4**), RUE and Tbase emerged as 2 parameters with significant impact, with RUE being the predominant influencer of productivity. In a scenario where the total sensitivity of the 10 parameters was 100 %, RUE accounted for 99 % of the sensitivity, Tbase accounted for 1 %, while the remaining parameters held negligible values. This research aligns with earlier studies by Confalonieri, Bellocchi [29] which demonstrated the significant influence of the RUE parameter.

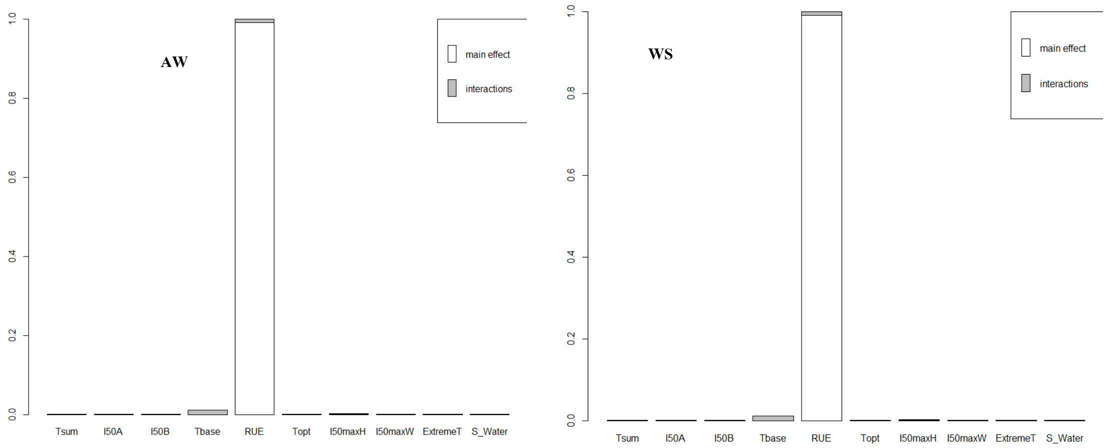

Figure 4 Impacts assessment by FAST (Fourier Amplitude Sensitivity Test). The RUE (Radiation Use Efficiency) parameter demonstrated very high sensitivity.

Analysis of the yield-limiting factor due to temperature

The limiting effect of temperature on SIMPLECrop modeling for maize plants was investigated in the data analysis (**Figures 5** and **6**). Regarding heat stress, in optimal conditions without the influence of high temperatures, the parameter f(heat) remained at 1.0. However, as Tmax (maximum temperature) exceeded Textreme, f(heat) decreased. When f(heat) approached 0, the vegetative biomass (stover) approached zero. **Figure 5** illustrates that the Autumn - Winter 2020 (AW) crop experienced several days with f(heat) less than 0.9, with some periods dropping as low as 0.6, such as on days 24, 55, and 65 DAP (days after planting). This indicates that the impact of heat on biomass in the Winter - Spring 2020 - 2021 (WS) crop was less severe than in the AW crop. In this model, heat stress accelerated canopy senescence by increasing I50B, which shortened the maturity date and reduced the yield of the AW crop.

In the AW crop, there were more periods where f(temp) approached the value of 1.0, indicating temperatures exceeding the optimal range for maize (> 30 °C), compared to the WS crop (**Figure 6**).

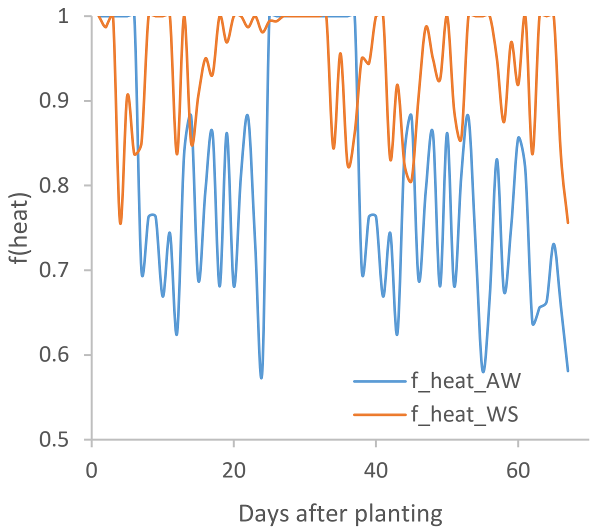

Figure 5 Modeling heat stress impact on maize.

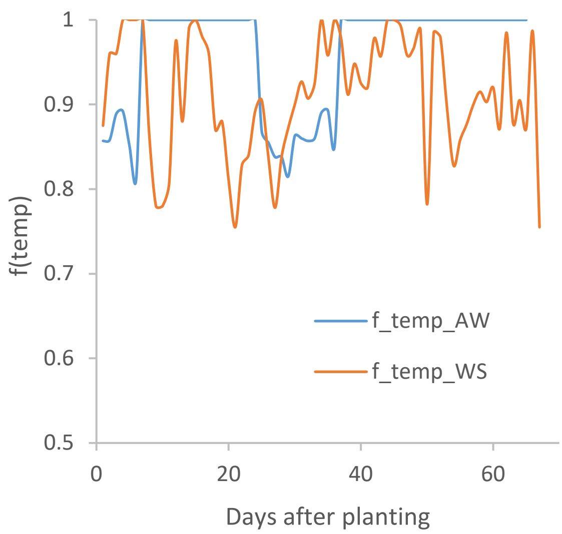

Figure 6 Modeling temperature impact on maize.

Further discussion with farming conditions in Cho Moi district, An Giang, Viet Nam, that considering heat stress on maize alone, WS crop would be more affected by biomass and grain yield. However, the weather in WS crops was more favourable for farming than Autumn - Winter 2020 due to strong wind and rain. That caused more falls in the Autumn - Winter 2020 crop at the time of harvest. The pollination stage was affected by severe wind and rain, producing higher unfilled grain rates [30].

Model assessment in the field

The findings presented in **Figures 7** and **8** demonstrated that the SIMPLECrop model, when applied to simulate the yield and biomass of maize under field conditions, exhibited relative root mean square of error (RRMSE) values between observations and simulations for both crops, ranging from 4.8 - 6.3 %. RRMSE value < 10 % indicates excellent crop modeling [31]. Furthermore, the NSE efficiency coefficient indicates the well-fit performance of the simulation program, allowing for reliable application in simulating and predicting maize yields across different seasons.

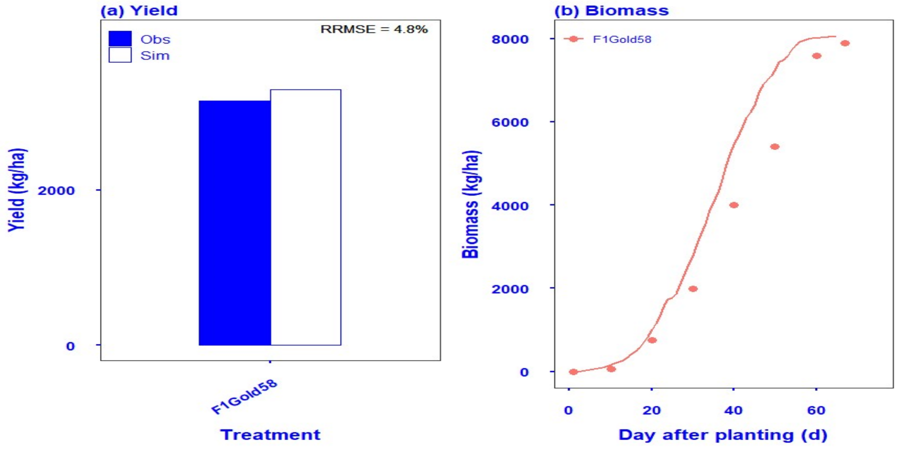

Figure 7 (a) Simulated (white column) and Observed (blue column) yield of maize AW. (b) Daily simulation biomass (solid line) the observation biomass (dot symbol). Simulated and drawn by Rstudio.

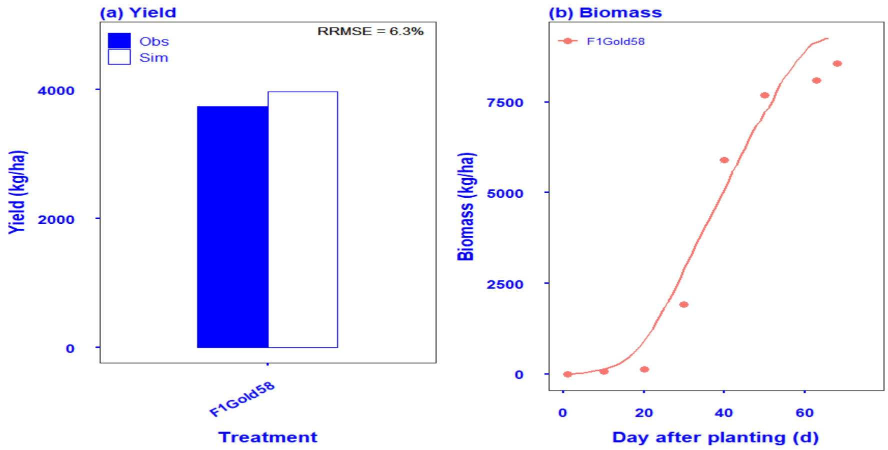

Figure 8 (a) Simulated (white column) and Observed (blue column) yield of maize WS. (b) Daily simulation biomass (solid line) was the observation biomass (dot symbol). Simulated and drawn by Rstudio.

Table 6 Dry biomass and grain yield of observation, simulation.

Season	Observation (kg/ha)		Simulation (kg/ha)		RRMSE (%)	NSE
	Biomass	Yield	Biomass	Yield		
Autumn - Winter 2020	7898	3146	8042	3297	4.8	0.86
Winter - Spring 2020 - 2021	8564	3741	9243	3975	6.3	0.93

The model runs with dry biomass, dry grain.

Overall, the SIMPLECrop model's calibration and assessment findings demonstrated that it could forecast maize biomass and grain yield in both the Autumn - Winter 2020 (AW) and Winter - Spring 2020 - 2021 (WS) seasons in An Giang province, Vietnam. There were significant positive connections between observed and simulated maize yields for the Autumn - Winter 2020 (AW) and Winter - Spring 2020 - 2021 (WS). The comparison with observations showed that the models were accurate in terms of yield (RRMSE was 4.8 % for the AW and 6.3 % for the WS). However, for maize crops, the model simulation results underestimated the yields in both the AW and WS seasons.

Simulation of the effect of variability of climate

Variability of temperature

After the model had been optimally run, in order to carry out simulations under certain temperature and CO_2 concentration conditions, the value of T (°C) or CO_2 (ppm) in the command lines within the Mainfunction was adjusted (either increased or decreased), and the model was run under the new conditions. This resulted in simulation outcomes for biomass and yield corresponding to each alteration. Code to adjust T in Mainfuntion of the model;

[Result$Tmean<-(weather$TMIN+weather$TMAX)/2] [+T]

Code to adjust CO_2 in Mainfuntion of the model:

[CO_2<-para$treatment$CO2] [+CO_2]

It is possible to increase or decrease T and CO_2 individually or simultaneously.

Biomass responses in temperature effect and CO_2 fertilization effect

In the simulation results of the model with a 5 °C temperature increase alone, under field conditions for maize plants, the biomass was observed to decrease. The reduction in biomass ranged from 5.2 % (in the Autumn - Winter 2020 season) to 19.3 % (in the Winter - Spring 2020 - 2021 season), as depicted in **Figure 9**.

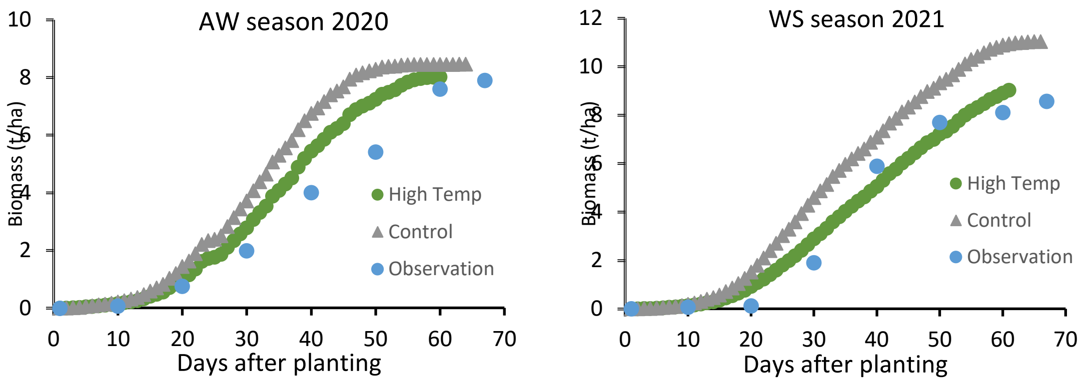

Figure 9 Total above-ground maize biomass under different atmospheric temperatures for the control and high temperature (+5 °C). Observed and controlled data from this experiment. Simulated (lines) and observed (symbols).

The data highlights the significant impact of temperature increase on maize plant biomass. In the experiments, the Winter - Spring 2020 - 2021 season generally yields higher biomass compared to the Autumn - Winter 2020 season. However, the simulation demonstrated that when subjected to a 5 °C increase in average temperature, both seasons experience a substantial reduction in biomass.

A study conducted by Abebe, Pathak [32] examined the response of maize plants to high-temperature stress. They found that maize biomass significantly decreased by approximately 12 % under elevated temperature conditions compared to the control group. Furthermore, the yield was negatively affected, with a reduction of approximately 8 % compared to the normal temperature condition. These results highlight the vulnerability of maize crops to heat stress and its potential impact on food production.

Variability of CO_2 concentration

*S*imulating a 250 ppm increase in CO_2 concentration, the maize stover biomass showed an increase, even though insignificant (about 2.5 %). The CO_2 fertilization effect was studied by Long, Ainsworth [33]. They found that a 250 ppm increase in CO_2 concentration led to a modest increase in maize biomass, approximately 5 %. However, the study also indicated that the CO_2 fertilization effect varied depending on environmental conditions, particularly temperature. At higher temperatures, the beneficial effects of elevated CO_2 on biomass were dampened, suggesting that temperature played a crucial role in mediating the response to increased CO_2 levels (**Figure 10**).

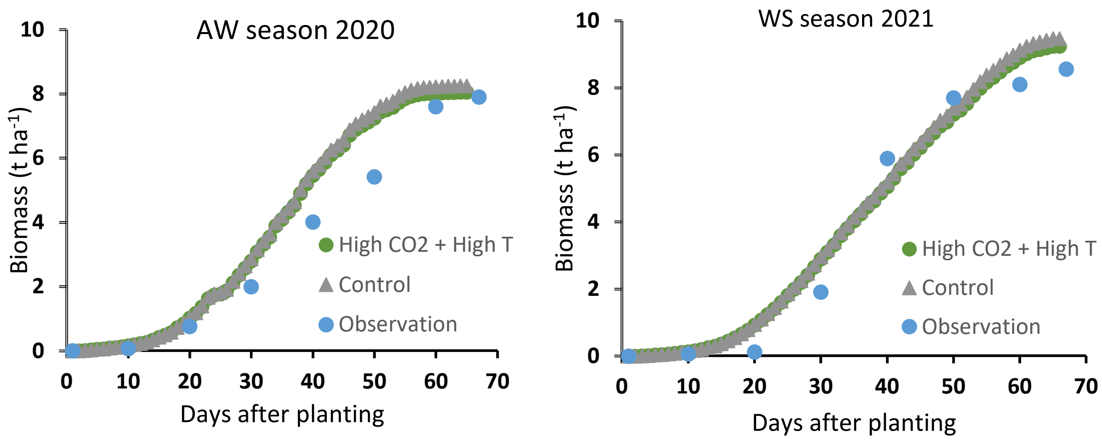

Figure 10 Total above-ground maize biomass under different atmospheric CO_2 concentrations for the control (400 ppm) and high CO_2 (650 ppm) observed total biomass from the experiment site. Simulated (lines) and observed (symbols).

Relative yield responses in temperature effect and CO_2 fertilization effect

Research by Guo, Dai [34] investigated the combined effects of elevated temperature and CO_2 concentration on maize growth. They observed that temperature conditions influenced the impact of elevated CO_2 on biomass and yield. Under moderate temperature increase (2 - 3 °C), the elevated CO_2 concentration led to a moderate increase in biomass and yield, approximately 7 - 10 %. However, under more severe heat stress (5 °C), the beneficial effects of elevated CO_2 were mitigated, and the increase in biomass and yield was reduced to approximately 3 - 5 %. This study highlights the importance of considering interactions between temperature and CO_2 levels in understanding crop responses. The significant reduction in maize biomass had a considerable impact on crop productivity and the overall sustainability of agriculture. The decrease in biomass had a negative effect on crop productivity, resulting in decreased energy production in plants. This reduction in biomass meant fewer resources were available for growth, reproductive development, and, ultimately, grain production

Additionally, the necessity for proactive measures and the adoption of advanced agricultural practices in response to changing climate conditions was underscored by the study. Simulation results highlighted that although elevated CO_2 levels had a positive effect on maize stover biomass, the observed increase was not substantial enough to counterbalance the adverse impact of the previously simulated 5 °C temperature rise.

The slight increase in stover biomass observed in the study could be attributed to the CO_2 fertilization effect. Elevated concentrations of CO_2 have the potential to enhance photosynthesis and increase the assimilation of carbon in plants. This process, in turn, may result in the accumulation of additional carbon-based biomass, including stover. The findings highlight the intricate and interconnected nature of plant growth responses to a range of environmental factors. Temperature and CO_2 concentration, when acting in concert, exert influence on various physiological processes, ultimately shaping crop biomass production.

Considering the limited influence of elevated CO_2 levels on maize stover biomass as observed in this study, it emphasizes the need for a thorough comprehension of the intricate interplay between climate variables and plant growth responses. Researchers and agricultural practitioners must concurrently account for various factors to devise effective strategies for sustainable crop management amidst shifting climate conditions. As global temperatures are projected to rise due to climate change, there is a growing concern about its potential impact on agricultural productivity.

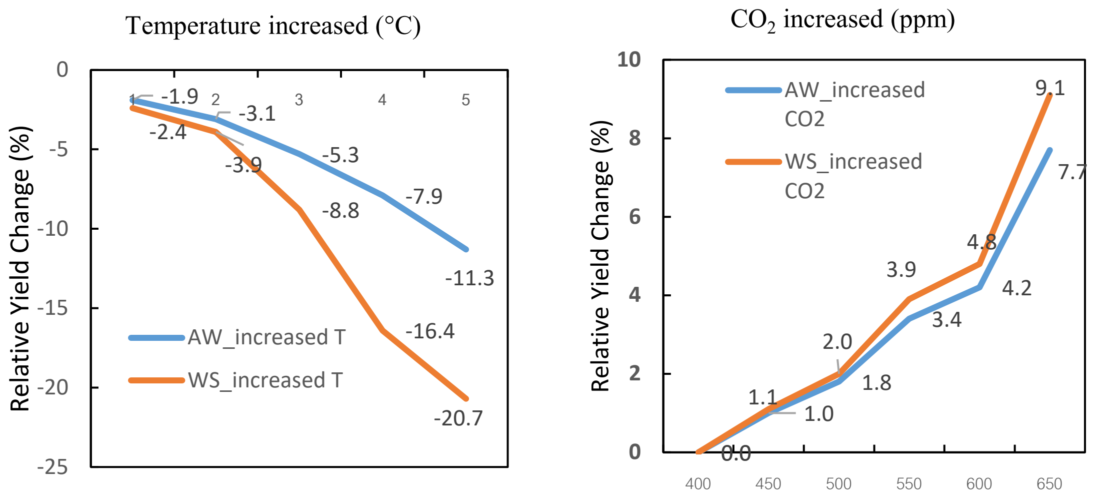

Figure 11 Simulated yields for maize with (a) increasing temperature and (b) elevated atmospheric CO_2 concentration (ppm).

Results and discussion

Annual rainfall was concentrated during the rainy season (from April to October). While the total annual rainfall did not show significant changes, there were intense and extreme rainfall events within short time periods that could adversely affect crops. The peak temperatures were also hotter and more prolonged. The rising temperatures led to a reduction in both biomass and grain yield for maize crops. These findings aligned with previous studies conducted by various authors [28,35-43]. Despite the increase in atmospheric CO_2 concentration, which acted as a fertilizer (contributing to yield enhancement alone), it was not sufficient to counteract the adverse effects of excessively high temperatures. Moreover, the soil in the experimental area was classified as clay loam with poor drainage, making it prone to waterlogging, especially in the case of maize. Poor water drainage could negatively impact crop growth and potentially lead to discrepancies in the simulation results.

Validation process

The validation process played a crucial role in ensuring the reliability of the SIMPLECrop model. Simulated values were rigorously compared against actual data, leading to the computation of validation metrics. Iterative adjustments were made to calibration parameters, including Tsum, HI, I50A, and I50B, to achieve a satisfactory model performance. These cultivar parameters in the SIMPLECrop model were essential for simulating the growth and development of crops, particularly in response to temperature variations. Calibration ensures that the model aligns with real-world crop behavior, making it a tool for understanding and predicting crop responses to changing environmental conditions [44]. Climate-related parameters, rainfall, irrigation, and soil data were integrated into the model without calibration, providing a realistic context for crop growth simulation.

Scientific contributions and practical applications and future development directions

Valuable insights into understanding the impact of climate change on crop productivity and the development of adaptive strategies for sustainable agriculture were contributed by the research outcomes. The SIMPLECrop' model can be considered a tool for policymakers and agricultural practitioners to make informed decisions and plan for future climate scenarios.

Limitations

The study focused exclusively on An Giang province, and micro-level soil data were absent. To enhance the robustness of future studies, expanding the geographical scope and incorporating detailed soil information is recommended. Moreover, the SIMPLECrop model, with its 4 "Cultivar parameters" and 9 "Species parameters", proved adaptable to local conditions with the input of observation data [15,45]. Parameters related to nutrient fertilization could be further customized as "module". Additionally, parameters related to productivity-limiting factors (e.g., pests, wind, storms) could be programmed as separate "modules" based on the type and severity of yield loss. Lastly, crop density and variety significantly impact biomass and yield. In this model, common local crop densities and varieties were utilized. The “Option” feature could be further developed to incorporate additional data as it becomes available from experiments.

Future research directions

Continuing the trajectory established by this study, future research should strive to address the limitations highlighted above. Delving deeper into the impacts of extreme weather events on crop productivity is of paramount importance. This entails conducting comprehensive investigations to elucidate how different crop varieties exhibit resilience or vulnerability to the spectrum of climate extremes.

Expanding the dataset to encompass a broader geographical scope is a promising avenue for future endeavors [46]. Such an extension would yield valuable insights into regional disparities in crop responses to the evolving climate landscape. Armed with this knowledge, researchers can tailor agricultural strategies to specific regions, promoting sustainability and resilience in the face of climate change.

Conclusions

The validation process involved comparing simulated and observed data, resulting in the computation of validation metrics. During the calibration process, 4 cultivar parameters (Tsum, HI, I50A, I50B) were employed. The SIMPLECrop model, simulated for maize in An Giang Province, performed exceptionally well. Evaluation results showed RRMSE and NSE values ranging from 4.8 to 6.3 % and 0.86 to 0.93, respectively, for open field conditions. During the sensitivity analysis for maize crops, 2 parameters, namely RUE and Tbase, consistently demonstrated the strongest influence within the model.

For maize, a 5 °C temperature increase led to a reduction in stover biomass by 5.2 % (in the Autumn - Winter 2020 season) to 19.3 % (in the Winter - Spring 2020 - 2021 season) and a yield decrease of 11.3 and 20.7 %, respectively. Simulating an increase in CO_2 concentration alone, ranging from 50, 100, 150, 200 to 250 ppm, resulted in increased biomass and yield. When simulating a 250 ppm CO_2 increase, the increases were about 2.5 % in biomass and 7.7 to 9.1 % in yield. However, under more severe heat stress (5 °C increasing), the beneficial effects of elevated CO_2 were mitigated, and the increase in biomass and yield was reduced to approximately 3 - 5 %. These findings emphasize the importance of considering interactions between temperature and CO_2 levels in understanding crop responses.

Acknowledgements

The authors express their sincere gratitude to Prof. Dr. Irfan Suliansyah, Dr. Feri Arlius, Dr. Irawati Chaniago, Assoc. Dr. Nguyen Thi Thanh Xuan, and Dr. Pham Van Quang for their invaluable support throughout my doctoral studies at UNAND, Indonesia, as well as their assistance in the research progress and the publication process. This research is funded by Vietnam National University, Ho Chi Minh City under grant number B2020-16-02.

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