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AGRONOMY & SOILS

Cotton Irrigation Scheduling: Which Approach is the Best Fit for Georgia?

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ABSTRACT

Cotton (*Gossypium hirsutum*) is one of the most difficult crops to manage irrigation effectively due to the crop's perennial physiology. In recent years, many new technologies have been developed to help improve irrigation management. The main objective of this study was to evaluate various irrigation management tools and to assist farmers in determining which method is best for their operation. Other objectives included monitoring soil moisture and determining the optimal irrigation application point of each method by logging total rainfall and irrigation distribution throughout the growing season. A three-year study was conducted at the University of Georgia (UGA) Stripling Irrigation Research Park near Camilla, GA where cotton was grown on loamy sand soil. A lateral movement, overhead sprinkler system equipped with a variable rate system allowed plots to be irrigated independently based on treatment. Irrigation treatments included 20- and 45-kPa weighted average soil water tension (SWT) measurements made using three Watermark SWT sensors placed in two of the three replicates. The UGA SmartIrrigation Cotton app (SI app), UGA Checkbook method, and a rainfed check were included in the trial. Each irrigation method was evaluated based on crop yield, irrigation water-use efficiency, and profitability. The analysis revealed significant variations in several metrics between treatments and validates the 45-kPa SWT threshold and SI app are top-performing advanced irrigation scheduling tools and showed the importance of advanced irrigation scheduling and the strengths and weaknesses of each method.

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The use of irrigation systems has increased significantly over the last two decades across the southern region of the Cotton Belt (Perry et al., 2017). Since 1900, irrigated land area has increased from 40.5 to 326.1 million ha in 2017 with an increase of 55.4 million ha since 1997 (Eisenhauer et al., 2021). This drastic increase has led irrigated agriculture to become the largest user of freshwater resources (Berthold et al., 2021). Reports from Dieter et al. (2018) have shown that irrigation accounts for 42% of all freshwater withdrawals, removing up to 277 million m^3 of water per day in 2015. Southeastern states account for approximately 18.4% of all irrigation water consumption, primarily by Arkansas, Florida, and Georgia (Hrozencik, 2023).

The increase in water usage has led to an increase in the number of systems and tools designed to optimize irrigation scheduling practices. Many of these tools are marketed commercially by private companies or are the results of public research developments from land grant universities or the United States Department of Agriculture. Several factors, such as initial investment price, time requirements, and performance determine the adoption of these methods (Porter et al., 2023). These scheduling methods include the University of Georgia (UGA) Checkbook method (Checkbook) and the UGA SmartIrrigation Cotton smartphone app (SI app), which are free to use but require a daily time investment to track local rainfall to calculate irrigation requirements (Bhattarai et al., 2020; Vellidis et al., 2016).

Many of the systems require the use of a weather station or soil moisture sensor systems to quantify soil water content. The most common sensor system measures soil moisture based on either soil water capacitance or soil water tension (SWT). Soil water capacitance is a measurement of the dielectric properties of the soil mainly based on soil water content to quantify its volumetric water content (Francesca et al., 2010; Gardner et al., 1998; Moncks et al., 2022). SWT is the other commonly used method for measuring soil water content. It is based on electrical resistance inside a granular matrix moisture sensor, such as a Watermark sensor (Irrometer Co., Riverside, Ca.) (El-Marazky et al., 2011; Rix et al., 2021). Research has shown that the optimum trigger point for SWT sensors can vary substantially based on subregion within the Cotton Belt (Flynn and Barnes, 1998; Grant et al., 2017; Porter et al., 2023; Vellidis et al., 2014, 2016). Studies have found optimum results range from 40 to 60 kPa for field-grown cotton (*Gossypium hirsutum* L.) (Flynn and Barnes, 1998; Grant et al., 2017; Porter et al., 2023; Vellidis et al., 2008, 2016).

Both under- and over-irrigation can impact cotton growth and development, yield, and profit. Drought stress or under-irrigation limits cotton growth and development, especially leaf area development, mainstem elongation, and reduces the number of fruiting sites (Chastain et al., 2016; Krieg and Sung, 1986; Loka and Oosterhuis, 2012; Pace et al., 1999). In addition, source strength is limited by drought due to reduced leaf area, which reduces up to 54% of the amount of photosynthate available to support a developing boll load (Chastain et al., 2014; Krieg and Sung, 1986; Pace et al., 1999). This results in substantial yield decline caused by drought stress-induced fruit shedding leading to a reduction in boll density of 33.7% and a yield decline of up to 58% compared to a well-watered crop (Balkcom et al., 2006; Chastain et al., 2016; Krieg and Sung, 1986; Lee et al., 2023; Loka and Oosterhuis, 2012; Lokhande and Reddy, 2014). Other studies have shown that over-irrigation can be detrimental to cotton yields, profitability, and groundwater resources (Ermanis et al., 2021; Geerts and Raes, 2009; Grant et al., 2017; Liu, et al., 2022B). Ermanis et al. (2021) showed reductions in yield as irrigation volume increased from 100% crop evapotranspiration (ET_c) to 125% ET_c, as calculated by the Penman-Monteith equation (Eq. 1). A similar study found that yield loss is driven by a reduction in radiation-use efficiency by up to 35%, which lowered overall dry matter accumulation, fruiting sites, and yield potential (Bange et al., 2004; Najeeb et al., 2016). Other abiotic problems can arise from over-irrigation, such as nutrient leaching and boll rot development (DeTar, 2008; Perry et al., 2017). Because of this delicate balance, cotton is regarded as one of the most challenging crops to irrigate effectively, as over- and under-irrigation both can be detrimental to yield and profitability (Liu et al., 2022B; Porter et al., 2023).

Most scheduling models are based on Food and Agriculture Organization Report 56 (Allen et al., 1998). This publication defined the process and established guidelines for determining localized crop coefficient (K_c) curves for crops such as cotton as seen in Ko et al. (2009) and Kumar et al. (2015). This allows for the calculation of ET_c based on local reference evapotranspiration data (ET_0) using the Penman-Monteith equation (Equation 1) (Allen et al., 1998; Ko et al., 2009).

$$ET_c = K_c \, X \, ET_0 \tag{1}$$

This model has been widely adapted for use by many water balance models such as the SI app (Vellidis et al., 2016).

The many new irrigation scheduling tools have overwhelmed producers who are attempting to determine which scheduling approach is the best fit for their operation. Therefore, the main objective of this multi-year study was to evaluate various irrigation scheduling tools and strategies based on yield, irrigation water-use efficiency (IWUE), and profitability to help producers determine which irrigation scheduling tools are best for their operation.

MATERIALS AND METHODS

The field experiments were conducted during 2020, 2021, and 2022 cotton growing seasons on a Lucy loamy sand (Loamy, kaolinitic, thermic Arenic Kandiudult) at UGA's Stripling Irrigation Research Park near Camilla, GA. Plots were designed using a randomized complete block design under a lateral movement, overhead sprinkler irrigation system equipped with a variable rate controller (Valley Irrigation, Valley, NE). Five treatments were replicated three times in 2020 and four times in 2021 and 2022. The plots measured 12.8 m long and 7.3 m wide, each containing eight rows of cotton.

Deltapine 1646 B2XF (Bayer Crop Science, St. Louis, MO) cotton seed was planted on 7 May 2020, 7 May 2021, and 25 April 2022, using 91.4-cm row spacing. Four irrigation scheduling treatments were replicated across all three years of this study, which included 45-kPa (optimal) and 20-kPa (wet) SWT thresholds, SI app, and Checkbook. To calculate SWT in these treatments, a weighted average approach was implemented by crop age and estimated root depth to determine when the irrigation trigger point was reached and irrigation was to be applied. Weights changed at 30 and 60 d after planting to prioritize areas with estimated maximum root growth throughout the growing season (Table 1). The SI app is a soil water deficit model that uses local weather, evapotranspiration (ET) data, and the K_c curve to estimate crop water use and irrigation requirements (Vellidis et al., 2016). Checkbook works as an historical ET calendar-based scheduling method that outlines weekly crop water requirements and serves as a budget for estimating irrigation needs. The final treatment was rainfed control, which was used as a baseline reference for comparison and IWUE calculation.

Three Watermark SWT sensors were integrated into a probe at depths of 20, 40, and 60 cm. The probes were installed in two of the three replications of each treatment. Data were logged and monitored hourly in all treatments and the collected data were used in the 20- and 45-kPa treatments to schedule daily irrigation events. The SWT probes were used only to monitor irrigation and SWT in all other treatments.

All plots received a 25-mm blanket irrigation event to ensure stand establishment and herbicide activation at the beginning of the growing season. Thereafter, each irrigation event was a 19-mm irrigation application applied to all three replications on the day that the threshold was reached based on daily readings. The exception to this was the UGA Checkbook method for which the total weekly water requirement, minus rainfall, was divided among three days and applied at the resulting rate. An example of this would be from 26 June 2020 through 2 July 2020, the weekly crop water requirement was 27.4 mm per week or 3.8 mm per day, according to the Checkbook published in the UGA Cotton Production Guide (Hand et al., 2023). During this period in the 2020 trial a total of 8 mm of rainfall was received in two small rain events; therefore, an additional 19 mm of irrigation was required for this week. Checkbook recommended two irrigation events: 14 mm applied on Monday and 11 mm applied on Wednesday of that week. Irrigation applications were adjusted based on the local weather forecast and scheduled according to the Checkbook recommended amount. Irrigation volumes were divided and limited by system capabilities to between 10 and 20 mm per event.

All irrigation was terminated once 10% of bolls had opened on average across the field according to UGA Extension recommendations; these termination points were reached on 4 Sept. 2020, 10 Sept. 2021, and 1 Sept. 2022 (Porter et al., 2023). From planting to harvest, plots received 542.5, 753.4, and 541.3 mm of rainfall throughout the 2020, 2021, and 2022 production seasons, respectively. Because the 10-year average rainfall between 25 April and 10 Sept. for this site is 510 mm, these years were above-average rainfall years; therefore, potentially lower amounts of irrigation were required to sustain yields. The center two rows of each plot were harvested on 26 Oct. 2020, 20 Oct. 2021, and 24 Oct. 2022, using a two-row John Deere 9930 cotton picker (Deere & Co., Moline, IL) with a bagging attachment in the basket. The seed cotton weight for each plot was determined immediately and a subsample pulled for processing at the UGA Cotton Microgin. The lint turnout value was calculated based on the data from gin processing and applied to all samples to calculate the total lint yield.

These data were used to calculate the IWUE of each scheduling method: mean rainfed yield was subtracted from plot yield and divided by irrigation amount (Equation 2) (Howell, 2001). This allows us to explain the total yield increase per mm of irrigation.

$$IWUE = \frac{\textit{Lint yield-Rainfed mean yield}}{\textit{Irrigation volume}} \quad (2)$$

A profitability analysis was also conducted based on each year's cotton market price and UGA enterprise budget estimated cost of pumping irrigation (Liu et al., 2021, 2022A). These estimates predict an average cost of $0.60 per ha-mm when using an electric pumping unit and $1.03 per ha-mm for a diesel-powered unit in 2020 and 2021 (Liu et al., 2021); $1.33 per ha-mm was used in 2022 for the diesel pumping system to compensate for higher fuel prices that year (Liu, et al., 2022A). The cost of irrigation was calculated by multiplying these values with the total irrigation amount applied as seen in Equation 3.

Table 1. Weights used for averaging depths for soil moisture sensor-based irrigation scheduling

	Soil Water Tension Average Weights		
Days after Planting	**15 cm**	**25 cm**	**35 cm**
Less than 30	**60%**	**30%**	**10%**
30 to 60	**40%**	**40%**	**20%**
More than 60	**30%**	**50%**	**20%**

$$\textit{Irrigation cost} = \textit{Volume irrigated x Pumping cost} \quad (3)$$

The lint value was calculated by multiplying the per-hectare yield by the estimated market lint value for that year (Equation 4).

$$\textit{Lint value} = \textit{Market value x Lint yield} \quad (4)$$

These estimates were \$1.74, \$2.20, and \$1.98/kg in 2020, 2021, and 2022, respectively (Liu et al., 2021). Irrigation profitability was measured by subtracting cost of irrigation from lint value; this does not give total profitability for all inputs but allows for the calculation of return on investment for each irrigation treatment (Equation 5).

$$\textit{Irrigation profitability=Lint value-Irrigation cost} \quad (5)$$

Analysis. Data from all three years were analyzed in JMP Pro 16 (SAS Institute, Cary, NC). Specifically, an initial mixed-effects analysis was conducted where year, treatment, and year x treatment were considered fixed effects and replication was considered a random effect. Because there was a significant interaction between year and treatment, statistical analysis was conducted separately within each year of the study. A mixed effects ANOVA was utilized within each year, where irrigation treatment was considered a fixed effect and replication was considered a random effect. There were three replicates in 2020 and four replicates in 2021 and 2022. Means separations for yield, IWUE, and profitability were considered significant at an alpha level of 0.05 with a Tukey HSD post hoc test.

RESULTS

2020. Results from the 2020 growing season showed no statistical differences in yield among the irrigated treatments. The rainfed check yielded significantly less than the other treatments with a mean yield of 936 kg/ha (p = 0.0012) (Table 2) showing a benefit of irrigation. However, a lack of statistical differences in yield between irrigated treatments could be attributed to few irrigation events occurring throughout the second half of the growing season for all treatments except the Checkbook method affecting irrigation variability (Fig. 1). This was especially true late in the growing season as the crop reached its peak water use (Bednarz et al., 2002; Liu et al., 2022B; Perry et al., 2017; Ritchie et al., 2007; Vellidis et al., 2014, 2016).

IWUE between treatments showed statistical variations where 45 kPa was more efficient than Checkbook and 20-kPa treatments (p = 0.0034). This was likely due to 45 kPa irrigating less than other treatments and was similar to the findings of Flynn and Barnes (1998), Grant et al. (2017), and Vellidis et al. (2008) who found the optimum threshold for sensor-based irrigation scheduling to be between 30 and 60 kPa. Comparatively, the Checkbook treatment was found to be the least water-use efficient but not different from the 20-kPa treatment, which was likely driven by over-irrigation. This is represented in Fig. 1, which also shows Checkbook continued to

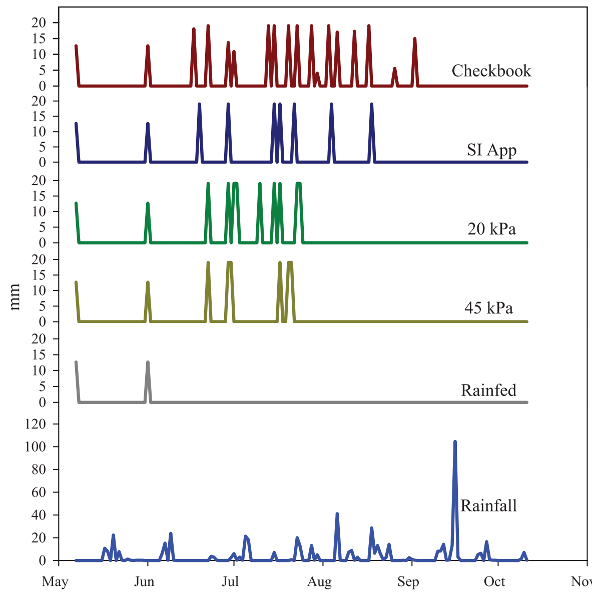

Figure 1. Irrigation and rainfall timing throughout the 2020 growing season.

recommend irrigation events through peak bloom, which was when water use was the highest despite substantial rainfall events (Allen et al., 1998; Bednarz et al., 2002; Chastain et al., 2016; Perry et al., 2017; Ritchie et al., 2007; Vellidis et al., 2016).

The profitability of irrigated treatments was comparable as well, with the rainfed treatment being the only treatment that differed statistically (p = 0.0019, p = 0.0026). However, the rainfed treatment was similar to the Checkbook method, which recommended greater irrigation volumes when considering a diesel system. This supports the findings of Ermanis et al. (2021) and Liu et al. (2022B) who documented negative impacts due to over-irrigation (Table 2).

2021. The 2021 growing season produced no significant difference in any of the performance metrics measured throughout this study (Table 3). Mean yields for all treatments were 1,304 kg/ha (p = 0.0843) representing above-average yields for both irrigated and rainfed treatments (USDA, 2023).

Table 2. Irrigation treatment performance in the 2020 growing season

Treatment	Lint Yield	IWUE	Electric Profit	Diesel Profit	Irrigation
	kg/ha	kg/mm	$/ha	$/ha	mm
45 kPa	1535 A[z]	4.29 A	2588 A	2528 A	139.7
20 kPa	1362 A	2.17 BC	2251 A	2167 A	196.9
SI app	1495 A	3.52 AB	2506 A	2437 A	158.8
Checkbook	1340 A	1.45 C	2164 A	2044 AB	279.4
Rainfed	936 B	-	1613 B	1602 B	25.4
p-value	0.0012	0.0034	0.0019	0.0026	

[z]Treatments with the same trailing letter are considered statistically similar.

Table 3. Irrigation treatment performance in the 2021 growing season

Treatment	Lint Yield	IWUE	Electric Profit	Diesel Profit	Irrigation
	kg/ha	kg/mm	$/ha	$/ha	mm
45 kPa	1335	1.34	2900	2875	59.9
20 kPa	1342	0.89	2893	2851	98.0
SI app	1305	0.85	2835	2810	184.4
Checkbook	1319	0.35	2792	2713	59.9
Rainfed	1215	-	2659	2648	25.4
p-value[z]	0.0843	0.3366	0.1388	0.1348	

[z]No statistical difference was seen in any of the metrics.

IWUE values for the 2021 growing season averaged 0.85 kg/mm ($p = 0.3366$), which were lower than the data seen in 2020. This was caused by consistent and adequate rainfall events and fewer irrigation events from mid-June through late August (Fig. 2). These rainfall events coincided with peak water use of the crop, which has been widely reported as occurring

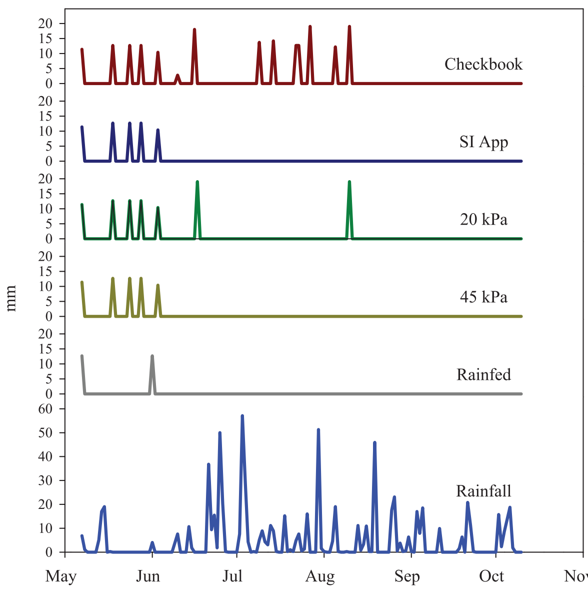

Figure 2. Irrigation and rainfall timing throughout the 2021 growing season.

through the blooming stage of development (Allen et al., 1998; Bednarz et al., 2002; Chastain et al., 2016; Hand et al., 2023; Perry et al., 2017; Ritchie et al., 2007; Vellidis et al., 2016). Profitability was consistent across all treatments with average profits of $2,816 per ha ($p = 0.1388$) for electric units and $2,779 per ha ($p = 0.1348$) for diesel pumping systems. The consistency in profitability is a result of low irrigation inputs across all treatments throughout the growing season (Table 3).

2022. The 2022 growing season saw the largest variations in treatments caused by many rain events that refilled the soil profile and were spread sporadically throughout the growing season leading to over-irrigation by all scheduling tools (Fig. 3). Because of the constant availability of moisture, the rainfed treatment saw increased yields compared to all other treatments ($p = 0.0005$) (Table 4). This was likely due to over-irrigation by many of the irrigated treatments, which could have led to excessive vegetative growth at the expense of boll production (Ermanis et al., 2021) or reduced radiation-use efficiency and nutrient leaching caused by waterlogging (Bange et al., 2004; DeTar, 2008; Najeeb et al., 2016; Perry et al., 2017). Much over-irrigation was due to thresholds being reached and irrigation events being initiated in the morning followed by a scattered, pop-up

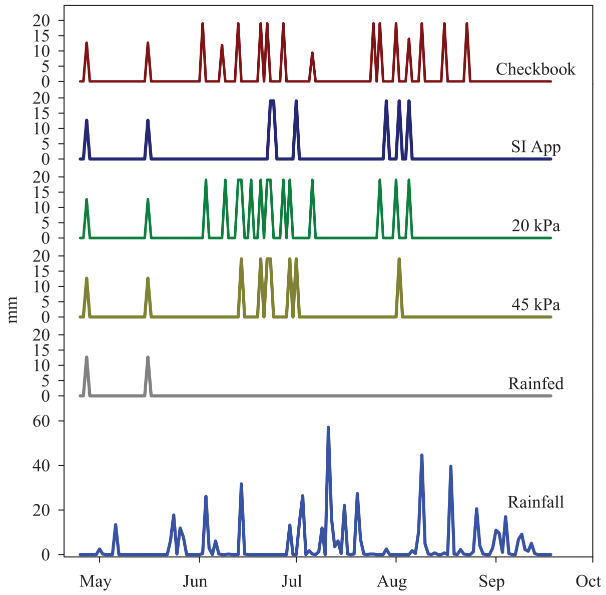

Figure 3. Irrigation and rainfall timing throughout the 2022 growing season.

rain event in the evening. Many of these rain events deposited substantive volumes of water negating the need for irrigation. This occurred four separate times across various treatments and highlighted the real-world challenges of implementing in-field irrigation studies.

As a result of the higher rainfed yields, IWUE was negative for all irrigation treatments as no yield benefit was observed from irrigation. IWUE was significantly lower for the SI app compared to Checkbook, however, both Checkbook and SI app were statistically the same as both sensor-based treatments (Table 4). Variations in IWUE such as these can be attributed to the timing of irrigation and provide us with a good indication of performance for each scheduling method ($p = 0.0582$).

The increased irrigation applications also reduced profitability compared to the rainfed treatment from both reduced yield and increased inputs. Although profitability was reduced compared to the rainfed treatment, the 45-kPa treatment's profitability was not considered statistically different from the Checkbook method or SI app, which were both comparable to the reduced profits of the 20-kPa treatment with electric pumping systems. This is likely because, in the development of the SI app, the Kc curve that was modified for use in South Georgia was set so that an estimated root zone soil water deficit of 50% coincided with a 40- to 50-kPa SWT (Vellidis et al., 2016). However, because the SI app is a model estimating field conditions, during rainy years such as 2022, it overestimated irrigation needs leading to performance similar to the lower SWT thresholds (Table 4). When considering a diesel-powered irrigation system, however, it was not comparable to the 20-kPa thresholds.

BARRIERS TO ADOPTION

Additional considerations for the adoption of advanced irrigation scheduling tools should be included when deciding which is the best for a particular producer, such as the number and size of fields and the time required for training and implementation of the tools. Training time has been documented as one of the largest barriers to adoption in the Rio Grande Valley with 39% of respondents surveyed affirming that training time was a major reason for slow adoption (Berthold et al., 2021). The cost of training time was not accounted for in this study because it varies based on each producer's situation. In general, sensor-based scheduling tools require a larger time commitment compared to the SI app, which is mostly automated assuming access to reliable weather data is available. Although many ET models such as the SI app are generally free to use, to optimize their performance they must have real-time access to accurate weather data, which can require the installation of weather

Table 4. Irrigation treatment performance in the 2022 growing season

Treatment	Lint Yield	IWUE	Electric Profit	Diesel Profit	Irrigation
	kg/ha	kg/mm	$/ha	$/ha	mm
45 kPa	1408 B[z]	-1.24 AB	2692 B	2548 B	158.8
20 kPa	1232 B	-1.28 AB	2264 C	2026 C	292.1
SI app	1346 B	-1.85 B	2581 BC	2452 B	139.7
Checkbook	1366 B	-0.88 AB	2543 BC	2319 BC	270.3
Rainfed	1604 A	-	3162 A	3143 A	25.4
p-value	0.0005	0.0582	<0.0001	<0.0001	

[z]Treatments with the same trailing letter are considered statistically similar.

stations (Davidson et al., 2022; Vellidis et al., 2016). Not only are current weather important but also reliable short-term forecasts. This affected all treatments in 2022 due to the large amount of sporadic rainfall that would have likely led to a reduction in irrigation events across all treatments had more accurate forecasts been available. Other barriers can be concerns about the effectiveness of the return on capital investment for the adoption of sensor-based scheduling (Berthold et al., 2021). However, the data shown in this study from 2020 show significant increases in profitability and no reduction in profits in 2021, proving they can be an effective tool for better irrigation management.

CONCLUSIONS

In conclusion, it was shown that over-irrigating cotton can be detrimental to the profitability of cotton production as observed in 2022. Therefore, it is crucial to carefully select the appropriate tool for making informed decisions about proper irrigation timing. Based on the results of this study, several high-performing tools are available to minimize the risk of reduced yields due to moisture stress. Scheduling based on a 45-kPa weighted average threshold consistently provided top-tier results as a sensor-based scheduling tool consistent with the findings of Flynn and Barnes (1998), Grant et al. (2017), and Vellidis et al. (2008, 2016). The UGA SI app also performed well as a soil water balance estimation model. In comparison, the Checkbook method required more irrigation events than other treatments in 2020 reducing IWUE. Similarly, the 20-kPa threshold over-irrigated the crop reducing profitability in 2022.

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