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Evaluation of DSSAT-CROPGRO Model for Greenhouse Tomato in Northern Ghana

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ABSTRACT

Water and nutrient constraints challenge greenhouse adoption by farmers in Ghana, with resource optimization experiments proving costly. Predictive modeling, such as the Decision Support System for Agrotechnology Transfer (DSSAT), offers a practical alternative for simulating crop yield influenced by fertilizer, irrigation, genotype, and micro-climate interactions. This study calibrated and validated the DSSAT model to predict indeterminate tomato yields in Northern Ghana under varying fertigation regimes and greenhouse conditions. Treatments included fertilizer rates (100%, 80%, and 60%), irrigation levels (100%, 80%, and 60%), and two tomato genotypes (Jalila F1 and Yetty F1). The model accurately simulated key parameters, including maximum leaf area index (RRMSE: 44.97–140.99; D-Value: 0.31–0.77), aboveground dry biomass (RRMSE: 16.88–25.04; D-Value: 0.66–0.81), and yield (RRMSE: 17.03–22.43; D-Value: 0.67–0.90). Results demonstrated the model's capacity to capture yield variations influenced by fertigation and genotype under dynamic greenhouse environments, closely aligning with observed data. The DSSAT model proves valuable as a decision-support tool, enabling farmers to optimize crop management strategies, conserve resources, and enhance sustainable food production in resource-limited settings.

INTRODUCTION

Many countries, including Ghana, rely on tomatoes as a key crop because of their high levels of vitamins and health benefits. However, tomato farming in Ghana has been severely impacted by factors such as disease (bacterial wilt, fusarium wilt), climate change, and prolonged droughts, which have resulted in drastically reduced yields over time (Baba *et al.,* 2013; Vigbedor, 2019; Nikolaou *et al.,* 2020). Also, importation process has resulted in significant financial losses and tragic incidents in Ghana as a result of the reliance on tomato imports (Robinson and Kolavalli, 2010). To mitigate the effects of drought and improve agricultural productivity, irrigation is crucial (Gbode *et al.,* 2022). The Ghanaian government introduced greenhouse technology in response to these challenges, which has been proven to be an effective method for producing high-quality tomatoes with higher yields. However, the adoption of greenhouse farming in Ghana has been hindered by challenges related to water and nutrient management (Forkuor *et al.,* 2022).

A multitude of variables interact with each other in complex ways to affect the growth and productivity of greenhouse crops. These factors include climate conditions such as temperature, humidity, photosynthetically active radiation, and carbon dioxide levels (Vilanova and Visioli, 2012), nutrition including water and nutrients in the soil or substrate (Sigrimis *et al.,* 2001; Van Henten and Bontsema, 2009), biotic factors like pests, diseases, viruses, bacteria, and weeds (Rabbinge *et al.,* 1993), as well as cultural management practices such as trellising, pruning, layering and spraying. Understanding their impact on crop growth requires a thorough examination and categorization of these factors due to their intricate relationships. Dynamic models, which emulate the behavior and interactions of these variables, are pivotal to this process.

According to Li *et al.* (2006), crop growth model was started in the 1960's as computerised representations of quantitative data about the dynamic interplay between the soil-plant-atmosphere continuums and major crop development processes that may be used to predict the growth (leaves, root, stems), total biomass and yield. It helps to design sustainable agronomic strategies, yield forecasting, industry planning, operations management and the significance of management decisions on environmental issues (Thimme *et al.,* 2013, and Qiaoxue *et al.,* 2018). Compared to traditional experimental methods, crop models have the advantage of evaluating large volumes of data in a cost-and-time-effective way, which is one of their main advantages. Moreover, crop models are useful tools for making decisions, conducting research, teaching, and transferring technology.

The classification of crop growth models varies between descriptive and explanatory models (Heuvelink and Marcelis, 1997). Analyzing the relationships between soil, water, plants, and environmental factors can be done using statistical correlations and regressions in descriptive models that are established theoretical frameworks and practical experience. Explanatory models, on the other hand, clarifies the cause-and-effect relationships between environmental conditions, cultivation management practices, and crop morphological development (Lin *et al.,* 2019). One such model, the HortSyst dynamic model, as described by Martinez-Ruiz et al. (2018), predicts key parameters such as dry matter production, nitrogen uptake, leaf area index, photo-thermal time, and crop transpiration. In greenhouses, this model is particularly advantageous for managing nitrogen and scheduling irrigation in soilless tomato cultivation. Effective strategies for controlling and managing greenhouse environments are commonly developed using the HORTISIM model (Cohen and Gijzen, 1997), just like in other cases. By incorporating factors like leaf area index and dry matter accumulation, the Vanthoor model recreates the greenhouse microclimate and crop development. The TOMSIM model (Heuvelink, 1999) simulates crop canopy light interception in relation to dry matter accumulation (Vanthoor *et al.,* 2011; Lin *et al.,* 2019). Additionally, the CROPGRO-Tomato model (also known as TOMGRO), developed by Jones *et al.* (1998), emphasizes the relationship between tomato growth and key greenhouse environmental factors, including air temperature, relative humidity, solar radiation, and CO2 levels, allowing for the scientific management and prediction of tomato growth and yield. While TOMGRO has been widely used in greenhouse experiments (Dayan *et al.,* 1993), it has been noted by Marcelis (1993) that the model is less effective at estimating certain parameters, such as the potential growth rate in a greenhouse environment.

The Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.7 is a highly used crop simulation software application that has crop simulation models like CERES, CROPGRO, and CROPSIM for over 32 crops. DSSAT has been in use for more than 25 years and has proven to be a valuable tool for crop modeling and analysis (Hoogenboom *et al.,* 2017). Various irrigation and fertilizer conditions under Abedinpour and Sarangi, 2018 have resulted in successful calibration and validation of the DSSAT-CERES model for grain yield and biomass. Additionally, Ahmed *et al.* (2017) used DSSAT-CERES for a climate change impact analysis on four different maize cultivars. The model has also been employed to study the effects of tillage systems, fertilizer rates, and crop rotations on yield and soil quality under Egyptian conditions (Harb *et al.,* 2016). In Bangladesh, DSSAT version 4.6 was used to estimate wheat growth and yield under varying irrigation and fertilizer treatments (Apurba *et al.,* 2018). Nath *et al.* (2017) validated the CROPGRO Soybean model in the Akola region of Vidarbha, India, and found that the model performed reliably well in simulating phenological phases. Similarly, Patil and Patel (2017) demonstrated the usefulness of the CROPGRO model in simulating chickpea phenology and yield. In Italy, the DSSAT-CROPGRO model was used to assess the impact of climate change on the efficiency of water and nitrogen use in processed tomato cultivation, concluding that reduced rainfall and increased air temperatures during the growing season would shorten tomato development, reduce yield, and necessitate higher irrigation and nitrogen fertilization in the face of water scarcity (Cammaranoa *et al.,* 2020). Additionally, Rinaldi *et al.* (2009) used the AEGIS/WIN GIS interface of DSSAT to estimate commercial tomato yield and irrigation water use efficiency, helping to identify the optimal irrigation scenario for tomato cultivation.

Given various management and environmental situations, the crop growth model can provide farmers with the essentials to help predict crop response. These models can assist in optimizing the use of resources, improving decision-making, and enhancing sustainability in greenhouse tomato production. The primary aim of this study is to calibrate and evaluate the DSSAT model for the precise prediction of greenhouse tomato yield, taking into account variables such as fertigation, genotype, and dynamic microclimate factors.

MATERIALS AND METHODS

Study Area and Experimental Design

The study was conducted in the Skills Development Fund (SDF) greenhouse facility, situated in the Savanna Agricultural Research Institute (SARI), Northern Region, Ghana (Longitude: 9.24'19.23" N; Latitude: 0.59'36.77" W; Altitude 812 ft) (Figure 1). The experiment was carried out in a Gothic Arc greenhouse made of polyethylene and insect proof net covering. Crops were cultivated in a soilless media (cocopeat) for about six (6) months, from April 26th, 2021 to October 22nd, 2021 (Greenhouse Environment /Raining season) and repeated in November 1st, 2021 to April 8th, 2022 (Greenhouse Environment 2 / Harmattan season). The study was bases on a 3 × 3 × 2 factorial experiment, laid out in split - split - plot design with fertilizer rates (100 %, 80 % & 60 %) combined with irrigation regimes (100 %, 80 %, 60 %) and tomato genotypes (Jalila F1 & Yetty F1). The eighteen (18) treatments were assigned to four (4) blocks and analyzed for leaf area index (LAIX), total above ground biomass (CWAD) and yield/fruit biomass (PWAD). The tomato varieties were nursed and transplanted after twenty-one (21) days at a crop density of 2.8 m^{-2} under drip irrigation. Fertigation recommendation by Peet and Welles (2005) for tomato was adopted with reference to the crop water requirement and irrigation schedule as deduced with the aid of a moisture sensor and water balance method. Soluble fertilizers Calcium nitrate ($CaNO_3$) [15.5-0-0+26.3], Potassium nitrate (KNO_3) [13-0-46], Mono ammonium phosphate (MAP) [12-61-0] and Magnesium sulphate ($MgSO_4$) [0-0-0-16-32.5] were used. The pH and electrical conductivity (EC) of fertigation solution at drip point was kept between 5.5 to 6.5 and 1 to 2.5 ds/m respectively. Harvesting started at eight weeks after transplanting and continued till the end of each experiment.

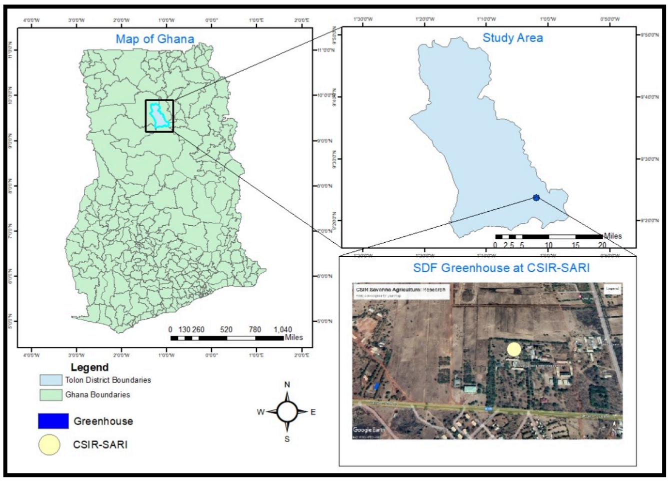

Figure 1. Map of the study area

Description of DSSAT Model

The Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.7 is a computer software application program that contains crop simulation models such as CERES (maize, wheat, sorghum), CROPGRO (tomato, bell pepper, cabbage and green bean) and CROPSIM (cassava, Wheat, barley) for more than 32 crops and has been in use for over 25 years (Jones et al., 1991; Hoogenboom et al., 2019). For the successful use of the DSSAT model, database management programs are integrated for soil, weather, crop management, experimental data, through utilities and application programs. Based on the soil-plant and atmospheric continuum, the DSSAT crop simulation model simulates crop growth, development and yield. Indications by Ritchie (1998), revealed that the model estimates the soil water balance of a crop or fallow land on a daily basis as a function of precipitation, irrigation, transpiration, soil evaporation, runoff and drainage from the soil profile. This research estimated the growth and yield effect of 100 %

irrigation regime, deficit irrigation regime of 20 % and 40 % combined with 100 %, 80 % and 60 % fertilizer rates on 2 tomato genotypes grown in soilless media (cocopeat) under greenhouse conditions (Raining season and Harmattan season).

Input Data for Model Calibration and Evaluation

The input data for the model calibration and evaluation consisted of the daily weather data across both greenhouse environments, soil data, crop management data in rapports to fertigation (irrigation and nitrogen fertilization) dates and input amount. For calibration, experimental data from the greenhouse environment 1 was used for calibration and evaluated with experimental data from the greenhouse environment 2. The interaction of 100 % irrigation regime by 100 % fertilizer rate by Jalila F1 and the interaction of 100 % irrigation regime by 100 % fertilizer rate by Yetty F1 were first used for calibration and further run for the deficit scenarios.

Growth Media and Weather Data

Growth media sample was analyzed for its initial physico-chemical properties namely; field capacity (33.50%), wilting point (10.8%), bulk density (1.5g/cm^3), saturated water content (48.20%), organic carbon (58%). The measured weather data for greenhouse environment 1 and 2, are presented in Table 1, and Table 2 respectively.

Table 1. Summary of Monthly Greenhouse Environment 1 Data (Raining Season) as Used for Calibration of DSSAT-CROPGRO Model

	Maximum Temperature	Minimum Temperature	Optimum Relative Humidity	Rainfall	Solar Radiation	Wind Speed
Months	**Tmax (°C)**	**Tmin (°C)**	**Opt. RH (%)**	**Rainfall (mm)**	**SRAD (MJ/m^2/d)**	**WIND (km/d)**
May-21	46.9	23.4	65.2	0	19.8	4.59
Jun-21	42.9	22.8	72.9	0	18	4
Jul-21	37.4	24.3	74.7	0	18.1	3.85
Aug-21	35.8	23.8	77.8	0	16.9	3.57
Sep-21	38.4	23.5	75.0	0	18.5	3.78
Oct-21	41.1	23.8	70.6	0	20.8	4.28

Table 2. Summary of Monthly Greenhouse Weather Data (Harmattan Season) as Used for Evaluation of DSSAT-CROPGRO Model

	Maximum Temperature	Minimum Temperature	Optimum Relative Humidity	Rainfall	Solar Radiation	Wind Speed
Months	**Tmax (°C)**	**Tmin (°C)**	**Opt. RH (%)**	**Rainfall (mm)**	**SRAD (MJ/m^2/d)**	**WIND (km/d)**
Nov-21	47.9	21.4	63.2	0	21	4.4
Dec-21	45.1	18.7	41.3	0	17.5	3.85
Jan-22	41.3	17.5	28.0	0	4.23	4.23
Feb-22	45.2	21.1	30.7	0	4.93	4.93
Mar-22	46.6	25.0	53.2	0	5.19	5.19
Apr-22	35.7	31.8	55.7	0.0	5.1	5.1

Crop Management Data

The genetic coefficient for the two genotypes (Jalila F1 and Yetty F1) was estimated for calibration and used for evaluation of experimental data from the greenhouse environment 2 (Table 3). Crop data including transplanting dates for each experiment, planting density, time and amount of nitrogen fertilizer (Figure 2a and 2b) and irrigation regime (3ace and

3bdf) were used for calibration and evaluation respectively. At the end of the first experiment (Raining Season), a total average of about 161.88 kg/ha N fertilizer was used, representing 100 % fertilizer rate, corresponding with a total average 100 % irrigation regime of 1,146.58 m^3/ha. Under the second experiment (Harmattan Season), the total average 100 % N fertilizer used was 308.98 kg/ha N, conforming with 2,366.86 m^3/ha of 100 % irrigation regime. A deficit of 40 % fertilizer rate and 40 % irrigation regime were the least applied under the raining season (86.89 kg/ha N and 905.97 m^3/ha respectively) and harmattan season (187.94 kg/ha N and 1,683.69 m^3/ha respectively).

Table 3. Genetic Coefficients of Indeterminate Greenhouse Tomato: DSSAT-CRGRO047 Model

Parameters	Definition	Genotype	
		Jalila F1	**Yetty F1**
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days)	33.5	32
FL-SH	Time between first flower and first pod (R3) (photothermal days)	5.5	5.6
FL-SD	Time between first flower and first seed (R5) (photothermal days)	35	36
SD-PM	Time between first seed (R5) and physiological maturity (R7) (photothermal days)	99.2	96
FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)	52	53.5
LFMAX	Maximum leaf photosynthesis rate at 30 ºC, 350 vpm CO2, and high light (mg CO_2/m^2-s)	1.3	1.36
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm^2/g)	685	675
SIZLF	Maximum size of full leaf (three leaflets) (cm^2)	467.1	390
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	0.95	0.93
WTPSD	Maximum weight per seed (g)	0.05	0.045
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	26	27
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)	98	96

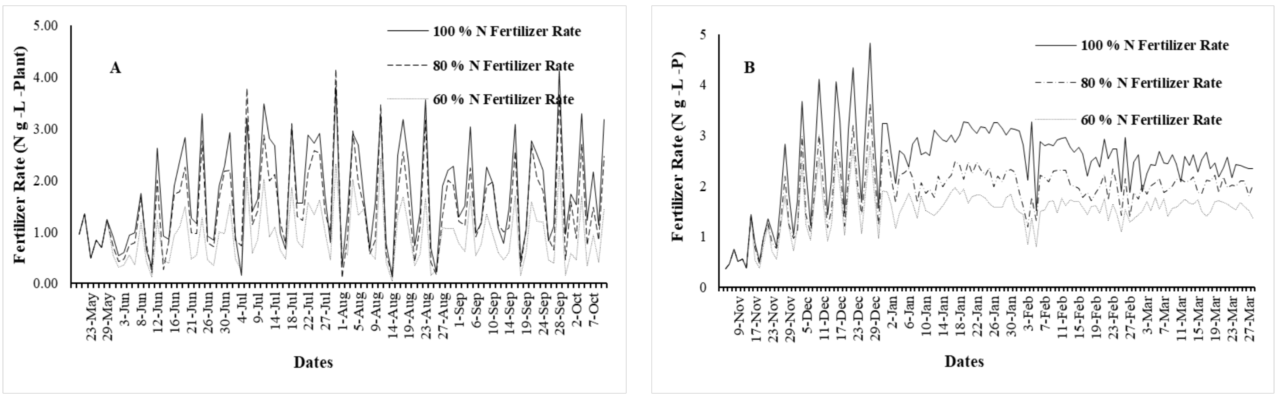

Figure 2. Nitrogen Fertilizer Rates Under Greenhouse Environment 1 (A) and Greenhouse Environment 2 (B)

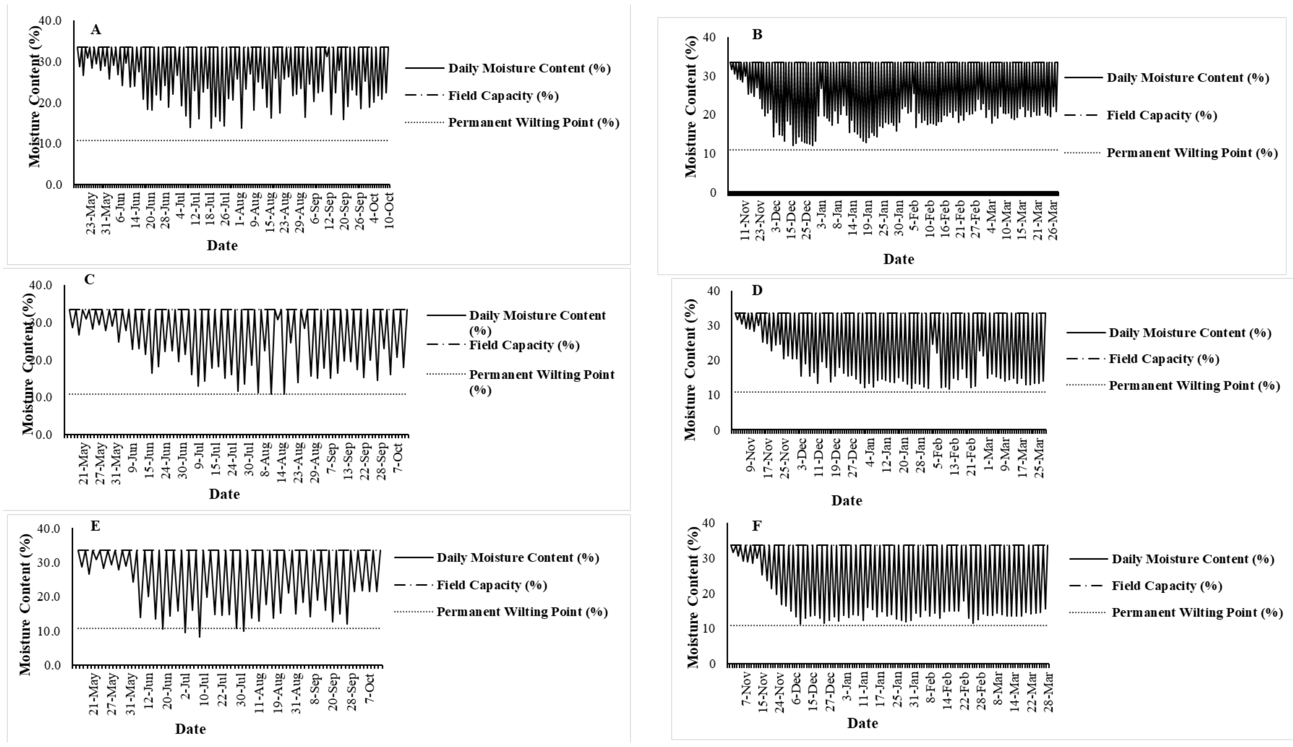

Figure 3. The Average Moisture Content Reading for 100% Irrigation Regime, 80% Irrigation Regime and 60% Irrigation Regime under Greenhouse Environment 1 (A, C and E respectively) and Greenhouse Environment 2 (B, D and F respectively).

Experimental data and simulated data for leaf area index (LAIX), total above ground biomass (CWAD) and yield/fruit biomass (PWAD) were calibrated and evaluated based two criteria; Relative root mean square error (RRMSE) and Willmott's d index.

A low RRMSE is required, as this would signify a better alignment between the simulated and observed data. The minimum value of zero implies a precise model performance. Relative root mean square error is defined as:

$$\text{RRMSE} = \frac{\left[\frac{1}{\text{n}}\sum\left(P_i - O_i\right)^2\right]^{0.5}}{\bar{O}} \times 100 \quad \text{.........Eqn. 1}$$

Where; Pi = model predicted value, Oi = observed value, i = index of observation, n = number of observations, $\bar{O}$ = the mean of observed values.

The Willmott's d index (Willmott *et al.,* 2012) is defined as:

$$d = 1 - \frac{\sum_{i=1}^{n}\left(P_i - O_i\right)^2}{\sum_{i=1}^{n}\left(\left|P_i - \bar{O}\right| + \left|O_i - \bar{O}\right|\right)^2} \quad \text{.................... Eqn. 2}$$

The Willmott d-value ranges from 0 to 1. The value 1 signifies a perfect prediction of observed data.

RESULTS AND DISCUSSION

Calibration and Evaluation of DSSAT-CROPGRO Model for Maximum Leaf Area Index of Greenhouse Tomato.

The averaging maximum leaf area index observed for the interactions of fertilizer rate, irrigation regime and Jalila F1 was 5.75 but underestimated to 3.79 upon calibration, recorded for greenhouse environment 1. Figure 4a reflects about 0.58 degree of agreement, RRMSE of 44.97% and correlation of 0.44 in observed and simulated and maximum leaf area index. The interaction of fertilizer rate, irrigation regime and Yetty F1 recorded an observed mean maximum leaf area index of 3.97 and a calibrated mean maximum leaf area index of 9.44 for greenhouse environment 1. Contrary to the Jalila F1 tomato genotype, Yetty F1 genotype was overly estimated, recording 0.42 degree of agreement, RRMSE of 100.26 % and 0.63 correlation in observed and simulated LAIX (Figure 4c).

When evaluated for the greenhouse environment 2, DSSAT-CROPGRO model showed that the simulated maximum leaf area index was consistently higher for the interactions of fertilizer rate, irrigation regime and Jalila F1, recording a RRMSE of 23.32 % and 0.77 degree of agreement (Figure 4b). Similarly, Figure 4d, shows that DSSAT-CROPGRO model simulated maximum leaf area index were consistently lower for the interactions of fertilizer rate, irrigation regime and Yetty F1, with a RRMSE of 140.99 % and 0.31 degree of agreement for greenhouse environment 2, during evaluation.
Similar to results, increasing irrigation water and nutrient supply to tomato results in increasing photosynthesis, leaf area index, biomass, fruit yield and water use efficiency in tomato under soilless cultivation (Ullah et al. 2021). Thus 100% irrigation regime combined with 100% fertilizer rates and either of the tomato genotypes, recorded the highest maximum leaf area index, aboveground biomass and fruit yield, whereas 60% irrigation regime combined with 60% fertilizer rate and tomato genotypes recorded the least maximum leaf area index, aboveground biomass and fruit yield. The differences between treatments observed was as seen in the simulated results. Boote *et al.* (2012) reported a poorly estimated (underestimation) tomato maximum leaf area index when evaluated with DSSAT-CROPGRO model. This could be due to the variability in the genetic traits of the indeterminate greenhouse tomato, the characteristics of soilless media and variation in greenhouse environmental conditions.

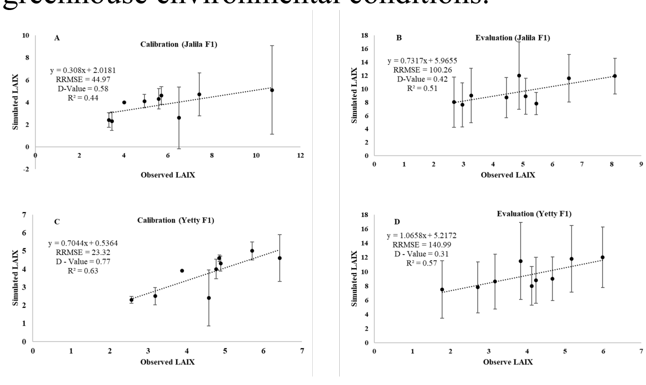

Figure 4. Leaf Area Index (LAIX) as Calibrated for Jalila F1 and Yetty F1 Under Greenhouse Environment 1 (A and B Respectively) and evaluated for Jalila F1 and Yetty F1 Under Greenhouse Environment 2 (C and D Respectively) for Combined Fertilizer Rate and Irrigation Regime using DSSAT-CROPGRO Model. Bars represent standard deviation.

Calibration and Evaluation of DSSAT-CROPGRO Model for the Aboveground Biomass of Greenhouse Tomato

The mean observed and simulated aboveground dry biomass for the interactions of fertilizer rate, irrigation regime and Jalila F1 were 5845.33 kg/ha and 5095.67 kg/ha respectively for greenhouse environment 1. Calibration in Jalila F1 showed a moderate agreement between observed and simulated CWAM (RRMSE = 24.86%, D = 0.73, R = 0.40) (Figure 5a). The aboveground dry biomass for the interactions of fertilizer rate, irrigation regime and Yetty F1 was calibrated with a RRMSE of 25.04 %, 0.66 degree of agreement and a lower correlation of 0.16. The mean observed and simulated aboveground dry biomass for the interactions of fertilizer rate, irrigation regime and Yetty F1 were 5539.56 kg/ha and 5252.33 kg/ha respectively for greenhouse environment 1 (Figure 5c).
The evaluation of aboveground dry biomass for the interactions of fertilizer rate, irrigation regime and Jalila F1 under greenhouse environment 2 indicated that the mean observed and simulated were 7663.11 kg/ha and 7518.89 kg/ha respectively. The mean observed and simulated aboveground dry biomass for Yetty F1were 7153.56 kg/ha and 7604.56 kg/ha respectively. An improved agreement was established during the evaluation of Jalila F1 (RRMSE = 22.10%, D = 0.81, R = 0.58) (Figure 5b) but a comparable accuracy in Yetty F1 (RRMSE = 22.10%, D = 0.75, R = 0.59) under greenhouse environment 2 (Figure 5d).

The aboveground dry biomass of processing tomato was well simulated by the DSSAT-CROPGRO model (Deligios *et al.* 2017, Cammarano *et al.* 2020).

Calibration and Evaluation of DSSAT-CROPGRO Model for Dry Fruit/Yield Biomass of Greenhouse Tomato

The dry fruit biomass for the interactions of fertilizer rate, irrigation regime and Jalila F1 was well simulated under greenhouse environment 1 with 17.03 %, RRMSE, 0.90 degree of agreement and 0.66 level of correlation. The averaging dry fruit biomass as observed and simulated were 3124 kg/ha and 3203.33 kg/ha respectively (Figure 6a). The Dry fruit biomass as simulated for the interactions of fertilizer rate, irrigation regime and Yetty F1 was well-estimated with a RRMSE of 21.85 %, 0.83 degree of agreement and 0.53 level of correlation under greenhouse environment 1 (Figure 6c). The mean dry fruit biomass as observed and simulated were 3068.78 kg/ha and 3288.89 kg/ha respectively.

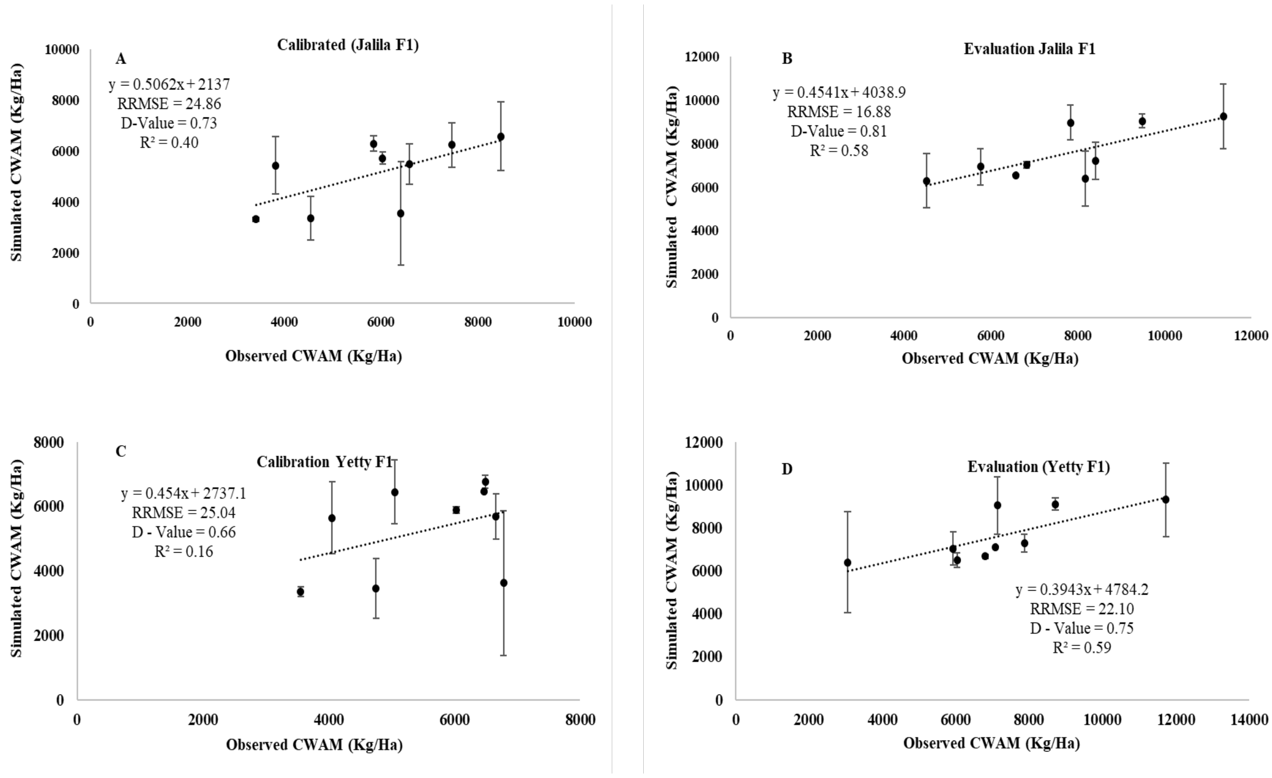

Figure 5. Aboveground Dry Biomass (CWAM) (kg/ha) as Calibrated for Jalila F1 and Yetty F1 Under Greenhouse Environment 1 (A and B Respectively) and evaluated for Jalila F1 and Yetty F1 Under Greenhouse Environment 2 (C and D Respectively) for the Combined Fertilizer Rate and Irrigation Regime Using DSSAT-CROPGRO Model. Bars represent standard deviation.

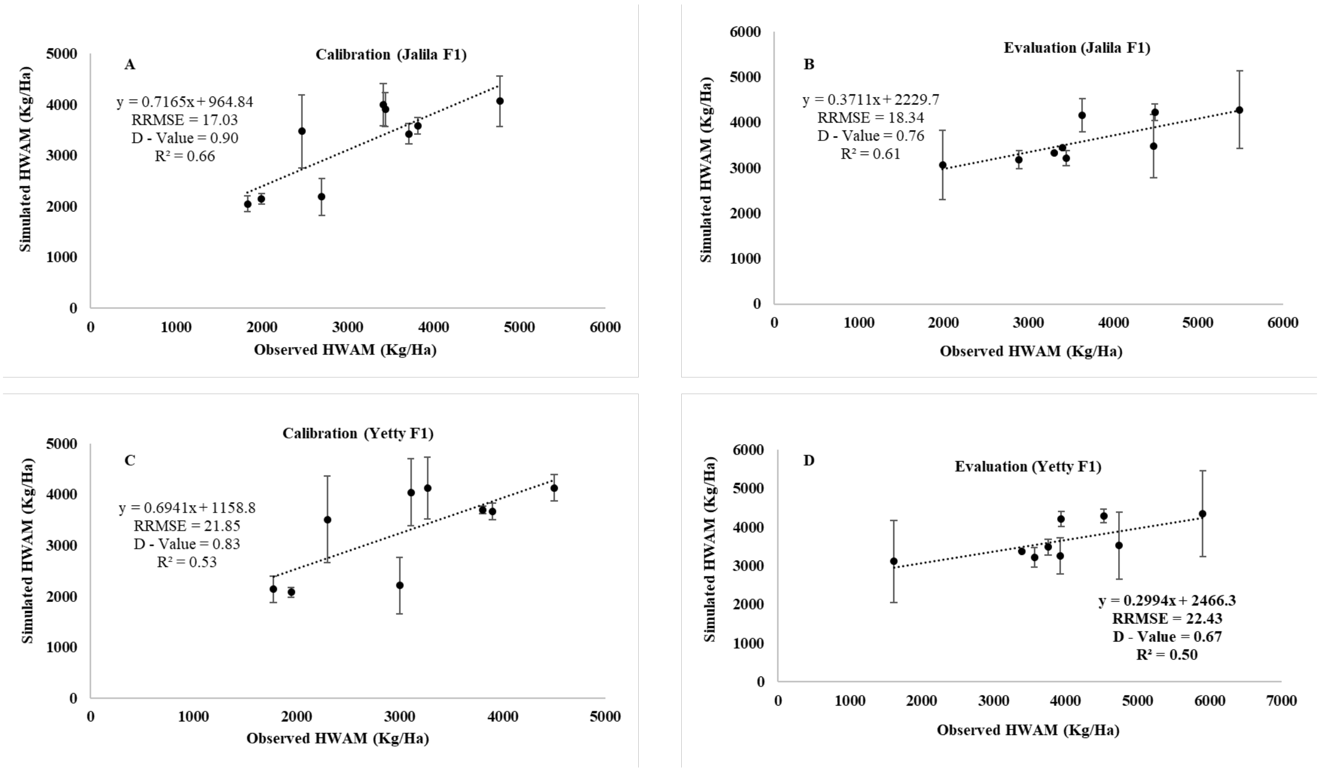

Figure 6. Dry Fruit/Yield Biomass (HWAM) (kg/ha) as Calibrated for Jalila F1 and Yetty F1 Under Greenhouse Environment 1 (A and B Respectively) and evaluated for Jalila F1 and Yetty F1 Under Greenhouse Environment 2 (C and D Respectively) for Combined Fertilizer Rate and Irrigation Regime Using DSSAT-CROPGRO Model. Bars represent standard deviation.

The evaluation of the dry fruit biomass for the interactions of fertilizer rate, irrigation regime and Jalila F1 was well simulated under greenhouse environment 2, with a RRMSE of 18.34 %, degree of agreement, 0.76 and a 0.61 correlation between the observed and simulated. The observed and simulated mean dry fruit biomass were 3679 kg/ha and 3595.22 kg/ha respectively (Figure 6b). Similarly, the dry fruit biomass for the interactions of fertilizer rate, irrigation regime and Yetty F1 was well simulated with a RRMSE of 22.43 %, degree of agreement, 0.67 and 0.50 degree of correlation between the observed and simulated. The mean dry fruit biomass observed and simulated under greenhouse environment 2, were 3929.11 kg/ha and 3642.67 kg/ha respectively as presented in Figure 6d. The dry fruit biomass was slightly over estimated under greenhouse environment 1 but slightly under estimated under greenhouse environment 2 in the case both genotypes. Amankwaa -Yeboah *et al.,* (2023) indicated that there was a strong agreement between the measured and DSSAT-CROPGRO simulated tomato yield under different irrigation and nutrient management, also, DSSAT-CROPGRO model can be used to simulate tomato fruit yield under future climate scenarios. Deligios *et al.* (2017) and Cammarano *et al.* (2020) established that the dry fruit/yield biomass of processing tomato was well simulated by the DSSAT-CROPGRO model. According to Deligios *et al.* (2017), the simulations could be better if the variability in the distribution of fertigation solution on the field and its effect on transpiration rate in indeterminate tomato plants is well captured as by the model. Variations in genetic traits of indeterminate greenhouse tomato, such as the crop response to harsh climate conditions, canopy height and its prolonged harvesting period could help improve the model efficiency.

CONCLUSION

The model was calibrated and evaluated for the effects of greenhouse environmental conditions and fertigation regimes on indeterminate tomato genotypes. The model responded reasonably well in simulating the maximum leaf area index, the total aboveground dry biomass and yield of the indeterminate greenhouse tomato. Furthermore, the model showed variation in the simulated growth and yield of indeterminate tomato genotypes under the influence of various fertigation regimes and greenhouse environments comparable to the observed. The model is valuable as a decision support system to help farmers and researchers ascertain the optimal crop management strategy from various stand points including genetics, fertigation regimes and greenhouse environments. It is recommended that the model be improved in terms of its response to soilless media, fertigation regimes, genetic traits of indeterminate tomato and climatic conditions especially in the tropical regions. As such employing the DSSAT CROPGRO model will help come up with strategic policies for improving the efficiency and sustainability of tomato production in Ghana, reducing the country's reliance on imported tomatoes and helping ensure food security for the growing population.

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CONFLICT OF INTEREST

The authors have declared no conflict of interest regarding the publication of the paper.

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