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A Review on: Performance Evaluation of Crop Simulation Model (APSIM) in Prediction Crop Growth, Development and Yield in Semi Arid Tropics

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Abstract
Crop Simulation Models (CSM) are computerized representations of crop growth, development and yield, simulated through mathematical equations as functions of soil conditions, weather and management practices. The Crop simulation models like agricultural production system simulator can save time and resources better prediction accuracy is the most important point that should be considered in decision making process. Most models are not tested or poorly tested, and hence their usefulness in decision making process is unproven. Therefore, this paper Reviews the performance of the APSIM CSM simulation accuracy with respect to the simulation of the growth, development and yield of the selected crops. APSIM model is reliable crop simulation model in predicting development, Growth and yield of different crops in the semi arid tropics.
Keywords: APSIM, CSM, Yield, Semi arid tropics

1. Introduction

A system is a limited part of a reality that contains interacting elements, and a model is a simplified representation of such systems (Whisler et al., 1986). This helps us to understand the world around us. Specifically, a crop model can be described as a quantitative scheme for predicting the growth, development, and yield of a crop, given a set of genetic features and relevant environmental variables (Monteith, 1996). Crop Simulation Models (CSM) are computerized representations of crop growth, development and yield, simulated through mathematical equations as functions of soil conditions, weather and management practices (Hogenboom et al., 2004).

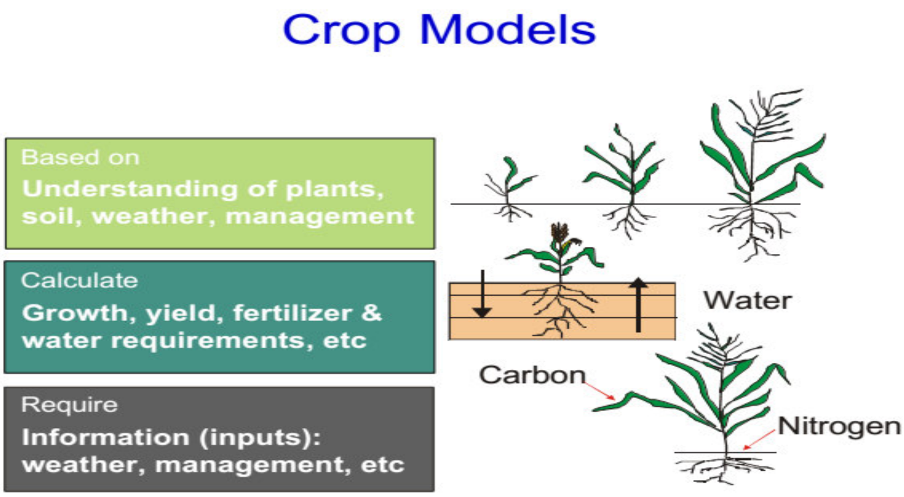

Figure: 1 Crop simulation models in predicting crop growth and yield

These models serve as a research tool for evaluating optimum management of cultural practices, e.g fertilizer use, and water use. Modeling crop yield response to management options and prevailing environmental conditions can be done through empirical and process-based (simulation) models and each approach have its merits and limitations (Park et al., 2005).

Empirical models, also called descriptive or regression models, are direct descriptions of observational data (e.g., response of maize yield to different rates of fertilizer) and driving variables. crop growth models are explanatory models and seek to explain the functioning of crops as a whole (Bouman et al.,1996) by simulating or imitating the behavior of a real crop in terms of growth of its components, such as leaves, roots, stems and grains (Jame & Cutforth ,1996). they do not only predict final biomass or harvestable yield, but also contain information about major processes involved in the growth and development of a plant and they often also provide information on externalities, such as soil erosion or N-leaching. The time steps are usually daily or sometimes even on an hourly basis and thus reduce the process-based modeling approaches use the knowledge or understanding of the crop yield formatting process through mathematical relations that are based on plant physiology, agro-climatic and plant-soil-atmosphere interactions (physiological and biochemical processes)(Kpongor ,2007).

Crop growth models have been used in numerous studies to help farmers around the world in day-to-day decision making, for example, to investigate the effects of management options such as sowing time, plant population density, irrigation regime (timing, frequency) and fertilizer applications in different conditions on long-term mean yield and yield probability (Bouman et al.1996).The time steps are usually on daily biases thus reduce the time interval involved considerably when compared to empirical-statistical models, which usually use seasons or years. Among the numerous crop growth models, the most widely used models are the Decision Support for Agro-technology Transfer (DSSAT) Agricultural production system simulator and Aqua crop models. CSMs (APSIM and DSSAT) which can play important roles in their application as decision support systems in crop growth, development and yield as a function of complex interaction of Soil, plant and atmosphere.

APSIM is a modeling environment that uses various component modules to simulate dynamically cropping systems in the semi-arid tropics (McCown et al.1996). It was designed “as farming systems simulator that sought to combine accurate yield estimation in response to management with prediction of the long-term consequences of farming practice on the soil resource” (Keating *et al*. 2003).

Although the crop simulation models can synthesize information quickly and inexpensively, the reliability/consistency of the model is based on the degree to which the model accurately reflects the natural process/Understanding of the natural process.

Statistical tools for evaluation of CSM model performance

According to (Addiscott and Whitmore, 1987; Loague and Green, 1991) the commonly used statistical tools presented as follows.

- Root mean square error (RMSE)
- Mean deviation
- Percent of deviation (D %
- Normalized Mean square Error
- coefficient of determination (R^2)

2. Performance Evaluation of Apsim Model in Simulating Growth, Development and Yield of Different Crops

2.1. Phenology

The general trend of the growth duration of sorghum in response to the different treatment of N (0, 40, and 80,120) and P (0, 30, and 60) fertilizer was reasonably well predicted by the model kopongor (2007) in (Figure 4.1). The model exaggerated (over estimated) the impact of nutrient stress in delaying crop phenology, expressed by the deviations between observations and predictions of GDDs at lower levels of input. This may be because the model assumes no limiting conditions of N in predicting maize phenology (Mutsaers and Wang, 1999). Similar observations are reported by Gungula et al. (2003) for other models in simulating maize phenology under N-stress in Nigeria (Table 1).

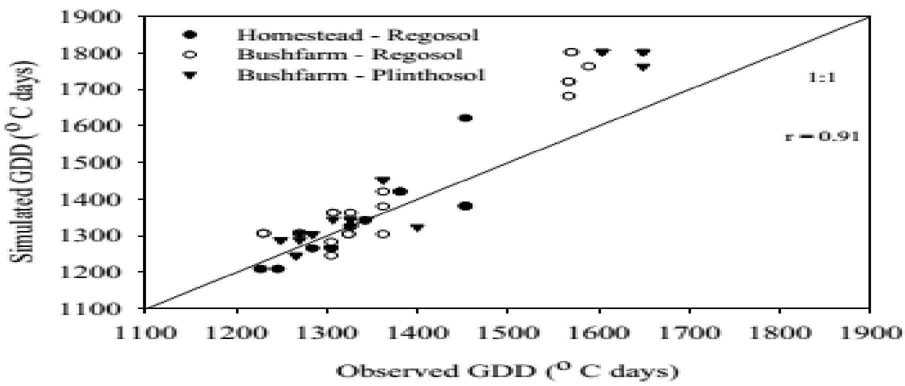

Figure 1: Comparison of observed and simulated duration of sorghum growth from emergence to flowering expressed in growing degree days (GDD), Navrongo, Ghana.

Table 1. Comparisons of predicted (PR) and observed (OB) mean days to silking under varying N rates for different maize cultivars.

	Varieties					
	S9325			TZLCOMP4C1		
N rates	PR	OB	% PD	PR	OB	% PD
$Kgha^{-1}$						
0	64	67	-4	66	69	-4
30	64	66	-3	66	67	-1
60	64	65	-2	66	64	3
90	64	63	2	66	66	0
120	64	64	0	66	66	0

Negative deviations indicate under prediction while positive deviations indicate over prediction. %PD: percentage prediction deviation, PR: Predicted, OB: Observed
Source :(kopongor, 2007)

Days to silking were delayed with increased N stress (Table1) in all the varieties tested (P0.01). This is an indication that maize development and phenology are influenced by N levels in the soil. There was a linear relationship between N rates and days to silking (Fig4.1). In most cases, the R^2 values were >0.7, indicating that N rates accounted for a high percentage in the variation of days to silking Gungula (2003). In the few cases where the R^2 values were low, other factors in the environment in the particular season might have acted to reduce the effects of N on days to silking. In the validation results, the predicted values of days to silking were significantly affected by N rates (P= 0.01), such that highest prediction error for silking date was 1 and 2 d (2 and 3% prediction error) for 90 and 120 kg N ha^{-1} (Table 1) At low N levels, there were greater differences between predicted and observed values, with the highest deviation observed from the 0 kg N ha^{-1} treatment in both the calibrated and observed results. This shows that silking is affected by N rates, but this has not been incorporated into the model. Hence, the model is not able to predict the effects of N stress on silking. The finding of Gungla (2003) corresponds with the finding of Kiniry(1991) who stated the CERES-Maize model assumes optimum N conditions in predicting maize phenology.Similar results were reported by Fosu, 2013) that days to maturity were closely predicted by the model at high N rates with low errors for most predictions (table 2). Greater deviations were however observed at low N rates. The authors stated that the CERES-Maize model can be reliably used for predicting maize phenology only under non-limiting N conditions. Thus, this indicated that is the incorporation of an N stress factor into the model is vital for more accurate phenology predictions in low-N tropical soils.

Table 2. Comparison of simulated and observed days to maturity at different N and P levels at Ejura, Ghana, 2008.

N and p level	Exp't1		Exp't2		Exp't 3		Exp't4		Over all	
Dorke	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	obs	D %
N1P1	90	93	89	94	91	95	94	96	91	95	- 4.2
N2p1	90	93	89	94	91	95	91	95	90	94	-4.4
N1P3	90	93	89	94	91	95	91	95	90	94	-4.4
N2p1	90	93	89	94	91	94	92	95	91	93	-2.1
N2P2	90	92	89	93	91	93	91	94	91	94	-3.2
N2p3	90	92	89	93	91	93	91	94	90	93	-3.2
N3p1	90	92	89	93	91	93	91	94	90	93	-3.2
N3p2	90	92	89	93	91	93	91	93	90	93	-3.2
N3p3	90	91	89	92	91	92	91	93	90	92	-2.1
N4P1	90	92	89	93	91	93	90	94	90	93	-3.2
N4P2	90	91	89	92	91	92	91	93	90	92	-2.2
N4p3	90	91	89	92	91	92	91	93	90	92	- 2.1
RMSE (days)		2.2		4.0			2.6			2.9	

Source: (Ecology and Development Series, 2013)
N.B Exp't: Experiment,RMSE: root mean square error,Sim: simulated, OB:Observed, D (%) : percent of deviation

2.2 Leaf Area Index

APSIM-Maize model simulated the maximum LAI well, with better accuracy for the Dorke maize (Fosu, 2013). Similarly Gungula *et al*., (2003) revealed that in most varieties, the number of leaves at anthesis was closely predicted by the model at higher N rates. At 0 kg ha^{-1} there were greater errors as most of the predictions were≥10% errors (≥2 leaves).This shows that the model can predict leaf appearance and subsequently leaf number more accurately at higher N rates than under high N stress conditions.

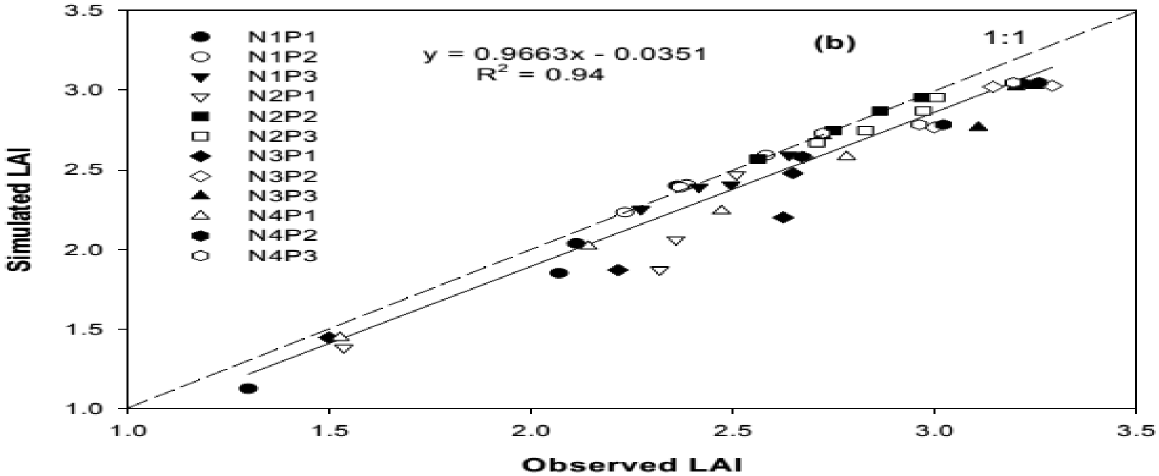

Figure. 2: Comparison of observed and simulated maximum LAI and Dorke maize cultivars at Ejura, Ghana, 2008. Indicate 0, 40, 80 and 120 kg N ha 0, 30 and 60 kg P ha^{-1}

Table 3. Comparisons of predicted (PR) and observed (OB) mean leaf number at anthesis under varying N rates for different maize cultivars

	Varieties					
	S9325			TZLCOMp3C1		
N rates	PR	OB	%PD	PR	OB	%PD
0	21	18	17	21	18	17
30	21	19	11	21	19	11
60	21	20	5	21	20	5
90	21	19	5	21	20	5
120	21	20	5	21	20	5

Source: (Gungula, 2oo3)

*Negative deviations indicate under prediction while positive deviations indicate over prediction. %PD: percentage prediction deviation, PR: Prediction OB: Observed

2.3 Grain Yield

Fosu (2013) the APSIM model simulated the trend of maize yield fairly well in the experiments of inorganic N and P fertilizer applications (Figure 4.2). Similar result was reported by Miao et al. (2006). The model explained 93 % of yield variability and performed well at non-zero N rates, with errors <10 %.

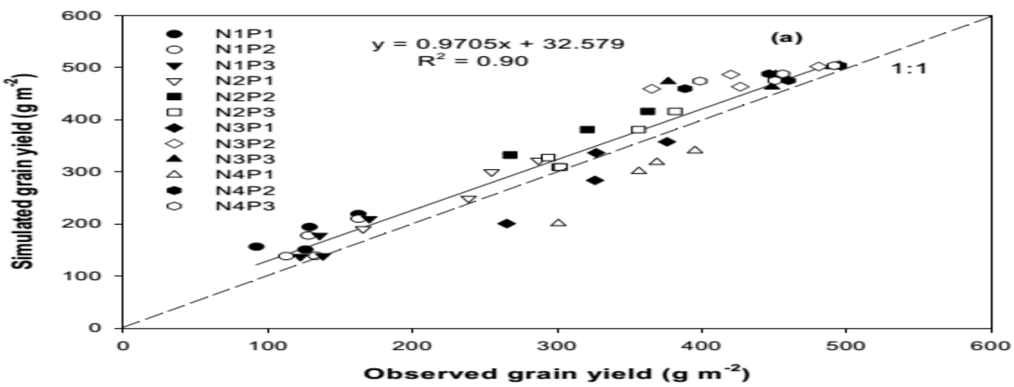

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Figure 3: Comparison of observed and simulated grain yield and Dorke maize cultivars at different levels of N and P at Ejura, Ghana, 2008.

Source :(Ecology and Development Series, 2013)

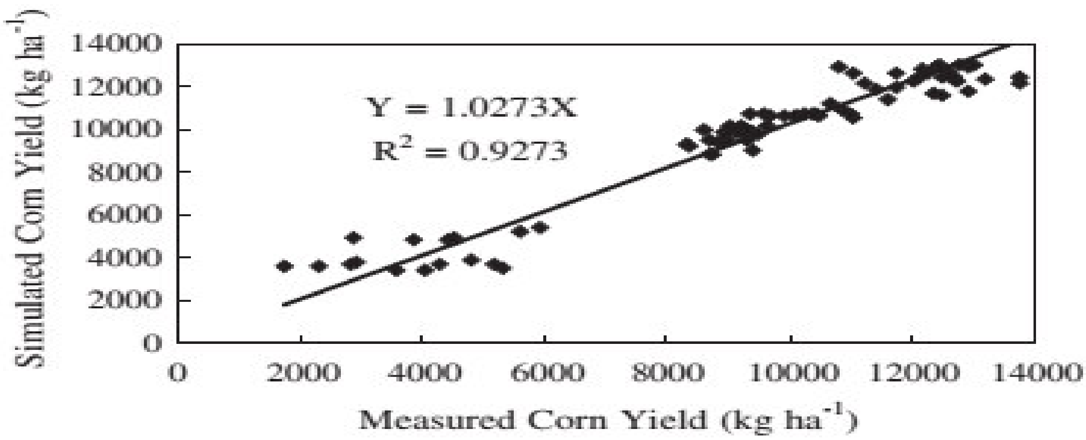

Figure 4: Simulated vs. measured corn yield across hybrids (33G26 and33J24), years (2001 and 2003), and N application rates (0–336 kg ha), And management zones.

Source :(Miao etal, 2006)

Similar results were reported by Kpongor (2007) who evaluated the application of the APSIM-Sorghum model version 4.0 to predict grain and biomass yield response of sorghum to inorganic P(0,30,60)kg/ha and N(0,40,80,120) kg/ha fertilizer in a semi-arid region of Ghana under two management systems. There was a good correlation between the observed and predicted total dry biomass.

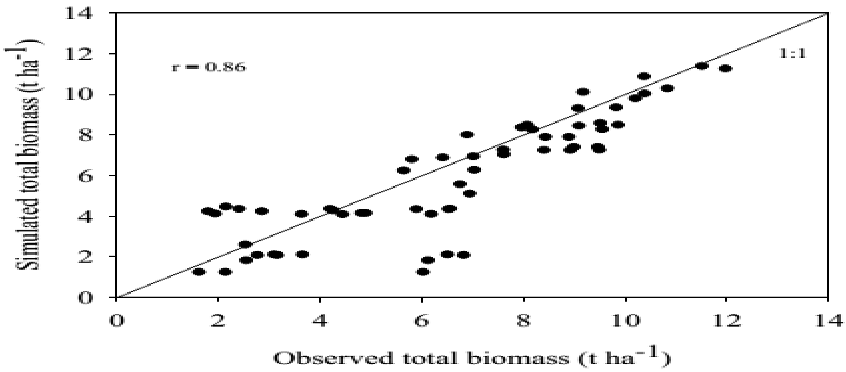

Figure 5: Comparison of mean of measured and predicted grain yield of sorghum grown in Navrongo, Ghana.

3. Conclusion

statistical tools indicated that Evaluation of the APSIM model revealed its credible performance in predicting development, Growth and yield of different crops such as sorghum, maize and wheat etc. Hence, agricultural production system simulator model (APSIM) can be used for better decision making in selection of suitable genotypes and management options for agricultural sustainability. To establish credibility for APSIM model and to recommend those for local use, careful calibration and validation are required.

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