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Integrating growth stage deficit irrigation into a process based crop model

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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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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,

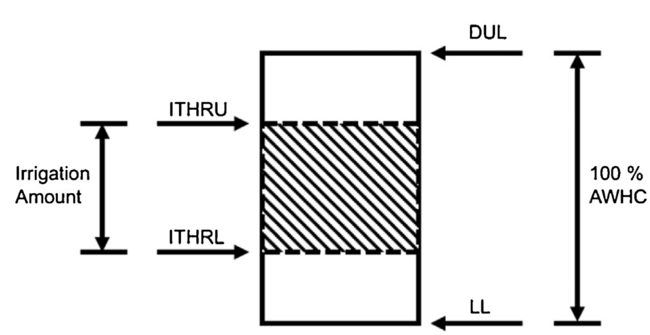

Fig. 1. Diagram illustrating the parameters used to schedule irrigation events based on soil water depletion in DSSAT v.4.6. in the automatic mode. The rectangle represents the water available to the plant within a soil column with length equal to the user specified management depth. The dashed space 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).