Simulative Evaluation of the Response of Maize and some Dual-Purpose Legumes to Water and Nutrient Amendments

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Abstract

The study evaluated DSSAT's CERES-Maize and CROPGRO models for their effectiveness in simulating the growth of maize, groundnut, and cowpea under dynamic nutrient amendments and water management practices in field experiments. The experiments were laid-out in split-plot with water management (rainfed and irrigated) as main plots and fertilizer (organic and inorganic fertilizer) as sub-plots during the maize trial, while, water management treatment (irrigated and rainfed) was the main plot and variety as the subplot during the cowpea and groundnut trials arranged in three replications. The CERES-Maize model's RMSE-observations standard deviation ratio (RSR) for simulating maize grain yield under irrigated and rainfed were 0.1624 and 0.0317 respectively, while that for the maize biomass under irrigated and rainfed were 0.4027 and 2.1676 respectively. Also, the CROPGRO model's RSR for simulating groundnut grain yield under irrigated and rainfed were 0.1058 and 8.0592 respectively, while that for the groundnut biomass under irrigated and rainfed were 1.1154 and 0.0161 respectively. In addition, the CROPGRO model's RSR for simulating cowpea grain yield under irrigated and rainfed were 8.1625 and 0.1019 respectively, while that for the cowpea biomass under irrigated and rainfed were 0.2677 and 0.2630 respectively. From the results, it was concluded that the CERES-Maize model was more suited to effectively scope alternate management practices under maize production whereas more research is needed to be able to confirm the effectiveness of the model in our environment.

Keywords: Crop production, CROPGRO, CERES-Maize, DSSAT

Simuler des amendements relatifs à l'eau et aux éléments nutritifs sur le maïs et certaines légumineuses à double usage

Résumé

L'étude a évalué les modèles CERES-Maïs et CROPGRO pour leur efficacité dans la simulation de la croissance du maïs, de l'arachide et du niébé dans le cadre de modifications dynamiques des nutriments et de pratiques de gestion de l'eau dans des expériences de terrain. Les expériences *ont été organisées en parcelles divisées avec gestion de l'eau (pluviale et irriguée) comme parcelles principales et engrais (engrais organique et inorganique) comme sous-parcelles pendant l'essai sur le maïs, tandis que le traitement de la gestion de l'eau (irrigué et pluvial) était la parcelle principale et la variété comme sous parcelle au cours des essais sur le niébé et l'arachide organisés en trois répétitions. Le rapport d'écart-type (RSR) des observations RMSE du modèle CERES-Maïs pour la simulation du rendement des céréales de maïs irriguées et pluviales était 0,1624 et 0,0317 respectivement, tandis que celui de la biomasse de maïs irriguée et pluviale était de 0,4027 et 2,1676 respectivement. De plus, le RSR du modèle CROPGRO pour la simulation du rendement des grains d'arachide irrigués et pluviaux était de 0,1058 et 8,0592 respectivement, tandis que celui de la biomasse d'arachide irriguée et pluviale était de 1,1154 et 0,0161 respectivement. De plus, le RSR du modèle CROPGRO pour la simulation du rendement des céréales de niébé irriguées et pluviales était de 8,1625 et 0,1019 respectivement, tandis que celui de la biomasse de niébé irriguée et pluviale était de 0,2677 et 0,2630 respectivement. D'après les résultats, il a été conclu que le modèle CERES-Maïs convenait mieux pour définir efficacement d'autres pratiques de gestion dans le cadre de la production de maïs, alors qu'une recherche plus poussée est nécessaire pour confirmer l'efficacité du modèle dans notre environnement.*

Mots clés: Production végétale, CROPGRO, CERES-Maïs, DSSAT

Introduction

Increased population pressure has resulted in the continuous use of available land and water resources in a bid to meet the demand in food supply. Farming systems in West Africa are dominated by smallholder family farming (Headey and Jayne, 2014; Mellor, 2014; Liu and Yamauchi, 2014). Rural families dynamically exploit their environment, in more especially, agricultural production to maintain or improve family welfare (; Gongruttananun & Saengkudrua 2016). The continuous exploitation of their farmlands in a bid to increase production and income has significantly affected the availability of soil nutrients for crop production. Thus, the cropping systems' evolution is putting less emphasis on nutrient conservation and restoration, resulting in a gradual deterioration in the soil structure and its fertility.

Nutrition and water are critical and are usually economically scarce inputs in crop production. According to Heng *et al*. (2005), poor soil fertility and erratic rainfall have been a great constraint to agricultural production in our globe. Water supply is the main source of variability in the yields of crops. Crops' total evapotranspiration or water use substantially differs as a result of limited soil's water or shortage or as a result of limited rainfall. The stochastic nature of rainfall makes the determination of the timing and level of fertilizer needed to secure optimal yields difficult as it leads to under or over-application of N based on the rainfall (Kinama et al., 1997). Targeting the water-use efficiency can lead farmers and researchers to more positive attitude towards surmounting challenges rather than blaming droughts for all low yields (French and Schultz, 1984). Yields of some crops in rainfed plots are usually low and as such optimal water-nutrients management in rainfed agriculture is essential in order to balance the water and nutrients requirements and improving crop production outcomes.

Crop-simulation models are utilized to develop suitable crop production strategies for increased and sustained crop yields as it helps to uncover the relationship between water availability and use, climate variability and agricultural productivity (Kinama, 1997). Crop simulation models, if appropriately applied, could be employed to evaluate alternate farm-management options and their outcomes in field trials. Several models such as Decision-Support System for Agro-technology Transfer (DSSAT) (Rezzoug et al., 2008), Agricultural Production Systems sIMulator (APSIM) (Gaydon *et al*., 2017; Salo *et al.,* 2016), Cropping Systems Simulation Model (CROPSYST) (Stockle *et al*., 2003; Salo et al., 2016), COUP Model Simulation (COUP) (Salo et al., 2016), Daisy model (DAISY) (Salo et al., 2016), Environmental Policy Integrated Climate Model (EPIC) (Salo *et al*., 2016), Farm ASSEssment Tool (FASSET) (Salo *et al.,* 2016), Highly Extensible Resource for Modeling Even-Driven Supply Chains (HERMES) (Salo *et al.,* 2016), Simulateur mulTIdisciplinaire pour les Cultures Standard (STICS) (Salo *et al*., 2016) and World Food Studies Simulation Model (WOFOST) (Salo *et al.,* 2016) have been used to examine the effects of several management options on field crops. These crop models have been historically used to predict field crops developments and yields under alternative management and weather scenarios. Dimes et al. (2011) used APSIM to simulate maize-bean cropping systems in Eastern and Southern Africa and found less yield variability from rainfall patterns between simulated and actual yields of the maize and bean crops. Liu *et al*. (2017) used the DSSAT-Century model to successfully simulate wheat yield and soil organic carbon under a wheat-maize cropping system. The study found that N application (150 kg/ha) increased yield in both simulated and field-measured wheat and concluded that, the model simulations on management practices which uses low N in wheat production was not sustainable. Soldevilla-Martinez et al. (2013) simulated various improved combinations of tillage-rotation under dryland conditions using the CERES and CROPGRO models in Spain. The study found that, the model predicted higher yields in conventional tillage than in the no-till, eventually leading them to conclude that using conventional tillage for vetch production and fallow were the best combination for the dry land conditions studied.

The integration and the difficulties in balancing of water and nutrients in crops production could be reduced and perhaps overcome at the initial stages of cultivation as crop simulation models give a better foresight analysis of crops' performance for each water and nutrient combination by which the researchers or farmers could choose the optimal combination to ensure appreciable yields and also yield gaps could be analyze . Modeling innovations can address increasing concerns on nutrition, sustainable food production, and natural resource management challenges (Reynolds et al., 2018). The crop simulation model could aid farmers and researchers to predict crops outcome parameters of given treatment combinations in a given agro-ecological zone prior to cultivation.

The models integrate the effects of soil, crop phenotype, weather, and management options that allow users to ask what-if questions and simulate results by conducting experiments which would have consumed a significant part of an agronomist's career within minutes (Mekuria *et al.,* 2013) for evaluation of options and early decision making. The research sought to evaluate the performance of Crop Environment Resource Synthesis (CERES)-Maize model on maize and

CROPGRO models on cowpea and groundnuts in the Ghanaian forest agro-ecological zone to ascertain how well they would be able to predict the crops outcome parameters and to ascertain whether there would be the need for further calibration of the models to give good crops outcomes' predictions for our Ghanaian forest agro-ecological zones. Potentially, crop modeling could significantly contribute to food and nutritional security in our globe, as there are new technologies and conceptual breakthroughs, which has contributed to a better comprehension of crops' performance and yield gaps, more efficient irrigation systems as well as optimized planting dates (Reynolds et al., 2018). The general objective of this study was to assess the performance of the CERES-Maize and CROPGRO models as a decision support tool in the SIIC-SR project, and more specifically to evaluate the DSSAT models for their ability to simulate maize, cowpea, and groundnut growth and yields under local climatic conditions and examine alternative management practices (water and nutrient management) to improve crops' yields.

Materials and methods

Site description

The study was conducted in the experimental fields of the CSIR-Crops Research Institute at Fumesua, Ghana during the 2016/2017 crop season. The study area is located in the forest zone and lies approximately on longitude 1° 32' W and latitude 6° 43' N with an average elevation of 295 m above sea level taken from GPS readings and corroborated from 1:25,000 topographic map of Ghana. The area experiences an average annual rainfall of 1200 mm received throughout two rain/wet seasons. The first rainy season begins from April to July whiles the second rainy season, which is mostly referred to as the minor season, spans September to November.

Simulation models' description

The CERES-Maize and CROPGRO crop simulation models are part of a suite of models developed through the International Benchmark Sites Network for Agro-technology Transfer (IBSNAT) project which can predict growth and yield of various maize and leguminous varieties under all agro-climatic conditions (). The version of the CERES-Maize model used is 4.5, which is embedded within the DSSAT 4.5. The Decision Support System for Agrotechnology Transfer (DSSAT) is a software package which integrates the effects of soil, crop phenotype, weather, and management options and allow users to ask what-if questions and simulate results by conducting, in minutes on a desktop computer, experiments which would have consumed a significant part of an agronomist's career. The CERES-Maize model has been extensively described by Jones *et al.* (1998), whereas the CROPGRO model has also been extensively described by Tsuji et al. (1994) and Boote et al. (1998a, 1998b).

CROPWAT 8.0, which was used for irrigation in the experiments, was developed by the FAO Land and Water Development Division (FAO, 1992). CROPWAT 8.0 for Windows is a computer program for the calculation of crop-water requirements and irrigation requirements based on soil, climate, and crop data. The CROPWAT model allows the development of irrigation schedules for different management conditions and the calculation of scheme water supply for varying crop patterns. CROPWAT 8.0 can also simulate under both irrigated and rainfed conditions.

Plant material

The maize variety used, *Obatanpa* is an improved material sourced from the CSIR-Crops Research Institute in Kumasi.

Obatanpa is a white dent medium maturing (between 105-110 days) open-pollinated variety. It is popular for its quality protein and widespread adaptation in the country. The cowpea varieties, *Padituya* and *Songotra* are improved materials sourced from the CSIR-Savannah Agricultural Research Institute at Nyankpala. *Padituya* is a white-coated, black helium variety maturing between 64-67 days. *Songotra* is a creamy white-coated, black helium variety maturing between 62-65 days. Two other cowpea varieties used, *Soronko* and *Asetenapa* are improved materials sourced from the CSIR-Crops Research Institute, Kumasi.

All four groundnut varieties, *Adepa*; *Nkosuor*; *Jenkaar*, and *Azizivi* are improved materials and sourced from the CSIR - Crops Research Institute, Kumasi. All the varieties used are semi-erect and matures between 110-120 days. The groundnut varieties are well-adapted to most groundnut growing areas across the country.

Experimental design

The experimental design used for the maize trial was a split-plot with water management (rainfed and irrigated) as main plots and fertilizer (organic and inorganic fertilizer) as sub-plots in three replications. The experiment was conducted for two seasons (April – August 2016 and 2017). The treatments used for the maize field experiment for both irrigated and rainfed plots were as follows: NMF = No mineral fertilizer; HMF = Half the recommended rate of mineral fertilizer; AMF = Full recommended mineral fertilizer; HOF = Half recommended rate of organic fertilizer; AOF = Full recommended organic fertilizer; and; HMOF = Half recommended mineral fertilizer + half recommended organic fertilizer.

The mineral fertilizer was applied in split, with the first application (half of the recommended amount) done 10 days after planting (DAP) whilst the second application was done four weeks after planting. All the organic fertilizer treatment was imposed 10 DAP. All treatments were well-watered until 21 DAP when water management (irrigation and rainfed) treatments were initiated. The split-plot design was also used for the individual trials involving cowpea and groundnut where the water management treatment (irrigated and rainfed) was allocated to the main plots whereas the variety was allocated to the subplots. All experiments conducted were subjected to three replications. For the irrigation treatment, the irrigation scheduling was done using CROPWAT 8.0 software following the description and applications given by FAO (1992). Data was taken on growth and yield parameters including plant height, stem girth, number of branches, number of pods as well as grain and biomass yield for all the crops. All other agronomic practices such as weeding, pests, and disease management were followed strictly as per the crop's management protocol.

Secondary data collection and management

Weather data

The required weather data for irrigation scheduling using the CROPWAT 8.0 were obtained from a weather station that lies on longitude 1° 32' W and latitude 6° 43' N at the CSIR-Crops Research Institute, Kumasi. The average weather for the 2016/2017 years is as shown in Table 1.

Historical weather data (spanning 30 years) set including minimum and maximum air temperatures, precipitation relative humidity, wind speed, and solar radiation were obtained from the weather station at the Department of Horticulture, Kwame Nkrumah University of

Table 1: Monthly means of weather components

Month	Rainfall, mm	Minimum Temperature, °C	Maximum Temperature, °C	Solar radiation, w/m^2	Wind, m/s
January	9.00	19.68	33.89	313.36	0.64
February	17.80	21.89	33.96	332.06	0.99
March	82.40	22.74	33.89	369.48	0.94
April	152.60	22.47	32.63	351.14	0.98
May	170.40	22.17	31.58	315.14	0.87
June	204.00	21.96	29.65	263.60	0.92
July	43.60	21.67	28.45	233.90	0.94
August	4.60	21.28	28.42	195.37	1.14
September	46.60	21.95	30.73	244.02	0.80
October	215.20	21.78	31.86	307.24	0.59
November	41.60	22.20	32.68	321.9	0.65
December	40.80	21.42	32.55	321.44	0.58

Science and Technology (KNUST). The historical weather data was approximated for use employing the Weatherman model of DSSAT. For both years of the trials (2016 and 2017), the highest average amounts of rainfall for the station was recorded in October at 215.20 mm whilst the lowest amount recorded was 4.6 mm in August. The maximum temperature of 33.96°C was recorded in February whilst the minimum temperature of 19.68 °C was recorded in January. Average maximum and minimum temperatures were 31.69°C and 21.76°C respectively as shown in Table 1.

Soil data

Soil samples were taken randomly from nine (9) locations from the experimental field prior to planting and bulked to the corresponding depth of 15, 30, 45, and 60 cm. Each sample was divided into two with one half used to determine the soil moisture content and the other half for analysis on soil physical and chemical properties. The analyzed data included soil series classification, surface slope, soil colour, permeability, and drainage class. Soil profile data by soil horizons included upper and lower horizon depths (cm), percentage sand, silt and clay content, bulk density, organic carbon, and pH (Table 2). Soil information was input into the DSSAT simulation model and recalled for all simulations pertaining to the experiments undertaken.

Model parameterization

The DSSAT shell includes default genetic coefficients for a range of species and cultivars. *Obatanpa* is generic to the DSSAT 4.5 version hence no genetic calibration was done. Local soil and weather data were used to calibrate the soil (S-Build) and weather (Weatherman) modules respectively. For validation purposes, the model outputs were tested using a Minimum Data Set (MDS) sourced from the experiments carried out at the CSIR - Crops Research Institute with input variables as shown in Table 3.

Table 2: Soil data used for the calibration of the DSSAT model

Soil depth (cm)	Lower limit cm^3/cm	Upper limit cm^3/cm^3	Sat SW cm^3/cm^3	Extr SW cm^3/cm^3	Init SW cm^3/cm^3	Bulk density, Mg/m^3	pH	Organic Carbon (%)
0 -5	0.053	0.177	0.400	0.125	0.176	1.60	5.10	42.00
5 – 15	0.053	0.177	0.400	0.125	0.176	1.60	5.10	42.00
15 – 30	0.053	0.177	0.400	0.125	0.176	1.60	5.70	31.00
30 – 45	0.081	0.195	0.410	0.200	0.192	1.61	5.50	0.58
45 – 60	0.081	0.195	0.410	0.200	0.192	1.62	5.50	0.58
60 – 90	0.132	0.283	0.42	0.108	0.232	1.62	5.59	0.43

Table 3: Input parameters used in the various crops' simulations

Management options		Input data	
	Maize	Cowpea	Groundnut
Planting date	19 June 2013	19 June 2013	19 June 2013
Row spacing	80 cm	60 cm	60 cm
Emergence date	24 June 2013	23 June 2013	26 June 2013
Planting depth	5 cm	5 cm	5 cm
Fertilizer application	1. Half of the recommended amount 10 DAP 2. 15kgN/ha 30 DAP 3. Full recommended amount 10 DAP 4. 30KgN/ha 30 DAP	None	None
Organic amendments	Full recommended – 5000kg/ha Half recommended – 2500 kg/ha	None	None
Cultivar	*Obatanpa*	*Soronko,* *Padituya,* *Asetenapa* *Songotra*	*Adepa,* *Nkosour* *Azivivi* Jenkaar
Planting density, m^{-2}	6	16	20

The cultivar, *Obatanpa* which is inherent in the DSSAT shell, was set as the default cultivar for all the maize yield simulations. The performance of the CERES-Maize under potential production conditions (no water stress) with no environmental modifications was tested using data from the irrigated experiment by simulating the yield under localized climatic conditions for the various months of the year. The model was run using 2 years of weather data (2012 to 2013) from the

CSIR-Crops Research Institute in the Ashanti Region. The growth analysis and developmental data, collected in the two seasons of the experiment on the cowpea and groundnut were also used for the CROPGRO model evaluation in order to determine the parameters that define the characteristics for its dual purpose.

The coefficients provided in the DSSAT model for various maturity groups provided the starting point in the process of determining the genetic coefficients. Candidate coefficients were selected and integrated into the cultivar data of CROPGRO (CPGR0045. CUL, CPGR0045. ECO, and CPGR0045.SPE). The values of the coefficients were then subsequently modified by running CROPGRO in an optimization shell until the error sum of squares (simulated minus observed) was minimized. The set of coefficients that produced the lowest Root Mean Square Error (RMSE) were then adopted and used in the simulations. The

Table 4: Modified genetic coefficients of groundnut and cowpea varieties used in the calibration of the CROPGRO model

Parameter	Groundnut				Cowpea			
	GH0003 *Adepa*	GH0004 *Nkosour*	GH0005 *Azivivi*	GH0006 *Jenkaar*	CP0030 *Soronko*	CP0031 *Padituya*	CP0032 *Asetenapa*	CP0033 *Songotra*
#ECO	PN0021	PN0021	PN0021	PN0021	CP0414	CP0414	CP0414	CP0414
CSDL	11.84	11.84	11.84	11.84	12.8	12.8	12.8	12.8
PPSEN	0	0	0	0	0.29	0.29	0.29	0.29
EM-FL	19.33	20.67	19	20.67	32	31.67	39	38
FL-SH	9.33	8.99	10	10.67	6.67	7.42	7.33	8.33
FL-SD	39	37.66	37.66	37.99	12.32	14.67	13.33	12.33
SD-PM	61.67	62.67	62	62.34	26.68	24.66	27.67	31.67
FL-LF	80	80	80	80	15	15	15	15
LFMAX	1.24	1.24	1.24	1.24	1	1	1	1
SLAVR	265	265	265	265	275	275	275	275.9
SIZLF	19	19	19	19	150	150	150	150
XFRT	0.77	0.77	0.77	0.77	0.5	0.5	0.5	0.5
WTPSD	0.69	0.61	0.64	0.6	0.05	0.05	0.05	0.05
SFDUR	29	36	38	32	5.5	5.5	5.5	5.5
SDPDV	6.42	7.23	5.63	6.22	8.5	6.8	11.03	11.23
PODUR	35	32	37	35	16.68	18.66	18.67	21.67
THRSH	85	80	82	84	0.83	0.81	0.78	0.75
SDPRO	0.27	0.27	0.27	0.27	0.3	0.3	0.3	0.3
SDLIP	0.51	0.51	0.51	0.51	0.65	0.65	0.65	0.65

values for critical short day length, specific leaf area of cultivar under standard growth conditions, maximum leaf photosynthesis rate at 30 C, 350 vpm CO_2, and high light, seed filling duration for pod cohort at standard growth conditions, fraction protein in seeds and fraction oil in seeds were not measured hence values from cultivars that have parameters close to the coefficients of the local cultivars were selected and used.

Corresponding coefficients for cowpea and groundnut (Table 4) were generated for the following: the slope of the relative response of development to photoperiod with time; the time between plant emergence and flower appearance; the time between first flower and first pod; the time between first flower and first seed; the time between first seed and physiological maturity; the time between first flower and end of leaf expansion; maximum size of full leaf (three leaflets); maximum fraction of daily growth that is partitioned to seed + shell); maximum weight per seed (g) (WTPSD); average seed per pod under standard growing conditions, time required for cultivar to reach final pod load under optimal and the maximum ratio of (seed/(seed+shell)) at maturity.

Statistical analysis

In addition to analysis of variance with SED at 5% for means separation, the following statistical and model performance indicators were used to evaluate overall model performance: Mean Bias, Mean Error, Root Mean Square Error (RMSE), Index of Agreement, and the RMSE-Observation Standard Deviation Error (Dust *et. al*., 2000; Law, 2015; Lecina *et. al,* 2003; Robinson *et. al.,* 2008).

Suppose m ... f data points; where *X or* ... *X or* X_{sJ} is the simulated val...

$$\text{Mean Bias} = \frac{1}{m}\sum_{j=1}^{m}\left(\hat{X}_j - X_j\right) \quad (1)$$

$$\text{Mean Error} = \frac{1}{m}\sum_{j=1}^{m}\left|\hat{X}_j - X_j\right| \quad (2)$$

$$\text{Root Mean Square Error (RMSE)} = \sqrt{\frac{1}{m}\sum_{j=1}^{m}\left(\hat{X}_j - X_j\right)^2} \quad (3)$$

$$\text{Index of Agreement (d)} = 1 - \frac{\sum_{j=1}^{m}\left(X_{s_j} - X_{o_j}\right)^2}{\sum_{j=1}^{m}\left(\left|X_{s_j} - \bar{X}_o\right| + \left|X_{o_j} - \bar{X}_o\right|\right)^2}, \quad (4)$$

where $0 \leq d \leq 1$

$$\text{RMSE - Observations Standard Deviation Ratio (RSR)} = \frac{\sqrt{\sum_{j=1}^{m}\left(X_{o_j} - X_{s_j}\right)^2}}{\sqrt{\sum_{j=1}^{m}\left(X_{o_j} - \bar{X}_o\right)^2}} \quad (5)$$

Results and Discussions

Maize

The interaction between water, and nutrient treatment was significant at the 5% significance level for all the response variables (Table 5). The treatment that was given 100% of the recommended organic fertilizer (AOF) yielded the highest grain under the maize field experiment and simulations. The treatment that received the full-recommended inorganic (mineral) fertilizer (AMF) yielded the highest biomass in the field experiment. AOF, however, yielded the highest biomass in the simulated experiment under irrigated and AMF for the rainfed conditions (Table 5).

The results of the model's performance metrics for simulating maize grain yield and biomass are displayed in Table 6. The mean bias and mean error of maize yield were 158.6667 each for irrigated and 242.6667 each for rainfed plots (Table 6). Also, the mean bias and mean error of maize biomass were 395.3333 each for irrigated and 234.1667 and 676.5000 respectively for rainfed plots indicating the model consistently over-estimates the maize yield and biomass for both the irrigated and rainfed

Table 5: ANOVA output for observed and simulated grain and biomass yield

Treatment Water	Nutrient	Grain Yield, kg/ha Observed	Grain Yield, kg/ha Simulated	Biomass Yield, kg/ha Observed	Biomass Yield, kg/ha Simulated
Irrigated	**AMF**	4037	4075	11317	11519
	AOF	4126	4232	11299	11619
	HMF	2601	2830	9134	9463
	HMOF	3431	3625	9240	10160
	HOF	2450	2646	9409	9456
	NMF	1068	1257	7999	8553
Rainfed	**AMF**	2363	2617	8634	9550
	AOF	2024	2468	9002	9153
	HMF	905	1091	8001	8319
	HMOF	2006	2120	9035	9400
	HOF	1945	2142	8430	9412
	NMF	698	959	8319	6992
		1.3	4.4	2.6	2.2
		24.68	91.0	195.2	172.7
		<0.001	<0.001	<0.001	<0.001

Table 6: Model Performance metric for Maize Yield and Biomass

Model Performance Metrics	Yield Irrigated	Yield Rainfed	Biomass Irrigated	Biomass Rainfed
Mean Bias	158.6667	242.6667	395.3333	395.3333
Mean Error	158.6667	242.6667	395.3333	395.3333
Root Mean Square Error	171.7042	263.3673	484.2468	484.2468
Index of Agreement	0.9932	0.9997	0.9583	0.9583
Nash-Sutcliffe Efficiency	0.9736	0.9990	0.8378	0.8378
RMSE-observations standard deviation ratio	0.1624	0.0317	0.4027	0.4027

(Table 6).

The index of agreement of maize yield of 0.9932 and 0.9997 respectively for irrigated and rainfed and that of the maize biomass were 0.9583 and 0.5647 respectively for irrigated and rainfed (Table 6). Thus, there is a very strong agreement between the observed and simulated maize yield for the irrigated and rainfed plots. It also had a very strong agreement between the observed and simulated maize biomass for the irrigated plots while the rainfed plots had a moderate agreement.

The RMSE-observations standard deviation ratio of maize yield of 0.1624 (a low RMSE of 171.7042) and 0.0317 (a low RMSE of 263.3673) respectively for irrigated and rainfed plots (Table 6). The RMSE-observations standard deviation ratio of maize biomass were 0.4027 (a low RMSE of 484.2468) and 2.1676 (a high RMSE of 798.0663) respectively for the irrigated and rainfed plots (Table 6). Thus, the RMSE-observations standard deviation ratio of maize yield indicates a very good performance rating of the model for simulating maize yield (Adnan et al., 2017; Soler et al. as cited in Adnan et al., 2019) for the irrigated and rainfed plots. Also, RMSE-observations standard deviation ratio of maize biomass indicates a very good performance rating of the model for simulating maize biomass (Adnan et al., 2017; Chisanga et al., 2015) for the irrigated, but the model had an unsatisfactory performance rating for simulating maize biomass for the rainfed plots.

Cowpea

The interaction between water and variety on each of the response variables was significant at the 5% significance level. Pod per plant for the cowpea varieties *Soronko* and *Padituya* were similar in both the irrigated and rainfed treatment for measured and simulated values except for the simulated pod per plant in the rainfed plots, where the *Soronko* was significantly higher than *Padituya* (Figure 1). *Asetenapa* and *Songotra* also showed a similar trend in pods per plant for both measured and simulated for the two water treatments (Figure 1). Figure 1 Effect of water by nutrient interaction on number of pods per plants for cowpea varieties under rainfed and irrigated conditionsCowpea varieties *Asetenapa* and *Songotra* had similar pod per

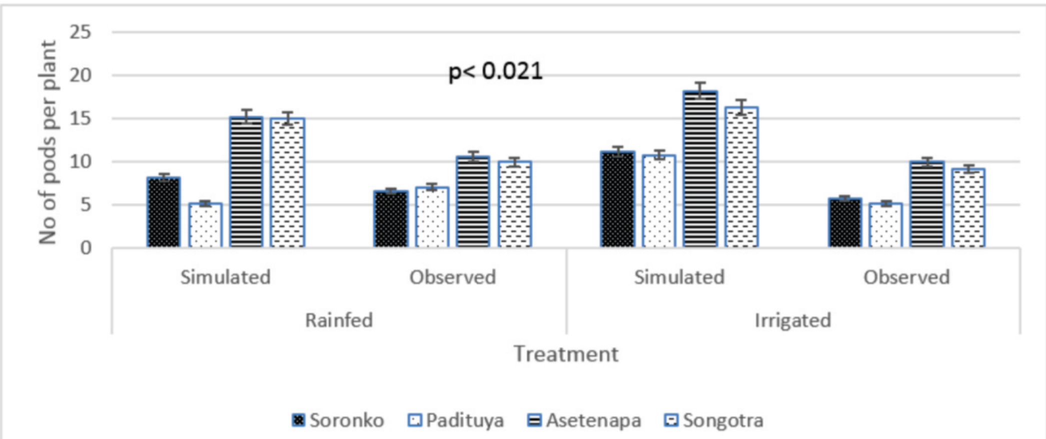

Figure 1: Effect of water by nutrient interaction on number of pods per plants for cowpea varieties under rainfed and irrigated conditions

plant and were significantly higher than *Soronko*, and *Padituya*, which were also mostly similar for both observed and simulated measurements (Figure 1). There were no significant differences between the total dry matter production for *Asetenapa*, *Soronko* and *Padituya* under both the simulated and observed values for the irrigated and rainfed treatments.

The interaction between water and variety on seed per pod was significant at the 5% significance level (Figure 2). For the observed seed per pod under rainfed conditions; the Cowpea variety *Asetenapa* had many observed seeds per pod which was significantly higher than *Songotra*, which was also significantly more than *Soronko*, and *Padituya* which had similarly observed seeds per pod (Figure 2). For the simulated seed per pod under rainfed conditions; the cowpea variety *Songotra* had many simulated seeds per pod which was significantly higher than *Soronko* and *Asetenapa* which had similar simulated seeds per pod and were also significantly higher than *Padituya* (Figure 2). For the observed seed per pod under irrigated conditions; Cowpea varieties *Asetenapa* and *Songotra* had similar seeds per pod, which were significantly more than *Soronko* which was also significantly more than *Padituya* (Figure 2). For simulated seed per pod under irrigated conditions; *Soronko*, *Padituya* and *Asetenapa* had similar seed per pod, which was significantly more than *Songotra* (Figure 2). The yields of all the varieties under irrigation were higher than its counterpart rainfed treatment, indicating that the crops respond positively to irrigation.

As shown in table 7, the interaction between water and variety of aboveground biomass was significant at the 5% significance level for the observed Cowpea biomass. Cowpea variety, *Songotra* had significantly higher observed aboveground biomass than *Soronko* and *Asetenapa* which had similar aboveground biomasses which was also significantly higher than *Padituya* under the rainfed conditions (Table 7). Similar trends

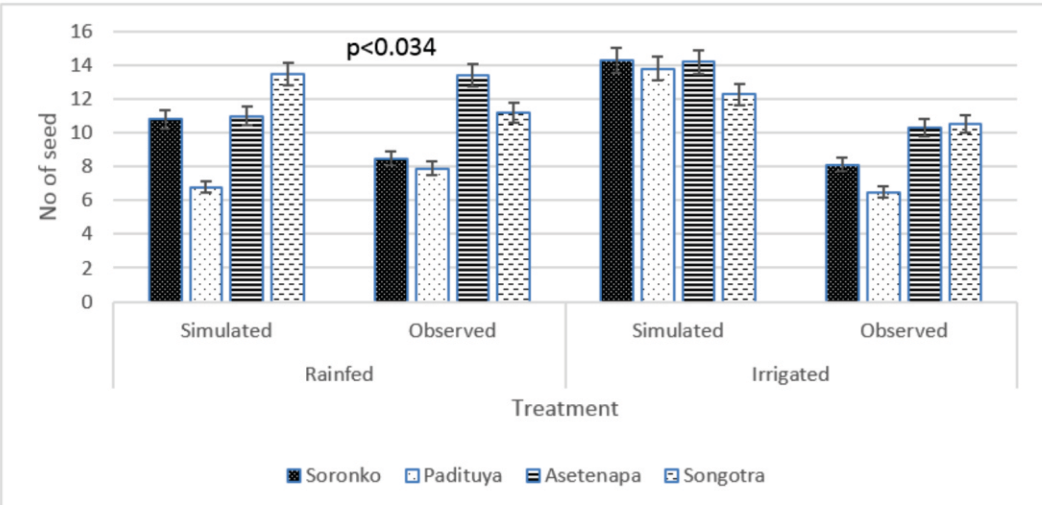

Figure 2: Effect of water by nutrient interaction on number of seeds per pod for cowpea varieties under rainfed and irrigated conditions

were observed for the irrigated conditions too (Table 7).

As shown in Table 8, the mean bias and mean error of cowpea yield were 561.50 each for irrigated and 237.7500 each for rainfed plots. Also, the mean bias and mean error of cowpea biomass were 2843.2500 each for irrigated and 1853.7500 each for rainfed plots indicating the model consistently over-estimates the cowpea yield and biomass for both the irrigated and rainfed plots.

The index of agreement of cowpea yield of 0.1732 and 0.9971 respectively for irrigated and rainfed and that of the cowpea biomass were 0.9762 and 0.9771 respectively for irrigated and rainfed plots (Table 8). Thus, there is a very strong agreement between the observed and simulated cowpea yield for the rainfed plots. It also had a very strong agreement between the observed and simulated cowpea biomass (Kristjanson et al., 2001) for the irrigated and rainfed plots while the cowpea yield for the irrigated plots had a very weak agreement (Table 8).

The RMSE-observations standard deviation ratio of cowpea yield of 8.1625 (a high RMSE of 566.6401) and 0.1019 (a low RMSE of 238.8394) respectively for irrigated and rainfed plots (Table 8). The RMSE-observations standard deviation ratio of cowpea biomass were 0.2677 (a low RMSE of 2890.1780) and 0.2630 (a low RMSE of 1862.2850) respectively for the irrigated and rainfed plots (Table 8). Thus, the RMSE-observations standard deviation ratio of cowpea yield for the rainfed and the cowpea biomass for both the irrigated and rainfed indicates a very good performance rating of the model for simulating cowpea yield (Bastos et al., 2002) for the rainfed plots and the cowpea biomass for both the irrigated and rainfed plots. Also, RMSE-observations standard deviation ratio of cowpea yield for the irrigated indicates an unsatisfactory performance rating of the model for

Table 7: ANOVA output for simulated and observed cowpea grain yield and aboveground biomass

Treatment Water	Variety	Grain Yield, kg/ha Observed	Grain Yield, kg/ha Simulated	Aboveground Biomass, kg/ha Observed	Aboveground Biomass, kg/ha Simulated
Irrigated	***Asetenapa***	833	1518	3376	6334
	Padituya	718	1209	2812	5973
	Songotra	890	1397	4833	6801
	Soronko	886	1449	3340	6626
Rainfed	***Asetenapa***	912	1128	2233	4081
	Padituya	574	850	2068	4002
	Songotra	932	1160	2821	4395
	Soronko	700	931	2313	4372
CV (%)		19.9	14.4	5.0	9.5
SED		130.8	142.0	122.5	412.0
P-value		0.438	0.587	<0.001	0.899

Table 8: Model Performance metric for Cowpea Yield and Biomass

Model Performance Metric	Cowpea			
	Grain Yield		Biomass Yield	
	Irrigated	Rainfed	Irrigated	Rainfed
Mean Bias	561.5000	237.7500	2843.2500	1853.7500
Mean Error	561.5000	237.7500	2843.2500	1853.7500
Root Mean Square Error	566.6401	238.8394	2890.1780	1862.2850
Index of Agreement	0.1732	0.9971	0.9762	0.9771
Nash-Sutcliffe Efficiency	-65.6255	0.9896	0.9283	0.9308
RMSE-observations standard deviation ratio	8.1625	0.1019	0.2677	0.2630

simulating cowpea yield for the irrigated plots (Table 8). According to Bastos et al. (2002), CROPGRO-Cowpea model is deficient in simulating for dry conditions and may need further calibration.

Groundnut

As shown in figure 3, the interaction between water and variety on groundnut pod per plant was significant at the 5% significance level (Figure 3). The groundnut variety, *Jenkaar* had the most observed pods per plant, which was significantly higher than *Azivivi's* pod per plant, which was also significantly higher than *Adepa* and *Nkosour* which had similar pods per plant under the rainfed conditions (Figure 3). Also, the groundnut varieties, *Jenkaar* and *Nkosour* had similar simulated pods per plant, which was significantly higher than the pods per plant for *Azivivi*, which was also significantly higher than that on *Adepa* under the rainfed conditions (Figure 3). In addition, the groundnut variety *Adepa* had more observed pods per plant, which was significantly higher than that on *Nkosour*, *Azivivi* and *Jenkaar*, which had similar observed pod per plant under the irrigated condition (Figure 3). Similar trend was also observed for the simulated pods per plant under the irrigated conditions (Figure 3). Also, the number of simulated groundnut pod per plant in the rainfed conditions were *Jenkaar* and *Nkosour,* which were similar, but significantly higher than *Azivivi*, which was also significantly higher than *Adepa* (Figure 3).

As shown in Table 9, the interaction between water and variety on groundnut observed and simulated yield and aboveground biomass was not significant at the 5% significance level.

As shown in Table 10, the mean bias and mean error of groundnut yield were 730.2500 each for irrigated and 657.2500 each for rainfed plots (Table 10). Also, the mean bias and mean error of groundnut biomass were 171.2500 and 247.7500 respectively for irrigated and 50.7500 and 182.2500 respectively for rainfed plots indicating the model consistently over-estimates the groundnut yield and biomass for both the irrigated and rainfed plots (Table 10).

The index of agreement of groundnut yield of 0.9969 and 0.1426 respectively for irrigated and rainfed and that of the groundnut biomass were 0.7408 and 0.9999 respectively for irrigated and rainfed plots. Thus, there is a

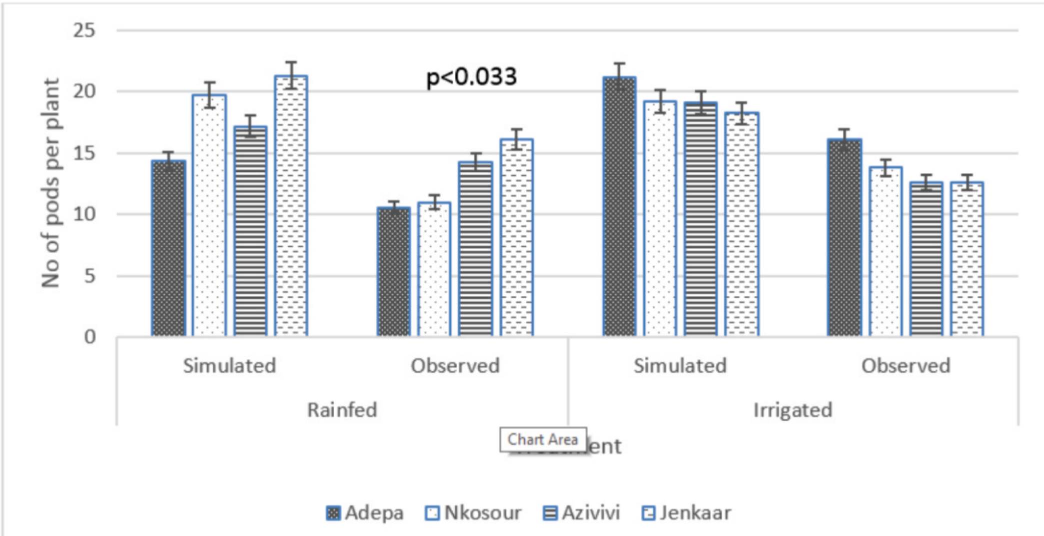

Figure 3: Effect of water by nutrient interaction on number of pods per plant for groundnut varieties under rainfed and irrigated conditions.

Table 9: ANOVA output for observed and simulated groundnut grain yield and aboveground biomass

Treatment		**Grain Yield, kg/ha**		**Aboveground Biomass, kg/ha**	
Water	**Variety**	**Observed**	**Simulated**	**Observed**	**Simulated**
Irrigated	*Adepa*	2257	3182	5146	5828
	Azivivi	2177	2872	5878	5892
	Jenkaar	2676	3243	5764	5906
	Nkosour	2230	2964	5233	5080
Rainfed	*Adepa*	1729	2320	4187	4340
	Azivivi	1765	2459	4209	4255
	Jenkaar	1871	2299	4379	4646
	Nkosour	1635	2551	4124	3861
CV (%)		9.5	16.0	6.8	6.6
SED		158.5	356.8	268.9	268.0
P-value		0.389	0.602	0.251	0.662

Table 10: Model Performance metric for Groundnut Grain Yield and above-ground Biomass

Model Performance Metrics	Groundnut			
	Yield		Biomass	
	Irrigated	Rainfed	Irrigated	Rainfed
Mean Bias	730.2500	657.2500	171.2500	50.7500
Mean Error	730.2500	657.2500	247.7500	182.2500
Root Mean Square Error	741.4336	680.6535	356.6837	203.7051
Index of Agreement	0.9969	0.1426	0.7408	0.9999
Nash-Sutcliffe Efficiency	0.9888	-63.9501	-0.2440	0.9997
RMSE-observations standard deviation ratio	0.1058	8.0592	1.1154	0.0161

very strong agreement between the observed and simulated groundnut yield for the irrigated plots and groundnut biomass for the rainfed plots; a strong agreement for the groundnut biomass for the irrigated plots while a weak agreement for the groundnut yield for the rainfed plots (Table 10).

The RMSE-observations standard deviation ratio of groundnut yield of 0.1058 (a low RMSE of 741.4336) and 8.0592 (a high RMSE of 680.6535) respectively for irrigated and rainfed plots (Table 10). The RMSE-observations standard deviation ratio of groundnut biomass were 1.1154 (a high RMSE of 356.6837) and 0.0161 (a low RMSE of 203.7051) respectively for the irrigated and rainfed plots. Thus, the RMSE-observations standard deviation ratio of groundnut yield for the irrigated plots and groundnut biomass for the rainfed plots indicate a very good performance rating of the model for simulating groundnut yield (Dangthaisong et al., 2006) for the irrigated plots and groundnut biomass for the rainfed plots (Table 10). Also, RMSE-observations standard deviation ratio of groundnut yield for the rainfed plots and groundnut biomass for the irrigated plots indicates an unsatisfactory performance rating of the model for simulating groundnut yield for the rainfed and groundnut biomass for the irrigated.

Conclusion

The study concludes that the CERES-Maize model indicated a very good performance rating of the model for simulating maize yield for the irrigated and rainfed plots. Also, the CERES-Maize model indicates a very good performance rating of the model for simulating maize biomass for the irrigated, but the model had an unsatisfactory performance rating for simulating maize biomass for the rainfed plots. The results also demonstrate that CROPGRO can be used to simulate legume but needs a rigorous calibration to integrate varietal information. The genetic coefficients determined and reported in this paper were not sufficiently accurate to be used to represent the various leguminous varieties used here. However, it is necessary to carry out long-term trials in varying sites to calibrate and validate the models for uses other than growth and yield simulations. The various models can therefore be used as a decision support tool in improving water and nutrient productivity and subsequently increase yields.

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