

SIMPLECrop Modeling for rice: Calibration, Validation, Evaluation and Sensitivity analysis in An Giang Province, Vietnam

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Abstract—Rice, a staple crop of global significance, is instrumental in securing food resources and fostering socio-economic well-being. Maintaining the stability and resilience of rice production is paramount in the context of a changing climate and increasing population. Advanced crop modeling techniques have emerged as indispensable tools for understanding and predicting crop responses to varying environmental conditions. This study, conducted in Vietnam's An Giang Province in the Mekong Delta, addresses the critical need for robust rice production models. The region's susceptibility to climate change-induced temperature and rainfall shifts underscores the urgency of developing precise predictive models for rice cultivation. Employing the versatile SIMPLECrop model, we endeavor to address the tests of calibrating, validating, evaluating, and conducting sensitivity analysis for rice cultivation in this specific locale. Calibration, the process of aligning model parameters with observed data, involved iterative adjustments using optimization techniques. The validation process compared model predictions with independent observed data. Our evaluation demonstrated relative root-mean-square error (RRMSE), Nash-Sutcliffe efficiency (NSE) values ranging from 4.2% to 5.5% and 0.87 to 0.90 for open field conditions. During sensitivity analysis, two parameters, RUE and T_{base} , consistently exhibited the highest influence within the model. In the field condition model assessment, the SIMPLECrop model excelled in predicting crop yields in open-field settings. The RRMSE values fell within the accepted range for crop modeling, and the NSE coefficient indicated a strong fit performance, ensuring reliable predictions of rice yields across seasons.

Keywords: Calibration, Evaluation, Rice Simulation, Sensitivity Analysis, Simplecrop Model

1. INTRODUCTION

Rice, as one of the staple crops worldwide, plays an important role in global food security and socioeconomic well-being. In the context of a changing climate and growing population, ensuring rice production's stability and resilience is paramount (Anderson *et al.*, 2020). As a means to address these challenges, sophisticated crop modeling techniques have emerged as valuable tools for studying and predicting crop responses to varying environmental conditions (Peng B. *et al.*, 2020).

In the fertile Mekong Delta of Vietnam, particularly in An Giang Province, rice cultivation is essential to the local economy and food supply (Cramb, 2020). The region's vulnerability to climate change-induced shifts in temperature, rainfall, and extreme events (Bayrak *et al.*, 2023) underscores the urgency of developing accurate and adaptable models for rice crop prediction and management. This study addressed this pressing need by employing a crop model (SIMPLECrop model), a versatile tool for simulating crop growth, to assess rice production in An Giang Province, Vietnam specifically. The importance of this research lies in its potential to offer practical insights into how rice farming in this region can adapt to the evolving climate and environmental dynamics.

In light of the above, our research contends with several significant challenges, including optimizing the performance of the SIMPLECrop model for rice, assessing its accuracy under local climatic conditions, and determining the model's sensitivity to different variables and parameters. These issues form the core problems that this research endeavors to address by processing calibration, validation, evaluation modeling and Sensitivity analysis. Calibration is the process of adjusting model parameters to minimize the differences between model simulations and observed data (Pereira *et al.*, 2020). It plays a vital role in ensuring that the model accurately represents real-world conditions. Calibration involves iterative adjustments of model parameters using optimization techniques. These parameters can include crop-specific growth coefficients, environmental factors, and soil properties (Wellens *et al.*, 2022).

The objective is to align model outputs with observed data, making the model suitable for specific regions or conditions. Validation assesses the model's performance by comparing its predictions with independent sets of observed data that were not used in the calibration process (Hadria *et al.*, 2007). It verifies the model's ability to generalize beyond the calibration dataset. Validation involves using data separate from the calibration dataset. Statistical metrics such as Root Mean Square Error (RMSE) and the Nash-Sutcliffe Efficiency (NSE) are commonly used to quantify the agreement between model predictions and observed data (Phuoc *et al.*, 2022). A well-validated model should demonstrate consistent accuracy across various scenarios assessment involves conducting sensitivity analyses and scenario testing. Sensitivity



analysis assesses how changes in input parameters affect model outputs (Phuoc *et al.*, 2022). This process provides insights into the model's behavior and limitations. Sensitivity analysis investigates the model's sensitivity to changes in input parameters and helps identify which parameters have the most significant impact on model outputs (Pham *et al.*, 2023). It provides information on the model's robustness and the parameters that require precise estimation.

This research brings novelty to the field by focusing on the specific case of rice cultivation in An Giang Province and employing the SIMPLECrop model for comprehensive calibration, evaluation and sensitivity analysis. Our objectives are two-fold: firstly, to create a precisely calibrated rice model that faithfully mirrors its growth and development within distinct environmental contexts, and secondly, to conduct simulations investigating the influence of temperature variations on yield-limiting factors. This exploration aims to provide deeper insights into the intricate interplay between temperature and crop productivity.

2. RESEARCH METHODOLOGY

2.1. Brief modeling description

The models were to construct a generic yet basic dynamic crop simulation model with few parameters, data needs, and no crop-specific processes, enabling easy application to a wide range of crops. The model used daily step time to mimic crop growth, development, and yield. The models took into account and expressed the soil, water, crop, and climatic elements using equations.

Crop yields were calculated using the quantity of biomass accumulated during plant growth and adjusted using the harvest coefficient (the proportion of biomass yielding economic value). Solar radiation, temperature, humidity, precipitation, CO₂ concentration, soil physicochemical qualities, and crop species all had an impact on accumulated biomass.

Using the R programming language, software was created to simulate cumulative biomass and crop production prediction based on the specified equations and parameter values.

+ Daily biomass growth rate

$$\text{Biomass rate} = \text{Radiation} * f_{\text{Solar}} * \text{RUE} * f(\text{CO}_2) * f(\text{Temp}) * \min(f(\text{Heat}), f(\text{Water})) \quad (1)$$

And

+ Cumulative average biomass rate [20]

$$\text{Biomass_cum}_{i+1} = \text{Biomass_cum}_i + \text{Biomass_rate} \quad (2)$$

$$\text{Yield} = \text{Biomass_cummaturity} * \text{HI} \quad (3)$$

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

TT and T_{sum} are calculated as follows:

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

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

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

$$f(\text{heat}) = \begin{cases} 1, & T_{\text{max}} \leq T_{\text{heat}} \\ 1 - \frac{T_{\text{max}} - T_{\text{heat}}}{T_{\text{extreme}} - T_{\text{heat}}}, & T_{\text{heat}} < T_{\text{max}} \leq T_{\text{extreme}} \\ 0, & T_{\text{max}} > T_{\text{extreme}} \end{cases} \quad (8)$$

$$f(\text{CO}_2) = \begin{cases} 1 + S_{\text{CO}_2}(\text{CO}_2 - 350), & 350\text{ppm} \leq \text{CO}_2 < 700\text{ppm} \\ 1 + 350 \times S_{\text{CO}_2}, & \text{CO}_2 > 700\text{ppm} \end{cases} \quad (9)$$

$$f(\text{water}) = 1 - S_{\text{water}} \cdot \text{ARID} \quad (10)$$

To gain a more comprehensive understanding of the detailed model description, definitions, and significance of each parameter, please refer to the referenced article (Zhao *et al.*, 2019).

2.2. Model parameters and input variables

2.2.1. Model parameter

This study used thirteen factors in the SIMPLECrop model to define a crop, in addition to climate-related data, irrigation, rain inputs, and soil properties as starting variables.

Cultivars parameters: T_{sum}, HI, I_{50A}, I_{50B} were determined from the observations of experiment data and the air temperature data.

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

2.2.2. Input variables

Weather (daily maximum/minimum temperature, rainfall, and solar radiation), atmospheric CO₂ concentration, sowing / harvesting date, irrigation, initial variables (biomass / cumulative temperature / fraction of solar radiation interception if different from zero), and four soil-characterizing variables, including a fraction of plant available water-holding capacity (AWC; one number for entire soil profile, limited by potentiometric potentiometric potentiometric potentiometric potention (RZD).

2.3. Model Calibration, Validation And Evaluation

2.3.1. Model calibration and validation

Were the first two steps for a simulation of crop modeling before the simulation was evaluated. Model validation in crop modeling referred to the process of assessing the accuracy and reliability of a developed crop model by comparing its predictions with observed or measured data. This procedure aimed to determine whether the model was capable of accurately simulating the behavior and responses of crops to varying environmental conditions, management practices, and other influencing factors.

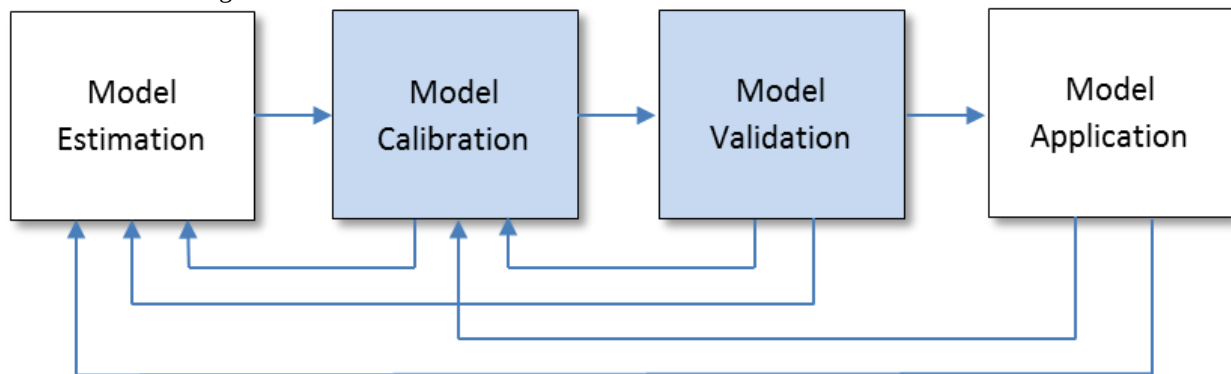


Figure 1. Construction sequence for a crop model application or simulation

Model calibration entailed an iterative process of adjusting parameters and characteristics within a generated model in order to get the best possible alignment between the model's predicted outputs and the field measurements or data obtained. If the model's performance was considered inadequate during calibration, validation became necessary. To improve the model's accuracy, parameters have to be adjusted, or the model's structure changed.

Four cultivar parameters and nine species parameters to determine crop types and to define cultivar differences were included in the model. The parameters of the species were derived from agreed values in literature, like RUE, Tbase, Topt, and SCO₂, from other crop models, if any, or calculated about crops with defined parameters.

Calibration of cultivar parameters was performed. The models calibrated the cultivars' parameters within a reasonable range (but kept the cultivar parameter constant for the same cultivar when grown in different seasons). This calibration referred to the aboveground dry matter accumulation (calibrated Tsum), a proportion of radiation interception (calibrated I50A and I50B), and ultimate yield (dry grain) data sets (calibrated HI).

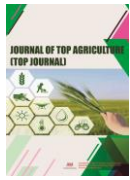
2.3.2. Model calibration and validation

The model's performance was evaluated using independent experimental data sets. Using the built crop data file, calculated soil parameters, and real daily weather data, the model simulated crop growth and development for each treatment. The observed data was then compared to the simulated findings.

For each crop, the models were evaluated using relative root-mean-square error (RRMSE), Nash-Sutcliffe efficiency (NSE), and meteorological, soil, water, and crop management factors. The following statistics were generated to assess model effectiveness in predicting observed yields:

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

$$RRMSE = \frac{RMSE}{\sum_{i=1}^n O_i} \times 100\%$$



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

Where:

n is the sample number,

O_i and S_i : the observed and simulated values of the i th observation ($i = 1$ to n).

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

2.4. Sensitivity Analysis

In crop modeling, sensitivity analysis determines how modest changes in input factors (such as temperature, precipitation, or cultivar traits) influence the model's output, often crop yields or biomass. It assists academics and farmers in understanding the model's sensitivity to various parameters and determine which inputs influence crop projections most. This study is critical for fine-tuning models, producing accurate forecasts, and improving agricultural operations in order to adapt to changing climatic circumstances and increase crop output. The Morris approach was used to do sensitivity analysis (Morris,) and FAST (Fourier Amplitude Sensitivity Test) (Xu and Gertner, 2011).

The Morris approach was used to select and discretize the parameters in the same standard space, spanning the complete volume of space in which they can transform. This strategy allows for identifying the most essential parameters in a complicated model's parameters. Simultaneously, it permitted assessing if the parameter's effects are trivial, linear, nonlinear, or interacting with other factors. This arrangement is based on the principal impact of a particular parameter. The assessment was carried out by computing r iterations (r orbitals) at r various places in the input, then calculating averages and standard deviations from which judgments about the sensitivity of each input parameter could be drawn.

The nonlinear effect factors in the FAST technique have excellent sensitivity and intensive interaction with other parameters, considerably influencing the input results. The Morris approach screens parameters with varied mean and standard deviation, but it is uncertain which parameter has the highest sensitivity and by what percentage. The FAST technique aids in the quantitative evaluation of each parameter (FAST refers to the influence scale from 0 -1).

The study question was to examine the volatility of ten variables that influence production. Based on the Morris technique's formula, which was a screening approach for influencing factors, this method estimated the variations of each parameter in two seasons AW (Autumn-Winter 2020), WS (Winter-Spring 2020-2021) in Cho Moi district (10° 23' 47"N, 105° 27' 41"E), An Giang province, Vietnam. If we only screen input parameters, we cannot know which parameter has the most incredible sensitivity and ratio of effect on ultimate yield. As a consequence, the FAST approach will help in quantifying each parameter. When comparing parameters with a nonlinear influence, high sensitivity, intensive interactions with other parameters, and considerable impact on input outcomes, these parameters' mean and standard deviation differed.

2.5. Data Processing

Rstudio language programming was utilized in this project to create agricultural yield modeling and simulation. Following collection, measurement, or analysis, the data was entered into and encoded by Microsoft Excel (*.csv) to create datasets based on crop name, crop management factor, soil factor, and weather factor.

Make folders for the following information:

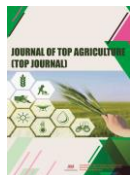
- A directory containing collected data files (observation data) filetype *.csv
- A directory containing input data (dataset) filetype *.csv, describing primary variables: simulation management, cultivar, soil, species parameter, treatment, irrigation.
- Mainfunction.R file is programmed to read and link formulas to calculate the figures of crop modeling
- Additional files to simulate future weather changes and files about sensitivity (Morris, FAST).
- A folder containing weather files such as temperature, CO₂, rain, SRAD (solar radiation)

Then, set up commands in the R language to operate the model.

3. RESULT AND DISCUSSION

3.1 Model Calibration, Validation, And Evaluation

After the model ran without errors, the simulated values of interest were compared to actual data, resulting in the computation of validation metrics. Following that, the simulation usually requires altering specific parameters and evaluating the model's performance, which is measured using the RRMSE value. If the results are unsatisfactory, a return



to the previous stage to recalibrate parameters within tolerable ranges may be necessary. The research used four cultivar parameters (Tsum, HI, I50A, and I50B) for the calibration procedure.

The results of the parameters used for calibrating the rice crops are presented in

Table 1.

Table 1. Model calibration and validation range for cultivar parameters

Name	Description	Range	Note
Cultivars parameters (calibration datasets)			
Tsum	Thermal time requirement from sowing to maturity in daily mean (°C days)	2778-3319	*
HI	Harvest index	0.41-0.49	*
I50A	Thermal time requirement after sowing fraction of light interception to reach 50% (°C days)	421-438	*
I50B	Represents natural senescence. Thermal time requirement from maturity backward for the light interception to reach 50% (°C days)	84.8-119.7	*
Species parameters (validation datasets)			
Tbase	Base temperature (daily mean T) for phenology development and growth (°C)	10	[16]
Topt	Optimal temperature (daily mean T) for biomass growth (°C)	30	[17]
RUE	Radiation use efficiency (above ground biomass + below ground, if the harvestable product is below ground) (g MJ/m ²)	1.24	[20]
I50maxH	The maximum daily increase in I50B due to heat stress (°C d)	100	[20]
I50maxW	The maximum daily increase in I50B due to water stress (°C d)	10	[20]
MaxT	Threshold for daily Tmax to start accelerating senescence due to heat stress (°C)	53.3-58.9	[20]
ExtremeT	Daily Tmax threshold when RUE becomes 0 due to heat stress (°C)	50	[20]
CO ₂ _RUE	A relative increase in RUE per 1ppm elevated CO ₂ above 350ppm	0.08	[20]
S_Water	Sensitivity of RUE to drought stress (ARID index)	1	[20]

Cultivar parameters used to calibrate

* Calibrated to suit the conditions where the experiment was performed.

From the above, the Tsum values fall within a relatively narrow range, spanning from 2778 to 3319 oC days. This suggests that the selected cultivars have distinct thermal time requirements for reaching maturity, which is critical for accurate crop modeling. I50A values showed a relatively tight range, spanning from 421 to 438 oC days. This parameter represented the thermal time required for a fraction of light interception to reach 50%, indicating the efficiency of light energy utilization in crop development. I50B values exhibited a wider range, varying from 84.8 to 119.7 oC days. I50B represented the thermal time required for the light interception to reach 50% during the natural senescence phase of the crop's lifecycle. The variations in this parameter highlight the cultivars' senescence patterns.

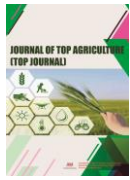
Tsum Range: The range of Tsum values, which represented the sum of temperatures required for crop development, was distinguished. These values have been calibrated and validated for rice in field conditions. The Tsum values in the greenhouse were higher than those in the field. This discrepancy was attributed to the higher daily average temperature accumulation in the controlled greenhouse environment.

Calibration of Harvest Index (HI): The Harvest Index (HI) is a parameter that represents the fraction of above-ground biomass allocated to the harvestable component of the crop, such as grains or fruits. HI varies due to a range of factors, including genetic variability, environmental conditions, management practices, and the crop's growth stage. This calibration allows the model to adapt to the specific requirements and genetics of the crop being studied, improving its accuracy. In this study, HI was not calibrated but instead utilized observed values. However, it's important to note that in the SIMPLECrop model, HI can indeed be calibrated because it is not a fixed constant.

I50A and I50B Variability: A reduction in the range of values for I50A and I50B in greenhouse conditions compared to field conditions was observed for rice. Conversely, an increase in the maximum variability of both I50A and I50B, with values trending upwards, was noticed for rice. After model calibration and validation, the evaluation results indicated that the RRMSE and NSE specified for open field conditions range from 4.2 % to 5.5 %, and 0.87 to 0.90, respectively. RRMSE value < 10% indicates good crop modeling (Jamieson *et al.*, 1991). Furthermore, the notable NSE efficiency coefficient indicates the well-fit performance of the simulation program, allowing for reliable application in simulating and predicting rice yields across different seasons.

Table 2. Dry biomass and grain yield of observation, simulation

Observation (kg/ha)	Simulation (kg/ha)	RRMSE (%)	NSE
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Crop season	Biomass	Yield	Biomass	Yield		
AW	10640	5040	11045	4762	5.5	0.87
WS	11985	5233	11598	5451	4.2	0.90

The model runs with dry biomass, dry grain.

AW (Autumn-Winter 2020), WS (Winter-Spring 2020-2021)

Overall, model calibration and evaluation results showed that the SIMPLECrop model could predict rice's biomass and grain yield in both AW and WS crop seasons in An Giang province, Vietnam. Significant positive relationships were found between observed and simulated rice yields for the AW and WS. However, the simulated yield underestimates AW yields and overestimates the WS for rice crops.

3.2 Sensitivity analysis with Moris and F.A.S.T methods

The research issue was to analyze the volatility of 10 parameters that affect rice yield. Based on the formula of the Morris method, which was a screening method for influencing factors, this method determined 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. The assessment found that in both crops, there were two parameters with high sensitivity affecting rice yield, specifically RUE and T_{base} (**Error! Reference source not found.**). 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 (**Error! Reference source not found.**).

Figure 2. Morris analysis for the AW 2020 (the left side) and WS 2020-2021 season

If we screened input parameters alone, we were unable to ascertain which parameter exhibited the highest sensitivity and exerted the most substantial impact on the ultimate yield. Consequently, the FAST technique proved valuable in quantitatively assessing each parameter. The results unveiled distinctions in their mean and standard deviation by comparing parameters with nonlinear influence, high sensitivity, extensive interactions with other parameters, and a notable impact on input. The analysis results (Figure 3) indicated that RUE and T_{base} were two characteristics with a substantial impact, with RUE having the most influence on productivity. If the overall sensitivity of ten parameters were 100%, the sensitivity of RUE would account for 99 %, the sensitivity of T_{base} would account for 1%, and the other parameters would have a non-significant value. The findings are also consistent with previous research. Confalonieri *et al.*, (2010), Paleari and Confalonieri (2016), when published study results, demonstrated that the RUE parameter had a considerable effect. In addition, depending on the individual farming conditions, climatic features, and soil qualities of rice, other metrics such as LAI (Leaf Area Index) and T_{opt} (optimum temperature) were significant (Morrison and Stewart, 2002).

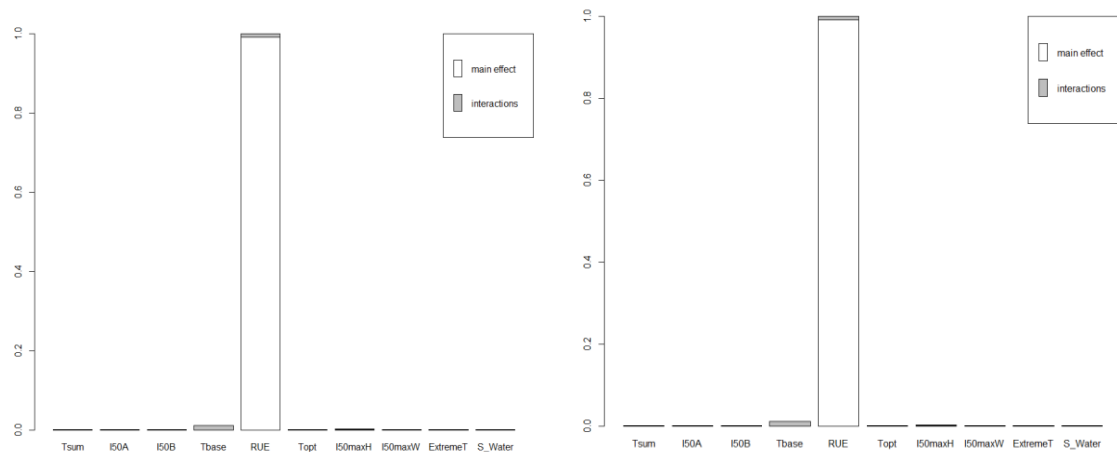


Figure 3. FAST assessment for the AW 2020 (the left side) and WS 2020-2021 season

3.3 Simulation of the impact of heat stress and temperature on rice yield in An Giang, Vietnam.

The discussion explored the limiting effect of temperature on SIMPLECrop modeling for rice plants (Figure , Figure). For heat stress, in optimal conditions without the impact of heat, $f(\text{heat})$ is equal 1.0 when $T_{\max} > T_{\text{extreme}}$, $f(\text{heat})$ gets smaller. When $f(\text{heat})$ approaches the value 0, the vegetative biomass (straw) approaches 0 (zero). Figure shows AW crop had many days with $f(\text{heat})$ less than 0.8 in the pre-flowering stage, but WS crop $f(\text{heat})$ 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 accelerated canopy senescence by increasing I50B, which shortens the maturity date and reduces AW yield.

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

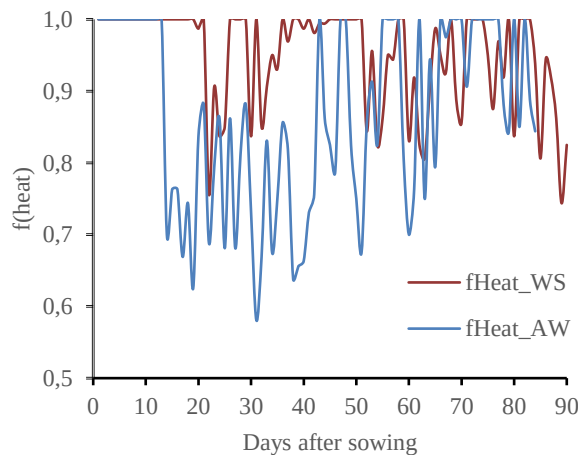


Figure 4. Assessing the Influence of Heat Stress on Rice Growth

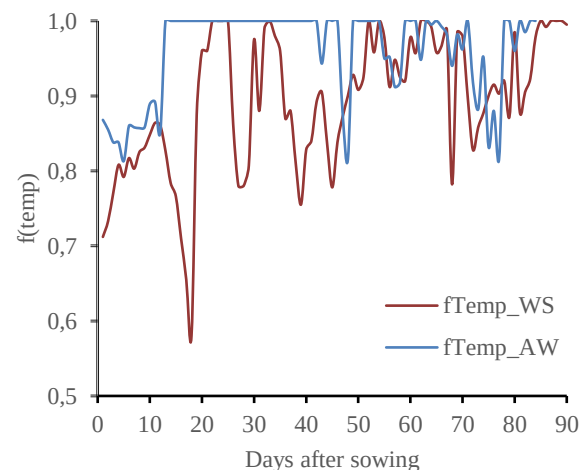
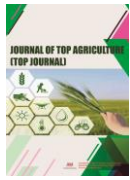


Figure 5. Assessing the temperature impact on rice growth

Further discussion with farming conditions in Cho Moi district, An Giang, Viet Nam, 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 (Liu *et al.*, 2016). For rice crops, it's important to note that the typical farming practice in the Mekong Delta involves almost continuous irrigation throughout the growth period. Therefore, the function $f(\text{water})$ equals 1, indicating the absence of water stress. In the case of upland rice, drought stress is still accounted for and calculated by this model (Zhao *et al.*, 2019).



The calibration and 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 are 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 (Oteng-Darko *et al.*, 2013). Climate-related parameters, rainfall, irrigation, and soil data were integrated into the model without calibration, providing a realistic context for crop growth simulation.

SIMPLECrop's performance in predicting crop yield under extreme conditions revealed potential areas for improvement. While the model performed well in simulating field conditions, it was observed to underestimate rice yield, particularly under high-temperature scenarios. Therefore, the accuracy of the model in extreme environments could be enhanced through further calibration and refinement of parameters specific to greenhouse conditions.

Future research efforts could focus on expanding the model's capabilities to incorporate additional crop species and exploring more complex climate variables. Moreover, integrating other relevant factors, such as water availability and nutrient management, could enhance the model's predictive capacity under varying agroecological conditions.

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

The calibration and validation process were pivotal in establishing the reliability of the SIMPLECrop model. Rigorous comparisons between simulated and actual data led 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 within the SIMPLECrop model are indispensable for simulating crop growth and development, especially in response to temperature fluctuations. Calibration ensures that the model accurately reflects real-world crop behavior, transforming it into a valuable tool for comprehending and forecasting crop responses to evolving environmental conditions (Oteng-Darko *et al.*, 2013). Climate-related parameters, such as rainfall, irrigation, and soil data, were seamlessly integrated into the model without requiring calibration, furnishing a realistic context for simulating crop growth.

The study's evaluation revealed potential areas for improvement in SIMPLECrop's predictive accuracy, particularly under extreme conditions. While the model demonstrated strong performance in simulating field conditions, it exhibited a tendency to underestimate rice yield, remarkably in high-temperature scenarios. Consequently, enhancing the model's precision in extreme environments may necessitate further calibration and the refinement of parameters specifically tailored to greenhouse conditions.

Looking ahead, future research endeavors could center on expanding the model's capabilities to encompass a broader array of crop species and delve into more intricate climate variables. Additionally, the incorporation of other pertinent factors, such as water availability and nutrient management, holds the potential to augment the model's predictive capacity under diverse agroecological settings.

Basic model with extensibility: The model provides a foundation by incorporating essential parameters influencing plant growth and development. It was designed to be extensible, allowing the inclusion of various crop species once the required species-specific data are available. This adaptability is a significant strength, as it makes the model flexible and suitable for different agricultural contexts.

Integration of key environmental factors: The model is grounded in soil properties, weather data, and crop-specific growth parameters. This comprehensive integration of environmental factors ensures that it accurately simulates the complex interactions between crops and their surroundings.

Parameter customization: SIMPLECrop allows for the flexible customization of parameters. This means that additional parameters can be introduced to the core model through options, tailoring the model to specific research questions and scenarios. This adaptability enhances the model's versatility and applicability in a wide range of agricultural studies.

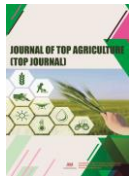
Spatial and temporal integration: The model successfully links spatial and temporal factors to simulate variations, making it useful for analyzing changes over time and across geographical locations. This capability is essential for assessing the impact of climate and environmental shifts on crop growth.

Open-source nature: SIMPLECrop is an open-source model. This open accessibility encourages collaboration and transparency, which are critical for the continued improvement and refinement of the model.

Need for additional data: One of the weaknesses of the SIMPLECrop model is the requirement for more diverse and detailed datasets that directly impact crop productivity. This includes factors such as fertilizers, crop varieties, planting densities, and various growth-limiting factors like wind, storms, drought, pests, and diseases. Similar to the "big prediction models" of predictive programs that benefit from the contributions of numerous scientists, SIMPLECrop could benefit from more diverse data modules.

Complexity and data requirements: Despite its extensibility, SIMPLECrop demands a substantial amount of data, including detailed information about soil properties, weather conditions, and species-specific parameters. Acquiring and managing such data can significantly challenge many agricultural research settings.

Calibration challenges: The flexibility to customize parameters is an advantage, but it can also be a challenge. Calibrating the model effectively requires a deep understanding of crop behavior, and finding accurate values for all parameters can be time-consuming and resource-intensive.



Data integration and accessibility: Efforts should be made to streamline the data acquisition process, possibly through data-sharing platforms or repositories. This would enhance the usability of the model by reducing the trouble of data collection for individual researchers.

User-friendly calibration tools: The development of user-friendly interfaces or tools for calibrating the model could help lower the entry barrier for researchers less familiar with complex calibration processes.

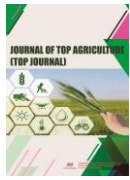
Documentation and community support: Providing comprehensive documentation and development of a supportive user community can facilitate model use, calibration, and troubleshooting, ultimately improving its accessibility and effectiveness.

4. CONCLUSION

Rice (*Oryza sativa*) exhibited higher grain yields in the Winter-Spring 2020 (AW) crop compared to the Autumn-Winter 2020-2021 (WS) crop when grown under field conditions in simulation and observation. This aligns with the local practical conditions, where the WS crop has been the preferred choice for rice cultivation over the past many years. The validation process involved comparing simulated and observed data, resulting in the computation of validation metrics. During the calibration process, four cultivar parameters (Tsum, HI, I50A, I50B) were employed. The SIMPLECrop model, simulated for rice in An Giang Province, performed exceptionally well. Evaluation results showed RRMSE and NSE values ranging from 4.2% to 5.5% and 0.87 to 0.90, respectively, for open field conditions. During the sensitivity analysis for rice crops, two parameters, namely RUE and Tbase, consistently demonstrated the highest influence within the model. The field condition model assessment showcased the capability of the SIMPLECrop model to predict crop yield in open-field settings. This underscores the potential utility of this model in forecasting agricultural productivity. The RRMSE values fell within the crop modeling range, while the NSE coefficient indicated a fit performance, ensuring reliable predictions of rice yields across seasons.

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