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The impact of nitrogen treatment and short-term weather forecast data in irrigation scheduling of corn and cotton on water and nutrient use efficiency in humid climates

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ABSTRACT

Irrigation adoption is increasing in humid regions to offset short-term dry periods, especially at the peak of the growing season. Low soil moisture at the peak growth stage impacts yield and limits the plant's capacity to uptake nitrogen, resulting in low nutrient use efficiency (NUE). However, heavy rainfall on fields with supplemental irrigation may result in waterlogging and surface runoff, leading to nutrient leaching and runoff. This ultimately can lead to lower NUE, poor water use efficiency (WUE), reduced yields, and water quality impacts. This makes irrigation management challenging in humid regions, as irrigators must avoid both limited and excess water conditions. This field study aimed to develop and test an irrigation management methodology using real-time soil water availability, crop physiological status, water needs, and short-term weather forecasts information from National Weather Service. A rule-based approach determined by soil moisture depletion and short-term weather forecasts was used to trigger irrigation to avoid both stress and excess water conditions. This method was tested in two years of field trials in Suffolk, Virginia to quantify its impacts on yield, NUE, WUE, and financial returns in corn and cotton under four nitrogen application treatments. The relative impact of irrigation and nitrogen treatment was quantified using mixed effects models. The yield, NUE and WUE were impacted by both precipitation and irrigation patterns. Significantly different yields were observed under Nrates treatments for both corn and cotton. The trends of economic returns were similar to yield and were significantly different between recent and historic prices. This study also discusses the impacts of reliability and practical challenges of using Weather Informed irrigation in a field study.

1. Introduction

Irrigation and nitrogen (N) play a significant role in crop growth, development, and productivity. Irrigated agriculture accounts for 70% of global water use (FAO, 2017). In the United States (US), irrigation accounted for 42% of freshwater withdrawals and 62% of the total water consumption (water not returned to the source after being withdrawn)-the highest consumption among all water use sectors in 2015 (Dieter et al., 2015). Irrigation adoption is also increasing in humid regions to offset short-term in-season droughts especially at the peak of the growing season (Paoletti and Shortridge, 2020; Walton, 2014). On the other hand, human acceleration of the N cycle has resulted in a tenfold increase in usage of mineral nitrogen fertilizer between 1911 (before the commercialization of the Haber-Bosch process) and 1960 (12 Tg N y-1), and another tenfold increase in the usage of nitrogen between 1960 and 2013 (110 Tg N y-1) (Battye et al., 2017). This increase is unlikely to be reversed in the near future as an estimated 48% of the world's population depended on N for food in the early 21st century (Erisman et al., 2008; Galloway et al., 2008). The increase in reactive N results in severe environmental issues, ranging from local water and air pollution to global climate change (Gruber and Galloway, 2008). Nitrogen leaching increases under higher water application and N fertilization (Wang et al., 2021; Muhammad et al., 2022). Therefore, careful consideration of the impacts of irrigation and N is important at the field scale for sustainable agricultural systems (Dai et al., 2019).

Croplands with a potential for N losses through deep percolation exist along the Atlantic coastal plain extending from Alabama northward through eastern VA and the Delmarva Peninsula (Potter et al.,

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2006). In northeast US, N losses average 44 kg per ha (39 pounds per acre) per year. Waterborne sediment accounted for the highest 34% of the losses, followed by 29% losses through volatilization and 17% losses dissolved in runoff and leachate (Potter et al., 2006). Excessive N application can have a significant economic impact on the growers. In the US, unused N results in fertilizer costs of about 6 billion dollars per year (Houlton et al., 2013). Yield loss associated with low nutrient use efficiency (NUE) ranges between 9% and 24% for corn and soybeans (Egli and Hatfield, 2014a, 2014b). Over 2021–2022, fertilizer prices are well above average, and the farm input prices increased more than double the general inflation rate in the US, largely impacting energy and fertilizer input prices (Langemeier, 2022). Although the optimum amount of N may vary with the crop type and field management practices, a common finding of previous research is that N uptake is highly dependent on soil moisture conditions (Dai et al., 2019; Sincik et al., 2013). Improvements in NUE and associated gains in environmental conservation were anticipated through precision N and water management. Still, that promise has yet to be realized due to limitations in adoption of technology primarily due to low returns based on current crop practices (Basso et al., 2019; Schimmelpfennig, 2016).

Traditionally, the main aim of irrigation scheduling techniques was to increase crop productivity with the optimum use of available resources. In the past two decades, various studies found the use of real-time soil moisture monitoring in irrigation scheduling to increase water use efficiency (WUE) without compromising the yield benefits (Camporese et al., 2021; Hanson et al., 2000; Kumar et al., 2022, Li et al., 2019; Moreira et al., 2016; Shang and Mao, 2006). Studies have also observed varying impacts of irrigation scheduling on NUE in different conditions. Ballester et al., (2021) tested NUE under three irrigation frequencies and lower than recommended fertilizer rates and found the intermediate irrigation frequency most effective for producing lint. Lu et al. (2021) found an increase in NUE with reduction in irrigation for wheat under monsoon climates. Da Cunha Leme Filho et al. (2020) compared two different irrigation treatments and four different N treatments for corn and found that NUE decreased with increasing application amounts and irrigation treatments didn't impact the NUE. Additionally, studies show that a N application beyond a range determined by soil, climatic and field management practices may result in yield losses and lower NUE (Gao et al., 2012; Zhang et al., 2015).

Irrigation and nutrient management are challenging in regions with sandy soils and humid climates. Sandy soils experience soil moisture deficit due to the lower water holding capacity of soils. At the same time, humid regions also encounter higher nutrient leaching when irrigation is paired with frequent intense precipitation events (Zurweller et al., 2019). Therefore, planning and adoption of water management practices to offset both moisture deficit and excess moisture conditions is vital for humid regions where supplement irrigation has a potential for widespread nutrient pollution through surface runoff and sub-surface leaching (Lassaletta et al., 2016; Li et al., 2018; Wang and Li, 2019). However, variation and unpredictability of precipitation still presents a significant uncertainty in management decisions that impact NUE and WUE. Previous studies have tried to maintain adequate soil moisture using frequent, light irrigation for humid regions rather than the less frequent heavy irrigation observed in arid regions (Sadler, et al., 2003). This method of high frequency and light irrigation has also been proven to improve WUE and NUE, limit N leaching, and maintain optimal N levels in corn and sandy soils (Liu et al., 2019; Hunsaker et al., 1998; Phene and Beale, 1976). However, the major limitation of this method is the financial and logistical burdens on farmers due to the increase in irrigation applications, especially at times of high gas prices and labor shortages.

Irrigation scheduling techniques that make use of weather forecasts could help address these issues to increase crop productivity, WUE, and NUE (Anupoju et al., 2021; Attia et al., 2021; Bergez et al., 2002; Bergez and Garcia, 2010; Nie et al., 2021; Vazifedoust et al., 2008; Zhang and Guo, 2016). Computational modeling studies have evaluated both seasonal and short-term forecasted precipitation in irrigation water management (Cai et al., 2011; Jamal et al., 2018; Sangha et al., 2020; Wang and Cai, 2009; Wilks and Wolfe, 1998). While the seasonal forecasts provide better lead time and can be used to support decisions about crop type, crop pattern and crop placement within irrigated or non-irrigated fields, short-term forecasts have higher accuracy for use in irrigation scheduling (An-Vo et al., 2019; Jamal et al., 2019; Sangha et al., 2020). The impact of using climate services has been studied using quantitative models or by dissemination of forecast among control groups of farmers and then evaluating the impacts on yield (Maini and Rathore, 2011; Mapanje et al., 2021). However, model results may be biased towards the assumptions of risk and trust level in forecast among the farmers relative to model (Roudier et al., 2014). Additionally, studies that use control groups to directly assess the impact of weather forecasts face the challenge of controlling the information that is leaked to the control group. This can be a major hurdle for such studies, as it is difficult to ensure that the control group is not influenced by the forecast information. Additionally, studies that use control groups to directly assess the impact of weather forecasts face the challenge of controlling the information that is leaked to the control group. This can be a major hurdle for such studies, as it is difficult to ensure that the control group is not influenced by the forecast information (Tall et al., 2018).

Studies have used both deterministic and stochastic weather forecasts in irrigation scheduling. However, the major limitation of deterministic irrigation scheduling methods is the inherent assumption that under a specific scenario, all meteorological parameters such as precipitation, wind speed, radiation are known with certainty. However, in practice actual weather often differs from the forecasted conditions. Therefore, the use of probabilistic weather forecasts in irrigation scheduling is helpful in developing optimal irrigation scheduling (Cai et al., 2011). But the effectiveness and challenges of using probabilistic weather forecasts, as well as their impact on NUE and WUE, have not been studied in a field experiment for major field crops.

The goal of this study is to develop a rule-based approach to irrigation scheduling using short-term weather forecasts and assess its impacts on yield, NUE and WUE for corn and cotton in humid climates. In conjunction with real-time soil water content, crop physiological status, and water needs, the weather forecast is used to determine the timing and volume of irrigation applied. This study was conducted over two years at a field station in Suffolk, Virginia, with our novel scheduling approach compared to a non-irrigated (NI) and reference irrigation treatment using four N levels. Additionally, the financial viability of the different treatments was analyzed based on fertilizer, fuel and sale price.

2. Material and methods

2.1. Study site and experimental setup

The two-year study (2020–2021) was conducted for corn and cotton at Virginia Tech's Tidewater Agricultural Research and Extension Center (AREC) at Suffolk, Virginia (Fig. 1). Soils at the study location were a moderately well-drained and deep Emporia fine sandy loam, and the site experiences an average of 787 mm of rainfall between May and October (USDA-WSS, 2023). Irrigation was applied using a Zimmatic™ lateral move variable rate irrigation (VRI) system. Water for the VRI system was supplied by a pond, and the system was powered by a diesel motor. The study was designed using split-plot arrangement with irrigation as main plot factor and N treatment as sub-plot factor under randomized split-plot design with four replicates for corn and cotton. Each plot was 4 rows wide and 15.2 m long. The row spacing for corn and cotton was 0.91 m, a standard practice in the Tidewater region. To minimize overlap of nutrient and irrigation treatments, 9.14 m alleys were used between each irrigation treatment and 6-meter border plots were planted between corn and cotton. The crop management and planting dates are summarized in Table 1.

Fig. 1. Location of Tidewater research station in Suffolk Virginia.

Table 1
Crop and irrigation management during the growing season.

	2020		2021	
	Corn	Cotton	Corn	Cotton
Planting Date	Apr 17	May 14	Apr 20	May 5
Harvest Date	Sept 2	Oct 29	Sept 13	Oct 21
Sidedress Date	June 5	June 30	June 2	July 1
Total Precipitation (planting through harvest; mm)	610	756	664	714
Irrigation applied: FI treatment (mm)	132	162	55.8	55.8
Irrigation applied: WI treatment (mm)	89	104	38.1	30.5
Irrigation applied: NI treatment (mm)	0	0	0	0

2.2. *Treatments and field data*

The study included four N treatments and three treatments for irrigation. The four N treatments were varied amounts at increments of 90 kg N ha^{-1} for corn. Nitrogen treatments of corn were 0, 90 kg N ha^{-1}, 180 kg N ha^{-1} and 270 kg N ha^{-1}. For cotton, N treatments varied at increments of 45 kg N ha^{-1} i.e., 0 kg N ha^{-1}, 45 kg N ha^{-1}, 90 kg N ha^{-1} and 135 kg N ha^{-1}. In all fertilizer treatments, liquid ammonium nitrate was subsurface-banded between the rows at side-dress in a split application with 25% of the N applied at planting in a starter band and 75% applied at V5-V7 in corn and matchhead square in cotton. The three irrigation treatments were non-irrigated (NI), full irrigation (FI), and weather-informed irrigation (WI). Under the NI treatment, irrigation was not applied. Under the FI treatment, the soil moisture was maintained above 70% of plant-available water capacity (PAWC) of the soil regardless of predicted precipitation and sufficient irrigation was applied to bring soil moisture back to field capacity. Thus, FI treatment was irrigated more often and at a greater depth than WI treatment. The FI treatment avoided conditions of limited soil moisture and the excess irrigation allows us to quantify the impact of excess soil moisture conditions. Finally, the WI treatment aimed to avoid water stress conditions but also avoid saturated conditions that could result in runoff and deep percolation based on VWC readings and rainfall forecasts.

The volumetric water content (VWC) in the field was monitored using Sentek Triscan® capacitance probes which sense VWC at every 100 mm (4 in.) to 1000 mm (36 in.) depth. One probe was installed in each irrigation treatment zone for each crop. All corn probes were in the 180 kg N ha^{-1} N treatment, and all cotton probes were installed in the 90 kg N ha^{-1} N treatment. A weather station was installed at the field to capture hourly field weather conditions including precipitation, temperature, solar radiation, dew point, vapor pressure, relative humidity, leaf wetness, wind direction and wind speed. The weather forecast information for the WI irrigation treatment was obtained from gridded 2.5 km by 2.5 km data products produced by the National Oceanic and Atmospheric Administration's (NOAA) National Weather Service (NWS). The probability of precipitation (POP) provides a probability of receiving precipitation of greater than or equal to 0.254 mm (0.01 in.) at any point in the forecast area and forecast period. This information was available at 12-hour intervals up to 7 days in advance. The quantitative precipitation forecast (QPF) provides a measurable amount of precipitation (greater than 0.254 mm) forecasted for any time within the forecasted period. QPF data was available at 6-hour intervals. Forecasts of reference crop evapotranspiration (FRET) is the expected depth of evapotranspiration (ET) from a reference crop (short crop with approximate height of 12 cm) under the forecasted weather conditions on a daily time step over the next 7 days. The reference ET value by crop coefficients for each crop growth stage using Food and Agriculture Organization Crop coefficients values for corn and cotton (Allen et al., 1998). An R-script ran daily to obtain the forecasted weather conditions for the next 72 h. Probabilistic quantitative precipitation forecasts (PQPF) were then calculated using POP and QPF. While POP obtained from NWS is the probability of precipitation above 0.254 mm, PQPF is the probability of precipitation above a specific threshold value. In this study, the threshold was assigned as the daily CET calculated using FRET; thus, the PQPF value of interest is the probability of rainfall exceeding CET, denoted the probability of exceedance (POE). PQPF is based on a climatological distribution which is similar to exponential distribution and calculated in two steps (Amburn and Frederick, 2006). Firstly, the conditional quantitative precipitation forecast (μ), defined as the expected depth of precipitation given that precipitation occurs is given by

$$\mu = \frac{QPF}{POP}$$

The conditional probability of precipitation exceeding CET given that precipitation occurs is calculated assuming an exponential distribution of expected rainfall depths:

$$\Pr(P > CET | P > 0) = e^{(-CET/\mu)}$$

The unconditional probability of precipitation exceeding CET (POE) is then given by

$$POE = \Pr(P > CET) = \Pr(P > CET|P > 0) * POP$$

The highest frequency of rainfall amounts is typically non-zero when the weather event is expected to cause widespread rainfall and POP is above 90. Under such circumstances, estimating exceedance probabilities using the gamma distribution where the alpha term equals 3 delivers more accurate results than the exponential distribution (Amburn and Frederick, 2006). Similar results for high POP have been observed in previous studies by Donald et al. (1970). Therefore, POE when POP was above 90% was calculated using.

$POE = (0.5 * (e^{\frac{-x}{\beta}} * ((\frac{x^2}{\beta^2}) + (\frac{2*x}{\beta}) + 2))) * POP$ where β = QPF / 3.

2.3. Irrigation Scheduling

To estimate soil moisture in the root zone, we first determined effective root depth based on crop stage and the observed changes in soil moisture revealed by soil moisture probes. Effective rooting depth was determined using the soil water extraction patterns observed using soil moisture sensors. Volumetric water content observations in shallow zones exhibited a daily pattern that included drawdown of soil moisture during daylight hours, whereas deeper volumetric water content observations did not exhibit these patterns. (Irmak and Rudnick, 2014) (Irmak and Rudnick, 2014). Each Sentek probe reported VWC as a percentage of the unit volume of soil for each of the nine VWC sensors spaced at 100 mm (4 in.) intervals. Once the effective root depth was determined, root zone soil moisture (RSM) was calculated using observed VWC for each sensor within the effective root zone. Soil field capacity (FC) for root zone was determined using VWC observed after 48 h of soil saturation in the field using soil moisture sensors in rootzone (Sui and Vories, 2020; Vories and Sudduth, 2021). WP for each sensor depth was determined based on soil texture. FC, WP and RSM reported as percent of the unit volume of soil were converted to inches of available water within the root zone using following equation:

$$RSM_{\mathrm{mm}} = \sum_{1}^{N} (\mathrm{VWC}_n * \frac{4}{100}) * 25.4$$

Where RSM_{mm} is soil moisture in inches, VWC_n is the VWC of sensor (measured in inches of water per inch of soil x 100) at n depth (in the increments of 102 mm), N is the number of sensors within the root zone. This value is multiplied by 0.04 to convert sensor readings to an estimate of water content in inches across the each 102 mm interval monitored by each individual sensor. It is then converted to mm by multiplying with 25.4.

The root zone depletion (DP) was measured as

$$DP_{obs} = 100 * \frac{FC - RSM_{\mathrm{mm}}}{PAWC}$$

where RSM_{mm} is the observed root zone soil moisture, PAWC is plant available water content measure as difference between soil moisture at wilting point and soil moisture at field capacity.

For both the FI and WI treatments, a set of decision rules were developed to determine the timing of irrigation as well as the depth of irrigation applied (Fig. 2). Three trigger levels were decided based on observed DP of soil moisture. Using these trigger levels, for FI Treatment, irrigation was applied if:

$\boldsymbol{DP_{observed}} > DP_1$ irrespective of POE

irrigation was applied for WI treatment when:

$DP_2 < \boldsymbol{DP_{observed}} < DP_3$ and $POE < 0.25$

$DP_3 < \boldsymbol{DP_{observed}} < DP_4$ and $POE < 0.6$

$\boldsymbol{DP_{observed}} > DP_4$ irrespective of POE

where,$\boldsymbol{DP_{observed}}$ is the observed depletion and values of DP1 through DP4 are presented in Table 2. In practice $DP_{observed}$ was not observed to fall below DP_4. Irrigation depth in the WI treatment was calculated as follows:

$$D_{WI} = (0.75 * PAWC) - RSM_{sensor} - QPF + ET_f$$

Irrigation depth in the FI treatment was calculated as

$$D_{FI} = PAWC - RSM_{sensor}$$

where D_{WI} and D_{WFI} is the depth of irrigation applied in mm under WI and FI treatment respectively, PAWC is the plant available water content (FC-WP), RSM_{sensor} is the current soil moisture in the root zone, QPF is

Table 2
Soil moisture depletion thresholds for each crop and irrigation treatment.

	Corn		Cotton	
	FI	WI	FI	WI
D1 (trigger FI)	30%	NA	30%	NA
D2 (trigger WI with low POE)	NA	40%	NA	50%
D3 (trigger WI with medium POE)	NA	50%	NA	55%
D4 (trigger WI regardless POE)	NA	60%	NA	60%

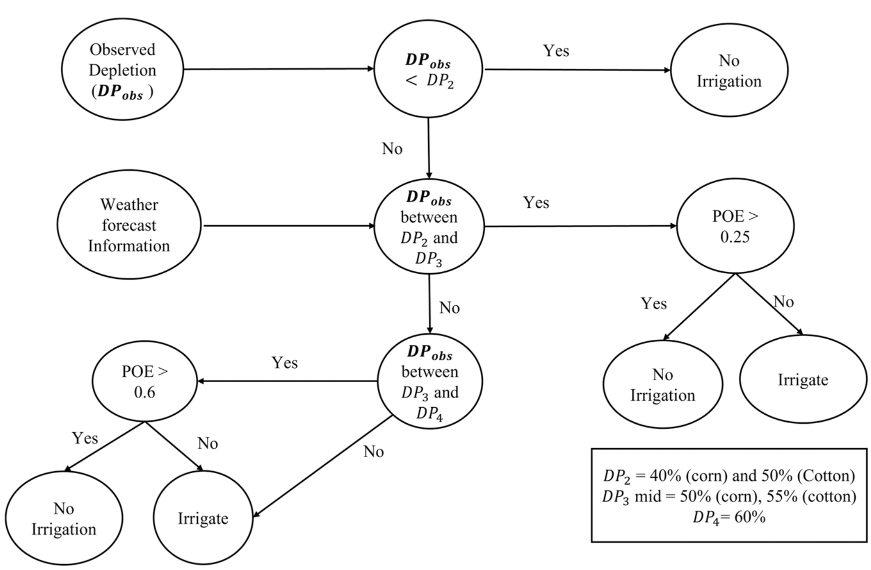

Fig. 2. Flow chart for probabilistic rule-based irrigation scheduling.

the depth of forecasted precipitation over the next 72 h, and ET_f is the forecasted crop evapotranspiration over the next 24 h. In instances where the prescribed irrigation depth exceeds 12.7 mm, this amount was applied over two irrigation events to avoid exceeding the infiltration capacity of the soil.

2.4. Data collection and analysis

The irrigation and nutrient treatments were analyzed based on yield, WUE and NUE. For corn, the entire plot was harvested at maturity using a small-plot harvester and yield was determined on a 15.5% moisture basis. In cotton, harvest was conducted 21 days after defoliation following Virginia Cooperative Extension recommendations for cotton (Frame et al., 2016). Case IH 2555 Cotton Picker modified with automatic weigh system using Harvester Master generic harvest system to weigh plots. Prior to harvest a 25-boll lint sample was collected to determine lint percentage and lint quality. Nitrogen uptake was quantified by biomass sampling a meter of row from each plot. For corn the biomass sample was taken at black layer and for cotton it was collected at 1st open boll. Data was check for normality and outliers were discarded.

The NUE is a widely used indicator to access the efficiency of N applications (Duan et al., 2014; Langholtz et al., 2021). NUE has been defined in several ways in the literature and can be broadly categorized as fertilizer-based, plant-based, soil-based or by approach of isotope-based, or systems-based (Congreves et al., 2021; Ladha et al., 2005). In this study, NUE was calculated using recovery efficiency i.e. the apparent increase in plant N uptake in response to the N inputs. This was calculated using the N uptake for the treatment relative to control and thus accounts for background soil N levels. The NUE was calculated as follows:

$$NUE = \frac{N_t - N_o}{N_{rate}}$$

where N_t is the N uptake in a specified nutrient treatment (kg N/ac), N_o is the N uptake in no fertilizer treatment and N_{rate} is the amount of N applied in a specific N treatment.

Irrigation WUE has been defined in several ways in the literature based on observations and standpoint of the discipline. WUE could be defined based on agronomic (e.g., using the ratio of produced biomass or economic yield) or physiological perspectives (e.g., CO_2 assimilation to water consumed) (BOS, 1985; Sinclair et al., 1984). In this study, irrigation WUE was calculated as an indicator of the efficiency of crop production system corresponding to the amount of irrigation applied. The WUE was calculated using the following equation. (Ullah et al., 2019).

$$WUE = \frac{Y_I - Y_{NI}}{D}$$

where Y_I is the yield of irrigated crop (kg ha^{-1}), Y_{NI} is the yield of NI crop and D is the depth of irrigation applied (kg ha^{-1}).

The profitability of different irrigation treatments was estimated by calculating the difference in variable operational costs of fuel for irrigation pumping, as well as the difference in revenue from yields under each treatment using recent prices for corn, cotton, and fuel (Table 3). Prices were based on average 2022 fuel prices obtained from US Energy Information Administration and crop prices were obtained from macrotrends (Macrotrends, 2022; Quinn, 2019; US EIA, 2022). This analysis is based on the variable input costs associated with irrigation fuel and doesn't consider investment, ownership, or labor costs. The fuel usage in each irrigation event and per acre inch of water applied were calculated using extension irrigation budgets developed by University of Georgia Department of Agricultural and Applied Economics assuming 65 acres of diesel-powered center pivot irrigation (University of Georgia, 2021). Fuel costs ($/AI) are calculated as follows:

$$FuelCost = 0.044 * HP * CF * T_{Coverage} * I_n$$

where 0.044 is a conversion factor with units' gallons/horsepower/hour, HP is horsepower of the engine, CF is cost of fuel per gallon, $T_{coverage}$ is average time for full irrigation application (hours), I_n is the total number of irrigation events during the growing season and was calculated as annual acre-inch applied divided by average application rate. This analysis assumed the use of a 65 HP pump and an average application time of 0.67 h per acre.

Change in financial returns from NI treatment were calculated for each treatment for both corn and cotton using equation

$$C_{returns} = \frac{R_T - R_0}{R_0} * 0.4$$

where $R_T$is the return from a given N and irrigation treatment and $R_0$is the return from NI and given treatment and 0.4 is conversion factor from $ per acre to $ per ha. Thus, all costs are calculated as a financial different relative to a baseline scenario of NI and corresponding N treatment.

Table 3
Cost of farm inputs and crop prices in the recent (2022) times.

	Recent
Fertilizer Cost ($ N per kg)	2.5
Fuel Cost ($)	5.5
Corn Price ($ per kg)	0.3
Cotton Price ($ per kg)	3.0

2.5. Statistical analysis

The impacts of N treatment and irrigation on NUE, WUE and yield were analyzed using liner mixed effects models from lme4 package in R (Bates et al., 2015). Linear mixed effects models consider both fixed effects (which are consistent across treatments groups) and random effects that vary across treatment groups. The N application and irrigation were considered as fixed effects and replicates were considered as random effects as follows:

$$y_{ij} = \alpha_{j[i]} + \beta_i x_i + \varepsilon_i \; for \quad N \quad and \quad Irrigation \quad treatment \quad \mathrm{i} = 1 \quad \mathrm{to} \quad 12$$

$$\alpha_{j[i]} = a + bu_j + n_j \; for \quad replicates \quad \mathrm{j} = 1 \quad \mathrm{to} \quad 4$$

where $\alpha_{j[i]}$is the varying intercept based on random replicates and the fixed the treatments, β_i and b are fixed slopes, a is the fixed replicate intercept,x_i and u_j represents predictor variables at treatment and replicate levels and ε_i and n_j are independent error terms. Regression models were fit separately for each year due to significant difference between yield across N rates in the years for corn and cotton. For each year, the interaction effects were evaluated between the treatments using ANOVA. Main effects were evaluated when no significant interactions occurred between the treatments. The mean difference of treatment effects (LSD) was performed using predictmeans function from predict means package (Lu et al., 2021). The predictmeans function is used to diagnose and make inferences from lmer models and generates means and standard errors and performs contrasts and multiple comparisons. A probability level of less than 0.05 was considered significant. All the data analysis was performed using the R studio 4.1 (R Core Team, 2021).

3. Results

3.1. Variation of precipitation, irrigation, and soil moisture through time

Table 4 presents a summary of rainfall and irrigation events in corn based on growth stage. Growth stages were determined by growing

Table 4
Precipitation and irrigation for corn with respect to crop stages for 2020 and 2021 growing season.

2020						2021				
Crop Stage	Start Date	End Date	Precipitation (mm)	FI (mm)	WI (mm)	Start Date	End Date	Precipitation (mm)	FI (mm)	WI (mm)
VE	04/17/20	04/30/20	111.8	0.0	0.0	04/20/21	04/29/21	5.8	0.0	0.0
V1	05/01/20	05/09/20	21.1	0.0	0.0	04/30/21	05/03/21	8.9	0.0	0.0
V2	05/10/20	05/17/20	0.0	0.0	0.0	05/04/21	05/13/21	9.9	0.0	0.0
V3	05/18/20	05/26/20	38.6	0.0	0.0	05/14/21	05/22/21	0.0	0.0	0.0
V6	05/27/20	06/01/20	20.6	0.0	0.0	05/23/21	05/28/21	4.3	0.0	0.0
V8	06/02/20	06/06/20	0.0	0.0	0.0	05/29/21	06/05/21	86.4	0.0	0.0
V10	06/07/20	06/09/20	33.3	0.0	0.0	06/06/21	06/07/21	0.0	0.0	0.0
V12	06/10/20	06/26/20	77.5	0.0	0.0	06/08/21	06/22/21	42.7	0.0	0.0
Vn-VT	06/27/20	07/10/20	26.9	25.4	25.4	06/23/21	07/07/21	67.3	17.8	12.7
R1	07/11/20	07/17/20	0.8	25.4	25.4	07/08/21	07/13/21	55.4	0.0	0.0
R2	07/18/20	07/23/20	0.3	50.8	25.4	07/14/21	07/20/21	36.3	19.1	12.7
R3	07/24/20	08/02/20	18.3	30.5	12.7	07/21/21	07/31/21	72.4	19.1	12.7
R4	08/03/20	08/12/20	128.5	0.0	0.0	08/01/21	08/11/21	115.3	0.0	0.0
R5	08/13/20	08/18/20	81.5	0.0	0.0	08/12/21	08/16/21	79.8	0.0	0.0
Mature	08/19/20	09/02/20	51.8	0.0	0.0	08/17/21	09/12/21	79.8	0.0	0.0
Total			610.9	132.1	88.9			664.0	55.9	38.1

degree days. Corn received 610 and 664 mm of rainfall in 2020 and 2021, respectively. July 2020 was the driest month in the growing season and received only 45.7 mm of rain. Therefore, four applications provided a total of 89 mm and 132 mm of irrigation for WI Irrigation and FI treatments, respectively, during the dry spell of July 2020 (Table 4). In 2021, May was the driest month in the growing season, and rainfall was more evenly distributed in the following months, with short dry spells at the end of June and July. In 2021, corn received three irrigation applications in June and July. Compared to FI, WI irrigation decreased irrigation by 43.2 and 17.8 mm in 2020 and 2021, respectively (Table 4). During both years, all irrigation treatments were between the V12 and R3 stages of corn (Table 4).

During the cotton growing season, the study area received 757 and 715 mm of rainfall in 2020 and 2021, respectively. In 2020, 104 mm of irrigation was applied for the WI treatment, and 163 mm was used for the FI treatment (Table 5). In 2021, three irrigation applications were made, and a total of 30.5 mm were applied for WI treatment, and 56 mm were applied for FI treatment. In both years, no irrigation was applied to the NI treatment of corn and cotton.

It should be noted that several major rainfall events occurred in 2020, which influenced the study results. Due to Hurricane Isaias, the study area received 127 mm of rain for six days between 3rd – 8th August. Corn was at the R2-R3 stage at the time of this tropical storm, and cotton was between the first flower and peak blooming (Table 4 and Table 5). Additionally, two heavy rainfall events occurred on the 9th and 18th of September due to Hurricane Sally. Corn was harvested at this time, and cotton was near the defoliation stage during these rainfall events. 241 and 260 mm of rainfall occurred in August and September 2020, respectively (Table 5).

3.2. *Corn results*

In 2020, ANOVA results indicate that yield varied significantly across N treatments, but not between irrigation treatments or Nrate x irrigation interactions. Across N treatments, yield was higher in 180 and 270 kg N ha^{-1} treatments than 90 kg N ha^{-1} and 0 kg N ha^{-1} ($P < 0.05$) (Fig. 3 B). Although insignificant, yield was higher in WI yields were higher than FI for the 180 kg N ha^{-1} treatment which is where the probe used for irrigation scheduling was located, but lower in the 270 kg N ha^{-1} and 90 kg N ha^{-1} applications (Table 6).

ANOVA results indicate that NUE was related to interactive effects between irrigation and N in 2020. NUE was higher at 180 kg N ha^{-1} under WI irrigation than 270 and 90 kg N ha^{-1} treatment under WI irrigation (Fig. 3 A). NUE was not significant between N rates and irrigation in both years. While not significant, WI resulted in the highest NUE (0.82) at 180 kg N ha^{-1} similar to NUE (0.81) at 270 kg N ha^{-1} with FI indicating better NUE with lower inputs (Table 6).

No significant relationships between irrigation treatment, N treatment, or their interactions were observed for WUE. While not significant, WUE was higher in WI irrigation than FI (Table 6). Taken together, 2020 data suggests that WI resulted in better NUE at 180 kg N ha^{-1} than other WI treatments. This could possibly stem from the fact that irrigation volumes in the 270 kg N ha^{-1} zones were still based on a sensor in the 180 kg N ha^{-1} zone. Better yields were observed at higher N treatments.

In 2021, yield varied across N rates and increase in yield was observed with an increasing N rate. However similar to 2020, yield was not significant for irrigation treatments or Nrate x irrigation interactions. Highest yield was observed at 270 N treatment and decreased

Table 5
Precipitation and irrigation for cotton with respect to crop stages for 2020 and 2021 growing season.

2020						2021				
Crop Stage	Start Date	End Date	Precip (mm)	FI (mm)	WI (mm)	Start Date	End Date	Precip (mm)	FI (mm)	WI (mm)
VE	05/15/20	05/28/20	55.6	0.0	0.0	05/06/21	05/19/21	8.1	0.0	0.0
Between VE and First Square	05/29/20	06/22/20	107.2	0.0	0.0	05/20/21	06/12/21	119.6	0.0	0.0
First square	06/23/20	06/27/20	7.1	0.0	0.0	06/13/21	06/19/21	0.0	0.0	0.0
Between First Square and First flower	06/28/20	07/11/20	26.9	25.4	25.4	06/20/21	07/04/21	81.0	17.8	10.2
Appearance of first flower	07/12/20	07/17/20	0.8	25.4	25.4	07/05/21	07/10/21	55.4	0.0	0.0
Between First flower and peak blooming	07/18/20	08/08/20	146.8	111.8	53.3	07/11/21	08/04/21	210.8	38.1	20.3
Peak blooming	08/09/20	08/16/20	81.8	0.0	0.0	08/05/21	08/12/21	13.2	0.0	0.0
Between peak blooming and first open boll	08/17/20	08/25/20	29.0	0.0	0.0	08/13/21	08/19/21	80.0	0.0	0.0
First open boll	08/26/20	09/04/20	22.9	0.0	0.0	08/20/21	08/28/21	18.5	0.0	0.0
Between first open boll and Defoliation	09/05/20	09/09/20	65.5	0.0	0.0	08/29/21	08/31/21	20.8	0.0	0.0
Defoliation	09/10/20	10/29/20	213.6	0.0	0.0	09/01/21	10/04/21	107.4	0.0	0.0
Total			757.2	162.6	104.1			714.8	55.9	30.5

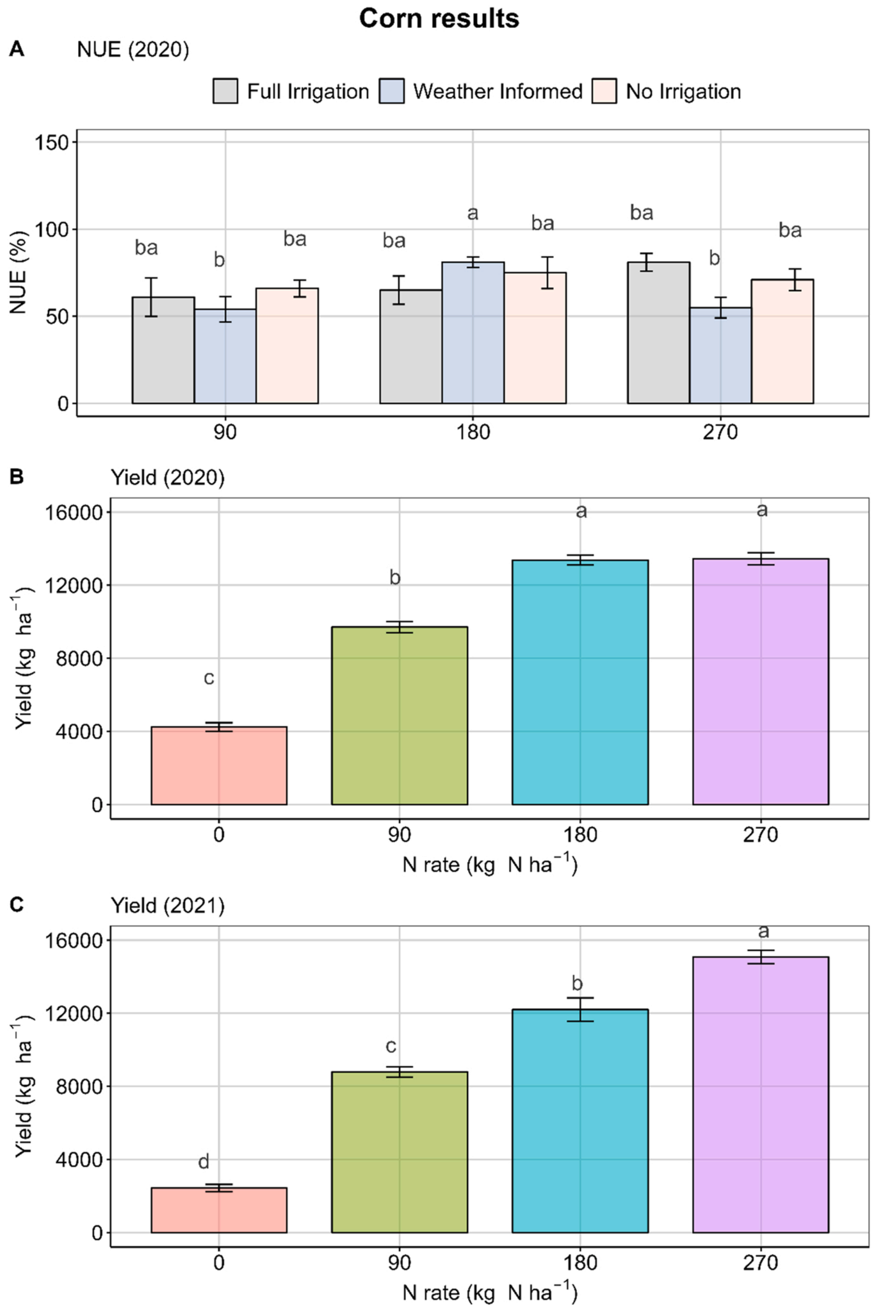

Fig. 3. Effect of N rate and Irrigation on Yield, NUE and WUE for Corn (Similar letters between the treatments indicate non-significance at a 0.05 level).

with N rates (Fig. 3 C). While not significant, WI yields were higher than FI under all N treatments (Table 6). In 2021, no significant relationships between irrigation treatment, N treatment, or their interactions were observed for NUE or WUE (Table 6). While not significant, WI showed improved NUE and WUE at 90 and 180 kg N ha^{-1} treatments. The WUE was higher under WI in all N treatments (Table 6).

3.3. Cotton results

In 2020, ANOVA results indicate a significantly different cotton yield under irrigation and Nrates but not the Nrate x irrigation interactions ($P < 0.05$) (Table 7). Cotton yields were higher at 135 kg N ha-1 treatment than 45 kg N ha^{-1} (Fig. 4 A). Cotton yields were lower under FI treatment from NI, indicating significantly higher yield losses due to FI ($P < 0.05$) (Fig. 4 B). While not significantly, cotton yields were better in WI than FI treatment (Table 7). ANOVA results indicate that no difference between NUE and WUE were observed under irrigation, N treatments and Nrate x irrigation interactions. WUE was negative for both WI and FI treatments due to lower yields than NI indicating that no yield benefits were observed with supplement irrigation in 2020 (Table 7).

As indicated in ANOVA results, significant difference in cotton yields were observed only under Nrate but not across irrigation treatments or Nrate x irrigation interactions in 2021. Overall, an increase in yields overall increased with N rates (Fig. 4 C). While not significant, yield was higher with WI irrigation than both FI and NI. ANOVA results indicate a significant difference in WUE under N treatments but not under irrigation or Nrate x irrigation interactions (Fig. 4 D). Although insignificant, WUE and NUE were higher for WI irrigation than FI and WI.

Table 6
ANOVA results for Yield, NUE, WUE for Corn in each year (*** significance at 0.001, ** significance at 0.01, * significance at 0.05,. significance at 0.1, ns not significant). LSD test between the treatments indicate significance at a 0.05 level and are denoted by the letters a through d. Treatments denoted with different letters (e.g., a and b) are significantly different from each other, while treatments denoted with ab are not significantly different from a or b.

Corn							
Treatment		2020			2021		
Nrate	Irrigation	Yield ($kgha^{-1}$)	NUE (%)	WUE (kg /ha/mm)	Yield ($kgha^{-1}$)	NUE (%)	WUE (kg /ha/mm)
0	**FI**	4224.2		1.93	2731.1		9.59
0	**NI**	3969.0		0.00	2195.6		0.00
0	**WI**	4534.4		6.36	2368.8		4.55
90	**FI**	9991.8	0.61 ba	4.82	8908.2	0.95	9.39
90	**NI**	9355.5	0.66 ba	0.00	8383.7	1.14	0.00
90	**WI**	9782.3	0.55 b	4.80	9090.9	1.30	18.56
180	**FI**	13,190.6	0.65 ba	-0.61	12,269.3	1.13	14.63
180	**NI**	13,271.0	0.76 ba	0.00	11,016.6	0.74	0.00
180	**WI**	13,647.4	0.82 a	4.24	13,335.0	1.22	49.43
270	**FI**	14,216.0	0.81 ba	12.45	14,253.8	0.88	-2.82
270	**NI**	12,571.7	0.71 ba	0.00	14,411.3	0.74	0.00
270	**WI**	13,546.6	0.55 b	10.97	15,918.5	0.87	39.56
ANOVA		ns	*	ns	ns	ns	ns
		2020			**2021**		
Nrate		**Yield**	**NUE**	**WUE**	**Yield**	**NUE**	**WUE**
0		4242.5c	0	2.76	2431.8 d	0	4.71
90		9709.8 b	0.60	3.20	8794.2c	1.13	9.31
180		13,369.6 a	0.74	1.21	12,201.1 b	1.06	17.4
270		13,444.7 a	0.69	7.80	15,082.7 a	0.83	16.21
ANOVA		* **	ns	.	* **	.	ns
		2020			**2021**		
	Irrigation	**Yield**	**NUE**	**WUE**	**Yield**	**NUE**	**WUE**
	FI	10,405.6	0.52	4.64	9706.7	0.73	10.66
	NI	9791.7	0.53	0	9110.5	0.65	0
	WI	10,377.6	0.48	6.59	10,065.4	0.85	25.06
ANOVA		.	ns	ns	ns	ns	ns

Table 7
ANOVA results for Yield, NUE, WUE for Cotton in each year (*** significance at 0.001, ** significance at 0.01, * significance at 0.05, ns represents non-significance at 0.05. LSD test between the treatments indicate significance at a 0.05 level and are denoted by the letters a through d. Treatments denoted with different letters (e.g., a and b) are significantly different from each other, while treatments denoted with ab are not significantly different from a or b.

Cotton							
	Treatment	**2020**			**2021**		
		2020	**2021**				
Nrate		**Yield**	**NUE**	**WUE**	**Yield**	**NUE**	**WUE**
0		1134.7c	0	-0.60	1038.3c	0	-3.46 b
45		1499.8 b	0.81	-0.50	1524.8 b	0.68	1.88 a
90		1681.9 ba	0.64	-0.79	1860.2 a	0.73	0.17 ba
135		1716.2 a	0.68	-1.53	2080.6 a	0.64	1.37 ba
ANOVA		* **	ns	ns	* **	ns	*
		2020	**2021**				
	Irrigation	**Yield**	**NUE**	**WUE**	**Yield**	**NUE**	**WUE**
	WI	1485.6 ba	0.46	-1.31	1685.3	0.56	1.33
	FI	1416.6 b	0.5	-1.26	1558.3	0.45	-1.36
	NI	1622.4 a	0.64	0	1634.3	0.52	0
ANOVA		*	.	ns	ns	ns	ns

3.4. *Profitability*

The trends for profitability were similar to those for yield, indicating the price increase in fuel inputs were compensated by the increase in yields especially at higher N rates (Fig. 5). In 2021, the corn returns were higher under WI irrigation at all N treatments. In 2020, FI resulted in economic losses at 180 kg N ha^{-1} treatment. Negative returns indicate economical losses due to additional irrigation primarily due to reduction in yield.

Economic trends for cotton were also similar to the yields in both years. In 2020, NI resulted in higher yields and economical losses were observed for both FI and WI irrigation treatments. In 2021, WI irrigation resulted in higher profits than FI at 45 kg N ha^{-1} and 90 kg N ha^{-1} irrigation whereas FI resulted in economic losses in 90 kg N ha^{-1} treatment.

4. Discussion

4.1. *Irrigation with respect to crop growth stage and impacts on yield, NUE and WUE*

Irrigation with respect to the crop stage plays a vital role in the overall yield and WUE of the crop. Irrigation for corn was applied near or after the tasseling stage (Table 4). Corn is susceptible to water stress during tasseling and early reproductive stages Previous studies have shown that the irrigation in the reproductive stages of crops is more important than in the early vegetative stages in order to achieve a high crop yield (Fang et al., 2014). Consideration of nutrient levels in irrigation management and information on site specific soil moisture conditions is highly important to prevent over- or under irrigation (Bondesan et al., 2022). The soil moisture sensor was installed in the

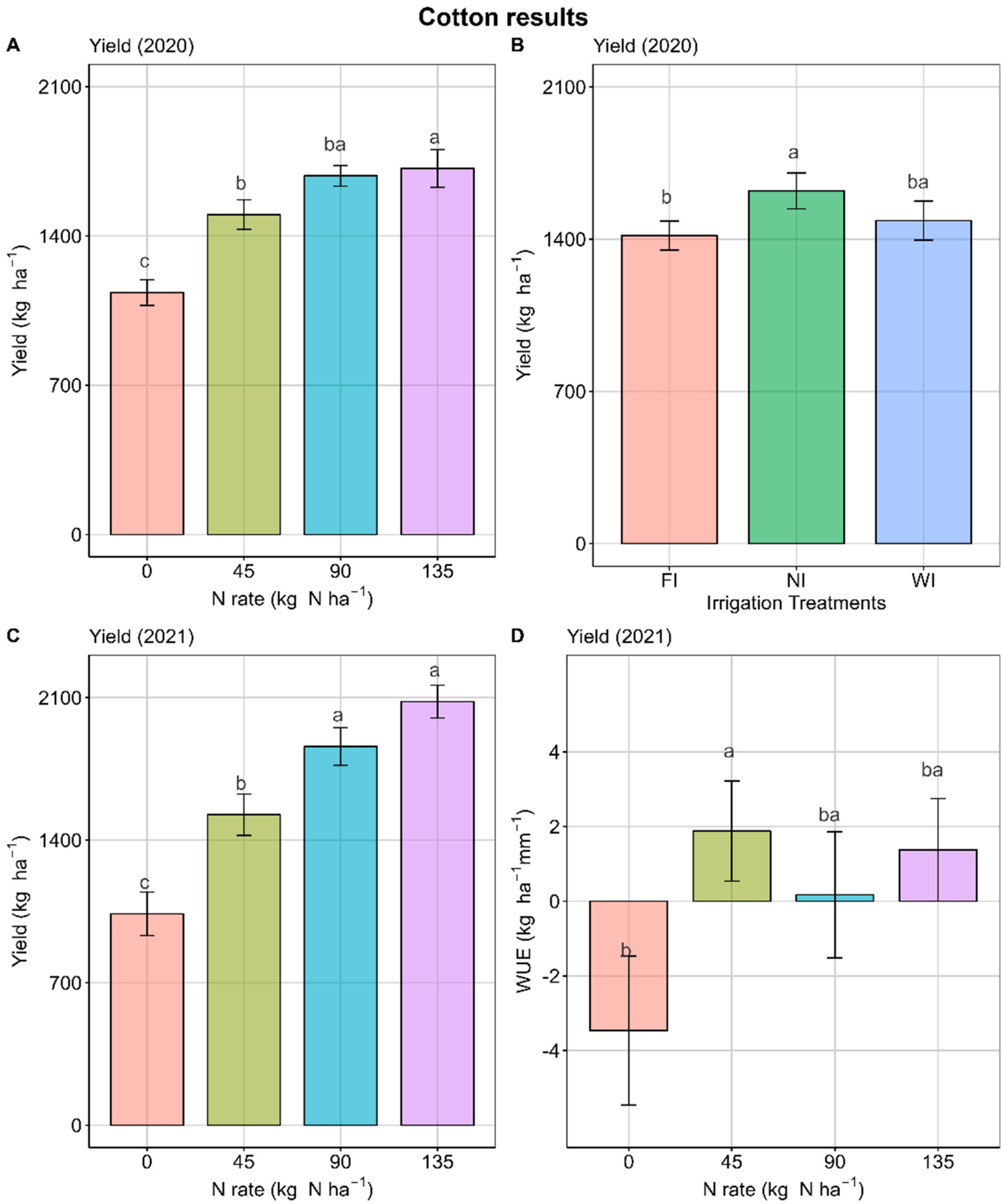

Fig. 4. Effect of N rate and Irrigation on Yield, NUE and WUE for Cotton.

180 kg N ha^{-1} treatment which might have resulted in under-irrigation of 270 kg N ha^{-1} treatment. Water stress affects the availability of crop N due to the reduction in mineralization and root activity (Qi et al., 2020; Shao et al., 2013). Lower NUE at 270 kg N ha^{-1} treatment under WI confirms this notion. Therefore, irrigation management is important at higher N rates to make use of increased N availability.

Our results are consistent with previous research demonstrating that higher N application doesn't necessarily correspond to higher N uptake. No significant difference in NUE was observed for N application rates in both years. Previous studies have observed a decrease in corn response to high N application rates, resulting in lower corn NUE (Ciampitti and Vyn, 2012; Salvagiotti et al., 2011). Additionally, in 2021, NUE was greater than 100% under WI and FI 90 kg N ha^{-1} and 180 kg N ha^{-1} treatment. In this study, NUE was calculated using recovery efficiency and incorporated both applied and soil N. NUE above 100% could be due to the priming effects of soil. Priming effects are short term changes in soil organic matter due to interactions between living and organic matter (Kuzyakov, 2010; Kuzyakov et al., 2000). It should also be noted that NUE from research plots is often greater than production fields under same practices due to difference in scales of fertilizer and irrigation management practices (Cassman et al., 2002; Dobermann, 2007).

Results in cotton in 2020 were notable due to the higher yields observed in the NI treatment relative to both irrigation treatments. For cotton, dry periods prompting irrigation occurred before the peak bloom (Table 5). Precipitation was frequent in the early growth stages (July) and was supplemented by one irrigation to maintain appropriate soil

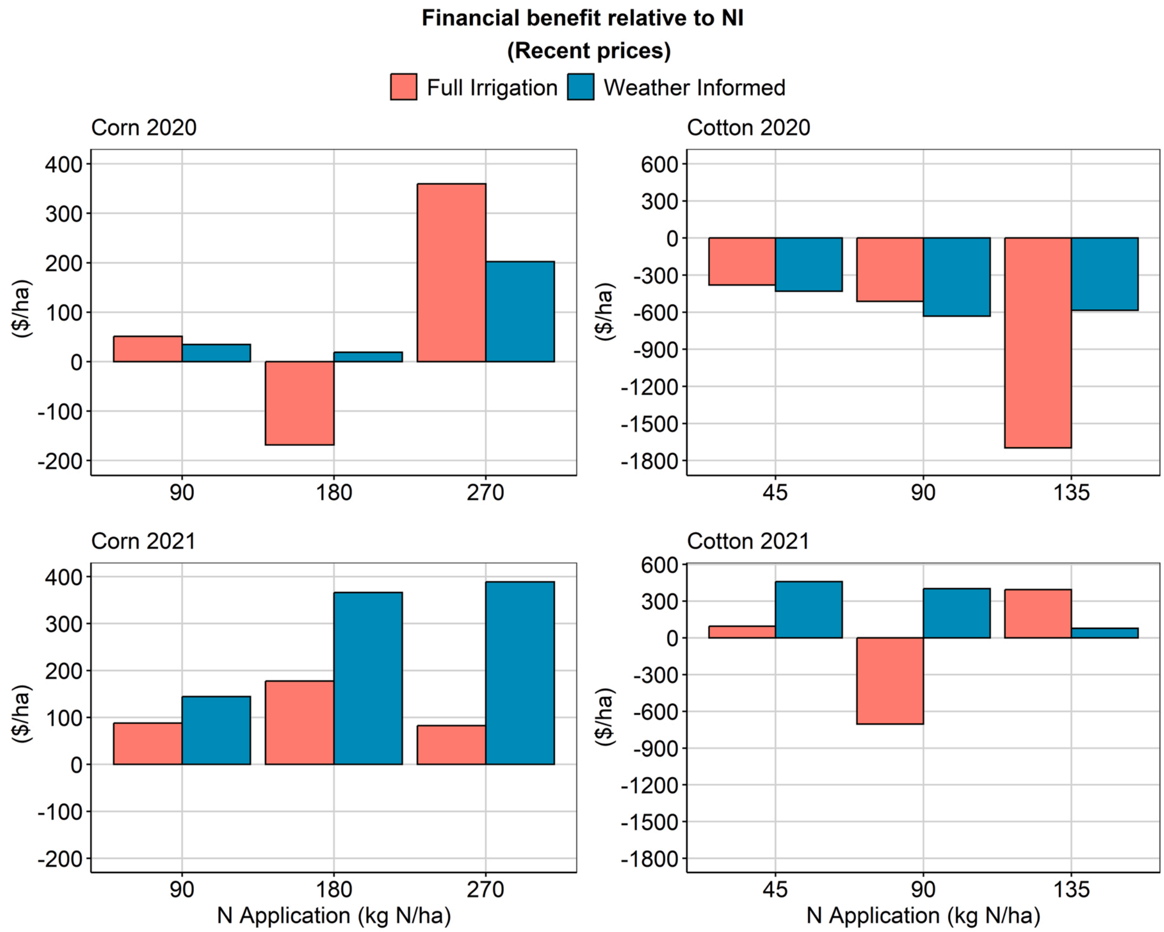

Fig. 5. Change in profits ($/acre) for corn and cotton under different Irrigation and N treatments as compared to NI treatment.

moisture. Irrigation in July and subsequent rainfall in August may have also leached more N below the root zone in the irrigated treatments, resulting in lower yields. Additionally, in 2020, two major rainfall events due to tropical storms were observed in the following weeks (2020–08–03 to 2020–08–09 and 8–13–2020 to 8–16–2020). The growth stage between the first square and first flower is moderately sensitive to water stress, but higher moisture more than crop water demand may result in excess vegetative growth and impacts cotton yield (Chalise et al., 2022; Ermanis et al., 2021; Perry and Barnes, 2015). Additionally, cotton yields were potentially impacted due to higher rainfall in the flowering stage, which may lead to flowers and young bolls falling off (Cetin and Basbag, 2010). These results suggest the need for irrigation strategies in cotton that are specific to the growth stage of the plant and potential for nutrient leaching instead of soil moisture data alone.

4.2. Challenges of weather informed irrigation and nutrient management in humid climates with sandy soils

Sandy soils of the coastal regions adds another layer of complexity to irrigation scheduling due to lower PAWC and a higher risk of nutrient leaching. (Davis et al., 2003). Supplemental irrigation in humid areas controls a narrow range of depletion, where the water storage capacity in the soil must be identified more effectively to accommodate the possibility of rainfall. As experienced in this study, conditions of moisture stress and excess can be separated by as little as a week. WI irrigation from this study provides an approach to maximize the soil storage reserve for rainfall after irrigation by leveraging weather forecast information to improve WUE without impacting the yields. However, the effects of irrigation can be seen in a dry or a normal condition under humid climates. The study years were relatively wet years which may have impacted the results in this study. The WI under some N treatments didn't perform better than NI and FI treatment. This has been observed in previous studies where irrigation decision using short term weather forecast did not account the longer outlooks beyond the weather forecast window and thus resulted in either excess or limited soil moisture conditions (Cai et al., 2011). Previous studies have incorporated weather forecast data into irrigation schedules and have proven that it can potentially reduce irrigation water through improved WUE (Cai et al., 2011; Gowing and Ejieji, 2001; Lorite et al., 2015; Wang and Cai, 2009). However, in this field study it was observed that the accuracy of soil moisture storage to accommodate rain is highly influenced by the forecast accuracy of the QPF. In-accuracy and uncertainties in short-term forecasts to maintain appropriate soil moisture conditions remains a key challenge, as we focus on farmers as end-users of climate forecasting services in humid areas.

One of the significant challenges in using WI irrigation is the resolution of the available forecast data. The NWS weather forecast information is available at a 2.5 km grid. The POP is calculated based on the likelihood that precipitation will occur and the expected areal extent of that precipitation. Convective rainfall in humid subtropical climates often results in high-intensity rainfall over very small spatial extents that are difficult to capture in observational data and gridded meteorological products (Schroeer et al., 2018). Farming decisions using POP for irrigation could lead to the application of irrigation followed shortly by rainfall, or the delay of irrigation even when no rainfall ultimately occurs. For instance, the study area received little to no rainfall between July 10th 2020 to July 27th 2020. As the depletion increased, precipitation with POP of 0.43 was expected to bring 12.7 mm of rain according to the forecast on July 21st, 2020, and irrigation was postponed. However, the study area didn't receive any rainfall. As a result, irrigation as triggered on 23rd July 2020. On the other hand, July 30th, 2020, we applied irrigation because the POP was 0.18; however, on the following day area received 6.35 mm of rainfall. One possible solution employed in recent studies includes various machine learning and deep learning techniques to improve the accuracy of the short-term weather forecast (Frnda et al., 2022; Rasp and Lerch, 2018). Additionally, studies have shown that use of longer time frame forecast may be helpful against seasonal droughts (Jamal et al., 2019).

4.3. Practical implications of forecast data for irrigation management

The use of forecast data poses a challenge regarding practical implications because of the accuracy of precipitation with lead time. Even at a well-equipped research station with efficient field management, incorporating weather forecasts is a challenge for implementation. At our study location field managers must prepare for irrigation (move irrigation pipes and enter application depths) the day before irrigating to ensure that an event could be initiated the following morning. Therefore research and recommendations particularly methods that prescribe frequent application of small irrigation depths or variable rate irrigation, must account for the wide range of labor required across different types of irrigation systems, and longer planning at the farm level to accommodate any misfunction of irrigating equipment and other field challenges.

Additionally, studies using the forecasts for irrigation scheduling must account for intra-day changes in forecasted precipitation. This is especially challenging for farmers during peak growing seasons, as a delay of just one day could lead to detrimental depletion levels. Moreover, the forecasted depth of precipitation was often underpredicted for high precipitation events resulting in over-irrigation, water logging, and surface runoff. For example, the weather forecast predicted 5.33 mm of rainfall on 48 h lead time, 7.36 mm on 24 h lead time, and 12.7 mm on the day of 6th August 2020. However, the study area received 41.9 mm of rainfall that day. Similarly, on 3rd August, 22.3 mm of precipitation was predicted 24 h in advance and increased to 25.4 mm on the day of the event, but the study area received 38.1 mm. Zhu and Pi (2014) also found significantly lower amounts of predicted heavy precipitation for 3-day or extended forecasts. This creates a challenge in identifying the adequate water storage capacity of the soil for rainfall, which is essential for humid regions and sandy soils.

Given potential inaccuracies in forecasted rainfall, growers using supplemental irrigation should be aware of the different impacts of excess or limited soil moisture throughout the growing season. For instance, many crops are less sensitive to water stress in early growth stages. Soil moisture depletion can be greater during early growth stages to avoid excess water and vertical nitrogen movement, but should be avoided during later growth stages when crops become more sensitive to water stress, even if rainfall is expected. In any case, precision fertilization strategies, such as split applications or fertigation, will be beneficial in reducing the risk and volume of nitrogen lost through leaching.

Additional research efforts are needed to make weather-informed precision irrigation beneficial and practical for growers. Research in precision irrigation in humid climates should include weather forecasts to better understand the tradeoffs between yield and irrigation inputs. In particular, research that quantifies the impacts of over and under irrigation on yields, profitability, and environmental impacts across different growing stages could support dynamic irrigation strategies that have a higher likelihood of maintaining optimal soil moisture levels in the face of imperfect weather forecasts. Future studies would focus on combining both short term and long term forecast in a field study. Climatic variations such as ENSO could be helpful to predict the frequency of tropical storms which could guide the longer outlook for irrigation. Additionally, the accuracy of weather forecast should be tested before the growing season and the correction factors could be developed at regional scales using machine learning techniques and regional climatic data.

5. Conclusions

Irrigation management is complicated in humid regions due to both moisture stress and excess conditions prevailing over a short period of time. Additionally, water stress is more prevalent due to lower water holding capacity of sandy soils which are more prone to N leaching under excess moisture conditions. This study quantified the impacts of using short term weather forecasts in two years of field trials for corn and cotton in humid climates under sandy soils. A split-plot experiment was used to assess yield, NUE, and WUE under three irrigation (no irrigation, weather informed and full irrigation) and four nitrogen treatments. Our weather-informed irrigation strategy was based on a novel approach that integrates probabilistic rainfall forecasts with soil moisture sensor data to avoid conditions of excess or depleted soil moisture. The yield varied significantly among N rates but not under irrigation treatments. NUE in corn was significantly different between WI irrigation at 180 and 270 kg N ha^{-1}. For cotton, the results in each year varied due to the amount of precipitation and irrigation with respect to crop stage. Financial analysis suggest that yield benefits associated with forecast-informed irrigation outweigh fuel costs, even though relatively favorable rainfall conditions in our study years led to good NI yields. One challenge in successfully using forecast data for irrigation is the accuracy of predicted irrigation amounts. Additional irrigation research that incorporates forecast accuracy could lead to further benefits. It is suggested that precision irrigation studies providing irrigation scheduling advice schedule advise must account for the practical need for growers to manage irrigation along with wide range of competing demands for their time and attention. Nevertheless, our results suggest that forecast-informed irrigation can improve yields, NUE, and WUE in humid climates where variable rainfall conditions and sandy soils make irrigation scheduling a challenge.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data and codes can be accessed from github repository of this project at " https://github.com/laljeet/Agwat_Tidewater".

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References

Allen, Richard, Luis Pereira, Dirk Raes, and Martin Smith. 1998. "Crop Evapotranspiration - Guidelines for Computing Crop Water Requirements - FAO Irrigation and Drainage Paper 56."

Amburn, S., Frederick, J., 2006. An Experiment in Probabilistic Quantitative Precipitation Forecasting. 86th AMS Annu. Meet.

Anupoju, V., Kambhammettu, B.P., Regonda, S.K., 2021. Role of short-term weather forecast horizon in irrigation scheduling and crop water productivity of rice. J. Water Resour. Plan. Manag. 147, 05021009, 10.1061/(ASCE)WR.1943-5452.0001406.

An-Vo, D.-A., Mushtaq, S., Reardon-Smith, K., Kouadio, L., Attard, S., Cobon, D., Stone, R., 2019. Value of seasonal forecasting for sugarcane farm irrigation planning.

European Journal of Agronomy: The Journal of the European Society for Agronomy 104, 37–48. https://doi.org/10.1016/j.eja.2019.01.005.

Attia, A., El-Hendawy, S., Al-Suhaibani, N., Alotaibi, M., Tahir, M.U., Kamal, K.Y., 2021. Evaluating deficit irrigation scheduling strategies to improve yield and water productivity of maize in arid environment using simulation. Agric. Water Manag. 249, 106812 https://doi.org/10.1016/j.agwat.2021.106812.

Ballester, Carlos, Hornbuckle, John, Brinkhoff, James, Wendy, C. Quayle, 2021. Effects of Three Frequencies of Irrigation and Nitrogen Rates on Lint Yield, Nitrogen Use Efficiency and Fibre Quality of Cotton under Furrow Irrigation. Agric. Water Manag. 248, 106783. https://doi.org/10.1016/j.agwat.2021.106783.

Basso, B., Shuai, G., Zhang, J., Robertson, G.P., 2019. Yield stability analysis reveals sources of large-scale nitrogen loss from the US Midwest. Scientific Reports 9 (1), 5774. https://doi.org/10.1038/s41598-019-42271-1.

Bates, D., Mächler, M., Bolker, B., Walker, S., 2015. Fitting linear mixed-effects models using. lme4. J. Stat. Softw. 67, 1–48. https://doi.org/10.18637/jss.v067.i01.

Battye, W., Aneja, V.P., Schlesinger, W.H., 2017. Is nitrogen the next carbon? Earths Future 5, 894–904. https://doi.org/10.1002/2017EF000592.

Bergez, J.E., Garcia, F., 2010. Is it worth using short-term weather forecasts for irrigation management? Eur. J. Agron. 33, 175–181. https://doi.org/10.1016/j.eja.2010.05.003.

Bergez, J.E., Deumier, J.M., Lacroix, B., Leroy, P., Wallach, D., 2002. Improving irrigation schedules by using a biophysical and a decisional model. Eur. J. Agron. 16, 123–135. https://doi.org/10.1016/S1161-0301(01)00124-1.

Bondesan, L., Ortiz, B.V., Morlin, F., Morata, G., Duzy, L., van Santen, E., Lena, B.P., Vellidis, G., 2022. A comparison of precision and conventional irrigation in corn production in Southeast Alabama. Precis. Agric. https://doi.org/10.1007/s11119-022-09930-2.

BOS, M.G., 1985. Summary of ICID definitions on irrigation efficiency. Summ. ICID Defin. Irrig. Effic. 34, 28–31.

Cai, X., Hejazi, M.I., Wang, D., 2011. Value of probabilistic weather forecasts: assessment by real-time optimization of irrigation scheduling. J. Water Resour. Plan. Manag. 137, 391–403, 10.1061/(ASCE)WR.1943-5452.0000126.

Camporese, M., Gumiere, S.J., Putti, M., Botter, G., 2021. Efficient irrigation of maize through soil moisture monitoring and modeling. Frontiers in Water 3. https://doi.org/10.3389/frwa.2021.627551.

Cassman, K.G., Dobermann, A., Walters, D.T., 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. Ambio 31, 132–140. https://doi.org/10.1579/0044-7447-31.2.132.

Cetin, O., Basbag, S., 2010. Effects of climatic factors on cotton production in semi-arid regions - a review. Res. Crops 11, 785–791.

Chalise, D.P., Snider, J.L., Hand, L.C., Roberts, P., Vellidis, G., Ermanis, A., Collins, G.D., Lacerda, L.N., Cohen, Y., Pokhrel, A., Parkash, V., Lee, J.M., 2022. Cultivar, irrigation management, and mepiquat chloride strategy: Effects on cotton growth, maturity, yield, and fiber quality. Field Crops Res. 286, 108633 https://doi.org/10.1016/j.fcr.2022.108633.

Ciampitti, I.A., Vyn, T.J., 2012. Physiological perspectives of changes over time in maize yield dependency on nitrogen uptake and associated nitrogen efficiencies: A review. Field Crops Res. 133, 48–67. https://doi.org/10.1016/j.fcr.2012.03.008.

Congreves, K.A., Otchere, O., Ferland, D., Farzadfar, S., Williams, S., Arcand, M.M., 2021. Nitrogen use efficiency definitions of today and tomorrow. Front. Plant Sci. 12.

Da Cunha Leme Filho, J.F., Ortiz, B.V., Balkcom, K.S., Damianidis, D., Knappenberger, T. J., Dougherty, M., 2020. Evaluation of two irrigation scheduling methods and nitrogen rates on corn production in Alabama. Int. J. Agron. 2020. https://doi.org/10.1155/2020/8869383.

Dai, Z., Fei, L., Huang, D., Zeng, J., Chen, L., Cai, Y., 2019. Coupling effects of irrigation and nitrogen levels on yield, water and nitrogen use efficiency of surge-root irrigated jujube in a semiarid region. Agric. Water Manag. 213, 146–154. https://doi.org/10.1016/j.agwat.2018.09.035.

Davis, R.L., Patton, J.J., Teal, R.K., Tang, Y., Humphreys, M.T., Mosali, J., Girma, K., Lawles, J.W., Moges, S.M., Malapati, A., Si, J., Zhang, H., Deng, S., Johnson, G.V., Mullen, R.W., Raun, W.R., 2003. Nitrogen Balance in the Magruder Plots Following 109 Years in Continuous Winter Wheat. J. Plant Nutr. 26, 1561–1580. https://doi.org/10.1081/PLN-120022364.

Dieter, C.A., Maupin, M.A., Caldwell, R.R., Harris, M.A., Ivahnenko, T.I., Lovelace, J.K., Barber, N.L., Linsey, K.S., 2015. Estimated Use of Water in the United States in 2015: U.S. Geological Survey Circular 1441, Circular.

Dobermann, A., 2007. Nutrient use efficiency - measurement and management. Fertil. Best Manag. Pract. Gen. Princ. Strategy Their Adopt. Volunt. Initiat. Vs Regul. Pap. Present. IFA Int. Workshop Fertil. Best Manag. Pract. Bruss. Belg. 7–9 March 2007 1–28.

Donald, J., Klein, W., Roberts, C., 1970. Conditional Probabilities of Precipitation Amounts in the Conterminous United States.ESSA Technical Memorandum WBTM TDL 18, Weather Bureau Office of Systems Development Techniques Development Laboratory, Silver Spring, MD.

Duan, Y., Xu, M., Gao, S., Yang, X., Huang, S., Liu, H., Wang, B., 2014. Nitrogen use efficiency in a wheat–corn cropping system from 15 years of manure and fertilizer applications. Field Crops Res 157, 47–56. https://doi.org/10.1016/j.fcr.2013.12.012.

Egli, D.B., Hatfield, J.L., 2014a. Yield gaps and yield relationships in central U.S. Soybean production systems. Agron. J. 106, 560–566. https://doi.org/10.2134/agronj2013.0364.

Egli, D.B., Hatfield, J.L., 2014b. Yield and yield gaps in central U.S. corn production systems. Agron. J. 106, 2248–2254. https://doi.org/10.2134/agronj14.0348.

Ermanis, A., Gobbo, S., Snider, J.L., Cohen, Y., Liakos, V., Lacerda, L., Perry, C.D., Aaron Bruce, M., Virk, G., Vellidis, G., 2021. Defining physiological contributions to yield loss in response to irrigation in cotton. J. Agron. Crop Sci. 207, 186–196. https://doi.org/10.1111/jac.12453.

Fang, Q.X., Ma, L., Nielsen, D.C., Trout, T.J., Ahuja, L. r, 2014. Quantifying corn yield and water use efficiency under growth stage–based deficit irrigation conditions. In: Practical Applications of Agricultural System Models to Optimize the Use of Limited Water. John Wiley & Sons, Ltd, pp. 1–24. https://doi.org/10.2134/advagricsystmodel5.c1.

FAO, 2017. Water Sustain. Food Agric. A Rep. Prod. G20 Pres. Ger.

Frame, W., Herbert, D., Mehl, H., Cahoon, C., Reiter, M., Flessner, M., 2016. Virginia Cotton Production guide.

Frnda, J., Durica, M., Rozhon, J., Vojtekova, M., Nedoma, J., Martinek, R., 2022. ECMWF short-term prediction accuracy improvement by deep learning. Sci. Rep. 12, 7898. https://doi.org/10.1038/s41598-022-11936-9.

Galloway, J.N., Townsend, A.R., Erisman, J.W., Bekunda, M., Cai, Z., Freney, J.R., Martinelli, L.A., Seitzinger, S.P., Sutton, M.A., 2008. Transformation of the Nitrogen Cycle: Recent Trends, Questions, and Potential Solutions. Science 320, 889–892. https://doi.org/10.1126/science.1136674.

Gao, Q., Li, C., Feng, G., Wang, J., Cui, Z., Chen, X., Zhang, F., 2012. Understanding yield response to nitrogen to achieve high yield and high nitrogen use efficiency in rainfed corn. Agron. J. 104, 165–168. https://doi.org/10.2134/agronj2011.0215.

Gowing, J.W., Ejieji, C.J., 2001. Real-time scheduling of supplemental irrigation for potatoes using a decision model and short-term weather forecasts. Agric. Water Manag. 47, 137–153. https://doi.org/10.1016/S0378-3774(00)00101-3.

Gruber, N., Galloway, J.N., 2008. An Earth-system perspective of the global nitrogen cycle. Nature 451, 293–296. https://doi.org/10.1038/nature06592.

Hanson, B, Orloff, S, Peters, D, 2000. Monitoring soil moisture helps refine irrigation management. Calif Agr 54 (3), 38–42. https://doi.org/10.3733/ca.v054n03p38.

Houlton, B.Z., Boyer, E., Finzi, A., Galloway, J., Leach, A., Liptzin, D., Melillo, J., Rosenstock, T.S., Sobota, D., Townsend, A.R., 2013. Intentional versus unintentional nitrogen use in the United States: trends, efficiency and implications. Biogeochemistry 114, 11–23. https://doi.org/10.1007/s10533-012-9801-5.

Hunsaker, D.J., Clemmens, A.J., Fangmeier, D.D., 1998. Cotton response to high frequency surface irrigation. Agric. Water Manag. 37, 55–74. https://doi.org/10.1016/S0378-3774(98)00036-5.

Irmak, S., Rudnick, D., 2014. Corn. Soil. -Water Extr. Eff. Rooting Depth a Silt-Loam Soil.

Jamal, A., Linker, R., Housh, M., 2018. Comparison of various stochastic approaches for irrigation scheduling using seasonal climate forecasts. J. Water Resour. Plan. Manag. 144, 04018028, 10.1061/(ASCE)WR.1943-5452.0000951.

Jamal, A., Linker, R., Housh, M., 2019. Optimal irrigation with perfect weekly forecasts versus imperfect seasonal forecasts. J. Water Resour. Plan. Manag 145, 06019003, 10.1061/(ASCE)WR.1943-5452.0001066.

Kumar, H., Srivastava, P., Lamba, J., Ortiz, B.V., Way, T.R., Sangha, L., Takhellambam, B.S., Morata, G., Molinari, R., 2022. Within-Field Variability in Nutrients for Site-Specific Agricultural Management in Irrigated Cornfield. J. ASABE 65, 865–880. https://doi.org/10.13031/JA.15042.

Kuzyakov, Y., 2010. Kuzyakov Y. Priming effects: interactions between living and dead organic matter. Soil Biol. Biochem. 42, 1363–1371 https://doi.org/10.1016/j.soilbio.2010.04.003.

Kuzyakov, Y., Friedel, J., Stahr, K., 2000. Kuzyakov Y, Friedel JK, Stahr K. Review of mechanisms and quantification of priming effects. Soil Biol Biochem 32: 1485–1498. Soil Biol. Biochem. 32, 1485. https://doi.org/10.1016/S0038–0717(00)00084–5.

Ladha, J.K., Pathak, H., Krupnik, J., Six, T., van Kessel, C, J., 2005. Efficiency of fertilizer nitrogen in cereal production: retrospects and prospects. In: Advances in Agronomy. Academic Press, pp. 85–156. https://doi.org/10.1016/S0065-2113(05)87003-8.

Langemeier, M. "Trends in General Inflation and Farm Input Prices." *farmdoc daily* (12): 56, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, April 25, 2022.

Langholtz, M., Davison, B.H., Jager, H.I., Eaton, L., Baskaran, L.M., Davis, M., Brandt, C. C., 2021. Increased nitrogen use efficiency in crop production can provide economic and environmental benefits. Sci. Total Environ. 758, 143602 https://doi.org/10.1016/j.scitotenv.2020.143602.

Lassaletta, L., Billen, G., Garnier, J., Bouwman, L., Velazquez, E., Mueller, N.D., Gerber, J.S., 2016. Nitrogen use in the global food system: past trends and future trajectories of agronomic performance, pollution, trade, and dietary demand. Environmental Research Letters 11 (9), 095007. https://doi.org/10.1088/1748-9326/11/9/095007.

Li, M., Li, J., Singh, V.P., Fu, Q., Liu, D., Yang, G., 2019. Efficient allocation of agricultural land and water resources for soil environment protection using a mixed optimization-simulation approach under uncertainty. Geoderma 353, 55–69. https://doi.org/10.1016/j.geoderma.2019.06.023.

Li, Y., Li, J., Gao, L., Tian, Y., 2018. Irrigation has more influence than fertilization on leaching water quality and the potential environmental risk in excessively fertilized vegetable soils. PloS One 13 (9), e0204570. https://doi.org/10.1371/journal.pone.0204570.

Lorite, I.J., Ramírez-Cuesta, J.M., Cruz-Blanco, M., Santos, C., 2015. Using weather forecast data for irrigation scheduling under semi-arid conditions. Irrig. Sci. 33, 411–427. https://doi.org/10.1007/s00271-015-0478-0.

Lu, Y., Wang, E., Zhao, Z., Liu, X., Tian, A., Zhang, X., 2021. Optimizing irrigation to reduce N leaching and maintain high crop productivity through the manipulation of soil water storage under summer monsoon climate. Field Crops Res. 265, 108110 https://doi.org/10.1016/j.fcr.2021.108110.

Macrotrends, 2022. Corn Prices - 59 Year Historical Chart [WWW Document]. URL https://www.macrotrends.net/2532/corn-prices-historical-chart-data (accessed 10.16.22).

Maini, P., Rathore, L.S., 2011. Economic impact assessment of the Agrometeorological Advisory Service of India. Curr. Sci. 101, 1296–1310.

Mapanje, O., Siziba, S., Mtambanengwe, F., Mapfumo, P., Unganai, L., 2021. Impact Clim. Inf. Serv. Smallhold. farmers' livelihood Outcomes 29–47.
Moreira, J.R., Sousa, H., Martinho, D., Marreiros, G., Carlos, Ramos, Kim, H., Yoe, H., & Corchado, J.M. (2016). OS 12-3 Management of irrigation through a Web-Based Intelligent Decision Support System.
Muhammad, I., Lv, J.Z., Yang, L., Ahmad, S., Farooq, S., Zeeshan, M., Zhou, X.B., 2022. Low irrigation water minimizes the nitrate nitrogen losses without compromising the soil fertility, enzymatic activities and maize growth. BMC Plant Biol. 22, 159. https://doi.org/10.1186/s12870-022-03548-2.
Nie, T., Jiao, Y., Tang, Y., Li, N., Wang, T., Du, C., Zhang, Z., Li, T., Zhu, S., Sun, Z., Li, F., 2021. Study on the water supply and the requirements, yield, and water use efficiency of maize in heilongjiang province based on the aquacrop model. Water 13, 2665. https://doi.org/10.3390/w13192665.
Paoletti, J.M., Shortridge, J.E., 2020. Improved representation of uncertainty in farm-level financial cost-benefit analyses of supplemental irrigation in humid regions. Agric. Water Manag 239, 106245. https://doi.org/10.1016/j.agwat.2020.106245.
Perry, C., Barnes, E., 2015. Cotton Irrigation and Water Management for Humid Regions.
Phene, C.J., Beale, O.W., 1976. High-frequency Irrigation for Water Nutrient Management in Humid Regions. Soil Sci. Soc. Am. J. 40, 430–436. https://doi.org/10.2136/sssaj1976.03615995004000030034x.
Potter, S., Andrews, S., Atwood, J., Kellogg, R., Lemunyon, J., Norfleet, L., Oman, D., 2006. Model Simulation of Soil Loss, Nutrient Loss and Soil Organic Carbon | NRCS (Conservation Effects Assessment Project (CEAP)).
Qi, D., Hu, T., Song, X., 2020. Effects of nitrogen application rates and irrigation regimes on grain yield and water use efficiency of maize under alternate partial root-zone irrigation. J. Integr. Agric. 19, 2792–2806. https://doi.org/10.1016/S2095-3119(20)63205-1.
Quinn, R., 2019. DTN Retail Fertilizer Trends [WWW Document]. DTN Progress. Farmer. URL https://www.dtnpf.com/agriculture/web/ag/news/crops/article/2019/01/16/fertilizer-prices-continue-rise (accessed 10.16.22).
R Core Team (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.
Rasp, S., Lerch, S., 2018. Neural networks for postprocessing ensemble weather forecasts. Mon. Weather Rev. 146, 3885–3900. https://doi.org/10.1175/MWR-D-18-0187.1.
Roudier, P., Muller, B., d'Aquino, P., Roncoli, C., Soumaré, M.A., Batté, L., Sultan, B., 2014. The role of climate forecasts in smallholder agriculture: lessons from participatory research in two communities in Senegal. Clim. Risk Manag. 2, 42–55. https://doi.org/10.1016/j.crm.2014.02.001.
Sadler, E., Camp Jr., C., Hook, J., 2003. Irrigation management in humid regions. Encycl. Water Sci.
Salvagiotti, F., Castellarín, J.M., Ferraguti, F.J., Pedrol, H.M., 2011. Economic optimal nitrogen rate as affected by yield potential and nitrogen supply in the Northern Pampas. Cienc. Suelo 29, 199–212.
Sangha, L., Lamba, J., Kumar, H., Srivastava, P., Dougherty, M., Prasad, R., 2020. An innovative approach to rainwater harvesting for irrigation based on El Niño Southern Oscillation forecasts. J. Soil Water Conserv. https://doi.org/10.2489/JSWC.2020.00085.
Schimmelpfennig, D., Farm, 2016.. Profits and Adoption of Precision Agriculture. Usda. Gov. http://www.ers.usda.gov/publications/pub-details/?pubid=80325.
Schroeer, K., Kirchengast, G., O, S., 2018. Strong dependence of extreme convective precipitation intensities on gauge network density. Geophys. Res. Lett. 45, 8253–8263. https://doi.org/10.1029/2018GL077994.
Shang, S., Mao, X., 2006. Application of a simulation based optimization model for winter wheat irrigation scheduling in North China. Agric. Water Manag 85 (3), 314–322. https://doi.org/10.1016/j.agwat.2006.05.015.
Shao, G., Li, Z., Ning, T., Zheng, Y., 2013. Responses of photosynthesis, chlorophyll fluorescence, and grain yield of maize to controlled-release urea and irrigation after anthesis. J. Plant Nutr. Soil Sci. 176, 595–602. https://doi.org/10.1002/jpln.201100185.
Sincik, M., Goksoy, A.T., Dogan, R., 2013. Responses of sunflower (Helianthus annuus L.) to irrigation and nitrogen fertilization rates. Zemdirb. -Agric. 100, 151–158. https://doi.org/10.13080/z-a.2013.100.019.
Sinclair, T.R., Tanner, C.B., Bennett, J.M., 1984. Water-use efficiency in crop production. BioScience 34, 36–40. https://doi.org/10.2307/1309424.
Sui, R., Vories, E.D., 2020. Comparison of sensor-based and weather-based irrigation scheduling. Appl. Eng. Agric. 36, 375–386. https://doi.org/10.13031/aea.13678.
Tall, A., Coulibaly, J.Y., Diop, M., 2018. Do climate services make a difference? A review of evaluation methodologies and practices to assess the value of climate information services for farmers: Implications for Africa. Clim. Serv. 11, 1–12. https://doi.org/10.1016/j.cliser.2018.06.001.
Ullah, H., Santiago-Arenas, R., Ferdous, Z., Attia, A., Datta, A., 2019. Chapter Two - Improving water use efficiency, nitrogen use efficiency, and radiation use efficiency in field crops under drought stress: A review. In: Sparks, D.L. (Ed.), Advances in Agronomy. Academic Press, pp. 109–157. https://doi.org/10.1016/bs.agron.2019.02.002.
US EIA, 2022. U.S. No 2 Diesel Retail Prices (Dollars per Gallon) [WWW Document]. URL https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMD_EPD2D_PTE_NUS_DPG&f=M (accessed 10.16.22).
USDA-WSS, 2023. Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Web Soil Survey. Available online at the following link: http://websoilsurvey.sc.egov.usda.gov/. Accessed [03/20/2023].
Vazifedoust, M., van Dam, J.C., Feddes, R.A., Feizi, M., 2008. Increasing water productivity of irrigated crops under limited water supply at field scale. Agric. Water Manag. 95, 89–102. https://doi.org/10.1016/j.agwat.2007.09.007.
Vories, E., Sudduth, K., 2021. Determining sensor-based field capacity for irrigation scheduling. Agric. Water Manag 250, 106860. https://doi.org/10.1016/j.agwat.2021.106860.
Walton, B., 2014. U.S. Irrigation Pushed Eastward By Drought and Financial Risks. Circ. Blue. URL https://www.circleofblue.org/2014/world/u-s-irrigation-pushed-eastward-drought-financial-risks/ (accessed 3.16.21).
Wang, D., Cai, X., 2009. Irrigation scheduling—role of weather forecasting and farmers. ' Behav. J. Water Resour. Plan. Manag. 135, 364–372. https://doi.org/10.1061/(ASCE)0733-9496(2009)135:5(364).
Wang, G.-Y., Hu, Y.-X., Liu, Y.-X., Ahmad, S., Zhou, X.-B., 2021. Effects of supplement irrigation and nitrogen application levels on soil carbon–nitrogen content and yield of one-year double cropping maize in subtropical region. Water 13, 1180. https://doi.org/10.3390/w13091180.
Wang, Z.-H., Li, S.-X., 2019. Nitrate N loss by leaching and surface runoff in agricultural land: A global issue (a review). In: Sparks, D.L. (Ed.), Advances in Agronomy, (Vol. 156,... Elsevier, pp. 159–217.
Wilks, D.S., Wolfe, D.W., 1998. Optimal use and economic value of weather forecasts for lettuce irrigation in a humid climate. Agric. . Meteorol. 89, 115–129. https://doi.org/10.1016/S0168-1923(97)00066-X.
Zhang, D., Guo, P., 2016. Integrated agriculture water management optimization model for water saving potential analysis. Agric. Water Manag., Spec. Issue.: Water Manag. Strateg. Irrig. Areas Overseen : Dr. Brent Cloth. 170, 5–19. https://doi.org/10.1016/j.agwat.2015.11.004.
Zhang, S., Gao, P., Tong, Y., Norse, D., Lu, Y., Powlson, D., 2015. Overcoming nitrogen fertilizer over-use through technical and advisory approaches: a case study from Shaanxi Province, northwest China. Agric. Ecosyst. Environ., Sustain. Intensif. China's Agric.: key role Nutr. Manag. Clim. Change Mitig. Adapt. 209, 89–99. https://doi.org/10.1016/j.agee.2015.03.002.
Zhu, A., Pi, H., 2014. A method for improving the accuracy of weather forecasts based on a comprehensive statistical analysis of historical data for the contiguous United States. J. Climatol. Weather Forecast 2. https://doi.org/10.4172/2332-2594.1000110.
Zurweller, B.A., Rowland, D.L., Mulvaney, M.J., Tillman, B.L., Migliaccio, K., Wright, D., Erickson, J., Payton, P., Vellidis, G., 2019. Optimizing cotton irrigation and nitrogen management using a soil water balance model and in-season nitrogen applications. Agric. Water Manag. 216, 306–314. https://doi.org/10.1016/j.agwat.2019.01.011.