Crop water requirements, biomass and grain yields estimation for upland rice using CROPWAT, AQUACROP and CERES simulation models

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Abstract: This study estimated crop water requirements using CROPWAT while AQUACROP and CERES models evaluated performance in simulating biomass and grain yield of upland rice's response to different irrigation schedules. NERICA 4 was subjected to five treatment given as: full (100% ET), good (80% ET), medium (60% ET), average (40% ET), and low (20% ET) and three replicates in a randomized block design. It was planted at the farmyard of the International Institute of Tropical Agriculture (IITA) Ibadan, Nigeria for two seasons 2015 and 2016 and the results of the first season were used in model calibration while second season's result was used invalidation. Biomass and grain yield values were obtained and compared with simulated values from AQUACROP and CERES and the results were analyzed using E-VIEWS, R, and Minitab 17 statistical tools. Results showed that there were significant differences among the models in the simulation of grain and biomass yield concerning irrigation schedule. CERES slightly underestimated leaf area index (LAI) while both CERES and AQUACROP slightly overestimated grains and biomass yields although CERES showed the highest precision in grain yield, AQUACROP showed the highest accuracy in biomass yield and slightly underestimated canopy cover. CROPWAT performed excellently and could be used to efficiently estimate water requirements and reference evapotranspiration. The models showed high performance and accuracy in simulation of crop water requirements, grain and biomass yield of rice respectively.

Keywords: NERICA 4, water requirements, yield, simulation models, irrigation scheduling

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1 Introduction

Food security in the world is challenged by increasing demand and threatened by declining water availability and the effects of climate change (Akinbile and Sangodoyin, 2011). This is because one major challenge facing a lot of Nations especially the Third World countries in this present time is the problem of water scarcity. In other words, absolute dependence on rainfall for future crop production has become a major constraint for sustainable food production (Koudahe et al., 2017). Water required by crops is supplied by nature in the form of precipitation, but once

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it is scarce or its distribution does not match with demand peaks, artificial water supply by irrigation becomes inevitable (Bouman et al., 2005). Irrigated agriculture, therefore, accounted for about 70% of freshwater use globally (Lafitte et al., 2005). Several irrigation methods are available and the selection of one depends on factors such as water availability, crop, soil characteristics, land topography, and associated cost. Rice is produced in at least 95 countries across the globe and provides staple food for more than half of the world's current population. Due to its importance, it ranks third after wheat and maize in terms of production, being the primary food source for more than three billion people living mostly in Asia and Africa. At the beginning of the 1990s, annual production was around 350 MT and by the end of the century, it reached 410 MT (Akinbile et al., 2015). As the population increased over this century, the projected demand for rice will grow to an estimated 2000 million metric tons by 2030 (FAO, 2007). Rice is one of the few crops grown nationwide and in all agro-ecological zones from the Sahel to the coastal swamps and could be cultivated in about 4.6 to 4.9 million hectares of land in Nigeria, but the actual area under cultivation is only 1 million hectares representing 22% of the total potential available area (Akinbile et al., 2015) and the sixth major crop in cultivated land area after sorghum, millet, cowpea, cassava and yam (Akinbile, 2013). Due to the underutilization of available resources in rice production, Nigeria resulted in importation which rose from 7,000 T in the 1960s to 657,000 T in the 1990s (Fujiie et al., 2010). Although, Nigeria is West Africa's largest producer of rice, producing an average of 3.2 million tons of paddy rice for the past five years (FAO, 2007) the country is also the World's second-largest rice importer, spending over US$300 million on rice imports annually which rose to US$1 billion in 2010 (Sanusi, 2011). Recent statistics showed that local production in Nigeria has risen to an average of 5.3 million tons as of the middle of 2019 due to land border closure by the State that resulted in the local production increase (Akinbile et al., 2019). In Nigeria, rice yields vary greatly across years due to markedly irregular rainfall distribution, and this random pattern makes it difficult to identify optimal farming practices and to make decisions on planting date or cultivar selection. This challenge is not only peculiar to Nigeria in West Africa but other parts of the continent and most especially Tanzania in sub-Saharan African as reported by Senthilkumar et al. (2018). This gap has made scientists and irrigation engineers devise means of predicting key factors required for optimum rice growth such as water, nutrients to arrive at a conclusion where approximately exact water quantities required are administered for optimum growth Balasubramanian et al. (2007) and one major tool for optimization is by modeling. Simulation models, therefore, provide a viable alternative to adequately plan for planting season and almost an efficiently predictable yield to meeting the growing demand of the increasing population to ensure food security especially in regions where the acute shortage is experienced (Adusumilli and Laxmi, 2011). In principle, crop simulation models can address these risk issues, and to factor out environmental effects from management effects (Yadav et al., 2011). Crop simulation models provide the means to qualify effects of climate, soil, and management on crop growth, productivity and sustainability of agricultural production. These tools can reduce the need for expensive and time-consuming field trials and could be used to analyze yield gaps in various crops including rice (Akinbile, 2013). Rice crop models are useful tools to evaluate the impact of changes on rice production as well as to assess the effectiveness of adaptation options. In general, these models dynamically describe the biophysical and physiological processes of growth, development, and yield and quantitatively predict the productivity of a crop concerning genotype, environment, and management (Hoang et al., 2016). The need to deploy these tools to address the risk of rice shortage to produce commensurate grain to meet the burgeoning population is inevitable. The objective of this study, therefore, was to deploy AQUACROP and CERES-Rice models to simulate biomass and grain yields at different irrigation schedules while CROPWAT was used in estimating crop water requirements of NERICA 4 upland rice and also to access their accuracy for optimum rice production.

2 Materials and methods

2.1 Study area

The study was carried out at the farmyard of the International Institute of Tropical Agriculture, (IITA), Ibadan, Nigeria. IITA is located between latitude 3°54′ E and 7°30′ N, at an elevation of 231 m above the mean sea level. It has an annual rainfall range of between 1,300 and 2,000 mm while its rainfall distribution pattern is bimodal. The annual mean temperature is 27.2℃ during the dry season and 25.6℃ during the rainy season. The soil class is *oxic paleustaff* which belongs to Egbeda Series and is described as IITA (2002) as Alfisol (Apomu sandy loam). The vegetation is a humid rain forest with an average relative humidity of between 56% and 59% during the dry season and 51%-82% during the wet season IITA (2002).

2.2 Land preparation, experimental design, and irrigation

Convectional land preparation was carried out in the third week in September 2015 and repeated as a dry-season experiment in 2016 while pre-wetting was performed in the 4th week of the same month. NERICA 4 upland rice was cultivated using convectional practices planted on the 25th of September on all the plots with dimension 5 x 5 m each. The experimental design was a Randomized Complete Block Design (RCBD) with 5 treatments based on the level of water application and three replicates. The water rates were full field capacity (100% ET) for treatment A, good (80% ET) for treatment B, medium (60% ET) for treatment C, average (40% ET) for treatment D, and low (20% ET) for treatment E.

2.3 Soil and environmental conditions

Soil physical and chemical properties of the study area were analyzed and results used as input parameters especially for CERES Rice and AQUACROP models. The parameters included: textural class, bulk density (BD), field capacity (*FC*), permanent wilting points (PWP), total available moisture (TAM), ions and metals such as manganese (Mn), magnesium (Mg), sodium (Na) and the soil pH. Others are potassium (K), phosphorus (P), Calcium (Ca) and Nitrogen (N). All these were determined using conventional methods and standard laboratory procedures at soil depths; 0-10 cm, 10-20 cm, 20-30 cm, and 30-40 cm respectively. The results of the soil analysis are as presented in Table 1.

Table 1 Physical and chemical properties of the soil

Soil depth (cm)	0-10	10-20	20-30	30-40
Sand (%)	74	68	57	60
Clay (%)	14	12	29	26
Silt (%)	12	10	14	14
Textural class	Sandy loam	Sandy loam	Sandy clay loam	Sandy clay loam
BD (g cm^{-3})	1.24	1.27	1.28	1.40
FC	0.20	0.28	0.29	0.25
PWP	0.06	0.12	0.09	0.13
TAM	0.12	0.12	0.13	0.12
Mn (ppm)	236.44	235.32	239.54	239.4
P (ppm)	6.05	7.52	7.04	7.85
N (%)	0.13	0.13	0.13	0.14
Na^+(cmol kg^{-1})	0.10	0.08	0.07	0.08
Ca^{2+}(cmol kg^{-1})	2.7	2.9	2.10	2.82
Mg^{2+}(cmol kg^{-1})	0.70	0.95	0.67	0.94
K^+(cmol kg^{-1})	0.5	0.5	0.5	0.47
pH(H_2O)	5.5	5.4	5.4	5.6

Similarly, weather parameters used for the models' simulation were obtained from IITA meteorological station which was solar radiation, maximum and minimum temperature, vapor pressure, sunshine hours, minimum and maximum relative humidity, rainfall, and wind speed. Soil moisture contents were determined using the gravimetric method at the specified depths. The samples were collected with a 40 mm core sampler and oven-dried at 105ºC for 48 hours. The linear water depth was determined by finding the product of soil moisture content (%) and the bulk density of each layer and root depth. The net irrigation requirement (*d*) (m^3/ha per year) was determined by using Equation 1.

$$d = \sum_{i=1}^{n} \frac{(M_{fci} - M_{bi})}{100} \times A_i \times D_i \qquad (1)$$

Where,

M_{fci} = FC in the *i*th layer of the soil (m^3 m^{-3}), measured 2 days after irrigation.

M_{bi}= moisture content before irrigation in the *i*th layer

(m^3 m^{-3}).

A_i = bulk density in the *i*th layer (g cm^{-3}).

D_i = depth of the *i*th soil layer in the root zone (mm).

n = soil layers in the root zone D.

The leaf area index (LAI) and canopy cover (CC) were measured using the Canopy Analyzer (LAI2200) model from 7 Days after Transplant (DAT)

The daily canopy cover CC (%) was computed by using the Ritchie equation used by Farahani et al. (2009):

$$CC = 11 - \exp(-\lambda\, X\, LAI) \tag{2}$$

Where:

λ = seasonal leaf extinction coefficient (0.46)

2.4 Models description

2.4.1 CROPWAT

CROPWAT is a decision support system developed by the Land and Water Development Division of FAO for the planning and management of irrigation. CROPWAT is meant as a practical tool to carry out standard calculations for reference evapotranspiration (ET_o), crop water requirements (CWR) and crop irrigation requirements, and more specifically the design and management of irrigation schemes (Adiana, 2014). The model calculates the CWR using the Equation 3:

$$CWR = ETo\ \times Kc\ \times A \tag{3}$$

Where;

ETo = reference evapotranspiration, (mm/day)

K_c = crop coefficient, (dimensionless)

A= planted area (m^2)

TAM in the soil for the crop during the growing season was calculated as:

$$TAM = (FC - WP)\ \times D \tag{4}$$

Where

WP = wilting point (θ_{wp})

D = current rooting depth of the crop (m)

While readily available moisture (RAM) (in mm) is calculated as;

$$RAM = TAM\ \times P \tag{5}$$

Where P is the depletion fraction

2.4.2 AQUACROP

AQUACROP is a water-driven model for simulating crop growth response to water under various management and environmental conditions, including climate change scenarios but, like most crop models as a function of water consumption (Raes et al., 2011, 2012; Steduto et al., 2012). It estimates daily evapotranspiration and partitions it into crop transpiration and soil evaporation. The model has four sub-models: the climate sub-model, which requires daily maximum and minimum air temperatures, rainfall, reference evapotranspiration (ET_o), and the mean annual carbon dioxide concentration in the bulk atmosphere; the soil water balance; the phonological development of the crop, growth and final yield; the management sub-model that combines water application and levels of fertilization (Adeboye et al., 2017; Raes et al., 2012). The crop transpiration where there is no water stress is expressed as:

$$Tr = CC^{*} \times Kc_{trx} \times ET_o \tag{6}$$

Where.

Tr = transpiration (mm)

CC^*= adjusted canopy cover for micro-advective effects (%).

K_{trx} = coefficient for maximum crop transpiration

ET_o = evapotranspiration (mm)

When there is no water stress, T_r is adjusted by using the water stress coefficient K_s (0-1) which explain the effects of soil moisture stress on reduction in the rate of canopy expansion, rate of senescence and closure of leave stomata.

The rate of evaporation when soil is covered by a crop is given as:

$$E_x = (1 - CC^{*}) \times Kc_{e,wet}\ \times ETo \tag{7}$$

Where

E_x = evaporation from bare soil (mm).

CC* = adjusted fraction of soil surface adjusted for micro-advective effects.

$Kc_{e,\ wet}$ = evaporation coefficient for fully wet and unshaded soil surface (Allen et al., 1998)

The final crop yield from the biomass is determined by using Equation 7:

$$Y = f_{HI}\ \times HI_o\ \times B \tag{8}$$

Where

HI_o = the reference harvest index

f_{HI} = adjusted factor integrating water stress factors relative to the inhibition of leaf growth and inhibition of stomata.

B = biomass (t ha^{-1}).

2.4.3 CERES-Rice

The CERES (Crop-Environment REsource Synthesis) model was used to predict the growth of rice development and yield taking into account the effects of weather, management, soil, water balance, and nitrogen balance. Timsina and Humphreys (2006) remarked that CERES simulates dry matter accumulation as a linear function of intercepted photosynthetically active radiation. CERES model defines the atmospheric demand for water (*Etp*) as the potential evaporation rate defined from some variant of the Penman equation (*Ep*), modified by the current value of LAI (Akinbile, 2013; Eitzinger et al., 2004; Mahmood, 1998). The water balance of CERES models performed as reported by Cheyglinted et al. (2001):

$$Etp = Ep[\,1 - \exp(\,-kLAI)] \tag{9}$$

Where

Etp = potential transpiration rate (mmd^{-1})

Ep = potential evapotranspiration rate (mmd^{-1})

k = extinction coefficient (dimensionless)

LAI = leaf area index (dimensionless)

2.5 Assumptions made during calibration

The following assumptions were used for the models' calibration.

CROPWAT model (Amiri et al., 2014)

i K_c values for initial stage (0.40), and mid-season (1.15)

ii Critical depletion fraction from initial to mid-season was (0.45) and harvest (0.50)

iii Yield response factor at the initial stage (0.20), development stage (0.80), mid-season (0.60), and late stage (0.20).

AQUACROP model

i Default atmospheric CO_2 concentration from 1902 to 2099 was 369.41ppm

ii Canopy performance under elevated CO_2 sink strength was 50%

2.6 Model calibration

The monthly climatic data of the study area (which includes temperature, humidity, wind speed and sunshine hour) were incorporated into the climate/ET_o module of the CROPWAT Model 8.0 which used the FAO-56 Penman-Monteith (PM) approach to calculate and give the corresponding monthly ET_o values. The crop water requirement and irrigation schedule were estimated after feeding the crop and soil input parameters such as planting date, maximum rooting depth, critical depletion fraction, yield response factor, crop height, crop coefficient, total available soil moisture, maximum rain infiltration rate, initial soil moisture depletion and initial available soil moisture into the models. The model contained different field management practices relative to salinity, the fertility of the soil, mulching and soil bunds for reducing runoff (Hsiao et al., 2009)

2.7 Input data requirement for models' validation

The input data for the simulation of variables are environmental and crop sub-model that can be adjusted for specific environments and crop varieties which included soil and crop parameters. (Adeboye et al., 2017; Raes et al., 2012).

Some of the soil parameters utilized were from four soil horizons, textural class, field capacity, wilting point, saturated hydraulic conductivity, and volumetric water content at saturation.

In the AQUACROP model, the development of the canopy was measured in terms of *CC* (equation 2) and root length. Crop-management factors incorporated in the model included planting date, planting depth, row spacing, and direction, some plants per square meter, age of seedling, fertilization application dates and amount, irrigation, residue applications, tillage, and harvest date. All these were as presented in Table 2 and were calibrated by using the measured parameters in Table 3 to predict *CC*, biomass and grain yield. Parameters that influence referenced variables were adjusted by using a trial and error approach to reduce the error between simulated and measured data. After entering crop phonological data such as days to maximum canopy cover, days to flowering, duration of flowering, days to senescence, and maturity as input parameters, canopy expansion rates were predicted by the AQUACROP model. Rooting depth and expansion activity were derived from Raes et al. (2011) while soil's FC, PWP, hydraulic conductivity at saturation point, and TAW were set according to the soil class as reported by Raes et al. (2011). All model parameters were adjusted with a trial and error approach until the model-based computations explained in close match field observations.

CERES-Rice model was calibrated with the data from the field experiment as shown in Table 3 while genetic coefficients of NERICA cultivars were as presented in Table 4. Weatherman utility in the DSSAT was used to create the weather file that was used by the DSSAT Rice model. Data used to create the weather file included station information while daily maximum and minimum temperature, daily solar radiation, daily rainfall and daily sunshine hours for a period of interest were imported into the DSSAT model. The data was edited and exported to the DSSAT format and was ready for use by the CERES-Rice model. Soil data tool (SBuild) under the tools section in DSSAT v 4.5 was used to create the soil database which was used for the general simulation purposes.

Table 2 AQUACROP model parameters used in simulating the response of rice yield

Description	value	Unit
Base Temperature	5.0	^oC
Cut –off temperature	30.0	^oC
Canopy cover per seedlings at 90% emergence (***CC$_o$***)	5.0	$cm^{-2}plant^{-1}$
Canopy growth coefficient (CGC)		Increase in *CC* relative to existing *CC* day^{-1}
Crop coefficient for transpiration at ***CC*** = (100%)	1.00	Full canopy transpiration relative to ET_o
Decline in crop coefficient after reaching ***CC$_x$***	0.30%	Decline per day due to leaf aging
Canopy decline coefficient at senescence (CDC)		The decrease in *CC* relative to *CC* per GDD
Water productivity normalized for ***ET$_o$*** and CO_2	15.0	gm^{-1} (biomass)
Soil water depletion threshold for canopy expansion - upper	0.15	As a fraction of TAW, above this leaf growth, is inhibited
Soil water depletion threshold for canopy expansion - lower	0.65	Leaf growth stops completely at this value
Leaf growth stress coefficient curve shape	3.0	Moderately convex shape
Soil water depletion threshold for stomata control –upper	0.5	Above this stomata begins to close
Stomata stress coefficient curve shape	3.0	Highly convex shape
Soil water depletion threshold for canopy senescence (P_{sen}) – upper threshold	0.7	Above this early canopy, senescence begins
Shape factor for water stress coefficient for canopy senescence	3.0	Convex curve
Coefficient describing the positive impact of restricted vegetative growth during yield formation on HI	None	HI increased by inhibition of leaf growth at anthesis
Coefficient describing the negative impact of stomata closure during yield formation on HI	Strong	HI reduced by inhibition of stomata at anthesis
Allowable maximum increase (%) of specified HI	10	
atmospheric CO_2 concentration from 1902 to 2099	369.41	ppm

Note: Source: Raes et al. (2012)

Table 3 Measured crop phenological stages used in simulating the response of rice yield

Description	A (100% ET)	B (80% ET)	C (60% ET)	D (40% ET)	E (20% ET)	Unit
Time from Sowing to emergence	10	9	11	15	16	Day
Time from tillering – Panicle Initiation	42	43	45	47	48	Day
Time from panicle Initiation – Heading	25	26	28	30	33	Day
Time from sowing to start of flowering	77	78	84	92	97	Day
Duration of flowering	6	6	8	9	9	Day
Time from sowing to start of senescence	86	85	82	79	78	Day
Time from sowing to maturity	110	110	110	110	110	Day

Table 4 CERES model parameters used in simulating the response of rice yield

Genetic parameters	Description	coefficients
P1	Time from seedling emergence to the end of the juvenile phase. This period is also referred to as the basic vegetative phase of the plant.	300
P2O	Critical photoperiod or the longest day length (in hours) at which the development occurs at a maximum rate.	5
P2R	The extent to which phasic development leading to panicle initiation is delayed for each hour increase in photoperiod above P2O.	450
P5	The period from the beginning of grain filling to physiological maturity	13.5
G1	Potential spikelet number coefficient as estimated from the number of spikelets per g of main culm dry weight (fewer lead blades and sheaths plus spikes) at anthesis.	54.0
G2	Single grain weight (g) under ideal growing conditions, i.e. nonlimiting light, water, nutrients, and absence of pests and diseases.	0.0250
G3	Scalar vegetative growth coefficient for tillering relative to IR64	1.00
G4	Temperature tolerance coefficient. Usually 1.0 for varieties grown in normal environments.	1.00

Note: Source: Amiri et al. (2014).

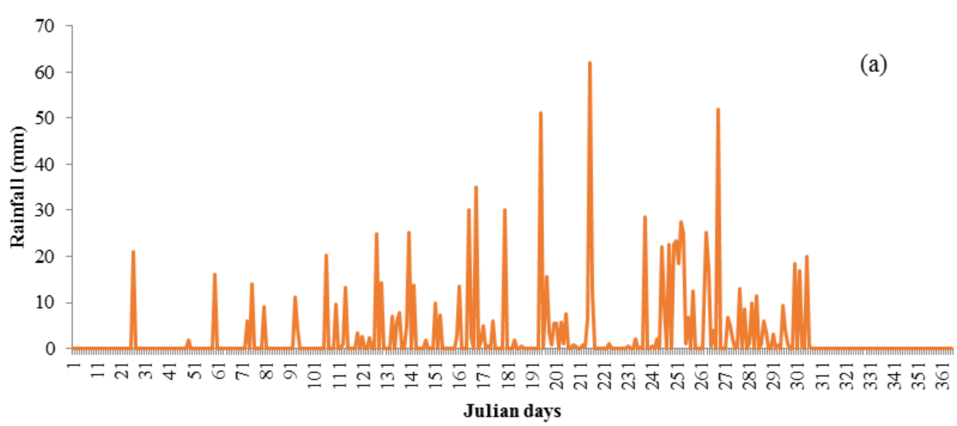
2.7 Statistical analysis

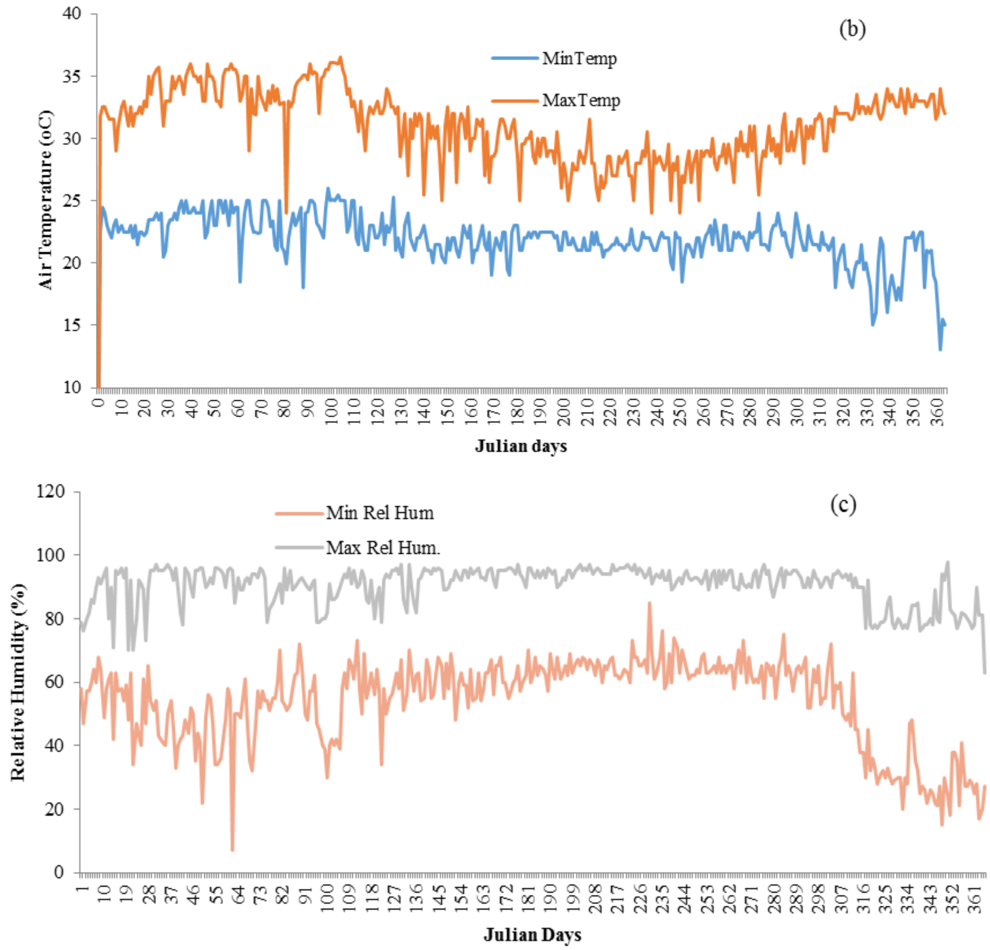
Apart from the conventional tools such as analysis of variance (One-way ANOVA), the least square difference (LSD), root mean square error (RMSE) and statistical package for social sciences (SPSS) used for the analysis especially between simulated and observed (field) values. Others such as ratio analysis software (R) and econometric analysis software (E-VIEWS) and MINITAB 17 were also used in determining the efficacy of the models in achieving the set-out objectives at $P < 0.05$ confidence levels.

3 Results

Soil in the study area is predominantly sandy loam with the percentage composition of sand, clay, and silt as presented in Table 1 which enhances rice production by encouraging root development and penetration. BD was found to be 1.27 g cm^{-3} which showed that the soil is well aggregated for rice production since this BD permits root development. Field capacity and permanent wilting point on all the plots were estimated to be 28% and 13% respectively. TAM was approximately 12% while the values obtained for all the metals and ions were all within permissible limits for optimum rice growth. Other soil nutrients such as Na, Mg, Mn, Ca, N, P and K were all within maximum permissible limits required for rice production in ordinary soil conditions.

Figure 1(a) to c shows the weather parameters consisting of rainfall, temperature and relative humidity of the study area within the period of research. From Figure 1(a), highest rainfall was recorded on the 213th Julian day with a value of 64 mm while minimum value of 0 mm was recorded from 1st to 27th, 30th to 59th and 309th to 365th Julian days respectively. For temperature as presented in Figure 1(b), the maximum temperature ranged between 24^{o}C and 36^{o}C while minimum temperature ranged was 13^{o}C and 25.5^{o}C respectively. In Figure 1(c), maximum relative humidity ranged between 65 and 100% while minimum relative humidity ranged from 8% to 67% respectively.





(a) Rainfall; (b)Air temperature; (c) Relative humidity

Figure 1 Rainfall, temperature and relative humidity against Julian days of the planting year 2015

The results of estimated ET_o using the Penman-Monteith (PM) model is as presented in Figure 2. ET_o values ranged between 2.7 mm day^{-1} in August and 4.3 mm day^{-1} in December. Reasonably high values ranging from 4.1 mm day^{-1} in January up to 4.2 mm day^{-1} in February were recorded which started declining in March with a value of 4.0 mm day^{-1} up to 2.7 mm day^{-1} in August.

Increased value of 3.2 mm day^{-1} in September and 4.3 mm day^{-1} in December were recorded. This was responsible for the high *ET* values recorded during the period. The same trend was observed from October through December implied that higher temperature and sunshine hours during those identified months would result in the higher ET_o and lower humidity values recorded.

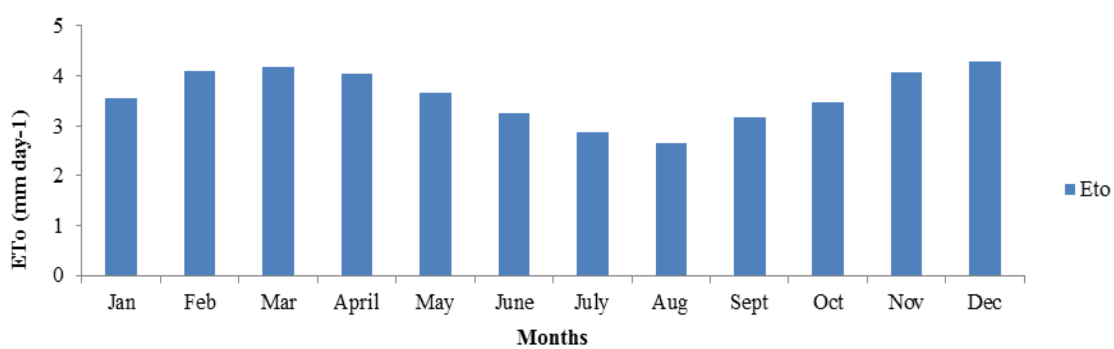


Figure 2 Monthly *ETo* estimated using Penman-Monteith (PM) for 2015

Figure 3 shows the output of the rainfall trend (both in mm/Dec and percentage) on the rice field and for the period of study using CROPWAT model. In September when the upland rice was planted, effective rainfall was 130.5 mm out of the total rainfall of 85.7 mm, representing 15.9% as estimated by CROPWAT. The trend reduced to 6.4 mm rainfall in November, representing 0.8% but the model predicted 822.0 mm (100%) in the same month although average rainfall was 1080.2 mm. No rainfall was recorded in December through February indicating the need for 100% irrigation to satisfy the consumptive water use of the rice crop in the study area.

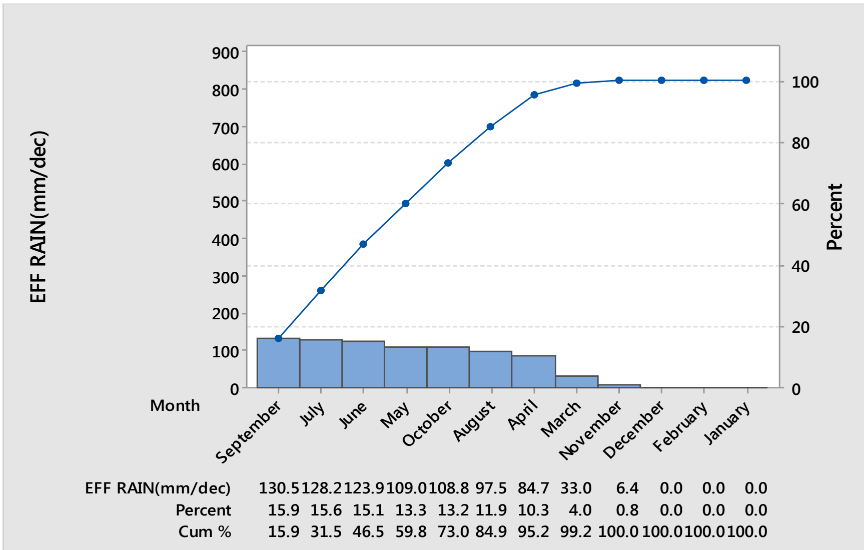


Figure 3 Average monthly effective rainfall file in the study area using CROPWAT model

Also, Figure 4 shows trend of the irrigation water requirement (IWR) generated for the entire growing season from September through January using the CROPWAT model. IWR ranged from 3.9% to 1.4%, the lowest on January 2 while the highest requirement was recorded on December 2 with a value of 48.3 mm (16.8%), rose to 288.10 mm (100%) on January 1 and stabilized till September 3. In October, effective rainfall was on the high side so irrigation water required was low. At the latter stage of growth, IWR decreased till the harvesting period since a further increase in irrigation water does not result in any corresponding increase in agronomic and yield development of the rice crop.

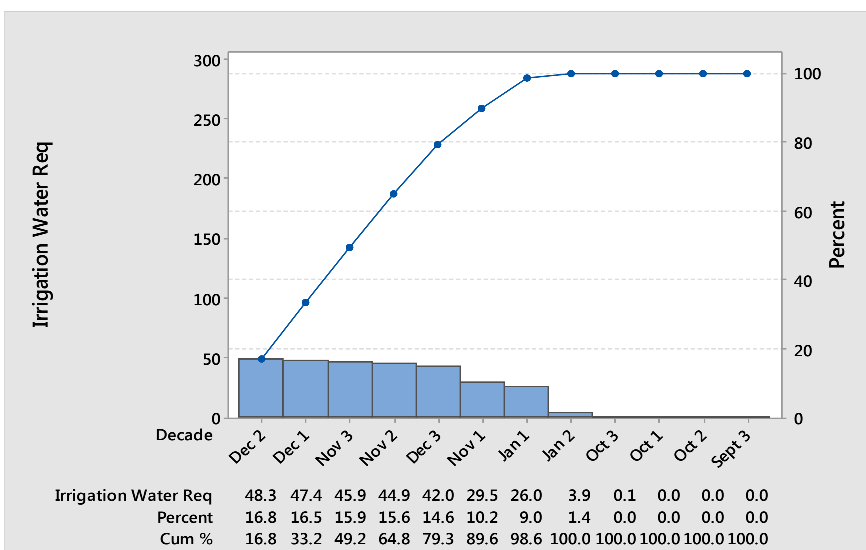


Figure 4 Irrigation water requirement from CROPWAT file

Figure 5 shows changes in the plant height of rice with days after planting (DAP) during the growing season. Treatment A had the highest height of 93 cm in 84 DAP while expectedly Treatment E was at least with 49 cm. beyond 100 DAP, a gradual decline in height in all the treatments was observed which indicated that further water application does not result in height increase. Identical orientation was observed in the measured LAI in all the treatments although the highest value was recorded in A while the least was in E (Figure 6a). When comparing with the predicted LAI using the CERES-Rice model (Figure 6b), an almost identical orientation was produced but with slightly lower values. Treatment A in the measured LAI recorded a value of 3.82 at 70 DAP while E produced 2.67, predicted LAI with CERES model produced 2.15 in treatment A and 1.46 in treatment E respectively (Figure 6a, 6b). The values of the five treatments are nearly equal, particularly at the maturity stage.

Figure 7 shows the measured canopy cover (*CC*) and the modeled using AQUACROP. Highest *CC* as was observed during the heading, flowering, and milky phases of the ripening stage (80 DAP) with the value 69.2% treatment (A), 62.72% treatment (B), 48.25% treatment (C), 38.1% treatment (D), and 26.21% treatment (E). At 100 DAP, canopy cover has reduced to 50.15%, 46.32%, 30.03%, 20.6%, and 13% from treatment A to E. This was because at maturity, leaves coloration has begun to change from lush green to brown and the canopy had started to collapse in readiness for harvesting. The predicted figure of *CC* also shows identical behavior with the highest value of 82.6% recorded in A, 81.2% in B, 80.1% in C, 78.5% in D and 68% in E respectively.

As for the predicted canopy cover using AQUACROP, the values was 0 at the initial stage for the five treatments and increased gradually at the vegetative stage (20 DAP) from 6.08%, 6.12%, 6.01%, 6.09% and 6.07% for the five treatments, to maximum canopy cover at flowering stage (80 DAP) with the value 82.55% treatment (A), 82.18% treatment (B), and 81.98% treatment (C) then decreased gradually from the maximum canopy cover as the senescence increases due to water stress which occurred at the maturity stage. It was observed that maximum canopy cover in treatment D was 70.2% at 60 DAP, and 63.7% for treatment E at 50 DAP. The increase in canopy development concerning variation in water application was due to an increase in crop transpiration which increased from 0.0 for all the treatments at the initial stage to 4.2, 4.1, 3.8, and 3.5 at the vegetative stage where the crop transpired most.

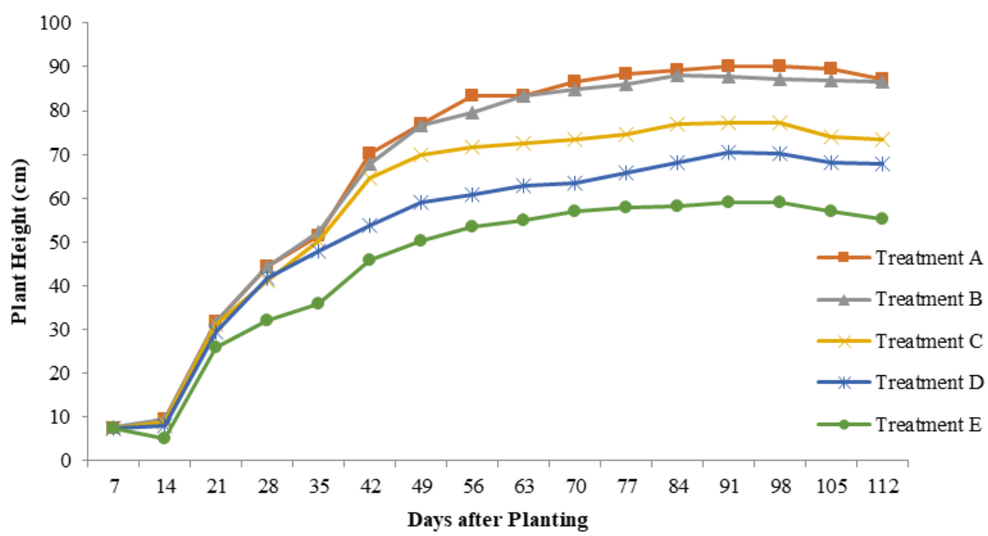
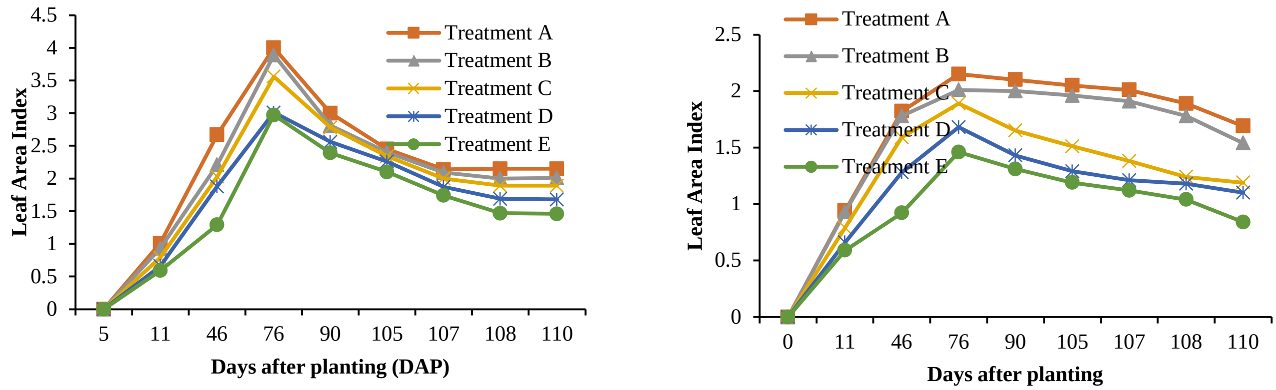
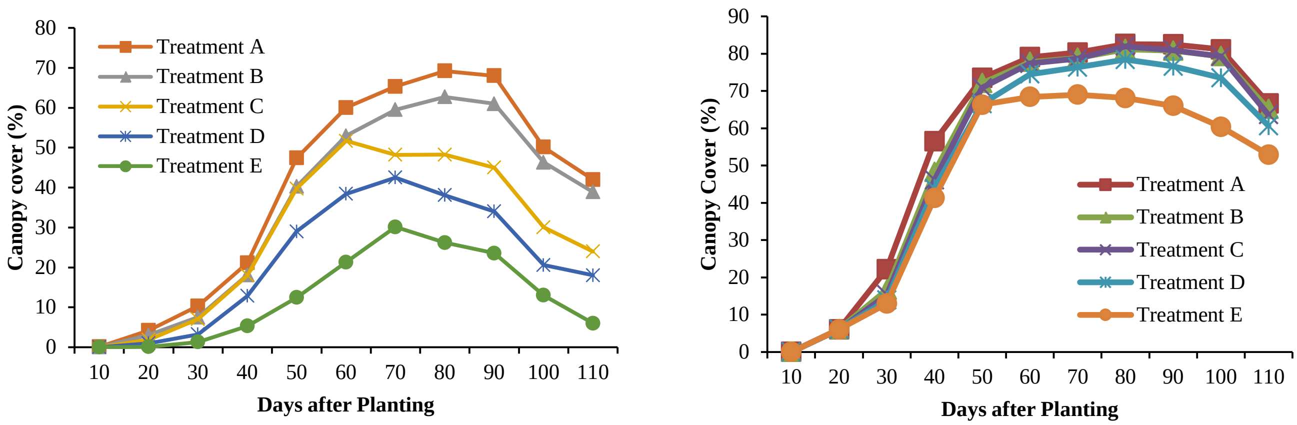


Figure 5 Measured Plant height among treatments at different stages of growth



(a) Measured LAI vs DAP (b) CERES-predicted LAI vs DAP

Figure 6: Measured leaf area index (LAI) with days after planting and predicted LAI with DAP using CERES model



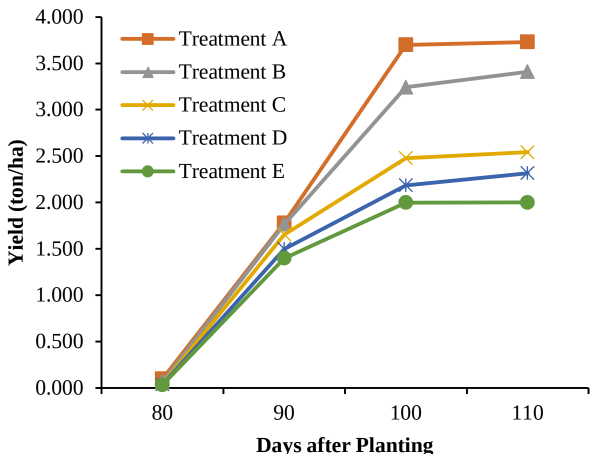
(a) Measured CC vs DAP (b) AQUACROP-predicted CC vs DAP

Figure 7 Measured canopy cover (*CC*) with DAP and predicted *CC* DAP using AQUACROP model

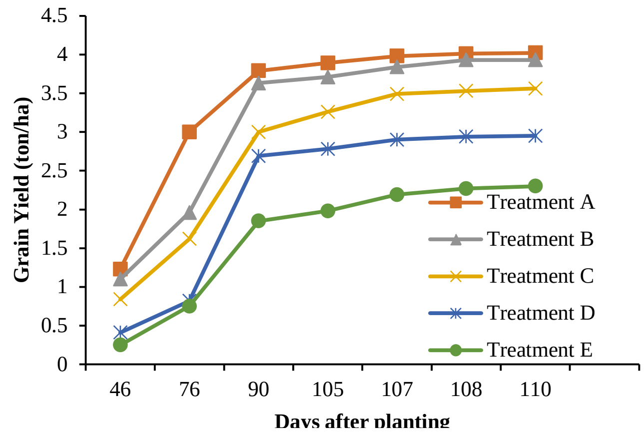
The highest yield of 3.02 tons ha^{-1} (grain) and 8.30 tons ha^{-1} (biomass) were recorded in treatment A on the field experiment. Also, treatment A of AQUACROP model produced the highest yield of 3.73 tons ha^{-1} (grain) and 12.89 tons ha^{-1} (biomass). Moreover, treatment A of the CERES model produced the highest yield of 4.02 tons ha^{-1} (grain) and 12.50 tons ha^{-1} (biomass). Reduction in yield from treatment A to E might be due to water deficit at the grain filling stage which adversely affects grain development mainly due to shortage of moisture that impaired nutrient uptake. Yield reduction due to water deficit was also observed by Feng et al. (2007).

Both AQUACROP and CERES models overestimated grain and biomass yields and again agreed with the findings of Akinbile (2013). This showed that the observed values from the field were less than normally expected results which might be a result of the shortcoming of the models. CERES Rice model showed the highest precision in grain yield than the AQUACROP model which showed the highest accuracy in biomass yield. This might be because the AQUACROP model used a constant harvest index for the estimation of grain yield in rice. Moreover, the AQUACROP model built on evapotranspiration of study crop estimates the yield from the daily transpiration considering key physiological characteristics of the crop. Whereas, CERES-Rice simulates grain yield using dynamic components such as potential spikelet number coefficient and single grain weight for each rice variety.

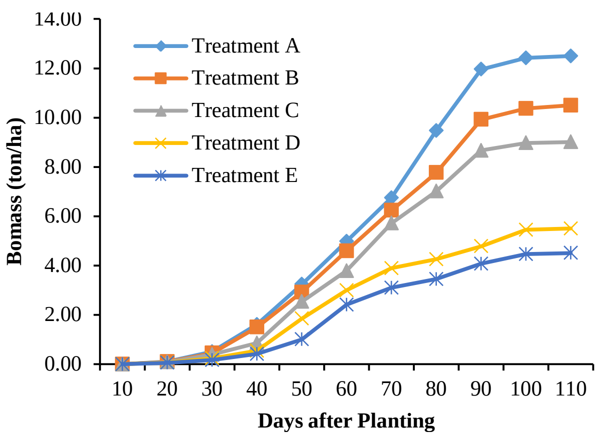
Two of the models used predicted grains yield and biomass in all the treatments as recorded in Figure 8. For the grain yield, AQUACROP expectedly predicted that no yield was recorded from 0 to 79 DAP and grain yield began at 80 DAP and increased till maturity at 100 DAP after which the yield increase became steady till harvesting at 110 DAP (Figure 8a). However, for the CERES model, grain yield began at 46 DAP and increased till 110 DAP with treatment A having the highest, 4.02 tons ha^{-1} and E the lowest value of 2.3 tons ha^{-1} (Figure 8b). For AQUACROP, the highest yield of 3.73 tons ha^{-1} was recorded in A while the lowest values of 2.0 tons ha^{-1} were recorded in E (Figure 8a). The two models over-predicted grain yield as the value of observed yield (3.02 tons ha^{-1}) in treatment A with 100% ET was slightly lower than the predicted values obtained. The same trend was recorded in the lowest observed values of 1.02 tons ha^{-1} in treatment E with 20% ET (Figure 8a). The decrease in yield especially in E might be due to stress which occurred at the vegetative stage.



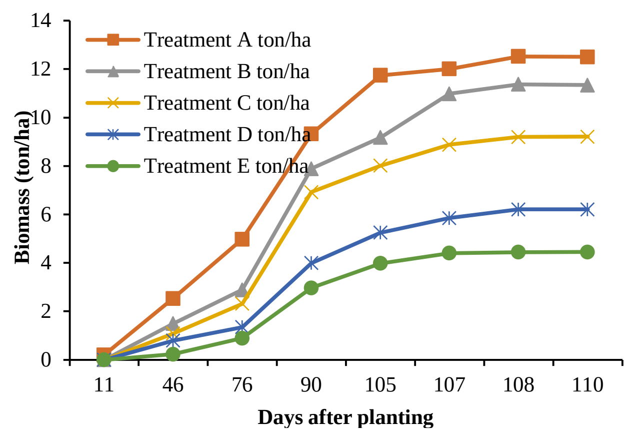
(a) Predicted grain yield versus days after planting using AQUACROP model



(b) Predicted grain yield versus crop age using CERES model



(a) Predicted biomass versus days after planting using AQUACROP model



Predicted biomass versus crop age using CERES model

Figure 8 Predicted grains yield and biomass with DAP using AQUACROP and CERES models

Similar observations for biomass yields were recorded for all the treatments using the two models, AQUACROP and CERES respectively as shown in Figure 8 (c, d) respectively. AQUACROP biomass production began at 30 DAP and increased up to 12.89 tons ha^{-1} at 100 DAP in treatment A while treatment E had 4.51 tons ha^{-1} on the same day (Figure 8c). This agreed with Raes et al. (2006) that biomass production increases as the water application increases. In CERES prediction, however, biomass production began at 46 DAP and increased up to 11.76 tons ha^{-1} at 110 DAP in treatment A while treatment E had 4.40 tons ha^{-1} (Figure 8d). The two models overestimated the biomass yield as the highest measured value of 8.3 tons ha^{-1} was recorded in treatment A and the lowest value of 4.2 tons ha^{-1} was recorded in treatment E (Figure 8b) when considered with the quantity of irrigation water applied. Table 5 shows the post-harvest agronomic parameters of the rice crop in all the treatments. From the values obtained, there was no statistically significant difference between treatments A and B in all the parameters considered. Plant height, no of leaves, no of panicles, LAI, grain yield and biomass which could strongly be traced to the irrigation water applied to the two treatments. Treatment A received 100% ET while treatment B received 80% ET and van Oort (2018) established a strong relationship between the behavioral responses of the agronomic parameters with the quantity of water applied in his studies. It was also established from the study that the treatment with the highest total irrigation water applied had the lowest average ET while the treatment with the lowest water applied had the highest ET.

Table 5 Irrigation water, average ET and measured plant parameters after harvest from field experiment

crop parameters	A	B	C	D	E
Plant height	83.2	81.3	69.5	61.2	46.2
No of leaves	12	12	10	10	7
No of panicles	370	360	345	286	150
LAI	2.01	1.91	1.79	1.9	1.37
Grain yield (ton ha^{-1})	3.02	3.01	1.73	1.25	1.02
Biomass (ton ha^{-1})	8.3	8.25	5.97	4.78	4.2
Irrigation water applied (mm)	1700	1360	1020	680	340
Average ET (mm)	285.6	293.8	297.2	310.6	337.1

4 Discussions

From the information supplied in Table 1, Akinbile et al. (2016a) reported that soils with the composition described are excellent for rice production since the higher sand content permits extensive root configuration and development which was supported by Bouman and Van Laar (2006) in their studies. Akinbile and Sangodoyin (2011) described maximum root depth in their studies to be less than 30 cm for the NERICA 4 upland variety, hence the maximum soil depth of 40 cm from where samples were obtained and analyzed to have a fair idea of the condition of the roots at such depth. The presence of nutrients such as phosphorus, potassium, nitrogen which are the main constituents of inorganic fertilizers in sufficient and appropriate quantities across the soil profile suggests the beneficial fertility of the soil even without introducing amendments and fertilizer which has been reported by Akinbile et al. (2016b) and supported by Amiri et al. (2014) and Confalonieri et al. (2005) in their respective studies. The average BD value of 1.30 g cm^{-3} is okay for optimum rice production while FC, PWP and TAW values are adequate for rice growth without water stress that could be inimical to the proper development of the agronomic parameters of the rice crop. The values recorded, especially for PWP are not serious enough to introduce alternate wetting and drying (AWD) techniques for plant crop survival.

The highest rainfall recorded on the 213th Julian day (August 2) suggests the peak rainfall which falls during the wettest month of the year (Figure 1a) by Akinbile (2013). During this period, temperature expectedly will be lowest while the values of relative humidity are also expected to be very high. This very high rainfall does not translate to increased metabolism or agronomic responses (since water loss could be experienced through percolation and/or seepage) but contributes significantly to the growth and yield development of the rice crop under rain-fed conditions. The maximum temperature ranged was between 24^{o}C to 36^{o}C which has some effect on the germination and development process of the seeds. Higher temperature range will lead to seed abortion as a result of heat while the lower temperature range will result in spikelet infertility (Balaghi, 2010). High temperatures were recorded during the periods of low or no precipitation while low humidity was also recorded during the same period too (Figure 1b) Mahmood (1998). These trends are normal climate change observations that are occasioned by extreme temperature variations and as reported by Confalonieri et al. (2005). The temperature, rainfall and relative humidity range for 2015 were within permissible ranges for optimum upland rice production.

From the results presented in Figure 2, an ET ranged identical to most conventional cereal crops was recorded which agreed with the findings of Akinbile and Sangodoyin (2011). Allen et al. (1998), Bouman et al. (2005), Kuo et al. (2001), and Lafitte et al. (2005) all reported that evaporation was pronounced during vegetative, ET during mid-season and transpiration takes place during maturity stages of crop development. Water loss through stomata and lenticels was pronounced in the mid-season stage, the stage when water need and water use is maximum (Akinbile, 2013; Akinbile and Sangodoyin, 2011).

The scenarios described in Figure 3 and Figure 4, as well as the observations reported, are the conventional behavioral pattern of crop-water-food nexus in climatic variability trends involving some of it parameters such as rainfall and temperature and is as reported by Akinbile et al. (2015) in their studies. From Figure 5, a strong correlation exists between the plant height and the quantity of water administered to the crop. Similar observations were reported in Figure 6 for LAI, particularly when comparing measured with CERES-predicted values. The trends established pointed to a relationship between the responses reported and water use. This agreed with the findings of Lafitte et al. (2005) who stressed that the leaf area index orientation is a function of water application. Also from the predicted results, it could be inferred that water application has a great influence on leaf growth as shown in Figure 6b and supported the inferences drawn by Amiri et al. (2014) and Feng et al. (2007).

Figure 7 shows the measured and AQUACROP-predicted values of *CC*. The behavior was similar to LAI as the highest canopy cover was observed during the ripening stage; at the same time, LAI was maximum in all the treatments. This agreed with the findings of Raes et al. (2012), Raes et al. (2011), and Steduto et al. (2009) that under severe water stress, the canopy development might be brought to a standstill and canopy senescence would be triggered. Also, when the crop transpiration is fully inhibited canopy cover no longer can increase (Hsiao et al., 2009). This observation agreed with the findings of Steduto et al. (2009) which have shown a linear relationship between biomass produced and water applied in identical circumstances.

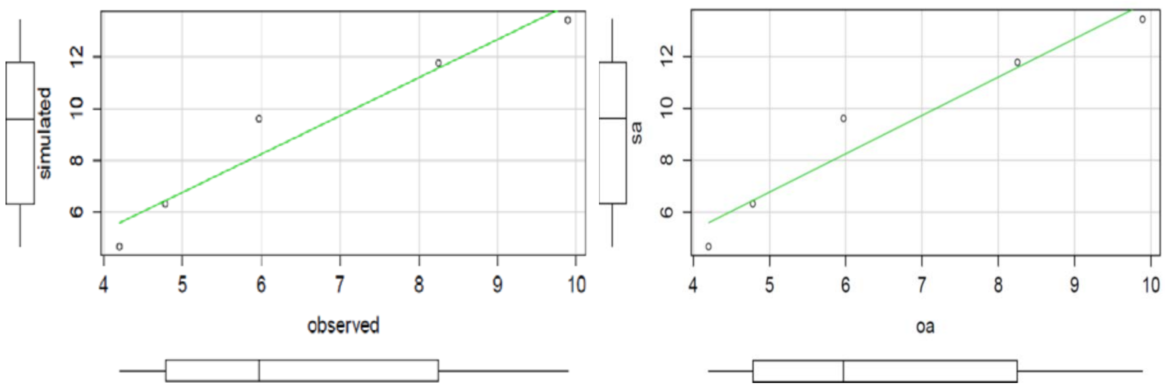
Results of agronomic, grain and biomass yields, irrigation water applied and average ET as presented in Table 5 shows a trend that is consistent with the quantities of water applied in all the treatments which showed that highest values applied resulted in lowest average ET and lowest water applied resulted in the highest ET. This trend was also established by Amiri et al. (2014), Eitzinger et al. (2004), and Akinbile (2013). This shows that a linear relationship exists between the agronomic parameters and irrigation water use while the continuous increase in water use at the maturity stage does not imply a corresponding increase in yield. Rinaldi (2004) justified this in one of his studies.

4.1 Statistical interpretation of models' performances

Four different tools of the ratio analysis package (R), Econometric Views Package (E-VIEWS), statistical package for social science (SPSS) and Minitab 17 were used to ascertain the correlation and co-variability between simulated and observed values in both AQUACROP and CERES models used for biomass yield, grain yield the results which were as presented in Figures 9-12 respectively. From Figure 9(a), the simulated values of biomass in both models are in good agreement with the observed values with low average absolute error and RMSE. Corresponding values for different treatments were also well simulated with the observed yields giving correlation coefficients of 0.96 for AQUACROP and 0.91 for CERES. From Figure 9(b), R-package showed that the CERES model had high precision in grain yield prediction under different irrigation schedules when compared with the AQUACROP model, while the AQUACROP model simulated biomass yield by more accuracy than CERES model.

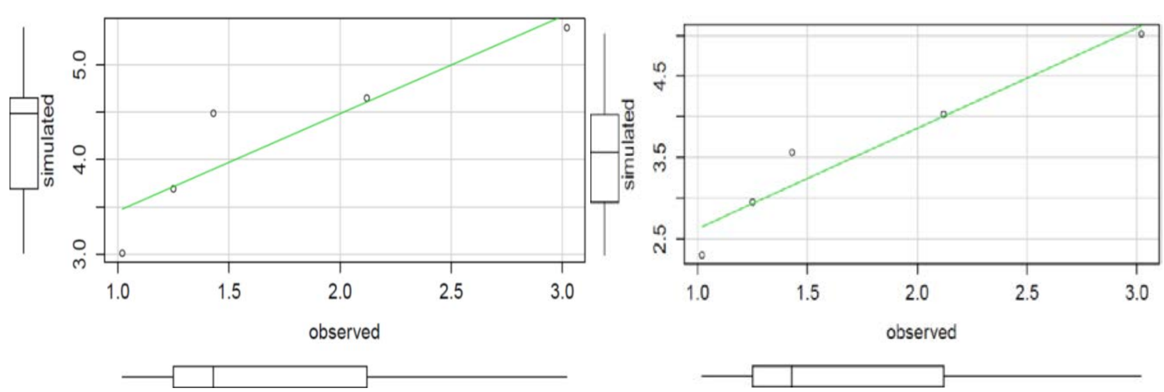
Using E-VIEWS, the simulated and observed values of biomass were strongly correlated in both AQUACROP and CERES models with the values 0.95 and 0.94, indicating that there is a perfect agreement between the simulated and the observed yields (Figure 10a). Similarly, a strong agreement existed between the simulated and observed values of grain yields with the correlation coefficient of 0.90 AQUACROP and 0.96 in CERES as shown in Figure 10(b). CERES model showed high precision in grain yield prediction under different irrigation schedules than the AQUACROP model, while the AQUACROP model simulated biomass yield by more accuracy than the CERES model.

The simulated values of biomass in both models are in good agreement with the observed values with low average absolute error and RMSE using SPSS and as shown in Figure 11(a). Corresponding values for different treatments were also well simulated with the observed yields giving correlation coefficients of 0.96 for AQUACROP and 0.91 for CERES. The simulated and observed values of grain yields under different water applications are well correlated as the coefficient of efficiency and the correlation coefficient is high as shown in Figure 11(b). CERES model showed high precision in grain yield prediction under different irrigation schedules than the AQUACROP model, while the AQUACROP model simulated biomass yield by more accuracy than the CERES model.



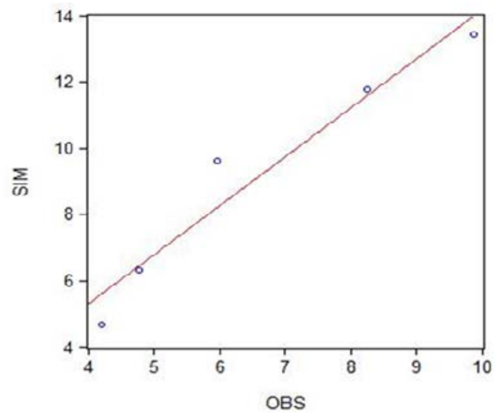
AQUACROP Model CERES Model

(a)simulated biomass yield

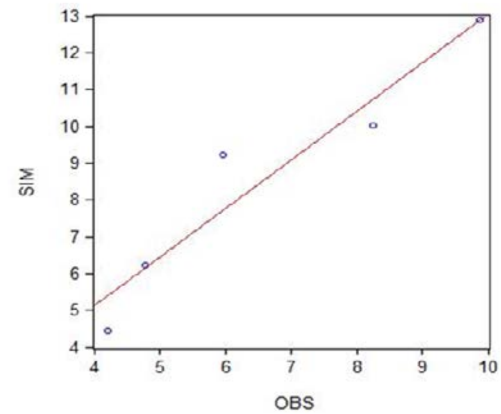


(b) simulated Grain yield

Figure 9 Comparison of observed and simulated Grain yield/simulated Grain yield in both models under different treatments with Ratio Analysis Package

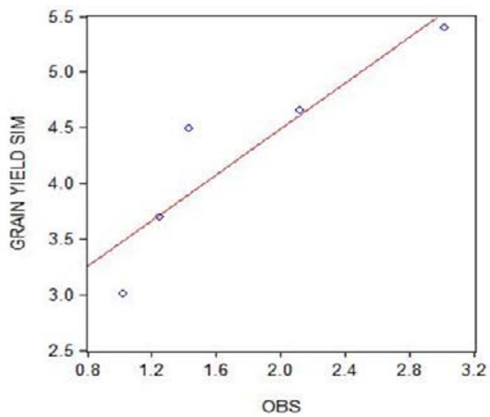


AQUACROP Model

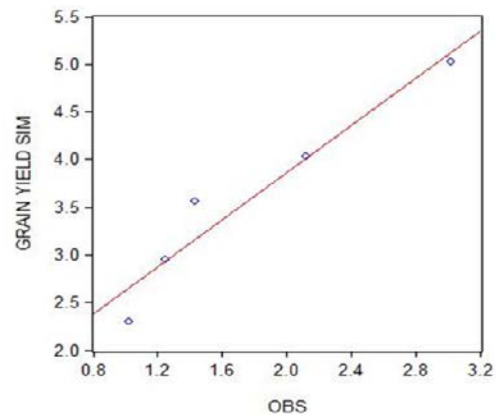


CERES Model

(a)simulated biomass yield



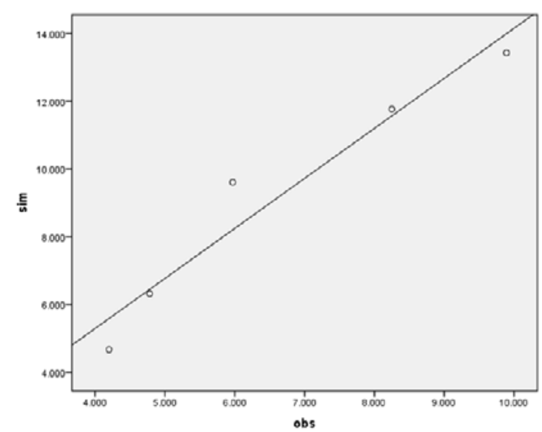
AQUACROP Model



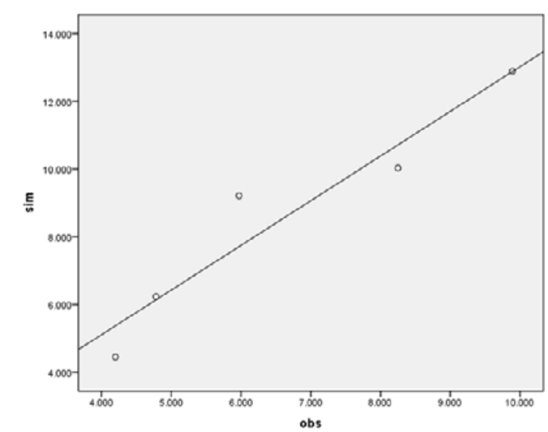
CERES Model

(b) simulated Grain yield

Figure 10 Comparison of observed and simulated biomass yield/simulated Grain yield in both models under different treatments with Econometric Views Package (E-VIEWS)

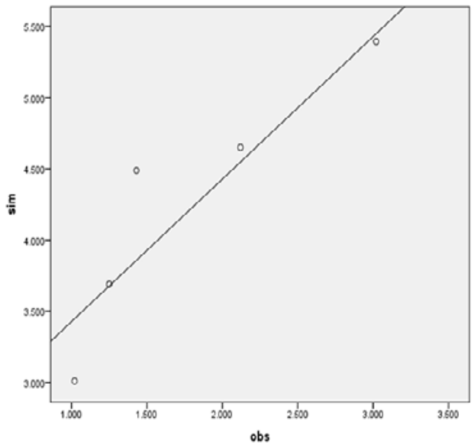


AQUACROP Model

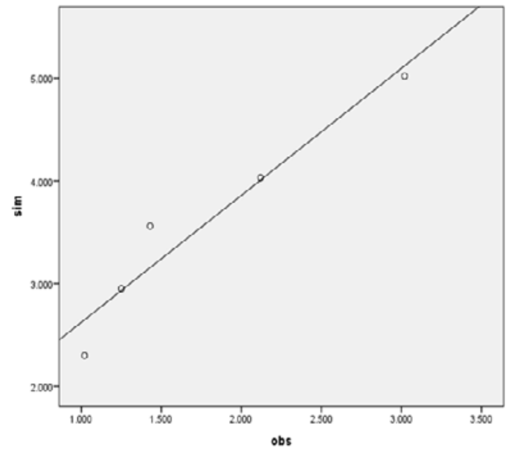


CERES Model

(a)simulated biomass yield



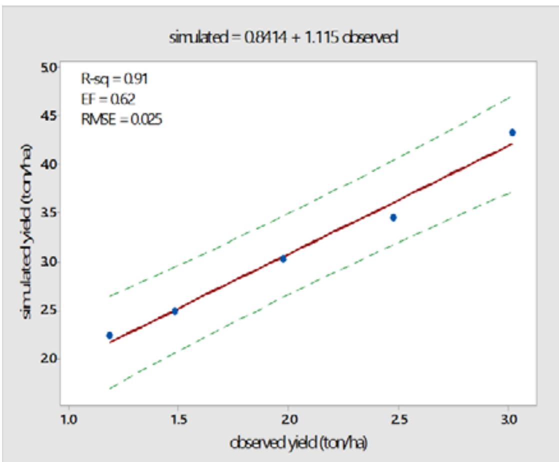
AQUACROP Model



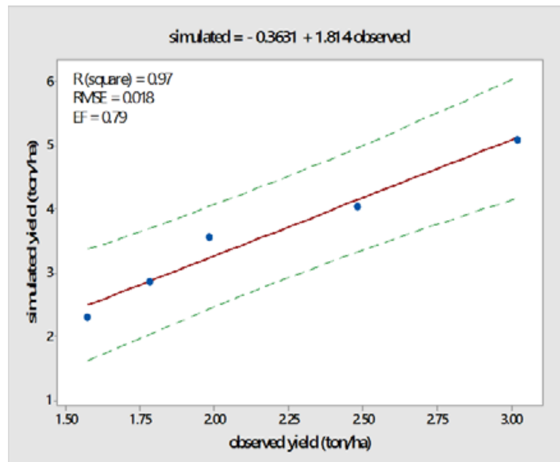
CERES Model

(b) simulated Grain yield

Figure 11 Comparison of observed and simulated biomass yield/simulated Grain yield in both models under different treatments with Statistical Package for Social Science (SPSS)

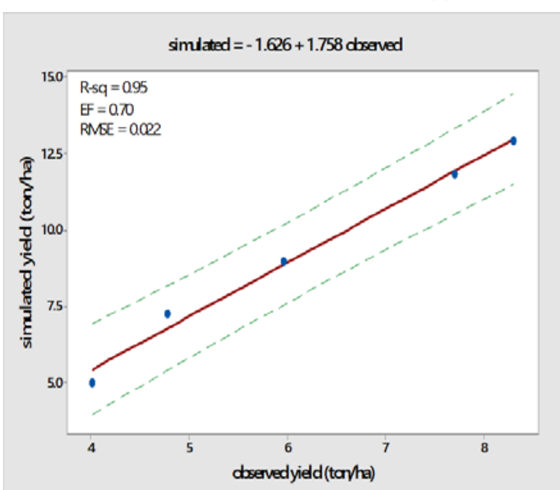


AQUACROP Model

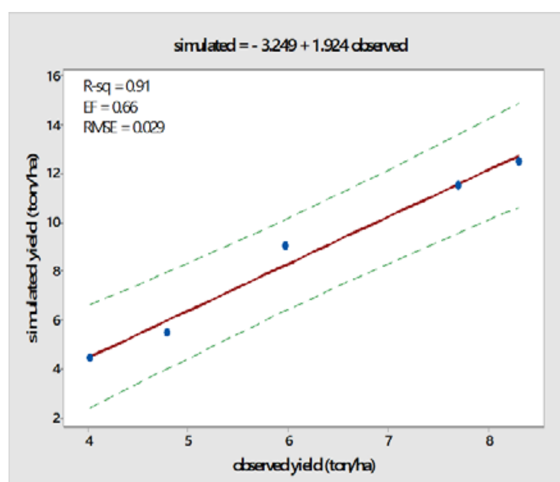


CERES Model

(a) Simulated Grain yield



AQUACROP Model



CERES Model

(b) simulated biomass yield

Figure12: Comparison of observed and simulated grain yield/simulated biomass yield in both CERES Model models under various levels of water application using Minitab software

Identical responses were recorded in biomass and grain yield when Minitab 17 was used to access the correlation between the performance of AQUACROP and CERES models, indicating the efficacy of these models in successfully predicting the biomass and grain yield concerning applied irrigation water (Figure 12a, 12b). This is a clear indication that these tools are very useful in irrigation schedule and rice production planning to ensure food security.

5 Conclusions

This study estimated crop water requirements using CROPWAT while AQUACROP and CERES-Rice models evaluated performance in simulating biomass and grain yield of NERICA 4's response to different irrigation schedules. From the study, it was established that 288.10 mm of irrigation water applied and 800 mm of effective rainfall as predicted by the CROPWAT model was required for optimum rice production in the region and as confirmed by other studies carried out in the same area. CERES model slightly underestimated LAI while both CERES and AQUACROP models slightly overestimated grains and biomass yields although CERES showed the highest precision in grain yield than the AQUACROP model which showed the highest accuracy in biomass yield. AQUACROP slightly underestimated canopy cover when compared with the measured values. There was no statistically significant difference in all the post-harvest parameters such as plant height, no of leaves, no of panicles, LAI, grain yield and biomass considered in the first two treatments (full and good) which could strongly be traced to the irrigation water applied. All the statistical tools (R, E-VIEWS, SPSS, and MINITAB 17) used showed similar relationships between the simulated and observed yield values and RMSE shows that the models' simulation performance was perfect since its value was closer to zero. The study, therefore, underscores the models' (CERES and AQUACROP) performance under different irrigation schedules for simulation of grain and biomass yield of rice while it also shows that CROPWAT could be used effectively and efficiently to estimate agricultural water requirements and reference evapotranspiration required for optimum production of rice.

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