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ORIGINAL PAPER

Scheduling irrigation with a dynamic crop growth model and determining the relation between simulated drought stress and yield for peanut

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Abstract A computer simulation model can be used as a tool to help explain the impact of drought stress on plant growth and development because it integrates the complex soil–plant-atmosphere system through a set of mathematical equations. The objectives of this study were to determine the impact of different irrigation scheduling regimes on peanut growth and development, to determine the capability of the CSM-CROPGRO-Peanut model to simulate growth and development of peanut, and to determine the relationship between yield and the two cumulative drought stress indices simulated by the peanut model. The CSM-CROPGRO-Peanut model was evaluated with experimental data collected during two field experiments that were conducted in four automated rainout shelters located at The University of Georgia, USA, in 2006 and 2007. Irrigation was applied when the simulated soil water content in the effective root zone dropped below a specific threshold value for the available soil water capacity (AWC). The irrigation treatments corresponded to irrigation thresholds (IT) of 30, 40, 60, and 90 % of AWC. The results showed that growth and development was reduced for the 30 and 40 % IT treatments which resulted in yield reductions that were 92 and 45 %, respectively, of the 90 % IT treatment. The Cropping System Model (CSM)-CROPGRO-Peanut model was able to accurately simulate growth and development of peanut grown under different irrigation treatments when compared to the observed data. We found an inverse relationship between the two simulated total cumulative drought stress indices for leaf growth (expansion) and photosynthesis and simulated pod yield. Knowing the cumulative drought stress value prior to harvest maturity could help with the prediction of potential harvestable yield.

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Introduction

Peanut (*Arachis hypogaea* L.) is a very important crop in the southeastern USA (Smith and Smith 2011) and other tropical and subtropical regions across the globe (Boriss and Kreith 2006). However, under rainfed conditions, peanut yield is variable, due in part to the effects of spatial and temporal variability of rainfall and other biotic factors. Yield reduction of peanut due to a soil water deficit has been reported worldwide (Nageswara Rao et al. 1985; Wright et al. 1991; Haro et al. 2008; Songsri et al. 2009). In Australia, Wright et al. (1991) reported that water stress that occurred during early crop growth reduced pod yield between 17 and 25 % depending on the cultivar. Irrigation has been reported to increase yield and improve quality of peanuts grown in the southeastern USA (Lamb et al. 1997). However, different types of cultivars respond differently to drought stress (Devi et al. 2010; Jongrungklang et al. 2011). Late-season drought for the long-season Virginia peanut types reduced pod yield more severely than for the Spanish types through a reduction in both the total number of pods per unit land area and kernel size relative to the fully irrigated crop (Wright et al. 1991). Drought stress also reduces total dry matter, pod weight, harvest index, water use efficiency, and specific leaf area, while it causes an increase in chlorophyll content and canopy temperature (Jongrungklang et al. 2008). Black et al. (1985), Patel and Golakia (1988), Stirling et al. (1989) and Reddy et al. (2003) found that peanut is most sensitive to water stress during flowering and pod filling. In an arid region of Sudan, Ishag (1982) found that the flowering rate depends on the irrigation frequency and is reduced when the frequency is less than once every 6 days. It is important to mention that the peanut fruit is a pod that contains up to five seeds. The peanut pod develops underground and starts as a needle like structure that is called a peg, which is an elongated ovarian structure (Putnam et al. 1991). Peg elongation is delayed by drought (Boote and Ketring 1990); adequate soil moisture in the peg elongation zone is critical for peg penetration, peg viability, and the formation of pods (Reddy et al. 2003; Haro et al. 2011). Jain et al. (1997) recommended that in the case of limited water supply, water saving should be made during periods other than the flowering and pod formation stages of peanut. Bandyopadhyay et al. (2005) defined water productivity as the ratio of pod yield to seasonal crop evapotranspiration, and the values found ranged from 0.48 to 0.60 kg m^{-3} for peanut grown during two cropping seasons in India.

It is well known that water demand is increasing in vast regions of the US and other areas across the globe. Farmers, therefore, need to maximize the production per unit water consumed to remain economically competitive and to sustain irrigated agriculture. Supplemental irrigation during drought stress is critical to produce high yield and top-quality peanut in the southeastern USA (Beasley 2007). In addition, accurate estimates of peanut water requirements are needed for water conservation (Suleiman et al. 2011). Computer simulation models, such those that are part of the Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al. 2010), have the potential to be an important aid for irrigation scheduling. At the same time, they can be used to help understand the impact of drought stress on plant growth and development, as these crop simulation models integrate the scientific knowledge that is known about the soil–plant-atmosphere complex. One of the main reasons for simulating a soil and plant water balance is to determine the potential yield reduction caused by soil water deficit. For the water balance, sources may be precipitation and irrigation, and losses are through evaporation, transpiration, surface runoff, storage in the soil, and deep percolation. The storage component in the soil is positive when soil moisture increases and negative if moisture is lost (White and Hoogenboom 2010). The daily soil water balance in DSSAT is based on the one-dimensional "tipping bucket" approach described by Ritchie (1998). It simulates soil–water flow and root water uptake for each individual soil layer. The DSSAT models typically consider the soil profile of a field that is described with discrete horizontal layers that can vary in water holding capacity, moisture content, and root length density, expressed in terms of mass and length (White and Hoogenboom 2010). Therefore, the potential root water uptake is a function of root length density, rooting depth, and root distribution and the actual soil water content for the layers where roots are present.

With respect to potential atmospheric demand, the model first determines potential evapotranspiration from weather variables and crop canopy conditions (White and Hoogenboom 2010). Potential evapotranspiration can be calculated either with the Priestley–Taylor method (Priestley and Taylor 1972) or with the Penman-Montieth-FAO-56 approach (Allen et al. 1998). The potential evapotranspiration establishes the upper limit for water uptake by the crop. Actual evapotranspiration is less than potential if sufficient soil water is not readily available to offset the demand.

For determining drought stress, a comparison between potential demand and potential root water uptake or plant extractable soil water is conducted. It is well known that when the soil dries due to soil water evaporation and plant water uptake, the conductivity of soil water decreases. As a result, root water uptake also decreases. When the ratio between potential root water for uptake and potential evapotranspiration ratio is less than 1.5 in the DSSAT models, the drought stress index for leaf and stem expansion is initiated. If this ratio drops below 1.0, then the drought stress index for photosynthesis and biomass production is initiated (Ritchie 1998). In the latter case, actual evapotranspiration is reduced, mimicking the partial closing of the stomata. Potential biomass production is assumed to be reduced in the same proportion as evapotranspiration. In other words, the crop functions (growth and assimilated production) were simulated at their optimum rates until water became scarce, or other factors such as nitrogen or temperature became limiting.

Crop simulation models have been used in many studies to asses drought stress and yield levels for a range of crops. Soler et al. (2007) reported that the CSM-CERES-Maize model was able to accurately simulate phenology and yield for four hybrids grown under irrigated and rainfed conditions in a subtropical environment in Brazil. Crop simulation models have been recommended to be used in dryland cropping systems including wheat, sorghum and soybean crops, as research tools for the semi-arid Great Plains of the USA (Staggenborg and Vanderlip 2005) because the overall trends were similar to the measured yield in the field despite inaccuracies for simulated yield for some years. Zhao et al. (2011) used the CSM-CERES-Wheat model to assess the risk of drought for a region of China. The yield gap between the simulated potential yield and the water-limited yield was used as a proxy to assess the effect of drought on winter-wheat yield. A strong linear relationship between the yield gap and the amount of precipitation in the growing season was observed for the years of the study. The spatial distribution of drought was considered useful for identifying vulnerable regions and for improving the management of drought. Chipanshi et al. (1999) studied the effect of drought stress on wheat yield using the CSM-CERES-Wheat model for three locations in Saskatchewan, Canada. Drought stress reduced grain yield, with the highest correlation coefficients occurring when drought stress occurred during ear growth, because of the effects on the potential for grain development. Chipanshi et al. (1997) showed that cumulative drought stress index during the season were highest for a sandy soil followed by the medium texture soil and clay soil.

During the past decade, agrometeorological models have been developed for peanut and used for specific studies, such as determining the water requirements (Da Assunção and Escobedo 2009). Cropping system simulation models such as the CSM-CROPGRO-Peanut model, included in DSSAT (Jones et al. 2003), APSIM (Keating et al. 2003) and CropSyst (Stockle et al. 2003), offer a good balance between complexity, input data requirements, and management variables to be simulated. Recently, AQUAMAN, a web-based decision support system for irrigation scheduling in peanuts was developed to assist Australian peanut growers with scheduling irrigations. It simulates the timing and depth of future irrigations by combining procedures from the Food and Agriculture Organization (FAO) guidelines for irrigation scheduling (FAO-56) with those of the Agricultural Production Systems Simulator (APSIM) modeling framework (Chauhan et al. 2011). However, the CSM-CROPGRO-Peanut model (Jones et al. 2003; Hoogenboom et al. 2004) has been used in many studies worldwide. This model was applied to study ENSO (El Niño Southern Oscillation) and planting date effects on peanut yield and N leaching in the southeastern USA (Mavromatis et al. 2002; Paz et al. 2007), to simulate irrigation applications and to study its impact on peanut yield in farmers' fields (Guerra et al. 2004), to evaluate peanut growth and yield in some farming zones of Ghana (Dugan and Adiku 2006), to characterize the inter-annual variation of peanut yield in Georgia, USA (Garcia y Garcia et al. 2006), to analyze the genotype x environment ($G \times E$) interaction over multiple years in Thailand (Phakamas et al. 2008b), to estimate cultivar coefficients for breeding applications in Thailand (Anothai et al. 2008), to assess potential yields and yield gaps of peanut grown in major growing regions of India (Bhatia et al. 2009), and to design a peanut ideotype for a target environment in Thailand (Suriharn et al. 2011). Results from studies conducted in Thailand using the CSM-CROPGRO-Peanut model showed that the model performed reasonably well in simulating phenology, dry matter accumulation, final biomass, and pod yield of the two peanut cultivars under three different soil moisture regimes (Dangthaisong et al. 2006). The model could predict the relative yield reductions from drought stress of the individual peanut cultivars quite accurately and could provide information on the time of occurrence and severity of drought stress during the growing season. These results indicated that the CSM-CROPGRO-Peanut model can be used in generating the required information to determine appropriate management under drought stress conditions (Dangthaisong et al. 2006).

So far, no specific studies have been conducted that focused on the role of the drought stress indices simulated with the CSM-CROPGRO-Peanut model, especially the cumulative drought stress during the growing season and how it relates to yield. The objectives of this study, therefore, were (1) to determine the impact of different irrigation scheduling regimes on peanut growth and development, (2) to determine the capability of CSM-CROPGRO-Peanut model to simulate growth and development of peanut, and (3) to determine the relation between yield and the cumulative drought stress indices as simulated by the peanut model.

Materials and methods

Field experiments

Two experiments were conducted in four rainout shelters, located at the Griffin Campus of The University of Georgia (latitude 33°15′46.05″N; longitude 84°17′07.08″W), during 2006 and 2007. The rainout shelters are automated structures that exclude natural rainfall from the field plots. They automatically cover the plots when rainfall is detected by sensors installed at the experimental site and they move to their original position once the rain stops. The advantage of rainout shelters is that they can be used to induce drought during the growing season. In this experiment, each rainout shelter contained an individual controllable drip irrigation system that corresponded to one irrigation treatment, with three replicates per treatment. The peanut cultivar Georgia Green (Branch 2008), which is a high-yielding runner-type peanut, was planted on May 22 in both 2006 and 2007. The plant density was 218,700 plants per hectare, row spacing was 0.9 m, plant spacing was 0.05 m, and planting depth was 0.03 m. There were five rows (12 m length), but only the three internal rows were used in this study, while the two external rows were considered as border rows.

The CSM-CROPGRO-Peanut model (Jones et al. 2003; Hoogenboom et al. 2004) was used to define the irrigation treatments by estimating the timing of irrigation and the amount of water to apply. The irrigation events were triggered when the simulated soil water content in the effective root zone dropped below a specific threshold of the available water capacity (AWC) and then irrigation water was added to bring the soil moisture to 100 % of the AWC. The available water capacity is calculated by the model as the difference between field capacity (water potential between 0.1 and 0.33 bar) and wilting point values (water potential of 15 bar) (Ritchie 1998). The irrigation treatments corresponded to 30, 40, 60, and 90 % of the irrigation threshold (IT). The model required daily weather data, including maximum and minimum air temperatures (°C), solar radiation (MJ m^{-2} day^{-1}) and precipitation (mm) as inputs. Actual weather data from the automated weather station installed in Griffin close to the experimental site were used until the current date and the daily weather data for the past 10 years were used to project the weather until the end of the growing season (www.Georgiaweather.net).

The soil in each shelter was a sandy soil, with a sand content above 90 % until a depth of 120 cm, and consequently had a low soil water retention capacity. An initial value of the soil water content for each depth was used as input of the model (Ritchie 1998). For the upper 5 cm of soil, the value of soil organic carbon was 0.94 % and the soil pH was 6.3. Soil samples were taken 1 month prior to planting at a depth of 0–20 cm and analyzed to determine nutrient requirements. Fertilizer, including 22 kg ha^{-1} of superphosphate (formula 0-46-0) and 28 kg ha^{-1} of sulfate of potash (51 % K2O and 18 % S), was applied prior to planting and incorporated into the soil. The soil water content was monitored with Time-Domain-Reflectometry (TDR) (CS615, Campbell Scientific Inc., Logan, UT) probes and with a soil profile probe (PR2/6, Delta-T Devices, Ltd.). In this study, the measurements of the volumetric soil water content with the PR2/6 probe were used because this device records soil moisture at different depths, including 0.1, 0.2, 0.3, 0.4, 0.6, and 1 m. For the PR2/6 probe, three access tubes were installed within the row and one access tube between the rows for each rainout shelter (irrigation treatment); the readings within the rows were used for the comparison of simulated and observed soil water content values. Soil water content was measured manually once a day in the morning, while two data loggers (DL6 Soil Moisture Logger, Delta-T Devices Ltd., Cambridge, UK) were used to obtain automated 15-min soil moisture readings. The data logger and PR2 probe were moved among the different treatments. The PR2 probe was calibrated for the sandy soils of the rainout shelters, using the gravimetric soil moisture method. For this, soil samples were taken following a standard procedure, weighed, dried in an oven for 24 h at 105 °C, and then weighed again to determine the mass of water that was in the original soil sample (Reynolds 1970).

Phenology was recorded five times per week. Growth analysis, including measuring the leaf area index (LAI), plant height and sampling biomass, was conducted approximately every 18 days. For growth analysis, destructive methods were used, including harvesting a 1-m section of the three central rows of each rainout shelter. Above-ground biomass was obtained by oven-drying the samples at 70 °C until constant weight. Leaf area of the 1-m section was measured with the LI-3100C area meter. Pod and seed yield and yield components (kernel weight and kernels' number) were obtained at final harvest by sampling a 3-m section of each of the three central rows.

Evaluation of the CSM-CROPGRO-peanut model

The observed data obtained from the two field experiments that were conducted in 2006 and 2007 were used for evaluation of the CSM-CROPGRO-Peanut model. The cultivar specific coefficients for the cultivar Georgia Green were obtained from Guerra et al. (2004), but further model calibration was performed. The cultivar coefficients were modified to simulate growth and development of peanut grown at the rainout shelters on a sandy soil. An iterative procedure (Hunt et al. 1993) was used to select the most appropriate value for each of phenological, developmental, and growth parameters. For model evaluation, simulated and observed values for the dates of first flower (R1), first pod (R3), and harvest maturity (R8) as well as maximum LAI, final biomass, final pod and seed yield and yield components, and water use efficiency (WUE) were compared for the different irrigation treatments. Simulated WUE was estimated as the ratio between simulated pod yield and total crop evapotranspiration calculated by the CSM-CROPGRO-Peanut model using the Priestley–Taylor method (Priestley and Taylor 1972). In addition, the daily values for the two drought stress coefficients related to expansive growth (leaf and stem) and photosynthesis as determined by the CSM-CROPGRO-Peanut model were analyzed to identify their relation with both the observed and simulated yield. These coefficients are calculated on a daily basis as the ratio between potential root water uptake ("supply") and potential evapotranspiration ("demand") (Ritchie 1998). The two drought stress indices differentiate themselves by an established value of the ratio between potential root water for uptake/potential evapotranspiration. When the ratio is less than 1.5 in the DSSATv4.5 models, the drought stress factor for leaf and stem expansion is initiated. If the ratio drops below 1.0, then the drought stress factor for photosynthesis and biomass production is initiated (Ritchie 1998). For instance, once the ratio reaches values less than 1.0 for the drought stress index for photosynthesis or 1.5 for the drought stress index for leaf and stem expansion, and if no additional water is added, drought conditions will usually continue and complete drought stress will occur when the ratio reaches zero. Crop failure will result when drought stress values near 0 continue for a longer period of time.

For display and output purposes, the stress indices are shown as (1—drought stress index). For any given day, a value of "0" means no stress while value of "1" means full stress. The total cumulative drought stress index for the growing season, calculated as the sum of daily values for each drought stress index from planting to harvest, was used to quantify the drought severity. The relationship between the total cumulative drought stress indices for all irrigation treatments and the corresponding pod yield was analyzed.

Statistical analysis

Different statistical indices were determined, including the coefficient of determination (r^2), root mean square error (RMSE), and the index of agreement (d) as proposed by Willmott et al. (1985) (Eq. 1).

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(Pi - Oi)^2}{\sum_{i=1}^{n}(|P'i| + |O'i|)^2}\right] \quad (1)$$

where n is the number of observations, Pi is a predicted observation, Oi is a measured observation, $P'i = Pi - M$ and $O'i = Oi - M$ (M is the mean of the observed variable).

According to the d-statistic, the closer the index value to one, the better the agreement between the two variables that are being compared and vice versa.

Model performance was evaluated using the values for RMSE and the d-index. The RMSE was calculated using Eq. 2.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Pi - Oi)^2}{n}} \quad (2)$$

where Pi and Oi refer to predicted and observed values for the studied variables, respectively, for example, days from planting to anthesis, days from planting to physiological maturity, maximum LAI, biomass at harvest, yield, and yield components.

The software SAS version 8th (SAS Inst. 2001) was used to perform the ANOVA statistical analysis of the observed yield and yield components. The means were compared with the Tukey–Kramer's test using a significance level of $P \leq 0.05$.

Results and discussion

Phenology

The weather conditions during the growing season have a significant impact on crop growth and development. In 2006, the average solar radiation was higher (26.4 MJ m^2 day^{-1}) than for 2007 (23.2 MJ m^2 day^{-1}) during the first 30 days after planting, and a similar trend was found between 31 and 60 days after planting, that is, 23.8 MJ m^2 day^{-1} for 2006 and 21.2 MJ m^2 day^{-1} for 2007. The average maximum temperature for the first 30 days after planting was also higher in 2006 (31.4 °C) than in 2007 (30.1 °C), as well as for the period from 31 to 60 days after planting, that is, 33.1 °C in 2006 and 31.0 °C in 2007. The average minimum temperature was very similar during the first 30 days after planting, that is, 17.9 °C for 2006 and 17.7 °C for 2007, but for the period 31–60 days after planting, the average minimum temperature was 21 °C in 2006 and 20.2 °C in 2007. For the last part of the growing season from 61 to 90 and from 91 to 120 days after planting, solar radiation and maximum and minimum temperature were higher in 2007 than 2006.

For the 30 % IT treatment, the observed anthesis was 4 days later in 2007 when compared to 2006 and physiological maturity was reached 4 days later in 2007 than 2006. For the 90 % IT treatment, the difference for both the observed anthesis and physiological maturity dates between the 2 years was only one day.

The observed anthesis occurred, on average for both years, at 32 days after planting for the 30 % IT treatment, which was 2 days later when compared to the other treatments that reached anthesis at 30 days after planting (Fig. 1). Simulated anthesis was predicted at 31 days after planting for the 30 % IT treatment and 30 days after planting for the other irrigation treatments.

The observed first pod stage was reached, on average for both years, at 46, 49, 53, 59 days after planting for the 90, 60, 40, and 60 % IT treatments, respectively. The model simulated first pod ranging from 51 days for the 90 % IT treatment to 56 days for the 30 % IT treatment. Ketring and Wheless (1989) reported that drought stress resulted in slower development and a reduction in the number of main stem nodes, which was confirmed by the results from this study.

The 30 % IT treatment was the first to reach harvest maturity at 144 days after planting (average of both years), while the 40 % IT treatment reached harvest maturity at

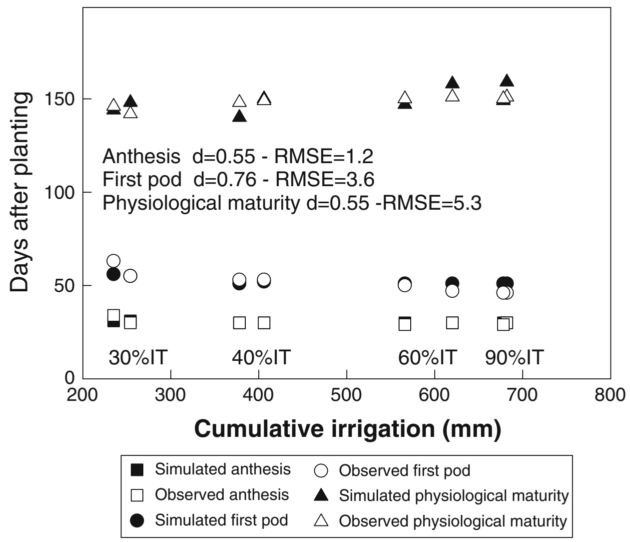

Fig. 1 Observed and simulated phenology versus cumulative irrigation for peanut grown in 2006 and 2007

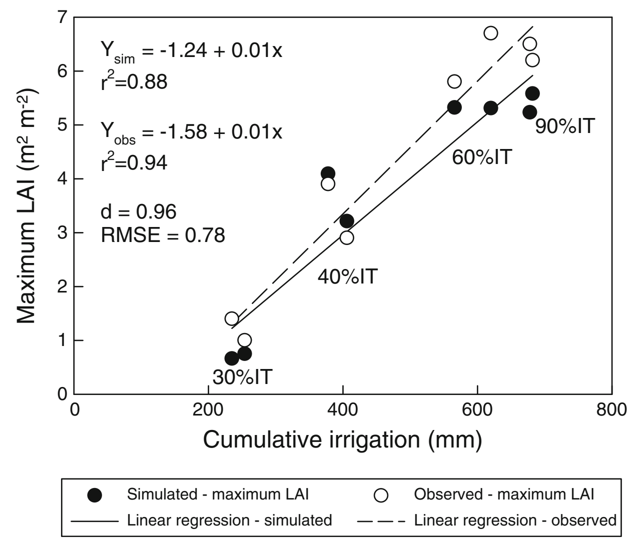

Fig. 2 Observed and simulated maximum LAI as a function of cumulative irrigation for peanut grown in 2006 and 2007

149 days after planting, and the 60 and 90 % IT treatments reached harvest maturity at 151 days after planting. The simulated days to physiological maturity ranged from 146 days for the 30 % IT treatment to 154 for the 90 % IT treatment. There was a 2- and 3-day difference in the entire cycle when compared to the observed days to maturity (Fig. 1).

The RMSE between simulated and observed growth stages was 1.2 for anthesis, 3.6 for first pod appearance, and 5.3 for physiological maturity. The differences between simulated and observed phenology were mainly due to the effect of drought stress on phenology.

Leaf area index and biomass

Soil water stress conditions have been reported to affect LAI of peanut (Haro et al. 2008). In our study, both the simulated and observed values for maximum LAI showed a relation with the irrigation treatments (r^2 of 0.94 and 0.88, respectively) (Fig. 2). The slopes of the linear regression for the simulated and for the observed values were very similar (0.010 and 0.012, respectively), and the t-statistic for the slopes was significant at the 0.05 critical alpha level, indicating that the slope was different from 1. The lowest observed maximum LAI (average of both years) was found for the 30 % IT treatment (1.2), while the highest observed maximum LAI was found for the 90 % IT treatment (6.3). The 60 and 90 % IT treatments had similar values for observed maximum LAI, ranging from 5.8 to 6.7 for the 60 % IT treatment and from 6.2 to 6.5 for the 90 % IT treatment. For the 30 % IT treatment, the simulated maximum LAI (0.75 and 0.66) was lower than the observed maximum LAI (1.0 and 1.4). However, LAI was more accurately simulated for the other treatments. The value for the index d between the observed and simulated LAI maximum was 0.96, indicating that that model was capable to simulate this variable accurately. We also found a high correlation between maximum LAI and maximum canopy height, with a correlation coefficient of 0.95.

Haro et al. (2008) found values of 3.93 for maximum LAI for peanut grown under water stress conditions and 6.2 for fully irrigated plots in Argentina. Patel and Golakia (1988) showed that continuous water deficit resulted in fewer and smaller leaves in a study conducted in India. Maximum seasonal LAI for peanut tends to be greater than for most crops (Kiniry et al. 2005), with reported values for maximum LAI ranging from 3 (Gardner and Auma 1989) to greater than 8 (Chapman et al. 1993). In our study, the observed maximum LAI (average of both years) ranged from 1.2 for the 30 % IT treatment to 6.3 for the 90 % IT treatment.

Observed total biomass at harvest, calculated as the sum of the aboveground biomass and pod biomass, was affected by the irrigation treatments, with an average for both years ranging from 1,197 kg ha^{-1} for the 30 % IT treatment to 12,312 kg ha^{-1} for the 90 % IT treatment. The biomass at harvest was in close agreement with cumulative irrigation, with r^2 of 0.76 and 0.98 for observed and simulated biomass, respectively (Fig. 3). The slopes of the linear regression for the simulated and observed biomass values were different from 1 ($P \leq 0.05$). The index d was 0.85, indicating an acceptable performance of the model for simulating total biomass at harvest. Previous studies also reported that drought stress reduced the total dry matter across peanut genotypes (Arunyanark et al. 2008, Pimratch et al. 2008).

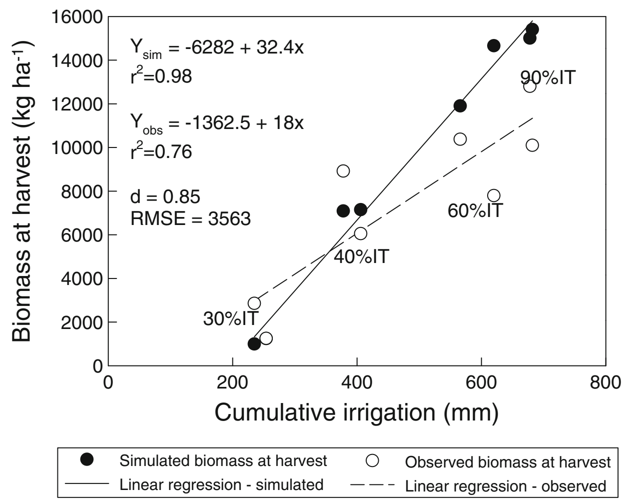

Fig. 3 Observed and simulated final total biomass at harvest maturity as a function of cumulative irrigation for peanut grown in 2006 and 2007

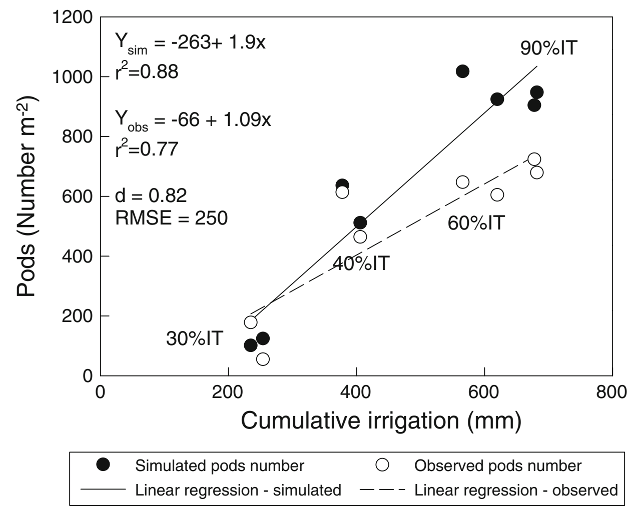

Fig. 4 Observed and simulated pod number as a function of cumulative irrigation for peanut grown in 2006 and 2007

Yield and yield components

The average observed pod number per square meter for both years ranged from 105 for the 30 % IT treatment to 643 for the 90 % IT treatment. The coefficient of determination between total pod number and cumulative irrigation was 0.77 for the observed and 0.88 for the simulated values. The slope of the linear regression for the simulated and for the observed values was significant at the 0.05 critical alpha level, indicating that the slope was different from 1. Simulated pod number per square meter (average of both years) ranged from 112 for the 30 % IT treatment to 925 for the 90 % IT treatment (Fig. 4). The simulated and observed pod number per unit area had an index d of 0.82, indicative of the model capability for simulating this variable accurately.

The ANOVA analysis of the observed pod number per square meter for different irrigation treatments using Tukey–Kramer test ($P \leq 0.05$) indicated that the number of pods for the 90 % IT treatment was significantly different from the 40 % IT and that this treatment was significantly different from the 30 % IT. Pandey et al. (1984) found that among yield components, the number of pods per unit land area was the most affected yield component by water stress, followed by the number of seeds per pod, while seed weight was the least affected. A positive linear relationship between pod yield and the number of pods per unit area were found across genotypes and seasons in Thailand, but no relationship was found between pod yield and weight per pod (Phakamas et al. 2008a). Similar results were found in an experiment conducted in Argentina, where across experiments, seed yield was strongly associated with the variation in seed number, and to a lesser extent to variation in seed weight (Haro et al. 2007).

As expected, the different irrigation treatments had a strong impact on observed final pod yield. A high coefficient of determination was obtained for pod yield and cumulative irrigation, that is, 0.86 for the observed and 0.96 for the simulated values (Fig. 5). Final pod yield was 380 kg ha^{-1} for the 30 % IT treatment, 2,744 kg ha^{-1} for the 40 % IT treatment, 3,790 kg ha^{-1} for the 60 % IT treatment, and 5,064 kg ha^{-1} for the 90 % IT treatments. The yield reduction was 92 and 45 %, respectively, for the 30 and 40 % IT when compared to the 90 % IT treatment. The ANOVA analysis of the observed yield for different irrigation treatments (random effects) using Tukey–Kramer test ($P \leq 0.05$) indicated that pod yield for the 90 % IT treatment was significantly different from the other three irrigation treatments, while the 30 % IT was significantly different from the 40 and 60 % IT treatment. Similar results were found in a study conducted in India, in which the lowest pod yield resulted from severe stress from emergence to maturity. However, important reductions in kernel yield have been reported when stress was imposed during the seed-filling phase (Nageswara Rao et al. 1985). Sarma and Sivakumar (1989) reported that drought stress imposed from flowering to the start of seed growth were important for both peanut yield and quality.

The simulated final pod yield (average of both years) ranged from 417 kg ha^{-1} for the 30 % IT treatment to 4,645 kg ha^{-1} for the 90 % IT treatment. The CSM-CROPGRO-Peanut model was able to simulate the yield reduction due to drought stress, which was evidenced by the statistics related to the performance of the model. The

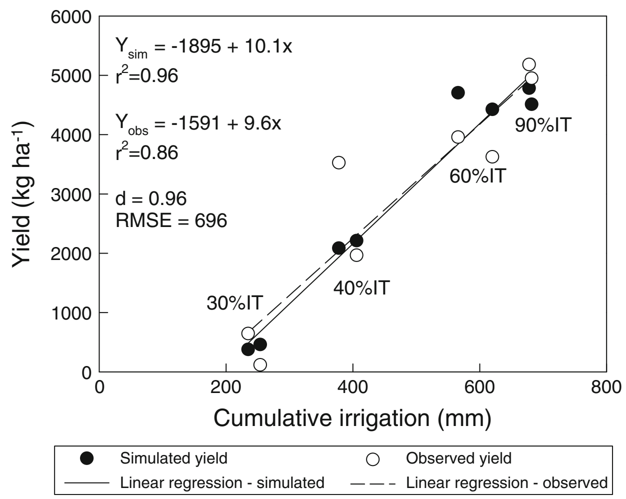

Fig. 5 Observed and simulated pod yield as a function of cumulative irrigation for peanut grown in 2006 and 2007

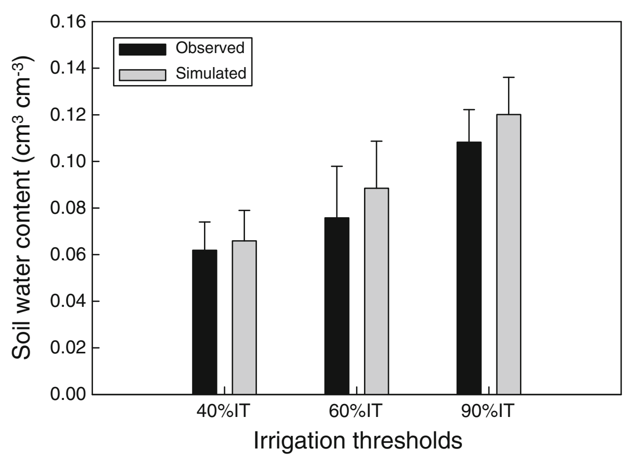

Fig. 6 Observed and simulated average soil water content and standard deviation for the different irrigation thresholds for peanut grown in 2006 and 2007

index d between simulated and observed pod yield was 0.96 and the RMSE was 696 kg ha^{-1}.

Soil water content and drought stress indices

The average soil water content and the standard deviation for the different soil depths throughout the growing season showed clear differences among the irrigation treatments (Fig. 6), for both the observed and simulated values. The observed soil water content averaged for the growing season across depths for both years was 0.062 cm^3 cm^{-3} for the 40 % IT treatment, 0.076 cm^3 cm^{-3} for the 60 % IT treatment, and 0.108 cm^3 cm^{-3} for the 90 % IT treatment.

The simulated soil water content for the two growing seasons across the four depths (10, 22, 37, and 52 cm) for the 2 years was in close agreement with the observed values (Fig. 7; Table 1), with a coefficient of determination of 0.75 between the simulated and observed values, RMSE ranging from 0.014 to 0.058, and the index d of agreement ranging from 0.23 (60 % IT in 2006) to 0.87 (90 % IT in 2007). The variation in the accuracy of the simulation of soil water content, expressed in a variation of the d-index for different depths, irrigation treatments and years, can in part be attributed to the measurement errors of the observed soil water content itself. For example, measures of soil water content with a PR2/6 probe can have inherent variation due to the position of the probe inside the access tube, particularly in sandy soils under drip irrigation.

Results from past studies related to the simulation of soil water content using the DSSATv4.5 models have mainly been reported for crops other than peanut. For example, Garrison et al. (1999) reported reasonable soil water content simulations using the CSM-CERES-Maize for a tile-drained field in Iowa, USA. Liu et al. (2011) found that there was agreement between simulated and observed soil water content simulated with DSSAT v4.5 for maize and soybean experiments conducted in Canada during 4 years.

As stated previously, the drought stress indices are calculated on a daily basis; a value of 0 means no stress while a value of 1 means complete drought stress (Ritchie 1998). The cumulative drought stress index for the growing season was calculated as the sum of daily values of drought stress and the total cumulative values of the different irrigation treatments were used to quantify the drought severity.

The cumulative drought stress index for photosynthesis at physiological maturity was 67 for the 30 % IT, 32 for the 40 % IT, 6 for the 60 % IT, and 0 for the 90 % IT treatments (Fig. 8). The cumulative drought stress index for leaf expansion as predicted by the CSM-CROPGRO-Peanut model was strongly affected by the irrigation treatment and the associated amount of irrigation that was applied. The 30 % IT treatment had a cumulative drought stress for leaf expansion of 79.2 at harvest maturity (Fig. 9), which indicated that the crop was exposed to many days of drought stress, which in turn explained the low yield obtained for this treatment. The 40 % IT treatment had a cumulative drought stress index of 40 at harvest maturity, also indicating a great exposure to drought conditions, while the 60 % IT treatment had a value of 10, indicating that the crop was exposed to drought stress during only a few days of the growing season. The 90 % IT treatment had a value of 0 for cumulative drought stress, indicating that this treatment was never exposed to drought.

The cumulative drought stress for photosynthesis at physiological maturity was 67 for the 30 % IT treatment, compared to 79.2 for the cumulative drought stress factor on leaf growth. The cumulative values of the drought stress index for photosynthesis were smaller than for leaf growth

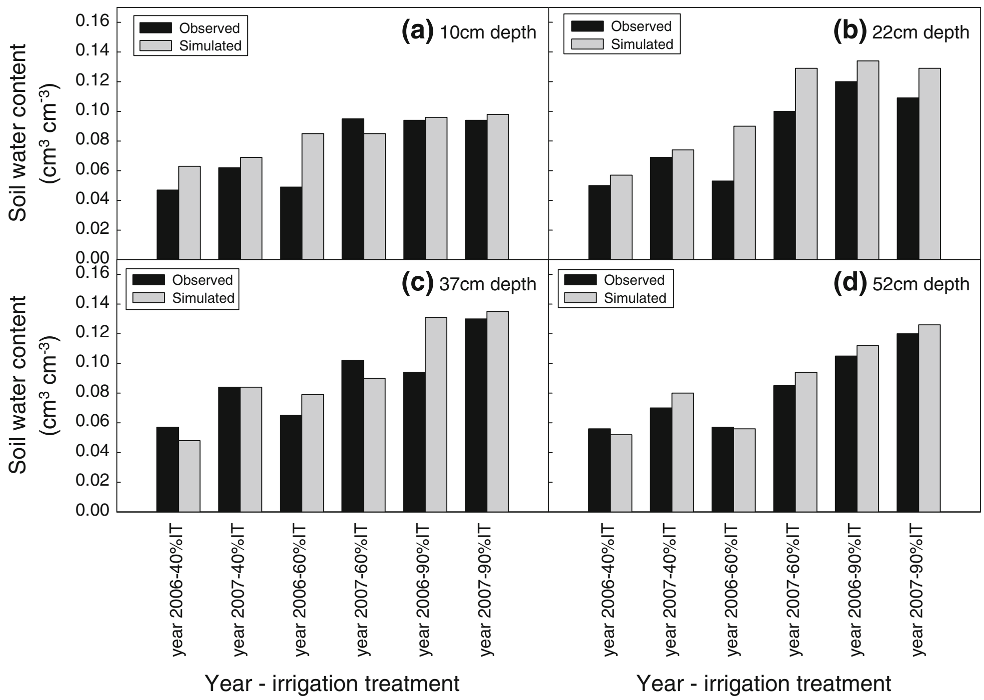

Fig. 7 Average observed and simulated soil water content for different soil depths **a** 10 cm, **b** 22 cm, **c** 37 cm, and **d** 52 cm, for the different irrigation thresholds for peanut grown in 2006 and 2007

expansion based on the inherent method of calculation, as explained previously.

There was an inverse relationship ($r^2 = 0.88$) between the cumulative drought stress coefficients for photosynthesis and observed pod yield (Fig. 8). Similar results were found for the cumulative drought stress index for leaf expansion, with a value of 0.89 for r^2 between this index and the observed pod yield.

There was also an inverse relationship ($r^2 = 0.96$) between the cumulative drought stress coefficients for photosynthesis and simulated pod yield (Fig. 8). Similar results were obtained when analyzing the cumulative drought stress index for expansive leaf growth versus the simulated pod yield ($r^2 = 0.95$; Fig. 9). The slopes and intercepts of the two lines for the observed and for the simulated values were significant ($P \leq 0.05$), with similar values, for example, −54 for observed and −55.8 for simulated, and 4,754 and 4,760 for observed and simulated, respectively. Therefore, calculating a cumulative drought stress for the entire growing season using both the photosynthesis drought stress index and expansive growth stress index can be a useful measure to indicate drought stress levels. Our study showed a high correlation between the two drought stress indices and the observed and simulated final pod yield.

It is important to note that Georgia Green, the runner-type cultivar that was used in this study, has been reported as drought susceptible (Rowland et al. 2008). However, different genotypes show different responses during extended periods of drought or during drought recovery (Harris et al. 1988; Arunyanark et al. 2008; Songsri et al. 2008). Drought tolerant cultivars are able to adapt to drought by maintaining physiological functions under dry spells in relation to the fully irrigated treatments throughout most of the season (Rowland et al. 2008). Therefore, the relation between cumulative drought stress indices and pod yield could vary for different genotypes depending on their genetic susceptibility to drought stress.

Water use efficiency

The observed WUE, estimated as the ratio between observed pod yield and evapotranspiration, increased as the cumulative irrigation through the growing season increased (Fig. 10). The average observed WUE for both years ranged from 0.18 kg m^{-3} for the 30 % IT treatment to 0.70 kg m^{-3} for the 90 % IT treatment. However, the 40 % IT treatment in 2007 had the highest WUE that can mainly be explained through the observed yield. This small difference in 2007 for the 40 % IT treatment was due to a heavy rainfall event (approximately 45 mm) around the critical period of flowering stage (R1) that affected the crop prior to closing of the rainout shelter, which in turn affected final pod yield.

The simulated WUE was estimated as the ratio between simulated pod yield and simulated evapotranspiration.

Table 1 RMSE and d-index between simulated and observed soil water content for the different soil depths and irrigation treatments (thresholds) for 2006 and 2007

Depth (cm)	Years	Irrigation threshold	RMSE	*d*-Index
5–15	2006	40 % IT	0.027	0.46
5–15	2007	40 % IT	0.020	0.80
5–15	2006	60 % IT	0.039	0.32
5–15	2007	60 % IT	0.028	0.34
5–15	2006	90 % IT	0.025	0.40
5–15	2007	90 % IT	0.014	0.54
15–30	2006	40 % IT	0.018	0.60
15–30	2007	40 % IT	0.032	0.72
15–30	2006	60 % IT	0.045	0.31
15–30	2007	60 % IT	0.037	0.44
15–30	2006	90 % IT	0.026	0.43
15–30	2007	90 % IT	0.027	0.36
30–45	2006	40 % IT	0.026	0.38
30–45	2007	40 % IT	0.034	0.77
30–45	2006	60 % IT	0.036	0.23
30–45	2007	60 % IT	0.058	0.25
30–45	2006	90 % IT	0.041	0.49
30–45	2007	90 % IT	0.031	0.24
45–60	2006	40 % IT	0.021	0.71
45–60	2007	40 % IT	0.037	0.67
45–60	2006	60 % IT	0.022	0.52
45–60	2007	60 % IT	0.037	0.69
45–60	2006	90 % IT	0.016	0.87
45–60	2007	90 % IT	0.036	0.33

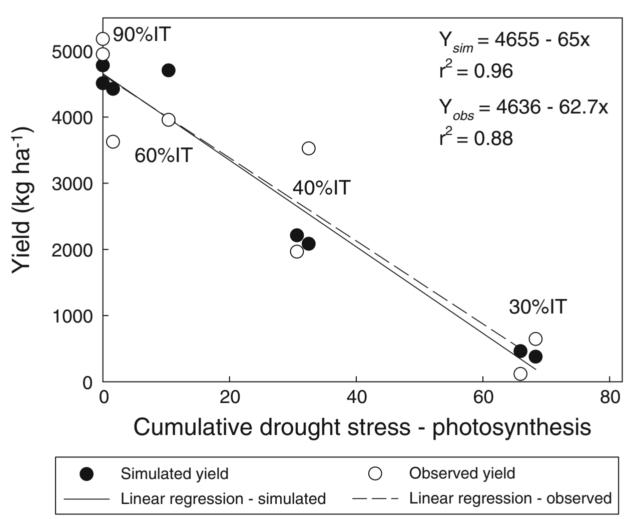

Fig. 8 Observed and simulated pod yield versus the simulated total cumulative drought stress index for photosynthesis for peanut grown in 2006 and 2007

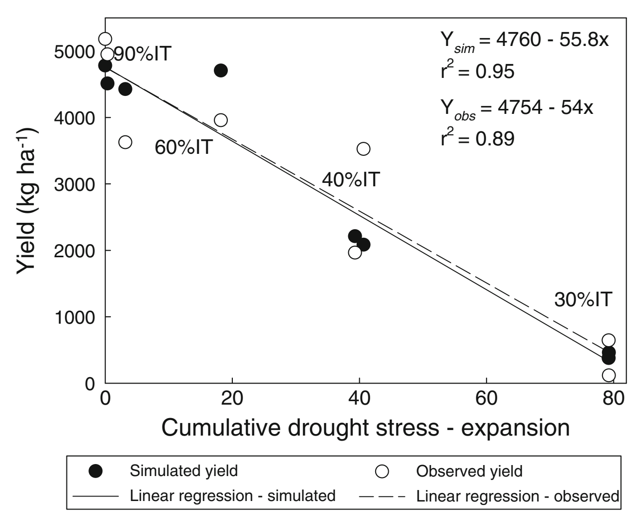

Fig. 9 Observed and simulated pod yield versus the simulated total cumulative drought stress index for expansive growth for peanut grown in 2006 and 2007

There was a positive relation between cumulative irrigation and simulated WUE; as the irrigation amounts increased, the values for simulated WUE increased. The 60 and 90 % IT treatments had the highest simulated WUE, which was 0.67 kg m^{-3}, on average (Fig. 10), while the 30 % IT treatment had the lowest WUE, with an average value of

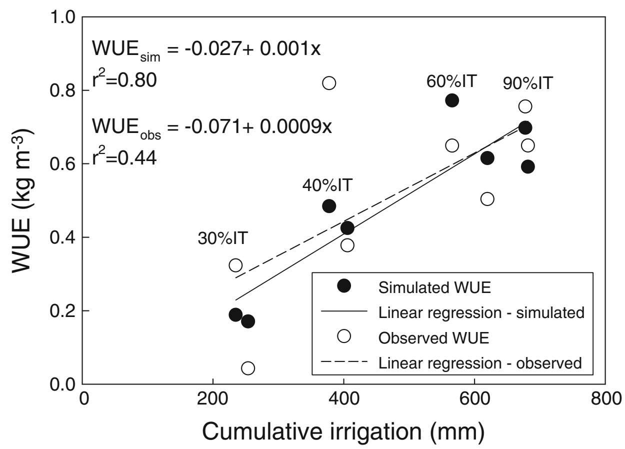

Fig. 10 Observed and simulated water use efficiency (WUE) as a function of cumulative irrigation for peanut grown in 2006 and 2007

0.18 kg m^{-3}. These simulation results are in agreement with previous studies based on observed data for calculating WUE. Abou Kheira (2009) reported a value of 0.53 kg m^{-3} for WUE for peanut grown under water stress conditions during flowering and pod formation stages and a WUE of 0.77 kg m^{-3} for fully irrigated peanut in a study conducted in Egypt. In another study conducted in Egypt in a sandy soil and under drip irrigation, El-Boraie et al. (2009) reported that the peanut pod WUE increased with increasing irrigation water quantity and/or with applying biofertilizer. Under water stress, WUE was reduced in different peanut varieties grown in Argentina (Collino et al. 2000). The differences between water stress and fully irrigated peanut yield were mainly due to a failure of the pegs to penetrate the dry soil surface under water stress regimes (Collino et al. 2000). Songsri et al. (2009) reported that drought reduced WUE, root dry weight, and harvest index on peanut grown in greenhouse conditions, but with differences between cultivars. Rowland et al. (2004) recommended the assessment of peanut varieties for WUE not only across different growing regions, but also different growing conditions, to provide better-informed varietal recommendations to growers for improved WUE without sacrificing yield.

Summary and conclusions

In this study, the impact of different irrigation scheduling regimes on growth and development of peanut was characterized using the cultivar Georgia Green. The experimental data were also used to evaluate the capability of the CSM-CROPGRO-Peanut model to simulate growth and development of this peanut cultivar. There was an inverse relationship between the simulated total cumulative drought stress index for expansive growth and photosynthesis and simulated grain yield. It was also determined that there was a positive linear relationship between simulated and measured WUE and the different irrigation treatments. This study could be a framework for developing methodologies to predict yield based on simulation of drought stress during the growing season.

The treatment that resulted in the highest pod yield was the 90 % IT treatment, and it was significantly greater than the other treatments. The 30 and 40 % IT treatments resulted in yield reductions that were 92 and 45 % of the 90 % IT treatment. The CSM-CROPGRO-Peanut model in general was able to simulate growth and development of peanut and the soil water content accurately for different irrigation treatments. Determining the cumulative drought stress value prior to reaching harvest maturity could help with the prediction of final harvestable yield. However, further studies are needed for genotypes with different drought stress tolerance. Since there is evidence that peanut is especially sensitive to water stress during flowering and pod filling stages, these studies should focus on the impact of the different cumulative drought stress indices on the different growth stages and associated yield.

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