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A modelling assessment of the maize crop growth, yield and soil water dynamics in the Northeast of Brazil

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Abstract

The present study aims to evaluate the APSIM-Maize model performance to use it as a decision-making tool to help improve production rates, reduce production costs and assess the potential impacts of climate change on crop yields in the Northeast of Brazil. The crop, soil and weather data used in the simulations were obtained from field experiments carried out in maize crops in 2008 and 2011 in two different edaphoclimatic regions in Alagoas State, Northeast Brazil. The approach we used explored the ability of APSIM to simulate growth variables and soil water dynamics of a maize variety (AL Bandeirante). During parametrization, we made some adjustments regarding the variety and soil organic matter to attain a better representation of the growth and soil water dynamics, respectively. The APSIM-Maize model predicted the leaf area index with a RMSE (Root Mean Square Error) ranging between 0.14 and 1.06 cm^2 cm^{-2} and the biomass production with an RMSE between 2.30 and 3.34 Mg ha^{-1}. The volumetric soil water content was satisfactorily predicted with RMSE ranging between 0.02 and 0.08 mm mm^{-1}. Results showed that this model is a useful tool for decision-making, which can be potentially used as a support in climate risk management and policies, aiming to improve regional production, provided it has been previously validated with independent datasets.

Key words: Agricultural systems; APSIM; Crop simulation model; Field experiment; Sowing date; *Zea Mays* L.
Abbreviations: ADD_Accumulated Degree-Day; APSIM_The Agricultural Production System Simulator; DAS_Days After Sowing; DOY_Day Of Year; DUL_Soil Water Content at Drained Upper Limit; k_Canopy Light Extinction Coefficient; LAI_Leaf Area Index; LL_Soil Water Content at Drained Lower Limit; PAR_Photosynthetically Active Radiation; RUE_Radiation Use Efficiency; SW_Soil Water Content; TDR_Time-Domain Reflectometry;

Introduction

Maize has a high socioeconomic value worldwide because its cereal is used to produce food for human and animal consumption. In addition, the grains are also widely used as a renewable energy source (Koizumi, 2015). The global average productivity in 2016 was 5.6 Mg ha^{-1} according to the Food and Agriculture Organization of the United Nations (FAO). At present, the USA is the largest maize producer in the world and in 2016 it produced 10.6 Mg ha^{-1} of grain and has an historical average of 7.1 Mg ha^{-1}. Brazil is the third largest maize producer as it produced 5.5 Mg ha^{-1} of grain in 2016 (FAO, 2018). However, climate and edaphic restrictions (e.g., soil with low fertility or low water retention capacity and salinity), as well as low technological levels and inadequate management practices are factors that contribute to Brazil having a historical average yield of only 2.8 Mg ha^{-1} (CONAB, 2018).

A huge demand for food due to the increasing global population has jeopardized the sustainability of agriculture and requires higher production levels without increasing planted areas. This requires using crop modelling to estimate the potential productivity of large regions with relatively low levels of productivity. Roxburgh and Rodriguez (2016) reported that the spatial variability of productivity is mainly associated with soil fertility and soil handling techniques (crop density, population and planting season) and a general lack of technical knowledge. In addition, the seasonal variability of productivity can be explained by the variability in rain producing weather systems. It is estimated that putting these factors aside, maize yield could increase by up to 120%. In Northeast Brazil, most of the maize crops are grown in rainfed conditions and are for self-sustaining, showing a historical average productivity of around 0.9 Mg ha^{-1} (last harvest of 2016-2017 = 2.5 Mg ha^{-1}). Productivity in Alagoas is still smaller with a historical average of only 0.5 Mg ha^{-1} between 1976 and 2017, which is 82.1 and 44.5% lower than the national and regional yield, respectively (CONAB, 2018). However, Ferreira Junior et al. (2014) and Lyra et al. (2010) showed that in this region, the yield can be increased to about 6.0 to 8.7 Mg ha^{-1} under experimental conditions based on good management practices.

Process-based mathematical models of plant growth are essential for identifying environmental restrictions, thus allowing higher levels of crop production. Agricultural modelling began in the 1960s aiming at simulating photosynthetic rates of crops (de Wit, 1965). Since then, the search for better methods to improve the performance of agricultural systems through process-based crop models has been a very active area of research in agriculture (Keating et al., 2003; Carberry et al., 1993; Muchow et al., 1990). The main application of crop modelling is crop management and environmental risk decision making. Nowadays, crop models are also widely used to evaluate the potential consequences of climate change on crop yields (Roberts et al., 2017; Bassu et al., 2014).

The APSIM (Agricultural Production System Simulator) is a modular modelling framework that simulates various interactions among plants, animals, soil, climate and agricultural management (Keating et al., 2003). Studies have shown that APSIM is suitable for many applications in agricultural production systems (Ojeda et al., 2016; Singh et al., 2014; Zeleke et al., 2014; Monhanty et al., 2012). Archontoulis et al. (2014) evaluated the overall performance of APSIM-Maize in the Midwestern United States. They concluded that the model can be used as a research and decision-making tool to provide agricultural support in the Midwest. Song et al. (2010) used APSIM-Maize to evaluate the effects of water stress on maize growth and yield under dryland conditions in southeast Queensland. Results showed that APSIM performed accurately, and therefore the model can be used as a tool to assess maize production with new cultivars in drier and less predictable environmental situations, provided the parametrization of cultivars and soil characteristics are accurate.

The main objective of this paper is to provide an overall assessment of the APSIM model performance in Northeast Brazil, aiming to use it as a tool to help improve regional production. More specifically, our goal is to assess the performance of the APSIM model to simulate growth, biomass, grain yield and soil water dynamics for a maize variety in two regions of Alagoas State, Northeast Brazil.

Results

Growth variable analyses

Leaf area index (LAI) measurements (Fig 2) showed the largest amplitudes for Rio Largo (Fig 2e-h) with a maximum value of 5.41 cm^2 cm^{-2} (Fig 2f) at 57 days after sowing (DAS). The smallest variation of LAI was found in Arapiraca during the fourth sowing date (Fig 2d), with a maximum value of 3.64 cm^2 cm^{-2} at 65 DAS. The LAI simulations for Arapiraca showed a percentage relative error of 21% (Fig 2) ranging between 12% (Fig 2a) and 29% (Fig 2b). For Rio Largo (Fig 2e-h), the model showed an averaged error of 29%. Moreover, the best performance was observed on the fourth sowing date (Fig 2f) with an error of approximately 14.2%.

The model performed very well in estimating LAI for Arapiraca with RMSE of 0.305 cm^2 cm^{-2} (Fig 2a-d), and *d* of 98.7%. In particular, the fourth sowing date (Fig 2d) showed the best agreement (*d* = 99.7%) and precision (RMSE = 0.14 cm^2 cm^{-2} and R^2 = 0.96), thus indicating a very good performance of the simulation. For this specific case, the highest performance was achieved after increasing the effective depth of the root system from 60 cm to 75 cm, which corresponded to a 25% drop in the simulation error. As the experiment was conducted under rainfed conditions, we considered this modification necessary due to the low water availability in the soil from the end of the vegetative stage in mid-September (DOY ~ 250, Fig 4d), until the harvest at the end of October (DOY ~ 297). The LAI predictions for Rio Largo showed a good agreement (*d*) of 95.0% and a reasonable precision (R^2 = 0.63). In addition, we observed a larger RMSE of 0.68 cm^2 cm^{-2} when comparing them with the results for Arapiraca. In general, all the LAI simulations were considered very efficient (i.e., 0 < EF < 1) as the EF for Arapiraca and Rio Largo were 0.95 and 0.87, respectively. A low EF of -0.15 (i.e., EF < 0) was observed only in one case (second sowing date in Rio Largo), indicating poor efficiency. The low EF, for this specific case, did not invalidate the simulation, however it means that the model predictions were worse than simply using the observed mean to replace the simulated value (Yang et al., 2014a).

The total biomass production obtained from the field experiment was larger in Rio Largo (Fig 3e-f) ranging from 15.2 Mg ha^{-1} (sowing 4 – Fig 3h) to 17.4 Mg ha^{-1} (sowing 2 – Fig 3f). Smaller values were obtained in Arapiraca which ranged from 10.3 Mg ha^{-1} (sowing 4 – Fig 3d) to 12.26 Mg ha^{-1} (sowing 2 and 3 – Fig 3b,c). The grain yield obtained from the field experiment in Arapiraca showed large variations among the sowing dates, i.e. 1.96 Mg ha^{-1} (sowing 4) and 4.11 Mg ha^{-1} (sowing 2), which in turn was the largest grain yield considering all sowing dates studied (Fig 3b). For Rio Largo, the grain yield obtained in the field experiment showed smaller values and less variations among the sowing dates, which ranged from 2.20 Mg ha^{-1} (sowing 4, Fig 3h) to 3.70 Mg ha^{-1} (sowing 2, Fig 3f). The experimental data shown above revealed that the largest values of total biomass and grain yield were associated with earlier sowing dates. As mentioned previously, both experiments were conducted under rainfed conditions and, therefore, the latest sowing season suffered from the low water availability in the soil between the vegetative period and the harvest due to the annual rainfall pattern in these regions (see Fig. 4). Hence, for the latest sowing date the reduction in rainfall was responsible for the smaller values of biomass and grain yield, mainly for Arapiraca (Fig 3d and Fig 4d).

The model estimated the biomass production for Arapiraca with a RMSE of 3.11 Mg ha^{-1} and underestimated the observations (above 20%) for all cases (Fig 3a-d). Despite these high underestimates, a good precision (R^2 = 0.86) was observed, as well as an agreement index (*d*) of 83.7%. This highest precision and smaller accuracy indicate that the total error may have contributed to a larger systematic component (Willmott, 1981). The results for the grain yield were also quite satisfactory as the error ranged between 12.9% (sowing 1) and 15.5% (sowing 3), within the accepted error threshold (± 20%) for the first three sowing dates (Fig 3a-c). The biomass predictions for Rio Largo were more accurate than those for Arapiraca (*d* = 92.6%), showing slightly less precision (RMSE ~ 2.31 to 2.63 Mg ha^{-1} and R^2 = 0.82). However, the grain yield was overestimated by the model around 42% for the first three sowing dates (Fig 3e-g).

Table 1. Sowing and harvest dates regarding the field experiments of Arapiraca (2008) and Rio Largo (2011) in Alagoas, Northeast Brazil.

Sowing date	Arapiraca		Rio Largo	
	Sowing	Harvest	Sowing	Harvest
Sowing 1	14/06	01/09	06/05	12/10
Sowing 2	22/06	16/09	19/05	16/10
Sowing 3	28/06	06/10	10/06	31/10
Sowing 4	05/07	24/10	30/06	04/11

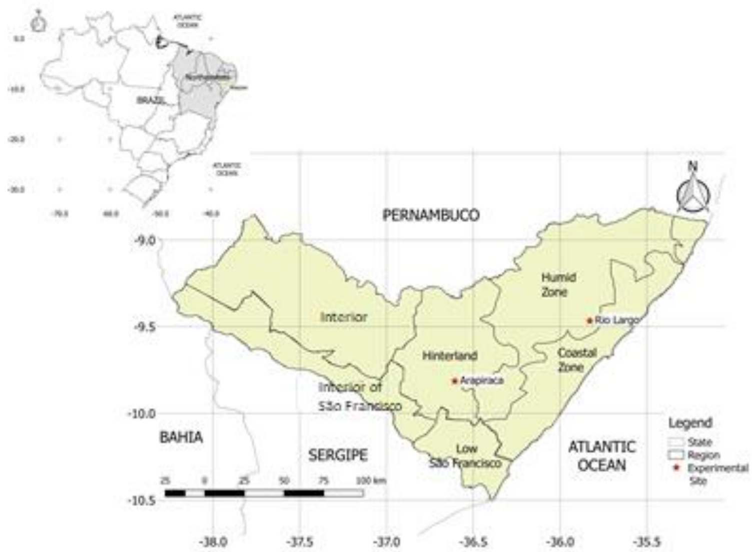

Fig 1. Map of the State of Alagoas in Northeast Brazil, showing the experimental site (red stars) locations.

Table 2. Soil hydrophysical properties: Bulk density (BD), 15Bar lower limit of soil water content (LL15), drained upper limit (DUL) and water content at saturation (SAT) used in APSIM-Maize module for the Arapiraca and Rio Largo simulations.

	Depth	BD	LL15	DUL	SAT
	cm	g cm^{-3}		mm mm^{-1}	
Arapiraca	0-30	1.33	0.063	0.102	0.40
	30-60	1.38	0.076	0.113	0.39
Rio Largo	0-10	1.36	0.12	0.20	0.40
	10-20	1.44	0.13	0.22	0.43
	20-30	1.52	0.14	0.24	0.43

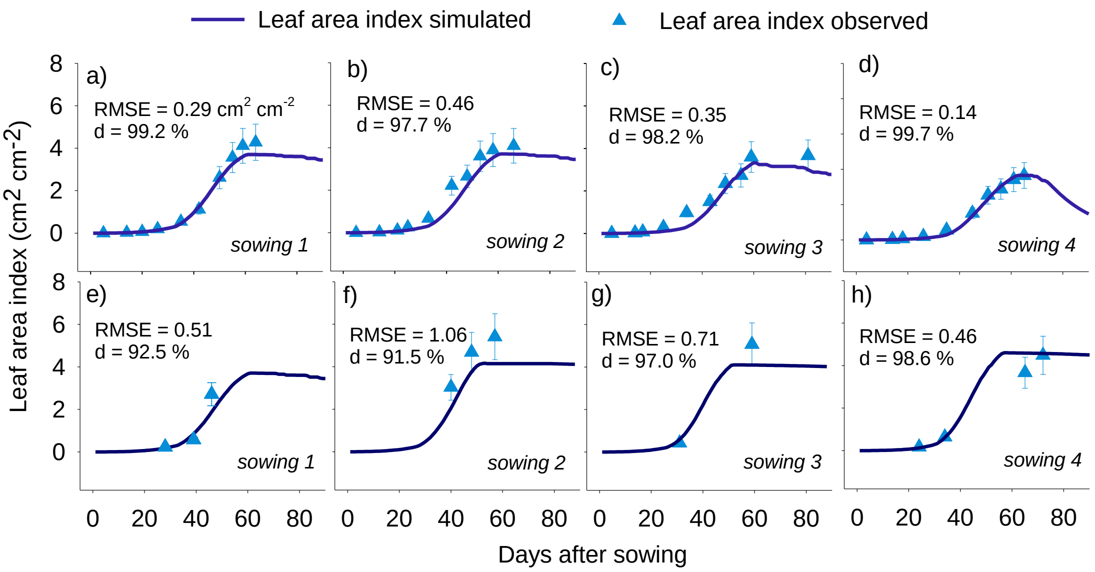

Fig 2. Measured and simulated leaf area index (LAI) as a function of days after sowing (DAS) for four sowing dates in Arapiraca (Fig 2a-d) and Rio Largo (Fig 2e-h).

Table 3. Soil chemical properties: water pH-value (pH), starting mineral N pools (NH_4 and NO_3), organic carbon (OC), biomass fraction (FBIOM) and inert OC fraction (FINERT), used for the Arapiraca and Rio Largo simulations.

	Prof. cm	NH_4 mg kg^{-1}	NO_3 mg kg^{-1}	OC %	FBIOM (0-1)	FINERT (0-1)	pH (water)
Arapiraca	0-30	3.30	6.45	2.66	0.023	0.46	5.23
	30-60	0.78	0.99	0.99	0.010	0.62	4.30
Rio Largo	0-10	1.30	1.75	1.03	0.035	0.39	5.52
	10-20	1.00	2.58	0.86	0.020	0.47	5.10
	20-30	1.00	2.12	0.77	0.015	0.52	5.00

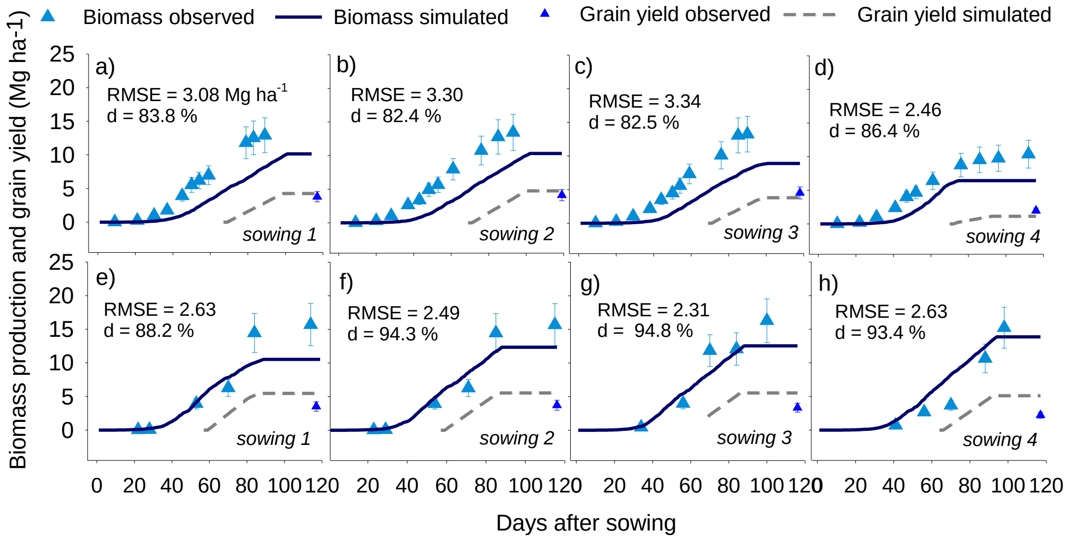

Fig 3. Measured and simulated aboveground biomass and grain yield (Mg ha^{-1}) for four sowing dates in Arapiraca, AL (Fig 3a-d) and Rio Largo, AL (Fig 3e-h). The statistical indices indicated in the panels refer to biomass.

Table 4. Parameters used to adjust the leaf area index (LAI) for the Arapiraca and Rio Largo simulations.

Parameter	Value APSIM	Value used	Description
x_lai	0.1 – 4.0	0.1 – 6.0	LAI range
leaf_no_dead_slope	0.00035	0.0002	Slope LAI – associated with leaf age senescence
lai_sen_light	4.0	6.0	Occurrence of induced senescence by light

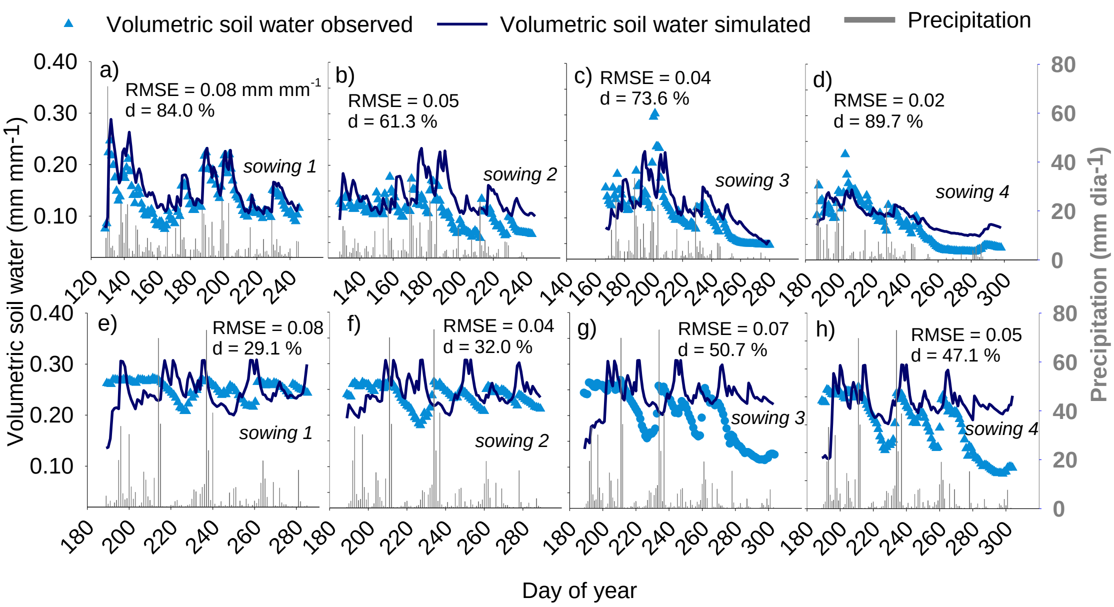

Fig 4. Measured and simulated volumetric soil water content (mm mm^{-1}) at the layer 0-60 cm and daily precipitation for four sowing dates in Arapiraca, AL (Fig 4a-d) and Rio Largo, AL (Fig 4e-h).

Table 5. Phenological parameters used in the parametrization of maize variety (AL Bandeirante) for the Arapiraca and Rio Largo simulations.

Parameter	Value	Description
tt_emerg_to_endjuv[1]	196.08	ADD between the emergency and the end of the juvenile stage.
tt_flower_to_maturity[2]	488.1	ADD between the flowering and maturity.
tt_flag_to_flower[3]	10	ADD the flag leaf appearance and flowering.
tt_flower_to_start_grain[4]	68.5	ADD flowering to grain filling
tt_maturity_to_ripe[5]	1	ADD between maturity and harvest.

[1]ADD between emergence to 4th fully expanded leaf (V4); [2]ADD between flowering (R1) to maturity (R6); [3]ADD between two days after tasseling (VT) to flowering (R1); [4]ADD between flowering (R1) to start of the grain filling (R2); [5]ADD between maturity (R6) to harvest.

Soil water dynamics analyses

The soil moisture observations using a TDR (Time Domain Reflectometer) indicated that for Arapiraca the maximum values of the volumetric soil water content (SW, mm mm^{-1}) ranged between 0.15 mm mm^{-1} (Fig 4d) and 0.24 mm mm^{-1} (Fig 4a) during the growing season considering all sowing dates. These values for Rio Largo were around 0.26 mm mm^{-1} (Fig 4e-h). Overall, the model estimated the soil water dynamics with a small error (less than ± 20%). The Arapiraca simulation for the first and last sowing dates (Fig 4a,d) showed smaller estimation errors, ranging from 14.5% (sowing 4) to 19.9% (sowing 1). For Rio Largo, the SW estimates showed an error of the order of 22.1% (Fig 4e-h).
The model simulated the soil water dynamics for Arapiraca (Fig 4a-d) and Rio Largo (Fig 4e-h) with an RMSE of 0.04 mm mm^{-1} and 0.06 mm mm^{-1}, respectively. The first sowing date for Arapiraca (Fig. 4a) showed that the model satisfactorily reproduced the pattern of measured soil water content (RMSE = 0.08 mm mm^{-1} and d = 84.0%), which showed successful soil water parametrization. This parameterization also performed well on the other sowing dates, in which the observations and simulations showed similar trends despite their different magnitudes in some cases. Thus, evidence was shown that the model succeeded in simulating the real process of the soil water dynamics. However, this result is not surprising because the APSIM's soil water module requires soil water content data at the drained upper limit (DUL) and lower limit (LL), both determined from experimental conditions (Archontoulis et al., 2014).

Discussion

The reasonable performance of LAI estimates in Rio Largo did not affect the accuracy of the estimates of biomass production although LAI is an important variable when calculating the intercepted light and photosynthesis in the model. Asseng et al. (1998) points out that it is surprising that LAI estimates do not seriously affect the biomass predictions. This apparent lack of sensitivity of the estimated LAI on the biomass, in some cases, could be explained by the fact that accurate LAI simulations are more important in early growth stages and during the grain filling period. However, less relevance is observed when the ground is fully covered (maximum LAI), where at that point an increase in LAI has a marginal effect on light interception. This may explain why the biomass production estimates were not adversely affected by relatively poor LAI estimates, although the biomass production was sensitive to modifications made in the LAI parametrization, such as those discussed below.
A reliable prediction of LAI is important to obtain good estimates of biomass production. The fitted parameters in calculating LAI were important for a better representation of the growth conditions, resulting in more reliable estimates of biomass production and grain yield. Following the procedure adopted by Archontoulis et al. (2014), the parameter associated with the leaf age senescence (*leaf_no_dead_slope*) was reduced from 0.00035 to 0.0002 to attain a better representation of the decay of the LAI curve due to leaf senescence. In addition, to better fit the LAI range (*x_lai*) parameter to the field observations, we expanded the LAI upper limit from 4.0 to 6.0. Note that the maximum LAI in Rio Largo was 5.6 (Fig 2e). In other words, the former upper limit considered in the model was not large enough to meet the LAI variations obtained in the field observations. Overall, the LAI estimates in this study were very satisfactory for Arapiraca, but not as much for Rio Largo, as previously mentioned. A study conducted by Archontoulis et al. (2014) in the Midwestern United States considered that APSIM-Maize predicted LAI satisfactorily with a precision of 21%. However, research carried out in Australia (Asseng et al., 1998; Meinke et al., 1997), using the APSIM-Wheat module, reported quite a poor performance in LAI predictions.
The biomass production (Fig 3) is highly dependent on the canopy light extinction coefficient (k), which in turn was maintained as the APSIM's default value. Ferreira Junior et al. (2014) found k = 0.62 for the AL Bandeirante variety, considering photosynthetically active radiation (PAR). This value corresponds practically to the same value considered in the model (k = 0.53), taking into account the proportionality to solar global irradiation (H_g). For the radiation use efficiency (RUE), we used APSIM's default values for maize in which RUE is considered as constant (1.6 g MJ^{-1}) until the beginning of the grain filling, then it is reduced to 1.4 g MJ^{-1} (Muchow et al., 1990) due to the reduction in the photosynthetic rate stemming from the senescence of the leaves. Recent studies carried out in the USA have reported that RUE for maize is about 1.67 g MJ^{-1} Hg, matching with the value used in our simulations (Archontoulis et al., 2014; Singer et al., 2009).
The model did not satisfactorily reproduce the soil water pattern for Rio Largo (Fig 4e-h), even using hydro-physical parameters determined experimentally. This was largely due to the soil type of the region, which has a compacted layer situated around 30 cm deep and did not properly reproduce by the drainage parameter of the model. It was noticed that the model overestimated the SW immediately after days or periods with large accumulated rainfall. On the other hand, it showed a better performance regarding the SW estimates for low rainfall periods. In other words, the model was able to recognize the compact layer, which reduces the drainage of the soil water, thus underestimating the drainage rates. For this very reason, the soil water conductivity parameter (SWCON, d^{-1}) was increased from 0.2 (Probert et al., 1998) to 0.6, using an iterative method to achieve a better agreement of SW. The SWCON parameter represents the water above DUL which is drained daily.

Using the APSIM-Maize in central western USA, Archontoulis et al. (2014) reported RMSE of 0.03 mm mm^{-1} for the soil water dynamics simulations. We obtained a similar precision in our results for Arapiraca (Fig 4a-d). A reasonable performance of APSIM in predicting SW was noticed when simulating the cotton crop in northern China (Yang et al., 2014b) with R^2 ranging from 0.33 and 0.56. Good precision was found for wheat in western Australia (Aseng et al., 1998) and canola in southern Australia (Zeleke et al., 2014), which reported R^2 of 0.92 and 0.94, respectively. Finally, the SW predictions in this study indicate a good efficiency of the APSIM model in calculating soil water dynamics under well drained soils (e.g., soil in Arapiraca) in close agreement with other studies (Aseng et al., 1998; Mohanty et al., 2012).

Materials and Methods

Experimental data

This study uses experimental data in rainfed conditions from two edaphoclimatic different regions in Alagoas State, located on the eastern coast of Northeast Brazil (Fig 1): 1) Arapiraca (9°48’55.1" S; 36°36’22.8" W; 260 a.s.l.) in 2008 and 2) Rio Largo (09°28´02"S; 35°49’43"W; 127m a.s.l.) in 2011. Arapiraca´s climate is (*As’*), according to the Köppen classification with a dry Summer and rainy Autumn and Winter; temperatures are high throughout the year (annual average air temperature of 25°C and precipitation totals between 750 and 1000 mm year^{-1}). The rainiest months are May and June (> 50% of the annual total). The soil is classified as dystrophic Red Yellow Latosol, with a sandy loam texture and the bulk density is 1.35 g cm^{-3} in the first 60 cm depth. The experimental design used was a randomized block design with six replicates and four sowing dates by treatment (Table 1). Row spacing was 0.80 cm and each experimental plot consisted of 12 rows 10 m long, which resulted in a stand population of 55,000 plants ha^{-1}. Further experimental details for Arapiraca can be found in Medeiros (2009).

The Rio Largo experiment was carried out at the Center of Agricultural Sciences at the Federal University of Alagoas (CECA/UFAL). The climate of the Rio Largo region is classified as *As* according to the Köppen classification, with monthly average minimum and maximum air temperatures of 17.2 and 35.2°C, respectively. The interannual rainfall variability is high, with an annual average of 1800 mm. The rainy season starts in early April and lasts until late August, with a total that corresponds to 70% of the annual total; the dry season spans from early October until the first half of February, representing about 16% of the total precipitation (Souza et al., 2004). The soil of Rio Largo site is classified as Distrocohesive Yellow Latosol, intermediate/clayey texture with an average density of 1.44 g cm^{-3} in its first 30 cm. The experimental design used was a randomized block design with five replicates and four sowing dates by treatment (Table 1). The experimental field was approximately 960 m^2 (0.096 ha and the plot dimensions were 8 x 6 m). Row spacing was 0.80 m, and each experimental plot consisted of 10 rows 6 m long; the stand population was 75,000 plants ha^{-1}. Further experimental details for Rio Largo can be found in Silva (2013).

For both sites, the depth of the radicular system set up in the model was 0.60 m, according to the field observations. The maize variety used was the AL Bandeirante, which were sown in four different dates during 2008 (Arapiraca’s site) and 2011 (Rio Largo’s site), as shown in Table 1.

Input datasets

The weather data were grouped in a *metfile*, containing daily data such as (i) global solar irradiation (MJ m^{-2}) obtained using a Pyranometer (CM3, Kipp & Zonen); (ii) air temperature and humidity (°C) obtained using a thermo-hygrometer (HMP45C, Vaisala Inc.); (iii) wind speed (m s^{-1}) obtained using a cup anemometer (051035/Young, Campbell Sci.); (iv) rainfall (mm), obtained using a pluviometer (TB3, Hydrological Service PTY, Sydney, Australia). All the above data were collected at agrometeorological stations using a datalogger (CR1000, Campbell, Sci. Logan, Utah). The soil water content (mm^3 mm^{-3}) measurements utilized to evaluate the simulated soil water dynamics were obtained using a TDR (model-CS616, Campbell Sci. Logan, Utah). The TDR calibration procedures for Arapiraca and Rio Largo can be found in Medeiros (2009) and Sarmento (2015), respectively.

APSIM configuration

The APSIM version 7.6 was used in this study on a daily time step. The simulations were configured using the following modules: MAIZE (crop module), FERTILIZER and SURFACEOM. The application of fertilizer was programmed using the “*operations schedule*” function – available in the APSIM’s management toolbox – that creates a chronology of all operations.

APSIM parametrization

The model parametrization was achieved according to an established logical pattern: (i) meteorological and soil variables, representative of the local environmental conditions, were inserted; (ii) phenological parameters of the maize variety were used to perform the crop parametrization; (iii) finally, an interactive approach was used to fit some variables such as soil water content, LAI and biomass. During the parametrization, several sensitivity analyses were carried out in order to better define the model response regarding the crop estimates. We also used some available information in the literature to complement the parametrization of the phenology and growth. The parametrization process was considered complete when an equilibrium between observed and simulated variables was attained.

The soil parametrization was performed by creating a soil file containing hydrophysical (Table 2) and chemical (Table 3) soil properties in each of the referred sites. The soil files consist of several submodules that include all the inputs necessary to specify the water balance and uptake of nutrients, which in turn were setup in the parametrization. Some soil chemical properties such as starting mineral N pools (NH_4 and NO_3), organic carbon (OC), biomass fraction (FBIOM) and inert OC fraction (FINERT), were used according to Probert et al. (1998) due to the lack of experimental data (Table 3). The soil surface organic matter residues were modified aiming at more precise estimates of the soil water dynamics. This modification was necessary to adjust the initial surface residue (*residue_wt*), whose value was suggested by Probert et al. (1998) of 5000 kg ha^{-1}. However, this value was not in agreement with the soil water measurements. For this reason, we reduced the initial surface residue to 1000 kg ha^{-1} for both sites, which allowed for better estimates. In addition, the depth of the radicular system in the Arapiraca simulation had to be increased (from 60 to 75 cm) for the fourth sowing date to obtain better predictions of LAI and biomass (see results).

Some modifications had to be made to achieve a better fit of the predicted LAI to the observations (Table 4). Firstly, the *x_lai* parameter, which represents the variation of LAI, was changed to fit into experimental LAI variation that achieved a maximum value of 5.6. This, in turn, exceeded the upper limit previously considered in the model (LAI = 4.0). Second, the *leaf_no_dead_slope* parameter was changed to represent the decay in the LAI curve according to Archontoulis et al. (2014). Finally, the *lai_sen_light* parameter, which indicates when the induced senescence occurs, was modified due to the same reason the parameter "*x lai*" was changed.

Nutritional management configuration

The nutritional management was programmed using the function "*fertilizer apply amount*", which in addition to indicating the fertilizer amount also specifies the constituents and application depth. The fertilizer application was shaped in order to represent the experimental applications, which in turn was performed by foundation fertilization and topdressing. The foundation fertilization in the Arapiraca site was 40 kg ha^{-1} of nitrogen (N), 60 kg ha^{-1} of phosphorus pentoxide (P_2O_5), 50 kg ha^{-1} of potassium oxide (K_2O) and 2 kg ha^{-1} of Zinc (Zn) and topdressing utilized 100 kg ha^{-1} of N. In the Rio Largo experiment, the following was used: 10 kg ha^{-1} of N, 60 Kg ha^{-1} of P and 45 kg ha^{-1} of K (foundation fertilization) and 60 kg ha^{-1} of N (topdressing) whose sources were ammonium sulfate ($(NH_4)_2SO_4$), single superphosphate (SSP) and potassium chloride (KCl). However, the model accepts only nutritional sources based on nitrogen (N) and phosphorus (P) and for this reason, fertilization using potassium as a source of nutrients was not considered in programming the nutritional management.

Foundation fertilization was programmed at the beginning of the simulation (sowing date) and there were two types of topdressing corresponding to the V4 (fourth fully expanded leaf at 15 DAS) and V8 (eighth fully expanded leaf at 30 DAS) phonological stages, according to the experimental practices. The N source used in the model was ammonia nitrate (NH_4NO_3) which contains about 34% of N (Malavolta et al., 2002). Since the APSIM does not accept the ammonia sulphate as a source of N, the NH_4NO_3 amount inserted into the model had to be adjusted by proportionality in order to correspond to the N applied experimentally. After this adjustment in the N, the fertilizer amount programmed for the Arapiraca simulation was 117.6 kg ha^{-1} of NH_4NO_3 in the foundation fertilization and 206 kg ha^{-1} of NH_4NO_3 for each topdressing programmed. For Rio Largo, it was programmed as 29.4 kg ha^{-1} of NH_4NO_3 in the foundation fertilization and 88.2 kg ha^{-1} of NH_4NO_3 for each topdressing.

Crop variety implementation

The APSIM platform does not include the maize variety (AL Bandeirante) used in the field experiment, hence the need to implement it in the model. The required phonological parameters, based on the accumulated degree-day (ADD) regarding varieties such as: ADD between the beginning and the end of the juvenile stage (*tt_emerg_to_endjuv*), between the flowering and maturity (*tt_flower_to_maturity*); the flag leaf appearance and flowering (*tt_flag_to_flower*) and flowering to the beginning of the grain filling (*tt_flower_to_start_grain*); and ADD between maturity and harvest (*tt_maturity_to_reap*) were introduced into the *maize.xml* file. These phenological parameters are shown in Table 5.

Statistical analysis

The performance of the APSIM model was quantitatively given by different statistical tests, such as i) model error (± 20%); and ii) Root mean Square Error (RMSE), indicating respectively the relative and absolute mean error, which both show a better fit when the indices approach zero; iii) determination coefficient (R^2); iv) Willmott's index of agreement (*d*) and v) modelling efficiency (EF), where these last three perform better when their values are high. These statistical variables are described in detail in Yang et al., (2014a).

Conclusions

From the model-observation comparisons, it can be concluded that the APSIM-Maize model satisfactorily predicted the LAI of the AL Bandeirante maize variety under well-drained soil conditions. The biomass production was satisfactorily predicted for Rio Largo. On the other hand, for Arapiraca, the model was able to attain a good performance only for the grain yield with an error less than ± 20% within the range considered acceptable. The soil water dynamic estimations showed good precision under well-drained soil. In the conditions under impaired drainage (Rio Largo's soil), the model did not properly predict the soil water dynamics. A better agreement was achieved after a drainage parameter adjustment, but despite this, the model was incapable of simulating SW accurately. Further adjustments in drainage parameters are still required in order to simulate the soil water dynamics and LAI variations more accurately. Finally, this study showed that the APSIM model is a very useful tool to help establish agricultural policies and optimize production systems in the region. In the present study, the model was evaluated for specific environmental conditions, and therefore these results should not be extrapolated to other conditions without the necessary adjustments.

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