Combining Soil Water Content Data with Computer Simulation Models for Improved Irrigation Scheduling

Collection
Research

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Highlights

- Stand-alone irrigation scheduling models were compared to models combined with soil water content data.
- Use of soil water content data reduced irrigation recommendations compared to stand-alone models.
- Cotton fiber yield and water productivity were often not significantly impacted by the reduced irrigation amounts.
- Weather station aridity and other measurement uncertainties must be addressed to improve the methodology.

Abstract. *Irrigation scheduling models can be used to guide irrigation management decisions, but their simulations often deviate from reality. Combining in-season field data with models may improve the simulations, leading to better irrigation decisions and improved agronomic outcomes. The objective of this study was to evaluate cotton fiber yield and water productivity outcomes from a field trial that compared three computer simulation models for irrigation scheduling: (1) AquaCrop-OSPy (AQC), (2) the CROPGRO-Cotton module within the DSSAT Cropping System Model (CSM), and (3) the pyfao56 evapotranspiration-based, soil water balance model (FAO). Six irrigation scheduling treatments were established, including the three models used as stand-alone scheduling tools (AQC, CSM, and FAO) and the use of the three models in combination with weekly soil water content (SWC) data from neutron moisture meters (AQCSWC, CSMSWC, and FAOSWC). Two cotton varieties were also evaluated (NexGen 3195 and NexGen 4936). The field trial was conducted during the 2021 and 2022 cotton growing seasons at Maricopa, Arizona. Seasonal irrigation amounts were different among irrigation scheduling treatments ($p < 0.05$), with 9–21% less water recommended for the AQCSWC, CSMSWC, and FAOSWC treatments as compared to AQC, CSM, and FAO. In 2021, the differences in irrigation amount did not lead to any statistical differences in fiber yield among irrigation treatments, but water productivity for the stand-alone CSM model was significantly reduced compared to the other five irrigation treatments ($p < 0.05$). In 2022, treatments based on soil water content data reduced yield by 15% as compared to stand-alone model treatments, but the reduction was significant only for FAOSWC. Water productivity differences in 2022 were due to the choice of model rather than the inclusion of soil water content data. In both years, the shorter-season cotton variety (NexGen 3195) yielded greater than the longer-season variety (NexGen 4926), and the former achieved greater water productivity than the latter through the yield improvements ($p < 0.05$). Taken together, the results suggest that combining soil water content data with irrigation scheduling models was useful for reducing irrigation amounts while often maintaining cotton fiber yield and water productivity; however, issues with weather station aridity and other measurement uncertainties must be addressed to improve the methodology.*

Keywords. *Cotton, Evapotranspiration, Irrigation, Management, Sensor, Simulation, Water.*

A variety of simulation tools have been developed for irrigation management and scheduling in recent decades. Many of these tools are based on the methodologies described in the Food and Agriculture Organization of the United Nations (FAO), Irrigation and Drainage Paper No. 56 (Allen et al., 1998), which uses ASCE (2005) standardized reference evapotranspiration (ET) with several crop coefficient methodologies to estimate crop ET for use in basic soil water balance calculations (Andales et al., 2014; DeJonge and Thorp, 2017; George et al., 2004; Hunsaker et al., 2005; Pereira et al., 2020; Rosa et al., 2012a, b; Thorp, 2022). The primary advantage of the FAO-56 approach is its simplicity and

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practicality for making in-season irrigation scheduling decisions; however, algorithms for estimation of crop growth, development, and yield are not included in the method. To address this limitation, FAO has more recently supported the development of AquaCrop (Raes et al., 2009; Steduto et al., 2009; Vanuytrecht et al., 2014), a crop water productivity model that bases crop production estimates on water productivity. AquaCrop has become rapidly and widely popular as an irrigation management tool for a variety of crops and environments worldwide, especially for irrigated cotton (*Gossypium hirsutum* L.) production (Farahani et al., 2009; García-Vila et al., 2009; Hussein et al., 2011; Linker et al., 2016; Masasi et al., 2020; Tsakmakis et al., 2019). More traditional crop growth models with explicit calculations of crop growth, development, and yield have also been applied for irrigation scheduling purposes (Chen et al., 2019; Guerra et al., 2004; He et al., 2013; Seidel et al., 2016; Thorp et al., 2017; Tojo Soler et al., 2013); however, the complexities of such models and their greater impracticality for in-season management decisions have led to the prioritization of simpler methods like FAO-56. Among the irrigation management studies using AquaCrop and other crop growth models, many were conducted purely *in silico* and lacked rigorous field testing of the simulated irrigation recommendations. Furthermore, the irrigation scheduling recommendations and outcomes from multiple models are rarely intercompared in the same study. To address these gaps, field studies are warranted to evaluate multiple irrigation scheduling models and compare the agronomic outcomes obtained by following their recommendations.

While simulation models offer a rapid way to synthesize knowledge on cropping system processes, uncertainties in the model input data and within the modeling framework can lead to deviations between simulations and reality. For example, Mun et al. (2015) thoroughly evaluated the uncertainties within the Mississippi Irrigation Scheduling Tool (MIST), finding that the relative uncertainty (i.e., margin of error) of simulated water balance components was about 9%. Also, Linhoss et al. (2017) conducted a global sensitivity and uncertainty analysis for the MIST, highlighted the dependence of such analyses on assumptions for prior probability distributions for model inputs, and found precipitation and crop coefficient inputs as most influential on modeling outcomes. Finally, Rhenals and Bras (1981) used a stochastic model to study the effects of ET uncertainty on irrigation scheduling decisions, finding that the effects were minimal when soil water content information also contributed to the decision. Practical implementations of models for in-season management decisions often reveal how modeling uncertainty can lead to unrealistic representations of the cropping system and reduced credibility of the simulated management recommendations. The effects of such uncertainties can likely be minimized through the collection of additional field data (e.g., soil water content data) to assist, constrain, or update model simulations.

Monitoring soil water status was likely the original irrigation scheduling methodology used by early human societies (Campbell and Campbell, 1982). In modern times, various electronic sensors for soil water content estimation have been developed, while neutron moisture meters and time domain reflectometry (TDR) sensors are recommended for irrigation scheduling research (Evett et al., 2012). In a recent review of literature (Datta and Taghvaeian, 2023), the choice of factory versus site-specific sensor calibration methods was identified as the primary factor impacting the accuracy of soil water content measurements, as compared to sensor type, installation orientation, or sensor use in field versus laboratory environments. Among the studies reviewed, soil water content sensing reduced irrigation applications by an average of 38%, 16%, and 20% as compared to traditional irrigation scheduling methods, computer simulation, and ET replacement, respectively. In addition, soil water content sensing increased yield by an average of 24% and 7% compared to traditional methods and ET replacement, respectively, while yields for computer simulation methods were similar. Sui and Vories (2020) compared soil water content sensors and a computerized water balance model (the Arkansas Irrigation Scheduler) to schedule irrigation for cotton in Missouri and soybean (*Glycine max* (L.) Merr.) in Mississippi. They determined that the number and timing of irrigation events triggered by the two methods were different. Also, while the soil water sensor data was difficult to interpret at the Missouri site due to spatially variable soil conditions, the scheduling model calculated greater soil water infiltration than indicated by the soil water content sensors, particularly for irrigation and precipitation events less than 25 mm. The literature tends to contrast soil water sensing and computer simulation tools as separate and unique irrigation scheduling technologies (Taghvaeian et al., 2020); however, strategies to combine these technologies could offer a more robust method to accurately predict irrigation requirements while reducing uncertainty.

The overall goal of this study was to seek irrigation management improvements by integrating soil water content data with computer models for cotton irrigation scheduling at Maricopa, Arizona. The specific objectives were as follows: (1) develop a practical methodology to combine soil water sensing data with three computer-based irrigation scheduling tools for in-season irrigation management decisions, (2) compare stand-alone irrigation scheduling models with models receiving assistance from soil water content data for two cotton cultivars during two growing seasons, and (3) evaluate seasonal irrigation amounts, cotton fiber yield, and water productivity among the treatments imposed during the field trial.

Materials and Methods

Field Experiment

A cotton field experiment was conducted at the University of Arizona's Maricopa Agricultural Center (MAC) near Maricopa, Arizona (33.079° N, 111.977° W, 360 m above sea level) during the 2021 and 2022 cotton growing seasons (fig. 1). The experiment tested the responses of cotton yield and water productivity for six irrigation scheduling approaches (table 1) and two cotton varieties (NexGen 3195 B3XF and NexGen 4936 B3XF). The irrigation scheduling methods were based on in-season simulations from three computer models, including (1) AquaCrop-OSPy (AQC;

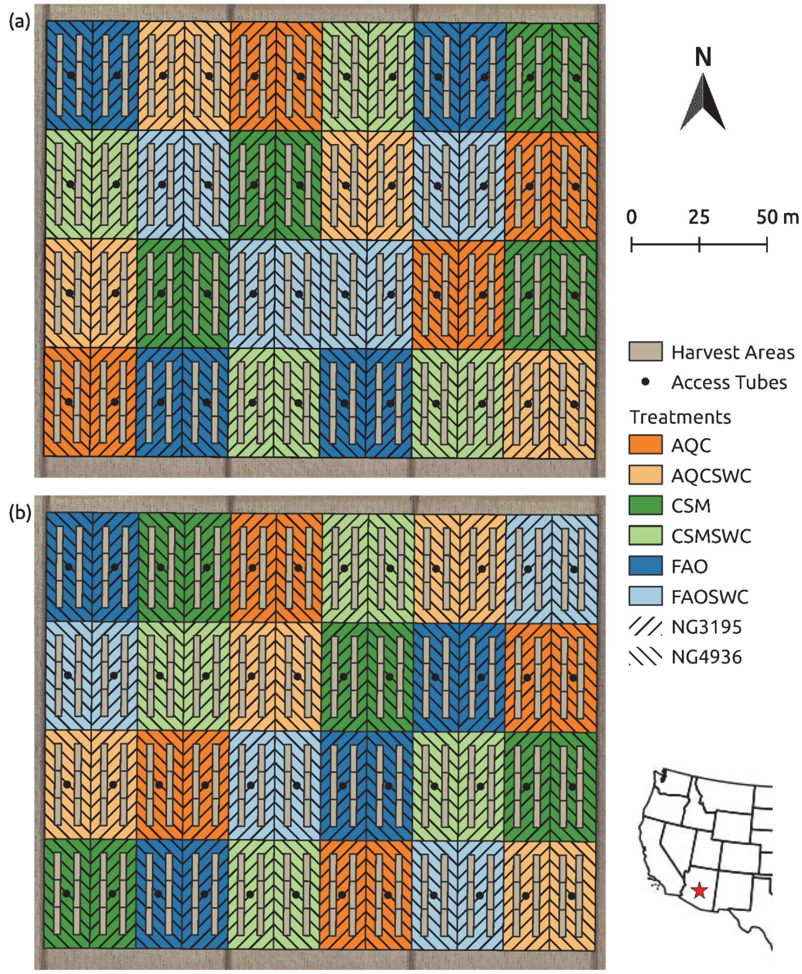

Figure 1. Plot maps for a cotton irrigation scheduling experiment during the (a) 2021 and (b) 2022 growing seasons at Maricopa, Arizona, USA. Six irrigation scheduling approaches were evaluated, based on AquaCrop-OSPy (AQC), CSM-CROPGRO-Cotton (CSM), and pyfao56 (FAO), both with and without additional information from weekly soil water content (SWC) measured at access tube locations. Two cotton varieties were also evaluated: NexGen 3195 and NexGen 4936.

Table 1. Six irrigation scheduling treatments were tested during the 2021 and 2022 cotton growing seasons at Maricopa, Arizona, USA. Irrigation recommendations were evaluated from three irrigation scheduling models: (1) AquaCrop-OSPy (AQC), (2) the CSM-CROPGRO-Cotton model (CSM), and (3) the pyfao56 evapotranspiration-based soil water balance model (FAO). Additional treatments involved updating the recommendations from each model based on weekly measurements of soil water content (SWC).

Treatment	Model	Description	SWC Updates	References
AQC	AquaCrop-OSPy	Stand-alone Python-based AquaCrop model	No	Kelly and Foster (2021)
AQCSWC	AquaCrop-OSPy	Python-based AquaCrop model with SWC updates	Yes	Kelly and Foster (2021)
CSM	CSM-CROPGRO-Cotton	Stand-alone CSM-CROPGRO-Cotton model	No	Jones et al. (2003)
CSMSWC	CSM-CROPGRO-Cotton	CSM-CROPGRO-Cotton model with SWC updates	Yes	Jones et al. (2003)
FAO	pyfao56	Stand-alone Python-based FAO-56 ET model	No	Allen et al. (1998); Thorp (2022)
FAOSWC	pyfao56	Python-based FAO-56 ET model with SWC updates	Yes	Allen et al. (1998); Thorp (2022)

Kelly and Foster, 2021), (2) the CROPGRO-Cotton module within the Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Model (CSM; Jones et al., 2003), and (3) the pyfao56 evapotranspiration-based soil water balance model (FAO) (Allen et al., 1998; Thorp, 2022). For three of the scheduling treatments, irrigation applications were based on the model recommendations with no assistance from in-season field data. For the other three scheduling treatments, the model recommendations were adjusted based on weekly soil water content measurements from neutron moisture meters in the plots (AQCSWC, CSMSWC, and FAOSWC). A split-plot, randomized complete block design was used with four replicated blocks (fig. 1). The six irrigation scheduling treatments were the main treatments replicated within each block. The two varieties were planted in subplots within each main plot. Subplots were 12.2 m (12 cotton rows) by 30.0 m, and the experiment required a total area of 2.8 ha.

The environment for cotton production in the Arizona low desert is arid and hot. Data from an Arizona Meteorological Network (AZMET; http://ag.arizona.edu/azmet) weather station approximately 1.2 km from the field site demonstrated air temperature patterns during the two growing seasons (fig. 2). Daily minimum and maximum air temperatures regularly exceeded 25°C and 40°C, respectively, from July through August, corresponding to days of year

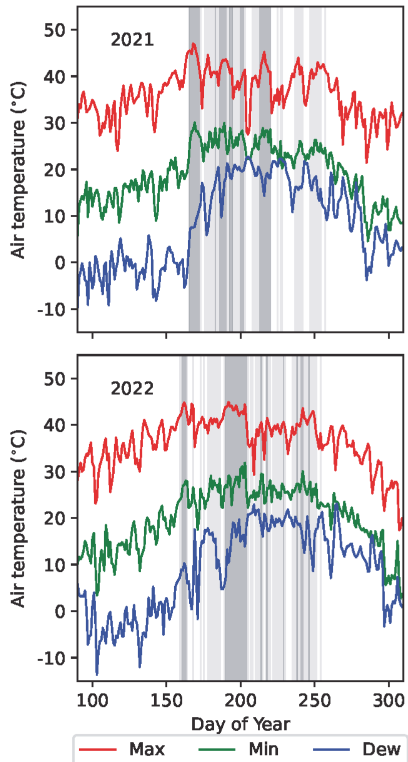

Figure 2. Daily maximum, minimum, and average dew point air temperatures during the 2021 and 2022 cotton growing seasons from 1 April (day of year 91) through 31 October (day of year 304) at Maricopa, Arizona, USA. Light and dark shaded regions indicate days with Level 1 and Level 2 heat stress, respectively.

(DOY) 182–243. This coincided with the time of cotton reproductive development, when heat stress can cause flower abnormalities and abscission of bolls aged 3–5 days (Brown, 2008). As such, AZMET also provided daily information on Level 1 and Level 2 heat stress conditions based on air temperature and humidity. The numbers of days during July and August with Level 1 and Level 2 heat stress conditions were 25 and 19 in 2021 and 31 and 21 in 2022, respectively, which represent normal heat stress conditions compared to other years in the past decade. The cotton growing season also straddles the Arizona monsoon season in July and August, where relative humidity and dew point temperatures rise sharply (fig. 2). As measured by the AZMET weather station, growing season precipitation from April through September (DOY 91–273) amounted to 223 and 105 mm during the 2021 and 2022 growing seasons, while precipitation during the monsoon season in July and August amounted to 214 mm and 46 mm, respectively. Weather anomalies prevailed in August 2021, as air temperatures were relatively cool and the field received more rainfall compared to other years in recent history. Standardized short crop reference ET (ET_{os}) from April through September amounted to 1321 and 1356 mm in the 2021 and 2022 growing seasons, respectively. Thus, irrigation was required to meet evaporative demand, and dryland production was not a realistic possibility.

Cover crops were grown in the winter months between cotton seasons to reduce soil nutrient variability and improve soil quality. The field was prepared for cover crop planting by deep ripping, moldboard plowing, disking, and either planing or laser leveling. Triticale (×*Triticosecale*, cv. 'Nextrit', Americot, Inc., Lubbock, Texas) was planted on 8 December 2020 (DOY 343) and 18 January 2022 (DOY 18) and terminated with glyphosate (RoundUp PowerMAX, Bayer CropScience, Monheim am Rhein, Germany) on 1 April 2021 (DOY 91) and 21 March 2022 (DOY 80), following the manufacturer's recommendations for application decisions. The cover crop was fully irrigated until termination in 2022, but an irrigation system malfunction resulted in early irrigation termination for the 2021 cover crop. No fertilizer was applied to the cover crops. Overall, the biomass production of the triticale cover crop was poor as compared to previous experiences with barley (*Hordeum vulgare* L.) cover crops.

A strip-tillage implement (1tRIPr, Orthman Manufacturing, Inc., Lexington, Nebraska) was used to prepare seed beds in the terminated triticale cover crop on 7 April 2021 (DOY 97) and 14 April 2022 (DOY 104). Upland cotton (*Gossypium hirsutum* L., cv. 'NexGen 3195 B3XF' and 'NexGen 4936 B3XF', Americot, Inc., Lubbock, Texas) was planted into the tilled strips on 20 April 2021 (DOY 110) and 21 April 2022 (DOY 111). The varieties were chosen based on their observed performance in Arizona fields during prior cotton growing seasons. NexGen 3195 was considered a shorter-season variety than NexGen 4936. The row orientation was north-south, and the row spacing was 1.02 m. Final plant densities after emergence were 9.4 and 8.7 plants m^{-2} in 2021 and 8.4 and 7.8 plants m^{-2} in 2022 for the NexGen 3195 and NexGen 4936 varieties, respectively. In both seasons, emergence rates were greater and early-season vigor was visually greater for NexGen 3195 as compared to NexGen 4936. Preemergent herbicide (Prowl H2O, BASF, Florham Park, New Jersey) was applied to the soil surface on 16 April 2021 (DOY 106) and 14 April 2022 (DOY 104) following the manufacturer's recommendations for application decisions. The herbicide was incorporated with light irrigation (10 mm) immediately after application. In-season applications of glyphosate herbicide (RoundUp PowerMAX, Bayer CropScience, Monheim am Rhein, Germany) were performed by a tractor-based sprayer as needed, amounting to two applications in 2021 and four applications in 2022. Control of lygus (*Lygus hesperus*) was achieved using three aerial applications of flonicamid (Carbine 50WG, FMC Corporation, Philadelphia, Pennsylvania) in 2021 and three tractor-based applications of sulfoxaflor (Transform WG, Corteva Agriscience, Indianapolis, Indiana) in 2022. Mepiquat chloride (GinOut, Nufarm Americas, Inc., Alsip, Illinois) was applied as a plant growth regular with sulfoxaflor in 2022. Following irrigation termination in September, cotton was defoliated with thidiazuron and diuron (Ginstar EC, Bayer CropScience, Monheim am Rhein, Germany), and a boll opener containing ethephon and urea sulfate (CottonQuik, Nufarm Americas, Inc., Alsip, Illinois) was also applied according to the manufacturer's recommendations. The defoliant and boll opener were applied on 21 October (DOY 294) and 5 November (DOY 309) in 2021 and on 30 September (DOY 273) and 14 October (DOY 287) in 2022.

Field Measurements

Soil water content was measured weekly via a field-calibrated neutron moisture meter (model 503, Campbell Pacific

Nuclear, Martinez, California). At planting, steel access tubes were installed centrally in each plot (fig. 1) using a tractor-mounted soil sampler (model 25-TS, Giddings Machine Co., Windsor, Colorado). From planting to harvest, the neutron moisture meter was deployed on a weekly basis (approximately 25 times per growing season) to measure soil water content from 0.1 to 1.9 m in 0.2-m incremental depths at each access tube. Soil water content data was typically collected as the first activity on Monday morning or the first working day of the week.

Soil properties at the field site were characterized via a soil sampling effort at 160 locations during 2016 and 2017 (not shown). The tractor-mounted soil sampler was used to collect cylindrical soil samples (0.04-m diameter × 0.4-m depth) at five incremental soil profile depths centered at 0.2, 0.6, 1.0, 1.4, and 1.8 m. Soil texture analysis was conducted in the laboratory using the hydrometer method of Gee and Bauder (1986), and the soil water holding limits of each sample were computed from texture data using the Rosetta pedotransfer functions (Zhang and Schaap, 2017). Ordinary kriging was used to spatially interpolate the drained upper limit (DUL) and lower limit (LL) at the access tube location in each plot (fig. 1). Geostatistics were conducted using the “geoR” package within the R Project for Statistical Computing software (www.r-project.org). The soil texture at the field site was primarily sandy loam and sandy clay loam, with DUL between 0.19 and 0.22 cm^3 cm^{-3} and LL between 0.09 and 0.11 cm^3 cm^{-3}.

Six zones were delineated in each plot for cotton yield measurements; each zone was 2.03 m (2 cotton rows) by 10.0 m. Cotton in each zone was machine-harvested with a two-row picker (Case IH 1822, Case IH, Grand Island, Nebraska) on 7 December 2021 (DOY 341) and 16 November 2022 (DOY 320). Cotton yield samples from each harvest zone were bagged and weighed separately in the field. After weighing, a yield subsample of approximately 150 g was collected from the two centermost harvest areas in each plot for moisture analysis (fig. 1). Subsamples were stored in sealed plastic bags until transfer to drying ovens, with wet and dry sample weights used to calculate moisture content. The remainder of the cotton yield samples from the two centermost harvest areas in each plot was transferred to the MAC ginning facility to separate fiber, cottonseed, and trash. Yield samples from the other four harvest areas in each plot were discarded after recording field weights. The mean wet bulk weight (kg ha^{-1}) for each plot was computed from the field weights and area of the six harvesting zones, and plot-average moisture content data and fiber turnout percentages were used to correct the wet bulk weight to dry fiber weights (kg ha^{-1}).

Field Management Decisions

Irrigation was applied using an overhead lateral-move sprinkler irrigation system with advanced geospatial technologies for site-specific irrigation applications within the georeferenced plot boundaries (fig. 1). The details of the irrigation system design and function have been elaborated in previous reports (Thorp et al., 2017; 2020b; 2022).

Uniform irrigation management was used to emerge the cotton crop. No pre-plant irrigation was conducted, except for the light irrigation (as aforementioned) to incorporate pre-emergent herbicide. For several weeks after cotton planting, uniform irrigation was applied every few days with daily amounts ranging from 10 to 31 mm before initiating irrigation treatments in mid-May. The total amounts of irrigation applied for crop emergence were 194 and 182 mm in 2021 and 2022, respectively. These irrigation events raised the field-average soil water content (surface to depth of 140 cm) to 0.200 cm^3 cm^{-3} in 2021 and 0.186 cm^3 cm^{-3} in 2022, while the field-average DUL was 0.205 cm^3 cm^{-3}. Thus, the efforts to emerge the cotton crop increased soil profile water content to slightly below the DUL prior to initiating irrigation treatments.

Irrigation Scheduling

Beginning in mid-May, three irrigation scheduling models were used on a weekly basis to predict irrigation amounts required to raise soil water content to the DUL: (1) AquaCrop-OSPy (Kelly and Foster, 2021), (2) the DSSAT CSM-CROPGRO-Cotton model (Jones et al., 2003), and (3) pyfao56 (Thorp, 2022). The weather data required as input for model simulations were compiled in three parts: (1) past in-season data through yesterday, (2) a 7-day forecast from today forward, and (3) the average weather from the past 36 years for days beyond the 7-day forecast. From the date of planting through yesterday, weather data were obtained from the AZMET station. From today through seven days into the future, local weather forecasting data were obtained from the National Digital Forecast Database (https://graphical.weather.gov/xml/rest.php). Beyond the seven-day forecast, weather data were specified as the average historical value from AZMET since the station was initiated in 1987. Weather data were compiled and formatted as necessary for input to each model. Identical inputs of daily minimum and maximum air temperature, average dew point air temperature, solar irradiance, and wind speed were used to compute daily standardized short crop reference evapotranspiration for simulating daily water demands with each model. The required soil data were based on interpolated estimates of soil hydraulic properties at the access tube locations (fig. 1). The required management information was specified as recorded from planting through yesterday. The models were setup to simulate the unique conditions of each field plot, and simulations were typically conducted on the same day that soil water content measurements were collected.

AquaCrop-OSPy (Kelly and Foster, 2021) was used to manage irrigation for the AQC and AQCSWC treatments. The model is a Python-based implementation of the AquaCrop model (Raes et al., 2009), featuring a water-driven methodology to compute crop biomass from transpiration using a water productivity parameter (Steduto et al., 2009). Canopy cover is computed instead of leaf area index (LAI), and crop yield is computed from biomass via a harvest index parameter. There is no partitioning of biomass to various plant organs. Air temperature drives calculations of crop phenology, and atmospheric CO_2 concentration affects water productivity and leaf expansion. Atmospheric water demand is established through inputs of daily standardized short crop reference evapotranspiration (ASCE, 2005), and transpiration and soil water evaporation are simulated from the reference ET, simulated canopy cover, and simulated soil water status. A layered soil profile (up to five layers) is considered for specifying the soil water limits and for redistribution of soil water. Roots grow deeper as the crop progresses through development stages, and a root extraction term is used to simulate root water uptake. Depending on the crop development stage, water stress effects from deficit soil water conditions can reduce canopy expansion rate, close stomata, accelerate canopy senescence, or adjust the harvest index. The required parameters for AquaCrop calculations of cotton development and growth were based on the default crop files provided with the model. Additional details about AquaCrop and AquaCrop-OSPy can be found in Steduto et al. (2009), Raes et al. (2009), and Kelly and Foster (2021).

The DSSAT CSM-CROPGRO-Cotton model (Jones et al., 2003) was used to manage irrigation for the CSM and CSMSWC treatments. The model uses mass balance principles to simulate carbon, nitrogen, and hydrologic processes and transformations that occur in agroecosystems. Simulations of cotton development proceed through a series of stages based on photothermal unit accumulation. Light interception is simulated based on an elliptical hedgerow canopy, and potential carbon assimilation is computed from leaf-level biochemistry equations with growth and maintenance respiration deducted. The model calculates stress effects from deficit soil water and soil nitrogen conditions, which can reduce the carbohydrate available for simulated plant growth. Assimilated carbon is partitioned into various plant parts, including leaves, stems, roots, bolls, and seed cotton (fiber + seed). Water deficits are simulated when the potential demand for water lost through plant transpiration and soil water evaporation is higher than the amount of water supplied by the soil through the simulated root system. DeJonge and Thorp (2017) reported on model updates to compute the required potential evapotranspiration using ASCE standardized reference evapotranspiration (ASCE, 2005) and a dual crop coefficient methodology (Allen et al., 1998) with basal crop coefficients (K_{cb}) estimated from simulated LAI. The model simulates a layered, one-dimensional soil profile with a tipping-bucket method for water redistribution and algorithms for calculating soil and plant nitrogen balances. The required cotton cultivar parameters were specified from previous model calibration efforts for other studies at or near the field site (Thorp et al., 2014b; 2015; 2017). Additional details about CSM-CROPGRO-Cotton can be found in Jones et al. (2003) and Thorp et al. (2014a).

A pre-release version of pyfao56 (Thorp, 2022) was used to manage irrigation for the FAO and FAOSWC treatments. The model is a Python-based implementation of the standardized evapotranspiration methodologies described by the ASCE (2005) and FAO-56 (Allen et al., 1998). Briefly, an ET-based daily soil water balance model is implemented with daily crop water use (ET_c) calculated as follows:

$$ET_c = \left(K_{cb}K_s + K_e\right)ET_{os} \tag{1}$$

where

ET_{os} = standardized short crop reference evapotranspiration (ASCE, 2005)

K_e = soil water evaporation coefficient

K_s = water stress coefficient for reducing daily transpiration during water-limited conditions.

The K_{cb} time series were specified using the standard trapezoidal crop coefficient curve (Allen et al., 1998), with initial, mid-season, and ending K_{cb} quantified as 0.15, 1.225, and 0.5, respectively. As recommended in FAO-56, the maximum K_{cb} at mid-season was adjusted to 1.225 based on AZMET relative humidity and wind speed data. Based on Hunsaker et al. (2005), lengths of time between trapezoidal inflection points were specified as 35, 50, 46, and 39 calendar days for the initial, development, mid-season, and late-season periods, respectively. The K_e and K_s coefficients were calculated as described in FAO-56. The model calculated soil water status on day i as follows:

$$D_{r,i} = D_{r,i-1} - P_i - I_i + ET_{c,i} + DS_i \tag{2}$$

where

$D_{r,i}$ = depth (mm) of root zone soil water depletion from the DUL at the end of day i

P_i and I_i = depths (mm) of precipitation and irrigation received on day i

$ET_{c,i}$ = daily crop water use (mm, eq. 1)

DS_i = depth (mm) of water lost to deep seepage.

Other use cases of pyfao56 for cotton studies in central Arizona are described by Thorp et al. (2018; 2022).

Model simulations were conducted on the same day that the soil water content data were measured, typically Monday or the first working day of the week. Two subsequent days were established as the irrigation days for the week, depending mainly on labor availability. Typically, the irrigation days were Tuesday and Friday; however, the Tuesday irrigation events were sometimes conducted on Wednesday and once on Thursday due to holidays or other labor availability issues. The three models were run iteratively to predict the irrigation amounts that would return each plot to the DUL on each irrigation day.

Because soil water content data were measured early in the day, the measured soil water states were attributed to midnight at the end of the previous day (i.e., yesterday), and the corresponding simulated soil water status and rooting depth data at the end of yesterday's time step were extracted from the output of each model. These data were used to estimate measured and simulated root-zone soil water depletion (D_r) for each plot. For pyfao56, D_r was explicitly calculated by the model (eq. 2), and no further computation was required. For AquaCrop-OSPy and CSM-CROPGRO-Cotton, which did not explicitly simulate D_r, and for the measured soil water content data, D_r (mm) was computed as follows:

$$D_r = \sum_{i=1}^{n} 10\left(\theta_{DUL,i} - \theta_{SWC,i}\right) \tag{3}$$

where

n = number of 1-cm soil layer increments in the root zone

θ_{SWC} = measured or simulated volumetric water content of the plot ($cm^3\ cm^{-3}$) at the ith soil profile increment

θ_{DUL} = volumetric water content at the DUL ($cm^3\ cm^{-3}$) at the ith soil profile increment.

Based on the three different rooting depth estimates from the three models, three different D_r estimates were computed from the measured soil water content data for each plot, whereas D_r estimates from each model were based only on the data simulated by that model. For ease of implementation via consistent iterative looping, all three models were run for all the plots regardless of the plot's treatment assignment, and all the various D_r estimates were also computed for all the plots.

The D_r computed from model output (eq. 3) was used to quantify the irrigation amounts required to raise soil water content to the DUL on each of two irrigation days per week. Models were run iteratively, incrementally adding 1 mm of irrigation on each irrigation day until the simulated D_r was less than 0.1 mm. For AQC, CSM, and FAO treatments, the model-recommended weekly irrigation rate (I_{mod}) was determined as the sum of the irrigation rates predicted for the two irrigation days, and estimates were based solely on the simulated data for the specific model assigned to the plot. For AQCSWC, CSMSWC, and FAOSWC treatments, the weekly irrigation recommendation from each model was further adjusted (I_{adj}) according to the difference between yesterday's measured and simulated D_r ($D_{r,m}$ and $D_{r,s}$, respectively):

$$I_{adj} = I_{mod} + D_{r,m} - D_{r,s} \quad (4)$$

In this way, the weekly model-recommended irrigation rates were adjusted based on information from the weekly soil water content measurements. No data was assimilated into the model simulations in this study. Instead, weekly irrigation rate predictions were computed from each model's output and then adjusted based on the difference between measured and simulated D_r at the beginning of the week.

Further adjustments to irrigation rates were required to ensure a practical irrigation application that maintained flow constraints for the overhead sprinkler and canal delivery systems. The irrigation recommendations from the measured and simulated data among plots were widely variable, likely due to differences in model formulation and uncertainty in both the measured and modeled data (discussed later). The difference in weekly rate recommendations among plots was between 50 and 125 mm, which was impractical to implement (due to flow constraints) and also likely somewhat unrealistic. As a result, weekly irrigation rate recommendations were bounded within a range defined as *a*% less than the minimum weekly ET rate predicted by the three models and b% greater than the maximum weekly ET rate predicted by the three models. In 2021, *a* and *b* were typically both specified as 10%. In 2022, *a* and *b* were typically specified as 20% and 0%, respectively, because models were found to overestimate water requirements, and cases of irrigation recommendations exceeding maximum simulated evapotranspiration were rare. Bounding the irrigation rates according to predicted ET reduced the range of weekly irrigation rates among plots to between 14 and 43 mm, which resulted in a much more practical implementation of site-specific irrigation within system delivery constraints. The plot that required the greatest amount of water established the 100% rate for the week, and the speed of the irrigation machine and number of passes were computed to provide the appropriate irrigation depth for the 100% rate. To minimize potential for overland flow and encourage infiltration at the application site, the speed of the irrigation system was maximized while also requiring an even number of passes so that the machine could be returned to its designated parking location at the end of each irrigation day. Irrigation depths for all other plots were controlled by the site-specific irrigation system. Using a geographic information system (GIS), a shapefile was created to delineate plot boundaries, and the shapefile was imported to the commercial software provided by the manufacturer of the site-specific irrigation equipment (FieldMAP, Lindsay Corporation, Omaha, Nebraska). After assigning rate percentages to each plot area to deliver the appropriate irrigation depth, the software produced a proprietary irrigation prescription file, which was uploaded to the control panel on the irrigation machine. Typically, the same site-specific irrigation prescription was used for all passes of the irrigation machine during a given week, and the number of passes required to administer the weekly irrigation rate was divided among the two scheduled irrigation days. Thus, practical considerations necessitated deviations of the applied irrigation rates from the rates specifically recommended by the modeling framework.

Fertilizer Management

Following the recommendations of Bronson (2021), liquid urea ammonium nitrate (UAN 32-0-0) was uniformly applied in three split applications in both growing seasons, amounting to seasonal nitrogen application rates of 149 kg N ha^{-1} each year. A fertigation trailer, which included a fertilizer tank, metering pump, and gasoline-powered generator, was hitched to the lateral-move irrigation machine, and fertilizer was injected into the overhead irrigation pipe. During fertigation events, the irrigation machine was operated at 25% full speed, which applied N fertilizer with 20 mm of water. To ensure uniform fertilizer application, no site-specific irrigation management was conducted during fertigation events. Fertilizer application dates were 8 June (DOY 159), 22 June (DOY 173), and 14 July (DOY 195) in 2021, and 7 June (DOY 158), 1 July (DOY 182), and 22 July (DOY 203) in 2022.

Statistical Analysis

Linear mixed models were computed using the "lme4" package within the R Project for Statistical Computing. The dependent variables were seasonal irrigation amount, cotton fiber yield, and water productivity, which was computed as a ratio of yield and irrigation amount. The fixed effects were the irrigation management treatment and the cultivar, and the replication and the irrigation management treatment nested in replication were fit as random effects. Likelihood ratio tests were conducted for one model that withheld the fixed effect and another that included it, which established whether the fixed effect contributed significantly to explained variability. Tukey's multiple comparisons tests were conducted to group the treatment means.

Results

2021 Growing Season

Seasonal irrigation amounts in 2021 were different among the six irrigation treatments ($p < 0.05$) but not between the two cultivars (figs. 3a and 3b). Mean irrigation amounts were 972, 866, 901, 823, 963, and 852 mm for AQC, AQCSWC, CSM, CSMSWC, FAO, and FAOSWC treatments, respectively. The three stand-alone models each recommended greater irrigation amounts as compared to their counterparts with assistance from soil water content data, and average seasonal irrigation differences amounted to 106, 79, and 111 mm between AQC and AQCSWC, CSM and CSMSWC, and FAO and FAOSWC treatments, respectively. The stand-alone CSM-CROPGRO-Cotton model recommended less water than the stand-alone AquaCrop and pyfao56 models in 2021 ($p < 0.05$), perhaps due to its greater detail in simulating crop growth and soil water movement within the soil profile. In fact, the irrigation amount recommended by the stand-alone CSM-CROPGRO-Cotton model was statistically identical to the amounts recommended by the AquaCrop and pyfao56 models with assistance from soil water content data. Overall, the incorporation of soil water content data into the scheduling methodology reduced irrigation amounts from 9% to 12% in 2021.

Fiber yields were different among cultivars in 2021 ($p < 0.05$), but fiber yields among the six irrigation scheduling treatments were statistically identical (figs. 3c and 3d). The shorter-season variety (NexGen 3195) provided an average yield of 1303 kg dry fiber ha^{-1}, which was statistically greater than the average yield of 1057 kg dry fiber ha^{-1} for the longer-season variety (NexGen 4936). The cool and wet late-season weather may have slowed the development of the longer-season variety, thereby reducing yield. The lack of a

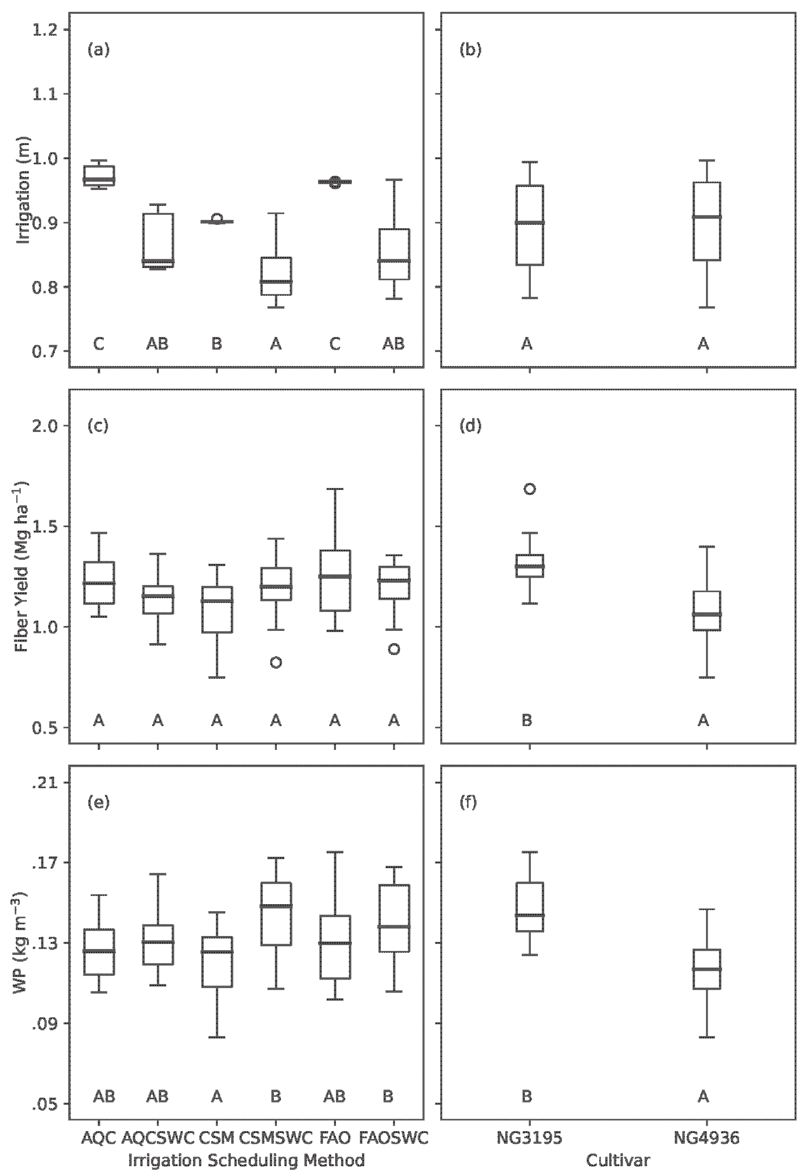

Figure 3. Box plots for seasonal irrigation, fiber yield, and water productivity (WP) among six irrigation scheduling methodologies (left side, variability from reps and cultivars) and two cultivars (right side, variability from reps and irrigation treatments) in the 2021 cotton growing season at Maricopa, Arizona. Irrigation scheduling was based on simulations with AquaCrop (AQC), the DSSAT Cropping System Model (CSM), and pyfao56 (FAO) both with and without assistance from soil water content (SWC) measurements. Letters under each box plot demonstrate the statistical groupings from Tukey's multiple comparisons tests.

fiber yield response among the irrigation scheduling treatments indicated an advantage for treatments that reduced irrigation, realized through improvements in water productivity. In 2021, water productivity was different among the six irrigation scheduling treatments and between the two cultivars (figs. 3e and 3f). The stand-alone pyfao56 and AquaCrop models, as well as all three models with assistance from soil water content data, achieved greater water productivity than the stand-alone CSM-CROPGRO-Cotton model. Furthermore, water productivity was statistically different between CSM and CSMSWC treatments but not between AQC and AQCSWC nor FAO and FAOSWC. Statistically greater water productivity was achieved for the shorter-season variety, primarily through its yield benefits. The use of soil water content data to adjust model-simulated irrigation recommendations improved water productivity by 4%, 20%, and 7% for AquaCrop, CSM-CROPGRO-Cotton, and pyfao56 models in 2021.

2022 Growing Season

As in 2021, seasonal irrigation amounts in 2022 were different among the six irrigation treatments ($p < 0.05$), but not between the two cultivars (figs. 4a and 4b). Mean irrigation amounts were 1069, 919, 1054, 910, 1138, and 896 mm for AQC, AQCSWC, CSM, CSMSWC, FAO, and FAOSWC treatments, respectively. As in 2021, the three stand-alone models each recommended significantly greater irrigation amounts than their counterparts that incorporated in-season soil water content data. Average differences in irrigation amounts between treatments in 2022 were greater than in 2021, with 150, 143, and 242 mm differences between AQC and AQCSWC, CSM and CSMSWC, and FAO and FAOSWC, respectively. The irrigation amounts for the three treatments that incorporated soil water content data were statistically identical to each other and statistically different from all three stand-alone models ($p < 0.05$). Also, the irrigation amounts from the stand-alone CSM-CROPGRO-Cotton model were significantly less than the amounts from the stand-alone pyfao56 model, while the amounts from the stand-alone AquaCrop model were not different from the other two models. Overall, the incorporation of soil water content data into the scheduling methodology reduced irrigation amounts by 14%, 14%, and 21% for AquaCrop, CSM-CROPGRO-Cotton, and pyfao56, respectively, in the 2022 growing season.

As in 2021, fiber yields were different between the two cultivars in 2022 ($p < 0.05$), with the shorter-season variety (NexGen 3195) again outyielding the longer-season variety (NexGen 4936). Mean fiber yields for NexGen 3195 and NexGen 4936 were 1578 and 1323 kg dry fiber ha^{-1}, respectively, in 2022 (fig. 4d). Yield differences were also found among the six irrigation treatments in 2022 (fig. 4c). Fiber yield for CSMSWC was not different from any other irrigation method, while the CSM and FAO treatments achieved greater fiber yield than AQC, AQCSWC, and FAOSWC ($p < 0.05$). For both the Aquacrop and CSM-CROPGRO-Cotton models, the significant reduction in seasonal irrigation (due to the incorporation of soil water content information in the scheduling methodology) did not lead to a significant reduction in fiber yield, although mean yields were reduced by approximately 15%. For pyfao56, fiber yield from the use of soil water content data (FAOSWC) was significantly less than yield from the stand-alone model (FAO). Also, fiber yields for AQC were significantly less than yields from CSM and FAO treatments, likely because CSM-CROPGRO-Cotton and pyfao56 have undergone more field testing at Maricopa than Aquacrop (Thorp et al., 2017; 2020b; 2022). While AquaCrop recommended similar seasonal irrigation amounts compared to the other two stand-alone models (fig. 4a), it generally recommended more water during the early growing season and also cut off the water earlier at the end of the season, which likely contributed to the AQC yield losses in 2022 (fig. 4b). While the incorporation of soil water content data into the scheduling methodology saved water in 2022, yield reductions from this approach were 16%, 15%, and 20% for AquaCrop, CSM-CROPGRO-Cotton, and pyfao56, respectively, indicating proportional yield reductions with irrigation reductions in 2022.

Water productivity among irrigation scheduling treatments in 2022 differed according to the choice of model (fig. 4e), with CSM-CROPGRO-Cotton treatments achieving greater water productivity than AquaCrop treatments ($p < 0.05$). Water productivity for the pyfao56 treatments did not differ from the water productivity achieved by the other two models. Finally, as in 2021, water productivity was greater for the shorter-season variety as compared to the longer-season variety (fig. 4f; $p < 0.05$), due mainly to the greater yield of the shorter-season variety.

Discussion

Station Aridity Effects

Because the stand-alone models recommended greater irrigation amounts than their counterparts with assistance from soil water content data, the results suggest that simulated soil water contents were generally less than measured soil water contents. It follows that the models may have overestimated ET, especially considering that irrigation was managed to minimize deep drainage and runoff in this study. Because all the models utilized weather data from the Maricopa AZMET station to compute ASCE (2005) standardized short crop reference evapotranspiration, an analysis of the suitability of this station to meet assumptions for short crop reference conditions was warranted. The effects of aridity, which can detract the station from ideal reference conditions, could likely have caused overestimated reference ET calculations and, in turn, underestimated simulated soil water contents and overestimated irrigation requirements.

A recent study evaluated aridity effects on 83 weather stations in the Oklahoma Mesonet (Singh et al., 2023). They used three metrics to evaluate aridity at each weather station location: mean dew point deviation, maximum relative humidity, and satellite-based normalized difference vegetation indices (NDVI). Under reference conditions, the minimum daily air temperature is expected to reach and perhaps fall below the average daily dew point temperature, while aridity can produce large positive differences between the minimum daily air temperature and the average daily dew point temperature (Temesgen et al., 1999). Also, ASCE (2016)

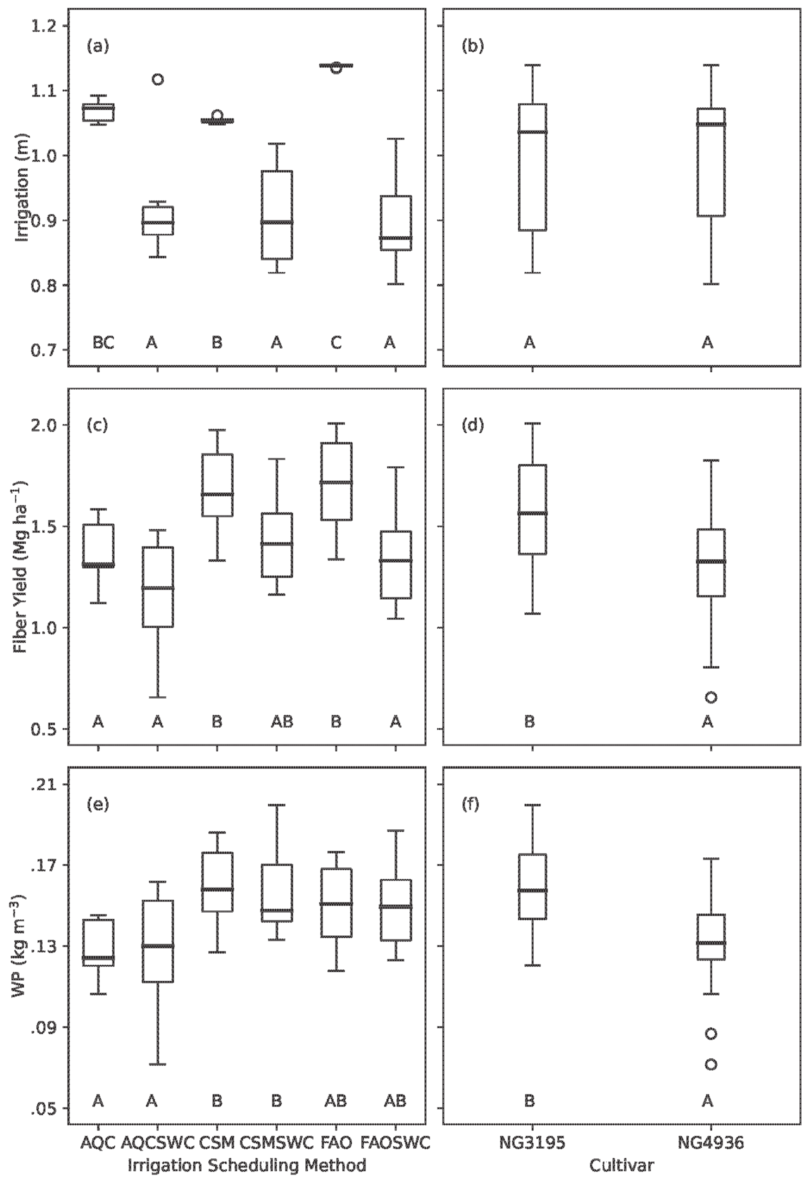

Figure 4. Box plots for seasonal irrigation, fiber yield, and water productivity (WP) among six irrigation scheduling methodologies (left side, variability from reps and cultivars) and two cultivars (right side, variability from reps and irrigation treatments) in the 2022 cotton growing season at Maricopa, Arizona. Irrigation scheduling was based on simulations with AquaCrop (AQC), the DSSAT Cropping System Model (CSM), and pyfao56 (FAO) both with and without assistance from soil water content (SWC) measurements. Letters under each box plot demonstrate the statistical groupings from Tukey's multiple comparisons tests.

suggested that humidity data may be questionable when the daily average dew point temperature is consistently 3-4°C lower than daily minimum air temperature. Based on this guidance, Singh et al. (2023) used a threshold of +2°C for the difference between the daily minimum air temperature and the average dew point temperature to indicate aridity at a weather station. In their study, the station experiencing the greatest aridity effect was at Kenton in the Oklahoma Panhandle, where daily dew point deviations exceeded the +2°C threshold on 54% of days and the mean dew point deviation was 3.3°C during a 20-year period from 2000 through 2019. By comparison, mean dew point deviation of the Maricopa AZMET station during the same period was 8.2°C, and the +2°C threshold was exceeded on 81% of days. Considering only the two years of the field study (2021 and 2022), the mean dew point deviation of the Maricopa AZMET station was 8.7°C (fig. 2), and the +2°C threshold was exceeded on 85% of days. Following ASCE (2016), Singh et al. (2023) also reasoned that maximum daily relative humidity will approach 100% for the reference condition, and they adopted a maximum relative humidity threshold of 80% to indicate aridity. Over the 20-year period of their study, stations experiencing the most severe aridity effects had an average maximum daily relative humidity of 83%, and measurements fell below the 80% threshold on 36% of days. By comparison, the average daily maximum relative humidity of the Maricopa AZMET station during the same period was 68%, and measurements fell below the 80% threshold on 70% of days. Considering only 2021 and 2022, the average daily maximum relative humidity of the Maricopa AZMET station was also 68%, and measurements fell below the 80% threshold on 71% of days. Clearly, per the metrics outlined by ASCE

(2016) and Singh et al. (2023), the Maricopa AZMET station has experienced severe effects of aridity.

It is difficult and costly to maintain adequate fetch around a weather station in a desert environment. The fetch around the Maricopa AZMET station is poor, amounting to 15 m by 13 m of irrigated, clipped grass. While the station is positioned in an agricultural area at the MAC, many of the neighboring fields lay fallow most of the time and receive regular tillage to remove weeds. Also, several farm buildings are positioned approximately 85 m upwind from the station. These weather station limitations likely resulted in overestimated irrigation recommendations from the scheduling models used in this study, particularly the recommendations from the stand-alone models, which were not adjusted based on in-season soil water content data. Future work should focus on evaluating techniques to correct weather data from this station. For example, Annex 6 of FAO-56 (Allen et al., 1998) suggests methods to correct minimum, maximum, and dew point temperatures collected from weather stations that deviate from reference conditions, although the text also cautions that errors and uncertainties introduced by these procedures are largely unknown. Relocating the Maricopa AZMET station away from farm buildings and maintaining better fetch around the station would also likely improve its ability to represent reference conditions and provide better estimates of reference evapotranspiration.

Uncertainty Considerations

While impacts of aridity on the weather station help explain the greater irrigation amounts recommended by the stand-alone models, it does not explain the yield reductions for models combined with soil water content in 2022 (fig. 4c). If the measured soil water content data were used correctly, one would not anticipate a yield loss from those treatments. From equation 3, several aspects of uncertainty in the depletion calculations may be responsible for this, including uncertainty in the soil water content measurements, soil water limit estimates (particularly the DUL), and the rooting depth calculations. Additionally, the technique for the treatment of soil water content above the DUL also likely impacted the results. The following paragraphs discuss these uncertainties in detail.

A calibration of the neutron moisture meter was conducted at the field site in 2016 and 2017. The methodology involved collecting and transferring wet soil samples to sealed plastic bags during the installation of access tubes, followed by the immediate deployment of the neutron moisture meter to estimate soil water content. Soil samples were collected from five 0.4 m soil layers to a depth of 2.0 m, and the sample volume was estimated from hole depth measurements and the diameter of the soil sampling cylinder. Wet and oven-dried soil sample weights and sample volume information were used to estimate the volumetric soil water content of each sample. Based on a comparison of 400 paired soil water content estimates from the neutron moisture meter and the soil samples, the neutron moisture meter could estimate soil water content with a root mean squared error of 0.027 cm^3 cm^{-3}, and the standard deviation of the absolute error was 0.019 cm^3 cm^{-3}. Although more comprehensive methodologies for neutron moisture meter calibration are now available (Evett et al., 2022), the rapid and crude approach used here provided evidence that reasonable estimates of soil water content could be obtained from the neutron moisture meter, while uncertainties remain.

The parameters for soil profile characterization in irrigation scheduling models are known to be both highly uncertain (Gijsman et al., 2003) and highly influential on the modeling outcomes (Thorp et al., 2020a). In this study, the hydrometer method of Gee and Bauder (1986) was meticulously followed to quantify soil texture at 160 sampling locations and 5 sampling depths across the field. Subsequently, the Rosetta pedotransfer functions (Zhang and Schaap, 2017) not only estimated the DUL and LL of each soil sample but also the associated uncertainty. Results from 792 soil samples at the field site revealed that the minimum, median, and maximum standard deviation associated with DUL estimates were 0.010, 0.016, and 0.025 cm^3 cm^{-3}, respectively. Therefore, the uncertainty of DUL estimation was similar to the uncertainty of soil water content measurement (previous paragraph), and two standard deviations of error could result in approximately ±0.050 cm^3 cm^{-3} deviation between estimated and actual values for either variable. The potential impacts on soil water depletion (D_r, eq. 3) are substantial (fig. 5). If estimates are contained within one standard deviation of the actual DUL and SWC values, the effects on depletion over a 1.5 m soil profile are maintained below 75 mm. This is equivalent to roughly the amount of cotton water used for one week in Arizona in mid-summer. However, if uncertainty is greater than one standard deviation, greater effects on depletion are possible. Furthermore, if the estimated DUL and SWC deviate from actual values in the same positive or negative direction, the impacts on depletion are less severe than if they deviate in opposite directions. The large effect of uncertainty on calculations of depletion may explain why yields were reduced for models with assistance from soil water content measurements in 2022. If DUL was underestimated or soil water content was overestimated, irrigation recommendations may not have been sufficient to completely avoid plant stress and associated yield reductions.

Another primary source of uncertainty in all the modeling frameworks was the rooting depth calculations. Data for evaluation of rooting depth simulations was not available, and in any case, rooting depth is extremely difficult to quantify accurately. While a maximum rooting depth of 150 cm was specified for each model, different algorithms were used for the daily advancement of rooting depth. It's possible that actual cotton rooting depths deviated from the rooting depths simulated by each model and perhaps did not ever reach a depth of 150 cm during the growing season. Uncertainty in the simulated rooting depth likely impacted the results because it was used for root-zone soil water depletion calculations from both the measured and simulated soil water content data (eq. 3). Related to the root depth issue was the treatment of soil water content above the DUL. At the outset, it was decided to treat any root-zone water content above the DUL as available to the plant. Therefore, if the water contents at the bottom of the (assumed) root zone were above the DUL, the excess water there could offset water deficits in shallower layers of the root zone (this situation was

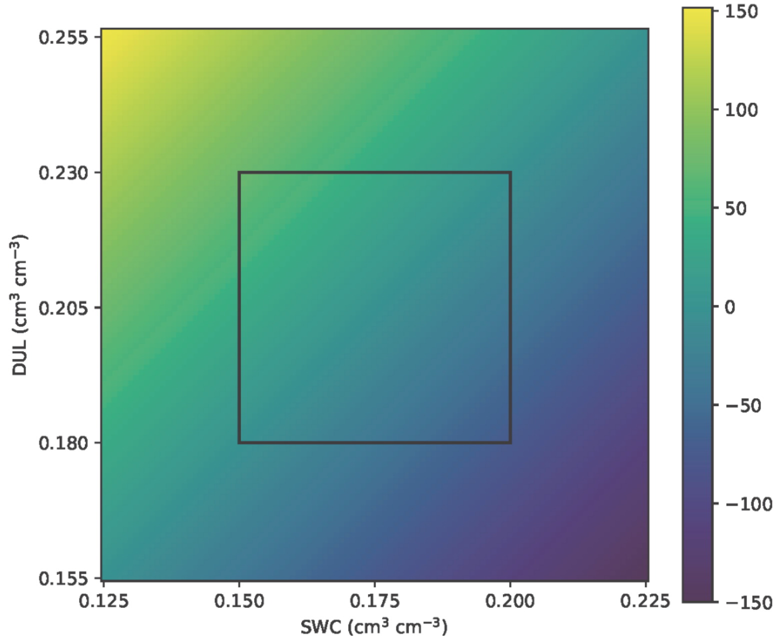

Figure 5. Potential changes in soil water depletion (ΔDr, mm) due to uncertainty in estimates of soil water content (SWC) and drained upper limit (DUL). Results demonstrate the uncertainty effects on soil water depletion when actual SWC and actual DUL are assumed as 0.175 cm^3 cm^{-3} and 0.205 cm^3 cm^{-3}, respectively. Assuming a soil profile depth of 1500 mm, actual depletion was computed as follows: (0.205 – 0.175) × 1500 = 45 mm. The ΔDr values were then computed as the difference between estimated and actual Dr: ΔDr = (DUL – SWC) × 1500 – 45. Values inside and outside the black square represent uncertainty effects within one standard deviation and between one and two standard deviations of the actual values, respectively.

commonly observed in the measured soil water content data). However, if the actual root zone was in fact shallower than the simulated rooting depth, then the roots would not have access to the deeper water, and the plant could therefore experience greater stress than determined through the modeling workflow. This issue is related to the uncertainty of knowing precisely where the roots are extracting water from the soil profile. In hindsight, it may have been better not to credit water deficits in the shallower layers of the root zone with water excesses above the DUL in the deeper layers of the root zone. This practice would likely have resulted in greater irrigation requirements and a greater yield for the treatments that incorporated soil water content data in 2022.

Taken together, the uncertainties in estimating evapotranspiration, rooting depth, soil water content, and drained upper limit collectively impacted and limited the core methodology as described in eqs. 3 and 4. Errors in evapotranspiration estimation due to weather station aridity mainly affected I_{mod} and $D_{r,s}$ in equation 4. Errors in rooting depth estimation directly affected n in equation 3, which in turn affected D_r calculations for both measured and simulated data sources. The potential error in the estimation of soil water content and drained upper limit (fig. 5) only further exacerbated the error in D_r calculations (eq. 3). Most surprisingly, as shown in figure 5, uncertainty could impact D_r in amounts that exceeded weekly water use estimates for the cotton crop! Figure 6 provides a broad synopsis of D_r for both seasons and among all plots and soil water measurement dates. Measured D_r (based on model-simulated rooting depths) exhibited first and third quartiles between -30 and 15 mm, respectively, while the full range of measured D_r was between -116 and 118 mm (fig. 6a). (Negative D_r indicated root-zone water status above the drained upper limit.) Simulated D_r exhibited first and third quartiles between 13 and 54 mm, respectively, while the full range of simulated D_r was between -25 and 146 mm. The difference between measured and simulated D_r exhibited first and third quartiles between -82 and -2 mm, which is why adjusted irrigation rates (I_{adj}, eq. 4) were usually less than modeled rates (I_{mod}). The ranges of these D_r values were very large and, in many cases, unrealistic. As a result, for purposes of irrigation scheduling during the field experiment, the weekly irrigation recommendations (I_{mod} and I_{adj}) were further constrained based on estimates of weekly water use computed by the models, as discussed in the methods. If D_r is to be used as a reliable metric for determining irrigation requirements, it must be estimated with greater certainty than demonstrated in this study.

Future Considerations

Improved integration of measurement systems and decision tools is needed to overcome the complications of the study. Most of the technologies deployed herein were designed and maintained independently. For example, the weather station was managed by an external entity and located 1.2 km from the field site. Also, the drained upper limit was characterized using pedotransfer functions developed from independent field data collected far from the research station. The three simulation models were developed by independent modeling groups and were not developed to receive specific feedback from soil water content sensors. Finally, the soil water content measurement system was deployed independently from other technologies used in the study. This research has made great efforts to bring together diverse technologies for the purposes of scientific irrigation

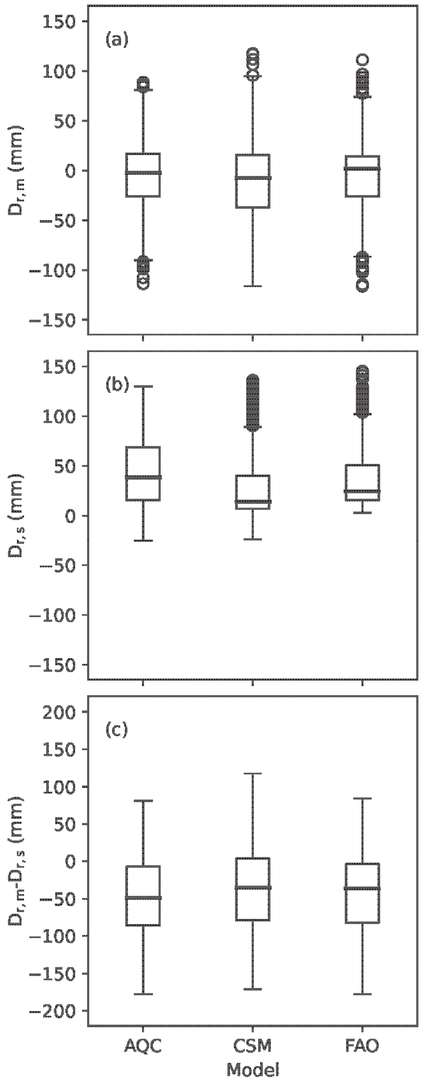

Figure 6. Box plots showing variability in (a) measured root-zone soil water depletion ($D_{r,m}$), (b) simulated root-zone soil water depletion ($D_{r,s}$), and (c) the difference between $D_{r,m}$ and $D_{r,s}$ across two cotton growing seasons at Maricopa, Arizona. Irrigation management was based on $D_{r,m}$ from neutron moisture meter data and $D_{r,s}$ from three simulation models: AquaCrop-OSPy (AQC), CSM-CROPGRO-Cotton (CSM), and pyfao56 (FAO).

scheduling, but biases and uncertainties continue to overwhelm, and further advancements are therefore needed. Perhaps measurement systems for meteorological variables, soil water content, and plant stress status could be combined for consistent data retrieval in time and space. Simulation models could then be designed to receive and synthesize the specific information collected by such devices, and data assimilation techniques could be developed to ameliorate uncertainty. Perhaps soil water limits could be directly derived from this information, reducing the requirement for independent soil sampling, soil texture analysis, and pedotransfer functions. For positive progress, better integration of sensing and modeling systems is needed to provide accurate metrics that lead to defensible and unambiguous management recommendations and that respond appropriately and precisely to management actions.

CONCLUSIONS

Results from two cotton growing seasons suggest that in-season soil water content data assisted three different irrigation scheduling models to reduce irrigation applications, often while maintaining fiber yield and water productivity, as compared to recommendations from stand-alone models. Issues with weather station aridity, uncertainty of rooting depth estimates, and field measurement errors were identified as the main complications in this study. The experience of making weekly comparisons between multi-model simulation output and near-real-time field data, ultimately leading to critical irrigation management decisions, was invaluable for understanding the deviations in the data and for assessing ways to improve the overall scheduling methodology. The results clearly demonstrated that irrigation recommendations can be improved through the incorporation of in-season field data with the irrigation scheduling models. Future efforts should focus on the development of techniques for integrating data from modern sensing systems into model simulations for improved information handling and decision-making skill.

Trends for the two cotton cultivars were similar in the two growing seasons, with the shorter-season cotton variety (NexGen 3195) yielding higher and achieving higher water productivity than the longer-season variety (NexGen 4936). The specific reason for this may be varietal rather than environmental, as personal communication with local farmers suggested that NexGen 3195 performed well throughout central Arizona in these growing seasons. However, the use of shorter-season cotton varieties may also help growers reduce risk through the avoidance of potentially yield-limiting weather scenarios.

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