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Real-time irrigation scheduling of maize using Degrees Above Non-Stressed (DANS) index in semi-arid environment

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A B S T R A C T

Irrigation scheduling methods have been used to determine the timing and amount of water applied to crops. Scheduling techniques can include measurement of soil water content, quantification of crop water use, and monitoring of crop physiological response to water stress. The aim of this study was to evaluate the performance of a simplified crop canopy temperature measurement (CTM) method as Irrigation Principles. Soil and Water Conservation Engineera technique to schedule irrigation for maize. Specifically, the Degrees Above Non-Stressed (DANS) index, which suggests water stress when canopy temperature exceeds the non-stressed canopy temperature (T_{cns}), was determined by estimating $\mathrm{T_{cns}}$ from a weather based multilinear regression model. The modeled $\mathrm{T_{cns}}$ had a strong correlation with observed T_{cns} with a pooled R^2 values of 0.94 across the 2018, 2019, and 2020 growing seasons. This DANS index was also highly correlated with the conventionally used Crop Water Stress Index (CWSI) with R^2 values of 0.67, 0.59, and 0.76 in 2018, 2019, and 2020, respectively. Furthermore, DANS had a strong linear relationship with soil water depletion above 60% in the 0.60 m soil profile with an R^2 of 0.78. The CTM method was also compared to more commonly used scheduling methods namely: soil moisture monitoring (SMM) and crop evapotranspiration modeling (ETM). Grain yield was significantly lower for the CTM method than for the ETM method in 2018 and 2020 but not in 2019. No significant differences were observed in Irrigation Water Productivity (IWP) in 2018; however, all treatments were significantly different with the CTM method having the greatest IWP in 2020. For attempting to trigger full irrigation with the CTM method, a fixed DANS threshold of 0.5 °C was found to be more appropriate than the literature value of 1.0 °C, but consideration of crop growth stage would further improve scheduling.

1. Introduction

Global population growth is anticipated to rise to an estimate of 9.2 billion people in 2050 which will consequently increase demand on available food sources and associated agricultural production resources, particularly water (Jury and Vaux, 2007). Stewardship of current water resources therefore necessitates adaptable and innovative methodologies to optimize water use while efficiently meeting demands, such as agricultural production for this increasing population. In water limited environments such stewardship includes development and adoption of irrigation water management methods and technologies to determine proper timing and depth of irrigation. Irrigation scheduling methods and technologies include soil moisture monitoring (SMM), plant sensors, proximal sensors, daily evapotranspiration modeling (ETM), visual observation, mimicking neighbors, and feel of soil, among others (USDA-NASS, 2019; Rudnick et al., 2020). Unfortunately, however, these methods vary widely in their ability to match irrigation with crop water needs (Rudnick et al., 2020).

For instance, a variety of sensors can be used in SMM to quantify soil attributes and associate them to soil water content within the crop root zone (Evett et al., 2012; Lekshmi et al., 2014). Typically, SMM methods involve the estimation of volumetric soil water content (θ_v) which is

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maintained above a trigger threshold often based on the management allowable depletion (MAD) concept. The θ_v measurements are influenced by instrument accuracy and must consider soil physical characteristics and crop development and rooting depth, which are complex parameters to estimate, when scheduling irrigation (Evett et al., 2012; Gu et al., 2020; Taghvaeian et al., 2020). Recently developed SMM measuring tools are also limited by their ability to represent large spatial areas at continuous temporal scales while long-established methods such as the neutron moisture meter (NMM) and gravimetric soil sampling are not widely utilized outside the academic research community due to complexity in application and associated costs (Evett et al., 2012). Alternatively, ETM and soil water balance based models have been employed to estimate crop water use, and this information is utilized to quantify how much water is needed to replenish the root zone storage via irrigation (Huffman et al., 2013; Anderson and French, 2019; Gu et al., 2020). However, the accuracy of model input parameters can affect the correctness of crop ETM based irrigation water management methods. Model inaccuracies are likely to arise from imprecise soil physical property estimation, inexact measurements of microclimate and resulting reference evapotranspiration (ET_r), and/or the use of generic crop coefficient (K_c) values (Gu et al., 2020).

Emerging irrigation water management techniques such as canopy temperature measurement (CTM) using infrared thermometers have been described as a non-destructive, affordable means to spatially and temporally monitor crop water stress for irrigation management (Jones, 2004; DeJonge et al., 2015; O'Shaughnessy et al., 2015; Ihuoma and Madramootoo, 2017). Commonly, the crop water stress index (CWSI) (Idso et al., 1981) has successfully been used to monitor water stress in a variety of crops, including sorghum (O'Shaughnessy et al., 2012), sugarbeet (King et al., 2021), maize (Payero and Irmak, 2006), and soybean (Payero and Irmak, 2006). However, adoption of CWSI as an irrigation scheduling method has been limited because its computation requires establishment or modeling of non-stressed and maximally stressed crop conditions, along with concurrent measurements of air temperature and relative humidity (DeJonge et al., 2015). Alternatively, simplified crop thermal indices such as Degrees Above Non-Stressed (DANS) have been developed by relating observed canopy temperature (T_c) to a single non-stressed canopy baseline temperature (T_{cns}) (Taghvaeian et al., 2014). Although this DANS method has been used for monitoring water stress in maize (DeJonge et al., 2015) and sunflower (Taghvaeian et al., 2014) in arid environments, there is opportunity to test the method's viability and transferability in different climatic regions to establish appropriate scheduling protocols and index thresholds. Furthermore, while initial T_{cns} baselines were suggested by maintaining and monitoring a non-stressed reference area (DeJonge et al., 2015), increased access to weather datasets presents an opportunity to alternatively model the T_{cns} which could further simplify the computation of the DANS index and increase the method's adoption as an irrigation water management tool by farmers.

This study was therefore focused on the implementation of CTM, specifically the DANS index, as a real-time irrigation water management tool in semi-arid, mid-western United States and highlights the method's development, implementation, and outcomes (e.g., applied irrigation, yield response, and performance metrics). This will contribute to the resources pool that water managers can consider reviewing as they determine which irrigation water management method to adopt in semi-arid environments. Additionally, the DANS index method was compared to the conventional SMM and ETM methods under similar environments and agronomic practices. The selection of irrigation water management methods to investigate was based on a technique's extensive usage in research (SMM method), common application amongst farmers (ETM method), and contemporary scheduling approaches used in recent years (CTM method).

The study objectives were 1) to develop and evaluate an empirical non-stressed canopy baseline T_{cns} for the degrees above non-stressed (DANS) index; 2) to compare the DANS index against conventional canopy temperature measurement method, CWSI; and 3) to evaluate the effectiveness of the DANS index against soil water monitoring and evapotranspiration model for irrigation scheduling by assessing soil water dynamics, irrigation water use efficiency, and grain yield.

2. Materials and methods

2.1. Site description

2.1.1. Experiment design

The field experiment was conducted in 2018, 2019, and 2020 at the University of Nebraska-Lincoln West Central Research, Extension, and Education Center in North Platte, Nebraska, USA (latitude 41.1° N, longitude 100.8° W, and elevated at 861 m above sea level). The predominant soil type is Cozad silt loam (Fluventic Haplustoll). Soil samples were collected in increments of 0.3 m to a depth of 3.0 m at 72 sampling locations in the experimental field and sent to a commercial laboratory (Ward Laboratories, Kearney, NE, USA). Soil physical and hydraulic properties are presented in Table 1. Particle size distribution in the 3 m soil profile ranged from 0.8% to 2.0% organic matter, 33.3–50.7% sand, 31.3–43.3% silt, and 14.9–23.5% clay content. Soil field capacity (FC) and wilting point (WP) were estimated following Saxton and Rawls (2006) and ranged from 0.217 to 0.298 and 0.096–0.151 $m^3\ m^{-3}$, respectively.

Pioneer 1197 AMT (Corteva Agriscience, Wilmington, Delaware, USA) maize (*Zea mays* L.) was planted on 27 April, 13 May, and 29 April in 2018, 2019, and 2020, respectively, in 0.76 m rows at a seeding rate of 84,000 seeds ha^{-1} under a no-till system following soybean in rotation. Nitrogen (N) fertilizer was prescribed based on soil residual N (Shapiro et al., 2019) and was applied to the entire field in the form of urea-ammonium-nitrate (UAN 32%). Prior to planting, 67 kg ha^{-1} of N was applied each year followed by an in-season application of 179, 157, and 126 kg ha^{-1} in 2018, 2019, and 2020, respectively. Pesticides were applied uniformly, as needed, to the entire study. The study field was harvested on 29 October, 7 November, and 30 October in 2018, 2019, and 2020, respectively, using a John Deere Model 9500 combine with a calibrated yield monitor.

A randomized complete block design was implemented, consisting of

Table 1
Field-average ± standard deviation of soil textural composition (sand, silt, and clay), organic matter content (OMC), field capacity (FC), and wilting point (WP) every 0.3 m to a soil depth of 3 m from 72 sampling locations. Soil texture and OMC were measured at a commercial lab (Ward Laboratories, Kearney, NE) and FC and WP were estimated using Saxton and Rawls (2006).

Soil Depth (cm)	OMC (%)	Sand (%)	Silt (%)	Clay (%)	Field Capacity ($m^3\ m^{-3}$)	Wilting Point ($m^3\ m^{-3}$)
0–30	2.0 ± 0.3	47.7 ± 5.7	33.3 ± 5.8	19.0 ± 2.8	0.25 ± 0.02	0.13 ± 0.02
30–61	1.5 ± 0.2	45.3 ± 5.5	33.8 ± 4.0	20.9 ± 4.9	0.26 ± 0.03	0.14 ± 0.03
61–91	1.7 ± 0.3	45.0 ± 9.7	32.4 ± 8.3	22.6 ± 6.7	0.27 ± 0.05	0.15 ± 0.04
91–122	1.6 ± 0.4	33.3 ± 5.2	43.3 ± 3.8	23.5 ± 3.0	0.30 ± 0.02	0.15 ± 0.02
122–152	1.0 ± 0.2	50.7 ± 4.7	33.8 ± 4.5	15.5 ± 2.2	0.22 ± 0.02	0.10 ± 0.01
152–183	1.0 ± 0.2	46.9 ± 5.7	34.9 ± 4.0	18.2 ± 4.2	0.24 ± 0.03	0.12 ± 0.03
183–213	1.1 ± 0.2	49.6 ± 6.0	31.3 ± 7.5	19.1 ± 4.3	0.24 ± 0.03	0.12 ± 0.03
213–244	1.1 ± 0.2	46.9 ± 5.1	36.1 ± 4.0	17.1 ± 2.3	0.24 ± 0.02	0.11 ± 0.01
244–274	0.8 ± 0.1	46.4 ± 4.9	35.8 ± 3.6	17.8 ± 2.4	0.24 ± 0.02	0.11 ± 0.01
274–305	0.8 ± 0.1	49.0 ± 4.2	36.1 ± 4.2	14.9 ± 2.5	0.22 ± 0.02	0.10 ± 0.02

four blocks each having 9 m by 72 m experimental plots. Three irrigation scheduling treatments were evaluated namely: soil moisture monitoring (SMM), crop evapotranspiration model (ETM), and canopy temperature measurement (CTM). Irrigation of 20 mm was applied when a treatment triggered. To further evaluate the three scheduling methods, it was necessary to compare the method's performances with a non-irrigated, low irrigated and excessively irrigated crops. The experiment design therefore, included treatments managed under different irrigation levels namely: rainfed (RF) which received no irrigation water, deficit irrigation (DI), and excess irrigation (EI). The DI and EI treatments were 60% (12 mm) and 140% (28 mm) of the SMM treatment, respectively, and followed the irrigation timing of the SMM treatment. The DI and EI treatments were included to properly evaluate whether the three irrigation treatments under, optimally or over irrigated as determined by the crop production function. The experimental units were individually irrigated by a subsurface drip irrigated (SDI) system. The SDI system consisted of laterals (drip lines) spaced at 1.52 m under alternate furrows and at a depth of 0.4 m below the soil surface. The drip tape type was T-Tape, TSX 515–12–340 with 0.3 m emitter spacing (Tarkalson and Payero, 2008).

2.1.2. Weather conditions

The research site in North Platte is located in a semi-arid climatic zone where the growing season evaporative demand greatly influences irrigation requirement (Klocke et al., 1989; Payero et al., 2005). The microclimatic data including air temperature (T_a), incoming solar radiation (R_s), wind speed at 3 m height (U_3), precipitation (P), and relative humidity (RH) were collected from an automatic weather station (North Platte 3SW Beta) that was 100 m away from the experimental field and is part of the Nebraska Mesonet network (https://mesonet.unl.edu).

During the experimental growing seasons, R_s ranged from 10.4 to 23.8 MJ m^{-2} d^{-1} with an average of 18.5 ± 5.1 MJ m^{-2} d^{-1} in 2018; from 12.0 to 24.3 MJ m^{-2} d^{-1} with an average value of 18.5 ± 4.8 MJ m^{-2} d^{-1} in 2019, and 12.0–25.3 MJ m^{-2} d^{-1} with an average value of 20.1 ± 5.0 MJ m^{-2} d^{-1} in 2020 (Table 2). This resulted in percentage ET_r differences from the 30-year long term seasonal total of − 8.8, − 15.9%, and 10.5% in 2018, 2019, and 2020, respectively, which suggested a greater evaporative demand and need for irrigation in 2020 in comparison to 2018 and 2019. Furthermore, the corresponding rainfall totals from May 1 to October 31 were 432, 503, and 235 mm in 2018, 2019, and 2020, respectively. These seasonal totals translated in 19.8% and 39.5% increase in rainfall above long-term average in 2018 and 2019 as compared to a 34.9% decline in 2020. These weather parameter differences suggested a drier than average year in 2020, a wetter than average year in 2019, and a slightly wetter than average year in 2018.

2.2. Data collection

Volumetric soil water content (θ_v) was measured weekly to bi-weekly from a depth of 0.15–1.80 m in 2018 and 0.15–2.59 m in 2019 and 2020, at increments of 0.30 m using neutron moisture meters (NMM) CPN 503 Elite Hydroprobe and CPN 503DR (InstroTek, CA USA). The CPN 503DR were gravimetrically calibrated for the site with R^2 of 0.977 and RMSE of 0.010 m^3 m^{-3}, respectively, while the CPN 503 Elite Hydroprobe was cross calibrated to the CPN 503DR with R^2 of 0.994 and RMSE of 0.004 m^3 m^{-3}, respectively (Lo et al., 2020).

During the 2018 season, one neutron access tube was placed within a crop row in three plots of each treatment. In 2019 and 2020, a pair of access tubes were placed in four plots of each treatment, with the two tubes straddling a crop row evenly and being 0.38 m apart perpendicular to the row direction.

Canopy temperature measurements were taken using SI-1H1 and SI-4HI series infrared thermometers (IRT) sensors (Apogee Instruments Inc. UT, USA). Due to limitations in sensor availability, an IRT sensor was installed in three SMM plots every year but in two CTM plots for 2018 and three CTM plots for 2019 and 2020. There were no IRT sensors installed in the ETM treatment. The IRT sensors were mounted approximately 1 m above the crop canopy and oriented at a 45° view angle towards the crop. To maximize the viewing of sunlit crop canopy during mid-afternoon hours, the IRTs were oriented in the northeast direction. The sensors were programmed to collect data every six

Table 2
Growing season weather parameters measured during the experimental period (2018–2020) and long-term seasonal weather outlook (1986–2015) for the research site.

Year	Month	T_{min} (°C)	T_{max} (°C)	RH_{avg} (%)	U_2 (m s^{-1})	P (mm)	R_s (MJ m^{-2})	ET_r (mm)
2018	May	10.3	24.1	67.3	2.6	147.1	19.4	169.5
	June	15.1	29.2	65.5	2.6	91.2	23.1	208.2
	July	16.7	30.4	64.2	1.9	62.5	23.8	196.1
	August	14.7	30.0	62.2	2.0	42.9	19.4	170.2
	September	12.3	26.4	67.4	2.7	13.0	14.8	161.5
	October	1.5	16.0	68.0	2.3	75.7	10.4	90.5
2019	May	4.6	17.6	68.7	2.6	109.2	15.8	117.5
	June	11.8	27.2	65.9	2.2	83.8	23.8	189.1
	July	17.1	30.3	68.6	2.1	175.0	24.3	198.7
	August	15.7	27.8	75.7	1.8	93.5	18.0	139.3
	September	12.5	28.4	65.6	2.6	25.4	17.3	168.7
	October	-2.0	14.7	62.6	2.9	16.3	12.0	105.7
2020	May	6.5	20.7	67.6	2.6	83.1	20.6	155.0
	June	14.6	32.3	56.9	3.3	12.2	25.3	282.8
	July	13.6	32.2	65.8	2.6	117.1	24.0	237.5
	August	15.2	31.8	62.4	2.6	4.8	22.3	231.5
	September	7.7	26.5	58.3	2.5	15.2	16.5	181.1
	October	-1.0	17.1	60.5	2.5	2.5	12.0	119.1
Long term average (1985 –2015)	May	7.2	22.3	63.6	3.2	75.6	20.6	185.0
	June	12.9	28.2	64.1	3.0	88.6	23.7	215.8
	July	15.8	31.2	64.9	2.8	63.0	23.5	228.1
	August	14.5	30.0	67.3	2.7	58.7	20.5	198.0
	September	8.6	25.6	63.3	2.8	39.2	16.4	158.6
	October	1.4	18.4	62.8	2.5	35.7	11.7	107.0

Note: T_{min} and T_{max} are the average daily minimum and maximum temperatures, respectively; RH_{avg} is the average daily relative humidity; U_2 is the average daily wind speed at 2 m height; R_s is the average daily incoming short wave solar radiation; ET_r is the cumulative tall crop reference evapotranspiration; and P is the cumulative precipitation.

seconds which was averaged over one minute and sampled using CR1000 measurement and control data loggers (Campbell Scientific, Inc., UT).

2.3. Irrigation scheduling methods

2.3.1. Soil moisture monitoring (SMM)

For irrigation scheduling, the top 0.91 m soil depth was considered as the effective root zone in the vegetative to early reproductive growth stages for irrigation management in this study following Kranz et al., (2008) and the root zone was expanded to 1.22 m in the late reproductive season to allow for extraction of water from a deeper soil depth (Yonts et al., 2008). The soil available water content (AWC) was computed as:

$$\mathrm{AWC} = \sum_{i}^{n}(\theta_{FCi} - \theta_{WPi})d_i + \ldots + (\theta_{FCn} - \theta_{WPn})d_n \tag{1}$$

where, θ_{FC} is the volumetric water content at field capacity (FC) (m^3 m^{-3}), θ_{WP} is the volumetric water content at wilting point (WP) (m^3 m^{-3}), and d is the soil depth ranging from i to n within the limits of the managed maize crop root depth as determined by the crop growth stage.

Depending on the crop growth stage, the allowable depletion (AD) value varied to reflect the crop's ability to extract water and tolerate water stress prior to irrigation events. These AD values were developed based off near optimal irrigation management conditions for maize at the research site in 2017 (Lo et al., 2019), which took into account the crop growth stage and approximate rooting depth. The AD values ranged from 27.4 mm at fifth leaf (V5) to 152.4 mm at kernel dent (R5.75) growth stage (Table 3). The difference between the average volumetric water content ($\overline{\theta}_v$) across the 0.91 m soil profile and θ_{FC} across the managed rooting depth was computed and denoted as the real time depletion value (RTD) (Eq. 2). A decision to irrigate was made when the RTD value exceeded a selected allowable depletion (AD) value.

$$\mathrm{RTD}_i = (\theta_{FCi} - \overline{\theta}_{vi})Rz_i \tag{2}$$

where, RTD is the real time soil water depletion (m) at time i, $\overline{\theta}_v$ is the average measured volumetric water content (m^3 m^{-3}), and R_z is the root depth (m).

2.3.2. Crop evapotranspiration model (ETM)

Irrigation was determined for the ETM treatment when soil water deficit (WD) exceeded the AD. A soil water balance model (Allen et al., 1998; Trout and DeJonge, 2018; Gu et al., 2020) was used to calculate WD (Eq. 3).

$$WD_j = ET_{aj-1} + RO_{j-1} + DP_{j-1} + WD_{j-1} - I_{j-i} - P_{j-1} \tag{3}$$

where, DP is deep percolation (mm); P is precipitation (mm); I is applied irrigation (mm); ET_a is crop evapotranspiration (mm); RO is runoff (mm); and subscripts j and j-1 represent the current day and previous day, respectively. Runoff (RO) was computed using the USDA Natural Resources Conservation Service (NRCS) runoff curve number method (USDA-NRCS, 1985) with a curve number of 75. Deep percolation was assumed to occur two days following a wetting event and was estimated using the cascading method (Djaman and Irmak, 2012). In this study all water above field capacity was assumed to drain. Maize ET_a was computed using the two step method (Allen et al., 1998) calculated as:

$$ET_a = K_c \times ET_r \tag{4}$$

where, K_c is a single crop coefficient and ET_r is alfalfa (tall crop) reference evapotranspiration. The K_c values were derived using data collected during the 2017 growing season and are presented in Table 3. Daily maize ET_a was measured from an onsite eddy covariance system. The field was fully fertilized and irrigated, and extended 230 m south of the tower. The system was installed with a maximum instrument height of 3.96 m, which allowed for a 1 m height above canopy. Latent heat flux data processing and filtering accounting for only the footprint from the maize field was done by LI-COR Biosciences (Lincoln, NE) using EddyPro software (version 6.2). ET_r was calculated using the ASCE standardized reference crop evapotranspiration equation (ASCE-EWRI, 2005; Rudnick and Irmak, 2014; Lo et al., 2019) using onsite weather data collected by the Nebraska Mesonet (https://mesonet.unl.edu/). The resultant K_c values were compared to K_c values previously measured at the experiment site (Gerosa, 2011) and within the experiment region (Hinkle et al., 1984) and were found to be similar and representative of a

Table 3
Average eddy covariance system derived *Kc* values per growth stage, corresponding values of allowable depletion (AD) and cumulative growing degree days (∑GDD) across the growing seasons.

Beginning growth stage	End growth stage	Average K_c	Managed root depth (mm)	AD (mm)	2017 ∑GDD (°C)	2018 ∑GDD (°C)	2019 ∑GDD (°C)	2020 ∑GDD (°C)
P	VE	0.22	–	–	56	72	47	43
VE	V1	0.22	–	–	77	96	71	62
V1	V2	0.22	–	–	94	116	114	82
V2	V3	0.22	–	–	131	154	171	116
V3	V4	0.22	–	–	175	201	214	188
V4	V5	0.24	–	–	223	248	268	241
V5	V6	0.33	457	27.4	281	295	319	294
V6	V7	0.44	610	35.6	324	345	373	350
V7	V8	0.52	762	44.5	368	391	412	401
V8	V9	0.60	914	53.3	404	433	437	462
V9	V10	0.66	914	53.3	450	460	474	507
V10	V11	0.75	914	53.3	482	486	509	560
V11	V12	0.81	914	53.3	520	512	552	588
V12	V13	0.88	914	53.3	560	554	593	627
V13	V14	0.96	914	53.3	600	583	622	650
V14	VT/R1	1.03	914	53.3	678	664	692	683
VT/R1	R2	1.03	914	53.3	811	798	820	832
R2	R3	1.03	914	53.3	902	888	917	929
R3	R4	1.03	914	68.6	1003	993	1017	1065
R4	R4.7	1.03	914	83.8	1150	1137	1159	1153
R4.7	R5.25	1.01	1219	111.8	1219	1231	1243	1232
R5.25	R5.5	0.88	1219	132.1	1302	1356	1362	1309
R5.5	R5.75	0.73	1219	152.4	1413	1411	1402	1365
R5.75	R6	0.53	1219	152.4	1454	1477	1421	1431

Note: The base and upper limit temperatures for GDD calculation were 10 and 30 °C, respectively (Nielsen and Hinkle, 1996; Rudnick and Irmak, 2014) well-watered maize crop.

2.3.3. Canopy temperature measurement (CTM)

Degrees Above Non-Stressed (DANS) thermal index was used as the CTM irrigation scheduling method. The computation of DANS (Eq. 5) ideally requires the maintenance of a well-watered non-stressed crop which is contrasted with the canopy temperature measured from the study treatments (Taghvaeian et al., 2014; DeJonge et al., 2015; Kullberg et al., 2017; Drechsler et al., 2019). The maintenance of a well-water-crop necessitates constant monitoring and frequent irrigation of the crop to prevent water stress yet irrigation system limitations amongst other constraints may be encountered. Additionally, the non-stressed crop ideally needs to be monitored for each growing season to reflect ongoing atmospheric demand. To satisfy the requirement of a non-stressed-canopy baseline, DeJonge et al. (2015) considered the lowest observed temperature from available treatments as the T_{cns} in both CWSI and DANS index computations. Alternatively, this study suggested that a modeled non-stressed temperature be used to approximate the well-watered crop conditions for the DANS index.

$$DANS = T_c - T_{cns} \tag{5}$$

A multilinear regression model was used to estimate T_{cns} (dependent variable) with weather parameters (T_a, R_s, and vapor pressure deficit (VPD)) as the independent variables. The lowest observed peak time (14:45–16:45 Central Daylight Time (UTC-5)) T_c measurements amongst treatments starting after 80% canopy closure were used in the regression analysis and model development.

Peak time T_c measurements were selected because greater standard deviations in measured T_c were observed across the treatments in comparison to those observed in the early morning or late-night hours of the day (data not shown). This diurnal variation in maize T_c values was also observed in research conducted by DeJonge et al. (2015) and suggested that spot thermal indices could be computed from temperature data collected 1–2 h after solar noon. The multilinear regression was done using R 3.5.0 (R Core Team, 2018) packages while the correlation statistics were computed in Microsoft Excel 365 (Microsoft Corporation, Redmond, WA, USA). The coefficients of the selected predictor parameters were significant at a p – value of 0.05 to the model. The data was filtered to remove cloudy day conditions as well as dates when VPD values were less than 1 kPa. In 2018, data from the 2017 growing season was used in the model, while in 2019 and 2020 the model included data sets from both 2017 and 2018 (Table 4). The resulting model RMSE values were 0.46 and 0.38 °C in 2018 and 2019, respectively.

Maize was considered minimally, moderately, and severely stressed at DANS values of 1.0 °C, 1.0–5.0 °C, and 5.0–8.3 °C, respectively, in a previous study in Colorado (DeJonge et al., 2015). In the current study, an irrigation threshold of 1 °C was selected in 2018, but this threshold was later lowered to 0.5 °C in 2019 and 2020 to better capture and respond to the onset of crop water stress. The difference between the observed (field measured) T_c and modeled T_{cns} was compared to the selected DANS index threshold value prior to making an irrigation decision. An irrigation decision was therefore made when the computed DANS value exceeded the set threshold (i.e., 1 °C in 2018 and 0.5 °C in 2019 and 2020).

Table 4
Multilinear regression equations used to calculate the non – stressed canopy temperature baseline, T_{cns} for DANS index computation and irrigation management during the 2018, 2019, and 2020 growing seasons. The Eq. 5.1 was used to model T_{cns} in 2018 while Eq. 5.2 was used to model T_{cns} in 2019 and 2020.

Equation number	VPD (kPa)	Equation	Adjusted R^2	RMSE °C
5.1	> 1	$T_{cns} = 0.8743T_a + 0.003284R_s - 1.4143VPD + 3.3350$	0.93	0.46
5.2	> 1	$T_{cns} = 0.8637T_a + 0.003581R_s - 1.4906VPD + 3.3853$	0.97	0.38

2.4. Crop Water Stress Index

The crop water stress index (CWSI) has been used as a measure of maize crop water thermal stress in studies conducted in the mid-west USA (Payero and Irmak, 2006; Singh et al., 2021). CWSI infers water stress as a function of thermal measurement and environment. In this research the computed DANS index was compared to empirically established CWSI index following Idso et al. (1981) (Eq. 6.1). The lower baseline (LB) (Eq. 6.2) was developed as a linear regression of the peak time VPD and T_{cns} - T_a differential. The field observed T_{cns} was used in the T_{cns} - T_a differential computation and subsequent LB development

$$CWSI = \frac{(T_{ci} - T_a) - LB}{UB - LB} \tag{6.1}$$

$$(T_{cns} - T_a) = (m \times VPD) + c \tag{6.2}$$

where, T_{ci} (°C) is the canopy temperature measured from any given treatment i, T_a is the corresponding average air temperature, ΔT (°C) is the difference between measured T_{cns} and T_a, LB (°C) is the lower canopy temperature baseline, and UB (°C) is the upper canopy temperature baseline, m is the slope, and c is the intercept. Peak time pooled data from 2017, 2018, and 2019 was used to define LB (LB = −1.6012VPD + 2.0677, R^2 = 0.75) for the CWSI computations. On the other hand, a constant value 4 °C was used as the upper baseline (UB) based on field observed measurements of canopy temperature from the deficit and rainfed treatments.

2.5. Performance assessment and statistical analysis

Differences in grain yield across irrigation scheduling treatments and years were investigated using the analysis of variance (ANOVA) statistical procedures in SAS Studio 3.8 software (SAS Institute, Inc., Cary, NC). The ANOVA analysis assumed normal distribution of variables, independence of variables and homogeneity of variances. The Fisher's protected least significance difference test was performed at 95% significance level. In addition, the impact of irrigation scheduling method on crop water productivity was evaluated using irrigation water productivity (IWP, Eq. 7) (Bos, 1980, 1985; Rudnick and Irmak, 2013; Lo et al., 2019; Evett et al., 2020).

$$IWP = \frac{Y_i - Y_{RF}}{I_i} \tag{7}$$

where Y is grain yield adjusted to 15.5% moisture content; I is applied irrigation; and subscripts i and RF represent irrigated and rainfed treatments, respectively.

3. Results and discussion

3.1. Modeled non-stressed canopy temperature and seasonal DANS index variation

A multilinear regression (Table 4) was used to model the non-stressed canopy temperature baseline which was required for the computation of the DANS index. The coefficient of determination (R^2) values for the regression between the peak time observed T_{cns} and modeled T_{cns} on non-cloudy days were 0.95, 0.94, and 0.96 in 2018, 2019, and 2020, respectively (Fig. 1). The corresponding growing season RMSE values were 0.46, 0.55, and 0.41 °C in 2018, 2019, and 2020, respectively. The higher RMSE values observed in 2019, which was the wetter growing season suggest that modeling of T_{cns} did not perform as well in wetter-than-average conditions at the experiment site. Despite

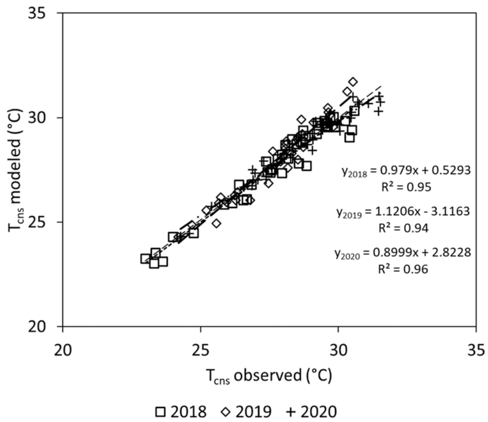

Fig. 1. Comparison of field observed and modeled non-stressed canopy temperatures (T_{cns}) in the 2018, 2019, and 2020 growing seasons. The modeled T_{cns} computed using the multilinear equations shown in Table 3 on non-cloudy dates.

this, the overall goodness of fit across the three experimental years suggested that modeled T_{cns} could be used in substitution to field measured T_{cns} during the computation of the DANS index. This model based T_{cns} could therefore further ease the adoption and application of the DANS index method for irrigation scheduling.

The variation in the DANS index per treatment contrasted against the selected thermal threshold values during the growing seasons of 2018, 2019, and 2020 are presented in Fig. 2. In 2018 a trigger threshold value of 1.0 °C was selected for the DANS index while in 2018 and 2020 the trigger threshold was 0.5 °C. In 2018, the DANS index for the CTM treatment in July was closer in magnitude to the DI treatment than to SMM treatment in which irrigation was managed to maintain full crop ET. This delay in irrigation (i.e., greater crop water stress) by the CTM treatment in 2018 was due to the higher stress threshold selected.

The DANS seasonal values ranged from −2 °C to over 8 °C across the three different growing seasons. Higher DANS index values were observed in the RF treatment after the R4 growth stage, at the onset of crop senescence. Taghvaeian et al. (2014) reported DANS values slightly over 8 °C and those below 0 °C for sunflower during different measurement times in the peak period and the negative values are assumed to indicate non-water stressed conditions. The 2019 growing season

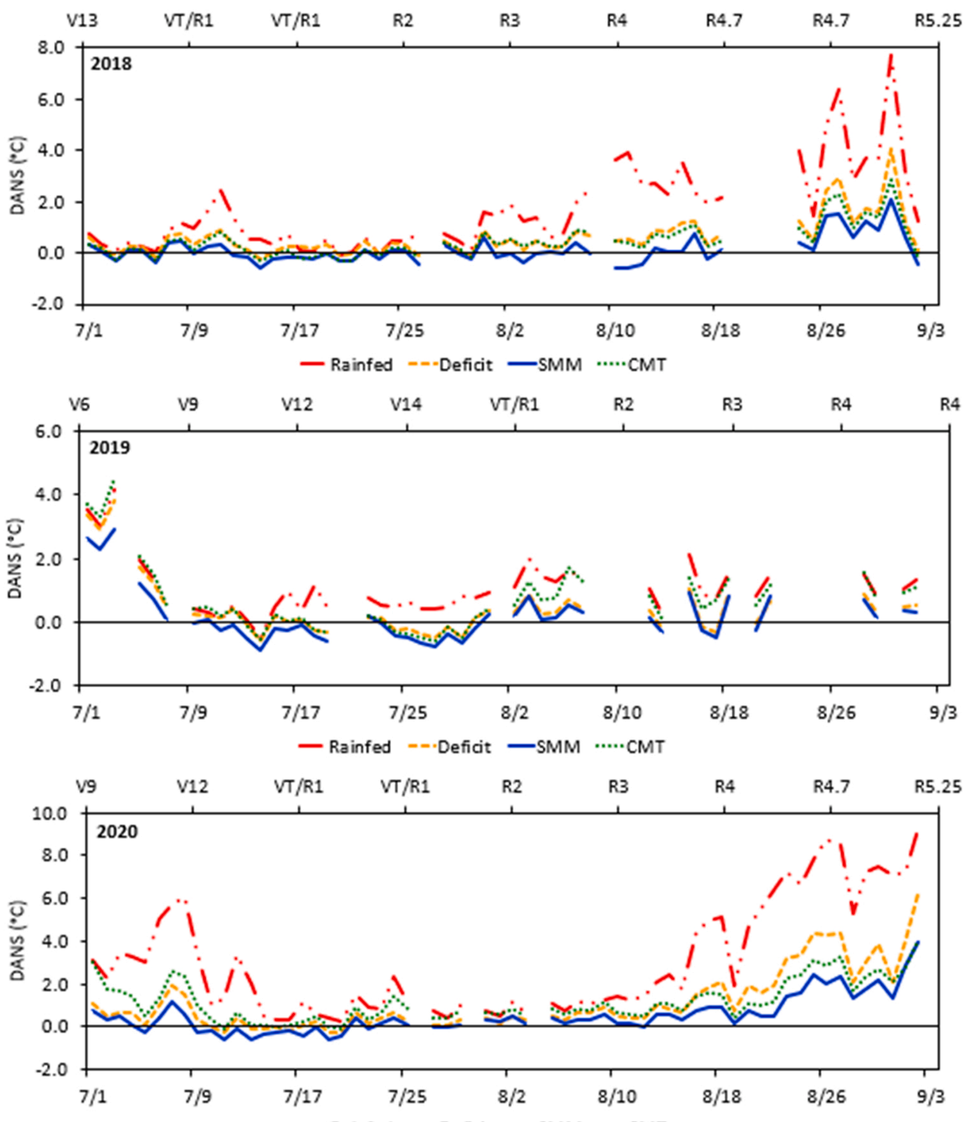

Fig. 2. Seasonal degrees above non-stressed (DANS) index variation for the rainfed (RF), deficit (DI), soil moisture monitoring (SMM), and canopy temperature measurement (CMT) treatments in 2018, 2019, and 2020.

received above normal rainfall, which resulted in less water stress and subsequently overall lower magnitude DANS values across the treatments. The season was also characterized with days that had VPD values of less than 1 kPa for which the DANS index was not computed for irrigation scheduling. Therefore, the greatest spread in DANS index values was observed in 2020 which was a dry year, while the above normal rainfall year of 2019 had the least difference in DANS values across treatments. The difference in DANS values indicated that the index was responsive to irrigation and could be used to infer crop water stress.

Slightly higher early season (V6 growth stage) DANS values in 2019 could be attributed to partial view of the soil surface by the IRT sensor prior to full canopy closure while the late season peak DANS values across the seasons were associated with crop maturity and onset of senescence. These higher range DANS values were not considered for the DANS index-based irrigation scheduling which renders that method unusable prior to full canopy closure or at the end of the growing season, if the need for irrigation water is warranted. In 2018 and 2019 there were slight differences in magnitude of DANS values during the early season (V8 to VT) due to reduced early crop water demand. On the other hand, the V8 to VT DANS values across treatments in 2020 were greater, reflecting the dry nature of the growing season. The mid reproductive season (R2 to R3) in 2018 and 2019 indicated difference in DANS values which could be attributed to differences in irrigation water applied as determined by the scheduling method. The extreme dry conditions in 2020 resulted in concurrent irrigation triggering by both the SMM and CTM treatments hence the lower differences in magnitude of DANS values during the R3 to R4 growth stages. Greatest differences in DANS were observed during the later reproductive stage (R4) especially in the RF treatment, which was attributed to early senescence. These in season variations in DANS values with growth stages suggested that a static DANS threshold as the one used in the study was likely to under or overestimate stress along the growing season.

3.2. CSWI-DANS relationship

The correlations between conventionally used CWSI and the DANS index for the RF, DI, SMM, and CTM treatments are presented in Fig. 3. The resulting correlation coefficients across the three experiment seasons were 0.67, 0.59, and 0.75 in 2018, 2019, and 2020, respectively. This correlation of the DANS index computed using modeled T_{cns} to conventionally used thermal stress CWSI suggested that DANS could also be used for crop water monitoring and irrigation scheduling.

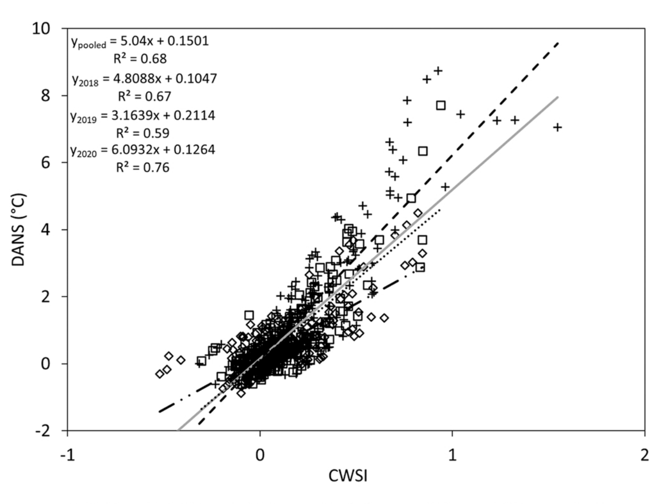

Fig. 3. Scatter plots and resulting regression equations of crop water stress index (CWSI) against the degrees above non-stressed (DANS) index in 2018, 2019, and 2020.

Taghvaeian et al. (2014) found that the correlation coefficients of CWSI and DANS for sunflower ranged from 0.80 to 0.86 across different hourly periods and that DANS was responsive to irrigation. The relationship between CWSI and DANS was stronger in the drier 2020 growing season which also had higher average T_c values across the treatments. The increased correlation in the drier growing season suggested that both indices were more responsive to crop water stress in water-limited conditions. Similarly, DeJonge et al. (2015) reported a correlation coefficient of 0.50 for mean canopy temperatures between 27 °C and 29 °C, and a higher correlation coefficient of 0.90 between CWSI and DANS for mean canopy temperatures greater than 29 °C in maize.

3.3. Seasonal irrigation patterns across scheduling treatments

Seasonal cumulative irrigation as applied by the three scheduling methods juxtaposed with rainfall and crop growth stage is presented in Fig. 4. The CTM method triggered irrigation later in the season, during the mid-reproductive growth stage in 2018 and a cumulative total of 102 mm was applied. The amount was relatively lower in magnitude than that applied by the SMM (166 mm) and ETM (193 mm) methods given the same environmental and soil physical conditions. This underestimation of irrigation water requirement was attributed to the higher DANS index irrigation trigger threshold of 1 °C observed and selected in 2018, which required more water stress to trigger irrigation than other methods during the late-vegetative and mid-reproductive growth stages. Although the CTM method responded to cumulative stress and triggered irrigation in the later part of 2018, it was evident that this late timing of the irrigation negatively impacted (Table 5) crop yield (Table 6). Studies by Han et al. (2018) and Lena et al. (2020) noted limitations of early-season leaf area index coupled with soil background and late season crop senescing in the computation of CWSI for maize. Therefore, the onset of early senescence prior to meeting a crop's full water demand could be a drawback to utilizing CTM based measurements in irrigation water management. Additionally, Payero et al. (2009) found that irrigation stress timed during the reproductive stage for maize grown in the same research site resulted in 17–33% of yield variation. The detection of crop water stress as well as the proper timing of an irrigation event were therefore key indicators of a scheduling method's appropriateness to manage irrigation.

Even though the irrigation threshold was lowered from 1.0° to 0.5°C following 2018, it was kept constant throughout the growing season yet crop response to water stress was likely to vary across growth stages. Thermal stress thresholds and baselines alike have typically been kept unvarying throughout the growing season unlike in soil monitoring where variables like MAD are adjusted to accommodate for crop growth and associated stress. An in-season dynamic threshold model for CWSI was developed by Osroosh et al. (2015) to monitor water stress in apple trees and it was found that the dynamic CWSI thresholds evaded false irrigation triggers, while accounting for growth changes in trees.

In all three growing seasons the CTM irrigation events were triggered after the SMM and ETM methods which alluded to early season mining of AWC prior to the method's triggering of irrigation. Starting water application later in the season compared to other methods, suggested that irrigation events triggered by the CTM were likely to happen at or after the onset of crop water stress and the method was likely better suited for DI practices.

The SMM cumulatively applied 166, 61, and 244 mm of irrigation in 2018, 2019, and 2020, respectively. The higher irrigation amount in 2020 resonated with the season's drier than normal climate which created a greater need for water as compared to 2018 and 2019. Although the seasonal irrigation initiation and timings of SMM was similar to the ETM method, there was a significantly higher application of water by the ETM method specifically: 19%, 100% and 33% in 2018, 2019, and 2020, respectively. While the ETM method may be an easier method to apply, the method is prone to incremental errors in estimation of water depletion in the soil (Gu et al., 2020) and runoff uncertainty. An

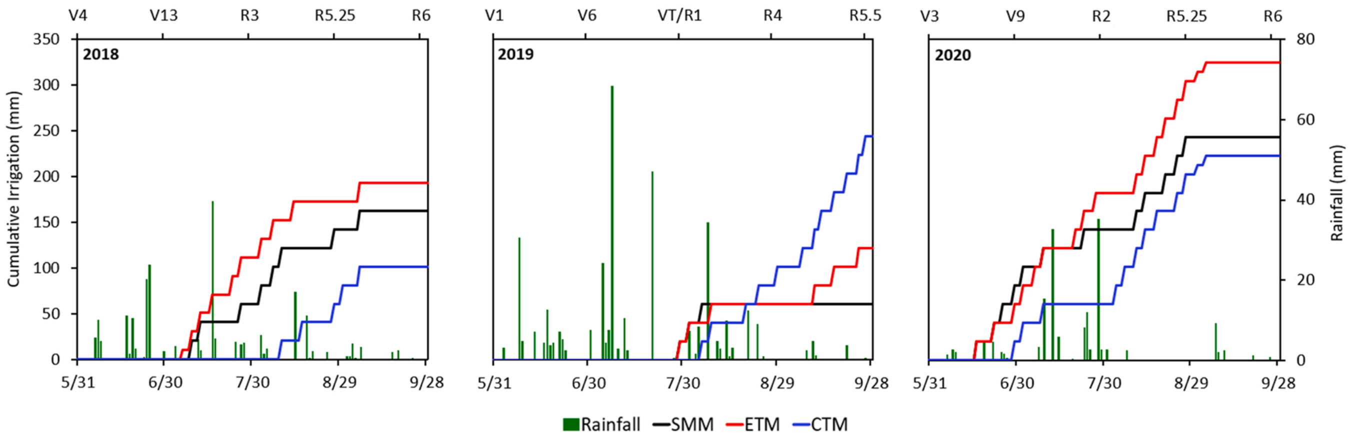

Fig. 4. Cumulative irrigation water applied, daily rainfall and corresponding growth stages across the 2018, 2019, and 2020 growing seasons for the scheduling method treatments. The corn growth stages are described as follows: V1 to Vn = first leaf to n[th] leaf, VT/R1 = tasseling and silking stage, R2 = blister stage, R3 = milk stage, R4 = dough stage, R5 = kernel dent stage, and R6 = black layer/physiological maturity.

Table 5
Linear relationship between DANS index and soil water depletion below 60% and above 60% at 0.6, 1.8, and 2.1 m for the 2020 growing season.

Depletion level	Soil depth (m)	R^2	Slope (°C/%)	Intercept
Below 60%	0–0.6 m	0.17	0.011	0.471
	0–1.8 m	0.33	0.028	-0.703
	0–2.1 m	0.32	0.026	-0.481
Above 60%	0–0.6 m	0.78	0.098	-6.663
	0–1.8 m	0.71	0.094	-5.572
	0–2.1 m	0.70	0.106	-6.334

alternative to 'stand-alone' scheduling methods could therefore be combining methods together to maximize their advantages. As an example, a combined approach could include measurement of the soil water and translation of these measurements into the irrigation decision (SMM method) while considering crop water needs and soil's water holding capacity (ETM method). Also, methods can be implemented concurrently ('parallel application') or utilization of one method after the other ('series application') depending on which strategy best identifies crop water stress along changing crop growth stages. A cost – benefit analysis of duo or multiple scheduling method application ought to be considered prior to adoption.

Table 6
Maize yield and irrigation water productivity (IWP) of the scheduling methods (SMM, ETM, and CTM) and the rainfed, deficit, and excessive irrigation treatments.

Parameter	Year	Treatments					
		Rainfed	Deficit	SMM	ETM	CTM	EI
Grain yield (Mg ha^{-1})	2018	12.09 ± 0.63d	16.18 ± 0.58b	17.23 ± 0.27a	17.84 ± 0.45a	15.09 ± 0.62c	17.47 ± 0.47a
	2019	12.5 ± 0.54d	13.67 ± 0.59c	13.84 ± 0.52 BCE	14.43 ± 0.79ab	15.26 ± 0.52a	14.05 ± 0.43b
	2020	7.45 ± 0.24d	12.48 ± 0.67c	14.50 ± 0.62b	16.29 ± 0.34a	15.01 ± 0.27b	16.04 ± 0.71a
	Pooled	10.68 ± 2.81	14.11 ± 1.89	15.19 ± 1.80	16.19 ± 1.71	15.12 ± 0.31	15.85 ± 1.72
IWP (kg m^{-3})	2018	N/A	4.30 ± 0.58b	3.19 ± 027a	3.10 ± 0.45a	3.01 ± 0.62a	2.47 ± 0.47a
	2019	N/A	3.08 ± 0.59a	2.05 ± 0.52a	1.74 ± 0.79ab	1.13 ± 0.52b	1.79 ± 0.43a
	2020	N/A	3.17 ± 0.67a	2.75 ± 0.62b	2.74 ± 0.34c	3.27 ± 0.27a	2.51 ± 0.71d
	Pooled	N/A	3.52 ± 0.68	2.66 ± 0.57	2.52 ± 0.70	2.47 ± 1.17	2.26 ± 0.40

Note: Values followed by similar letters across the rows are not statistically significant (P > 0.05) and the data was analyzed separately by year

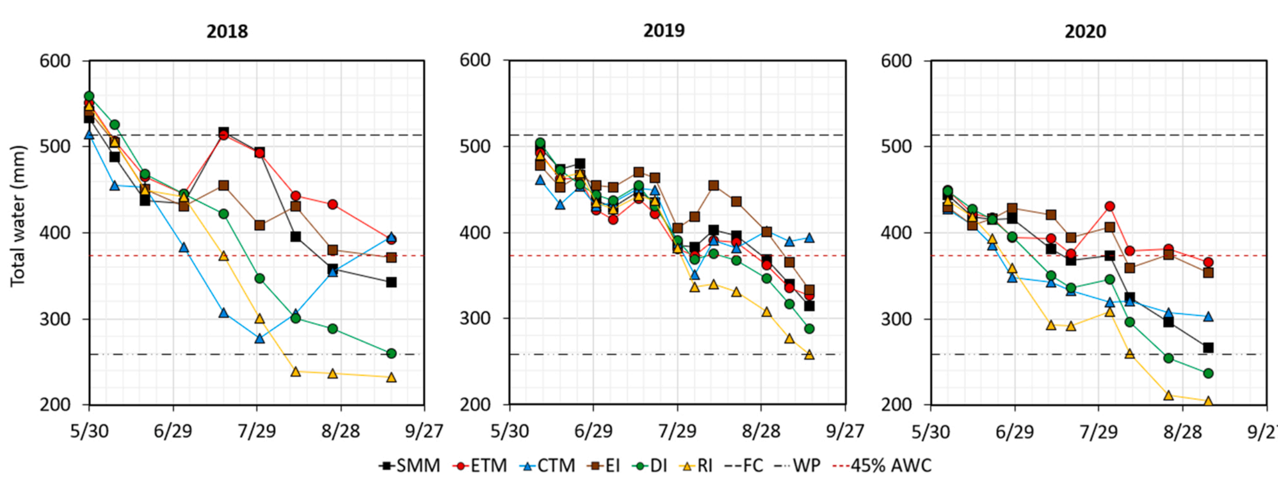

Fig. 5. Distribution of neutron moisture meter measured total water (TW) in the 1.8 m soil profile during the growing seasons in 2018, 2019, 2020.

3.4. Soil water dynamics

The initial total water (TW) content following recharge from the off-season precipitation (October to April) amongst the three scheduling treatments ranged from 533 to 553 ± 11 mm in 2018, 492–461 ± 20 mm in 2019, and 428–450 ± 11 mm in 2020 (Fig. 5). Although there were notable interannual differences in initial TW due to variation of previous season and off-season precipitation, in-season initial values of TW were within a similar magnitude range, across the experimental treatments. Since the rainfall received during the season was assumed to be constant across the treatments, subsequent in season variations in soil water content were primarily attributed to irrigation water applied. There was evidence of a greater separation of TW values of the CTM method compared to the SMM and ETM methods in 2018. Also, early season TW values were lower for the CTM compared to the DI and RI treatments. These low magnitude TW values in the CTM treatment were attributed to reduced frequency of irrigation events as triggered by the CTM method in the early portion of 2018 due to the high DANS index canopy stress threshold of 1.0 °C. In 2018 the end of season TW for the SMM was 40 mm less than that for the ETM which was influenced by fewer irrigation events. This difference suggested that the SMM allowed for potential extraction of soil water by the roots from deeper soil layers which reduced irrigation. Drawing down of water in the soil profile could save on application of irrigation water and provide a greater storage volume for off-season precipitation which could be utilized by crops in subsequent growing seasons.

The 2019 growing season received above normal rainfall of 580 mm (Table 2) which resulted in less irrigation water applied across treatments but on average a higher amount of end of season TW across the soil profiles of the treatment plots compared to 2018 and 2020. The 2019 beginning and ending TW values for the scheduling treatments ranged from 498 to 315 for SMM, 492–326 mm for ETM, and 461–394 mm for CTM scheduling methods. The CTM end of season TW value was greater than that of the other treatments in 2019, including the EI treatment (334 mm), indicating that more irrigation events than agronomically viable were triggered for the CTM method. This irrigation application error suggested that deciding on an appropriate irrigation cutoff date which considers soil water status and a crops growth stage was essential. It also suggested that crop canopy thermal response was possibly varied across crop developmental stages. These possible differences in DANS index values ought to be accounted for in baseline development, irrigation threshold selection, and irrigation cutoff timing for subsequent studies. The drier-than-normal growing season of 2020 experienced a steady decline in soil TW across all treatments (Fig. 5) despite more applied irrigation than 2018 and 2019. Crop water demand driven by both increased soil and atmospheric water deficits were key contributors to the low TW values.

The combination of the irrigation water trends and soil TW variations across treatments suggested that prompt detection of crop water stress influenced irrigation triggering and scheduling. From this research, the three main indicators that infer crop water stress in a suggested chronological order of occurrence can be stated as: i) micro-climatic evaporative demand, ii) soil moisture decline, and iii) crop thermal physiological response. If all other factors are kept constant, then the implications could be that the ETM and SMM methods were more likely to trigger irrigation concurrently while the CTM method triggered irrigation in response to an already experienced degree of crop water stress. The instances where all methods trigger at a time could suggest that the CTM was responding to a crop water stress episode experienced previously rather than presently. These observations regarding timing of irrigation and influences could imply that the CTM method if solely used is best suited to manage deficit irrigation rather than fully irrigated cropping systems. This deduction of use of CTM methods is so because crop water stress is required to have occurred before it's detected by the CTM method. Hence, even in cases when water stress is detected at the onset, full irrigation coupled with non-stress conditions can never be fully met which renders the CTM methods as one best for deficit irrigation practices.

3.5. DANS variation with percentage soil water depletion

To investigate the relationship between the DANS index and soil water, DANS was linearly compared with percent soil water depletion in the 2020 growing season on neutron-based soil water measurement dates at depths of 0.6, 1.8, and 2.1 m (Fig. 6). The comparison was made under two percent depletion levels i.e., below 60% depletion and above 60% depletion which were denoted as below and above respectively. Stronger linear relationships with DANS were observed for percent depletion values above 60% compared to percent depletion below 60% across the measurement depths (Table 6). DANS was slightly correlated with percent depletion below 60% at 1.8 m depth compared to the other depths with a R^2 value of 0.33 and 0.028 °C (slope) rise for every percent increase in depletion. The 1.8 m depth was within the active maize crop root zone and this relationship evidenced that the DANS index was able to characterize soil water status albeit weakly at 60% soil water depletion. At a percent depletion greater than 60%, DANS values were strongly correlated with percent depletion values with R^2 values of 0.78, 0.71, and 0.70 at 0.6, 1.8, and 2.1 m, respectively. The correlation of the index at higher depletion levels across soil depths suggested that the DANS index was best suited to manage irrigation under deficit and/or water stress conditions. Similarly, Katimbo et al. (2022) discussed that the maize crop CWSI was better correlated with soil water depletion greater than 80%. Extreme values of DANS and the corresponding near out-of-range percent depletion values were observed in the RI treatments (Fig. 6). In addition to soil water dynamics, these extreme values are likely to correlate highly with other factors such as daily weather conditions and it is suggested to further investigate the sensitivity of the DANS index with key weather-based parameters as well as effect of crop growth stage.

3.6. Crop yield response across the irrigation scheduling methods

The variation of the yield and IWP across the scheduling treatments is shown in Table 6. The average yield across the SMM, ETM, and CTM irrigation scheduling treatments was 16.72 ± 1.45, 14.51 ± 0.71, and 15.27 ± 0.92 Mg ha^{-1} in 2018, 2019, and 2020, respectively. In all three growing seasons the scheduled treatments' yields were greater in magnitude and significantly different from the RF treatment. Interannual differences in yield values were also observed within similar scheduling method treatments. Irmak (2015) discussed that variations of yield across years for the same experimental treatment was attributed to seasonal climate differences.

Despite the irrigation differences amongst the SMM, ETM, and EI treatments in 2019, as discussed in Section 3.3, the grain yield for these three treatments was not significantly different ($P > 0.05$) (Table 6). Additionally, the CTM method's grain yield was not statistically different from that of the ETM method in 2019 despite having applied significantly more irrigation water. Since 2019 was a wetter than normal year, the statistical influence of irrigation and effect of scheduling method was indistinct. In 2020 the SMM and CTM where statistically similar ($P > 0.05$) while the ETM was similar to the EI treatment. The CTM scheduling method based on the DANS index performed best under dry conditions in which the method was more suited to identify crop water stress.

Irrigation water productivity values averaged across the scheduling treatments varied from 3.10 ± 0.09, 1.64 ± 0.47, and 2.92 ± 0.30 kg m^{-3} in 2018, 2019, and 2020, respectively. In all the experimental seasons, the IWP decreased with applied irrigation water similar to findings presented by Klocke et al. (2007), Lo et al. (2019), and Payero et al. (2008) at the same location. The CTM treatment had the least value of IWP in 2019 because excess irrigation coupled with the wetter than normal rainfall patterns reduced the impact of irrigation on

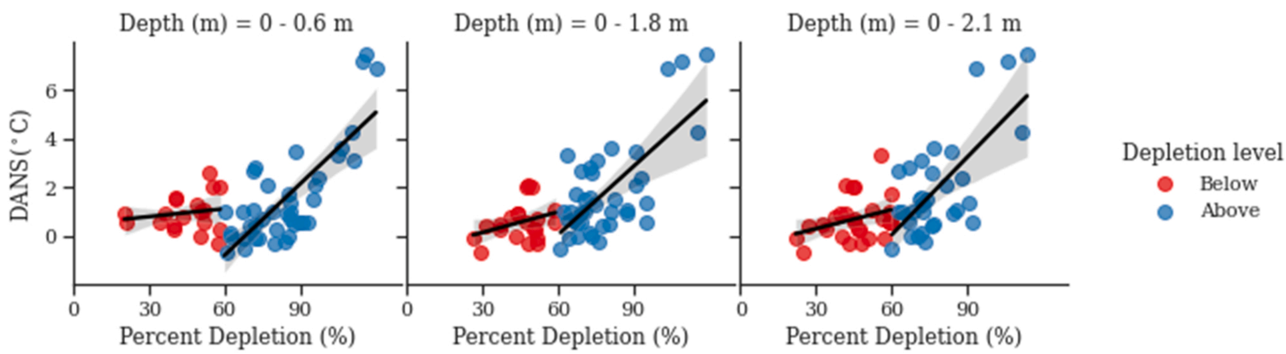

Fig. 6. Comparison between degrees above non-stressed (DANS) index and percent soil water depletion at soil profile depths of 0.6, 1.8, and 2.1 m during the 2020 growing season.

grain yield. During the normal year of 2018 the IWP were statistically similar across the scheduling treatments while in the wetter year of 2019 SMM and CTM were similar to the ETM model but not to each other. Significant differences in IWP across scheduling treatments occurred in 2020 with the CTM treatment having the greatest value. Since higher values of IWP indicated lower irrigation inputs per grain yield produced, growers under water limited conditions might opt for irrigation scheduling methods that maximize IWP for optimal profitability (Payero et al., 2008). For instance, the CTM method had a larger value of IWP in 2020 which could suggest that it was a suitable method for irrigation in limited water conditions. The reliability of IWP as reference metric for irrigation method performance may however only be limited to the dry growing season of 2020 where majority of the water applied contributes to crop evaporation with minimum runoff and/or deep percolation losses (Djaman and Irmak, 2012). Hence the evaluation of irrigation scheduling methods in the wetter years requires alternative reference metrics.

3.7. Practical considerations for application of DANS index-based irrigation scheduling

The transferability of the DANS index to other regions for irrigation water management is likely to be influenced by climatic and site specific factors. For example, it is postulated that for similar climatic conditions, there will be a gradual increase in the DANS index values in heavy clay soils which have a greater water holding capacity compared to a rapid increase of DANS values in sandy soils with low water holding capacities. In sandier soils crops are more prone to incur water stress faster which will be detected by the DANS index and will require frequent but shallow depths of application to avoid loss via percolation. On the other hand, crops planted on heavy clay soils which can accommodate deeper depth of irrigation water are likely to experience and indicate high DANS index values at a later time. Comparison of the thermal response of crops across soil types in localized and generalized settings is a research line to be investigated.

Considering climate, the numerical difference between the stressed and non-stressed baseline temperature is greater in arid compared to humid and sub-humid regions which also corresponds to a greater evaporative demand in the arid regions compared to humid regions. As such, a unit increase in canopy temperature above the non-stressed baseline temperature in humid regions likely accounts for greater stress level compared to that in arid regions. As such it is hypothesized that the DANS index threshold for a given crop will be lower in humid compared to arid regions to account for the same degree of stress. Further infield investigations are required to test this hypothesis. It is also important to note that the DANS index is only reflective of a point in time water stress intensity level. Further work to explore cumulative changes in DANS index over time and how these related to water stress indictors such as soil moisture are also recommended.

It was also hypothesized that since the DANS index varied across growth stages, growth-specific baselines and trigger thresholds could further improve the method.

4. Conclusions

This study evaluated the performance of canopy temperature based (CTM) irrigation scheduling using the degrees above non-stressed (DANS) index as compared to commonly applied soil moisture monitoring (SMM) and crop ET model (ETM) based irrigation scheduling techniques under semi-arid climatic conditions in three growing seasons of 2018, 2019, and 2020. This study used a modeled non-stressed canopy temperature (T_{cns}) in the computation of the DANS index and the comparison between the modeled and field observed T_{cns} had coefficient of determination (R^2) values of 0.88, 0.81, and 0.84 in 2018, 2019, and 2020, respectively. The utilization of a modeled rather than an observed T_{cns} could further ease the application and adoption of thermal indices specifically the DANS index in crop water stress monitoring. Also, the DANS index matched closely to CWSI, a conventionally used thermal indicator of crop water stress, with R^2 values of 0.64, 0.61, and 0.75 in 2018, 2019, and 2020, respectively.

In 2018 and 2019 the grain yields from the SMM and ETM methods were statistically similar but different from the CTM method while in 2020 the grain yield of the SMM and CTM were statistically comparable but dissimilar from those of the ETM treatment. Across the scheduling treatments more irrigation water was applied during the 2020 dry year and the CTM method had the highest IWP of the scheduling treatments. On the other hand, the IWP was statistically similar for the scheduling treatments in the normal 2018 year. These differences in dry compared to wet and normal years further authenticated that CTM based irrigation scheduling was better suited for deficit irrigation conditions. For irrigation scheduling, the selected thermal index thresholds played a great role in irrigation efficiency for the CTM method and lowering the DANS index trigger threshold from 1.0° to 0.5°C improved the method's performance in 2020 under the experiment conditions.

The DANS index values were observed to vary across crop growth stage in this study, and it is therefore suggested that growth stage-based irrigation trigger threshold values could be adopted. For example, growth stage specific thresholds could be set lower in the early season to capture onset of water stress but increase overtime to reflect crop's increased root zone as well as early senescence. Based on observation of the DANS crop growth stage variations in this study, threshold value range could be characterized as: 0.4 °C < DANS threshold < 0.5 °C during high water sensitive growth stages (tasseling and silking), DANS threshold = 0.5 °C post silking to mid-reproductive growth stages, and 0.5 °C < DANS threshold < 1 °C in late reproductive stage. The testing of growth stage-based thresholds and baselines is suggested for future research.

Data Availability

Data will be made available on request.

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Conflict of interest

The authors hereby declare no known conflicting interests that influenced this research and manuscript.

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