Agricultural and Forest Meteorology 243 (2017) 84–92

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Integrating growth stage deficit irrigation into a process based crop model

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ARTICLE INFO

Keywords:
Water use
Rainfed
Crop model
Decision support
Deficit irrigation
Schedule

ABSTRACT

Current rates of agricultural water use are unsustainable in many regions, creating an urgent need to identify improved irrigation strategies for water limited areas. Crop models can be used to quantify plant water requirements, predict the impact of water shortages on yield, and calculate water productivity (WP) to link water availability and crop yields for economic analyses. Many simulations of crop growth and development, especially in regional and global assessments, rely on automatic irrigation algorithms to estimate irrigation dates and amounts. However, these algorithms are not well suited for water limited regions because they have simplistic irrigation rules, such as a single soil-moisture based threshold, and assume unlimited water.

To address this constraint, a new modeling framework to simulate agricultural production in water limited areas was developed. The framework consists of a new automatic irrigation algorithm for the simulation of growth stage based deficit irrigation under limited seasonal water availability; and optimization of growth stage specific parameters. The new automatic irrigation algorithm was used to simulate maize and soybean in Gainesville, Florida, and first used to evaluate the sensitivity of maize and soybean simulations to irrigation at different growth stages and then to test the hypothesis that water productivity calculated using simplistic irrigation rules underestimates WP. In the first experiment, the effect of irrigating at specific growth stages on yield and irrigation water use efficiency (IWUE) in maize and soybean was evaluated. In the reproductive stages, IWUE tended to be higher than in the vegetative stages (e.g. IWUE was 18% higher than the well watered treatment when irrigating only during R3 in soybean), and when rainfall events were less frequent. In the second experiment, water productivity (WP) was significantly greater with optimized irrigation schedules compared to non-optimized irrigation schedules in water restricted scenarios. For example, the mean WP across 38 years of maize production was 1.1 kg m^{-3} for non-optimized irrigation schedules with 50 mm of seasonal available water and 2.1 kg m^{-3} with optimized irrigation schedules, a 91% improvement in WP with optimized irrigation schedules. The framework described in this work could be used to estimate WP for regional to global assessments, as well as derive location specific irrigation guidance.

1. Introduction

Global factors such as population growth and climate change continue to put increasing stress on the agricultural system and drive increased irrigation demand in regions with unsustainable water supply. This is especially evident in areas that rely heavily on groundwater resources (Famiglietti, 2014; Scanlon et al., 2012). Although human water use is only about 10% of the maximum renewable freshwater available in the world, the uneven distribution of water resources in time and space make certain areas particularly susceptible to water shortages (Oki and Kanae, 2006). These include large agricultural areas in the states of Texas and California (Roy et al., 2012) that have experienced devastating droughts in recent years (Griffin and Anchukaitis, 2014; Nielsen-Gammon, 2012). Agriculture, the second largest water use sector in the US after thermoelectric power (Maupin et al., 2014), and the largest user of water resources worldwide (Hoekstra and Mekonnen, 2012), is strongly affected by water shortages. For example, the impact of the 2015 drought on California's

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http://dx.doi.org/10.1016/j.agrformet.2017.05.001
Received 9 December 2016; Received in revised form 20 April 2017; Accepted 2 May 2017
Available online 24 May 2017

agricultural sector is estimated as 2.7 billion dollars (Howitt et al., 2014), and the 2012 drought produced an estimated loss of 31.5 billion dollars across the U.S. largely due to harvest failure for maize, sorghum, and soybean (NCDC, 2016). These drought events also reduce groundwater recharge rate and increase pressure from irrigated farms on major aquifers (Famiglietti, 2014), creating challenges for groundwater managers and farmers alike. Process based cropping system models can provide insight on agricultural water management strategies at field to regional scales.

Cropping system models have been used to understand how economic trends, agricultural policies, and water use interact (de Fraiture, 2007); to quantify the global yield gap due to nutrient and water management (Mueller et al., 2012); and to project regional yields in response to climate change (Elliott et al., 2014a; Estes et al., 2013). The Decision Support System for Agrotechnology Transfer (DSSAT; Hoogenboom et al., 2012; Jones et al., 2003) is a valuable tool for projecting agricultural yields in a changing climate. It has recently been used for large-scale simulations of cropping systems both gridded (Elliott et al., 2013) and as part of crop model ensembles (Asseng et al., 2013; Elliott et al., 2014a, 2014b), i.e. multiple models simulating the same weather and management data set. For example, Elliott et al. (2014a) compared water supply projections from ten global hydrologic models, such as Water – Global Assessment and Prognosis (WaterGap; Döll and Siebert, 2002) and Water Balance Model (WBM; Fekete et al., 2002), and water demand projections from six global gridded crop models. They concluded that 20–60 Mha of irrigated cropland worldwide may have to switch to rainfed management by the year 2100 because of water shortages.

Effective water management decisions may help farmers and policy makers cope with water scarcity in drought prone and water limited areas by maximizing yield per unit of water applied. A critical method for managing water limitations at the farm level is through deficit irrigation, i.e. the application of water below crop water requirements (Fereres and Soriano, 2007). Crops under deficit irrigation will experience some level of water stress during the season and often have lower yields than fully irrigated plants. Multiple studies show that targeting irrigation applications to the most sensitive growth stages increases crop productivity per unit of water applied (Geerts and Raes, 2009). In northeastern Colorado, for example, Fang et al. (2014) showed, using the Root Zone Water Quality Model (RZWQM), that in water limited scenarios high corn yield and water use efficiency can be achieved if the crop is fully irrigated in the vegetative stages and deficit irrigation takes place in the reproductive stages. A key step in the investigation of deficit irrigation with models is the generation of optimized deficit irrigation schedules. For example, a popular approach to evaluate the potential of deficit irrigation strategies is the use of crop water productivity functions (Geerts and Raes, 2009). Water productivity expresses the relation between marketable yield and water use. When cropping system models are used to generate crop water productivity functions, irrigation strategies are often based on soil water depletion and expert knowledge (Garcia-Vila et al., 2009; Geerts et al., 2009; Ma et al., 2012), or maintaining irrigation frequency and changing application amount based on percentage crop water demand (Saseendran et al., 2015). More recently, statistical approaches (Geerts et al., 2010) and optimization algorithms (Kloss et al., 2012; McClendon et al., 1996; Schütze et al., 2012) have been proposed to generate these irrigation schedules. Further research is needed to develop computationally inexpensive approaches to generate optimized, unbiased, and reproducible irrigation schedules and crop water productivity functions in water limited scenarios.

In this paper, a new irrigation scheduling algorithm was developed for DSSAT models that improves on the existing algorithm by explicitly restricting water availability and allowing growth stage specific parameters. Growth stage specific parameters, as opposed to seasonal parameters, are used to optimize water use by irrigating only when crop yield is most sensitive to water stress. This new algorithm was then used for two computational experiments. In the first experiment, the sensitivity of irrigation water use efficiency to different irrigation schedules was evaluated. In the second experiment, we tested the hypothesis that non-optimized deficit irrigation strategies underestimate crop water productivity in water limited scenarios relative to optimized deficit irrigation strategies.

2. Materials and methods

2.1. Model description

All the simulations described in this work were performed using a customized version of DSSAT v4.6 (Hoogenboom et al., 2015). DSSAT is a point-based biophysical model that runs on a daily time step and simulates crop growth and development in a hectare of land as a function of weather, detailed soil profile, cultivar specific physiological parameters, and farm management. DSSAT tracks carbon, nitrogen, water, and energy budgets. The software simulates dozens of crops using crop specific models. Most crop specific models implemented in DSSAT derived either from CERES-Maize (Jones et al., 1986) or SOYGRO (Wilkerson et al., 1983). The former usually are referred as CERES models, e.g. CERES-Sorghum, CERES-Wheat, and CERES-barley (Lopez et al., 2017; Otter-Nacke et al., 1991; Ritchie and Otter, 1985; White et al., 2015), and the latter as CROPGRO models, e.g. CROPGRO-Peanut, CROPGRO-faba bean, and CROPGRO-tomato (Boote et al., 2012, 2002; Suriharn et al., 2011). Additional details on DSSAT can be found in Jones et al. (2003).

The DSSAT v4.6 automatic irrigation algorithm depends on one state variable, the volumetric water content (VWC) of a hectare of land within a determined soil management depth (IMDEP). Irrigation takes place when VWC reaches a lower threshold (ITHRL; Fig. 1). This threshold is specified by the user as percentage available water holding capacity (AWHC), which is the drainage upper limit minus permanent wilting point (Gijsman et al., 2002), and then converted back to VWC by the model based on location specific soil properties. The irrigation amount may be fixed or based on an upper water holding capacity threshold (ITHRU). This work expands the existing DSSAT automatic irrigation scheduling algorithm to simulate crop growth in water limited environments automatically. In the past this could only be done manually.

2.2. Improved irrigation algorithm

The DSSAT v4.6 automatic irrigation algorithm was expanded in two fundamental ways (Fig. 2). The new algorithm allows users to set a restriction on the amount of water available for irrigation (AVWAT) during the growing season or during specific growth stages. Therefore,

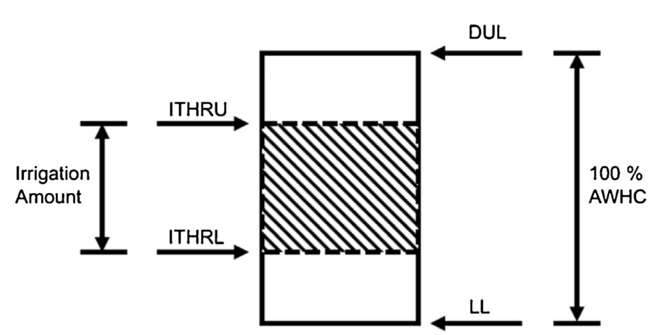

Fig. 1. Diagram illustrating the parameters used to schedule irrigation events based on soil water depletion in DSSAT v.4.6. in the automatic mode. The rectangle represents the water available to the plant within a soil column with length equal to the user specified management depth. The dashed space represents the irrigation amount when the soil reaches ITHRL. ITHRU: Irrigation threshold upper limit. ITHRL: Irrigation threshold lower limit. DUL: Drainage upper limit. LL: Lower limit or wilting point. AWHC: Available water holding capacity (DUL − LL).

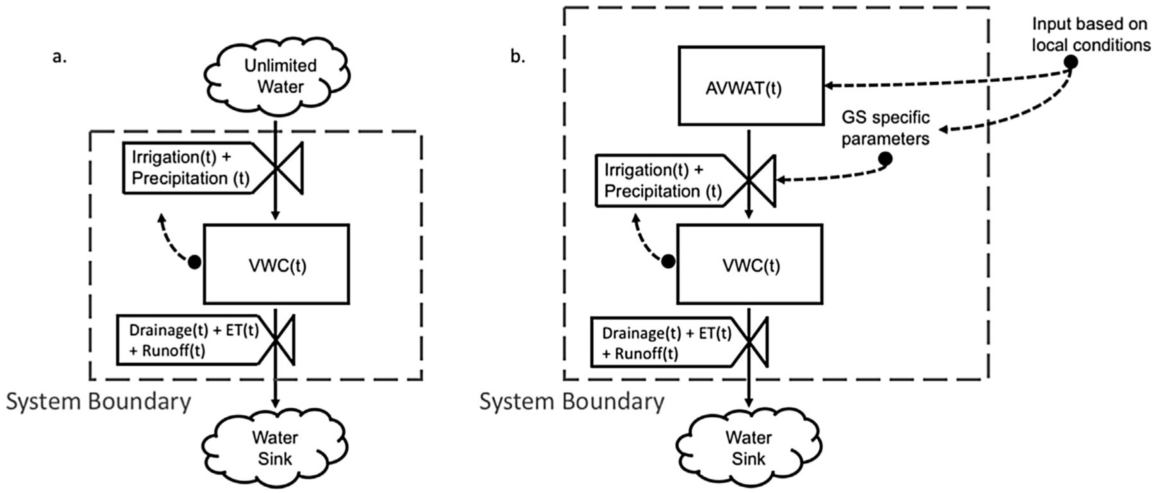

Fig. 2. Forrester diagram (Forrester, 1961) of automatic irrigation algorithm. (a) Irrigation algorithm as implemented in DSSAT v4.6. (b) Modified irrigation algorithm. t: time; VWC: volumetric water content; ET: evapotranspiration; AVWAT: available water for irrigation during the growing season; GS: growth stage.

in the new model the source of water for irrigation is within the system boundaries and tracked by the state variable AVWAT. Second, it allows users to set growth stage specific irrigation parameters by setting upper and lower soil moisture irrigation thresholds. Combined, these two improvements permit the investigation of deficit irrigation strategies. Essentially, the new automatic irrigation scheduler allows the user to set different irrigation criteria based on the growth stages most susceptible to water stress and allows the user to set a limitation on the amount of water available during the season.

The new automatic irrigation algorithm (Fig. 3) combines user inputs and state variables from the various crop model components to estimate irrigation date and amount based on daily VWC calculations. It is a FORTRAN subroutine called by the DSSAT main program as part of the management module, and is therefore accessible to all crop modules in DSSAT. It is designed with significant flexibility to accommodate a range of modeling scenarios including water limitation over the whole season, during one growth stage, or during a set of growth stages, and supports two different methods to determine each irrigation application date and amount, user-defined or calculated based on soil water content. Should the user not set a seasonal water limitation, water supply is assumed to be unlimited. Alternatively, the user may decide to have a water limitation but not use a growth stage based irrigation strategy. In such case, the model will program all irrigations based on a single VWC threshold throughout the season until available water is depleted. Finally, the user can set a water limitation only during specific growth stages and draw water from an unlimited supply in others. Growth stages may widely differ among crop models. In this work, CERES-Maize and CROPGRO-Soybean growth stages were evaluated (Table 1), however, the new irrigation functionality can be used in all crop models available in the DSSAT platform.

2.3. IWUE sensitivity to growth stage based irrigation

A sensitivity analysis was conducted to quantify yield and irrigation water use efficiency (IWUE) when irrigating only during a single growth stage. The site for both, maize and soybean simulations, was the University of Florida Agronomy Farm in Gainesville, Florida (29° 38″ 3″ N, 82° 21; 44′ E). The soil, cultivar, and environmental conditions were those described by Bennett et al. (1989, 1986) and Wilkerson et al. (1983) for maize and soybean, respectively. Maize cultivar 'McCurdy 84AA' was planted on February 26th 1982. In the soybean experiment, cultivar 'Bragg' was planted on June 15th 1978. The soil was a Millhopper fine sand.

The sensitivity analysis evaluates deficit irrigation strategies developed by limiting water applications to specific growth stages (Table 2). The water losses and yield savings of each of these strategies were then quantified by comparing the outputs of these simulations with the outputs of a well-watered (WW) simulation. Simulations were conducted using the same irrigation parameters for soybean and maize. For the WW simulations, the irrigation management depth (IMDEP) was set at 30 cm and irrigation took place when the water holding capacity threshold ITHRL was equal to or below 80% AWHC. Irrigation amount was calculated so that the soil was refilled to 100% AWHC within IMDEP. For each of the evaluated deficit irrigation strategies, irrigation was applied only during a specific growth stage, setting ITHRL at 80% AWHC and ITHRU at 100% AWHC, the crops were not irrigated for the rest of the season. For all simulations, irrigation application efficiency was set at 85%, assuming an efficient irrigation system.

Irrigation water use efficiency was calculated after Howell (2001) using the following equations:

$$IWUE = \frac{Y_i - Y_0}{W}$$

Where Y_i represents the irrigated yield, Y_0 is the non-irrigated yield, and W is the amount of water used for irrigation during the season in the irrigated treatment.

2.4. Optimization

The objective of the optimization is to identify sets of irrigation parameters that produce the maximum yield given a seasonal water limitation. The parameter ITHRL, that affects irrigation frequency and amount, was optimized for each of the six growth stages defined in Table 1 for maize. The target objective model output was simulated grain yield. The experiment described by Bennett et al. (1989, 1986) was simulated using 38 years of weather data (1978–2015) for Gainesville, Florida. For each year, simulated yield was optimized for eight different seasonal water restrictions (50, 100, 150, 200, 250, 300, 350, and 400 mm).

In order to find optimized parameter sets, three different heuristic optimization algorithms were evaluated: global differential evolution (Mullen et al., 2011), generalized simulated annealing (Xiang et al., 1997), and a simple evolutionary algorithm (Wagon, 2004). The algorithms were implemented in R v. 3.2.3 (R Core Team, 2016) using packages DEoptim (Mullen et al., 2011), GenSA (Xiang et al., 2012), and adagio (Borchers and Borchers, 2012), respectively. For each growth stage, ITHRL was set at a minimum of 5 and a maximum of 100% AWHC. Other parameters passed to the R functions were: F = 0.8, CR = 0.9, and itermax = 10 to DEoptim, maxcall = 300 to GenSA, and N = 21 to simpleEA. Summarized briefly, F is a differential

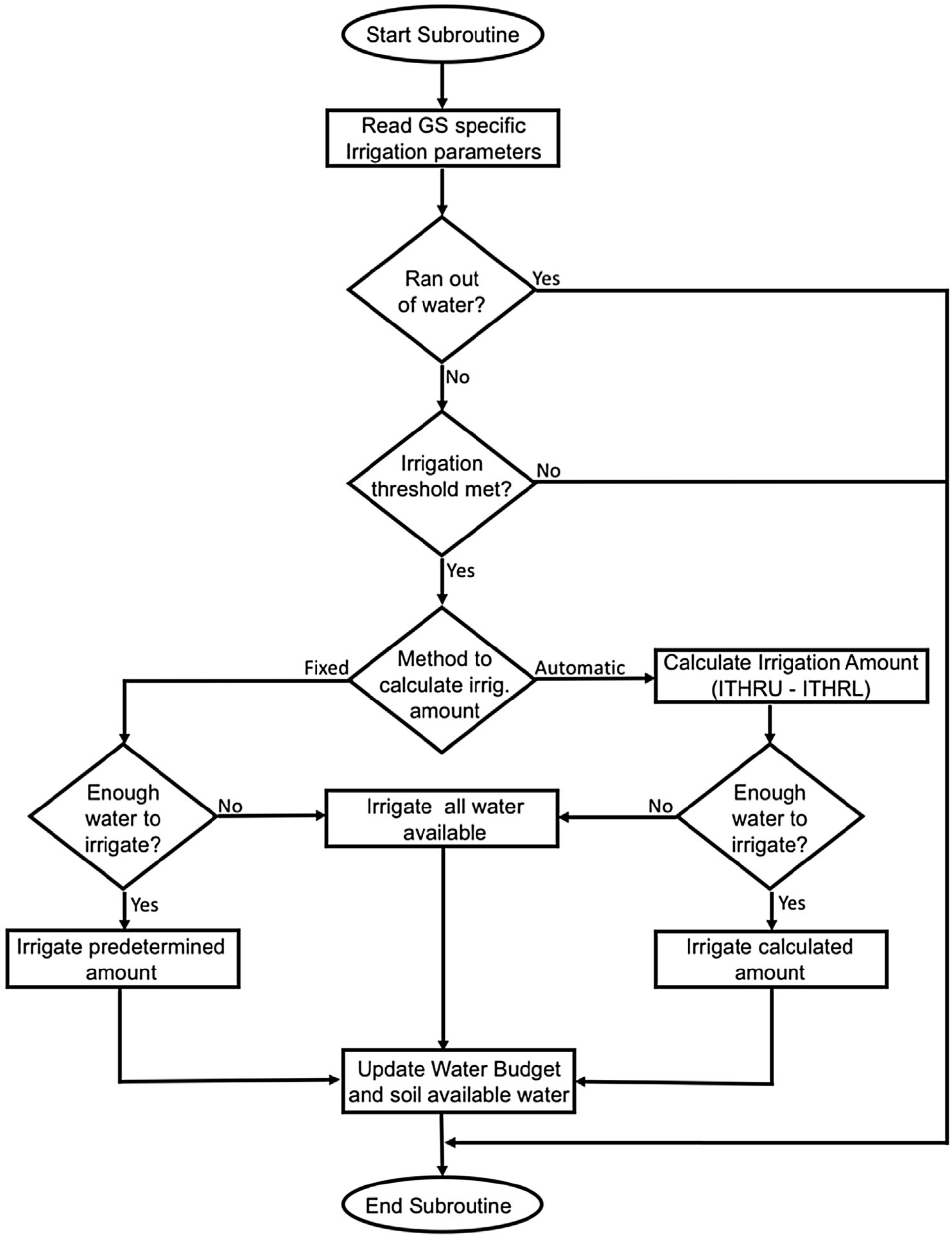

Fig. 3. Flow chart of irrigation subroutine. GS: Growth Stage, ITHRU: upper water holding capacity threshold, ITHRL: lower water holding capacity threshold.

Table 1
Growth Stages evaluated in the sensitivity analysis.

Crop	DSSAT Code[a]	Naming Convention[b]	Duration (days)	Description
Maize	GS014		12	Start of simulation.[c]
	GS009	VE	18	Emergence.
	GS001		5	End of juvenile phase.
	GS002		42	Floral initiation.
	GS003	R1	11	Some visible silks outside the husks.
	GS004	R2	41	Kernels are white on the outside and resemble a blister in shape.
Soybean	GS014		5[d]	Start of simulation.
	GS001	VE	40	Emergence.
	GS005	R1	20	One flower at any node.
	GS006	R3	26	0.5 cm pod at one of the 4 upper nodes with unrolled leaves.
	GS009	R6	40	Full size green beans at 1 of 4 upper nodes with unrolled leaves.

[a] Growth stage code used in DSSAT v4.6.
[b] Naming convention for maize (Richie et al., 1982) and soybean (Fehr et al., 1971) growth stages.
[c] Simulation was started one day prior to planting, using reported initial conditions.
[d] Mean soybean growth stage duration. Individual simulations may be up to one day different from the mean. Growth stage duration did not change for maize across the sensitivity simulations.

Table 2
Treatments used to simulate the sensitivity of irrigation water use efficiency (IWUE) to growth stage based irrigation.

Maize					
Treatment	Well-Watered Growth Stage				
	GS009	GS001	GS002	GS003	GS004
WW	X	X	X	X	X
GS009	X				
GS001		X			
GS002			X		
GS003				X	
GS004					X
Soybean					
Treatment	Well-Watered Growth Stage				
	GS001	GS005	GS006	GS009	
WW	X	X	X	X	
GS001	X				
GS005		X			
GS006			X		
GS009				X	

weighting factor which typically takes values between 0 and 1, CR is the crossover probability, also between 0 and 1, itermax and maxcall are the maximum number of times that the optimization function is called in R, and N is the number of random points introduced each generation. More details about the optimization algorithms and parameters can be found in the references above.

Optimized irrigation schedules were compared with a non-optimized irrigation approach using the same eight seasonal water restrictions described above. The non-optimized approach uses the same irrigation scheduling parameters used in the WW simulations until water runs out, with no adjustments on the irrigation strategy based on the water limitation. As in the optimization simulations, the non-optimized approach simulated 38 years (1978–2015) of corn production in Gainesville Florida. Weather data from this location was obtained from the NASA Climatology resource for agro climatology (available at http://power.larc.nasa.gov/cgi-bin/agro.cgi) and the National Climatic Data Center (NCDC). Non-optimized irrigation schedules were obtained by setting parameter ITHRL at 80% AWHC and

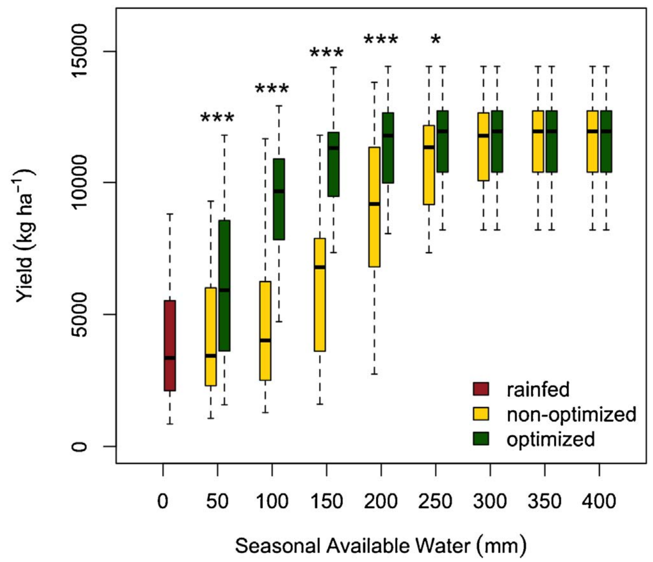

Fig. 5. Distribution of simulated seasonal maize grain yield across 38 years of climate data (1978–2015) in Gainesville Florida. Eight irrigation restriction scenarios were evaluated with different Seasonal available water. Three irrigation methods were simulated: rainfed, non-optimized (irrigation application with parameters ITHRL = 80% and ITRU = 100% until available water is depleted), and growth stage optimized (Optimized ITHRL calculated with global differential evolution algorithm). Asterisks indicate statistically significant differences at $P < 0.05$ (*), < 0.01 (**), and < 0.001 (***).

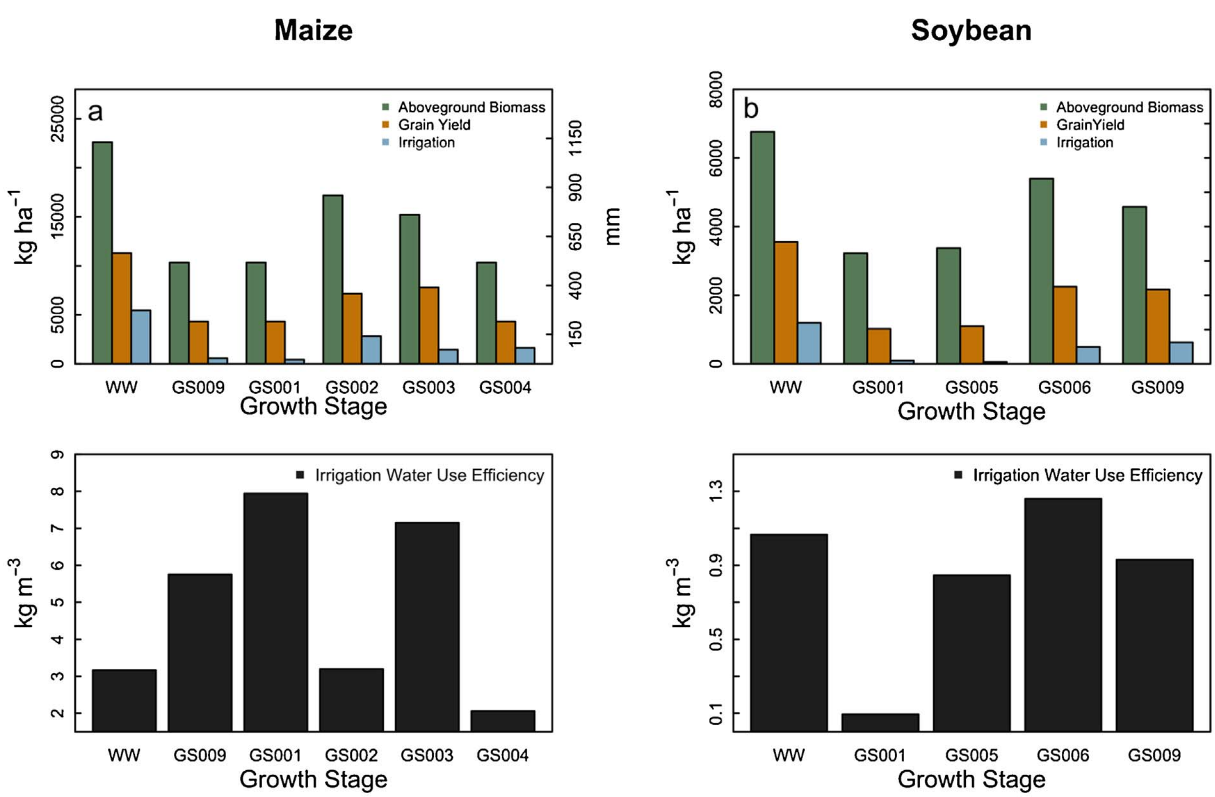

Fig. 4. Aboveground biomass (kg ha^{-1}), grain yield (kg ha^{-1}), and seasonal irrigation (mm) amount of maize and soybean under various irrigation regimes (a, b). Irrigation water use efficiency (c, d). Each yield bar represents a simulation were irrigation was applied only at the specified growth stage.

Table 3
Optimized seasonal maize yield (kg ha^{-1}) and computing time (s) across 38 years of climate data (1978–2015) in Gainesville Florida using different optimization algorithms.

Algorithm	Seasonal Water Available						Elapsed time[a] (s)	
	50 mm median	IQR[a]	100 mm median	IQR	150 mm median	IQR	median	IQR
Global Differential Evolution	5920	4906	9663	3045	11308	2417	93.6a[b]	9.1
Generalized Simulated Annealing	5750	4839	9470	3228	11334	2338	42.3b	5.7
Simple Evolutionary Algorithm	5920	5357	9408	3205	10950	2438	33.3b	9.7

[a] Interquartile range.
[b] Numbers followed by the same letter within a column do not differ.

Table 4
Mean yield, evapotranspiration, and water productivity for maize in different water availability scenarios. Asterisks indicate statistically significant differences at $P < 0.05$ (*), < 0.01 (**), and < 0.001 (***).

AVWAT[a] (mm)	Yield (kg ha^{-1})		Evapotranspiration (mm)		Water Productivity (kg m^{-3})	
	Optimized	Non-optimized	Optimized	Non-optimized	Optimized	Non-optimized
50	6214	4034***	393	383	1.5	1.0***
100	9393	4575***	438	424	2.1	1.1***
150	10784	6069***	478	458	2.3	1.3***
200	11417	8895***	509	493	2.2	1.8***
250	11654	10820*	530	521	2.2	2.1
300	11682	11468	538	539	2.2	2.1
350	11682	11657	543	547	2.2	2.1
400	11682	11672	540	549	2.2	2.1

[a] Seasonal Available Water.

ITHRU at 100% AWHC throughout the season. Water productivity (WP) was calculated by dividing grain yield by actual evapotranspiration.

2.5. Statistical analysis

The statistical analyses were conducted in R (R Core Team, 2016). The null hypothesis was evaluated using the Kruskal and Wallis rank sum test, and mean separation was performed using post-hoc pairwise multiple comparison test according to Nemenyi (Nemenyi, 1962; Sachs, 1997).

3. Results and discussion

A new automatic irrigation algorithm for DSSAT was developed and used to: 1. simulate the sensitivity of IWUE to growth stage based irrigation, and 2. optimize yield for eight water restriction scenarios. Maize IWUE ranged between 2.1 kg m^{-3} and 7.9 kg m^{-3}, soybean IWUE ranged between 0.09 kg m^{-3} and 1.3 kg m^{-3} (Fig. 4). There were significant differences in yield between optimized and non-optimized simulations. For example, across eight seasonal available water scenarios simulated for 38 years using historic weather data, the optimized simulations produced on average 5649 kg ha^{-1} of grain more than the non-optimized simulations in the 100 mm seasonal available water scenario (Fig. 5). Because of these yield differences, water productivity (WP) was significantly higher in the optimized simulations with low seasonal available water, i.e. between 50 and 200 mm (Table 4).

3.1. Irrigation water use efficiency sensitivity to growth stage based irrigation

Irrigation water use efficiency was higher than the well-watered treatment for reproductive stages R1 (GS003) in maize and R3 (GS006) in soybean (Fig. 4), consistent with Bustomi Rosadi et al. (2007) and Kirda et al. (1996), who found that prioritizing the reproductive growth stages at the expense of mild stress during vegetative growth can improve IWUE. This suggests that prioritizing irrigation at specific growth stages might improve IWUE in both crops. IWUE in maize was also high when irrigation took place during vegetative stages GS009 and GS001 (Fig. 4). However, rather than a physiological difference between maize and soybean, this is explained by the contrasting rainfall patterns across maize and soybean growing seasons during the first 45 days after planting (DAP). While both maize and soybean growing season cumulative rainfall 45 DAP was abundant (331 mm for maize and 271 mm for soybean), rainfall events were more frequent during the soybean growing season compared to the maize growing season (24 rainfall events compared to 15). Because the water holding capacity of these sandy soils is so low (approximately 50 mm to a 1 m soil depth), frequent rainfall events are more effective in preventing drought stress than abundant rainfall, as most of the water will be lost to drainage. The results of this sensitivity analysis highlight the complex interactions between rainfall frequency and amount, and irrigation scheduling. Irrigation amounts and yields depend on the timing of the irrigation application, the growth stage at which the plant is most susceptible to water stress, and the frequency and volume of the rainfall events during the growing season. Therefore, simply understanding at which stages crops are more susceptible to drought stress does not suffice to derive optimized deficit irrigation schedules.

3.2. Optimized water limited yield

To calculate grain yield with an optimized irrigation schedule, three optimization algorithms were used. There were no significant differences in the 38-year median grain yields across algorithms (Table 3). However, while not a limitation in the context of this study, global differential evolution required significantly more computing time than the generalized simulated annealing and the simple evolutionary algorithm (Table 3). Therefore, for larger assessments in time, space, or scenarios, where computing time is a limitation, generalized simulated annealing and the simple evolutionary algorithm should be preferred.

The potential yield difference between optimized and non-optimized irrigation strategies were calculated to quantify the potential benefits of using optimized deficit irrigation schedules. The non-

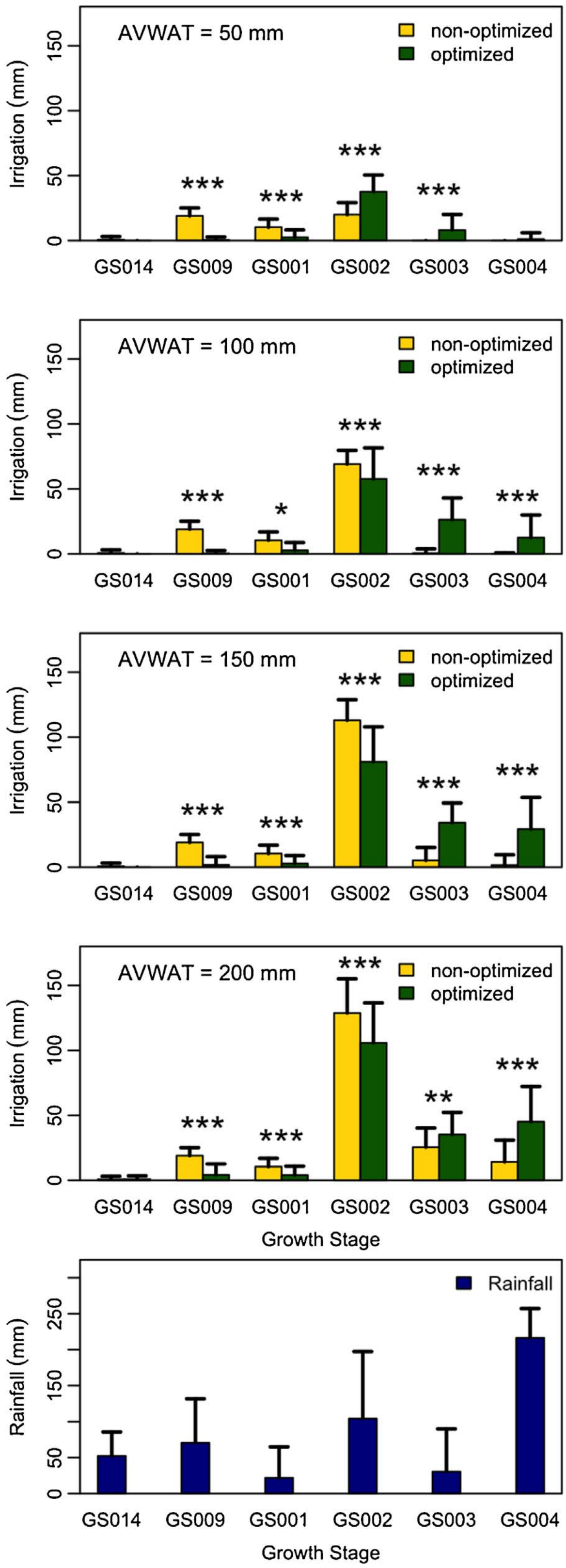

Fig. 6. Mean simulated irrigation and rainfall by growth stage across 38 years of climate data (1978–2015) in Gainesville Florida for selected water restriction scenarios in maize optimized simulations. Bars represent standard deviations. AVWAT: Seasonal water available. Non-optimized: irrigation application with parameters ITHRL = 80% and ITRU = 100% throughout the season. Optimized: Optimized ITHRL calculated with global differential evolution algorithm. Asterisks indicate statistically significant differences at $P < 0.05$ (*), < 0.01 (**), and < 0.001 (***).

optimized irrigation strategy used a single soil water threshold to schedule irrigation events throughout the season and across treatments until water ran out. The yield difference between optimized and non-optimized irrigation schedules was highest for the 100 mm of seasonal available water scenario, and relatively low in seasonal water availability scenarios of 300 mm or higher. Based on the results of this study, it can be inferred that optimized deficit irrigation is particularly effective in water restriction scenarios between 50 and 200 mm of water for this location. Summed over the growing season, optimized irrigation schedules use less water than non-optimized schedules each growth stage (Fig. 6), highlighting that a simple growth stage based deficit irrigation approach is not sufficient to optimize yield in water restricted scenarios if rainfall and irrigation frequency and amount are not considered.

3.3. Applications of optimized irrigation schedules

A potential application of optimized irrigation schedules from this algorithm is the generation of novel irrigation strategies adapted to farmers' local conditions. Unlike previous methods (e.g. Geerts et al., 2010), optimized irrigation recommendations derived using the algorithm described in this article do not require an intermediate statistical analysis step. In addition, parameter bounds can be used to prevent the model from scheduling irrigations that cause adverse consequences due to factors not considered by the model. For example, the model does not simulate lodging, and high volumetric water content is associated with increased lodging in wheat (Berry et al., 2004; Easson et al., 1995). To generate optimized wheat deficit irrigation strategies that prevent lodging, low ITHRU values should be passed to the model at lodging susceptible growth stages

The modeling framework described in this work can also provide better estimates of WP. Water productivity is defined as the ratio of marketable yield (e.g., grain yield for maize and soybean) to evapotranspiration (Geerts and Raes, 2009). To determine the best deficit irrigation strategy to calculate water productivity with limited water, some studies rely on expert knowledge (Garcia-Vila et al., 2009), and others on single seasonal soil water depletion thresholds using parameters similar to ITHRL (Geerts et al., 2009). However, our simulations show that estimated water productivity calculated with a non-optimized approach, which could result from using expert judgement or a single ITHRL threshold for the whole season, was significantly lower for seasonal available water scenarios between 50 and 200 mm than the optimized approach (Table 4). These results suggest that optimized irrigation schedules should be used to derive crop water productivity curves rather than strategies derived using a single seasonal threshold.

3.4. Limitations of optimized irrigation schedules

Factors not considered in this study, like residue management, crop rotations, or disease incidence, may affect irrigation schedules. Residue management and crop rotations could alter soil water holding capacity and therefore affect irrigation frequency. Irrigation applications may also increase the incidence of fungal diseases under specific conditions (Blad et al., 1978). These factors can also be modeled in DSSAT with the appropriate calibration and validation data sets (e.g., Fang et al., 2010; Singh et al., 2013).

It is also important to acknowledge that model simulations are imperfect, and some level of uncertainty in every simulation is expected (Spiegelhalter and Riesch, 2011). For the particular case of the maize simulations, the uncertainty can be partially assessed by calculating the relative mean squared error of prediction (RMSE) between the simulated yield and the data observed by Bennett et al. (1989, 1986). The RMSE of these simulations for the 1982 experiments is 16%. This is comparable to RMSE values reported by Asseng et al. (2013) for wheat (~10% fully calibrated and ~23% partially calibrated). Model uncertainty should be considered when interpreting simulation results.

For example, the difference in yield between optimized and non-optimized simulations in the 250 mm available water scenario is 8%, which while statistically significant should be interpreted with caution given model uncertainty.

4. Conclusions

A new modeling framework for the evaluation of irrigation strategies in water limited areas was described. This approach links water availability to crop yield using a crop model, weather data, and soil information. The new irrigation algorithm will be available to a broad audience in the next release of the DSSAT cropping system model (DSSAT v4.7).

In this study, we showed that calculating water productivity estimates with non-optimized irrigation schedules may result in underestimation of water productivity. Optimized irrigation schedules could be useful to derive location specific irrigation schedule guidance for farmers and to calculate water productivity functions for regional assesments.

Funding source

This work was supported by the NASA Applied Sciences Program (NNH11ZDA001N-WATER); and the USDA National Institute of Food and Agriculture (2015-68007-23133)

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