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Assessing crop model improvements through comparison of sorghum (*sorghum bicolor* L. moench) simulation models: A case study of West African varieties

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ABSTRACT

Better defining niches for the photoperiod sensitive sorghum (*Sorghum bicolor* L. Moench) varieties of West Africa into the local cropping system might help to improve the resilience of food production in the region. In particular, crop models are key tools to assess the growth and development of such varieties against climate and soil variability. In this study, we compared the performance of three process-based crop models (APSIM, DSSAT and Samara) for prediction of diverse sorghum germplasm having widely varying photoperiod sensitivity (PPS) using detailed growth and development observations from field trials conducted in West Africa semi-arid region. Our results confirmed the capability of each selected model to reproduce growth and development for varieties of diverse sensitivities to photoperiod. Simulated phenology and morphology organs during calibration and validation were within the closet range of measured values with the evaluation of model error statistics (RMSE and R^2). With the exception of highly sensitive variety (IS15401), APSIM and Samara estimates indicate the lowest value of RMSE (<7days) against the observed values for phenology events (flowering and maturity) compared to DSSAT model. Across the varieties, there was over-estimation for simulated leaf area index (LAI) while total leaf number (TLN) fitted well with the observed values. Samara estimates were found to be the closet with the lowest RMSE values (<3 leaves for TLN and <1.0 m^2/m^2 for LAI) followed by DSSAT and APSIM respectively. Prediction of grain yield and biomass was less accurate for both calibration and validation. The predictions using APSIM were found to be closest to the observed followed by DSSAT and Samara models respectively. Based on detailed field observations, this study showed that crop models captured well the phenology and leaf development of the photoperiod sensitive (PPS) varieties of West Africa, but failed to estimate accurately partitioning of assimilates during grain filling. APSIM and SAMARA as more mechanistic crop models, have a higher sensitivity of the adjustment of key parameters, notably the specific leaf area for APSIM in low PPS varieties, while SAMARA shows a higher response to parameters changes for high PPS varieties.

1. Introducton

Sorghum (*Sorghum bicolor* L. Moench) is the fifth most important cereal crop in the world and the dietary staple of more than 500 million people in more than 30 countries (ICRISAT, 2009). Besides being a staple food for human, it serves as an important source of feed and fodder for animals particularly in semi-arid regions. In West Africa, sorghum production is primarily grown under rainfed conditions and the length of the growing period (LGP) is mainly a function of the date of the first rains (Sivakumar, 1988), which is delayed with latitude and varies widely from year-to-year. Sorghum is a short day, photoperiod sensitive crop with progress towards flow-

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ering accelerated as daylength decreases (Folliard et al., 2004). In West Africa, favourable conditions for sorghum cultivation extend from May to November corresponding with the wet season and with the majority of the growth cycle occurring under decreasing daylength, explaining why cycle duration shortens when sowing is delayed. Farmers have traditionally used photoperiod sensitive (PPS) varieties, that allows for grouped flowering at the end of the rainy season for a wide range of planting dates (Traoré et al., 2000). This feature is useful to minimize post maturity losses such as grain mold, insect and bird damage, which typically affect early maturing varieties. Furthermore this photoperiod characteristic help to avoid incomplete grain filling associated with late maturation and late season soil water shortage (Vaksmann et al., 1996). The extensive genetic and phenotypic diversity of sorghum (Clerget et al., 2008; Murray et al., 2008) and its adaptation to harsh climatic and cropping conditions (Nasidi et al., 2010) offers the opportunity to develop multi-purpose plants providing food, fodder or fuel for a multitude of environmental conditions, including the semi-arid environments found in West Africa.

Traditionally, field trials are used to evaluate the performance of the different planting material under a range of climate conditions. However, field trials are time consuming and financially demanding and often difficult to extrapolate to other sites and seasons. Hence, crop-climate models can help with the interpretation of experimental data and, after careful calibration and validation, can be used in a prospective way in conjunction with field data to draw recommendations for improved climate-induced risk adaptation strategies. For sorghum, there are crop models implemented in simulation frameworks such as DSSAT – (Jones et al., 2003), APSIM – (Holzworth et al., 2014) or Samara (Dingkuhn et al., 2011). These models differ in their description of certain plant physiological and soil related processes and consequently in their outputs. Thus, comparing different modelling approaches can help reveal the uncertainties relating to crop growth and yield predictions (Palosuoa et al., 2011) including those which relate to model structure, which is the most difficult source of uncertainty to quantify (Chatfield, 1995). Model comparison will also help to identify those parts of the model that produce systematic errors and require improvements (Adam et al., 2012). Recently, there is a growing body of studies comparing models (Asseng et al., 2013; Bassu et al., 2014, Li et al., 2015). Although, the three models compared in this study have been widely applied in Africa and elsewhere, little calibration and validation exists in literature for the diverse PPS sorghum germplasm used by farmers across West Africa. Considering the growing importance of crop simulation for assessing the impacts of current and future climate, improving the ability of such models to simulate more accurately the response of crops to environmental conditions is an important step in making realistic assessment of the impacts of climate and other management practices on crop performance Therefore, the objectives of this study are to; (i) calibrate and validate sorghum models implemented in the model frameworks of APSIM, DSSAT and Samara for the PPS varieties using detailed field trial data and (ii) identify major strengths and weaknesses among the models to give recommendations for improvement.

2. Materials and methods

Extensive literature is available describing APSIM (Holzworth et al., 2014), DSSAT (Jones et al., 2003; White et al., 2015) and SAMARA (Dingkuhn et al., 2011). The following section highlights only the main differences in model design related to this study.

2.1. Model design differences

2.1.1. Phenology

the main difference between APSIM-DSSAT vs. SAMARA resides in the way photoperiod is taken into account. For APSIM and DDSAT it is a linear relation expressed with the critical PP and the slope of the curve, to extent the thermal time to flag leaf initiation. SAMARA implements the model 'impatience' (Dingkuhn et al., 2008) using the concept of threshold-lowering that vary with plant age. It implements decreasing day length requirements during the photoperiod sensitive phase. As the photoperiod sensitive phase progresses, the requirement of day length to trigger flowering is decreased.

2.1.2. Leaf development

though all models used the concept of phyllochron and specific leaf area, Samara adds to this by a more detailed description of plant morphology, including size and time of appearance of organ cohorts (leaves, tillers, internodes) and their senescence. It does not simulate individual organs but bases crop growth and development on the definition of the potential organ size adjusted according to source and sink relations.

2.1.3. Biomass production

is driven by intercepted light in all models. However, SAMARA calculates gross primary production first, and then steps down to potential net primary production by estimating daily respiration demand. APSIM and DSSAT use a simple RUE concept which takes respiration losses implicitly into account. In APSIM, RUE is based on global radiation while DSSAT on Photosynthetic Active Radiation (PAR). In APSIM on a daily basis, two estimates of the daily biomass production are calculated, one limited by available water for transpiration, and the other limited by radiation. The minimum of these two estimates is the actual biomass production for the day. The main differences between APSIM and DSSAT lie on the biomass partitioning. DSSAT available assimilates are distributed to stem, leaf, root and grain (pod) according to the development stage, with priorities to the different organs according to the development stage. For APSIM the partitioning is directly linked to thermal time through partitioning coefficients. Samara partitioning of biomass to organs is based on source sink relation. Since aggregate supply can be greater or smaller than aggregate demand, growth can be source or sink limited. An inter-organ competition factor controls organs size, and feedbacks on growth and senescence processes.

2.2. Calibration data

2.2.1. Site

The experimental data used for model calibration were collected from an on-station field trial during 2013 growing season at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Bamako, Mali Republic (12.52^{0}N and −8.07^{0}W). Daily climatic condition was monitored during 2013 growing season using automatic weather station (AWS) installed within the station (<500 m to the experimental site). The data observed include rainfall, solar radiation, maximum and minimum temperature, relative humidity, and wind speed and direction. Long-term (1970–2010) daily climatic records were obtained to establish comparison with the cropping year at the station. The record shows that 2013 total rainfall (1190 mm) was a little above the long-term average (1970–2010) and classified as a wet year. The analysis of monthly rainfall at the station indicates a distinct mono-modal pattern with the peak amount in August and varied between May and October (Fig. 1). Over 50% of the total rainfall was received in the month of July and August, while both minimum and maximum temperatures decrease uniformly throughout the growing season.

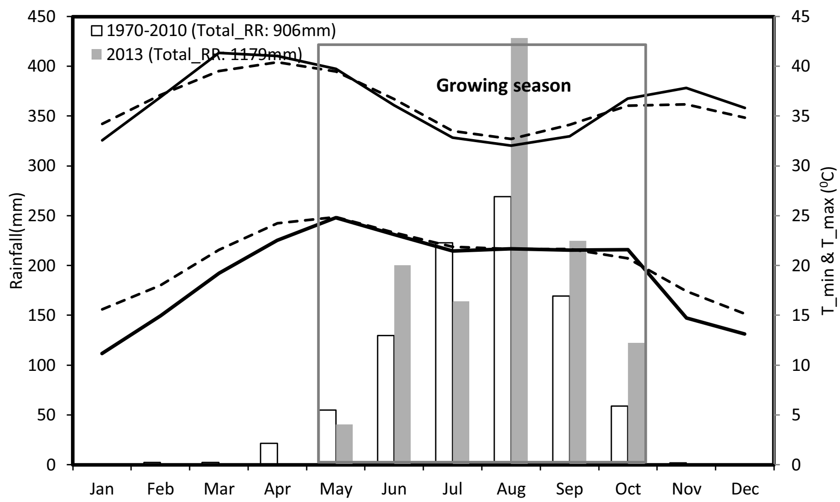

Fig. 1. Comparison of the long-term (1970–2010) monthly rainfall, minimum air temperature and maximum air temperature and cropping year 2013.

Table 1
Comparison of growing season climatological indices for long- term (1970–2010) period and cropping year (2013) which include onset date of growing season (OGS), cessation date of growing season (CGP), Length of growing season (LGP), number of rainy days (NRD), total growing season rainfall (GSR), average minimum temperature(T_min) and maximum temperature (T_max), average solar radiation (Srad),Day length (DL minimum and maximum) at the study site.

Parameters	1970–2010	St.dev	2013
OGS	02-Jun	7	09-Jun
CGS	20-Oct	9	05-Nov
LGP (days)	141	19	149
NRD (days)	60	7	64
GSR (mm)	906.7	46.7	1179
Tmin (°C)	21.6	2.0	21.3
T_max (°C)	35.5	3.2	35.5
Srad (MJ/m^2)	24.7	2.2	18.7
DL_min (Hr)			11.26
DL_max (Hr)			13.15

NB: St.dev means standard deviation.

To further define the climatology of the station/area (Table 1), the onset date of growing season was computed after Omotosho et al. (2000), while cessation of rainy season was computed after Traoré et al. (2000). Average monthly air temperature varies from 26.2 °C to 32.3 °C; average solar radiation observed was 18.7 MJ/m^2/day. Also, growing season astronomical day length varies from 11 h 15 min to 12 h 45 min and civil daylength from 12 h 10 min to 13 h 38 min.

The soil of the experimental plot is a well-drained, sandy loam (55% sand, 35% silt, and 20% clay), soil organic carbon content was low (0.24%) and associated with this, total N was measured as 225 mg/kg. High available phosphorus (Bray-I) of 94.5 mg/kg can be traced to a long history of P fertilizer use on the station, with a 2.47 cmol/kg CEC and a pH water of 5.3. Parameters in APSIM related to water dynamics such as runoff curve number and evaporation terms were defined as Probert et al. (1998) and Hoffmann et al. (2016).

2.2.2. Experiment

The experimental protocol was designed to observe crop phenology, morphology and above ground dry matter dynamics, yield and yield components under non-limited water and nutrient supply. The experiment had variety (four) and sowing date (three) as treatments in a randomized complete block design (RCBD) with four replications. The varieties CSM63E, CSM335, Fadda and IS15401 were selected in this study for their contrasting phenology and morphology as well as their responses to photoperiod. The duration of their crop growing cycle varies from early to late maturity and characterized as Guinea landrace plant group (Harlan and de Wet, 1972). Their geographical origin emerged from both Mali and Burkina Faso. Variety CSM63E-locally named “Jakumbe” is early (85–100days) maturing of intermediate height type, producing relatively low biomass, and having low PPS. Variety CSM335 otherwise called “Tieble” is a traditional local variety with medium physiological maturity ranging from 105 to 135 days, intermediate plant height, high biomass, low grain and moderate PPS. Variety Fadda is an improved hybrid, medium maturity days (100–135), high-yielding dual purposes (biomass and grain), intermediate plant height and also moderate PPS. IS15401 also called Soumalemba is a late maturity variety varied from 100 to 155 days, improved traditional tall variety, high-yielding dual purposes (biomass and grain), and high PPS.

The varieties were sown on June 14 representing early planting date (PD_1), July 9 representing medium planting date (PD_2) and August 5 representing late planting date (PD_3) respectively. These sowing dates covered the widest range of farmer’s sowing window for sorghum in the Sudano-Sahelian zone. Plant population was 67,000 hills/ha (0.75 m between rows and 0.20 m between hills), which was achieved by thinning to 1plant/hill, 15 days after planting (DAP). The crop was fertilized using 100 kg/ha of di-ammonium phosphate at sowing and 50 kg/ha of Urea (46%N) at 40 days after planting. Insecticides were used according to local recommendations and weeding was done manually. Each plot was 8 by 5.25 m and contained seven rows. The outer two rows were excluded from sampling in order to prevent border effect on the measurements.

Leaf area index (LAI) and above-ground biomass (separated into leaf, stem and panicle) were sampled within three rows at 1 m^2 per sampling time, every 15 days interval, beginning from 25DAP for PD_1, 27 DAP for PD_2 and 30 DAP for PD_3 until grain filling stage. The samples were oven dried at 72 °C for 72 h. At maturity, harvest was done on 4 m^2 area within each plot for the determination of final biomass and grain yield. The fresh weights of these samples were taken and thereafter sub-sample of 20% of the total harvested leaves and stems together with the total harvested panicles grain were oven-dried at 72 °C for 72 h. Phenology and leaf development were recorded as emergence, 50% flag leaf date, 50% flowering and maturity dates, total leaf number (TLN).

2.2.3. Calculation of derived parameters

Additional parameters for calibration were calculated as follows:

Daily growing degree-days (GDD, °C day) were calculated as (Streck, 2002):

$$GDD = (T_{mean} - T_b)/day \quad (1)$$

Where T_b is the base temperature, assumed 11 °C as found in most literature for sorghum (Folliard et al., 2004; Clerget et al., 2004) and T_{mean} is the daily mean temperature. The accumulated growing degree-days from planting (AGDD) was calculated by adding up the GDD values, i.e. AGDD = Σ GDD.

Phyllochron was calculated for each variety on the late planting date (PD_3) because the late sowing had the least effect of photoperiod on the appeared leaf. Phyllochron value was derived from the linear regression between the number of leaves produced and the thermal time in each sampled period. The thermal time (°C) necessary for the appearance of a leaf is equal to 1/b, where b is the slope of the regression.

The coefficient of light extinction was computed from measurements made with a LAI-2000 plant canopy analyzer. The fraction of radiation intercepted was calculated by multiplying the instrument output DIFN (Diffuse Not Intercepted) by a value of 0.94 assuming only 6% of visible light reflected by green canopy (Dingkuhn et al., 1999). Light extinction coefficient K_{df} is then calculated inverting Lambert-Beer's law as:

$$K_{df} = -\ln(0.94PAR_{transmitted}) * LAI^{-1} \quad (2)$$

Representative values of K_{df} for the four varieties at different development stages were in both cases derived by regressing of $\ln(PAR_{transmitted})$vs. LAI (Dingkuhn et al., 1999). Radiation Use Efficiency (RUE) was calculated as the slope of the linear regression between values of above ground biomass and cumulated APAR – Absorbed photosynthetically active radiation (calculated using Eq. (3)) (Sinclair and Muchow, 1999). The Photosynthetic Active Radiation (PAR) was calculated from daily solar radiation (SR; obtained from weather station records during growing period), assuming that PAR comprised 45% of SR (Howell et al., 1983). Meanwhile, daily *f*APAR time series was estimated by Lambert-Beer formula using the k values in Lambert- Beer's law

$$APAR_d = PAR_d \times fAPAR_d \quad (3)$$

In the equation the subscript letter d refers to the daily value and $fAPAR_d = 1\text{-}\exp^{-k^*LAI}$.

2.3. Validation data

For model validation we used the results of field experiments carried out between 2000 and 2008 for two locations (Bamako and Cinzana, Mali). The details of these experiments have been reported by Clerget et al. (2004, 2007, 2008). The agronomic practices and relevant observations used for this study are presented in Table 2.

2.4. Calibration and evaluation of the models

First we calibrated the models by matching observed results from the 2013 field experiment with model outputs. Within this process we used the derived parameter for parameterization of the models. The calibration procedure followed four phases which include phenology, morphology, above-ground biomass and grain yield. Thereafter, we used the additional data set to validate the models independently. For calibration and validation, we assessed the goodness-of-fit between model simulated and observed values of yield and above-ground biomass as well as phenological events. Model-estimated (simulated) were compared with observed using the following listed statistics;

1. Root mean square error (RMSE):

$$RMSE = [n^{-1}\Sigma(\text{simulated}-\text{observed})^2]^{0.5} \quad (4)$$

2. The normalized root mean square error (NRMSE) express in percent, calculated according to Loague and Green (1991) with Eq. (4)

$$NRMSE = [n^{-1}\Sigma(\text{simulated}-\text{observed})^2]^{0.5} X \frac{100}{M} \quad (5)$$

M is the mean of the observed variable. NRMSE gives a measure (%) of the relative difference of simulated versus observed data. The simulation is considered excellent with a NRMSE less than 10%, good if the NRMSE is greater than 10% and less than 20%, fair if the NRMSE is greater than 20% and less than 30% and poor if the NRMSE is greater than 30% (Jamieson et al., 1991).

3. Linear regression (1:1) plot was taken as an indicator to inform whether the models under- or overestimated measured yields, i.e. the direction and magnitude of bias.

4. Additionally, for comparison, the traditional R^2 regression statistic (least-squares coefficient of determination) was calculated though it does not take into account model bias, which is central when assessing the performance of simulation models.

2.4.1. Sensitivity analysis

A sensitivity analysis was carried out on the three models used (APSIM, DSSAT and Samara) from the data used for calibration. Five (5) model parameters were changed by adding or subtracting 10% to the calibrated values and the effect on the flowering date, maximum LAI, final above ground biomass (AGB) and grain yield were calculated. Similar to Zuidema et al. (2005), such an analysis will identify parameters that have a strong influence on modelled output, in this case sorghum production, and therefore need to be estimated accurately.

3. Results

3.1. Calibration

3.1.1. Photoperiod sensitivity

Estimated model-fitted for crop developmental phases (Fig. 2) showed how the varieties responded to photoperiod between the emergency and flag leaf initiation (E-FI) stage. These ranged from low PPS for CSM63E to high PPS for IS15401. The results show a decrease in thermal time (E-FL) with the late PD_3 observed reducing daylength hour, which signified the level of PPS across variety. CSM63E indicated as low sensitive to photoperiod variety with the lowest thermal time E-FI across the sowing dates ranging from 103 to 57 °C days. Also, CSM335 and Fadda are moderately sensitive to photoperiod varieties with the observed thermal time E-FI at a medium ranged between 330 and 117 °C days while the highly sensitive variety (IS15401) observed the longest thermal time E-FI ranging from 464 to 196 °C days.

All models reproduced the photoperiod sensitivity of the varieties satisfactorily. Table 3 presents the final calibrated genetics coefficients for variety's sensitive to photoperiod (PPS). In APSIM, the critical photoperiod hours 1&2 were the same for all varieties; the values were adjusted to 12.8 h for photoperiod_crit_1 and 13.2 h for photoperiod_crit_2. The calibrated photoperiod slope varied between 150 °C/H (CSM63E) and 900 °C/H (IS15401). In DSSAT the photoperiod hour ranging from 12.6H (CSM335 and IS15401) to 13.2H for Fadda with lowest PPS coefficient (P2) for CSM63E (50 °C day) and highest value for IS15401 (450 °C days) resulted in the best match with observed phenology. The PPS calibration in Samara followed a different modelling approach by using a dimensionless value ranging from 0.3 for highly sensitive varieties to 0.95 for insensitive varieties (Dingkuhn et al., 2008). The low PPS variety (CSM63E) was calibrated with coefficient value of 0.85 while high PPS variety (IS15401) obtained a coefficient value of 0.5.In terms of critical photoperiod hours (lower and upper limits).

Table 2
Summary of experimental data usedfor model validation.

Cultivar	Site/Year	Sowing date	Planting density (plants/ha)	Management	Observations
CSM63E	Samanko; Cinzana/2007	Samanko: 16 Jul & 01-Aug. Cinzana:18-Jul & 04-Aug.	67000, 133000, 200000 & 267000	Pre-sowing–100 kg/ha of DAP + 100 kg/ha CaSO4 (Gypsum fertilizer) + 100 kg/ha KCL; 100 kg/ha Urea + 100 kg/ha DAP (18-466-0) at 30DAP and 100 kg/ha Urea at 50DAP.	50% Flowering & maturity dates.Total biomass, grain yield & total leaf number
	Cinzana/2008	12-Jul and 01-Aug.	67000, 133000, 200000 & 267000	Same as above	Same as above
CSM335	Samanko/2005, 2006, 2007 & 2008	15-Jun 27-Jun and 13-Jul 05-Jun and 03-Jul 08-Jul	67000, 133000 & 200000	Pre-sowing–100 kg/ha CaSO4 + 100 kg/ha DAP (18-46-0) + 100 kg/ha KCL, 100 kg/ha Urea +100 kg/ha DAP (18-46-0) at 30DAP and 100 kg/ha Urea at 50DAP.	50% Flowering & maturity dates. Total biomass, grain yield & total leaf number
	Cinzana/2008:	12-Jul	67000, 133000 & 200000	Same as above	50% Flowering & maturity dates. Total biomass & grain yield.
Fadda	Samanko, Cinzana/2008	Samanko:08-Jul, Cinzana: 12-Jul	67000, 133000 & 200000	Same as above	Same as above
IS15401	Samanko/2000, 2008	05-Jul and 11-Aug 30-Jun	67000	Pre-sowing–100 kg/ha CaSO4 + 100 kg/ha DAP (18-46-0) + 100 kg/ha KCL, 100 kg/ha Urea + 100 kg/ha DAP (18-46-0) at 30DAP and 100 kg/ha Urea at 50DAP.	50% Flowering & maturity dates. Total biomass, grain yield&Total leaf number.

Note: Samanko- Mali (12.52^{00}N; $-8.07\ ^{00}$W; and Cinzana (13.25^{00}N; -5.97^{00}W); Soil/climate: Sandy loam/daily rainfall, minimum and maximum temperatures (T-max & T-min), Solar Radiation (Srad), Relative humidity (RH).
Source: Clerget et al. (2008).

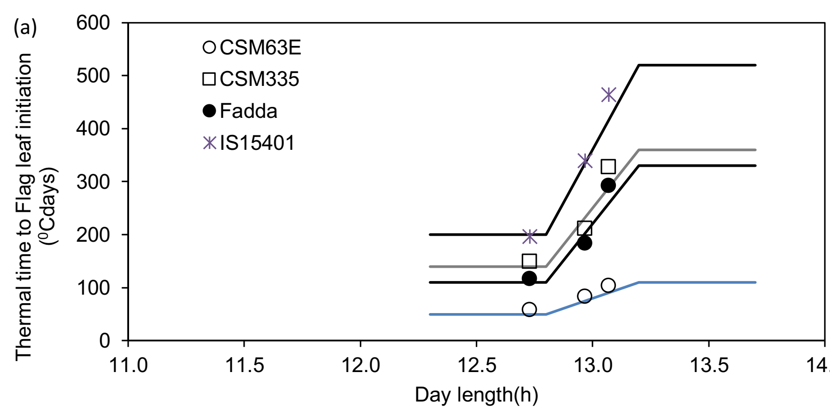

Fig. 2. Estimated model-fitted crop growth stages between emergency and flag leaf initiation (E-FI) indicating cultivar's response to photoperiod sensitivity (PPS).

Table 3
Cultivar's genetics coefficients for photoperiod sensitivity phase (PPSen) calibrated using observed Phenologyand day length range over three planting dates (PD_1–PD_3) in DSSAT-CERES-Sorghum, APSIM and SAMARA sorghum modules.

Model	Parameters	Unit	CSM63E	CSM335	Fadda	IS15401
APSIM	Day length to inhibit flowering (photoperiod_crit1)	H	12.8	12.8	12.8	12.8
	Day length to insensitive photoperiod_crit2)	H	13.2	13.2	13.2	13.2
	Photoperiod slope	°C/H	150	600	600	900
DSSAT	P2 – End of juvenile to end of panicle initiation (PI) (day length and photoperiod sensitivity coefficient)	°C day	50	142	102	450
	P2O – Critical photoperiod or the longest day length at which development occurs at a maximum rate.	H	12.8	12.6	13.2	12.6
	P2R – Extent to which phasic development leading to panicle initiation (expressed in degree days) is delayed for each hour increase in photoperiod above P2O	°C day	150	500	600	550
Samara	Photoperiod-sensitivity phase (PPSen)		0.85	0.6	0.65	0.50
	Lower day length limit of PP response(SeuilPP)	H	11	11	11	11
	Upper day length limit of PP response(PPCrit)	H	13.5	13.5	13.5	13.5

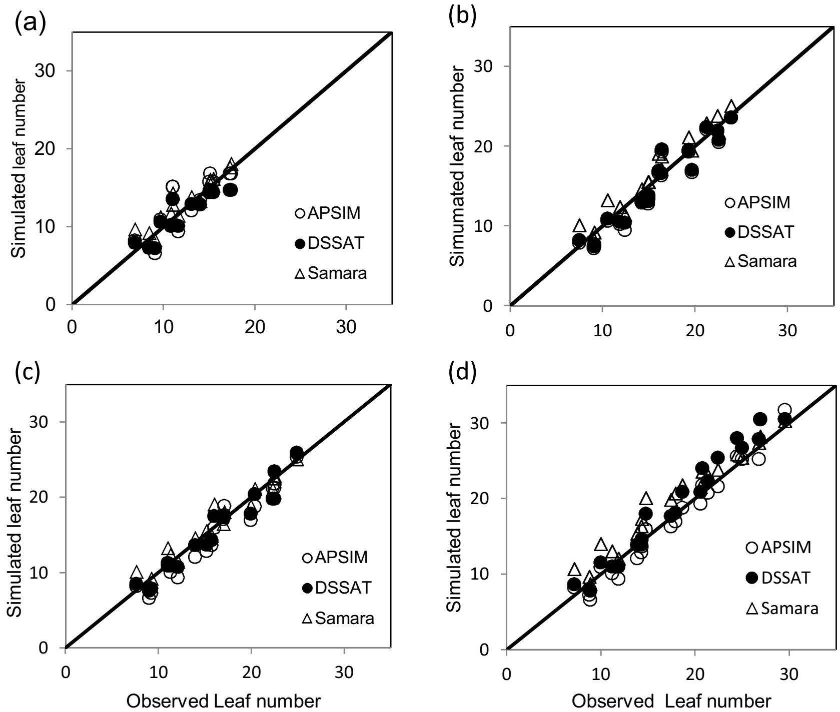

Fig. 3. Model-simulated leaf number (LN) against the observed LN during calibration across the three planting dates. (a) CSM63E: APSIM – RMSE = 2.1 leaves, R^2 = 0.66; DSSAT- RMSE = 1.7 leaves, R^2 = 0.71; Samara – RMSE = 1.6 leaves, R^2 = 0.84. (b) CSM335: APSIM – RMSE = 1.7 leaves, R^2 = 0.92; DSSAT- RMSE = 1.5 leaves, R^2 = 0.93; Samara – RMSE = 1.5 leaves. (c) Fadda: APSIM – RMSE = 1.7 leaves, R^2 = 0.95; DSSAT- RMSE = 1.4 leaves, R^2 = 0.94; Samara – RMSE = 1.3 leaves, R^2 = 0.95. (d) IS15401: APSIM – RMSE = 1.5 leaves, R^2 = 0.97; DSSAT- RMSE = 1.8 leaves, R^2 = 0.97; Samara – RMSE = 2.2 leaves, R^2 = 0.96.

3.1.2. Development phases

Although the calibrated genetics coefficients for the crop development phases were very similar, naming conventions between models are different (Table 4). The models were calibrated for about six or seven coefficients that defined their growth stages between emergence and maturity. In APSIM, CSM63E obtained the lowest value (190 °C day) from emergence to end of the juvenile stage phase followed by medium varieties (Fadda and CSM335) while IS15401 the late maturity obtained the highest value of 220 °C day. End of juvenile stage to panicle initiation varied from 50 to 180 °C day across the varieties, the least value (50 °C day) was obtained by CSM63E while the highest value (180 °C day) was obtained from late maturity variety (IS15401). All the varieties observed similar characteristics from flag leaf to flowering and also from flowering to start of grain, the calibrated values are 170 and 80 °C day. DSSAT model coefficients parameter also varied among the varieties with the early maturity variety CSM63E having the lowest value (190 °C day) indicated as P1 (thermal time from seedling emergence to the end of the juvenile phase) while the late maturity variety IS15401 had the highest value of 550 °C day. P2 indicates as end of the juvenile phase to panicle initiation, the obtained values ranged between 50 °C day (CSM63E) and 450 °C day (IS15401). Also, varieties expressed similar characteristics, thermal time from end of panicle initiation to anthesis (PANTH) except for late variety (IS15401) that differs with calibrated value of 640.5 °C day.Thevaluesof P3 (thermal time from the end of flag leaf expansion to anthesis) and P5 (thermal time from beginning of the grain-filling to physiological maturity) varied between varieties. The calibrated values ranged from 170.5 to 300.5 °C day for P3 and 400 to 480 °C day for P5.

For Samara model, only the basic vegetative phase (BVP) differed among the varieties, the calibrated values ranged from 260 °C day for CSM63E to 450 °C day for IS15401. Maturation phase #1 (SdjMatu1) and maturation phase #2 (SdjMatu2) did not vary much

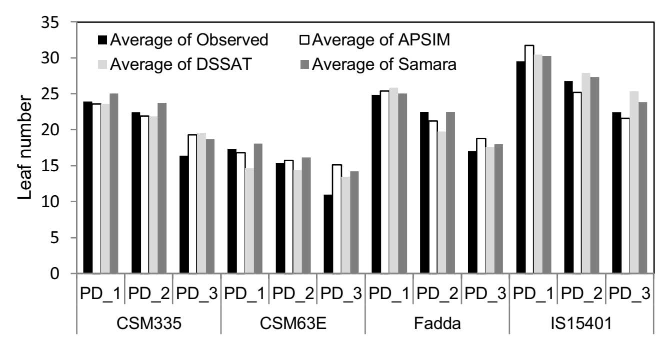

Fig. 4. Comparison between the model-simulated and observed for leaf number over the three sowing dates. The significance difference of mean between the models and observed at 5% level of probability ($P < 0.05$) are as follows; 0.24 (CSM63E); 0.37 (CSM335); 0.77 (Fadda) and 0.32 (IS15401) respectively.

among the varieties. The thermal time from end of the juvenile phase to panicle initiation (PSP) is defined according to the photoperiod sensitivity, as explained in Section 3.1.1. Also, duration from flowering to end of grain filling (SdjMatu_1) ranged from 350 °C day to 400 °C day and SdjMatu_2 obtained a fixed value of 40 °C day across varieties. Furthermore, the simulated phenology (flowering and maturity) were observed to be in good agreement with the field-observed values (Table 5). The models captured the strong effect of planting date on growth development to a wide extent. Across the varieties, APSIM and Samara simulations showed the lowest value of RMSE against the observed values for flowering and maturity compared to DSSAT. Strengthening this result, there were no significant differences of mean between the model-simulated and observed for most of the varieties except for CSM335 ($P < 0.02$ for flowering) and also Fadda and IS15401 ($P < 0.03$ for maturity). This demonstrates the ability of the models to capture the photoperiod sensitivity of the different varieties.

Table 4
Cultivar's genetics coefficients for crop growthcalibrated from observed Phenology over three planting dates (PD_1–PD_3) in DSSAT-CERES-Sorghum, APSIM and SAMARA sorghum modules.

Model	Parameters	units	CSM63E	CSM335	Fadda	IS15401
APSIM	Thermal time — emergence to end of juvenile	°C day	190	220	200	200
	Thermal time — end of juvenile to panicleinitiation	°C day	50	140	120	180
	Photoperiod slope	°C day	150	600	600	900
	Thermal time — flag leaf to flowering	°C day	170	170	170	170
	Thermal time — flowering to start of grain	°C day	80	80	80	80
	thermal time — flowering to Maturity	°C day	530	420	550	461
	Thermal time — SUM		1170	1630	1720	1991
DSSAT	P2O – Critical photoperiod or the longest day length at which development occurs at a maximum rate.	H	12.8	12.6	13.2	12.6
	P1 – seedling emergence to end of juvenile phase	°C day	190	450	420	550
	P2 –End of juvenile to end of panicle initiation (PI) (day length and photoperiod sensitivity coefficient)	°C day	50	142	102	450
	PANTH – Thermal time from the end of tassel initiation to anthesis	°C day	617.5	617.5	617.5	640.5
	P3 –Thermal time from end of flag leaf expansion to an thesis	°C day	170.5	202.5	152.5	300.5
	P4 –Thermal time from anthesis to beginning grain filling	°C day	81.5	81.5	81.5	85.5
	P5 – Thermal time from beginning of grain filling to physiological maturity	°C day	400	440	500	480
	Thermal time— SUM	°C day	1509.5	1933.5	1873.5	2506.5
Samara	Germination phase (SdjLevee)	°C day	50	50	50	50
	Basic vegetative phase (BVP)	°C day	260	350	350	450
	Photoperiod-sensitive phase (PPSen)	°C day	0.85	0.6	0.65	0.52
	Reproductive Phase (SdjRPR)	°C day	400	400	400	400
	Maturation phase #1 (SdjMatu1)	°C day	350	380	380	400
	Maturation phase #2 (SdjMatu2)	°C day	40	40	40	40
	Thermal time— SUM	°C day	1100	1220	1220	1340
Observed	Thermal time – emergence to maturity (PD_1 – PD_3)	°C day	1526	1951	1902	2209

Table 5
The effect of sorghum varieties photoperiod sensitivity on the simulated phenology (duration to flowering and Maturity) over three planting dates. The bracket () indicates the RMSE between the models and observed for each variety.

	Flowering DAP					Maturity DAP			
Cultivar	Sowing	Observed	APSIM	DSSAT	Samara	Observed	APSIM	DSSAT	Samara
CSM 63E (Low Ppsen)	PD_1	67	67	68	68	98	97	99	101
	PD_2	63	63	66	62	92	93	95	95
	PD_3	59	61	61	56	85	90	89	90
	Mean (RMSE)	63	64 (1.2)	63 (2.2)	62 (1.9)	92	93 (3)	94 (3)	95 (4)
	P < 0.05	0.51				0.26			
CSM 335 (Local & Medium Ppsen)	PD_1	105	106	105	100	133	129	134	133
	PD_2	85	90	94	86	111	114	126	120
	PD_3	76	83	84	73	105	107	120	110
	Mean (RMSE)	89	93 (5)	94 (7)	86 (3)	116	117 (3)	127 (12)	121 (6)
	P < 0.05	0.02				0.06			
Fadda (Hybrid & Medium Ppsen)	PD_1	99	100	102	96	130	130	136	129
	PD_2	80	84	82	82	110	115	116	115
	PD_3	70	76	74	69	100	107	113	105
	Mean (RMSE)	83	87 (4)	86 (3)	82 (2)	113	117 (5)	122 (9)	116 (4)
	P < 0.05	0.05				0.03			
IS15401 (High Ppsen)	PD_1	130	125	120	116	155	151	156	153
	PD_2	108	100	112	99	134	126	145	137
	PD_3	83	87	106	84	100	113	117	126
	Mean (RMSE)	107	104 (6)	113 (14)	100 (10)	130	130 (9)	139 (12)	139 (15)
	P < 0.05	0.26				0.03			

3.1.3. *Leaf appearance rate and light interception*

As displayed in Table 6, APSIM variety's genetics coefficients for leaf appearance rate followed two steps i.e. leaf appearance to develop most leaf ligule (leaf_app_rate_1) and last leaf ligule (leaf_app_rate_2). The calibrated values (53 °C d/leaf and 26.5 °C d/leaf) were the same for all the varieties. These values justified the increase in the leaf number (>20) per plant for most of the varieties; it also prevent over-simulation of TLN against the observed values. DSSAT and Samara followed a similar pattern for all the varieties; both models expressed the interval in thermal time between successive leaf tip appearances (degree days) as PHINT; corresponding to the phyllochron interval. DSSAT calibrated values varied from 55 to 60 °C d/leaf while Samara varied from 38 to 40 °C d/leaf. The calibrated value was the same for CSM63E, CSM335 and Fadda with a value of 60 °C d/leaf in DSSAT and of 40 °C d/leaf in Samara. IS15401 indicates slightly lower value of 55 °C d/leaf for DSSAT and 38 °C d/leaf for Samara. This value justified the longer thermal time of vegetative phase resulting to more leaf produced by the variety. Although, none of the models reproduced the estimated phyllochron values for PD_3 that had limited effect of photoperiod, the simulated leaf number showed a close match with observed values for all the varieties with lowest error statistics estimated (Fig. 3). The RMSE and R^2 ranging from 1.3 to 2.2 leaves and 0.66 to 0.97 for the simulated leaf number of all the varieties and models. Samara and DSSAT simulations showed to be the most accurate for most varieties while APSIM performance was the best for IS15401 as indicated by the estimates of RMSE and R^2. Furthermore, the models captured the differences in observed leaf number relative

Table 6
Cultivars genetics coefficients for the leaf appearance rate (Phyllochron), light extinction coefficient (K_{df}), radiation use efficiency (RUE) and partitioning of yield formation directly calibrated from both observed and measured data in the DSSAT-CERES, APSIM and Samara sorghum modules respectively.

			Units	CSM63E	CSM335	Fadda	IS15401
Leaf appearanceand light interception	APSIM	Leaf appearance rate (leaf_app_rate_1)	°C d/leaf	53.0	53.0	53.0	53.0
		Leaf appearance rate (leaf_app_rate_2)	°C d/leaf	26.5	26.5	26.5	26.5
	DSSAT	PHINT – Degree days required for a leaf tip to emerge	°C d/leaf	60	60	60	55
	Samara	Phyllochron	°C d/leaf	40	40	40	38
	Observed	Phyllochron estimated	°C d/leaf	56.3	43.5	41.3	48.6
	APSIM	Light extinction coefficient (K_{df})		0.7; 0.4; 0.4	0.7; 0.4; 0.4	0.7; 0.4; 0.4	0.7; 0.4; 0.4
	DSSAT	Light extinction coefficient (K_{df})		0.85	0.85	0.85	0.85
	Samara	Light extinction coefficient (K_{df})		0.80	0.80	0.55	0.80
		Inter-node Length Maximum (mm)		280	450	450	500
		Leaf Length Maximum (mm)		950	1000	1000	950
	Observed	Average estimated (PD_1 – PD_3)		0.83	0.83	0.82	0.80
Biomass production	APSIM	Radiation use efficiency (RUE)	g/MJ	1.25	1.75	1.85	1.75
	DSSAT	Radiation use efficiency (RUE)	g/MJ	3.80	3.80	5.2	3.80
	Samara	T – Conversion signifies RUE	g/MJ	4.50	5.00	6.5	5.20
	Observed	Average estimated (PD_1 – PD_3)	g/MJ	3.3	5.0	6.9	5.8
Biomass partitioning	APSIM	K- Grain number determination	g/grain	0.0018	0.00083	0.0088	0.00183
		Maximum grain filling(MaxGFrate)	g	0.050	0.019	0.033	0.05
	DSSAT	G1 – Scaler for relative leaf size	fraction	40	0.8	4.5	4.5
		G2- Scaler for partitioning of assimilates to the panicle (head).	fraction	0.5	1.0	2.5	2.5
	Samara	PoidsSec Grain (1000-grain weight)	g	0.021	0.028	0.028	0.028
		Panicle Structure MassMax	g	3.0	3.0	3.5	3.5
		Coefficient of Panicle SinkPopulation	fraction	6.5	10.0	7.5	10.0
		Coefficient of PanicleMass	none	0.17	0.15	0.3	0.18
		Tillers ability	fraction	0.02	0.05	0.06	0.05
		Coefficient LeafDeath	fraction	0.2	0.2	0.2	0.02

to the sowing dates (Fig. 4). There was no significant difference of means ($P < 0.05$) between the mode-simulated and observed values. Across planting date, the highest TLN was obtained at early (PD_1) which was significantly higher than medium (PD_2) and both were significantly higher than TLN at late (PD_3). Due to shortening of the vegetative phase, late (PD_3) observed a reduction of about seven (7) leaves compared to early (PD_1) resulting from variety's response to variation of sowing date. This result indicated that the end of vegetative phase could be largely dependent on temperature and variation in planting date.

The simulated LAI for the varieties show over-estimation against the observed LAI with the high values of estimated error statistics. The RMSE and R^2 estimate ranging from 0.56 to 1.46 and 0.3 to 0.83 by all the models (Fig. 5). For most varieties, Samara estimates were closer to the observed values compared to APSIM and DSSAT. Though not shown, the over-estimation could be linked to early senescent leaf observed from the field trial for all the varieties with exception of CSM63E. Leaf senescence might not be properly simulated by the models but Samara was different from APSIM and DSSAT due to its ability to simulate based on organo-genesis of plant growth which including the senescent rate of the leaf production through the Coefficient Leaf Death, as well as detailed leaf characteristics description.

The light extinction coefficients, K_{df} values showed that there was no significant difference between varieties but it slightly differed across the planting dates (result not shown). Pooling the sowing dates together for each variety, the average estimated observed value of K_{df} was 0.8. The result suggests that aspects of canopy architecture affecting K_{df}, such as leaf angle distribution, did not differ among these diverse varieties. As shown on Table 6, the K_{df} value of 0.85 was used in DSSAT for all varieties, APSIM was 0.7, 0.4,0.4 which indicates extinction coefficient for green leaf while Samara was calibrated with K_{df} value of 0.80 (except for Fadda variety).

3.1.4. Radiation use efficiency, and partitioning for yield formation

There was a strong effect of variation of sowing date on estimated RUE between PD_1 and PD_3 from field trial with the high values obtained from early PD_1 and decreased with late PD_3. On the average, the highest value was observed for Fadda (6.9 g/MJ), followed by IS15401 and CSM335 (5.8 g/MJ and 5.0 g/MJ) while CSM63E gave the lowest value of 3.3 g/MJ respectively. The model-calibrated values confirmed the genotypic differences as estimated from field experiment (Table 6). For APSIM, RUE was determined for each vegetative phase between emergence and maturity during the crop growth cycle while DSSAT and Samara calibrated as a single value between emergence and maturity. The APSIM calibrated coefficients ranged from 1.25 g/MJ (CSM63E) to 1.85 g/MJ (Fadda–improved hybrid). In DSSAT, the calibrated RUE value was 3.8 g/MJ for CSM63E, CSM335 and IS15401 while Fadda obtained higher value of 5.2 g/MJ, which justified for the high biomass production as hybrid. Also, the T-conversion signifies RUE in the Samara, the values ranged from 4.5 g/MJ for CSM63E to 6.9 g/MJ for Fadda. Across the models, only Samara calibrated RUE were closer to the field-estimated (except for CSM63E).The model-calibrated values were found to be higher than the commonly used range found in literature e.g. Sinclair and Muchow (1999) used1.2–1.4 g/MJ as calibrated value for sorghum. Interestingly, there was a relatively good agreement between the model-simulated and observed for total above-ground biomass. APSIM estimated the lowest RMSE (1536 kg/ha), NRMSE (11.5%) and a strong correlation ($R^2 = 0.9$) followed by DSSAT and Samara (Fig. 6a).

For DSSAT, the G2, scaler for partitioning of assimilates to the panicle, ranged from 0.5 mg/day for CSM63E to 2.5 mg/day for improved hybrid Fadda and IS15401. Samara estimate described as function of coefficient of panicle sink population multiplied by panicle structural mass maximum divided by 1000-grain weight (Coeff_Pan_Sink_Pop*Pan_Struct_Mass_Max/1000-grain weight). Panicle structure mass maximum (Pan_Struct_Mass_Max) was calibrated between 3.0 g (CSM63E and CSM335) and 3.5 g (Fadda and IS15401). The simulation outputs showed that APSIM and Samara estimates for grain yield were closer to the observed values compared to DSSAT (Fig. 6b). Across the variety, APSIM indicated a better agreement relative to the observed values with estimated lowest RMSE (397 kg/ha), NRMSE of 20.3% and R^2 of

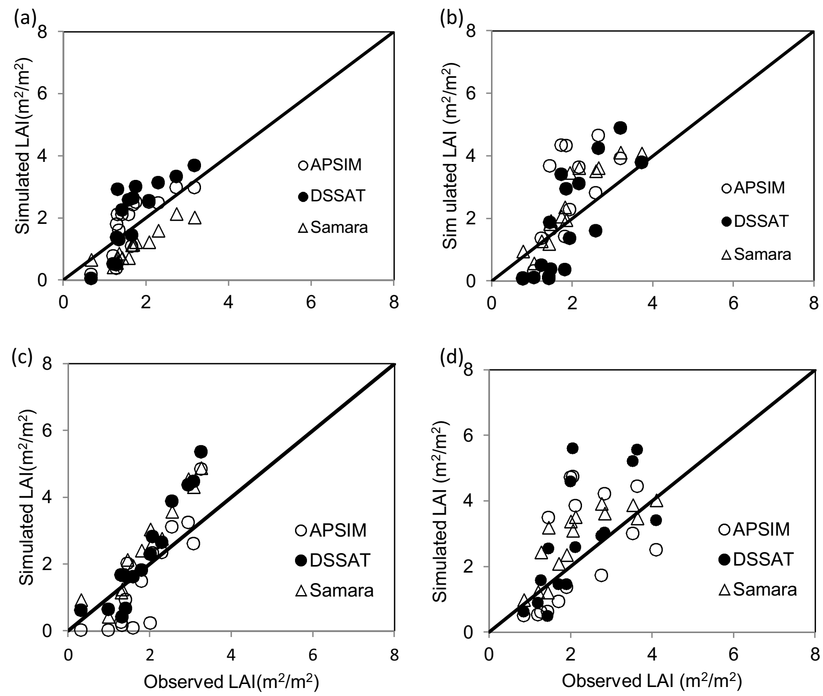

Fig. 5. Model-simulated leaf area index (LAI) against the observed LAI during calibration across the three planting dates. (a) CSM63E: APSIM – RMSE = 0.56 m^2/m^2, R^2 = 0.62; DSSAT- RMSE = 0.81 m^2/m^2,R^2 = 0.64; Samara – RMSE = 0.68, R^2 = 0.87. (b) CSM335: APSIM – RMSE = 1.4 m^2/m^2, R^2 = 0.45; DSSAT- RMSE = 1.1nm^2/m^2, R^2 = 0.62; Samara – RMSE = 0.8 m^2/m^2, R^2 = 0.83. (c) Fadda: APSIM – RMSE = 0.92 m^2/m^2, R^2 = 0.73; DSSAT- RMSE = 0.92 m^2/m^2, R^2 = 0.89; Samara – RMSE = 0.87 m^2/m^2, R^2 = 0.91. (d) IS15401: APSIM – RMSE = 1.46 m^2/m^2, R^2 = 0.31; DSSAT- RMSE = 1.4 m^2/m^2, R^2 = 0.68; Samara – RMSE = 0.9 m^2/m^2, R^2 = 0.78.

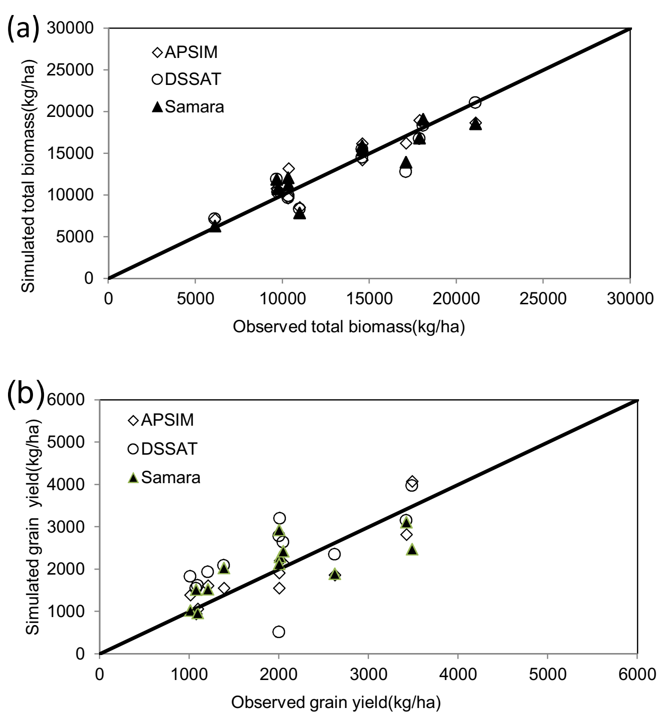

Fig. 6. (a) Saimulated total biomass against observed total biomass for all cultivars during calibration across the three planting dates. APSIM: RMSE = 1536 kg/ha, NRMSE (%) = 11.5, R^2 = 0.87; DSSAT: RMSE = 1708 kg/ha, NRMSE (%) = 12.8, R^2 = 0.85; Samara: RMSE = 1840 kg/ha, NRMSE (%) = 13.8, R^2 = 0.82. (b) Sbimulated grain yield against observed grain yield for all varieties during calibration across the three planting dates. APSIM: RMSE = 397 kg/ha, NRMSE (%) = 20.3, R^2 = 0.8; DSSAT: RMSE = 771 kg/ha, NRMSE (%) = 39.5, R^2 = 0.5; Samara: RMSE = 538 kg/ha, NRMSE (%) = 27.6, R^2 = 0.6.

0.8. Samara and DSSAT slightly over-estimated with the RMSE (538 and 771 kg/ha), NRMSE (27.6 and 39.5%) and R^2 (0.6 and 0.5) respectively.

3.2. *Validation*

The validation for the simulated phenology and TLN against observed values over the different growing seasons for all the varieties showed a good match with a minimum statistical error (Fig. 7). For the duration to flowering (Fig. 7a), Samara had the lowest RMSE of 6.6 days and R^2 of 0.8 while APSIM and DSSAT estimates were close with RMSE of 8.3 and 8.7 days. In the case of duration to physiological maturity (Fig. 7b), APSIM showed the lowest RMSE value of 7.6 days and followed by DSSAT with RMSE of 8.9 days, both had correlation (R^2) of 0.9 while Samara estimates was the highest with the RMSE of 9.2 days and correction (R^2) of 0.8. In general, the model-simulated for phenology shows a slight over-estimation against the observed with a reasonable bias error. For TLN, Samara estimates indicate the lowest RMSE (0.7 leaf) followed by APSIM and DSSAT (Fig. 7c).

The model-simulated for both grain yield and total above ground biomass showed significant variations against the observed data (Fig. 8). None of the models could closely reproduce observations across the varieties. Average total above ground biomass showed a significant over-estimation for all the models against observed values. The statistical analysis found APSIM performed the best predictions having the lowest RMSE, NRMSE (%) and R^2 compared to DSSAT and Samara. For both grain yield and total biomass, APSIM results showed the lowest RMSE (472 and 2452 kg/ha), NRMSE (22.6 and 23.3%) and R^2 (0.7 and 0.8). Meanwhile, RMSE (762 and 4058 kg/ha), NRMSE (35.7 and 38.8%) were highest for Samara.

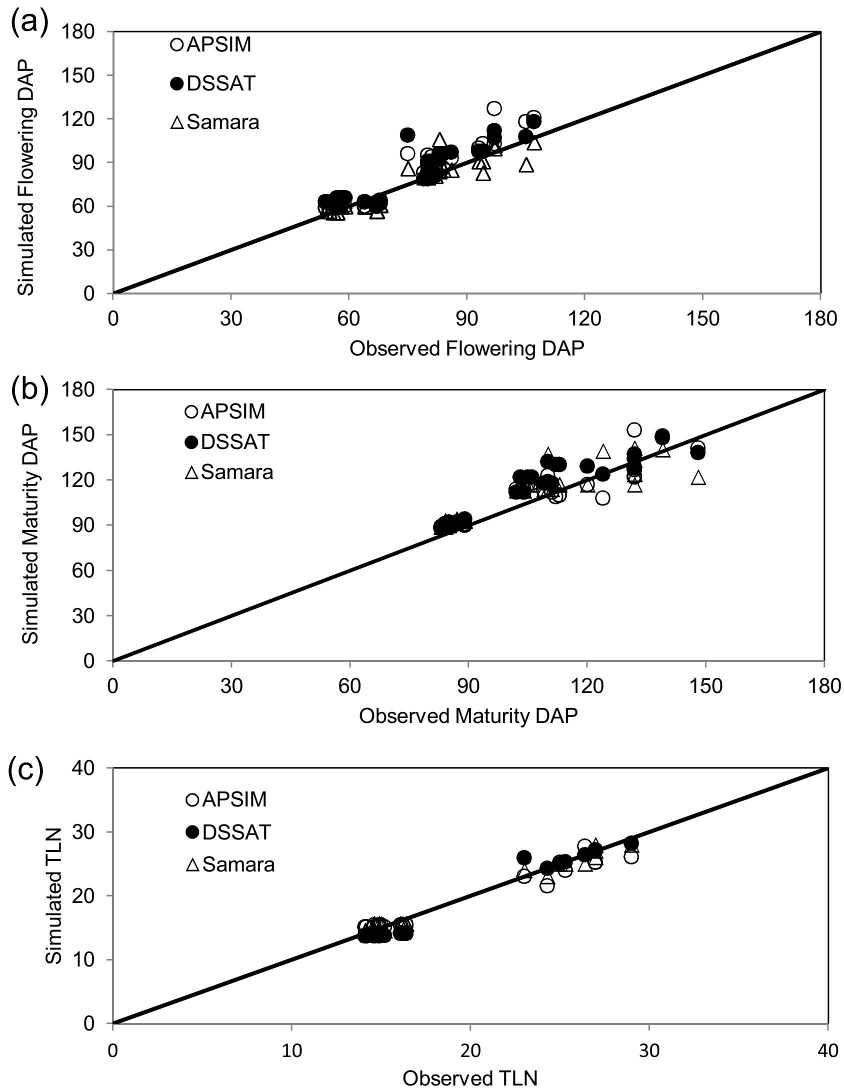

Fig. 7. Model comparison for simulated phenology and total leaf number (TLN) against observed values for all the cultivars over different growing seasons, planting density and planting dates. (a) Flowering: APSIM – RMSE = 8.3days; R^2 = 0.9; DSSAT- RMSE = 8.7days; R^2 = 0.8; Samara – RMSE = 6.6days; R^2 = 0.8. (b) Maturity: APSIM – RMSE = 7.6days; R^2 = 0.9; DSSAT- RMSE = 9days; R^2 = 0.9; Samara – RMSE = 9.2days; R^2 = 0.8. (c) TLN: APSIM – RMSE = 1.2 leaves; R^2 = 0.96; DSSAT- RMSE = 1.3 leaves; R^2 = 0.97; Samara – RMSE = 0.7 leaves; R^2 = 0.99.

3.3. *Sensitivity analysis*

Changes in key parameters showed the strong effect on key variables for SAMARA (Fig. 9). DSSAT was most affected only by change of RUE values. Also, we can notice that for SAMARA the changes of + or − 10% mostly affect maximum LAI. The other outputs variables are resulting from this variable, and therefore, because of compensatory mechanism included in Samara, the effect of parameters change smoothen out as the output variables are emergent variables. This trend of compensatory mechanism is accentuated the more PPS the variety is (from CSM63E to IS15401).The opposite is observed for APSIM and DSSAT to a lesser extent. PPsens (representative of the sensitivity to PP of the variety) and Phyllo (phyllochron) are two parameters associated with the phenology process. However, we notice the increasing effect of the phyllochron, i.e. leaf appearance rate, in APSIM lead to grain yield changes up to 25% for photoperiod sensitive varieties. In SAMARA, their effect is more notable on LAI (also about + or − 25%) for low PPS variety and more for grain yield for high PPS variety (+ or − 10%). Regarding parameters associated with leaf development (SLA and coef_ext), APSIM is highly sensitive to SLA, especially for photoperiod insensitive variety, while SAMARA presents the opposite behaviour, being more sensitive to change of SLA for high PPS varieties. Finally, all models, including DSSAT, are responsive to change in RUE value.

4. Discussion

A comparison of crop simulation models served two purposes: (i) a comparison of the three models for their ability to predict crop growth and development with detailed information linked to photoperiod is during calibration and (ii) identification of the reasons for systematic model error. When an error has been identified, steps can be taken to improve model performance on the basis of better analysis of the processes involved. As found from the study, some aspects of the models were satisfactory (e.g. phenology and leaf number) but there was also a clear indication for model improvements should be sought for the parts that present high significant error (e.g. LAI and grain yield). These errors could be attributed to three possible sources; (i) model structure (ii) bad parameterization or (iii) quality of field trial data.

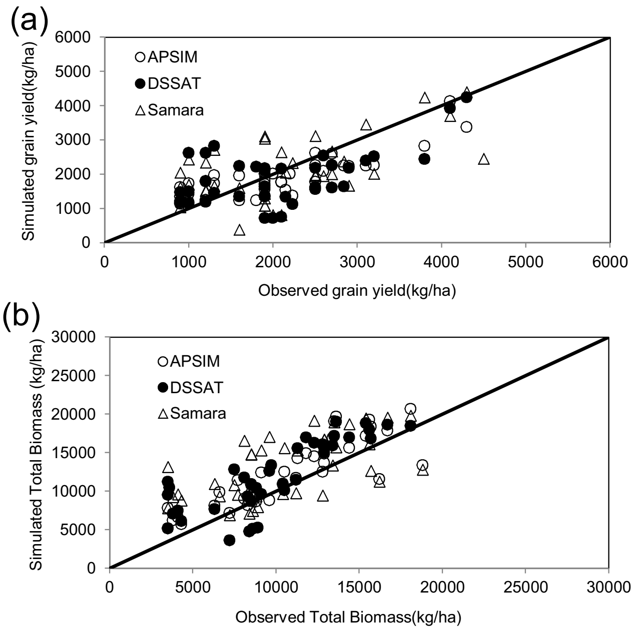

Fig. 8. (a) Model comparison for simulated grain yield and total biomass against the observed values for all the cultivars over different growing seasons, planting density and planting dates.
(a) Grain yield: APSIM – RMSE = 472 kg/ha; NRMSE (%) = 22.6; R^2 = 0.68; DSSAT-RMSE = 719 kg/ha; NRMSE (%) = 34.8; R^2 = 0.4; Samara – RMSE = 762 kg/ha; NRMSE (%) = 35.7; R^2 = 0.4.
(b) Total biomass: APSIM – RMSE = 2452 kg/ha; NRMSE (%) = 23.3; R^2 = 0.75; DSSAT-RMSE = 3138 kg/ha; NRMSE (%) = 36.8; R^2 = 0.66; Samara – RMSE = 4058 kg/ha; NRMSE (%) = 38.8%; R^2 = 0.45. The significance difference of mean at 5% level of probability ($P < 0.05$) are as follows; 0.25 for grain yield and 0.00008 for Total biomass.

4.1. Ability of models to predict crop growth and development

The results confounded the models adaptability to predict West African diverse photoperiod sensitivity varieties. In addition, the validation presented over different growing seasons (non-limiting water and nutrients supply) and locations (Bamako and Cinzana) corroborates the strength of models for simulating phenology and growth of sorghums for semi-arid varieties (Fig. 8a & b). The results showed a near perfect fit of for the model-simulated phenology (flowering and maturity) against the corresponding observed values. The result suggests that crop models can be used to determine the crop duration for the widest rangeof sorghum varieties in West African semi-arid region, reinforcing the conclusion of Traore et al. (2007). However, an error of more than 7 days for time to maturity for the high PPS variety (IS15401) by all models, which suggests further improvement for capturing photoperiod sensitivity for such varieties. The imperfect model fit can be expected to have significant effect on other parts of the simulation results for example LAI. Although, the models validation captured final biomass and yield values, the estimated error was larger compared to phenology and morphology simulations. Indeed, the model uncertainty might be related to inadequate prediction of partitioning for simulating above ground biomass at the early growing phase (vegetative) and grain yield formation particular for the PPS varieties.

4.2. Uncertainty and models improvements

4.2.1. Model structure

With respect to model structure, we observed the strength of SAMARA for simulating accurately total leaf number and consequently being the best model to simulate LAI, while for DSSAT and APSIM the strength relies in grain yield estimation. Model-estimated for TLN agreed jointly with the observed values both for the calibration and validation. Samara ranked as the best estimates with the lowest RMSE, NRMSE (%) and R^2 seen for most varieties except IS15401, followed by APSIM and DSSAT respectively. In general, APSIM and DSSAT over-estimated LAI suggesting that leaf senescent rate was not well captured. In comparison, Samara gave the lowest RMSE and NRMSE (%) and strong R^2 for all the varieties (with exception CSM63E). As observed from the calibration and the sensitivity analysis, APSIM and DSSAT simulations show more response to biomass accumulation while Samara responds more to LAI, due to the detail organogenesis procedure for the plant growth beginning from crop emergence. In addition, Samara addressed the drawback already mentioned in the literatures by Ewert et al. (2002), Traore et al. (2007) and Adam et al. (2011) in order to better represent the leaf area development in crop model. The approach chosen was derived from the plant level model ECOMERISTEM (Dingkuhn et al., 2006) which included the capability to simulate competition for assimilates (supply) among growing organs (demand) and to adjust accordingly the growth rate and final size of different organs in the plant. Also, as shown in Fig. 6, SAMARA appears to capture better the leaf senescence.

As observed during the calibration process, the time-course results (figures not shown) across the varieties indicated that only Samara model exhibited the ability to reproduce closely the observed values of above-ground biomass at early vegetative stage of the crop sampled at different times during growing season. Also the sensitivity analysis clearly demonstrated the higher sensitivity of SAMARA on predicting LAI rather than aboveground biomass and grain, both variables highly depend on the good simulation of LAI.

4.2.2. Model parameters

The sensitivity analysis showed the importance of key parameters for the prediction of keys variables. For APSIM and DSSAT, we noticed that the effect of changing these parameters was more important on final outputs such as aboveground biomass or grain yield, while for SAMARA, the effects was on LAI, a key process to simulate as discussed previously. The sensitivity analysis did not reveal a strong effect of phenology parameters on outputs variables. However, during the model parameterization, we pointed out the difficulties to assess critical parameters such as GDD from emergence to end of the juvenile stage. This parameter needs to be decoupled from the effect of PP on crop development. Another factor noticed that can influence model error between the simulated and observed results was planting density as shown on model validation results for grain yield and total biomass. For instance, the model calibration was performed on a specific planting density (67000 plants/hills), thereafter validated with different planting densities. We thereby suggest that model estimation errors could be reduced for total biomass and grain yield, if the same level of plant populations is considered. Indeed, the way model response to different level of nutrient supply might be a need to refine the effect of plant density on plant growth in the current sorghum models.

4.3. Field data

Finally, uncertainty might come from the quality of field trial data. We can discuss the importance of sowing dates trials to assess the phyllochron (Clerget et al., 2007) properly while in our case though the late PD_3 sowing was a late sowing, it might not late enough to assess the phyllochron properly. Also, the field trials used for evaluation were considered to be non-limited by nutrients, however, it might be possible that the trials experiences some nutrient or water deficiencies. APSIM and DSSAT respond to soil parameterization (e.g. SLPF in DSSAT and initial nitrogen in APSIM) as well nutrients supply. As observed during calibration, the effect of soil parameterization and nutrients in APSIM and DSSAT led to model over-estimation of LAI against the field observed values.

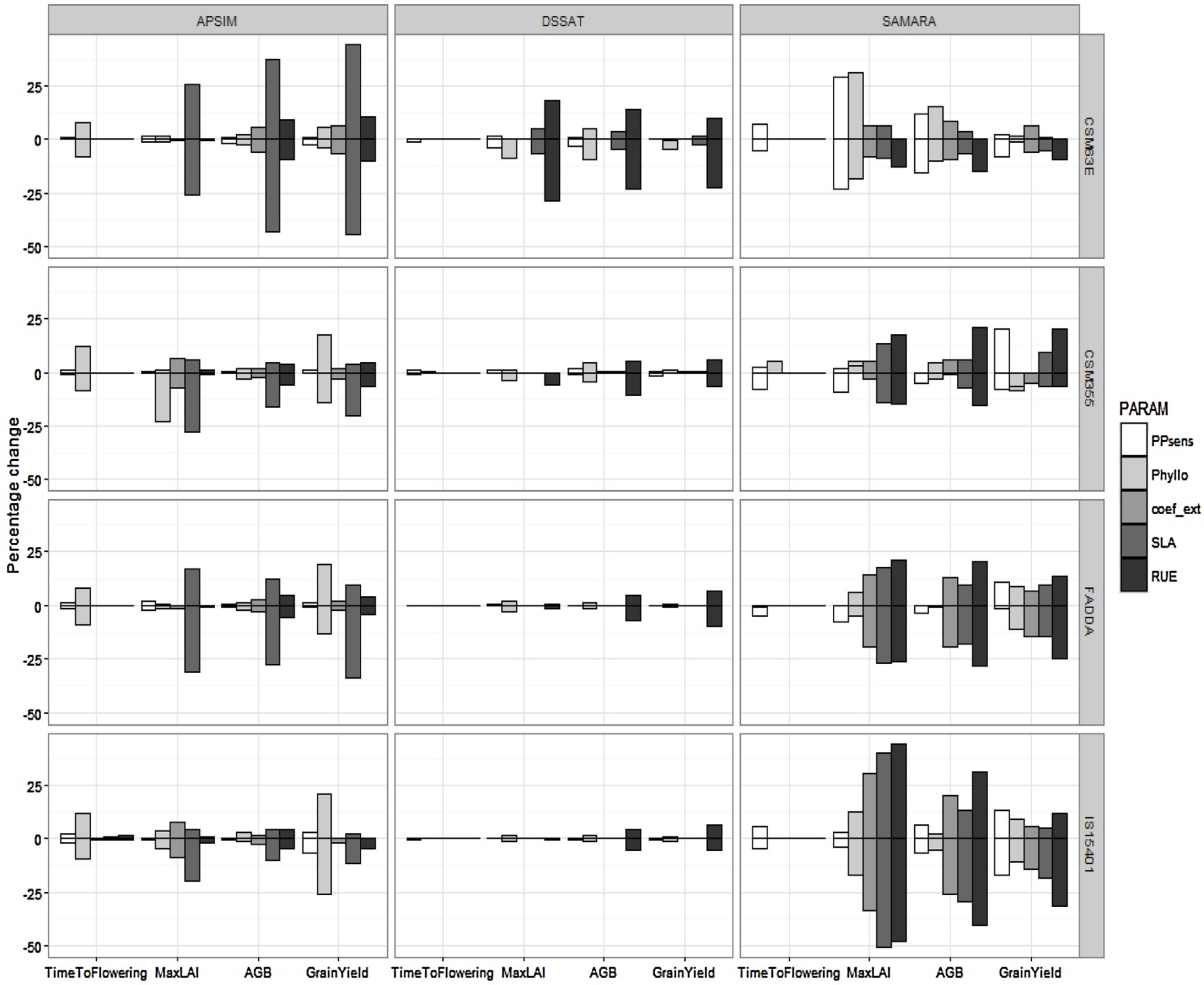

Fig. 9. Results of the sensitivity analysis for changes in keys model parameters for sorghum varieties across three models. The percentage change was obtained by adding or subtracting 10% to the calibrated value of the keys model parameters.

The estimated RUE was significantly higher than those found in the literatures for sorghum (Kiniry et al., 1989; Muchow, 1989). The high RUE values (>3.0 g/MJ) obtained could be linked to the variety–specific traits especially for the PPS sorghums found in West Africa.

5. Conclusion

A novel and clear merit of this study is that three widely applied crop growth simulation models for sorghum were tested for predicting the growth of diverse and PPS varieties. The models were able to reproduce phenology and leaf development against a detailed field data set with minimum error estimates over different growing seasons. Samara demonstrated an ability to reproduce the LAI dynamics and early biomass production better during the vegetative phase compared to APSIM and DSSAT. This could be attributed to the inter-organ competition factor that controls organs size, and feedbacks on growth and senescence processes. Grain yield and biomass needs better description of partitioning process – the level of uncertainty in simulating final grain yield and biomass were found to be lower in APSIM and DSSAT compared to Samara. Based on this study, we highlight the importance of simulating LAI dynamics and demonstrate the importance of simulating the competition for assimilates (supply) among growing organs (demand) with adjustments tothe growth rate and final size of different organs in the plant during the vegetative phase.

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