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Research Paper

Developing irrigation water conservation strategies for hybrid bermudagrass using an evapotranspiration-based smart irrigation controller in inland southern California

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ABSTRACT

A three-year (2017–2019) irrigation research trial was conducted to evaluate the response of hybrid bermudagrass to a wide range of irrigation scenarios and assess the efficacy of Weathermatic Evapotranspiration-based (ET-based) smart controller for autonomous landscape irrigation management during dry seasons in inland southern California. The irrigation levels applied throughout the experiment ranged between 39% and 103% reference ET (ETo) and the irrigation frequency restrictions imposed were 3, 5 and 7 d/wk. Normalized difference vegetation index (NDVI) data were continuously collected to evaluate the response of hybrid bermudagrass ['Tifgreen' *Cynodon dactylon* (L.) Pers. × *C. transvaalensis* Burtt-Davy] to irrigation treatments. Plots were also visually assessed and scaled from 1 (dead plot) to 9 (ideal turfgrass) following the National Turfgrass Evaluation Program (NTEP) standards. Turfgrass water response function (TWRF) was introduced as a statistical regression model to estimate hybrid bermudagrass quality response (NDVI values) to irrigation levels over time. In the years 2018 ($p < 0.01$) and 2019 ($p < 0.001$), the irrigation levels showed a significant effect on NDVI values. The irrigation frequency restrictions showed no significant impact on NDVI in any of the years. We observed a high correlation ($r = 0.84$) between visual rating (VR) and NDVI data. The TWRF shows a high accuracy (RMSE = 0.047, no units), and estimated NDVI values were highly correlated ($r = 0.89$) with measured NDVI values. A comparison between the California irrigation management information system (CIMIS) reference evapotranspiration (ETo) versus temperature-based ETo estimations by the controller revealed the smart controller on average over-irrigated by 12%, 2% and 3% throughout the experimental periods in 2017, 2018 and 2019, respectively. A long term (34 years) analysis using CIMIS ETo data and TWRF model revealed 75% ETo as the minimum irrigation application to maintain the acceptable hybrid bermudagrass quality in the inland southern California semiarid climate for months with high irrigation demand (i.e., May to November). The results also showed that hybrid bermudagrass could withstand more severe deficit irrigation treatments for shorter periods depending on ETo demand.

1. Introduction

An ever-growing population, combined with increasing water scarcity, has created urgency for integrated and sustainable water resources management across the state of California. Climate variability and change likely further impact available water resources (Vicuna et al., 2007). For this reason, it is vital to establish novel water conservation strategies for metropolitan areas in the state to enhance urban water use efficiency, keep landscape plants alive under continued drought and water restrictions, and guarantee the long-term sustainability of water resources.

Turfgrasses provide functional and recreational benefits to society and the environment and are also considered to be an essential part of the landscape and ecological systems (Monteiro, 2017). Turfgrass has become an important crop in the United States based on the maintained acreage, including residential, commercial, and institutional lawns, parks, golf courses, and athletic fields. Across the nation, residential lawns account for the largest sector of turfgrass. Typically, more than half of household water is used outdoors, mainly for irrigating landscapes (Mayer et al., 1999). Landscape water use in summer months can

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Fig. 1. Weathermatic ET-based smart irrigation controller and two enclosures housing the Data Snap data loggers (left) and a photo taken on September 4, 2017 showing an overview of the research plots (right).

account for up to 90% of total municipal water use in the southwestern United States (Cooley and Gleick, 2009). A significant portion of the applied water for landscape irrigation could be wasted due to over-irrigation, inefficient irrigation and broken or poorly maintained irrigation systems. A recent case study in three Kansas cities revealed that more than 60% of the surveyed homeowners (i.e., over 3000 homeowners) did not know how much water their lawns required and more than 70% did not know how much irrigation water they applied (Bremer et al., 2013).

Substantial advancements in smart urban irrigation technologies over the past two decades (mainly due to the development of computer technologies and the application of electromagnetic approaches to estimate soil water content) have led to the design, implementation and production of affordable smart irrigation controllers (Cardenas-Lailhacar et al., 2008). More recently, the commercialization of wireless sensing technologies and the rapid development of smartphone applications have further enhanced the capability to optimize site-specific urban irrigation management. Mayer et al. (1999) studied the water usage of single-family homes in twelve North American locations and showed households with automatic irrigation timers used 47% more water outdoors than those not using timers, revealing that the automation of urban irrigation systems without proper irrigation management leads to an over-application of water. The same study reported residential areas with in-ground sprinkler irrigation systems used 35% more water outdoors than areas with no in-ground systems (Mayer et al., 1999).

Literature indicates that the implementation of ET-based smart irrigation controllers provides opportunities to improve water use efficiency in residential areas by estimating the crop water demand and depletion of available soil water by incorporating weather data in irrigation scheduling. Davis et al. (2009) reported, on average, a 43% reduction in applied water using ET-based smart controllers compared to a time-based treatment in Florida. Other case studies in Florida and Nevada (Devitt et al., 2008; Davis and Dukes, 2016) reported that the ET-based controllers typically help conserve water as compared to fixed irrigation rates with no smart technology, yet Davis and Dukes (2016) emphasized it is crucial to evaluate the reliability of the algorithms used by available ET-based commercial controllers.

In some states, including California, Texas and Florida, the use of smart controllers is mandated or incentivized by law, yet much of the scientific research on the application and reliability of novel landscape irrigation management approaches, including the use of smart controllers, has been done in humid regions where the main objective was to avoid over-irrigation when rainfall is abundant (Dukes, 2012). Currently, information is lacking about the efficacy of ET-based smart irrigation technologies to autonomously implement water conservation and deficit irrigation strategies in inland southern California, the main objective of this study.

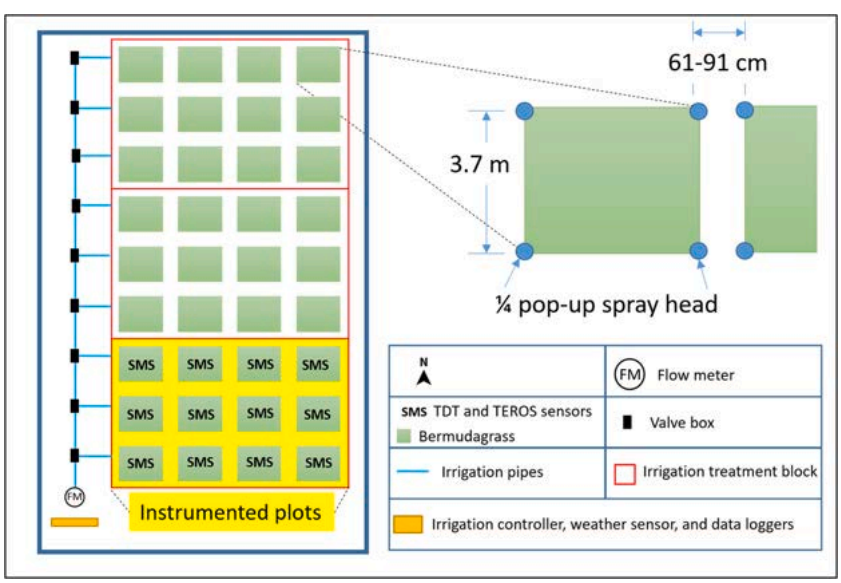

Fig. 2. The layout of the research site located at the University of California Riverside Agricultural Experiment Station.

In order to develop efficient water conservation strategies in urban settings, it is vital to quantify the response of landscape species to watering frequency restriction and deficit irrigation scenarios. The crop water production functions (CWPFs) are statistical models developed for agricultural crops to estimate the response of the crop (in terms of relative yield) to the varying deficit and full irrigation levels. The CWPFs have a wide range of applications including in irrigation scheduling and economic analysis (Haghverdi et al., 2014). Since turfgrass response to deficit irrigation is evaluated based on the esthetic values rather than relative yield, the term turfgrass water response function (TWRF) is proposed and hereafter used in this study. Consequently, the particular objectives of the study are to (i) evaluate the response of hybrid bermudagrass to a wide range of irrigation strategies including varying irrigation levels and frequency restrictions, (ii) determine the minimum irrigation requirement to maintain the desired quality level of hybrid bermudagrass, (iii) analyze the dynamics of near-surface volumetric soil water content and soil tension under a wide range of irrigation treatments, and (iv) develop a regression-based TWRF for hybrid bermudagrass irrigation management in inland Southern California.

2. Materials and methods

2.1. Experimental site

A three-year (2017–2019) hybrid bermudagrass irrigation research study was conducted at the University of California Riverside Agricultural Experiment Station (33°57′47.0″N 117°20′13.4″W) in Riverside, California. The soil at the research site is classified as a well-drained-low runoff Hanford coarse sandy loam (websoilsurvey.sc.egov.usda.gov) with a soil volumetric water content of 22.5% at 33 kPa. The climate at Riverside is semi-arid, with a long-term average (1986–2016) reference ET (ETo) and rainfall of 1471 and 220 mm year^{-1}, respectively.

2.2. Irrigation trial

A total of 36 plots were organized in a factorial complete randomized block design with repeated measures to study the response of hybrid bermudagrass ['Tifgreen' *Cynodon dactylon* (L.) Pers. × *C. transvaalensis* Burtt-Davy] to 12 irrigation treatments (6 irrigation levels × 2 irrigation frequency restrictions) replicated three times (Figs. 1 and 2). Table 1 summarizes the irrigation treatments.

Plots sized 3.7 m × 3.7 m with approximately 60–90 cm border between the plots to eliminate plot edge effect and avoid interference between adjacent plots. Plot and irrigation system establishment was completed from Jan to April 2017. The plots were covered with sod in May 2017 and for several months non-limiting water was provided for root development and grass establishment. Each plot was equipped with a Hunter PGV-101G solenoid valve (Hunter Industries, Inc., San Marcos, CA) which controlled and supplied water to 4 quarter-circle, 102 mm tall pop-up sprinkler heads (Toro O-T-12-QP) with operating pressure range and flow rate of 276–517 kPa and 0.001–0.545 m^3 h^{-1}, respectively. A pressure regulator was installed to regulate pressure to approximately 380 kPa upstream of the irrigation plots. The sprinklers were equipped with a factory-installed, pressure-compensating disc to regulate the flow and maintain steady water pressure (Toro Co., Bloomington, MN, USA). We followed standard cultural practices to maintain the plots throughout the experimental periods. A triplex mower was set to mow the plots roughly at the height of 13 mm twice per week. The fertilizer was applied uniformly to all plots. The borders were sprayed regularly with herbicides ("Roundup Pro" and "Makaze") to control the weeds.

A Weathermatic Smartline (SL) 4800 ET-based smart irrigation controller connected to an SLW5 wireless weather sensor was used to apply irrigation across the treatments (Telsco Industries, Inc, Garland, TX, USA). An SLFSI-T10 flow sensor (Telsco Industries, Inc, Garland, TX, USA) in 2017 and 2018 and a Badger Meter Recordall Turbo flowmeter (Badger Meter, Inc., Milwaukee, WI, USA) in 2019 were connected to the controller for automatic leak detection and water application monitoring. The controller utilized on-site measured temperature data and latitude based solar radiation estimations to calculate ETo using the Hargreaves equation (Hargreaves and Samani, 1985). The estimated ETo was used by the controller to determine the water deficit each day at midnight based on user-defined "plant type" values for each treatment (irrigation application = plant type × ETo). For each treatment, the plant type value was calculated as the percentage of ETo divided by the efficiency of the irrigation system. The next irrigation was then applied based on the water deficit accumulated since the last irrigation event for each treatment. The controller converts the irrigation application into irrigation runtime values based on the user-defined estimated precipitation rate of the irrigation system. The controller set back the water deficit to zero when watering was finished. While the irrigation frequency restrictions eliminated water applications on specific weekdays, to avoid light irrigation, the controller was programmed to use the default deficit threshold (3.81 mm) as the amount of deficit that must be accumulated before any irrigation occurs.

Plots were irrigated overnight to minimize evaporative losses and wind drift. Total daily irrigation run time was divided into multiple irrigation applications to avoid a runoff. The controller was wired such that all three replications were irrigated at the same time. The trials started on July 9, May 1, and June 1 and ended on October 5, September 12 and October 19 in 2017, 2018 and 2019, respectively. Throughout the experiment, all the irrigation applications were automatically calculated and applied by the irrigation controller using plant type and watering cycles values programmed by the research team at the beginning of the experimental period. All plots were switched back to the uniform non-limiting irrigation for recovery each year after the termination of the experiment.

Table 1
Irrigation treatments imposed throughout the 3-year hybrid bermudagrass irrigation research experiment conducted at the University of California Riverside Agricultural Experiment Station.

2017 Trial, Start: July 9, 2017 | End: October 5, 2017	
	Irrigation levels (% ETo): 35% , 45% , 50% , 60% , 65% , 70%
	Watering Days: 3 days per week, 5 days per week
2018 Trial, Start: May 1, 2018 | End: September 12, 2018	
	Irrigation levels (% ETo): 35% , 40% , 45% , 50% , 55% , 60%
	Watering Days: 3 days per week, 7 days per week (no restriction)
2019 Trial, Start: June 1, 2019 | End: October 19, 2019	
	Irrigation levels (% ETo): 35% , 40% , 45% , 50% , 55% , 60%
	Watering Days: 3 days per week, 7 days per week (no restriction)

*The controller used the user-defined "plant type" information to convert ETo to irrigation application (Irrigation application = plant type × ETo). For each treatment, the plant type was calculated as the irrigation levels (% ETo) divided by the irrigation efficiency of the system.

2.3. Data collection and analysis

Two types of soil moisture sensors were used in this study, including TEROS 21 (METER Group, Inc., Pullman, WA, USA) soil tension and SDI-12 Digital Time Domain Transmissometer (TDT) soil water content sensors (Acclima Inc., Meridian, ID, USA). The TEROS 21 sensor has a measurement range of 9–100000 kPa with a 0.1 kPa resolution and accuracy of ± (10% of reading + 2 kPa) from 9 to 100 kPa, according to the manufacturer. TEROS 21 measurements represent the matric potential of the soil since its ceramic disc comes into hydraulic equilibrium with the surrounding soil. The Acclima TDT sensor measures the soil permittivity and subsequently estimates the soil volumetric water content (VWC) by transmitting an electromagnetic wave along a waveguide (rod) through the soil and calculating the propagation time. The TDT sensors have a measurement range of 0–100% VWC with a 0.06% resolution and ± 2% VWC typical accuracy, as reported by the

manufacturer.

One experimental block (a total of twelve plots) was instrumented with soil moisture sensors. One TEROS 21 and one TDT sensor were installed roughly at the center of each plot in the active turfgrass rootzone approximately 127–152 mm deep. The DataSnap (Acclima Inc., Meridian, ID, USA) and EM50 (METER Group, Inc., Pullman, WA, USA) loggers were used to collect soil moisture data every 30 min.

The normalized difference vegetation index (NDVI, Eq. (1)) was selected as the main parameter to monitor turfgrass response to the imposed irrigation treatments since it provides consistent objective values representing overall turfgrass health and quality (Bell et al., 2009):

$$NDVI = \frac{NIR - R}{NIR + R} \tag{1}$$

where NIR and R are near infrared and red reflectance values, respectively.

The NDVI data were collected using the active light source optical GreenSeeker handheld sensor (Trimble Inc., Sunnyvale, CA, USA). The sensor has an oval field of view, approximately 51 cm wide at 122 cm above the ground, and a measurement range of 0–0.99. The sensor emits brief bursts of red and infrared light and then measures the reflectance value for each band. The GreenSeeker was held at the waist height (~ 1 m) and hovered over the center of each plot (~ 3–4 m^2) while the trigger remained engaged, so the sensor continuously sampled the scanned area and reported the average NDVI. The measurements were done under cloud-free conditions within two hours of solar noon. The NDVI data were collected for a total of 12 times in 2017 (July 7 to September 22), 18 times in 2018 (May 1, 2018, to September 24, 2018) and 16 times in 2019 (June 1, 2019, to October 19, 2019). Plots were also visually assessed and scaled from 1 (dead plot) to 9 (ideal turfgrass) following the National Turfgrass Evaluation Program (NTEP) standards (Shearman and Morris, 1998). The visual ratings were done 3, 18 and 12 times in 2017, 2018 and 2019, respectively. The visual score six was considered roughly the minimum acceptable quality for residential areas.

The NDVI and visual ratings were statistically analyzed using PROC GLIMMIX in SAS 9.4 software package (SAS Institute Inc, 2014). Each year was independently analyzed for the treatment effects since the irrigation application and duration of the experiment differed across the years. For all the response variables, irrigation levels, irrigation frequencies, and the date of data collection were considered the fixed effect while block and its interaction with irrigation levels and irrigation frequencies were the random effects. The treatment effects were considered significant at p-values ≤ 0.05. All graphs were created using the plotting software package Veusz 3.2.1 (Sanders, 2018).

The daily ETo data were collected from a nearby California Irrigation Management Information System (CIMIS; station number 44) weather station located approximately 250 m away from the experimental site. The CIMIS uses a revised version of the Pruitt-Doorenbos modified Penman equation (which utilizes a unique cloud factor value for each station and a wind function developed at the University of California, Davis) to calculate ETo using hourly weather data (Eching, 1998). The irrigation runtime data reported by the smart irrigation controller were converted to percent ETo values (after adjusting for the irrigation treatment and irrigation efficiency) and compared against the CIMIS data.

We focused on high ETo demand months in this study when significant precipitation is highly unlikely. Repeating the experiment for three years with adequate recovery periods between the years enabled us to test a wide range of irrigation treatments and generate enough data points necessary to develop TWRF. We used a multiple linear regression with interactions and quadratic terms included to develop hybrid bermudagrass TWRF. The data for all three years were combined. The average NDVI values for treatments were used as the response variable. The primary input variables included applied irrigation levels (%ETo), irrigation frequency restrictions, and cumulative ETo (since the beginning of the experiment for each particular year). All possible regression equations were developed and ranked based on correlation coefficients (with 0.7 as the minimum acceptable value) using SAS 9.4 software (SAS Institute Inc., Cary, NC, USA). Then, the list of input variables of the top model was finalized using multiple regression diagnostics including the Shapiro–Wilk W statistic to check the normality of the residuals, the condition index to monitor the collinearity between the variables, and the first and second moment specification test to check the equal residual variance. The RMSE and correlation coefficient were calculated to evaluate the performance of the TWRF.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_i - M_i)^2} \tag{2}$$

$$r = \frac{\sum_{i=1}^{n}\left(E_i - \overline{E}\right)\left(M_i - \overline{M}\right)}{\sqrt{\sum_{i=1}^{n}\left(E_i - \overline{E}\right)^2 \sum_{i=1}^{n}\left(M_i - \overline{M}\right)^2}} \tag{3}$$

where E and M are estimated and measured NDVI values. $\overline{M}$ and $\overline{E}$ are the mean-measured and the mean-estimated NDVI values, and n is the total number of measured data points for the entire experiment ($n = 564$).

3. Results

3.1. Performance of the controller

Table 2 summarizes the irrigation treatment values (i.e., percentages of ETo), programmed irrigation levels into the controller (i.e., irrigation treatment values divided by the irrigation efficiency), and applied water throughout the experiment. The applied water values are based on the actual average precipitation rate of the system measured by the calibrated flowmeter in 2019. The typical industry practice is to estimate precipitation rate and distribution uniformity of landscape sprinkler irrigation systems using a catch-can test. We ran two catch-can tests in 2017 and 2018 to determine the uniformity and precipitation rate of the irrigation system following the ANSI/ASABE S626 procedure (ASABE, 2016). The tests were conducted on days that were not windy (wind speed less than 2.24 m s^{-1}), with 10 min test periods. In 2017, the test

Table 2
Irrigation treatments (T1–T6), versus programmed and applied irrigation levels throughout the 3-year hybrid bermudagrass irrigation research experiment conducted at the University of California Riverside Agricultural Experiment Station.

Irrigation	T1	T2	T3	T4	T5	T6
Treatment-2017	35	45	50	60	65	70
Programmed-2017	45	58	65	78	84	91
Applied-2017	54	63	74	83	93	103
Treatment-2018	35	40	45	50	55	60
Programmed-2018	43	49	56	62	68	74
Applied-2018	50	58	66	72	79	86
Treatment-2019	35	40	45	50	55	60
Programmed-2019	46	53	59	66	72	79
Applied-2019	39	44	49	56	62	66

*Programmed irrigation levels are equal to treatment levels divided by the irrigation efficiency in each year. The irrigation efficiency was set to 0.77, 0.81, and 0.76 in 2017, 2018 and 2019. In 2017 and 2018 the precipitation rate of the irrigation system was calculated using early trial catch-can tests and set to 25 and 22 mm h^{-1}, respectively. In 2019, the precipitation rate was set to 29 mm h^{-1} based on flow data from a calibrated flowmeter. Consequently, the abovementioned applied irrigation levels for years 2017 and 2018 were also recalculated using the 29 mm h^{-1} precipitation rate.

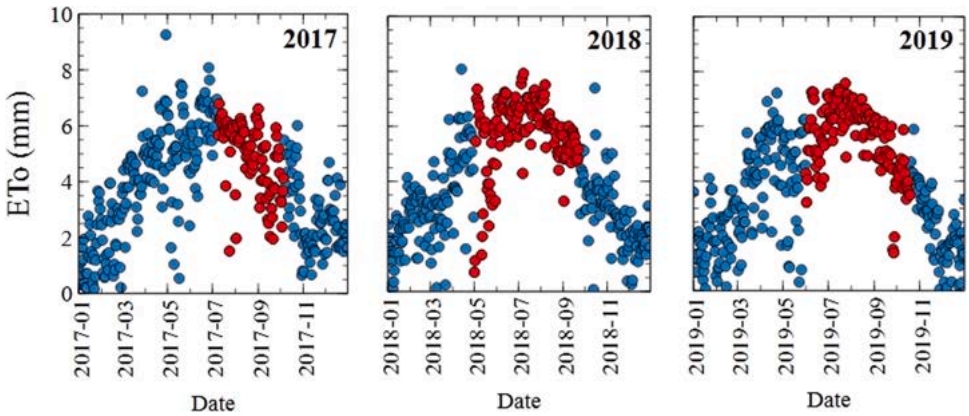

Fig. 3. Changes in daily ETo (mm) in years 2017, 2018 and 2019 obtained from a CIMIS weather station located nearby the experimental site. The trial periods are highlighted in red. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

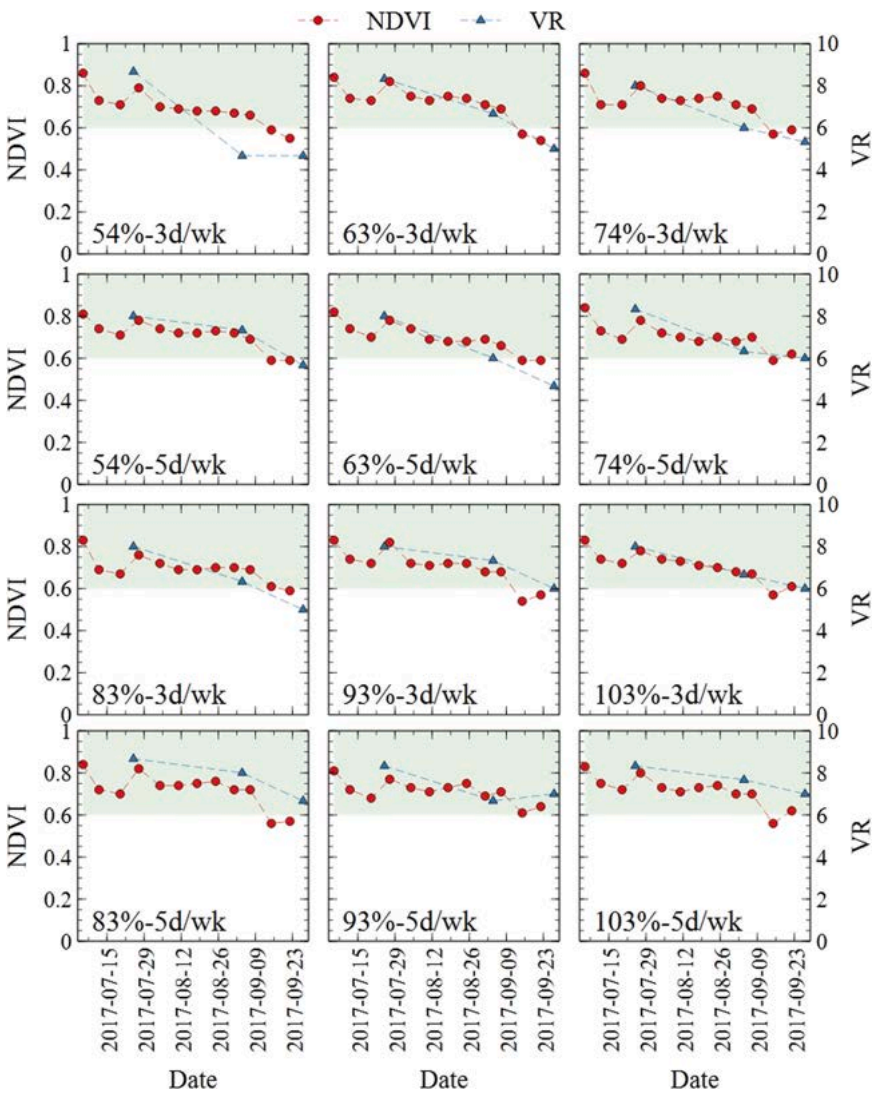

Fig. 4. Changes in visual ratings (VR; blue) versus normalized difference vegetation index (NDVI; red) values over time across the irrigation treatments imposed in 2017. The VR and NDVI values greater than 6 and 0.6, respectively, are highlighted in green to show the acceptable quality for residential areas. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

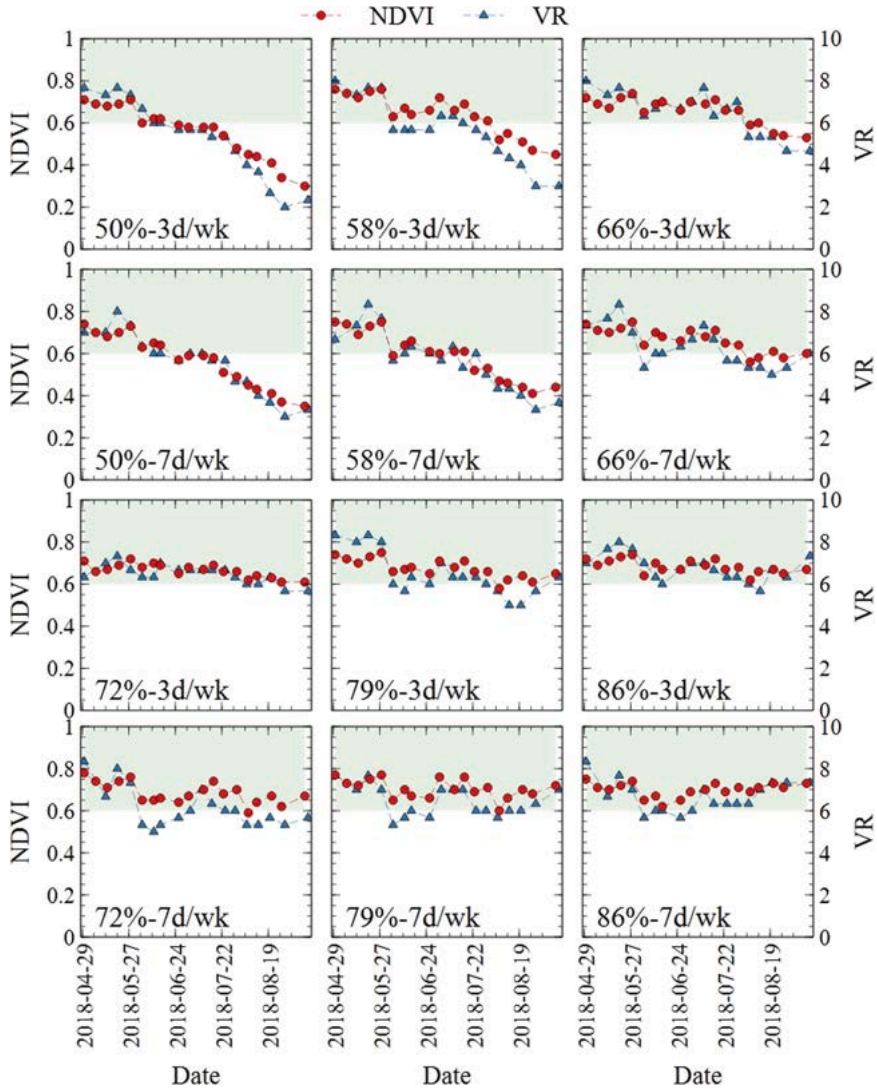

Fig. 5. Changes in visual ratings (VR; blue) versus normalized difference vegetation index (NDVI; red) values over time across the irrigation treatments imposed in 2018. The VR and NDVI values greater than 6 and 0.6, respectively, are highlighted in green to show the acceptable quality for residential areas. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

was repeated four times, each time using 120 catch devices. In 2018, the test was repeated three times, each time using 60 catch devices. Based on the results of the catch-can tests, the irrigation efficiency (i.e., the low half distribution uniformity) and precipitation rate were set to 0.77 and 25 mm h^{-1} in 2017 and to 0.81 and 22 mm h^{-1} in 2018. In 2019, the factory-calibrated Badger flow meter data were utilized to calculate a precipitation rate of 29 mm h^{-1} for the system and the irrigation efficiency was set to 0.76 (equal to the average flow measured by the flow meter divided by the flow estimated based on 2018 catch can test).

Fig. 3 depicts the dynamics of CIMIS ETo values in the years 2017, 2018 and 2019. The cumulative ETo in the years 2017, 2018, and 2019 were 1431, 1503, 1469 mm, respectively. The cumulative ETo values in the experimental periods were 434, 840, and 790 mm in 2017, 2018, and 2019, respectively. The average daily ETo throughout the experimental periods was 5, 6, and 6 mm day^{-1} in 2017, 2018, and 2019, respectively. The precipitation was negligible during the trial with only 12 mm, 8 mm, and 1 mm in years 2017, 2018 and 2019, respectively.

Analysis of the CIMIS data reveals that the smart controller over irrigated the plots by an average of 12% (range: 10–15%), 2% (range: 1–5%) and 3% (range: less than one up to 6%) throughout the experimental periods in 2017, 2018 and 2019, respectively. The analysis of irrigation runtime data showed that the actual irrigation frequencies for the 3 d wk^{-1} treatments varied between 2.8 and 3 d wk^{-1} in 2017 and between 2.7 and 2.9 d wk^{-1} in 2018. In 2019, 3 d wk^{-1} treatments had an average frequency of 4.3 d wk^{-1}. That is likely because the controller was programmed to irrigate the 3 d wk^{-1} treatments late at night; therefore, it had sometimes crossed midnight to complete the irrigation cycles. The 5 d wk^{-1} treatments were irrigated between 2.8 and 4.6 d wk^{-1} in 2017. No frequency restrictions (i.e., 7 d wk^{-1} irrigation treatment) resulted in 3.8–6.5 d wk^{-1} irrigation in 2018 and 3.4–5.9 d wk^{-1} irrigation in 2019.

3.2. Impact of irrigation treatments: NDVI & visual rating

Figs. 4–6 depict the dynamics of VR versus NDVI values over time across the irrigation treatments imposed in 2017, 2018 and 2019, respectively. Fig. 7 shows the relationship between NDVI and VR values. To make a reliable comparison, only readings that were made on the same date or one day apart in 2018 and 2019 were used. The *r* value of 0.84 indicated a strong correlation between NDVI and VR. The fitted linear regression showed an NDVI value of 0.6 as the minimum acceptable quality corresponding to VR of 6.

Table 3 summarizes the results of the statistical analysis. In our study, the 2018 and 2017 trials were the longest and shortest among the three years. The June 2018 NDVI and VR data were impacted by improper mowing hence were removed from the statistical analysis but are shown in Figs. 4–6 and 7–8. The NDVI values ranged from 0.50 to 0.88 in 2017, from 0.29 to 0.84 in 2018 and from 0.25 to 0.81 in 2019. In the years 2018 ($p < 0.01$) and 2019 ($p < 0.001$), the irrigation levels showed a significant effect on NDVI values. The irrigation frequency restrictions showed no significant impact on NDVI in any of the years. Restricting irrigation frequencies slightly decreased the NDVI in 2017 and 2018 but not in 2019. The interaction of irrigation level and frequency showed a significant impact on NDVI in 2019 ($p < 0.05$). The 2017 NDVI values followed a similar pattern across the irrigation treatments such that the differences were not statistically significant. The 2018 and 2019 NDVI values were lower for more severe deficit irrigation treatments as expected.

The VR values ranged from 3 to 9 in 2017, from 2 to 9 in 2018, and from 2 to 8 in 2019. The irrigation quantity showed a significant effect on VR values in 2018 ($p < 0.001$) and 2019 ($p < 0.001$) but not in 2017. The irrigation frequency had a significant impact only in 2019 ($p < 0.05$). Restricting irrigation frequency caused lower VR values in 2017 and 2018, but not in 2019. The interaction of irrigation level and irrigation frequency showed no significant impact on VR in any of the years.

Fig. 8 illustrates the dynamics of NDVI values over time across the irrigation treatments for the years 2017, 2018 and 2019. The NDVI values greater than 0.6 are highlighted in green to proximate the acceptable hybrid bermudagrass quality for residential areas. All 2017 treatments showed a similar response over time. A steady decrease in NDVI values occurred as the trial progressed, yet treatments stayed in the accepted quality range for almost the entire duration of the experiment. The last two NDVI values, however, were close to or slightly lower than the 0.6 NDVI threshold. The lowest 2018 irrigation treatments (50% and 58% ETo) showed a constant decrease in NDVI over time to

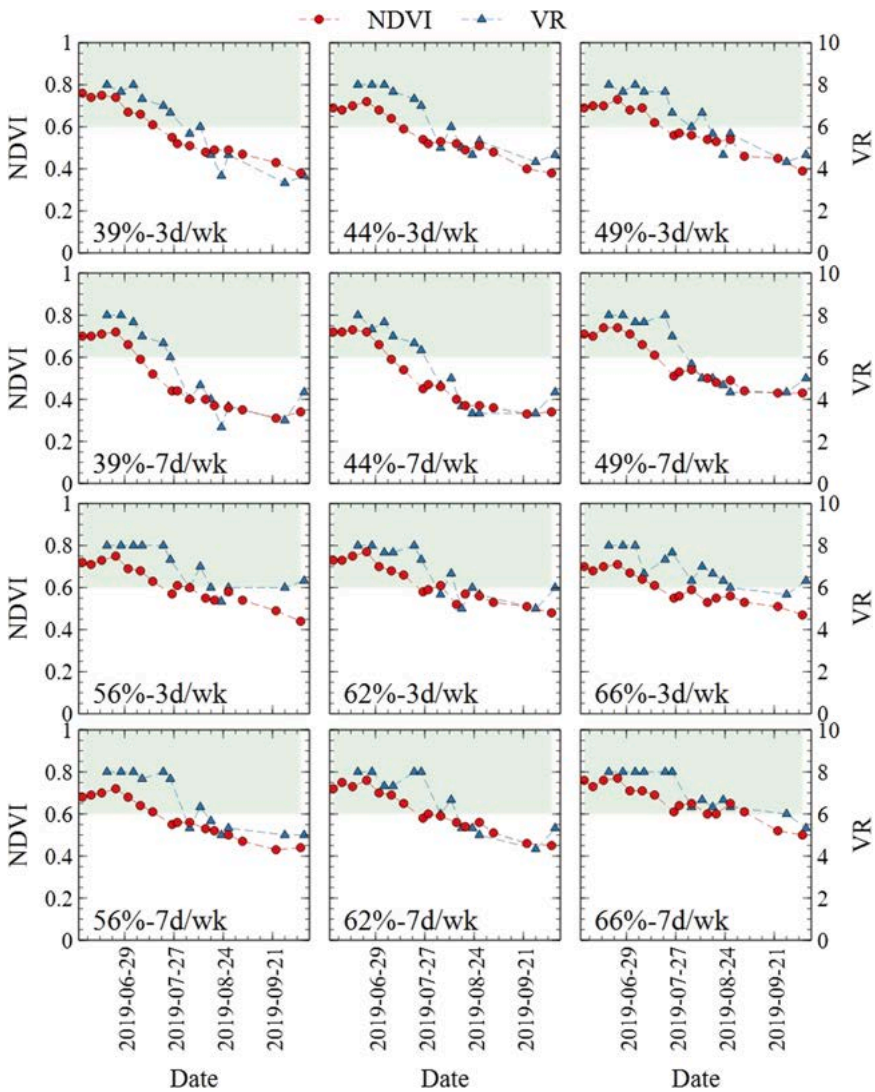

Fig. 6. Changes in visual ratings (VR; blue) versus normalized difference vegetation index (NDVI; red) values over time across the irrigation treatments imposed in 2019. The VR and NDVI values greater than 6 and 0.6, respectively, are highlighted in green to show the acceptable quality for residential areas. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

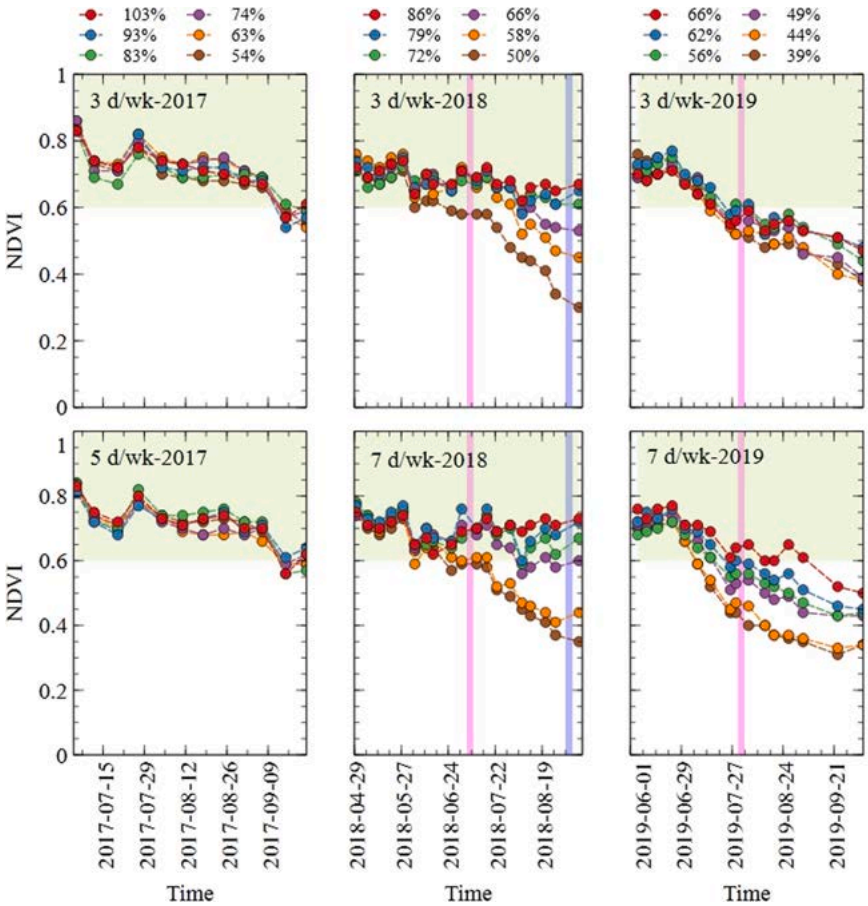

Fig. 7. Changes in normalized difference vegetation index (NDVI) values over time across the irrigation treatments imposed in 2017, 2018, and 2019. The cumulative ETo in 2017, 2018 and 2019 trial periods were 378 mm, 777 mm, 741 mm, respectively. The pink and purple strips mark the dates when the cumulative ETo passed 378 and 741 mm, respectively. NDVI values greater than 0.6 are highlighted in green to show the accepted quality range for residential areas. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

values below the 0.6 threshold in early to late July. Other 2018 treatments illustrated a more gradual reduction in NDVI values over time such that the top three irrigation levels (i.e., 86%, 79%, and 72% ETo) stayed in the acceptable quality range. The lowest 2019 irrigation treatments (39% and 44% ETo) had significantly lower NDVI values compared to the other treatments. All 2019 treatments showed a similar trend of continuous reduction in NDVI values down to 0.4–0.5 levels for the 3 d wk^{-1} treatments. For the 7 d wk^{-1} treatments, the same overall trend was observed, but the lowest irrigation treatments (i.e., 39% and 44% ETo) showed a greater reduction in NDVI values compared to the other treatments. All treatments reached NDVI values less than 0.6 threshold toward the end of the 2019 experiment. The downward trend in quality over time suggests that most of the 2019 irrigation levels were not sustainable and could only maintain the quality in the acceptable range for a certain period of time.

Fig. 9 illustrates the dynamics of visual rating (VR) values over time across the irrigation treatments for the years 2017, 2018 and 2019. The VR greater than 6 are highlighted in green to show the acceptable hybrid bermudagrass quality for residential areas. The 2017 VR of 103% and 93% ETo and 3 d wk^{-1} treatments reduced over time (like the rest of the treatments), yet stayed above the minimum acceptable VR of 6. The VRs were slightly higher for the 5 d wk^{-1} treatments such that only 63% and 54% ETo levels fell below the minimum quality level toward the end of the trial. The lowest 2018 irrigation treatments (50% and 58% ETo) had significantly lower VR values compared to that of other treatments. The top three 2018 irrigation levels (i.e., 86%, 79% and 72% ETo) had VR greater than 6 for most of the experimental period. The VR of 50% and 58% ETo irrigation levels in both frequencies fell below the minimum threshold towards the end of June 2018. The VR values for all the 2019 treatments gradually diminished over time. The 66% ETo had the highest VR values and stay above the minimum threshold for most of the experimental period. The lowest 2019 irrigation treatments (39% and 44% ETo) had significantly lower VR values than the other treatments.

3.3. Soil water dynamics

Fig. 10 shows the dynamics of mean daily soil tension and VWC values across the irrigation treatments in three years of the experiment. The 2017 VWC across 5 d wk^{-1} treatments showed a gradual reduction over time, more pronounced for the 74%, 63% and 54% ETo irrigation levels. The VWC values of the greatest irrigation level (103% ETo), however, showed a relatively slight fluctuation and an increase toward the end of the experiment. A similar trend was observed for the 7 d wk^{-1} treatments, but VWC for the top three irrigation levels (103%, 93% and 83% ETo) showed low fluctuations over time. Overall, soil tension followed the same pattern of variation as VWC. The soil tension fluctuated around pF 2–2.5 (9.8–31 kPa) for the irrigation level of 103% ETo. The soil tension decreased to roughly pF of 4.5 (3100 kPa) and VWC of 7.5% for the 54% ETo irrigation level and 5 d wk^{-1} frequency. For 54% ETo and 5 d wk^{-1} treatment, the soil tension and soil moisture content decreased to roughly a pF of 4–4.5 (981–3100 kPa) and VWC of 10%. The top three 2018 irrigation treatments (86%, 79% and 72% ETo) showed similar VWC patterns consisting of a gradual reduction till the May/June and then slight fluctuations with minimum to no decrease over time. The 50% and 58% ETo treatments showed a more pronounced reduction in VWC and soil tension levels down to 15% and pF 3.5–4 (310–981 kPa) for the 3 d wk^{-1} frequency and 13% and pF 4–4.5 (981–3100 kPa) for the 7 d wk^{-1} frequency. The soil tension and VWC of 2019 treatments with no frequency restriction (7 d wk^{-1}) showed a sharp reduction at the beginning of the experiment. Afterward, the soil tension and VWC more gradually diminished toward the end of the trial. The 3 d wk^{-1} treatments followed a somewhat similar pattern but with

Table 3
Statistical analysis of the hybrid bermudagrass response in terms of visual rating (VR) and normalized difference vegetation index (NDVI) to irrigation treatments imposed in years 2017, 2018 and 2019 (each year was analyzed separately).

2017			**2018**			**2019**		
ETo%	NDVI	VR	ETo%	NDVI	VR	ETo%	NDVI	VR
54%	0.70 a	6.50 ba	50%	0.55c	5.26c	39%	0.54c	5.62c
63%	0.71 a	6.44 b	58%	0.61 BCE	5.62c	44%	0.54c	5.83c
74%	0.71 a	6.67 ba	66%	0.66 ba	6.42 ba	49%	0.58 b	6.29 b
83%	0.71 a	7.11 ba	72%	0.68 a	6.39 b	56%	0.60 ab	6.59 ba
93%	0.71 a	7.22 ba	79%	0.70 a	6.63 ba	62%	0.62 ab	6.73 ba
103%	0.71 a	7.28 a	86%	0.70 a	6.88 a	66%	0.63 a	6.99 a
	2017			**2018**			**2019**	
Days	NDVI	VR	Days	NDVI	VR	Days	NDVI	VR
3 d/w	0.70 a	6.59 b	3 d/w	0.64 a	6.18 a	3 d/w	0.59 a	6.50 a
5 d/w	0.71 a	7.14 a	7 d/w	0.65 a	6.22 a	7 d/w	0.57 a	6.18 b
	2017			**2018**			**2019**	
	p-value			*p*-value			*p*-value	
I	NS	NS	I	**	***	I	***	***
F	NS	NS	F	NS	NS	F	NS	*
I × F	NS	NS	I × F	NS	NS	I × F	*	NS
T	***	***	T	***	***	T	***	***
I × T	NS	NS	I × T	***	***	I × T	***	***
F × T	NS	NS	F × T	*	*	F × T	***	**
I × F × T	NS	NS	I × F × T	NS	NS	I × F × T	NS	NS

NS, ***, ** and * are non significant or significant at $p \leq 0.001$, 0.01, and 0.05, respectively.
Means sharing a similar letter are not significantly different, based on Turkey's Test at $\alpha = 0.05$.
The irrigation levels were adjusted based on the actual water application calculated using the calibrated flow meter data in 2019. I, F, and T in the table refer to irrigation levels, frequency restrictions and time (i.e., repeated measures of NDVI and VR each year over time), respectively.

much higher fluctuations, except for the 66% ETo treatment, which showed almost no reduction in VWC over time. The noticeable spikes in soil tension values toward the end of the 2019 experiment is attributed to several cloudy days with very low evaporative demands.

3.4. Turfgrass water response function

The TWRF developed using the combined three years data is:

$$NDVI = 0.604 - 0.110 \times 10^{-2}(CETo) + 0.521(I) - 0.407\left(I^2\right) + 0.176 \times 10^{-6}\left(CETo^2\right) + 0.101 \times 10^{-2}(I)(CETo) \quad (4)$$

where I is the relative irrigation level (ETo percentages) and $CETo$ is the cumulative ETo (mm). Fig. 11 shows the scatter plot of the estimated versus measured NDVI values. The slope and shape of the developed TWRF clearly illustrate how higher deficit irrigation levels fell below the minimum acceptable quality much quicker than moderate deficit irrigation scenarios. The TWRF showed high accuracy (RMSE = 0.047) and estimated NDVI values are highly correlated ($r = 0.89$) with measured NDVI values.

4. Discussion

4.1. Response of hybrid bermudagrass to deficit irrigation treatments

The reported water requirement for warm-season grasses varies substantially in the literature. Wherley et al. (2015) developed crop coefficients (Kc) for four warm-season turfgrass species, including 'Tifway' bermudagrass [*Cynodon dactylon* (L.) Pers. × *C. transvaalensis* Burtt-Davy] using three seasons data collected from non-stressed, well-watered turfgrass in Florida. They reported fluctuations in Kc values over time with roughly 0.8 and 0.3 as Kc values for active growth periods (periods with greatest pressure deficit and solar radiation) and slow-growing late fall and dormant winter seasons, respectively. They showed that a commonly used Kc value of 0.6 for warm-season turfgrass underestimated actual ET during active growth periods, a fact that was also observed in our study. Pinnix and Miller (2019) reported Kc values of 0.44–0.59 (± 0.10 standard deviation) for 'Tifway' hybrid bermudagrass in North Carolina. These values are substantially lower than the values reported for Florida by Wherley et al. (2015) and our results also suggest a much higher irrigation requirement for bermudagrass. We attribute the spatial variability in reported warm-season turfgrass water requirements among these studies to the environmental conditions, a fact that was also mentioned by Pinnix and Miller (2019), who also emphasized the need for development and use of local Kc values for turfgrass.

We used the fitted TWRF to estimate the response of hybrid bermudagrass to multiple levels of irrigation using the long term (34 years) ETo data obtained from the CIMIS station located in the study area. Fig. 12 shows the maximum, minimum and average NDVI values for six months (May to November). The results suggest 75% ETo as the minimum irrigation application to maintain the minimum acceptable hybrid bermudagrass quality in the inland southern California semiarid climate during the high water demand months (i.e., May to November). The results suggest that imposing more severe deficit irrigation levels is feasible for shorter periods before the hybrid bermudagrass quality starts to fall below the minimum acceptable quality. The hybrid bermudagrass ability to withstand drought varies roughly between 25 and 75 consecutive days for 40–70% ETo irrigation levels, respectively. The results also reveal that the variation in weather conditions have a more pronounced impact on hybrid bermudagrass quality when more severe deficit irrigation scenarios are imposed. For example, depending on weather conditions (i.e., ETo demand), it may take twice as long (roughly 50 versus 25 days for years with min and max ETo demands, respectively) for a 40% ETo irrigation application to result in unacceptable hybrid bermudagrass quality. In contrast, the variation in weather conditions (i.e., ETo demand) has a much less noticeable impact on hybrid bermudagrass quality (NDVI levels) for a 70% ETo irrigation application.

Our soil moisture data suggest that hybrid bermudagrass likely maintains acceptable quality when near-surface (i.e., 127–152 mm deep) soil tension and VWC values fluctuate around pF of 2.5–3 (31–98 kPa) and VWC of 20–25%, respectively. For the study site, the laboratory-measured VWC of soil surface (0–20 cm) at soil tensions of 10 and 33 kPa are 30% and 22%, respectively. Further studies are needed to determine whether these values could be used as triggering

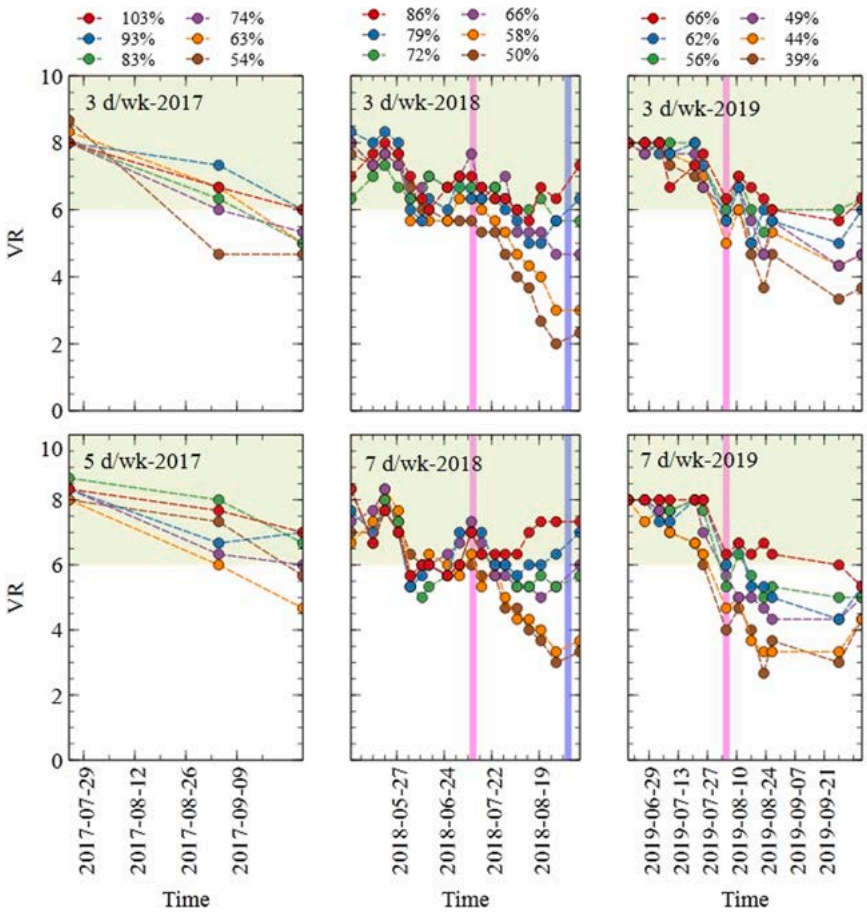

Fig. 8. Changes in visual rating (VR) values over time across the irrigation treatments imposed in 2017, 2018, and 2019. The cumulative ETo in 2017, 2018 and 2019 trial periods were 378 mm, 777 mm, 741 mm, respectively. The pink and purple strips mark the dates when the cumulative ETo passed 378 and 741 mm, respectively. VR values greater than 6 are highlighted in green to show the accepted quality range for residential areas. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

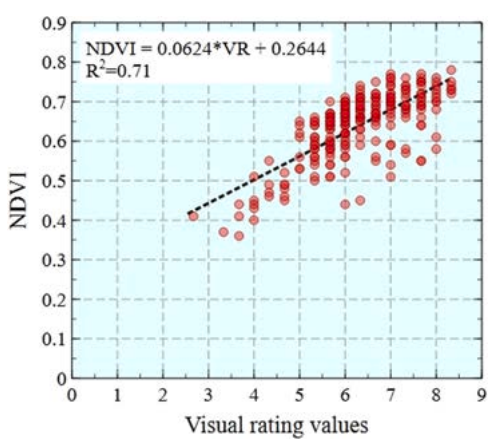

Fig. 9. Relationship between visual rating and NDVI values for selected 2018 and 2019 data.

thresholds for efficient autonomous irrigation management of hybrid bermudagrass using soil moisture based smart irrigation controllers in the region with similar soil type.

4.2. Autonomous deficit irrigation using weathermatic ET-based controller

Davis and Dukes (2010) emphasized the importance of manufacturer programmed and user-defined settings on proper irrigation scheduling using ET-based smart controllers. Our results showed that accurate estimation of irrigation precipitation rate and proper selection of plant factor (i.e., optimum fraction ETo irrigation replacement to conserve water while maintaining the minimum acceptable landscape quality) are critical factors for reliable autonomous deficit irrigation scheduling by ET based controllers in summer months in the arid region of inland Southern California.

The catch-can test in our study underestimated the precipitation rate of the irrigation system in 2017 and 2018. This might be related to non-uniformity of water applied (i.e., not as much water is being applied in all spots leading to a lower catch can calculated precipitation rate) and inherent errors in getting water into catch devices (e.g., water hitting the cans at an angle and splashing out). More studies are needed to evaluate the reliability, accuracy and uncertainty of the catch-can test to estimate the precipitation rate of irrigation systems.

The accuracy of ETo estimations also impacts the performance of the ET-based smart controllers. Grabow et al. (2013) observed, on average, about 10% more water applied by ET-based treatments than by a timer-based treatment in North Carolina and suggested overestimation of ETo by the ET controllers as a potential reseason for the overirrigation observed. Davis et al. (2007) reported a 32% overestimation of ETo by the Weathermatic Smart Line Series controller in Florida. The Hargreaves equation (Hargreaves and Samani, 1985), with on-site temperature measurements and latitude-based solar radiation estimations, showed promising performance in our study, on average 5.7% overestimation compared to CIMIS ETo. Further studies are needed to evaluate the year-round performance of the Hargreaves equation (Hargreaves and Samani, 1985) in inland southern California as well as other areas with different climate patterns across the state of California.

According to Grabow et al. (2013), the ability of smart controllers to take the precipitation into account when scheduling irrigation and impose irrigation frequency restrictions are likely the main factors impacting their potential water saving. Davis and Dukes (2010) also

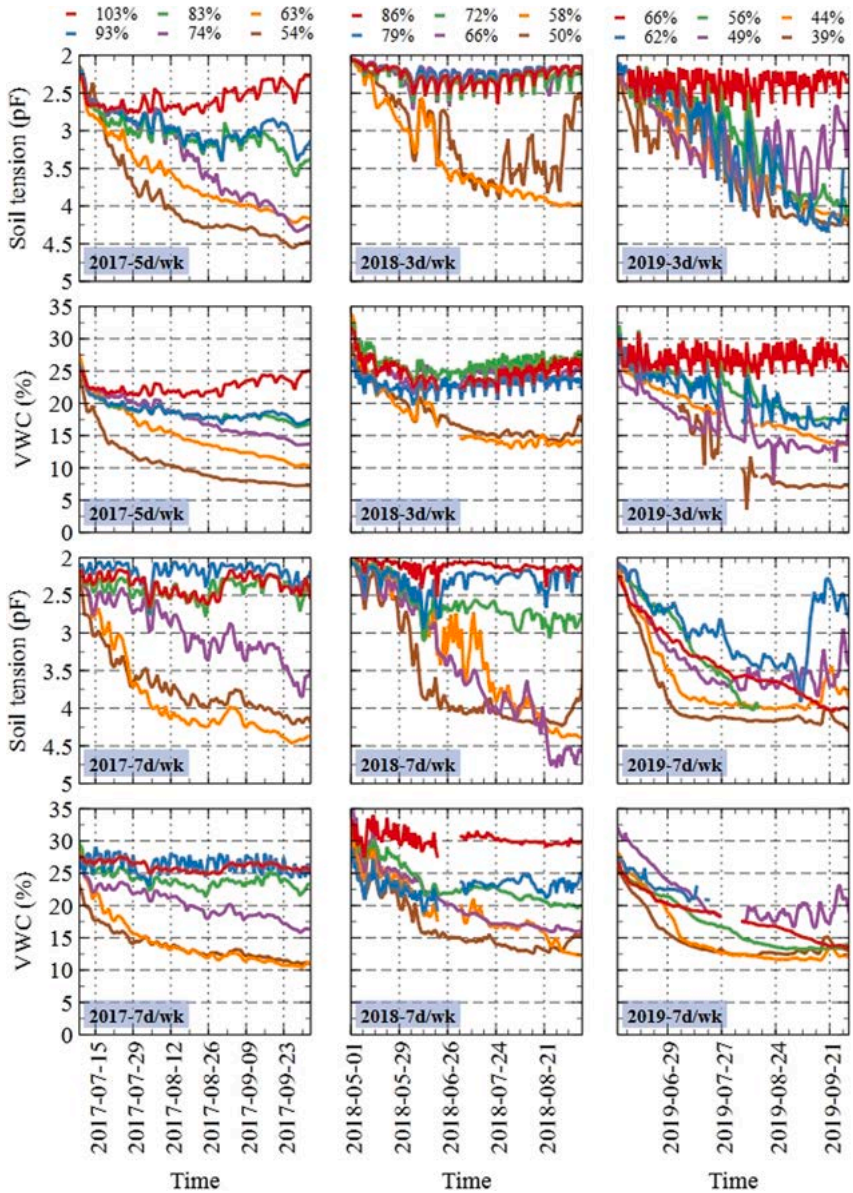

Fig. 10. Soil tension (pF, log-transformed soil tension in cm of water) and volumetric water content (VWC) fluctuations across the 12 irrigation treatments imposed in 2017, 2018 and 2019. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

reported that weather conditions and particularly considerable rainfall in rainy summer seasons in Florida reduced the irrigation adequacy and scheduling efficiency of ET based controllers. We focused on high ETo demand months in this study when significant precipitation is highly unlikely. More studies are needed to evaluate the year-round performance of the ET-based controllers and, in particular, their accuracy over rainy seasons in inland Southern California.

The common perception is that less frequent watering encourages deep rooting and improves turfgrass quality. Although we did not measure rooting depth, our turfgrass quality assessment did not support the idea of quality improvement due to less frequent irrigation. We attribute this at least in part to the low water holding capacity of our soil due to its high sand content. No watering restriction with proper identification of minimum deficit threshold, to avoid light irrigation applications, might be the optimum programming choice during dry months in inland Southern California. This setting allows the controller to identify the right irrigation frequencies dynamically based on the weather patterns. In inland southern California, summer periods with heatwaves cause very high ETo demand when more frequent irrigation is needed to avoid drought injury. At the same time, less regular watering is desirable in periodic cool and cloudy days with much smaller ETo demand.

4.3. Turfgrass quality assessment via handheld NDVI versus VR

We used NDVI as the main parameter to monitor the response of turfgrass to varying degrees of deficit irrigation due to its reported high correlation with turfgrass tissue moisture content, $r = 0.95$, and crop coefficient, $r = 0.90$ (Fenstermaker-Shaulis et al., 1997). Overall, we also observed a good match between the VR and NDVI data across irrigation treatments and in all three years of the experiment (Figs. 4–6). This finding is in line with the reported results by Bell et al. (2009) and Trenholm et al. (1999). Bell et al. (2009) compared the Greenseeker handheld sensor NDVI with VR values and reported the highest correlations for the bermudagrass with r values of 0.79 and 0.85 in the years 2003 and 2004, respectively. Trenholm et al. (1999) studied three hybrid bermudagrass cultivars and reported r values ranging from 0.70 to 0.90 between turfgrass VR and NDVI. Our results suggest NDVI of 0.6

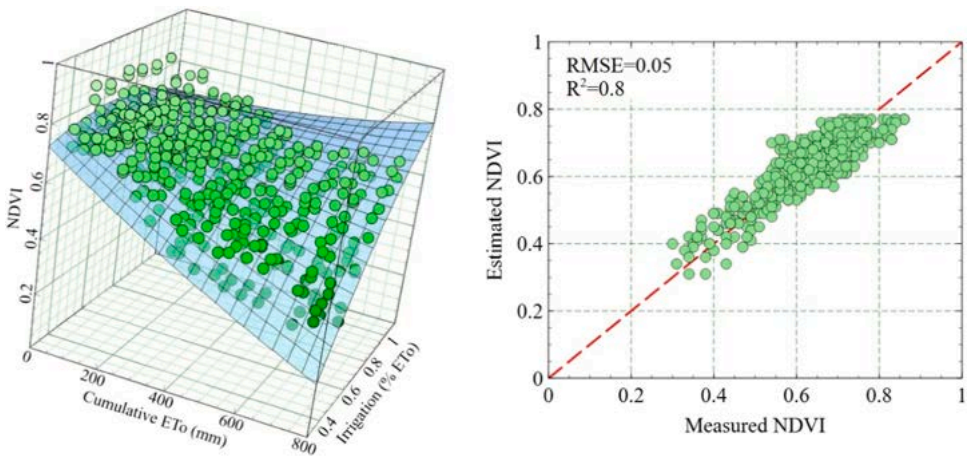

Fig. 11. Left: Combined 2017, 2018 and 2019 data (green circles) showing the response of hybrid bermudagrass (NDVI values) to applied irrigation levels (% ETo) over time (expressed as cumulative ETo values). The blue surface shows the turfgrass water response function (TWRF) regression model fitted to the data. **Right:** Measured versus estimated NDVI values (for the entire data set; i.e., 2017, 2018 and 2019).

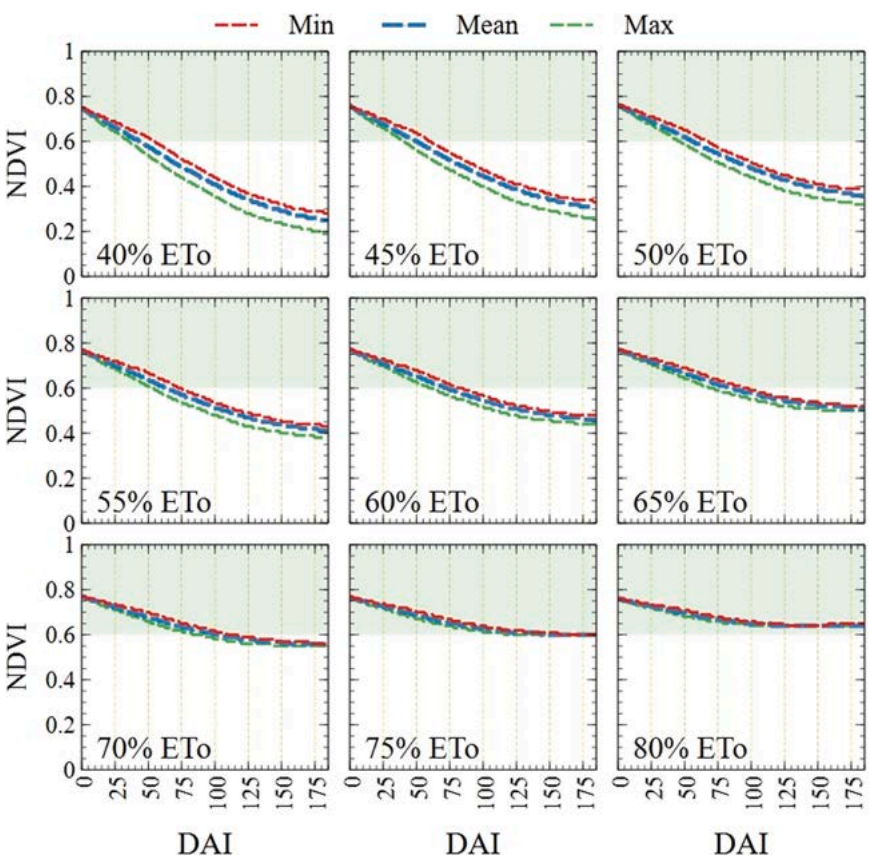

Fig. 12. Hybrid bermudagrass response estimation to varying irrigation scenarios in semiarid inland southern California climate using the turfgrass water response function (TWRF) based on long term ETo data (1986–2019) obtained from a nearby California irrigation management and information system (CIMIS-44) station. The simulated period is from May 1 to October 31. The minimum, mean and maximum scenarios represent cumulative ETo values of 852, 944, and 1110 mm, respectively. DAI: days after initiation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

could be used roughly as the minimum threshold indicating acceptable quality for hybrid bermudagrass turf [‘Tifgreen’ *Cynodon dactylon* (L.) Pers. × *C. transvaalensis* Burtt-Davy] in the inland southern California region. Johnsen et al. (2009) evaluated the utility of remote sensing to measure plant stress in creeping bentgrass (*Agrostis stolonifera L.*) fairways. They noticed that reflectance measurements could detect water stress up to 2 days before visual observation. We did not see early detection of drought injury based on NDVI data as compared to VR, which is likely attributed to our weekly data collection protocol compared to the more frequent data collection by Johnsen et al. (2009).

5. Conclusion

This study focused on developing irrigation water conservation strategies for hybrid bermudagrass, a warm-season grass underused in residential areas but is relatively drought tolerant and is starting to be used more widely across California. The Weathermatic ET-based smart controller used in our study showed acceptable accuracy with on average 5.7% overestimation of ETo compared to CIMIS. NDVI and VR values were highly correlated ($r = 0.84$) in our study; therefore, we suggest the application of handheld measured NDVI data for fast and consistent evaluation of overall hybrid bermudagrass turfgrass response

to different irrigation regimes. The regression-based TWRF, introduced in our study as a statistical model to estimate the response of turfgrass to different irrigation strategies, showed a good fit to experimental data. Our long term analysis using TWSF indicated that 75% ETo irrigation application could maintain the hybrid bermudagrass quality in the acceptable range for residential areas in dry seasons in inland southern California. Our results showed that depending on weather patterns (ETo demands), more severe deficit irrigation scenarios could be implemented for shorter periods before the hybrid bermudagrass quality falls below the minimum acceptable threshold.

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. The authors declare that they have no conflict of interest.

Acknowledgment

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Conflict of interest

The authors declare no conflict of interest.

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