Journal of Applied Agricultural Science and Technology
7(3): 197-216 (2023)
E-ISSN: 2621-2528
ISSN:2621-4709

LITERATURE REVIEW CROP MODELING AND INTRODUCTION A SIMPLE CROP MODEL

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***Abstract**. Modeling science has been applied by many advanced countries in many fields, such as geology, meteorology, climate change, crop productivity, environment, erosion, and landslide. The crop model simulates the processes of agriculture. The writing of this article is descriptive qualitative using the Systematic Literature Review (SLR) method. So far, each model has its advantages and disadvantages but generally is based on the physiology of the growth and development of crops in relationship with soil, climate, solar radiation energy, and limiting factors to plant growth. There have been many models for rice that can forecast yield and biomass or predict future climate change dynamics. Meanwhile, many models such as DSSAT, AquaCrop, Oryza, APSIM, EPIC need more data to operate their modeling, which in many cases, data is not readily available. In this review, we would like to introduce the model "SIMPLE" which includes only thirteen parameters and four of which describe cultivar characteristics. Another advantage of "SIMPLE" is that it can be adapted for many crop species and added variable modules such as nutrient dynamics, water stress, temperature stress, or pests. It is entirely open source based on R programming, but limitations still exist that have been mentioned in the review.*
***Keywords**: crop modeling; biomass; yields*

1. Introduction

Digital agriculture - a combination of digital and geospatial technologies to monitor changes in the external environment, such as weather, rain, wind, and soil nutrients, as well as calculate economic efficiency in the farming process has been noticed. In particular, the application of crop modeling is one of the achievements applied by many developed countries in digital agriculture (Queiroz *et al.*, 2021).

Crop modeling is a modern tool for simulating or predicting plant growth and yield in the greenhouse and in the field and assessing climate change's impacts. Up to now, many crop models have been used to simulate significant crops such as cassava, rice, corn, green beans, and banana (Gao *et al.*, 2021). A crop model can be described as the numerical computational process to predict plant growth, biomass, and yield, yielding results between the environment and crop relationships (Wang *et al.*, 2017).

Received December 5, 2022; Accepted June 11, 2023; Published August 25, 2023
https://doi.org/10.55043/jaast.v7i3.123

Crop models are used for production purposes, experimental research, business, or for managers to make agricultural policy decisions such as time of sowing and area to be cultivated. The efforts of scientists have led to the development of advanced models, from single-plant scales such as CERES (Timsina & Humphreys, 2006) to others for assessing soil productivity affected by the action of surface processes such as EPIC (Williams *et al.*, 1989). The decision support system for agrotechnology transfer (DSSAT) model help has been used for the last 15 years by researchers worldwide (Hoogenboom *et al.*, 2019). APSIM models have been created to imitate biophysical processes in the field for economic forecasting that are widely used in Africa to evaluate the effect of corn-mucuna crop rotation on irrigation water, yield, and climate change impacts (Wang *et al.*, 2002).

Climate change globally, in Vietnam or An Giang province, is also in a similar situation. In an annual assessment of the countries most affected by extreme weather changes between 1997-2016, Vietnam was categorized 5th in the Global Climate Risk Index 2018 and 8th in the Global Climate Risk Index (Eckstein *et al.*, 2017). 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. In An Giang province, the average annual temperature increased by 0.8 ºC (0.4-1.2 ºC) from 2016-2035 compared to the period of 1986-2005. It further rose to 1.4 ºC (1.0-2.0 ºC) from 2046-2065 under the RCP4.5 scenario. The current trend indicates a likely acceleration in temperature increase. Under the RCP8.5 scenario, temperatures are projected to rise by 0.9 ºC (0.6-1.3 ºC) from 2016-2035 and by 1.9 ºC (1.4-2.6 ºC) from 2046-2065.

Managers and rice production companies need a tool to plan and make decisions and estimate their productivity to be exported or the amount of straw after each crop to be used for other purposes. The models introduced above have the disadvantage that they are complicated to run simulations, and many criteria are needed, but the necessary data are not always available (Zhao *et al.*, 2019). An example that shows the existence of these models is the need for multiple parameters. DSSAT needs to collect many data and many parameters to define a simulation. The EPIC model needs 22 parameters. The AquaCrop model needs 29 parameters (Raes *et al.*, 2009), while our model (SIMPLE model) only needs 13 parameters (Hoogenboom *et al.*, 2019).

The study aimed to create a versatile crop model called SIMPLE (Simple Generic Crop Model) that can be adapted to simulate development, growth, and yield for various crops. While there are existing models for crops like soybean, rice, and cotton, there is a lack of such models for many other crops. The SIMPLE crop model comprises 13 parameters, including four for specific cultivar characteristics, allowing flexibility for different crop types. The model requires common inputs such as daily weather data, crop management information, and soil water holding parameters. However, the simulation results are still highly accurate, reducing the need for extensive time and cost-consuming input data creation. The first objective of the paper is an overview of commonly used crop models. The second objective is to review the calculation formulas to describe the SIMPLE. The third one involves performing a sensitivity analysis to find out how SIMPLE reacts to changes in temperature, CO_2 concentration, and the effects on biomass and yield as well as analyze the benefits and limitations of this model. Despite claims that the model is straightforward and based on fundamental crop physiology, it is also accurate, simple to use, and does not require the measurement of numerous complex parameters (Zhao *et al.*, 2019).

2. Research methods

The Systematic Literature Review (SLR) approach was used to write this descriptive qualitative article about crop modeling. The SLR approach is used to find, examine, assess, and analyze several existing research related to topic areas of interest and research questions (Mengist *et al.*, 2020). The stages of this by-line study follow the PRISMA methodology:

- ✓ Access, read, and research journals from several standard publishers Elsevier, Springer Nature, ScienceDirect, Google Scholar, and indexed journals_SINTA with keywords (crop modeling, rice, calibration, evaluation, climate change) for some simulation models of yield, biomass, or other purpose are widely used in the world for crops and rice in particular.
- ✓ Read the description of the functions, advantages, and disadvantages of models such as OZYZA, APSIM, DSSAT, AQUACROP, EPIC. And compare them with the SIMPLE crop yield estimation model developed by our research team.
- ✓ Describe the SIMPLE model for each specific formula. Present its advantages and limitations.

3. Crop modeling

3.1. What is crop modeling?

Asseng *et al*. (2014) defined that “Crop models are mathematical algorithms that capture the quantitative information of agronomy and physiology experiments in a way that can explain and predict crop growth and development”. Systems analysis and crop modeling are becoming crucial instruments in contemporary agricultural research (Antle *et al.* 2017). A crop comes to terms with our overview of the key and ecological phenomena that govern crop growth and development in mathematical equations and logical processes (Yin *et al.*, 2021).

A formal method for doing quantitative learning about how a crop grows in interaction with its environment is using crop models. These models predict crop development, growth, yield, water, and nutrient absorption using meteorological data and other information about the agricultural environment. Crop models incorporate various types of data, including daily meteorological variables (such as solar radiation, maximum and minimum temperatures, and precipitation), irrigation information, soil properties, initial soil conditions, cultivar attributes, and crop management practices (Boote *et al.* 2018b). Crop models are mathematical algorithms that analyze and forecast crop growth and development by collecting quantitative data from agronomy and physiology trials (Chenu *et al.*, 2017). They can reproduce a wide range of seasons, places, climates, and scenarios in a very short time. (Hoogenboom *et al.*, 2019). Crop models benefit agriculture in a variety of ways, including investigating the interactions between the atmosphere, the crop, and the soil, aiding in crop agronomy, pest control, breeding, and natural resource management, and analyzing the impact of climate change (Asseng *et al.*, 2014).

3.2. Example of some crop models

3.2.1. ORYZA

Oryza platform is a rice crop model representing over 30 years of global study. Since the 1970s, IRRI has been active in crop modeling, and from the mid-1980s to the mid-1990s, it was a member of the Simulation and Systems Analysis for Rice Production (SARP) Project (Bouman & Laar, 2006). This project implements the general crop growth model MACROS in collaboration with Wageningen University and Research Centre (WUR) and 16 Asian national agricultural extensions, and the ORYZA model series for rice followed it. IRRI's modeling efforts have now expanded and applied the ORYZA series.ORYZA version 3 (ORYZA v3), or simply ORYZA, is an ecophysiological model that simulates rice development and growth in lowland, upland, and aerobic rice environments, including water, C, and N balance (Bado *et al.*, 2018).

Oryza's strength extends to rice production systems in challenging settings such as drought, salt, and severe heat (Li *et al.*, 2017). ORYZA V3, the most recent model (Li *et al.*, 2017). ORYZA model adjusts rising research demands in agricultural digitalization.

ORYZA supports the collection and processing of massive amounts of data. Recent research focused on improving the capacity to sequence rice genes and applying current technologies on a small or big scale using GIS technology (Snigdha, 2022).

Only one type of process condition can be chosen in a simulation (Yu & Cui, 2022). Up to the version of ORYZA (v3) that has limited this drawback, the threshold of each triggering condition can still only be specified as a fixed number throughout the growing season. Furthermore, in the ORYZA2000 simulation, the amount of water for each irrigation can only be specified as fixed (Yu & Cui, 2022).

3.2.2. APSIM

The Agricultural Production Systems Simulator (APSIM), a modular modeling tool, was developed by the Australian Agricultural Production Systems Research Unit. APSIM models were developed to mimic biophysical processes in agricultural systems as well as the ecological and economic consequences of management strategies in present or future farming systems.

APSIM is a widely used modeling tool to show management practices under different conditions of management (Whitbread *et al.*, 2010). Separate modules can be integrated with the software addressing various crops and soil functions, including water balance, N and P transformation, and soil pH (Huth & Carberry, 2009).

The APSIM model can help agricultural decision-making, designing cropping systems for productivity or resource management goals, evaluating seasonal climatic projections, and investigating difficulties. Agribusiness supply chain concerns, risk assessment for government policies (Keating *et al.*, 2003).

This model was used in Zimbabwe to explore the impact of maize-mucuna rotation on maize yield. It shows the role of water in the soil, as well as the influence of climate change in maize cultivation (Masikati *et al.*, 2014).

Several kinds of APSIM model limitations exist:

- Experiments on the micronutrient answer

APSIM assumes that, aside from N and P, all plant nutrients are unlimited. Furthermore, APSIM's inability to quantify plant responses to micronutrient stress has limited the use of experimental datasets investigating these concerns.

- Greenhouse gas (GHG) emissions from rice cultivation

APSIM has been effectively used in an experiment on greenhouse gas emissions in wet rice cultivation (Gaydon *et al.*, 2017).

- Non-rice crop salinity reaction (Kivi *et al.*, 2022).

3.2.3. DSSAT

For the past 15 years, the model for agrotechnology transfer has been in place. Crop models for 16 different crops are included in this package, as well as tools for reviewing and applying crop models. The DSSAT crop models have grown more difficult to maintain in recent years since various sets of computer code were utilized for different crops, and little attention was paid to software architecture at the crop model level (Eitzinger *et al.*, 2017). As a result, DSSAT has been improved and expanded to reflect scientific advances. Crop modeling utilizing DSSAT has been updated, and scientific discoveries have been included (Zhen, 2022). The revised DSSAT cropping system model (CSM) is modular, with features segregated along scientific field borders and built for simple module maintenance or assembly (Alderman, 2020).

Due to the crop model's inadequacies, DSSAT version has the most significant constraint. The system has models for just a few crops, and those models do not respond to all environmental and managerial aspects (Hoogenboom *et al.*, 2019). Components for predicting the impact of tillage, pests, intercropping, extra soil water, and other variables on crop performance are missing (Jones *et al.*, 2013). They are especially beneficial in major global locations where weather, water, and N are major variables influencing crop production. They have also proved useful in showcasing possible applications and in educating. Model efficiency can be greatly reduced when affected by the environment. The researchers debated whether and then, if so, how fast and effectively to create more detailed crop models. For instance, the effect of soil P availability or P in conjunction with soils high in acid sulfate on plant development and production is not yet predicted by DSSAT models (Rauff & Bello, 2015).

The development of more widely agreed procedures for programming, data standards, documentation, and model quality is a restriction that should be overcome by the worldwide scientific community. Even though most functionalities may be used by research users with little computer knowledge, several have been criticized for being overly complicated, imprecise, or constrictive. The DSSAT is limited to homogeneous field-scale investigations, which is a major drawback (Jones *et al.*, 2013). Even though it does not have a spatial simulation, version 4.0 has been updated (Boote *et al.*, 2018a).

3.2.4. AQUACROP

This crop model can simulate the yield of important herbaceous crops under adequate irrigation and water shortage conditions. In this model, transpiration is first estimated and then converted to biomass using a crop-specific measurement parameter: biomass water yield, adjusted for flight requirements, atmospheric vapors, and atmospheric CO_2 concentrations (Raes *et al.*, 2009). The goal of standardization is to transform AquaCrop into a multi-site and seasonal crop model for simulating the yield of important herbaceous crops under both adequate irrigation and water shortage conditions. In this model, transpiration is initially estimated and then converted into biomass using a crop-specific measurement parameter called biomass water productivity, which is adjusted for atmospheric vapors and atmospheric CO_2 concentrations (Raes *et al.*, 2009). Simulations are usually performed over thermal time, although they can also be performed on AquaCrop using a minimal number of obvious and often straightforward parameters in an attempt to balance simplicity and accuracy. This model is primarily designed for end-users, including those in farming, government agencies, non-profit organizations, consulting engineering firms, and extension services. It also aims to satisfy the requirements of economists and policy specialists that utilize fundamental models for forecasting and scenario analysis (Akinbile, 2020).

However, under full irrigation circumstances, the model performs brilliantly. Differences are to be expected when crop models are calibrated using actual ground data. According to *Shirazi et al.* (2021), agricultural models assume optimal growing circumstances when in reality, growth might be hampered by weeds, pests, diseases, pollution, or other unexplained variables (Shirazi *et al.*, 2021).

3.2.5. EPIC

The EPIC crop development model was developed to analyze fertility as it varies due to erosion across the United States (Izaurralde *et al.*, 2017). Because soil fertility is assessed in agricultural output, the model should be capable of replicating crop yields for soils with differing degrees of erosion degradation. Using a single crop growth model with unique parameter values for each crop, EPIC replicates all the crops (Nantasaksiri *et al.*, 2021).

The processes simulated include leaf solar radiation absorption, biomass conversion, biomass division into roots, aboveground mass, economic yield, root development, water consumption, and nutrient uptake (Ramos *et al.*, 2017). The model has been tried in the United States and numerous other nations.

The weakness of this model is that it requires at least 22 to depict topographic conditions (Izaurralde *et al.*, 2017).

4. SIMPLE Model description

To compute agricultural output, a SIMPLE model multiplies the harvest index (HI) and the proportion of cumulative above-ground biomass from sowing to maturity (Equation 1) (Zhao *et al.*, 2019).

$$Yield = Biomass\_cum \times HI \qquad (1)$$

The harvest index (HI) is determined as the ratio of grain to total dry matter, and Biomass cum is calculated using Equation (2) (Zhao *et al.*, 2019).

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

$Biomass\_cum_i$ is the cumulative biomass until day number i.

Biomass_rate is the rate of daily biomass increase through the effective use of radiation - RUE of canopy transferred to biomass (Monteith, 1965). Stress factors such as drought, high temperature, and high CO2 levels in the atmosphere impact daily fluctuation in crop biomass (Ahmed & Ahmad, 2020).

$$Biomass_{rate} = Radiation * fSolar * RUE * (fCO2) * f(Temp) * \min((f(Heat), f(Water)) \qquad (3)$$

"fsolar": the fraction of the solar radiation intercepted by the crop canopy based on Beer-Lambert's law of light attenuation" (Zhao *et al.*, 2019), fCO_2 is the CO_2 effect, f(Heat) represents heat stress, whereas f(Water) represents water stress. f(Heat) represents heat stress, whereas f(Water) represents water stress (Equation 4).

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

In which

I50A: the total temperature required for leaf growth to collect 50% of solar energy while it is taking place

I50B: The needed cumulative temperature from maturity till half of the radiation is blocked during canopy senescence

fSolar-max: the maximum radiation intercepted.

TT is the cumulative mean temperature which is calculated as follows Equation (5-6) (Zhao *et al.*, 2019)

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

$$TT_{i+1} = TT_i + \Delta TT \quad (6)$$

Here, TT_i: total temperature untill day i; ΔTT: T: the daily average temperature (TMAX + TMIN)/2, and T_{base} is the base temperature (°C) (Zhao *et al.*, 2019).

Temperature stress, heat stress, drought stress, water stress, and CO_2 impact are calculated by Equation (7-12).

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

T_{base} and T_{opt}: base and optimal temperature of certain crop.

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

With: T_{heat}: heat threshold temperature, and $T_{extreme}$: extreme threshold temperature

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

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

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

ARID: standardized index:

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

PAW: plant-available water content in the soil texture (Woli *et al.*, 2012). ETo: the reference evapotranspiration.

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

4.1. Model parameters and input data

The SIMPLE model has 13 parameters, four of which are for cultivar characteristics. Tsum, I50A, and I50B were calculated using experimental data and air temperature data. The HI was computed in the manner stated in Wnuk *et al.* (2013). The rest of the characteristics were taken from the literature.

The model's data calibration and validation were carried out by running several simulations using cultivar parameter settings within a suitable range (excluding keeping soil parameters the same for all the trials). From seeding through maturity, the biomass in both studies was monitored every 10 days (for rice experiments). The simulation outcomes were validated using the observed data. I50A and I50B were recalibrated after each model run based on daily mean temperature above Tbase and iterative simulation until excellent fit experimental findings were obtained. The best-fitting set of cultivar parameters was then utilized to do sensitivity analysis.

Table 1. Input variables of the modeling

Input variables	**Description**	**Unit**
Weather	TMAX (Daily maximum temperature)	ºC
	TMIN (Daily minimum temperature)	ºC
	RAIN (Daily rainfall)	mm
	SRAD (Daily solar radiation)	MJ m^{-2} day^{-1}
Soil characteristics	CO_2 concentration in the atmospheric	ppm
	AWC (soil available water content)	-
	RCN (Runoff curve number)	-
	DDC (Deep drainage coefficient)	-
	RZD (Root zone depth)	mm
Crop management	SowingDate	-
	HarvestDate	-
	Irri (Irrigation)	mm
Initial	InitialBio	Kg
	InitialTT (Cumulative temperature)	ºC day
	InitialFsolar (Solar radiation interception)	-

Notes: *The daily sun radiation (MJ m^{-2} day^{-1}) was obtained from the POWER Data Access Viewer's Agroclimatology Community.*

4.2. Model evaluation and calibration

4.2.1. Model evaluation

The model's performance will be evaluated using independent experimental data sets. For each treatment, the model may be used to mimic crop development and growth by using the constructed crop data file, derived soil properties, and actual daily weather data. These simulated results will then be compared with the observed data.

The slope, intercept, and root-mean-square error (RMSE) for each crop, as well as the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), and percent bias (PBIAS) would be used to evaluate the models throughout weather, soil, water, crop management variables (Equation 13).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}}$$

$$R^2 = \frac{\left[\sum(O_i - O_{mean})(S_i - S_{mean})\right]^2}{\sum(O_i - O_{mean})^2 \sum(S_i - S_{mean})^2} \qquad (13)$$

where:

n: is the number observed

O_{mean} and S_{mean} : are the observed and simulated means, respectively.

O_i and S_i are the ith observation's observed and simulated values (i= 1 to n).

The lower the RMSE number, the better the match between simulation and reality (Uno *et al.*, 2005). R^2 is a coefficient of determination that spans from 0 to 1 (Menard, 2000). NSE is a number that varies from 0 to 1. NSE of 1 indicates that the model is perfectly suited.

Table 2. Hierarchical assessment of the reliability of the simulation results of crop yield predictive model

Level	**Effective coefficient (NSE)**
Very good	0.75 < NSE ≤1.00
Good	0.65 < NSE ≤ 0.75
Achieved	0.50 < NSE ≤ 0.65
Not achieved	NSE ≤ 0.50

After creating the simulation yield model and the real yield, the model will be tested. The efficiency coefficient (Nash Sutcliffe Efficiency - NSE) would be used to compare the values between observed and crop modeling to evaluate the accuracy of the agricultural yield simulation software (Equation 14).

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - O_{mean})} \qquad (14)$$

This coefficient is proposed by Nash-Sutcliffe (Zeybek, 2018). Statistical correlation study of simulated and observed data values.

4.2.2. Model calibration

Cultivar's parameters in this crop modeling include four parameters T_{sum}, HI, I_{50A}, I_{50B}. Species parameters consist of T_{base}, T_{opt}, RUE, I_{50maxH}, I_{50maxW}, T_{max}, T_{ext}, S_{CO2}, S_{water} but species parameters will not be calibrated.

The species' parameters will be obtained from agreed-upon values in the literature, like RUE, T_{base}, T_{opt}, and S_{CO2}, from other crop models if any, or calculated with crops with defined parameters.

The models will be calibrated cultivars' parameters within a reasonable range.

This calibration is carried out using the following variables: dry matter accumulation (aboveground) (calibrated Tsum), radiation intercept (calibrated I50A and I50B), and ultimate yield (dry grain) (calibrated HI). The model requires daily weather data and other parameters in Table 2.

4.3. Sensitivity analysis

The methods of Morris (Morris, 1991) and FAST (Fourier Amplitude Sensitivity Test) (Xu & Gertner, 2011) have been employed for conducting sensitivity analysis. In this study, the Morris (1991) method is the method in which the parameters will be selected and discretized in the same standard space, covering the entire volume of space in which they can transform. This approach identifies the essential parameters in a complicated model's parameters. Simultaneously, it enables identifying whether the parameter's effects are trivial, linear, nonlinear, or interacting with other factors.

4.3.1. Morris method

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, which will give 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.

As a control treatment, the set of parameters that provided the best match between simulation and observation was utilized to assess the sensitivity for a better understanding of the influence of future climate change on agricultural productivity.

4.3.2. FAST method

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 the Morris method, but it is unknown which parameter has the main 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).

Once only screening input parameters means we cannot know which parameter has the main sensitivity and ratio of impact to final yield. Therefore, the FAST method will help to evaluate each parameter quantitatively. When comparing parameters with a nonlinear impact, high sensitivity, intense interactions with other parameters, and significant impact on input results showed that these parameters had different mean and standard deviation. The analysis results showed that RUE and T_{base} were two parameters with significant impact, in which RUE was the parameter having the main influence on productivity. If the overall sensitivity of ten parameters is 100 percent, RUE's sensitivity accounts for 99 percent, T_{base}'s sensitivity accounts for 1%, and the remaining parameters have non-significant values.

4.4. Relative yield responses in higher temperature and CO_2 concentration

Yuliawan and Handoko (2016) found that higher warmth reduced wet rice production by 11.1% in Karawang, Indonesia, using the Shierary Rice Model in a GIS simulation research. When utilizing the ORYZA model to simulate rice production, Krishnan *et al.* (2007) predicted a 7.63 percent yield drop when the temperature reached 4 degrees Celsius above ambient. The drop in yield was attributable to the sterility of rice spikelets at higher temperatures.

According to Hao *et al*. (2014), free-air CO_2 enrichment improved rice grain production by 30.7 percent at 320 ppm, boosted by the Oryza1 model. There are favorable impacts on rice yield in addition to higher CO2 concentration, but more crucially, other extreme effects (maximum temperature and/or increased night temperature) (Xu *et al*., 2020) brought a stronger 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} (increasing). 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. 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. In terms of models, A wide range of environmental circumstances impacts the uncertainty in estimating rice production using existing crop models (Li *et al.*, 2015).

5. Advantages and limitations

5.1. The advantages of SIMPLE

As its name suggests, the SIMPLE model is simple to use from simple metrics. The SIMPLE model requires fewer parameter inputs, such as 9 species and 4 cultivar-related parameters (Table 1). It applies to some crops for which there is little knowledge and data due to its simplicity, especially for uncommon fruits, vegetables, grains, and legumes. 14 crops, including numerous common grains and legumes, for which large datasets are available, have parameterized the SIMPLE model. Because there were so few equations and factors in the Straightforward model, it was simple to understand and include more crops, even less-researched ones like bananas and carrots (Zhao *et al.*, 2019). The model is now accessible in numerous simulation frameworks, including R programming.

Several agricultural simulation models, such as EPIC, DSSAT, APSIM, CropSyst, AquaCrop, and statistical models, have been developed for significant crops (Chisanga *et al.*, 2022). A significant amount of data and parameters are still required (Ewert *et al.*, 2005). The EPIC model (Izaurralde *et al.*, 2017) necessitates the use of 22 parameters. the AquaCrop model (Foster *et al.*, 2017) needs 29 parameters, while SIMPLE only needs 13 parameters (Zhao *et al.*, 2019).

The second benefit of this model (SIMPLE) is that other parameters such as fertilizer, planting time, harvesting, or soil nutrition may be added and utilized for a variety of plants such as oil and fiber crops, vegetables and fruits, agricultural food, and feed. Statistical models, on the other hand, have been used to explore the impact of climate change on crops (Lobell & Asner, 2003). Some statistical models for assessing climate effects have been developed recently (Liu *et al.*, 2016). They do, however, lack the biophysical methods of genetics and crop management (Lobell, 2007)

SIMPLE also has the other benefit of being easy to apply to R programming. For example, four features are used to characterize soils factor in the SIMPLE model, and the data can be obtained from the world soil database. The SIMPLE model offers the advantage of seamless integration with R programming, making it easy to implement and utilize. According to the literature, the model incorporates four key soil features as factors in its characterization. These features can be obtained from the world soil database, providing a reliable and comprehensive source of data for soil-related parameters in the SIMPLE model. This integration with R programming and utilization of readily available soil data enhances the accessibility and practicality of the SIMPLE model for simulating crop development, growth, and yield.

In addition, SIMPLE crop model has the following benefits:

- User-friendly interface: The SIMPLE crop model stands out for its user-friendly interface, particularly within Microsoft Excel. This accessibility has made it widely adopted by researchers, students, and farmers with varying levels of modeling expertise. According to Kim *et al.* (2017), the simplicity of the interface allows users to quickly set up simulations and obtain valuable crop growth insights.

- Simplified modeling approach: The simplicity of the SIMPLE crop model lies in its focus on key factors influencing crop development, such as planting date, planting density, water availability, and nutrient supply. This approach enables users to efficiently run simulations without complex parameterization. As highlighted by Wallach *et al.* (2021), this simplified modeling approach reduces the time and effort required for model setup and calibration.

- Flexibility and adaptability: The adaptability of the SIMPLE crop model is a notable advantage, as it can be customized for various crops and agricultural systems. Users can tailor the model inputs to match specific crop characteristics, management practices, and environmental conditions. This versatility makes it applicable in diverse contexts. As demonstrated by Teixeira *et al.* (2013), the SIMPLE model can be adapted for crops such as soybeans, providing accurate predictions of crop growth and yield.

- Real-time decision support: The computational efficiency of the SIMPLE crop model enables real-time decision support for farmers. By inputting current field data and relevant environmental conditions, the model can provide timely information on crop growth stages, water, and nutrient requirements, and yield predictions. This helps farmers make informed decisions about irrigation scheduling, fertilizer application, and harvest timing. As noted by Kadiyala *et al.* (2015), the SIMPLE crop model facilitates data-driven decision-making for improved crop management.

- Educational tool: The SIMPLE crop model serves as a valuable educational tool for teaching crop modeling and agricultural systems. It is a user-friendly interface, and visual outputs facilitate comprehension of crop growth dynamics among students and researchers (Gautam & Subedi, 2022). As highlighted by Todorovic *et al.* (2018), the SIMPLE model has been successfully used in educational settings to enhance understanding of crop physiology and management practices.

- Integration with Excel: The integration of the SIMPLE crop model with Microsoft Excel provides additional advantages. Excel's data management, visualization, and analysis capabilities can be leveraged alongside the model. Users can easily import and export data, conduct sensitivity analyses, and create graphs and reports. According to Thiele and Nuske (2015), Excel integration enhances the usability and analytical capabilities of the SIMPLE crop model.

Even though they are straightforward, the basic biological responses to high temperature, drought, and CO_2 concentrations are accurately characterized to predict biomass and agricultural outputs (Gautam & Subedi, 2022). It provides basic physical responses to warming a simple structure. The SIMPLE model may reproduce regional variations based on environmental data, soil characteristics, and agronomic practices (Zhao *et al.*, 2019).

5.2. Limitation

The SIMPLE model does not estimate diffused light because of the relationship between radiation efficiency and factors like water availability and carbon dioxide. If used in a wide range, it is necessary to calibrate the light diffusion parameter (Yang *et al.*, 2013).

Planting density, seeding depth, and pests can also impact growth and yield. The late-stage drought can affect the grain yield obtained through the harvest index, which is also a limitation of this model. However, the upgraded version may need additional modules (Moser & Barrett, 2006). Because of this, even SIMPLE model is expanded with different variables. Like other crop models, it does not consider pests' effects.

6. Conclusion

The overall review of the SIMPLE model has provided an introduction and comparison to other models. The model, alongside its counterparts, offers a user-friendly interface, flexibility, and adaptability. It allows the analysis of the influence of weather conditions, soil properties, and crop varieties in various regions. While acknowledging its limitations, the study proposes innovative solutions to enhance its accuracy and applicability. Further research is needed to refine and validate the model's performance under diverse agro-climatic conditions. This comprehensive overview emphasizes the significance of plant growth simulation models, such as the SIMPLE model, in the realm of scientific and practical applications, especially within the context of digital agriculture and the challenges posed by unpredictable weather patterns.

Acknowledgments

This research is funded by Vietnam National University - Ho Chi Minh City under grant number B2020-16-02. The writers would like to thank the Promoter and Co-Promoters who gave advice and instructions to publish this article.

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