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RESPONSIVENESS OF OBAATANPA MAIZE GRAIN YIELD AND BIOMASS TO SOIL, WEATHER AND CROP GENETIC VARIATIONS

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ABSTRACT

Use of crop growth simulations models such as those incorporated into Decision Support System for Agro technology Transfer (DSSAT) are useful tools for assessing the impacts of crop productivity under various management systems. Maize growth model of DSSAT is Crop Environment Resource Synthesis (CERES) -Maize. To predict maize grain yield and biomass using CERES-maize under Guinea savanna agro ecological conditions with different weather scenarios, data on maize growth, yield and development as well as data on soil and weather was collected from field on-station experiment conducted during the 2010 growing season at Kpalesawgu, Tamale-Ghana. Twenty on-farm experiments were also conducted in the Tolon-Kunbungu and Tamale Metropolitan districts in Northern Ghana to determine the responsiveness of maize grain yield and biomass to soil, weather and crop genetic variations. The cultivar coefficient was however calibrated with data collected from the on-station field experiment at Kpalesawgu. The cultivar coefficient was however calibrated with data collected from the on-station field experiment at Kpalesawgu. Data on phenology, grain yield and biomass from the field experiment were used for model validation and simulations. Validation results showed good agreement between predicted and measured yields with a Normalized Random Square mean Error (NRSME) value of 0.181. Results of these sensitivity analysis results showed that the DSSAT model is highly sensitive to changes in weather variables such as daily maximum and minimum temperatures as well as solar radiation, however, the model was found to be least sensitive to rainfall. The model also found to be sensitive to crop genetic and soil variations. Model predictions of the responsiveness of the yield and biomass to changes in soil, weather and crop genetic coefficients were found to be good with an r^2 values between 0.95 to 0.99 except when predicting maize grain yield using changes in minimum temperature with an r^2 value of 0.8577.

Keywords: Genetic variations, Grain yield, Soil, Biomass, Weather.

INTRODUCTION

Maize is the most important cereal crop produced in Ghana and it is also the most widely consumed staple food in Ghana with increasing production since 1965 (FAO, 2008; Morris *et al*., 1999). In Ghana, maize is produced predominantly by smallholder resource poor farmers under rain-fed conditions (Bart-Plange *et al*., 2004). Low soil fertility and low application of external inputs as well as unreliable rainfall pattern are among the major reasons that account for low productivity in maize. The soils of the major maize growing areas in Ghana are low in organic carbon (<1.5%), total nitrogen (<0.2%), exchangeable potassium (<100 mg/kg) and available phosphorus (< 10 mg/kg) (Adu, 1995, Benneh *et al*., 1990). Farmers in the Guinea savanna agroecological zone are mainly poor and as such rely heavily on rainfed agriculture precisely weather dependent. Uncertainty in rainfall patterns affects farmers yield and subsequently affects their income levels. There is therefore the need to quickly assess the impact of weather variables such as rainfall, temperature and solar radiation on the yield of maize using modern tools such as Decision Support System for Agrotechnology transfer (DSSAT). Prior knowledge would guarantee farmers commitment in allocation of scarce resources into maize production. The objective of this experiment is to model the effect of soil, crop genetic

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factors and weather variables- temperature, rainfall and solar radiation on maize grain yield. This was done through the assembling of minimum data set needed to run the DSSAT model which includes soil information (Tables 1 and 2), weather (Table 3), and crop genetic or cultivar coefficient (Table 4).

The Maize model included into DSSAT is CERES-Maize, and has been tested and used by many researchers around the world for various applications. CERES is a family crop-soil-climate computer model at the core of computer software (DSSAT) (IBSNAT, 1994). DSSAT integrates these crop models to asses yield, resource use and risk associated with different crop production practices. Therefore to use DSSAT as a tool for management decisions in sustaining economically and environmentally safe agriculture, the CERES-Maize needs to be evaluated and calibrated in the Guinea savanna agro ecological conditions where this experiment was carried out.

The objective of this study was to model the impact of soil characteristics, weather and crop genetic factors that affect maize yield and biomass in the Guinea savanna agro-ecological zone of Ghana, using short-term field experiments and DSSAT V 4.5. Although the DSSAT model can synthesize information quickly and inexpensively, the reliability of the model is based on the degree to which the model accurately reflects the natural process.

Table 1. Soil chemical attribute used for running the DSSAT model.

	Mean	Min.	Max.	Std. deviation	Std. Error of Mean	Variance	CV
pH (1:2.5 Water)	5.053	4.700	5.300	0.203	0.052	0.041	4.019
mg (Cmol./kg soil)	1.435	0.400	2.540	0.565	0.146	0.319	39.352
K (Cmol./kg soil)	0.197	0.110	0.270	0.047	0.012	0.002	23.978
ECEC (Cmol./kg soil)	4.027	2.510	5.310	0.747	0.193	0.588	18.545
Organic Carbon (%)	0.237	0.060	0.480	0.158	0.041	0.025	66.611
Calcium (Cmol./kg soil)	1.613	0.670	2.540	0.464	0.120	0.216	28.788
Total Nitrogen (%)	0.028	0.110	0.060	0.015	0.004	0.001	52.956

Source: Field data, 2010.

Table 2. Soil physical attribute used for running the DSSAT model.

	Mean	Min.	Max.	Std. deviation	Std. Error of Mean	Variance	CV
Bulk Density (g/cm^3)	1.613	0.670	2.540	0.464	0.120	0.216	28.788
Clay (%)	21.31	17.000	36.100	4.510	1.170	20.360	21.180
DULL (mm/mm^3)	0.167	0.124	0.294	0.046	0.012	0.002	27.516
Silt (%)	14.45	0.020	32.100	6.260	1.620	39.200	43.340
SLL (mm/mm^3)	0.106	0.078	0.180	0.028	0.007	0.001	26.722
Stones (%)	26.1	4.000	37.000	9.610	2.480	92.440	36.840

Source: Field data, 2010.

MATERIALS AND METHODS

Study area: The study was carried out in the Northern region of Ghana. Field experiment was done at Kpalesawgu, a suburb of Nyankpala near the Savanna Agricultural Research Institute's experimental field. The site is located about 16 km west of Tamale and lies on latitudes N 090 24' 15.9''and longitude W 0010 00' 12.1''of the interior Guinea Savanna agro-ecological zone of Ghana, which has a mean daily temperature of 26 ^{0}C (SARI, 1996). This area has a uni-modal rainfall pattern averaging about 1100 mm annually (Dankyi *et al*., 2005). The Guinea Savanna zone was strategically selected for a number of reasons: (i) it is an important breadbasket area, (ii) it is an important growing area for maize, (iii) the highest concentration of past soil fertility management research is located within this area, (iv) the nearness to large local and regional markets for inputs and outputs. The study covered a period from June to December 2010.

Experimental Design: A randomized complete block design with four replications was used for the on-station experiment at Kpalesawgu. The plot size was 5.0 m × 15.0 m with plant spacing of 80 cm × 40 cm. Treatments applied were N-P_2O_5-K_2O 0-0-0, 40-60-60, 80-60-60, 120-60-60, 150-60-60, 120-0-60, 120-45-60, 120-90-60, 120-60-0, 120-60-45 and 120-60-90 kg/ha.

The blocks were arranged from east to west with eleven plots each and a surface area of 75 m^2 (15 m long and 5 m wide) separated by 1m alley and has eight rows per plot. Similarly twenty on-farm experiments were conducted in the Tolon- Kunbungu and Tamale Metropolitan districts. 4 treatments (0-0-0, 40-60-60, 80-60-60 and 120-60-60 kg/ha N-P_2O-K_2O_5) were assigned to each farmer. The plants were monitored and phenological data as well as management information were collected. These include sowing date, date of fertilizer application, date of flag leaf stage, date of flowering, date for grain filling and date of maturity. The phonological stages were noted when 50% of plant population attained that stage. Final total biomass and grain yield were also measured from a plot size of 9 m^2 by harvesting above-ground biomass and separating them into the various components according to the procedure described in Hoogenboom *et al*. (1999). Grain yield and total biomass were expressed in t ha^{-1}. Soil samples (both disturbed and undisturbed) were taken at different horizons (0–10, 10–20, 20–30, 30–40, 40–50, 50-60, 60-70, 70-80, 80-90, 90-100, 100-110, 110-120, 120-130, 130-140, and 140-150 cm). Soil organic carbon, pH, soil particle distribution, wilting point, field capacity, bulk density and saturation were all determined as described in Hoogenboom *et al*. (1999), (Table 1 and 2).

Table 3. Monthly total rainfall, monthly means, solar radiation, sunshine hours, maximum and minimum temperature between 1971-2010 at Tamale, Ghana used for running the model.

Month	SRad (MJm^{-2} d^{-1})	Tmax(^0C)	Tmin(^0C)	Rain	Nwet	SunH
Jan	11.0	35.1	18.8	2.3	0.2	7.4
Feb	11.8	37.2	21.8	8.1	0.6	7.5
Mar	12.4	37.7	24.9	38.4	3.1	7.3
Apr	12.5	36.2	25.2	70.3	5.3	7.3
May	12.2	34.1	24.2	117.9	8.1	7.3
Jun	11.9	31.9	23.0	133.0	9.5	7.1
Jul	11.9	30.2	22.8	161.7	10.6	6.8
Aug	12.1	29.6	22.6	185.7	12.6	6.6
Sep	12.2	30.2	22.4	214.1	14.4	6.9
Oct	11.9	32.2	22.6	85.5	7.6	7.4
Nov	11.3	34.9	21.5	11.6	0.9	7.8
Dec	10.7	34.6	19.2	3.0	0.3	7.4

Source: Council for Scientific and Industrial Research-Savanna agricultural Research Institute, Weather station, Nyankpala, Tamale-Ghana.

The experimental field had been under fallow since 2008. Before then sorghum was planted. The land was ploughed, harrowed and ridged. Maize variety *Obaatanpa* was planted on 18th June, 2010 with a spacing of 80 cm x 40 cm.

Three seeds were planted and later thinned to two plants/ hill. Thinning was done before fertilizer was applied. 50 % of the nitrogen and all the phosphorus and potassium were applied two weeks after planting. The remaining nitrogen was applied five weeks after planting. The fertilizer was banded on both sides of the plant and buried.

Model Calibration: A calibration of a model can generally be defined as an adjustment of some parameters and functions of a model so that predictions are the same or at least very close to data obtained from field experiments (Penning de Vries, 1989). For crop growth models the calibration involves determining genetic coefficients for the cultivar (Table 4) to be grown in a location. For the current study various crop growth development parameters were used to calibrate DSSAT. These values include silking date, physiological maturity date (black layer formation), grain weight, number of grains per plant and number of grains per square meter.

The calibration procedure of the CERES-Maize model consisted of making initial estimates of the genetic coefficient and running the model interactively, so that simulated values match as closely as possible the measured data. The values of the thermal time from seed emergence to the end of the juvenile stage (P1), the photoperiod sensitivity coefficient (P2), and the thermal time from silking to maturity (P5), were computed using observed silking and physiological maturity dates. Potential kernel number plant^{-1} (G2) and grain growth rate (G3) are input parameters to determine the potential grain yield. The DSSAT model acts to reduce this potential as a result of suboptimal environmental conditions. As suggested by Kiniry (1991), when these values are not obtained in these conditions, an alternative is to calibrate these parameters by running the model on existing data sets. The calibration procedure was performed using the GENCALC in DSSAT (Hunt *et al.*, 1994).

Table 4. The genetic coefficients of used for modeling the *obaatanpa* maize variety in CERES-maize model at Kpalesawgu, Ghana.

Codes	Definitions	Values
P1	Thermal time from seedling emergence to the end of the juvenile phase during which the plant is not responsive to changes in photoperiod (expressed in degree days).	320.00
P2	Photoperiod sensitivity coefficient	0.100
P5	Thermal time from beginning of grain filling to physiological maturity (expressed in degree days).	945
G2	maximum kernel number plant^{-1}	350
G3	Potential kernel growth rate	8

Statistical Evaluation: Despite the fact that a considerable amount of information on agricultural modeling has been published in the last decades, there is no standard methodology to evaluate the predictive ability of a model. In fact, it has been subject to a considerable debate (Addiscott *et al*., 1985). As attempts to evaluate these models have increased, various ways of evaluation has been suggested (Addiscott and Whitmore 1987, Loague and Green, 1991, Willmott, 1982, Wallach, and Goffinet, 1989). For the present study the methods of Addiscott and Whitmore 1987) were followed to analyze simulation accuracy.

An analysis of the degree of coincidence between simulated and observed values were carried out by using Root Mean Square Error (RMSE) (Willmott, 1982), and the ratio of RMSE over the average (Stockel *et al.,* 1997), Loague and Green 1991), Mean Difference (MD). The RMSE has been widely used as a criterion for model evaluation (Legnick *et al.,* 1994; Jemison *et al.,* 1994; Retta *et al.,* 1996; Kiniry *et al.,* 1997; Ma *et al.,* 1998). RMSE is calculated by:

$$\mathrm{RMSE} = \sqrt{1/N \sum (Oi - Pi)2}$$

Where P and O are the predicted and observed values for the observation, and N is the number of observation within each treatment. RMSE is measure of the deviation of the simulated from the measured values, and is always positive. A zero value is ideal. The lower the value of RMSE the higher the accuracy of the model prediction.

The MD is a measure of the average deviation of the predicted and observed values and is calculated by:

$$\mathrm{MD} = 1/N \sum (Oi - Pi)$$

The positive and negative signs of the MD reflect that, on average, the model is over estimating or under estimating the observed values, respectively. A t-test was used to determine whether MD is significantly different from zero (Addiscott and Whitmore 1987).

Weather: Weather data used by the model in running simulations were daily rainfall amount, daily solar radiation, minimum and maximum daily temperature. A summary of weather parameters for the growing season is presented in Table 3. These were collected from a weather station located in the study area. Forty years historical weather data for the study area were used as input data for the DSSAT Weatherman to simulate 40 years weather data for the study area. This was used to evaluate the impact of weather on crop, nutrient and water productivity.

Field experiments: Result of the on-station field experiment conducted is presented in Table 5a. Highest observed mean yield was recorded when 120-90-60 kg/ha N-P_2O_5-K_2O was applied. However when no mineral fertilizer was applied 231 kg/ha grain yield was recorded (Table 5a). Simulated results showed close agreement when higher amounts of mineral fertilizer were applied (Table 5b). The model however over predicted situations where no mineral fertilizer were applied. This is because the model assumed there was no water stress during the cropping season which is not the reality. However, in reality there were periods in the growth of the plant where there was shortage of water.

Grain yields obtained from on-farm experiment were lower than those obtained from the on-station experiment (Tables 6b and 7b). This confirms the inadequacy in adhering to agronomic practices by farmers such as frequent weeding and timely application of mineral fertilizer. A minimum and maximum yield of 290 and 1867 kg/ha grain weight was recorded from the ten on-farm fields located in the Tolon Kunbungu district (Table 6b). Similarly minimum and maximum stover weight recorded was 206 and 7956 kg/ha (Table 7a). A minimum and maximum yield of 118.8 and 1868.8 kg/ha grain weight was recorded from the ten on-farm fields located in the Tamale Metropolitan district (Table 7b). The differences in yields are attributed to differences in initial soil fertility status of the experimental fields.

Table 5a. Observed yield of maize, total biomass and stover weight in response to mineral fertilizer application at the on-station experiment at Kpalesawgu, Ghana.

Treatment N-P_2O_5- K_2O (kg/ha)	Tot. Biomass (kg/ha)	Stover (kg/ha)	Yield (kg/ha)
0-0-0	764	533	231
40-60-60	7301	6092	1208
80-60-60	9627	7124	2503
120-60-60	10181	6392	3789
150-60-60	10431	6909	3522
120-0-60	2313	1055	1258
120-45-60	9940	6701	3239
120-90-60	11392	7562	3831
120-60-0	9537	6223	3314
120-60-45	9975	6203	3772
120-60-90	10374	6796	3578

Table 5b. Simulated yield of maize, total biomass and stover weight in response to mineral fertilizer application at the on-station experiment at Kpalesawgu, Ghana.

Treatments N-P_2O_5-K_2O (kg/ha)	Mat Yield (kg/ha)	Mat Yield (kg/ha)	Treatments N-P_2O_5-K_2O (kg/ha)	Mat Yield (kg/ha)	Mat Yield (kg/ha)
	Simulated	Observed		Simulated	Observed
0-0-0	870	231	120-45-60	3506	3239
40-60-60	2110	1208	120-90-60	3990	3831
80-60-60	3634	2503	120-60-0	3628	3314
120-60-60	3795	3789	120-60-45	3726	3772
150-60-60	3646	3522	120-60-90	3647	3578
120-0-60	1392	1258			

Table 6a. Observed stover weight in response to mineral fertilizer application from ten on-farm experiment in Tolon Kumbungu district in Northern Ghana.

Treatment N-P_2O_5-K_2O (kg/ha)	Mean	Min.	Max.	Std. Dev.	Mean Std. Error	Var.	Coeff. Var.
0-0-0	325	174	544	111	35	4810	34
40-60-60	4189	2431	5700	1027	325	1055000	25
60-60-60	4589	3888	6031	628	199	394556	14
80-60-60	4828	3894	5744	669	212	447415	14
120-60-60	4989	3819	5988	650	206	422993	13

Table 6b. Observed maize grain yield in response to mineral fertilizer application from ten on-farm experiments in Tolon Kumbungu district in Northern Ghana.

Treatment N-P_2O_5-K_2O (kg/ha)	Mean	Min.	Max.	Std. Dev.	Mean Std. Error	Var.	Coeff. Var.
0-0-0	339.4	290.6	380.7	30.2	9.6	913.4	8.9
40-60-60	508.1	412.5	612.5	60.5	19.1	3654.9	11.9
60-60-60	1087	993.8	1175	51.2	16.2	2621.5	4.7
80-60-60	1300	1069	1450	112	36	12622	9
120-60-60	1569	1260	1867	210	66	44082	13

Table 7a. Observed maize stover weight in response to mineral fertilizer application from ten on-farm experiments Tamale Metropolitan district in Northern Ghana., Ghana.

Treatment $N-P_2O_5-K_2O$ (kg/ha)	Mean	Min.	Max.	Std. Dev.	Mean Std. Error	Var.	Coeff. Var.
0-0-0	394	206	550	102	32	10383	26
40-60-60	4558	3488	5538	635	201	403039	14
60-60-60	4650	3875	5744	614	194	376814	13
80-60-60	5741	5012	6988	627	198	393127	11
120-60-60	6213	4431	7956	1070	339	1145837	17

Table 7b. Observed maize grain yield in response to mineral fertilizer application from ten on-farm experiments in Tamale Metropolitan district in Northern Ghana.

Treatment $N-P_2O_5-K_2O$ (kg/ha)	Mean	Min.	Max.	Std. Dev.	Mean Std. Error	Var.	Coeff. Var.
0-0-0	191.9	118.8	262.5	38.2	12.1	1458.8	19.9
40-60-60	867.0	662	1238	150	48	22605	17
60-60-60	1141.9	1037.5	1237.5	58.2	18.4	3385.9	5.1
80-60-60	1522.0	1256	1694	119	38	14186	8
120-60-60	1824.4	1743.8	1868.8	37.6	11.9	1410.2	2.1

Validation of the Model: Data for model validation include silking and maturity dates, grain yield, grain weight, and above ground biomass. omparison between measured and predicted maize yield showed good agreement. The NRMSE was 0.181 (Loague and Green, 1991). Comparison between predicted and simulated yield at harvest maturity for all treatments is presented in Figure 1.

Simulated and observed grain yield for 120-60-60, 150-60-60 and 120-90-60kg/ha $N-P_2O_5-K_2O$ were 3795.0 and 3789 kg/ha, 3646 and 3522.0 kg/ha, 3990 and 3831 kg/ha, respectively.

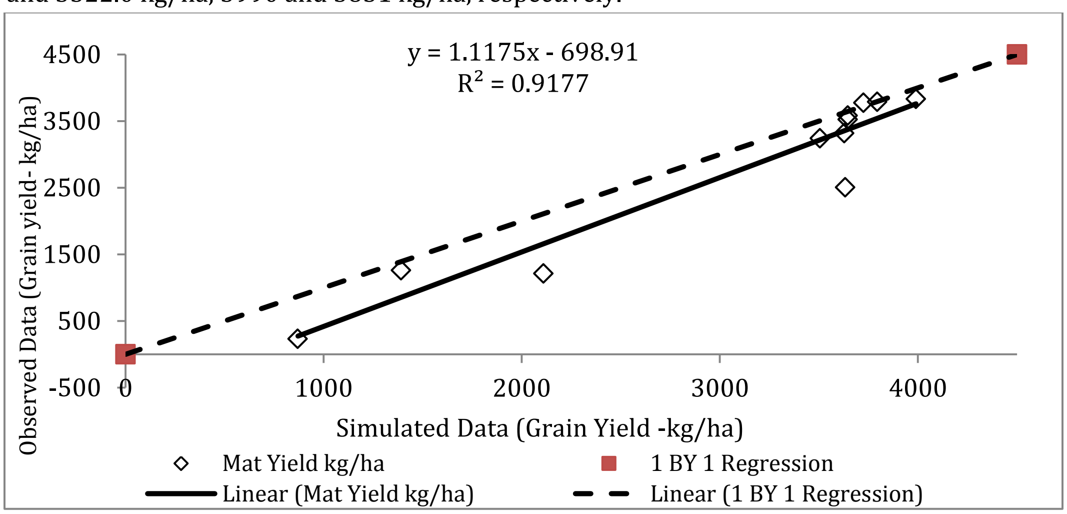

Figure 1. Comparison of grain yield predicted by the DSSAT model with measured values.

Even though 120-90-60 kg/ha $N-P_2O_5-K_2O$ gave the highest mean yield, there was no significant (Lsd = 0.05) difference between predicted and observed mean yields when 120-60-60 kg/ha $N-P_2O_5-K_2O$ was applied. Both simulated and observed mean harvest maturity yields increased with increased N and P. However, the effect of K on mean yield was minimal. This suggests that K is not limiting in soils in the Guinea savanna agro-ecological zone of Ghana.

Results of simulated and measured top weight at maturity and by-product produced at maturity for all treatments are presented in Figures 2 and 3 respectively. Similarly the model prediction for top weight at maturity and by-product produced at maturity was considered excellent with NRSME of 0.097 and 0.090 (Loague and Green, 1991) respectively. Thus the model prediction was in close agreement with measured values.

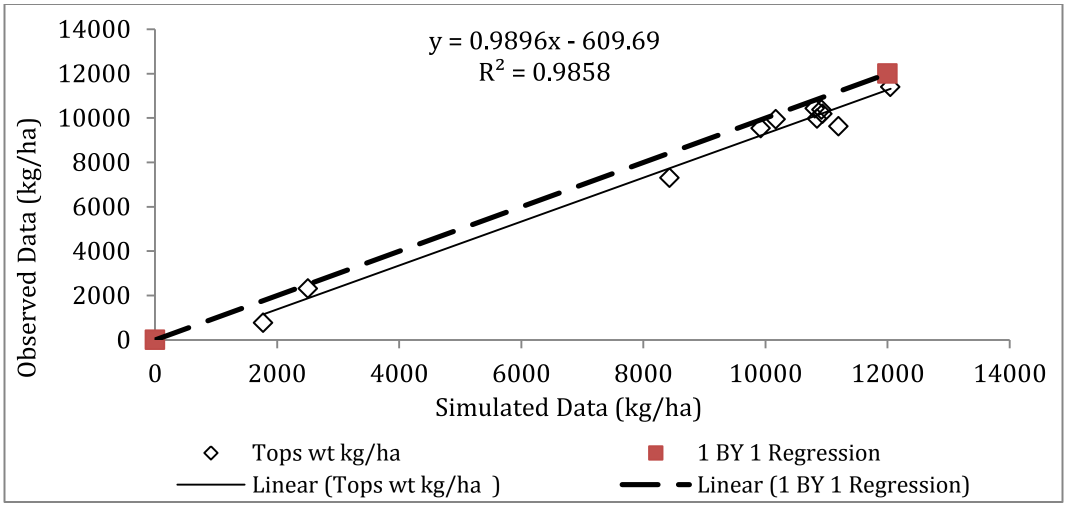

Figure 2. Comparison of top weight at maturity predicted by the DSSAT model with measured values.

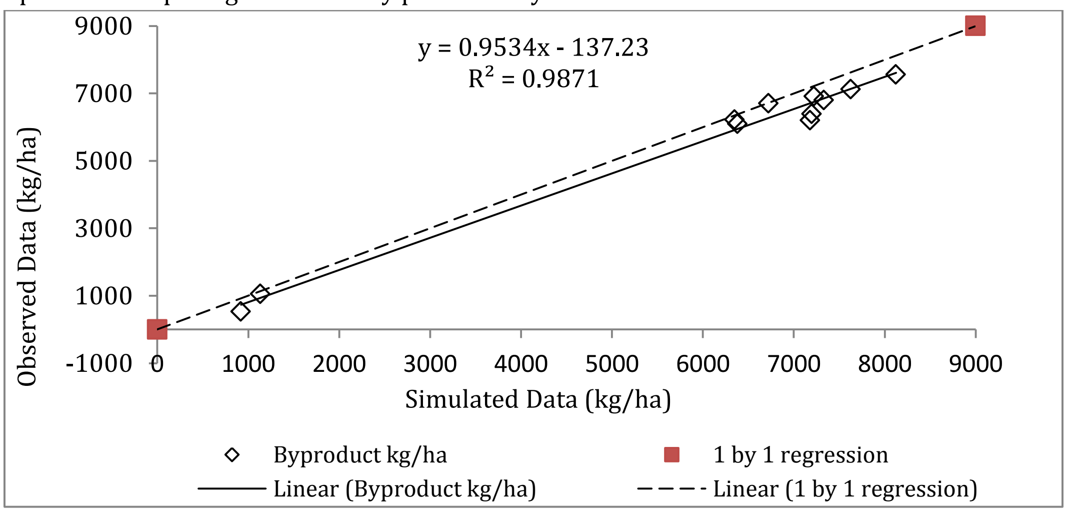

Figure 3. Comparison of by-product produced at maturity predicted by the DSSAT model with measured values.

RESULTS AND DISCUSSION

Sensitivity analysis is the study of how the uncertainty of the model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input. It is however a measure of the effect of change in one factor on another factor. Sensitivity analysis is potentially useful in all phases of the modeling process: model formulation, model calibration and model verification. It however provided objective criteria of judgment for different phases of the model-building process: model calibration and corroboration. This was done to uncover any technical error that might arise during data input in the DSSAT.

Results of the model sensitivity to weather variables are presented in Figures 4a, 4b, 4c and 4d. Simulated harvest maturity grain yield are most sensitive to air temperature, both maximum and minimum. A 1 ^{0}C decrease in maximum temperature resulted in 5.9 and 2.57 % increase in yield and top weight at maturity, respectively (Figure 4a). The yield and top weight at maturity increase jumped to 12.07 and 14.7 % by decreasing the daily maximum (TMAX) temperature by 2 ^{0}C. The TMAX effect on yield was non-linear. Increasing TMAX by 1 ^{0}C and 2 ^{0}C reduced harvested yield by 1.45 and 6.38 % respectively. However, increasing TMAX by 1 ^{0}C and 2 ^{0}C resulted in 10.44 and 13.21 % reduction in top weight respectively.

Similarly, increasing and decreasing minimum daily temperatures (TMIN) had significant effect on yield and top weight at maturity. Decreasing TMIN by 1 and 2 ^{0}C resulted in the yield increased by 4.3 and 13.6 % with an increase in top weight by 2.31 and 14.7 %, respectively. However, unlike the TMAX, the effect of TMIN on yield was linear. Increasing TMIN by 1 and 2 ^{0}C resulted in yield decrease by 1.77 and 3.16 % with decrease in top weight at maturity by 10.17 and 13.16 respectively. This suggests that errors in input values of air temperature will result in large inaccuracies in yield and biomass predictions. Therefore, if reliable model predictions are to be expected, temperature data should be at or close to experimental site.

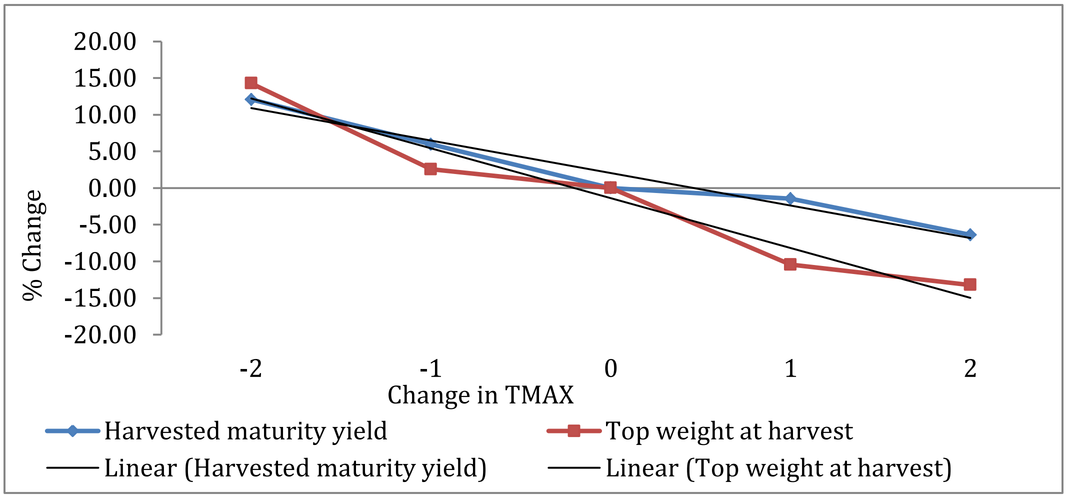

Figure 4a. Model sensitivity to changes in maximum temperature

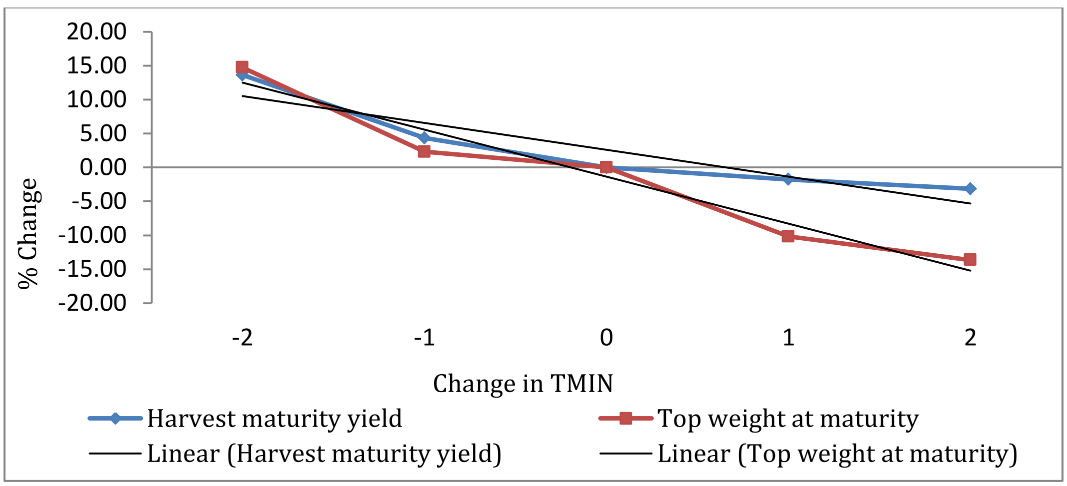

Figure 4b. Model sensitivity to changes in minimum temperature

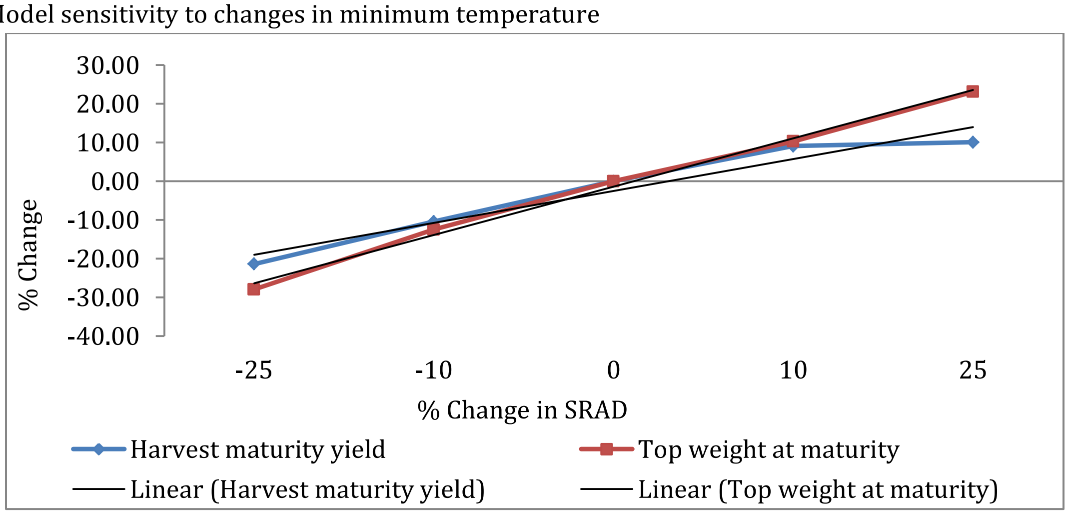

Figure 4c. Model sensitivity to changes in solar radiation.

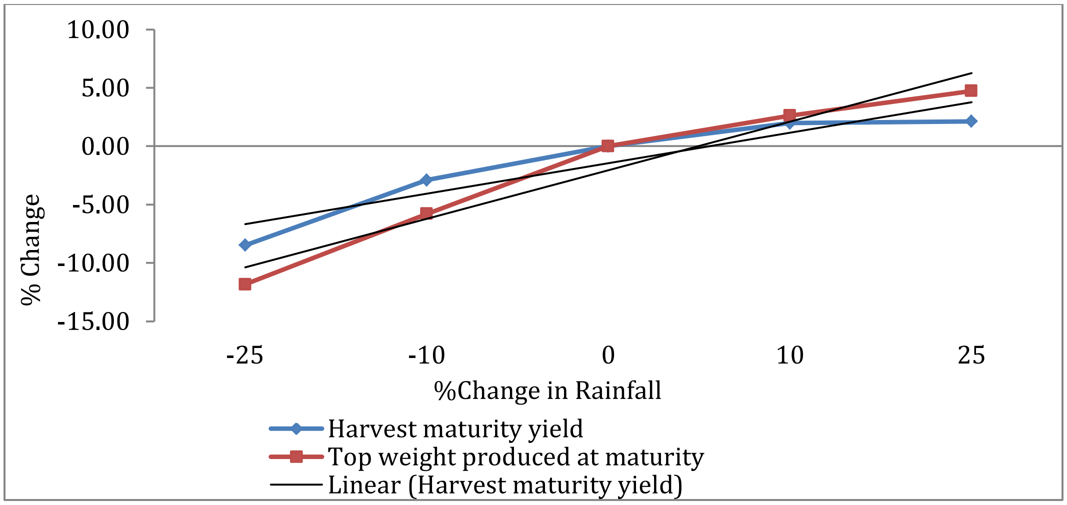

Figure 4d. Model sensitivity to changes in solar radiation.

Both yield and top weight at maturity were influenced by changes in solar radiation (SRAD) (Figure 4c). A 10 and 25 % increase in solar radiation resulted in yield increase by 9 and 10%. Increasing SRAD by 10 and 25 % increased top weight by 10.3 and 23.12 %.

However, decreasing SRAD by 10 and 25% decreased yield by 10.41 and 21.40 respectively. Similarly, top weight was also decreased by 12.48 and 27 % respectively. The effect of SRAD on top weight at maturity was linear.

Even though an increase in rainfall by 10 and 25 % resulted in an increase in yield and biomass, sensitivity to rainfall in predicting yield was minimal (Figure 4d). A 10 and 25 % increase in rainfall resulted in 1.98 and 2.13 % increase in yield with an increase in top weight by 2.62 and 4.75 % respectively. Meanwhile, a decrease in rainfall by 10 and 20 % resulted in 5.84 and 11.84% respectively. However, the rainfall effect on both yield and biomass was found to be linear. In reality, there was shortage of water during some part of the growing season, however, the model failed to predict. Based on these facts, it would be reasonable to expect yield reduction in following a substantial reduction in rainfall.

Crop genetic parameters: Figures 1, 2 and 3 summarize results of simulated yield and biomass sensitivity to variation in three crop genetic parameters. These are thermal time from silking to physiological maturity (P5), maximum kernel number per plant (G2) and potential kernel growth rate (G3). Simulated yield was the most influenced by G2 and G3. A 10 and 25 % increase in G2 and G3 increased yield by 7.38 and 18.50 %; and 9.99 and 24.98 % respectively. Reducing G2 and G3 decreased yield and top weight at maturity by 10.01 and 25.1 %; and 3.99 and 8.25 % respectively.

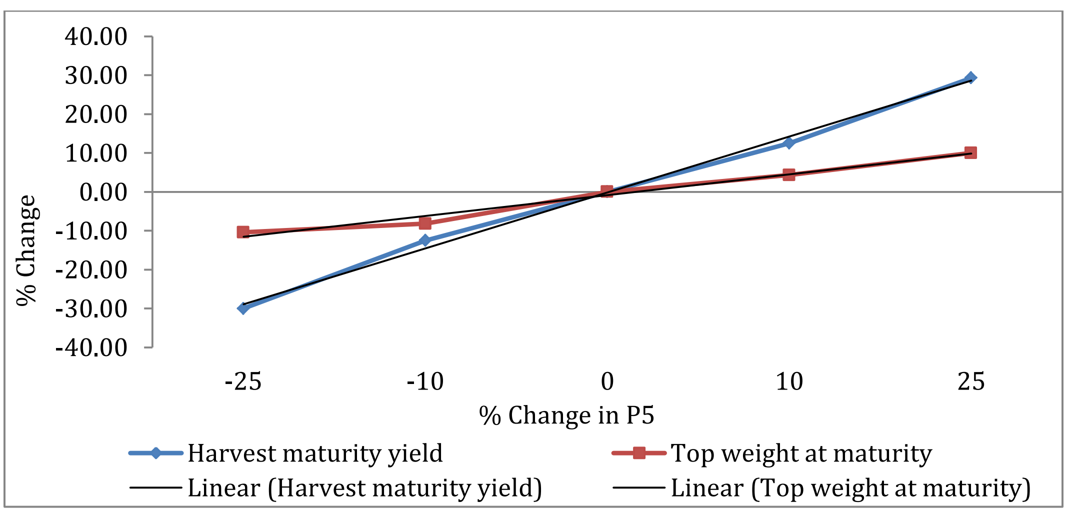

Figure 5a. Sensitivity analysis for the thermal time from silking to physiological maturity (P5).

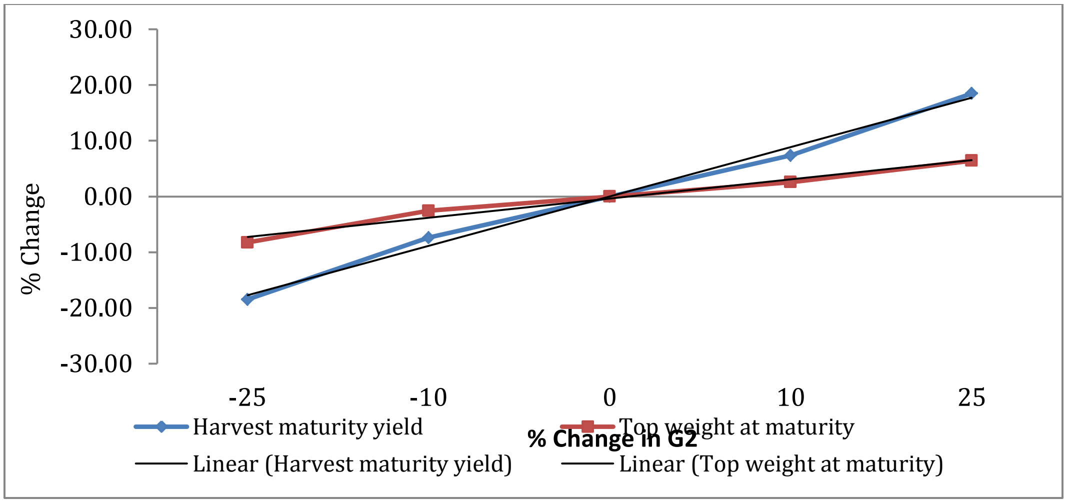

Figure 5b. Sensitivity analyses for the potential kernel number coefficient (G2).

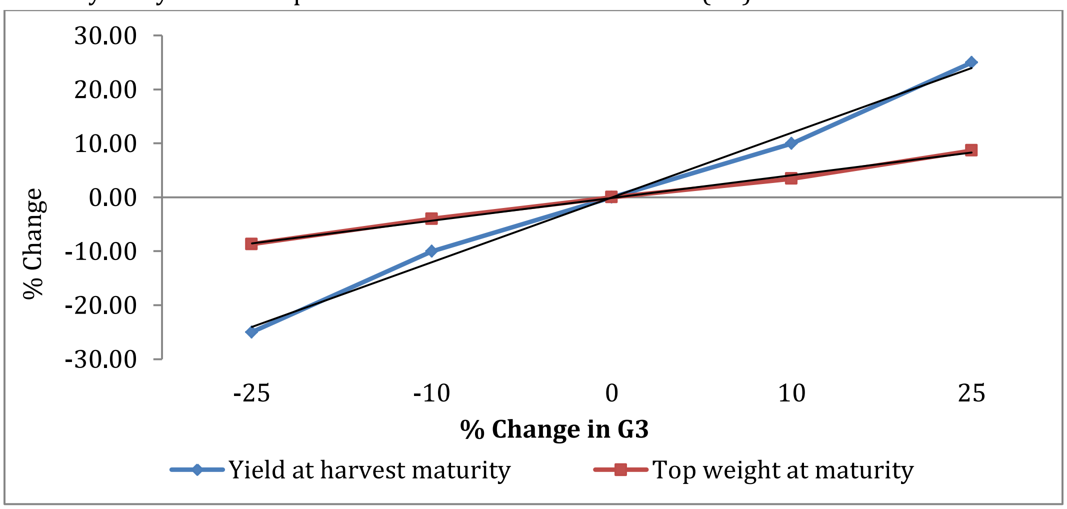

Figure 5c. Sensitivity analysis for the potential kernel growth rate (G3).

Figures 2 and 3 indicate that the impact of G2 on the yield and top weight are close to linear and that the variation in G2 has clear linear effect on predicted values. This implies that the model may be using a simple empirical relationship in determining the effect of G2 and G3 in crop production. Changes in P5 were much critical in yield and top weight at maturity than those in G2 and G3. A 10 and 25 % increase in P5 resulted in 12.49 and 29.30 % increase in yield and an increase in top weight at maturity by 4.33 and 10.01 % respectively. Similarly, a decrease in P5 by 10 and 25 % resulted in decrease in yield by 12.25 and 30.01 % respectively.

Soil parameters: Results of DSSAT model sensitivity to changes in soil water parameters are shown in Figures 6a, 6b and 6c. Simulated yield and top weight were slightly affected by changes in drained upper limit (DUL). Increasing DUL by 10 and 25 % resulted in an increase in yield by 1.45 and 4.08 % respectively. This also resulted in an increase in top weight at maturity by 2.42 and 6.41 % respectively. Decreasing DUL by 10 and 25 % also resulted in a decrease in yield by 1.40 and 3.64 % respectively. Similarly, top weight at maturity also decreased by 3.29 and 7.44 % respectively. It was established that DUL effect on both yield and top weight was linear. This further indicates the relationship between plant extractable soil water and DUL as soil water content decreases with decreasing values of DUL.

The model was also found to be sensitive to changes in saturation water content (SAT). A 10 and 25 % increase in SAT resulted in 2.0 and 6.44 % increase in yield and 2.77 and 6.44 increase in top weight at maturity. Similarly, a 10 and 25 % decrease in SAT resulted in decrease in yield by 3.37 % and 10.30 %. Top weight at maturity also reduced by 3.37 and 10.30 % with a decrease in SAT by 10 and 25

%, respectively. The model output was also sensitive to lower limit of plant extractable water (Figure 6b).

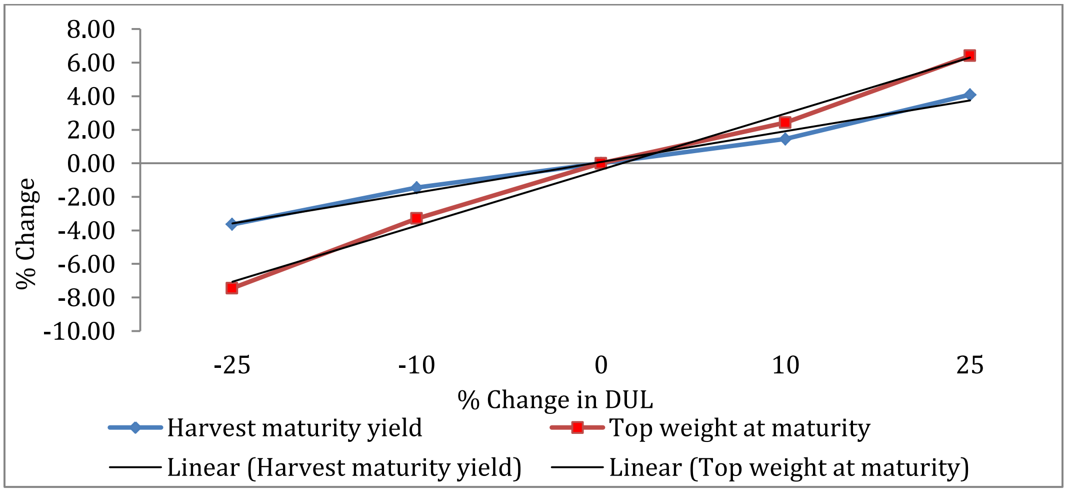

Figure 6a. Model sensitivity to changes in drained upper limit of available soil water.

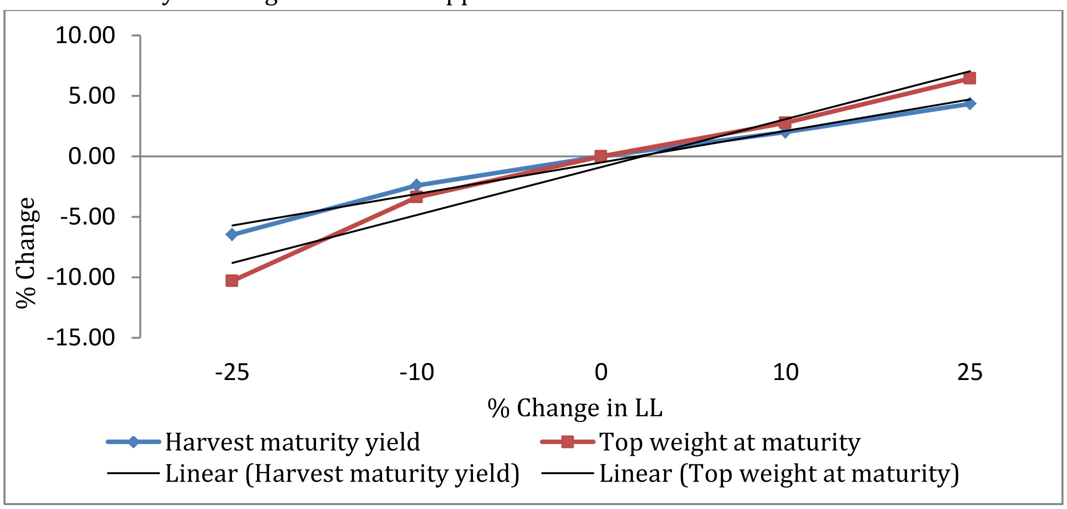

Figure 6b. Model sensitivity to changes in lower limit of available soil water

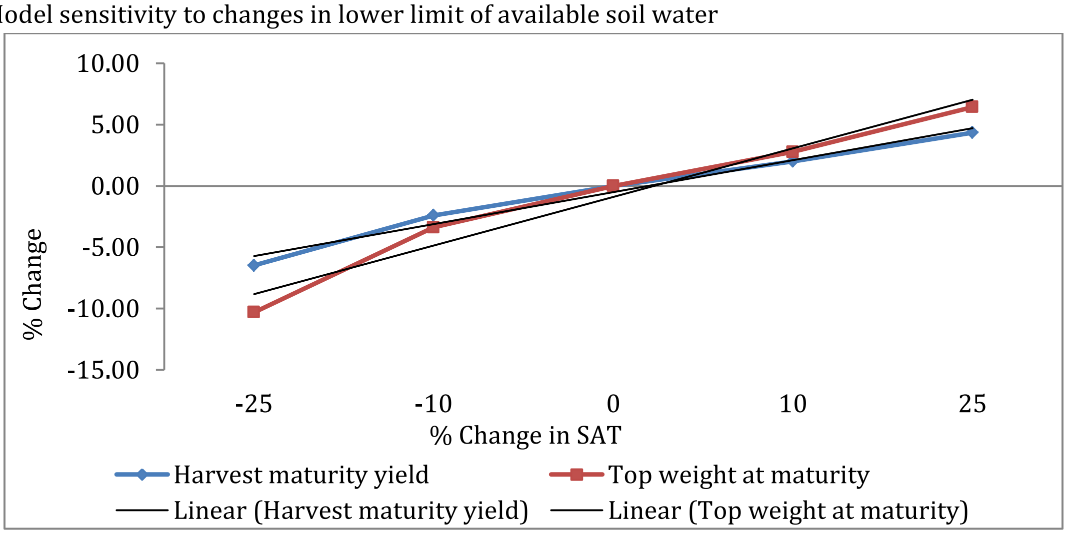

Figure 6c. Model sensitivity to changes in saturated limit of available soil water.

Summary of equations that can be used to predict *obaatanpa* maize grain yield and biomass to changes in variations in weather pattern as well as soil and crop genetic parameter is presented in Tables 9, 10 and 11).

Where Y is the amount of change and x is the change in variables.

Table 9. Predicting change in *obaatanpa* stover weight with change in temperature, solar radiation and rainfall.

Weather variables	Biomass		Yield	
	Equation	R^2	Equation	R^2
Max. Temp.	$y = -6.798x + 19.032$	0.99536	$y = -4.4295x + 15.328$	0.9662
Min. Temp.	$y = -6.9242x + 19.42$	0.95330	$y = -3.9685x + 14.513$	0.8577
SRAD	$y = 12.496x - 38.895$	0.99530	$y = 8.2477x - 27.2670$	0.9464
Rainfall	$y = 4.1574x - 14.528$	0.94970	$y = 2.6113x - 9.28850$	0.8711

SRAD sis solar radiation

Table 10. Predicting change in *obaatanpa* stover weight with change in crop genetic variables.

Crop Genetic	Biomass		Yield	
	Equation	R^2	Equation	R^2
P5	$y = 5.3369x - 16861$	0.9794	$y = 14.364x - 43.238$	0.9958
G2	$y = 3.4452x - 10.701$	0.9757	$y = 8.8722x + 26.617$	0.9931
G3	$y = 4.2141x - 12.748$	0.9962	$y = 11.987x - 36.003$	0.9931

Table 11. Predicting change in *obaatanpa* stover weight with changes in soil characteristics variables.

Soil characteristics	Biomass		Yield	
	Equation	R^2	Equation	R^2
DULL	$y = 3.3437x + 10.413$	0.9931	$y = 1.834x - 54124$	0.9874
LL	$y = 3.9627x - 12.782$	0.9653	$y = 2.606x - 3241$	0.9786
SAT	$y = 3.9627x - 12.782$	0.9653	$y = 2.6061x - 8.3241$	0.9786

DULL-Drained upper limit of soil water; LL- Lower Limit of soil water; SAT-Saturated available soil water.

CONCLUSION

The use of crop growth simulations models such as those incorporated into Decision Support System for Agro technology Transfer (DSSAT) are useful tools for assessing the impacts of crop productivity under various management systems. The maize growth model of DSSAT is CERES-Maize. The model was found to be sensitive to temperature and solar radiation. However the model was least sensitive to rainfall. The DSSAT model showed an inverse relationship to maize grain yield when temperature, rainfall and solar radiation are increased or decreased. There is linear relationship between increasing and decreasing thermal time from silking to physiological maturity, potential kernel number coefficient and potential kernel growth rate; and maize grain yield. The DSSAT model was found to be sensitive to thermal time from silking to physiological maturity, potential kernel number coefficient and potential kernel growth rate.

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