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Using Thermal Imaging to Measure Water Stress in Creeping Bentgrass Putting Greens

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USING THERMAL IMAGING TO MEASURE WATER STRESS IN CREEPING BENTGRASS PUTTING GREENS

by

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USING THERMAL IMAGING TO MEASURE DROUGHT STRESS IN CREEPING BENTGRASS

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Abstract: Thermal imaging is a developing tool that can help turf managers reduce water consumption and improve irrigation scheduling, but in-depth studies are needed to maximize this potential. This study evaluated the ability of thermal imaging to identify water stress in a creeping bentgrass (*Agrostis stolonifera '007'*) putting green. Water use and canopy temperature (T_c) were measured for plots subjected to three levels of measured water replacement (full, half, and none) to evaluate changes over a range of soil water potentials (SWP). Water use was consistent across the irrigation treatments up to several days before observed wilt with crop coefficients (K_c) between 0.83-1.01. As drought conditions progressed (SWP <-1501kPa), K_c decreased. Segmented linear regression was used to quantify the trends and identify the critical value of -1501 kPa. Various metrics utilizing T_c were evaluated for a response to water stress. Two metrics, standard deviation of T_c and T_c relative to non-water stressed turf, show potential to indicate periods of stress prior to visible wilt. A strong diurnal pattern was observed in all T_c metrics confirming the need to normalize T_c for current weather conditions. Multiple regression using 2018 data was used to develop a model using weather parameters of air temperature, solar radiation, relative humidity, and wind speed to estimate T_c values of a non-water stressed baseline. A two parameter model using air temperature and solar radiation input provided a strong fit (adjusted R^2=0.955) and when applied to unpublished dataset from a 2016 study measuring T_c on a creeping bentgrass putting

green. This study shows water use remained consistent until SWP reached a wilting point, followed by a sharp decrease in water use approaching K_c of zero. We show that metrics utilizing T_c can be early indicators of water stress in turfgrass. However, further research with different microclimates and plot sizes would be needed to identify specific values of these metrics that quantify water stress. We also describe a multiple regression model to predict T_c of non-water stressed baseline under various weather conditions. Understanding how T_c of turf with no water stress behaves in different weather can improve identification of water stress.

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LIST OF ABBREVIATIONS

0WR	No Water Replacement
100WR	Full Water Replacement
50WR	Half Water Replacement
AWDN	Automated Weather Data Network
CWSI	Crop Water Stress Index
ET	Evapotranspiration
ET_m	Measured Evapotranspiration
ET_o	Reference Evapotranspiration
FLIR	Forward-Looking Infrared
HPRCC	High Plains Regional Climate Center
K_c	Crop Coefficient
NWSB	Non-Water Stressed Baseline
Rel_{NSWB}	Canopy Temperature Relative to Non-Water Stressed Baseline
RH	Relative Humidity
R_n	Net Radiation
SD_{Tc}	Standard Deviation of Canopy Temperature
SR	Solar Radiation
SWP	Soil Water Potential
T_{Δ}	Difference Between Predicted and Measured Canopy Temperature
T_a	Air Temperature

T_c	Canopy Temperature
VPD	Vapor Pressure Deficit
VWC	Volumetric Water Content
WS	Wind Speed

CHAPTER 1: INTRODUCTION

1.1 Abstract

Improved irrigation scheduling has the potential to reduce water consumption and improve playing conditions on putting greens. Deficit irrigation and limited irrigation application frequency are valuable strategies to reducing water consumption and maintaining plant health. To maximize the benefits from these strategies, it is critical to have an understanding of creeping bentgrass water use, specifically as it nears water stress since creeping bentgrass is the most common turf species used on putting greens in the United States. As soil moisture reaches a critically low level, water uptake and turgor pressure in leaves are reduced. This triggers a decline in the rate of transpiration which, in turn, results in an increase in canopy temperature (T_c) when compared to a non-water stress plant. This change in T_c has been used as an indicator of water stress in crops but specific values and spatial and temporal pattern changes have not been identified for a creeping bentgrass putting green. Since T_c fluctuates significantly with weather conditions, numerous metrics such as T_c versus a non-water stressed baseline (NWSB) and variation in T_c have been utilized to detect changes in T_c attributable to water stress. Progress in thermal imaging technology has made it an increasingly practical tool to frequently and autonomously measure and interpret T_c and related metrics of plant water use over a large area. If we can improve understanding of creeping bentgrass water use and T_c as the plant approaches water stress, then thermal imaging could be utilized to inform irrigation decisions and reduce water consumption.

1.2 Literature Review

Creeping bentgrass (*Agrostis stolonifera*) is a cool-season turfgrass that is commonly used in golf courses. It is the most common species used in putting greens with over 27,000 acres of creeping bentgrass putting greens across the United States (Lyman *et al.*, 2007). Its tolerance of low mowing and highly aggressive (stoloniferous) growth habit make it ideal for putting green applications (Warnke *et al.*, 2003). Due to its vigorous growth habit, creeping bentgrass requires frequent inputs of water, fertilizer, and cultivation to provide an acceptable hard and fast putting surface that allows the ball to roll faster. Precise management of soil moisture in putting greens helps to create the ideal putting green surface conditions for golf. Expensive equipment and many man hours are required to monitor and maintain soil moisture in a range that provides quality playing conditions and plant health. Responsible use of water resources is critical to the success and sustainability of golf course operations.

Golf courses in the United States used an estimated 1.859 million acre-feet of water in 2014, with 156,000 acre-feet coming from municipal drinking water (Gelernter *et al.*, 2015). This is greater than 1.6 billion gallons each day. At an average cost of $298 per acre-foot, over 500 million dollars were spent on water at golf courses. Note, golf course water consumption has decreased (a 22% reduction from 2006 to 2014) due to fewer courses and improved conservation and irrigation practices. However, further improvement in irrigation efficiency will be financially and environmentally beneficial as water scarcity is projected to increase in coming years, particularly in the Pacific and Southwest regions where golf course water use is the highest (Gelernter *et al.*, 2015, Marston *et al.*, 2020).

The goal of efficient irrigation scheduling is to minimize the use of water resources while maintaining plant health to avoid water stress. Deficit irrigation and reduced irrigation application frequency are two strategies that are known to reduce water consumption (Gómez-Armayones *et al.*, 2018). A study on deficit irrigation from DaCosta and Huang (2006b) showed that creeping bentgrass mowed at fairway height (9.5mm) can be maintained at an acceptable quality when replacing only 60% of actual evapotranspiration, including through the summer months when water consumption is at its peak. Similarly, Sass and Horgan (2006) showed no decline in creeping bentgrass quality maintained at greens height (5mm) when replacing 80% of measured water loss compared to 100%. Fu and Dernoeden (2009) showed that deep, infrequent irrigation used less water and provided better quality and color in creeping bentgrass. When irrigating equal amounts of total water at 1-, 2-, or 4-day intervals, Jordan *et al.* (2003) showed improved root length density at the less frequent 4-day interval. Irrigating only when the turf is near water stress decreases irrigation frequency and lowers the required inputs for a healthy playing surface (DaCosta and Huang, 2006a; Fu and Dernoeden, 2009). Understanding how the plant uses water can help to identify water stress and inform irrigation decisions.

Transpiration is movement of water vapor from inside the leaf, through stomata on the leaf surface, and into the atmosphere. Transpiration serves many purposes for the plant. It supports the movement of water and nutrients from the soil and into the plant where it supports vital functions. Open stomata allow water vapor to escape, called transpiration, and CO_2 to enter the turf leaf and sustain carbon assimilation during photosynthesis. Transpiration is beneficial to the plant as it dissipates excess heat energy as liquid water is converted into gaseous water vapor. This movement of water from the soil through the plant to the air is driven by a water potential gradient (from high potential in the soil to low potentials in the air). Under sufficient water supply the water potentials may be as high as ~-10 kPa in the soil, ~-100 in roots to -1,000 kPa in leaves, and ~-100,000 kPa in the air (Rye *et al.*, 2016). The water potential values will affect the transpiration rate. For instance, as soil moisture decreases, the water potential of the soil becomes more negative, reducing the gradient and decreasing the rate of transpiration. Similarly, changes to water vapor in the atmosphere, or the vapor pressure deficit (VPD), will affect the gradient. More moisture in the atmosphere (increased humidity) increases the water potential of the air, reduces the gradient, and decreases the rate of transpiration where drier air would increase the rate. Evaporation of soil moisture directly into the atmosphere is another component of soil water loss and needs to be factored into irrigation decisions.

Evapotranspiration (ET), the sum of water lost through transpiration from leaves and evaporation from soil, is a common measurement used to inform irrigation decisions (Beard, 1973). The rate of ET is affected by many factors including available soil moisture, stomatal conductance, and microclimatic conditions including solar radiation, relative humidity, and wind speed (Feldhake *et al.*, 1983, Aronson *et al.*, 1987, DaCosta and Huang, 2006a). ET estimations are used to determine when to irrigate and how much water to apply. Common methods of estimating ET include the simple pan evaporation, lysimetry with the water balance equation, eddy covariance, and empirical calculations using weather data and/or estimations of physical characteristics of the plant (Romero and Dukes, 2016). One of the most commonly used empirical calculations for ET is the Penman-Montieth equation (Allen *et al.*, 1998). The FAO implementation of this equation makes some assumptions about the crop such as: assumed crop height of 0.1m, a fixed surface resistance of 70 s m^{-1}, and an albedo of 0.23. Those assumptions combined with relevant weather data produce a sufficient estimate of a reference ET (ET_o) on an hourly, daily, or monthly interval. Access to reference ET values is readily available to turfgrass managers from several non- and forprofit weather data services. However, this calculated reference ET needs to be adjusted for the particular vegetation surface of interest using a crop. A crop coefficient (K_c) is developed for individual crops or species to relate the ET_o to actual water use for the plant of interest. The K_c is calculated as:

$$K_c = \frac{ET_m}{ET_o} \tag{1}$$

where K_c is the crop coefficient, ET_m is the actual evapotranspiration of the crop, and ET_o is the reference evapotranspiration. Published K_c values for cool-season species such as creeping bentgrass range from 0.8 to 1.3, meaning actual ET is 80-130% of the reference evapotranspiration (Aamlid *et al.*, 2016). However, water use can vary with cultivar, season, management regime, and other factors (DaCosta and Huang, 2006a). The rate of ET can also be affected by available soil moisture (Huang, 2008). If the ET rate can be measured frequently and accurately, irrigation can be withheld until soil moisture approaches a critical level (before the plant wilting point without jeopardizing plant health), thus reducing water consumption.

As soil moisture is depleted via ET, water potential in the soil decreases, requiring a greater force to move water from the soil into the plant. If soil moisture continues to decrease, it eventually reaches the wilting point, where the water potential gradient is no longer strong enough to move water into the plant and the plant experiences water stress. The soil water potential (SWP) at which this occurs varies across soils and species but is approximately -1500 kPa (Ritchie, 1981). When the plant can no longer extract sufficient water from the soil, symptoms of water stress, commonly referred to as drought stress, can appear. A loss of visual quality, change in color (leaf firing), loss of turgor pressure in leaves, and a rise in T_c are all symptoms of drought stress (Stier *et al.*, 2020). The loss in turgor pressure causes wilting of the leaves and triggers a reduction in stomatal conductance. As stomata close, transpiration and thus, transpirational cooling, are reduced. The lack of transpirational cooling, in turn, causes an increase in T_c. This can be explained through the energy balance equation:

$$R_n = H + LE \tag{2}$$

where R_n is net radiation incident up on the canopy, H is the sensible heat flux, and LE is the latent heat flux or energy consumed in the process of transpiration as liquid water in the leaf is converted to gaseous water vapor as it exits stomata (Martin *et al.*, 2005a). As the energy from sunlight (quantified as R_n) is absorbed by the leaf, it is partitioned into H, where it is emitted from the leaf, or LE, where the energy is consumed in transpiration. As ET declines due to insufficient moisture or other factors, a greater portion of the energy absorbed by the canopy is emitted as H and measured as an increase in T_c (relative to T_a) when compared to a fully transpiring plant with sufficient soil moisture. Canopy temperature measurements have been used as an indicator of drought stress in other species such as: cotton (Alchanatis *et al.*, 2010, Sela *et al.*, 2007a), grapevine (Moeller *et al.*, 2007), olive (Ben-Gal *et al.*, 2009), and pepper (Camoglu *et al.*, 2018).

Results were less conclusive in earlier research when trying to measure stress in turfgrasses: Kentucky bluegrass (*Poa pratensis*) (Throssell *et al.*, 1987), bermudagass (*Cynodon dactlyon*) (Carrow, 1993; Jalali-Farahani *et al.*, 1993), and creeping bentgrass maintained at fairway heights (Martin *et al.*, 1994) but technology has improved significantly since these studies were conducted. (Horst *et al.*, 1989) stated that different calculations are necessary to quantify stress for each species, season, and mowing height. Specific metrics, values and spatial and temporal patterns need to be identified for creeping bentgrass in a putting green management regime. Canopy temperature alone, however, cannot be used as a drought stress metric due to the interaction of weather and T_c (Carlson *et al.*, 1972). These weather parameters include air temperature (T_a), solar radiation (SR), relative humidity (RH), and WS. Accounting for these factors is critical in using Tc to detect the drought stress. A number of stress indices involving T_c have been developed to measure drought stress in plants. The most commonly used metric is the crop-water stress index (CWSI) developed by (Idso, 1982):

$$CWSI = \frac{(T_c - T_a)_{act} - (T_c - T_a)_{LL}}{(T_c - T_a)_{UL} - (T_c - T_a)_{LL}} \tag{3}$$

where $(T_c - T_a)_{act}$ is the measured canopy temperature minus air temperature, $(T_c - T_a)_{LL}$ is canopy temperature minus air temperature at the lower limit of water stress, and $(T_c - T_a)_{UL}$ is the canopy temperature minus air temperature at the upper limit of water stress. The upper and lower limits are commonly referred to as the water-stressed baseline and non-water-stressed baseline (NWSB), respectively. To accurately measure stress, good estimations of these baselines are needed but they can be difficult to predict due the effects of constantly changing weather. Taghvaeian *et al.* (2013) found that baselines will vary based on local conditions. Payero *et al.* (2005) developed a strong model (r^2=0.89) to predict the NSWB of tall fescue (*Festuca arundinacea*) using multiple regression with factors: T_a, SR, VPD, and wind speed. They speculated that this model would be applicable across locations, but it has not been widely tested at other sites or on other species.

Another stress index that has been theorized but never tested in turfgrass is the variation of T_c over a given area (Fuchs, 1990), partly because the technology to easily measure this has not been available until recently. The value in this metric is that it only requires measurement of actual T_c and no estimates or models are needed. Regardless of the metric, a deeper understanding of the relationship between soil moisture, plant water use, and T_c is needed to incorporate these metrics into irrigation scheduling decisions on creeping bentgrass putting greens.

Thus, as soil moisture decreases, changes in T_c patterns are expected, as was observed in Feldhake *et al.* (1984). If these changes in soil moisture can be detected through T_c metrics, irrigation scheduling decisions can be streamlined and improved. To improve interpretation of these metrics, understanding of how ET and soil moisture change as creeping bentgrass begins to exhibit drought stress is needed. While Salaiz *et al.* (1991) reported daily ET for various species of creeping bentgrass to be between 3.2-12.5 mm d^{-1} when mowed at 12.5mm, research is lacking for ET and T_c values of creeping bentgrass as soil moisture decreases and the plant experiences moisture stress.

Advances in technology and digital image analysis have made thermal imaging a practical tool for measuring T_c for large areas (Costa *et al.*, 2010, Jones, 2004, Jones and Leinonen, 2003). Infrared cameras are used to create thermal images through the detection of emitted radiation from the surface of interest in the infrared portion of the spectrum (780nm-14μm) and converts the emitted energy into a temperature measurement which is represented by a colored pixel. Thermal cameras can be hand-held and mobile or mounted in a location and wirelessly transmit data. A single piece of equipment could provide remote, continuous, automated, and non-destructive measurements of T_c. Additionally, thermal images provide the spatial distribution of T_c, potentially identifying underlying issues, such as leaky irrigation heads. If data interpretation utilizing T_c metrics can be improved and incorporated into user-friendly software, it would be widely useful to golf course managers in scheduling irrigation to minimize the use of water resources while maximizing plant health.

The goal of this thesis research is to improve understanding of creeping bentgrass water use as soil moisture decreases and improve interpretation of T_c data in creeping bentgrass putting greens with the aim of improving irrigation efficiency. Specific objectives include i) quantify water use and SWP as soil moisture changes in creeping bentgrass for a sand-based putting green, ii) relate changes in creeping bentgrass T_c to soil moisture status, and iii) create a model to predict the T_c of a NWSB under varying weather conditions.

CHAPTER 2: WATER USE PATTERNS OF A CREEPING BENTGRASS PUTTING GREEN WITH DIFFERENT IRRIGATION STRATEGIES

2.1 Abstract

Efficient irrigation scheduling is critical for putting greens management to minimize water consumption, sustain plant health, and maximize playability. This study was conducted to improve understanding of water use in creeping bentgrass (*Agrostis stolonifera* Hud. *'007'*) under different irrigation strategies in conditions suitable for putting green management to help maximize efficiency of irrigation scheduling. Water use was quantified using crop coefficients (K_c) values calculated by dividing values of potential ET (ET_o) by measured ET (ET_m) gathered from weighing lysimeters. Irrigation strategies evaluated include full ET_m replacement (100WR), half replacement (50WR) and no water replacement (0WR). Segmented regression was used to quantify data trends. Measured evapotranspiration (ET_m) and K_c values changed with soil water potential in 0WR treatment. We observed two distinct trends in water use as SWP decreased: i) consistent water use with sufficient soil moisture conditions, characterized by healthy, green turf, and ii) rapid decrease in water use with limiting soil moisture, characterized by plant wilt, thinning, and leaf firing. The critical point, when water use began to decline, was identified to be -1501kPa. The sufficient soil moisture conditions showed K_c values of 0.88-0.92 where soils nearing wilting point rapidly approach a K_c of zero. These results suggest that water use remains consistent for creeping bentgrass until a critical point of -1501 kPa is reached and water use declines. Improved knowledge of the relationships between K_c and SWP will help managers understand how creeping bentgrass uses water over a range of soil moisture conditions, leading to more informed irrigation decisions and a reduction in water consumption.

2.2 Introduction

As water resources become more limited, turfgrass managers must adapt and use less irrigation and maintain plant viability. One way to reduce water consumption is through efficient irrigation scheduling. Efficient irrigation scheduling minimizes water use while maintaining plant health. To improve irrigation efficiency, it is critical to understand plant water use. Turfgrass water use is known to vary significantly with species, irrigation frequency, and soil moisture (Biran *et al.*, 1981). Cool-season grasses, like creeping bentgrass and Kentucky bluegrass rate very high in water use (ET rates >10 mm d^{-1}) compared to warm-season grasses (6 to 7 mm d^{-1}), like bermudagrass (*Cynodon dactylon*) or zoysiagrass (*Zoysia matrella*) (Beard and Kim, 1989). Water consumption is reduced when irrigation is only applied at the onset of plant wilt. Minimizing excess soil moisture reduces the amount of water lost through ET, thus reducing the amount of water consumed in turfgrass management.

Evapotranspiration is the sum of water loss due to evaporation from the soil and transpiration through plant leaves (Beard, 1973). The rate of ET is controlled by many factors, including microclimate, plant available water and stomatal conductance (Feldhake *et al.*, 1983; DaCosta and Huang, 2006a; DaCosta and Huang, 2006c). Microclimatic factors affecting ET rate include T_a, solar radiation, relative humidity, and wind speed. Water potential is another factor that influences interactions between soil, water, plants, and atmosphere. A water potential gradient determines the movement of water from the soil (greatest potential) to the plant and then to the air (least potential). This differential is called the VPD and it is the driving force of ET. The total water potential of the soil becomes greater (more negative) as soil moisture is depleted, meaning more energy is required from the plant to remove water from the soil. At a level of soil moisture called the wilting point, the plant can no longer extract water from the soil and begins to wilt. The water potential at which this occurs is thought to be around -1500 kPa (Ritchie, 1981), however this value will vary with plant and soil characteristics. Understanding the SWP at which the plant begins to wilt can help to inform irrigation decisions, providing managers with greater control over soil moisture and water resources.

Plant control of ET is also accomplished through regulation of stomatal conductance. Stomata are pores on the leaf surface that facilitate gas exchange between the leaf and the atmosphere. Adjacent guard cells control the pore size of each stoma which regulate conductance in response to various environmental stimuli. Water stress triggers the production of abscisic acid which causes the guard cells to close leaf stomata and reduce the rate of transpiration. In a study evaluating minimum required irrigation for Kentucky bluegrass mowed at 5mm, a decrease in ET rate was measured after 3 weeks of deficit irrigation (Minner, 1984). However, research in closely mowed creeping bentgrass, the most commonly used species in putting greens in the United States (Lyman *et al.*, 2007), is lacking.

Weighing lysimeters allow for the measurement of ET in turfgrasses. Through a water balance approach (Allen *et al.*, 1998), repeated mass measurements of the lysimeters are used to calculate the amount of water lost via ET from a turf stand, producing a measured ET value (ET_m). This has been the standard method to measure ET in turfgrass (Romero and Dukes, 2016) due to its relative simplicity. Weighing lysimeters have been used to measure and compare ET rates of various species of turfgrass (Biran *et al.*, 1981; Aronson *et al.*, 1987; Kim and Beard, 1988; Fu and Dernoeden, 2009). Lysimeter studies report daily ET values for ten cultivars of creeping bentgrass to range from 3.2 mm d^{-1} to 10.7 mm d^{-1} when mowed at 12.5 mm (Salaiz *et al.*, 1991). However, lysimetry it is not free of error. Factors that require attention to minimize error are: 1) matching vegetative and soil conditions inside the lysimeter to the surrounding area, 2) providing sufficient depth of rooting, 3) minimizing the gap between the lysimeter and soil profile, 4) allowing sufficient fetch for consistent wind conditions (Allen *et al.*, 2011). Despite these concerns, weighing lysimeters are a cost-efficient option to measure water use. These ET_m values can be compared to a reference ET value (ET_o) value to calculate a crop coefficient term (K_c).

Crop coefficients provide a means for turf managers to approximate how much water has been consumed by the turf. A more accurate K_c will lead to more precise application of irrigation water, will help to minimize water waste and allow for enhanced playing conditions, in putting green situation. Crop coefficients vary with species, season, and location (eg., soil and climate). In a study evaluating water use for various creeping bentgrass cultivars mowed at 12.5 mm, measured K_c values range from 0.68 to 0.79 in mid-June and 0.91 to 1.26 in mid-August when crop water use is at its maximum (Salaiz et al., 1991). However, turf in the study was irrigated to non-limiting soil moisture conditions. No reports of water use values over a range of soil moisture could be found. DaCosta & Huang (2006) report acceptable turf quality for fairway height creeping bentgrass (9.5 mm) when replacing only 60% of ET_m (equal to 0.60 K_c) in summer months of the humid Northeast while replacing only 40% ET_m was sufficient in fall months. Thus, deficit irrigation is a valid strategy to minimize water consumption in locations with frequent precipitation using Kc values to estimate ET. However, specific replacement K_c values for creeping bentgrass putting greens could not be identified. Further understanding of creeping bentgrass water use rates and changes under water stress could improve irrigation efficiency and reduce water consumption on many golf courses around the country.

The objectives of this study are to i) measure water use rate of CBC putting greens as soil moisture transitions from field capacity to the wilting point, ii) quantify the SWP associated with the wilting point for a creeping bentgrass putting green, and iii) evaluate ET_m and K_c in a CBC putting green that received three different levels of irrigation.

2.3 Materials and Methods

Site Description

This study was conducted in the summers of 2017 and 2018 at the UNL East Campus Turfgrass Research Center in Lincoln, NE (40°50'N, 96°39'W) on a '007' creeping bentgrass (*Agrostis stolonifera* Hud.) research field maintained as a United States Golf Association (USGA) putting green. The turf stand was established during August 2016 with the 40 cm root zone is 85% sand/15% peat moss by volume and built according to USGA recommendations for a putting green (USGA, 2014). Overhead irrigation was withheld but natural precipitation was allowed (due to practical considerations). Individual plots were irrigated by hand, using a flowmeter attached to a hose, as part of treatments. Plots were mowed five days each week with a walk-behind reel mower (Greensmaster eFlex® 2100, The Toro Company, Bloomington, MN). Height of cut was 3.3 mm in 2017 and 2.8 mm in 2018. Nitrogen fertilizer (46-0-0) in the form of urea was applied at a rate of 12 kg ha^{-1} every 14 days. To aid water penetration into the soil, a surfactant, Revolution (modified alkylated polyol; Aquatrols, Paulsbury, NJ), was applied on 22 June 2017 and 11 June 2018 at rates of 9.5 and 19.0 L ha^{-1} respectively.

Experimental Design

The study area consisted of 12 plots arranged in three replicate blocks of four treatments. Treatments were arranged in a randomized complete block design and were randomized to plot separately for each year. Each plot measured 2.1 x 1.4 m with a 0.6 m buffer zone around each plot (Fig. 2.1). All plots began collection periods at field capacity.

Three water replacement treatments were used to evaluate the relationship between ET_m, K_c, and SWP. A fourth treatment, involving irrigating based on a proprietary stress index, was excluded from this study. Treatments included replacing 0, 50, & 100% of ET_m (0WR, 50WR, & 100WR). ET_m was calculated via a weighing lysimeter located in the center of each plot (described below). Irrigation was applied by hand-watering with hose depending on ET_m values. This was typically every 2-3 days without precipitation events. Lysimeters were removed prior to irrigation and weighed. A flowmeter attached to the hose allowed a precise amount of irrigation to be applied. Irrigation was applied slowly and carefully to ensure that water being applied stayed in the intended area and did not run into the empty lysimeter hole. Lysimeters were then replaced and irrigated slowly using a water bottle with a proportional amount of water to the plot. This process ensured irrigation applied to lysimeters entered the soil profile rather than spilling into the lysimeter/wall gap. Water was replaced on the plots every 2-3 days to allow for a measureable amount of water to be applied but replacement was more frequent when ET_m values were higher. The collection periods were ended when the lysimeters of 0WR plots no longer showed decreasing weight due to water loss indicating they were completely dry.

Lysimetry

Weighing lysimeters (Fig. 2.2), 16.7 L in volume, were installed in the center of each plot and extended the full depth of soil profile with the bottom resting on the gravel layer. Existing turf and root zone mix were used in lysimeters to match conditions of the surrounding turf. The soil around the lysimeter was secured with 10 mm thick polyvinyl chloride tubing. Lysimeters were removed and weighed on an Ohaus (Pine Brook, NJ) Explorer® Precision High Capacity Balance EX35001 four to seven times weekly. Water leaching through the lysimeter was captured in a removable catch can attached to the bottom of the lysimeter. A water balance equation was used to calculate water lost to ET_m:

$$ET_m = LYS_{Prev} - LYS - Leachate - Precip \quad (4)$$

where LYS_{Prev} is the mass of the lysimeter from the previous day after water has been replaced, *LYS* is the mass of the lysimeter that day prior to water replacement, *Leachate* is the mass of leachate collected in the catch can, and *Precip* is the mass of precipitation incident on the area of the lysimeter.

This ET_m value was then used to calculate a measured crop coefficient using eq. 1. ET_o data were gathered from the Nebraska Mesonet Lincoln IANR Station using the High Plains Regional Climate Center (HPRCC) Daily Penman equation:

$$\rho_w LE(ET_o) = \frac{\Delta}{\Delta + \gamma}(R_n - G) + \frac{\gamma}{\Delta + \gamma}(1.1 + 0.017W)(e_s - e_a) \quad (5)$$

where ρ_w is density of water, LE is the latent heat flux ET_o is reference evapotranspiration, Δ is slope of the saturation vapor pressure temperature relationship, γ is the psychrometric constant, R_n is net radiation (estimated from global solar radiation), G is heat flux in soil (estimated as zero), W is daily wind run, e_s is saturated vapor pressure, and e_a is actual vapor pressure with vapor pressure values calculated daily (Walter-Shea *et al.*, 2021)

To start each dry down run at field capacity soil moisture, plots were irrigated for three hours and allowed to sit overnight to allow excess water to flow through the soil profile with initial lysimeter weights recorded in the morning. Plots were allowed a longer period to let excess water flow through in 2018 due to some unexpected data in 2017 that indicated soil moisture may have been maintained above field capacity.

Weather Data

Hourly weather data were collected from the Nebraska State Climate Office Nebraska Mesonet Lincoln IANR station. This station is located 1km to the southwest of the research plots. Weather values recorded from this station include T_a, relative humidity, soil temperature, solar radiation, wind speed, wind direction, and ET_o. Reference ET was calculated daily using the HPRCC Daily Penman equation.

Data Collection

Data were collected during two growing seasons: 26 June through 2 August 2017 (38 days) and 26 June through 27 July 2018 (32 days). Weather data provided by the NSCO are hourly averages with the reference ET being a daily value; lysimeter and soil moisture data were measured 4 to 7 times per week, as previously described. The date of visible wilt was recorded when symptoms of water stress such as leaf firing and loss of turgor pressure were clearly observed when lysimeters were measured.

Volumetric water content (VWC) through time-domain reflectometry was measured using a FieldScoutTDR 300 hand-held soil moisture meter (Spectrum Technologies, Inc., Aurora, IL) as an average of five readings within each plot. VWC was measured before each weighing event. The 7.6 cm length rod was used in the standard soil-type mode.

Water Retention Curve

A water retention curve was created to relate the measured soil VWC obtained from the TDR 300 to the SWP. This curve was generated from a total of 12 intact soil cores (one from within each plot of the study area) after the data collection period in 2018. Each core had a height of 7.6 cm and a diameter of 8.9 cm. The 12 cores were saturated overnight and then weighed. Water was then removed from the cores at various pressures using a ceramic plate extractor (15 bar Ceramic Plate Extractor, Soilmoisture Equipment Corp; Santa Barbara, CA). Ceramic plate extractors removed water at pressures of 0.33, 1.00, 3.00, and 5.00 MPa with each core being weighed after each round of pressure. Volumetric water content was calculated at each pressure using the measured weight, oven dry weight, and volume of the core (Grossman and Reinsch, 2002; Blanco-Canqui *et al.*, 2007).

Data Analysis

A segmented linear regression was calculated with the Solver data package in Microsoft Excel to relate the *x-variable* (SWP) and *the y-variable* (VWC) *vs z*. Segmented linear regression identifies a critical value where K_c abruptly changes with a change in SWP. Fisher's least significant difference was calculated in JMP® 13 (SAS Institute Inc., Cary, NC) for SWP, ET_m, and K_c by date.

2.3 Results

Weather

In 2017, mean daily T_a for the collection period (26 June to 2 Aug) was 25.3 ±3.0 °C, ranging from 18.5-31.9 °C. There was 207 mm of precipitation across six rain events over the 38 days of the study period (Fig. 2.3). An average of 104 mm of precipitation fall during this period in Lincoln, Nebraska. From 12 July through 2 August only a minor rain event of 4.3 mm occurred on 17 July. These 20 days of minimal precipitation allowed for significant dry-down of 0WR plots in which differences were observed in relation to irrigated plots. Mean SR was 218 ±55 W m^{-2} for the collection period. Relative humidity was 70 ±7%. Wind speed averaged to 4.1 ±1.6 m s^{-1}. Mean VPD was 1.11 ± 0.41 kPa. Mean ET_o was 5.98 ±1.82 mm. The greatest ET_o value from the weather station dataset was on 21 July with 9.55 mm. On this day, mean T_a was 31.9 °C, SR was 261 W m^{-2}, RH was 53%, WS was 7.2 m s^{-1}, and VPD was 2.34 kPa.

In 2018, mean T_a for the collection period was 25.5 ±2.6 °C. There was a total 99 mm of precipitation across three rain events over the 32 days of the study period (Fig. 2.4). An average of 89 mm of precipitation fall during this period in Lincoln, Nebraska From 6 July to 27 July, a small rain event of only 6 mm occurred on 19 July for a total of 21 days with minimal precipitation where significant dry-down occurred on 0WR plots. Mean SR was 234 ±55 W m^{-2}. Relative humidity was 72 ±7%. Wind speed averaged to 3.2 ±1.8 m s^{-1}. Mean VPD was 1.05 ±0.42 kPa. Mean ET_o was 5.84 ±1.77 mm. The greatest ET_o value was recorded 29 June with 10.97 mm. On this day, mean T_a was 31.2 °C, SR was 270 W m^{-2}, RH was 57%, WS was 10.1 m s^{-1}, and VPD was 2.06 kPa.

Irrigation Applied

The longer collection period and greater mean ET_o in 2017 lead to greater number of irrigation events and irrigation quantity than in 2018. In 2017, 100WR plots received 302.7 mm of irrigation across 19 irrigation events for an average of 15.9 mm per event. The 50WR plots received 174.3 mm of irrigation for an average of 9.2 mm per event. In 2018, 100WR received 120.8 mm of irrigation across 8 irrigation events for an average of 15.1 mm per event. The 50WR plots received 58.9 mm of irrigation for an average of 7.4 mm per event. Water replacement for 50WR plots was greater than 50% of 100WR both years simply due to ET_m of 50WR being greater than 50% of ET_m for 100WR. 0WR plots received no supplemental irrigation in either year.

Soil Moisture

The soil water-retention curve (Fig. 2.5) allows for the extrapolation of SWP based on the measured VWC. To relate VWC (%) and Ψ_s (kPa), a logarthimic curve was found to fit the model at R^2=0.955. The model indicates that field capacity soil moisture conditions (between -33 & 0 kPa) occur from 12.9 – 13.4% VWC with the commonly cited permanent wilting point of -1500 kPa occurring at 2.7% VWC.

Starting soil moistures were similar in both years (Fig. 2.6), ranging from 14.7% to 22.2% VWC. It is presumed that the starting soil moistures were greater than 15% at FC due to insufficient time to drain before starting data collection period. The 100WR treatment was maintained near or above field capacity in both years, ranging from 14.3 to 22.2% VWC in 2017 and 8.0 to 19.4% VWC in 2018. In 2017, VWC for 50WR treatment was within 130 kPa (2.0% VWC) of 100WR on all dates except 10 July when the difference was 409 kPa (6.0% VWC). Greater separation of treatments was observed in 2018, where 50WR was within 130 kPa of 100WR until 13 July at which point the difference increased gradually to 654 kPa (5.3% VWC) on 27 July, the end of the study.

The 0WR treatment had the most dry-down in both years, with soil moisture levels ranging from 20.6 to 5.6% VWC in 2017 and 16.4 to 2.1% VWC in 2018. In 2017, rain events on 29 June and 3 July replenished soil moisture in 0WR plots. In the following eight rain-free days, VWC fell from 17.9% to 9.8% (179 to -428 kPa) on 11 July. The 37.3 mm rain event on 12 July increased VWC to 18.3%. Over the next 11 rain-free days, VWC fell to 6.9% (-786 kPa) with visible wilt (Fig. 2.8) occurring on 24 July. The 78 mm rain event on 26 July caused a brief spike in soil moisture followed by quick drop off to lowest measured value of 5.6% VWC (-1030 kPa) of 2017. In 2018, rain events on 30 June and 4 July prevented dry-down of 0WR plots. On 5 July, VWC was measured at 16.4% (104 kPa). The following 22 days had minimal rain, allowing 0WR plots to dry-down. On 13 July, after eight rain-free days VWC fell to 4.2% (-1252 kPa) with visible wilt of the turf occurring on that day. Soil water potential fell consistently (~176 kPa day^{-1}) from 6 July to 16 July, at which point the rate of decline decreased to ~24 kPa day^{-1}.

Water Use

To compare water use across treatments, two measurements of ET were considered: i) ET_m to represent the total amount of water lost, calculated using lysimeter weights in the water balance equation (Eq. 4), and ii) K_c, calculated as the quotient of ET_m and ET_o (Eq. 1). This method is used to normalize water use based on weather conditions and allows for treatment comparisons across days. In the 2017 collection period, lysimeters were weighed on 27 of the 38 days with 16 of those days being unaffected by precipitation. In the 2018 collection period, lysimeters were weighed on 25 of the 32 days with 21 days being unaffected by precipitation. Only days unaffected by precipitation (heavy rain events affected lysimeter weights for multiple days) were used for analysis.

There was a notable difference in water use measurements between 2017 and 2018 (Figs. 2.8 and 2.9). In 2017, water use was inconsistent and unexpectedly high for 100WR treatments, showing 54% greater mean ET_m than 2018, while mean ET_o was only 2% greater. The high values in 2017 suggested that the initial soil water content was much greater than field capacity, leading to inaccurate water use values for the 100WR treatment. This led to a modification in methods for the second year of data collection, yielding more realistic and consistent results. This is an example of potential complications of lysimetry.

In 2017, daily mean ET_m was 6.1 mm with an average K_c value of 0.96 for 50WR (Fig. 2.8). Crop coefficient values were greater than 0.70 on all days of measurement across all water replacement treatments except on 4 July when K_c was 0.55, suggesting no limiting soil moisture conditions in the collection period. Mean ET_m values for 0WR were 5-20% less than 50WR for all dates up to 19 July, at which point, water use began to decline for 0WR after 55.6 mm of ET_m. This decline in ET_m and K_c coincided with a drop in soil moisture, measuring 13.4% on 19 July and 9.2% on 20 July. From 20 July to 2 August, K_c declined from 0.73 to 0.00, suggesting that a soil moisture threshold had been crossed, preventing the creeping bentgrass from removing the water from the soil. In comparison with observed visible wilt on 24 July, the decrease in water use began 5 days earlier.

In 2018, 100WR and 50WR daily mean ET_m measured 5.7 and 5.5mm, respectively. Daily values ranged from 1.6 to 10.2 mm for both treatments, with half of all values falling between 4.5 and 6.6mm. Mean K_c values were 0.93 and 0.90 for 100WR and 50WR, respectively. Daily K_c values ranged from 0.52 to 1.39, with half of all values falling between 0.85 and 0.98. There was no clear relationship between ET_m and soil moisture for these two treatments. Measured K_c for 50WR & 100WR remained consistent throughout the 2018 collection period (see Fig. 2.7), falling below 0.70 only twice: 29 June (0.66 for 100WR) and 25 July (0.52 for both treatments) with the following day measuring greater than 0.70 on both occasions. The lack of any decrease in K_c for 50WR as soil moisture decreased to -969 kPa or 5.6% VWC by the end of the collection period suggests that water use for the bentgrass putting green did not vary with SWP in this range.

However, water use did decline for 0WR plots at lower SWP than were experienced by the 50WR plots. 0WR plots displayed two distinct trends of water use categorized into: sufficient and insufficient soil moisture. In the period of sufficient soil moisture (26 June to 13 July), K_c for 0WR plots was greater than 0.70 and ET_m was generally within 5% of 50WR & 100WR. The period of insufficient soil moisture (16 July to 27 July) is characterized by a sharp decrease in water use, where K_c measured 0.21 on 19 July and ended at just 0.06 on 27 July, the final day of day of data collection. This closely coincides with observed visible wilt on 13 July.

To quantify the two distinct trends of water use for the 0WR treatment, segmented least square regression (R^2=0.95) was applied to the SWP as a function of K_c. This regression shows a slope of zero for K_c when SWP is greater than the critical point of -1501kPa, indicating -1500 kPa as a critical soil water potential value for creeping bentgrass (Fig. 2.10). This supports the findings in the 50WR and 100WR treatments that water use remains consistent (near the y-intercept value of b=0.88) at levels of sufficient soil moisture, which agrees with measurements from 50WR and 100WR treatments. When SWP drops below the critical value of -1500 kPa (soil gets drier), the slope for K_c trends downward (m=0.0012) indicating that water use declines rapidly once the soil dries past this critical point. The positive slope for the insufficient soil moisture segment illustrates a downward trend in water use due to the more negative SWP values representing a drier soil. The 0WR treatment crossed this critical point of SWP on the 15 July, two days after observed visible wilt, after a cumulative 66.4 mm of ET_m up to this date of the study period.

2.4 Discussion

Change in Water Use with Soil Moisture

We found two distinct trends, or phases, of water use in a creeping bentgrass putting green: i) consistent water use with measured K_c around 90%, associated with SWP greater than -1501 kPa (wilting point), and 2) a sharp decline in water use with K_c approaching zero, occurring after soil dries down past the wilting point threshold identified in this study. This wilting point, calculated using segmented regression of ET_m and SWP, closely agrees with the accepted WP of -1500 kPa mentioned in Ritchie (1981) and (Aamlid *et al.*, 2016). This number is applied to a wide variety of species and soil types so confirmation of this value in a creeping bentgrass putting green could help to increase precision of soil moisture management in similar situations. Biran et al (1981) shows a similar trend of consistent ET followed by quick decline in water use for both warm- and cool-season grasses but a dearth of presented data makes it difficult to quantify. The rapid transition from healthy to visibly wilted turf observed in the 0WR plots emphasizes the need for managers to understand the relationship between measured soil moisture and SWP. Understanding that water use is consistent at a wide range of SWP's could aid turf managers in reducing irrigation frequency and minimize the excessive use of water resources. To our knowledge, no research has previously been conducted on water use of creeping bentgrass as it transitions from field capacity to wilting point in a putting green situation.

Overly frequent irrigation combined with soil moisture maintained above field capacity is a potential cause of the unexpectedly high water use measurements in 2017. In 2018, we adjusted by allowing more time for excess water to drain from lysimeters after irrigating plots to field capacity to start the study. Aamlid et al (2016) observed K_c values of various cool-season turf species up to three times greater on the first day after irrigation (1.67-2.85) compared to measurements from the following days (0.81-0.91). Our study, like Aamlid et al (2016), measured no leachate on these days indicating that excess water was quickly evaporated away. Allowing more time for drainage before initiating the study and irrigating less frequently in 2018, K_c values were in line with values reported in the literature (Aamlid *et al.*, 2016, Salaiz *et al.*, 1991). By reducing irrigation applications and controlling soil moisture below field capacity, managers can avoid this unnecessary water loss.

Applicability of these data can be improved through repetitions under different management regimes like species and mowing height, and also by increasing the number of study locations (e.g., soil type and climate). In this study, days with rainfall events prevented more frequent lysimeter weight measurements. Subsurface movement of water from an adjacent plot into the northernmost block of the study was suspected and may have led to increased soil moisture measurements for those experimental units. An oasis effect was observed on some lysimeters (Fig. 2.11) where turf inside the lysimeter had a limited rooting depth, and thus limited access to water (Fig. 2.2) as compared to the vegetation in the plot. Turf surrounding the lysimeter was able to reach soil moisture deeper in the soil profile, potentially down to the gravel layer.

ET_m and K_c Rates in a Creeping Bentgrass Putting Green

In 2017, we observed K_c values on well-watered plots between 0.52 and 2.22 for the 100WR treatment, with half of all measurements between 0.89 and 1.36. In 2018, after adjusting our methods to account for the unnecessary water use, K_c for 100WR measured 0.52 to 1.39. For 50WR, we saw values between 0.52 and 1.30 with half of all values between 0.86 and 1.00. These values agree with findings from Salaiz *et al.* (1991) who found K_c values from 0.60 to 1.31 across ten different creeping bentgrass species. These species had ranges of K_c values spanning up to 0.50 units which is similar to values we observed for the 50WR treatment in both years and 100WR treatment in 2018 while the wider range for 100WR treatment can be explained by too frequent irrigation at field capacity soil moisture. Our K_c measurements trend slightly lower potentially due to a lower mowing height (2.8 mm compared to 12.5mm in the Salaiz *et al.* study) leaving less plant material to transpire water. (Poro *et al.*, 2017) concluded that adjustments to K_c are justified for different cut creeping bentgrass height in a study conducted in the humid northeast (both green and fairway heights were evaluated).

Our measured daily ET_m values ranged from 1.6 to 14.3 mm for 100WR in 2018 with half of those falling between 5.8 to 12.3mm. We saw 1.6 to 7.8 mm for 50WR treatment in 2018 with half of those falling between 4.4 and 6.4mm. These numbers agree well with those of Salaiz et al. (1991) who measured ET_m values of 3.2 to 10.7 mm across the ten species. We attribute our lower ETm values to those reported due to a lower mowing height.

Future Research

We propose combining findings from this study with simultaneous T_c measurements to gain insight on how creeping bentgrass putting greens transition into drought stress. Early identification of drought stress using remote sensing can lead to quicker, more precise management decisions.

2.5 Conclusion

This study reveals temporal water use patterns as creeping bentgrass undergoes water stress when managed as a putting green. Crop coefficients remained consistent for all treatments when SWPs were greater than -1501kPa, which we define as the wilting point for creeping bentgrass under study conditions. At values below this wiling point, water uptake decreased and eventually ceased at which point the turf entered dormancy. With minimal difference in water use and visual quality between 50WR and 100WR, we see that over-irrigation will lead to unnecessary consumption of water resources with no benefits to plant health or aesthetics. Increasing understanding of water use patterns for this species in this management regime will help to increase efficiency of water resources and provide managers with better control of their facilities.

2.6 Tables & Figures

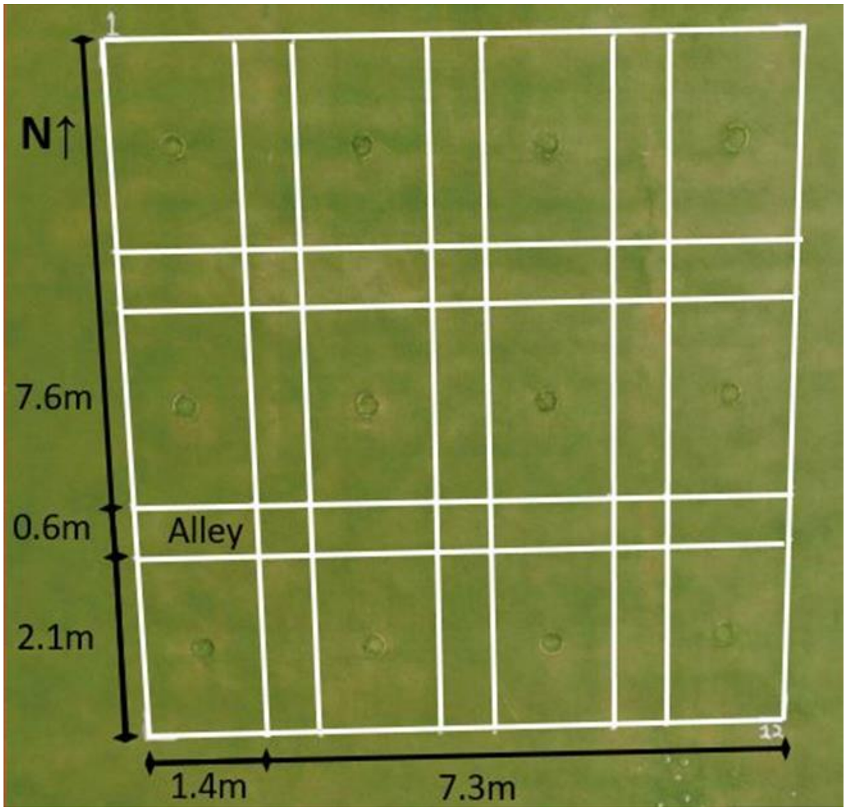

Figure 2. 1 Layout of research area.

Lysimeters are located in the center of each plot. Treatments were randomized to plot each year. Alleys prevented sub-surface movement of water between treatments.

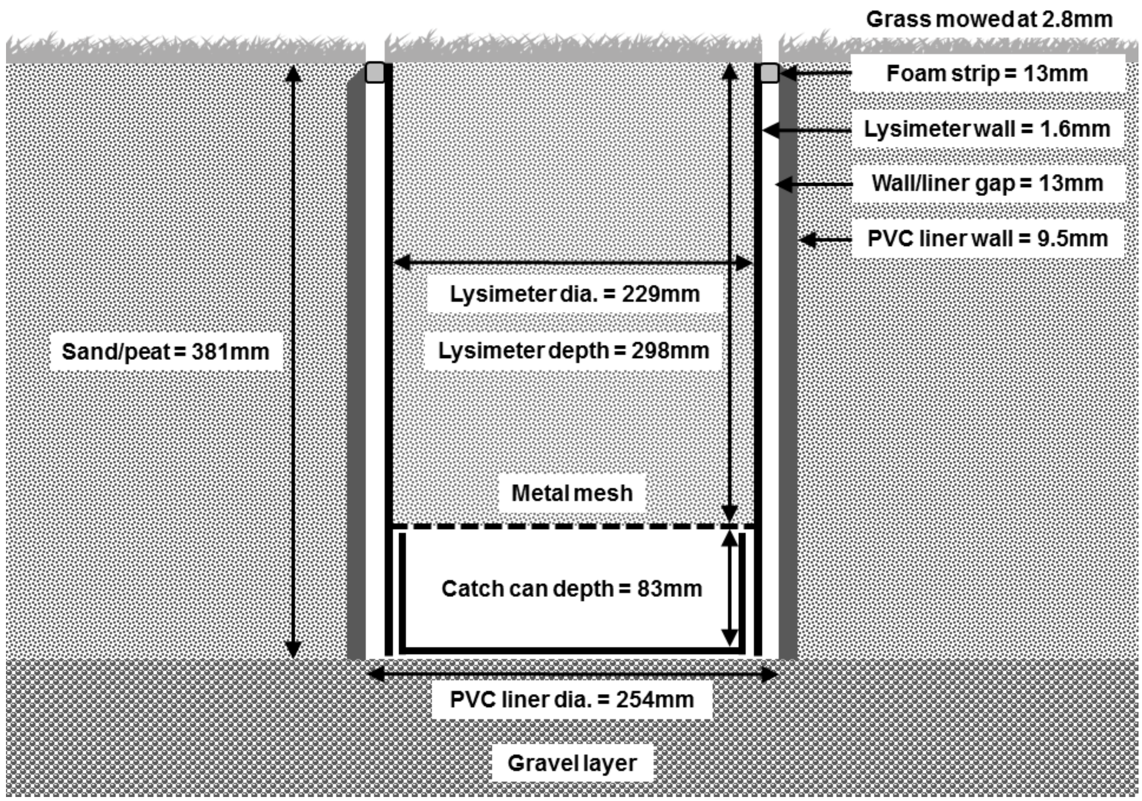

Figure 2. 2 Diagram of lysimeter measurements.

Diagram showing how the lysimeter fit into surrounding field conditions. Lysimeters rested in a PVC tube extending the length of the soil profile. A foam strip surrounded the top of the lysimeter to minimize the wall/liner gap at the surface. Catch cans were removable to allow measurement of leachate volume.

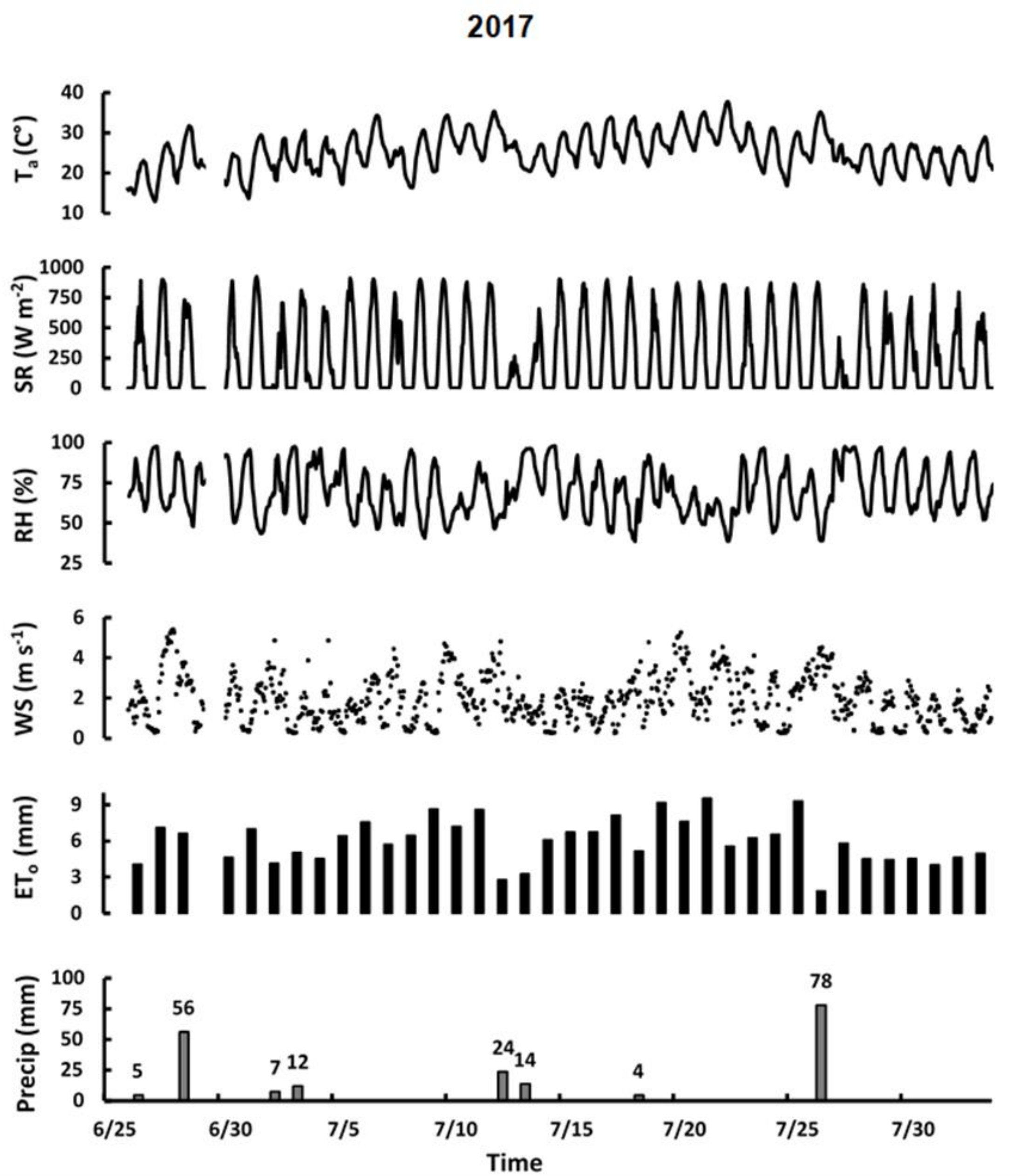

Figure 2. 3 Weather trends from 2017 that influence water use.

Hourly trends for air temperature (Ta), solar radiation (SR), relative humidity (RH), and wind speed in 2017. Data for reference ET (ET_o), and precipitation in (Precip) is daily. Weather data missing for 29 June.

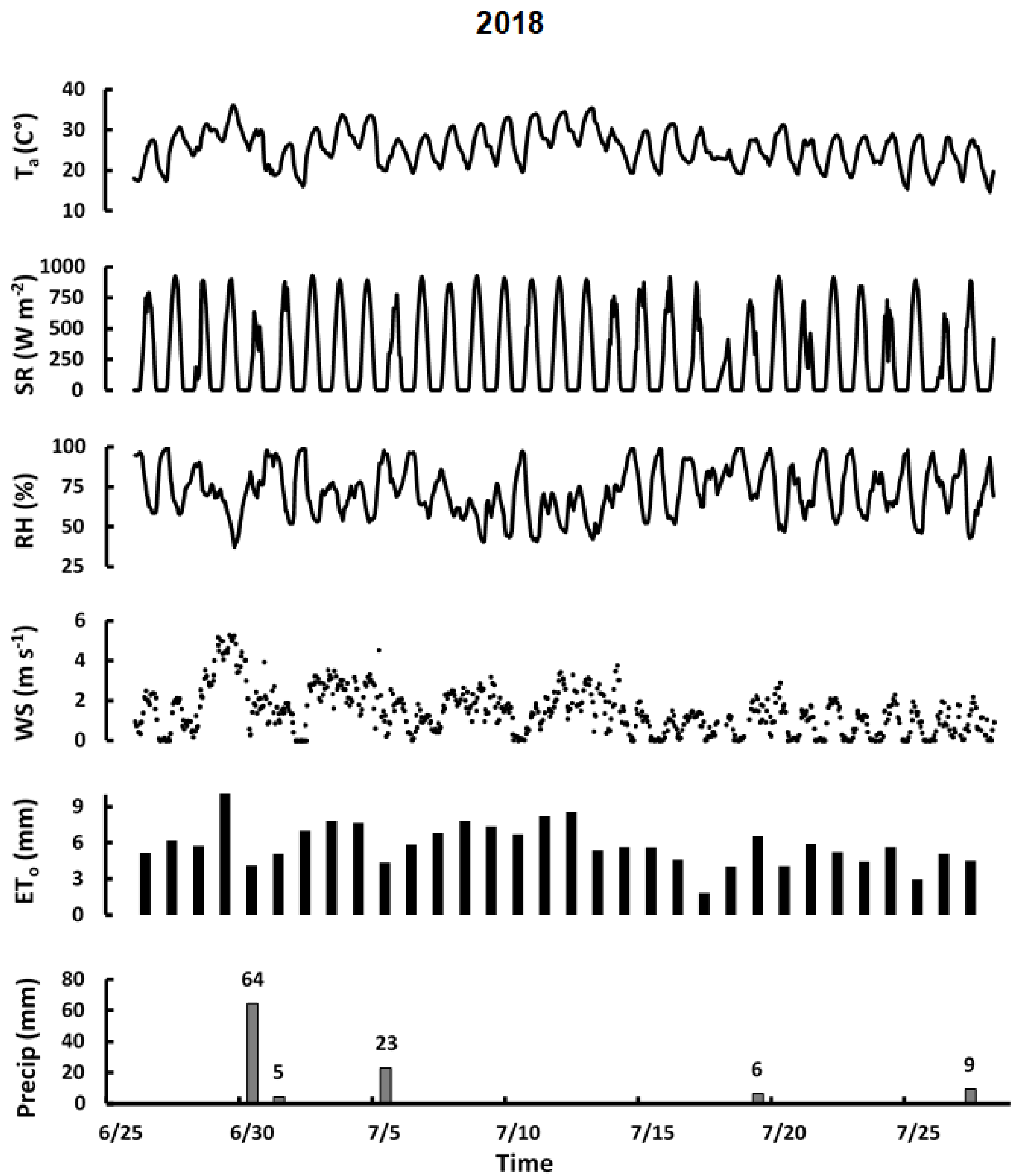

Figure 2. 4 Weather trends from 2018 that influence water use.

Hourly trends for air temperature (Ta), solar radiation (SR), relative humidity (RH), and wind speed in 2018. Data for reference ET (ET_o), and precipitation in (Precip) is daily.

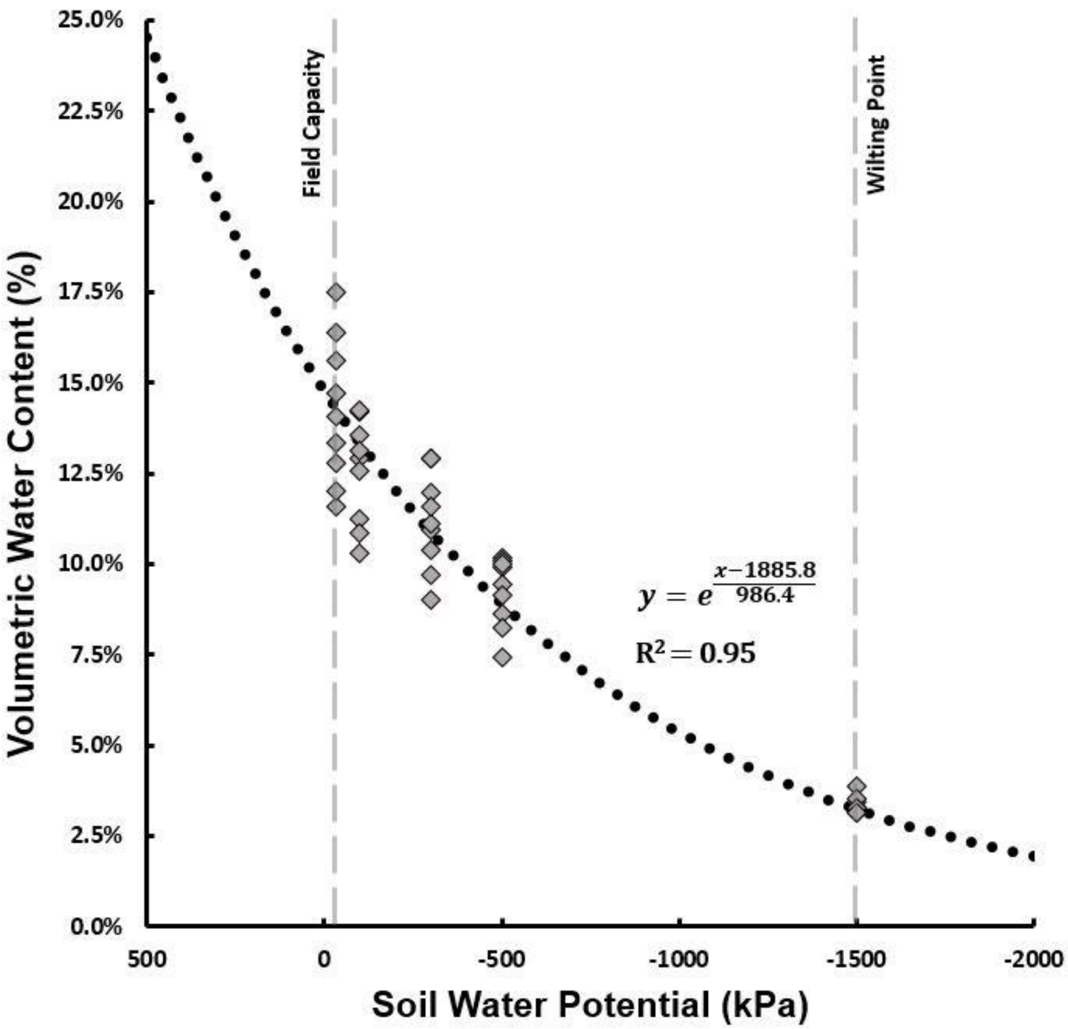

Figure 2. 5 Water-retention curve for research area to convert volumetric water content to a soil water potential.

Field capacity (dashed line = -33 kPa) occurs 12.9% VWC while wilting point (dashed line = -1502 kPa) is 2.7% VWC. The logarithmic equation for converting VWC to SWP was determined based on pressure required to remove water from cores using ceramic plate extractors at -33, -100, -300, -500 kPa while the -1500 kPa measurements were from oven dried soil. Soil cores were collected in 2018.

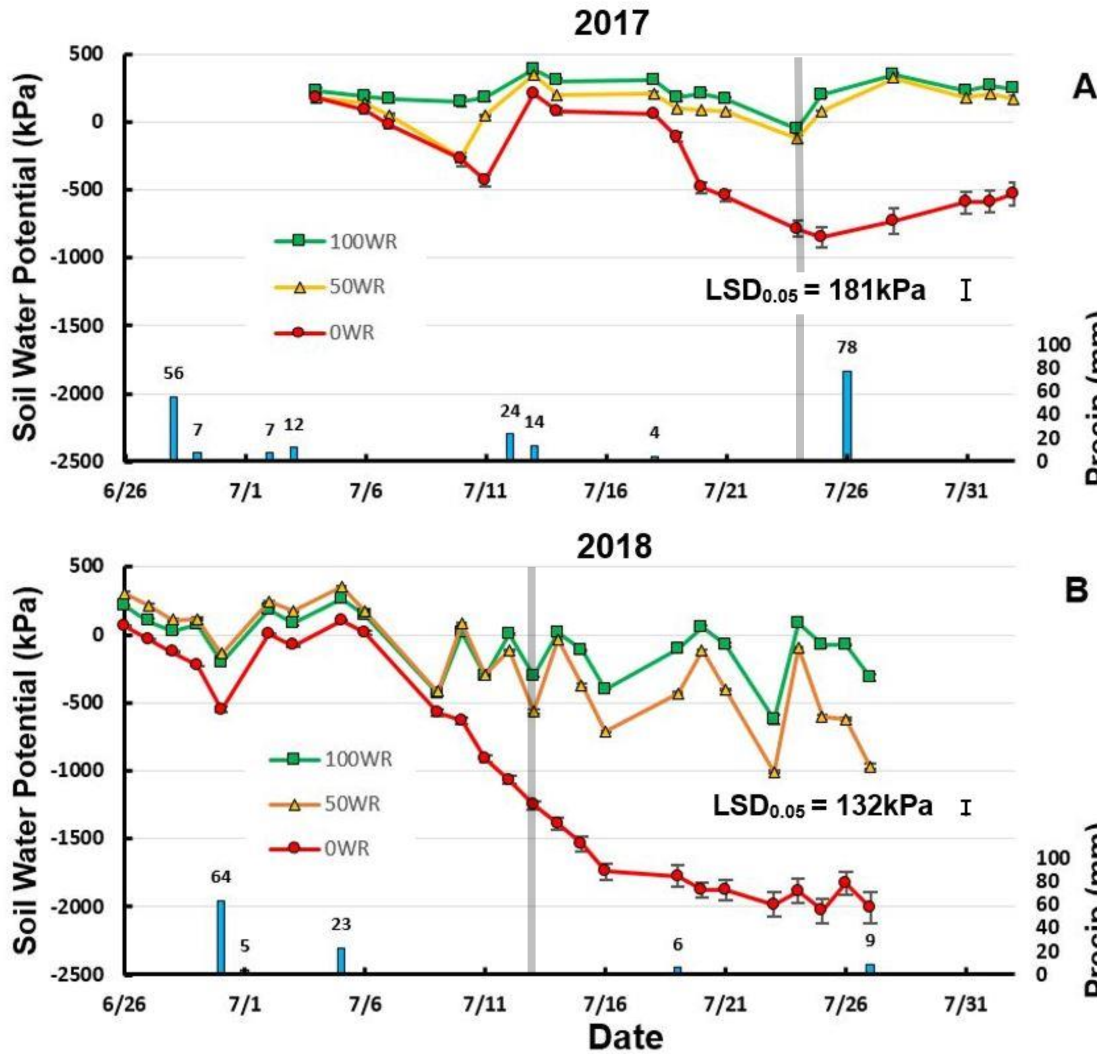

Figure 2. 6 Trends of soil water potential by treatment for both years.

Average Soil water potential for each treatment during data collection periods in 2017 (A) and 2018 (B). Rain events denoted along the x-axis. Treatments are full water replacement (100WR), half water replacement (50WR), and no water replacement (0WR). Standard error is shown. Treatment differences greater than Fisher's $LSD_{0.05}$ are significantly different. Gray line denotes first day visible wilt was clearly observed.

Figure 2. 7 Images of 0WR plots on day of visible wilt

Images of discoloration and leaf firing on 0WR plots indicating visible drought stress.

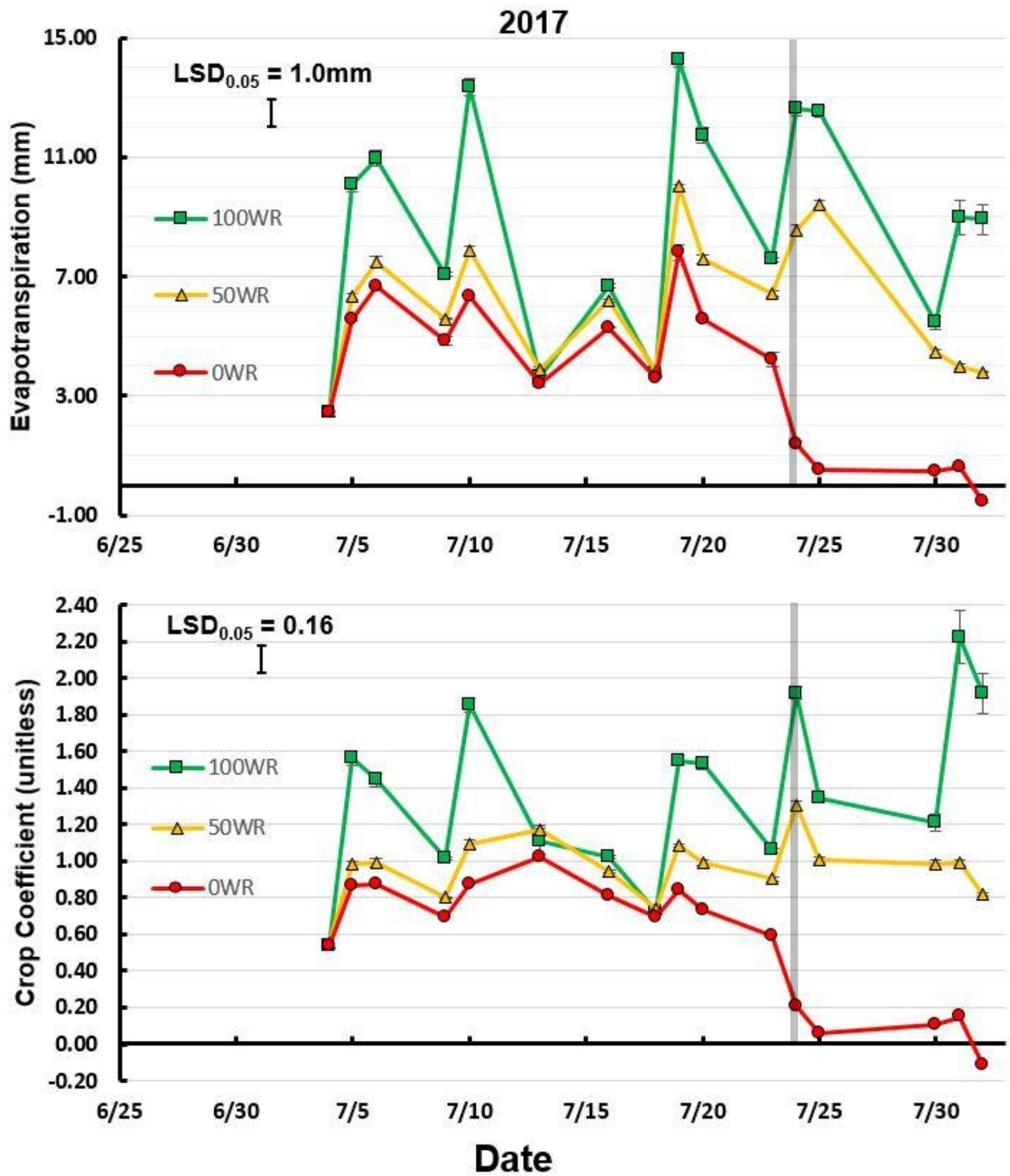

Figure 2. 8 Average Water use data by date for all treatments in 2017.

Average Crop coefficients calculated using Daily Penman equation. Treatments are full water replacement (100WR), half water replacement (50WR), and no water replacement (0WR) (n=4). Standard error is shown. Treatment differences greater than Fisher's LSD$_{0.05}$ are significantly different. Only days unaffected by rain are shown. Gray line denotes first day visible wilt was clearly observed.

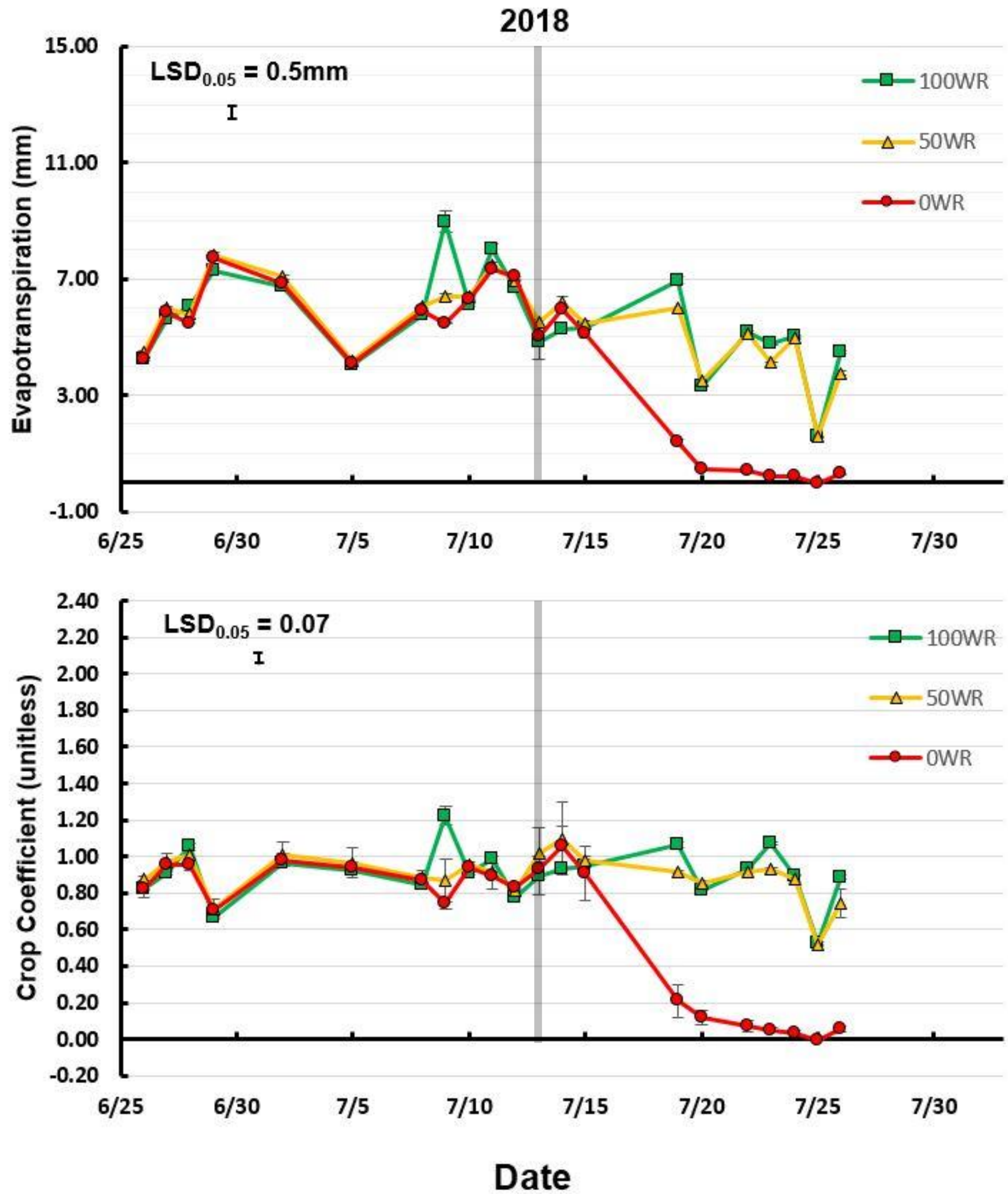

Figure 2. 9 Average Water use data by date for all treatments in 2018.

Average Crop coefficients calculated using Daily Penman equation. Treatments are full water replacement (100WR), half water replacement (50WR), and no water replacement (0WR) (n=4). Standard error is shown. Treatment differences greater than Fisher's LSD0.05 are significantly different. Only days unaffected by rain are shown. Gray line denotes first day visible wilt was clearly observed.

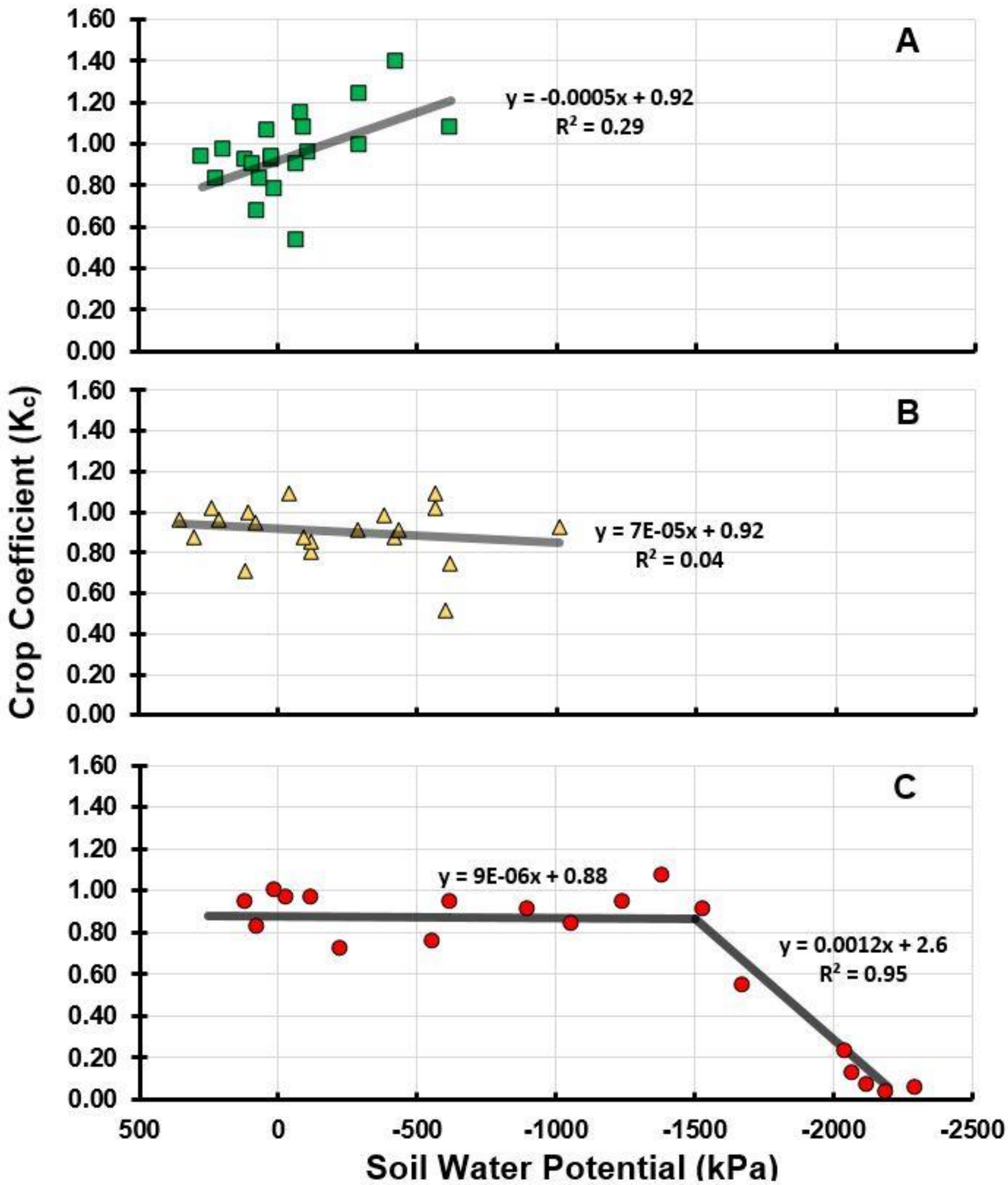

Figure 2. 10 Relationship of measured crop coefficients and soil water potential from 2018.

Crop coefficients from 2018 as a function of soil water potential for full water replacement (A), half water replacement (B), and no water replacement (C). Trendlines are shown for each treatment with segmented linear regression used to calculate two distinct trends of water use for the no water replacement treatment.

Figure 2. 11 Image of oasis effect in 2018.

Image of Plot 4 (0WR) on 7/25/2018. Here we see the “oasis effect” of the lysimeter due to physical separation from the soil profile. We suspect subsurface movement of water from the area at the top of the image created this difference in soil moisture between the lysimeter and the upper half of the plot.

CHAPTER 3: USE OF CANOPY TEMPERATURE TO MEASURE WATER STRESS IN CREEPING BENTGRASS

3.1 Abstract

Canopy temperature measured via thermal imagery can provide insight regarding spatial plant-water status of turf but improved data interpretation is needed to inform irrigation scheduling practices. This study was conducted to better understand how T_c of creeping bentgrass (*Agrostis stolonifera '007'*) is affected by soil moisture and weather. A camera system recorded various metrics utilizing T_c along with current weather information on a ten-minute interval. Responses from this data were related to visual observance of wilt to evaluate their usefulness in irrigation scheduling. To further improve detection of water stress, multiple regression analysis was used to create a model (n=3216) to predict T_c of a non-water stressed turf using four weather parameters: T_a, SR, RH, and WS. Here we show that metrics such as Relative to Non-Water Stressed Baseline (Rel_{NWSB}) and Standard Deviation of T_c (SD_{Tc}) over a measured area can be used to indicate drought stress prior to visible wilt. In 2017 and 2018, Rel_{NWSB} for plots receiving 0WR exceeded 4 °C in the mid-afternoon one day prior to visible wilt, where plots receiving 50WR did not exceed 2 °C at any point. The SD_{Tc} metric exceeded 2 °C for 0WR two days prior to visible wilt in 2017 when non-water stressed plots did not regularly exceed 1 °C. Results for SD_{Tc} in 2018 are inconclusive. Models using T_a and SR were most predictive when tested on a 2016 dataset with the median difference between predicted and measured T_c (T_Δ) at 0.90±1.27 °C. While results improve the understanding of relationships between T_c, soil moisture, and weather, further research is necessary to develop precise decision-making tools.

3.2 Introduction

Thermal imaging is emerging as a useful tool for the management of turfgrass. It provides both qualitative and quantitative spatial and temporal data to the manager. Qualitative data are measured as infrared radiation collected by the detector via a lens and composed into thermal imagery. A color scale relates each pixel of the image, corresponding to an area on the surface, to a temperature. This image shows the spatial relationship of T_c and helps to identify hot spots or other underlying issues. Collected over time, provides temporal coverage. For the quantitative aspect, values of T_c measurements can be extracted from each pixel of the image to give a more precise measurement than visually assessing temperatures using the color scale provided with each image. While both sets of information can be useful for decision making in turfgrass, interpretation of quantitative Tc data needs to be improved to be fully utilized by turf managers for efficient water use.

Canopy temperature is a measure of infrared radiation emitted from the surface of plant leaves. The amount of radiation emitted is related to the amount of solar and thermal radiation absorbed by the plant material. This absorbed radiation can be partitioned into two measurable categories, explained by equation (2):

$$R_n = H + LE \tag{6}$$

where R_n is net radiation incident on the canopy, H is the sensible heat flux or energy, and LE is the latent heat flux or energy consumed in the processes of transpiration as liquid water in the leaf is converted to gaseous water vapor as it exits stomata (Martin *et al.*, 2005b) and evaporation of water from the soil and plant surface. As plant health declines due to drought stress or other factors, transpiration rate will decrease leading to a decrease in energy absorbed in LE, an increase in temperature and an increase in sensible energy (H); the surface temperature is detectable through thermal infrared cameras.

Canopy temperature data from infrared thermometry or thermography has been used to gain insight into plant-water status of various crops such as cotton (Alchanatis *et al.*, 2010; Sela *et al.*, 2007b), grapevine (Moeller *et al.*, 2007), olive (Ben-Gal *et al.*, 2009), and pepper (Camoglu *et al.*, 2018). These techniques have also been tested on various species and management regimes of turfgrass such as: Kentucky bluegrass (Throssell *et al.*, 1987, Martin *et al.*, 1994), bermudagrass (Carrow, 1993; Jalali-Farahani *et al.*, 1993) and creeping bentgrass (Martin *et al.*, 1994) but no research can be found for creeping bentgrass maintained at putting green heights. Healthy, unstressed turf is thought to maintain a T_c slightly below ambient T_a due to transpirational cooling. An increase of T_c in relation to T_a would indicate reduced transpiration and thus, an increase in plant stress.

A number of factors are known to influence T_c, such as: T_a, SR, WS, and soil moisture (Carlson *et al.*, 1972). Stress indices utilizing T_c data have been developed to quantify the level of water stress in plants. Fuchs (1990) proposed that the variation of T_c over a given area would indicate water stress. Using T_c variation would eliminate the need for multiple measurements to detect stress. One of the more common stress indices is the empirical crop water stress index (CWSI) developed by Idso (Idso, 1982):

$$CWSI = \frac{(T_c - T_a)_{act} - (T_c - T_a)_{LL}}{(T_c - T_a)_{UL} - (T_c - T_a)_{LL}} \qquad (7)$$

where $(T_c - T_a)_{act}$ is the measured canopy temperature minus air temperature, $(T_c - T_a)_{LL}$ is canopy temperature minus air temperature at the lower limit of water stress, and $(T_c - T_a)_{UL}$ is the canopy minus air temperature at the upper limit of water stress. The upper and lower limits are commonly referred to as the water-stressed baseline (WSB) and non-water-stressed baseline (NWSB), respectively.

Accurate estimations of the WSB and NWSB are needed to make the CWSI a practical decision-making tool for turf managers. Constantly changing weather conditions and thus, changing T_c, create a range of potential values for baselines (Taghvaeian *et al.*, 2014). Researchers have created models that predict these baselines under various conditions using different weather factors (Payero *et al.*, 2005; Martin *et al.*, 1994; Throssell *et al.*, 1987) including air temperature and vapor pressure deficit but no attempt to model these baselines for a creeping bentgrass putting green could be found.

The purpose of this study is to evaluate if frequent measurements of T_c and weather parameters can be used to detect early signs of water stress in a creeping bentgrass putting green. More specific objectives include: i) observe the T_c under various weather conditions, ii) understand how soil moisture affects the T_c, and iii) develop a model to predict the T_c of NWSB for a creeping bentgrass putting green using weather parameters.

3.3 Methods & Materials

Site Description

This data for this chapter was collected simultaneous to the data from Chapter Two on the same research plot (Fig. 2.1), a creeping bentgrass (*Agrostis stolonifera ‘007’*) putting green. Data was collected in two periods: 26 June through 3 August of 2017 and 26 June through 27 July of 2018. The study area consisted of 12 plots arranged in three replicate rows of four treatments with data from the fourth treatment omitted from this this study. Each plot measured 2.1 x 1.4 m with a 0.6 m buffer zone around each plot. Overhead irrigation was withheld but natural precipitation was allowed. Rain tarps were used to cover the research area on two occasions (26 July 2017 & 17 July 2018) when a brief rain event was identified ahead of time. Plots were irrigated by hand, using a flowmeter attached to a hose, as part of treatments. Buffer zones were unirrigated. Plots were mowed five times weekly with a walk-behind reel mower (Greensmaster eFlex® 2100, The Toro Company, Bloomington, MN). Height of cut decreased gradually from 4.1 to 3.3 mm in 2017 and was maintained at 2.8 mm in 2018. Nitrogen fertilizer (46-0-0) in the form of urea was applied at a rate of 12.21 kg ha^{-1} semi-weekly. A surfactant, Revolution (Modified Alkylated Polyol), was applied on 22 June 2017 and 24 May 2018 at rate of 9.5 and 19.0 L ha^{-1} respectively.

Lysimeters

To measure ET and calculate K_c, a 16.7 L weighing lysimeter was buried in the center of each plot. Existing turf and root zone mix were used in lysimeters to match surrounding conditions. Lysimeters were removed and weighed on an Ohaus (Pine Brook, NJ) Explorer Precision High Capacity Balance in the morning on days of measurement. Sizable precipitation events would affect lysimeter weights for 1-2 days so no data was collected on these days. K_c values and measured ET (ET_m) and were calculated in the same manner as in Chapter 2 (equations 1 and 4 respectively). Measurements of ET_m and K_c on days following rain events were excluded.

Irrigation Treatments

Three irrigation treatments were employed to evaluate how ET_m and K_c varied at different soil moisture levels. Treatments were three levels of water replacement: 0, 50, & 100% (0WR, 50WR, & 100WR). A fourth treatment, using a proprietary formula to schedule irrigation, was conducted simultaneously but data is omitted from this research.

Amount of water to be replaced was determined with ET_m values measured with the water balance equation (Eq. 4) for individual plots. Irrigation was applied after all lysimeters were weighed. Plots were irrigated using a TeeJet XR8006 (TeeJet, Wheaton, IL) while lysimeters were removed. Irrigation volume was monitored with a flowmeter. Lysimeters were then replaced and irrigated separately from the plot with a water bottle using a proportional amount of water as the rest of the plot received. This ensured that all water applied entered the soil and no water was lost into the wall/liner gap (Fig. 2.2).

Treatments were arranged in a randomized complete block design for each study year. All plots were irrigated to field capacity at the onset of the study in each year.

Camera System

A camera system (Hawkeye System® by Itricorp, Haymarket, VA) consisting of a FLIR (forward-looking infrared) camera to measure canopy temperature (Tc) and an RGB camera for standard color imaging was mounted near the research site (Fig. 3.1). The camera system was mounted to a pole 7 m above the ground and 20 m away from the study area. The system faced north and was angled toward the ground at 15°.

The FLIR, or thermal, camera was sensitive to infrared radiation between wavelengths of 7-13.5 µm. The thermal camera contains an uncooled vanadium oxide microbolometer detector. Camera lens provides a 25° field-of-view and an image of 320x240 pixel resolution. The system recorded separate images from both cameras on a ten-minute interval and stored the digital images in a database where the images and thermal data could be accessed. Each pixel in the thermal image, representing $3.8 cm^2$ on the surface, provides an average thermal measurement within the pixel area. The system allows for each plot to be selected and measured separately, eliminating the need for additional image processing after the fact. The mean and standard deviation of the thermal measurements for each plot are extracted from the images, referred to as T_c and SD_{Tc}.

In this research, a new T_c metric was defined to evaluate water stress. This metric, canopy temperature relative to a non-water stressed baseline (Rel_{NWSB}), is defined as:

$$Rel_{NWSB} = T_{100WR} - T_c \tag{6}$$

where T_{100WR} is the canopy temperature of the 100WR treatment and T_c is the canopy temperature of the plot of interest. Negative values indicate a greater T_c for the plot of interest in relation to 100WR, indicating reduced transpiration and increased stress. The 100WR represents a non-water stressed baseline in this study since soil moisture remains sufficient, allowing the turf to fully transpire.

A weather station (AmbientWeather WS-1002-WIFI, Ambient Weather, Chandler, AZ) was located on the north side of the research area. The camera system collected current weather data simultaneous to each image capture.

Weather Data

Hourly weather data was collected from the AWDN as part of the HPRCC. Weather observations from a nearby the Nebraska State Climate Office Mesonet Lincoln IANR Station were retrieved from the High Plains Regional Climate Center website. Hourly averaged values downloaded from the site include T_a, RH, soil temperature, SR, WS, wind direction, and ET_o, calculated in the same manner as Chapter Two. This weather station was located approximately 1km to the southeast of the study area on the University of Nebraska campus. Weather data from Mesonet station was checked against the ten-minute readings from the AmbientWeather station to ensure accuracy.

Soil Moisture Measurements

A FieldScoutTDR 300 hand-held time-domain reflectometry soil moisture meter (Spectrum Technologies, Inc., Aurora, IL) was used to measure soil volumetric water content (VWC) in the standard soil-type mode using a 7.6 cm length rod. VWC was measured at five locations within each plot before each lysimeter weighing event. An average VWC was calculated for each plot. A water-retention curve relating VWC readings with SWP measurements (see Section 2.3).

Data Analysis

Multiple regression models to predict T_c based on current weather conditions were developed using the 'Regression' function in Microsoft Excel 2016. Weather factors used to calculate T_c were T_a, SR, RH, and WS. Numerous combinations of these factors were tested to evaluate which factors are needed to develop a sufficient model. Weather data from the 2017 and 2018 data collection periods were used. Canopy temperature of three reps of 100WR were averaged to determine T_c of the NWSB. Multiple regression formulae were applied to a dataset from 2016 to evaluate accuracy of predictions. The 2016 dataset includes three days of T_c and weather data from a creeping bentgrass plot at the UNL Turfgrass Research Center with soil moisture maintained near field capacity, similar to the 100WR treatment of this study. Adjusted R^2 was used to account for number of factors used to create model. Adjusted R^2 and R^2 are equal for single factor models.

3.4 Results & Discussion

Canopy Temperature and Weather

Figure 3.1 shows a strong diurnal pattern of T_c peaking in the mid-afternoon and reaching its lowest level pre-dawn at all levels of water replacement. The diurnal variation in T_c, often greater than 20 °C in the summer, can be attributed to diurnal change in weather conditions.

In 2017, T_a ranged from 9.7 – 37.7 °C with daily highs between 23.1 – 37.7 °C. Daily peak of SR ranged from 267 – 961 W m^{-2} with a mean value of 820 W m^{-2}. Relative humidity ranged from 25.5 – 98.0% with a mean value of 68.1%. Mean WS was 2.0 m s^{-1}.

In 2018, T_a ranged from 14.6 – 36.1 °C with daily highs between 19.7 – 36.1 °C. Daily peak of SR ranged from 416 – 930 W m^{-2} with a mean value of 824 W m^{-2}. Relative humidity ranged from 37.1 – 99.8% with a mean value of 71.5%. Mean WS was 1.4 m s^{-1}.

Canopy temperature measurements ranged from 9.3 – 41.3 °C for 50WR and 100WR treatments and 8.7 – 47.8 °C for 0WR in 2017. In 2018, the ranges were 13.8 – 42.8 °C for 50WR and 100WR and 13.4 – 55.1 °C in 0WR. Temperature ranges were smaller for 50WR and 100WR due to higher evaporation rates (Chapter 2) due to sufficient soil moisture (high VWC). The highest and lowest Tc values were observed in the 0WR treatment when soil moisture was insufficient for plant transpiration.

Linear regression analysis on the 2018 dataset shows that R_s followed by T_a are the most influential factors on T_c with R values of 0.89 and 0.84, respectively (Fig. 3.3). Both show strong positive correlation. Relative humidity showed a negative correlation with an R value of 0.76. Wind speed showed a weak, positive correlation with an R value of 0.48. The correlation of WS and T_c might be expected to increase if weather station was located on-site and measurements were recorded simultaneously due to frequent changes in WS in each microclimate.

Soil Moisture

As demonstrated in Chapter 2, ET_m values were relatively constant when soil moisture was readily available to plants (high soil water potential, SWP) but decreased when SWP value fell below -1501 kPa in 2018when soil water was bound too tightly to the soil to be utilized by the plants through transpiration, resulting in drought stress indicated by reduced ET_m.

In 2018, all treatments started with a positive SWP, meaning soil moisture was sufficient and slightly above field capacity at the time of measurement. Both 50WR and 100WR plots maintained SWP values greater than -1006 kPa (Fig. 3.4), indicating sufficient soil moisture throughout and no drought stress (note: no plant wilting was observed in these treatments). SWP for 100WR plots were greater than those for 50WR plots on all dates from 12 July through the end of data collection as expected since 100WR plots receiving more irrigation and will benefit from higher ET. Pattern of SWP for 0WR was similar to the two other treatments until 10 July, five days after a rain event of 23mm. Following that rain event, SWP for 0WR fell from 104 kPa to -1501 kPa on 15 July and to -2030 kPa on 25 July.

In 2017, the first day of visible drought stress was 24 July. In 2018, visible drought stress occurred on 13 July. Metrics indicating the onset of drought stress prior to these dates could be useful in irrigation scheduling.

Canopy Temperature Minus Air Temperature

In 2018, $T_c - T_a$ ranged between -10 and 10 °C for all treatments on all days until 13 July (Fig. 3.5). Values followed a diurnal pattern coinciding with times when T_a, reached a maximum in the mid-afternoon and minimum at pre-dawn (Figure 3.1)) when ET rates were relatively constant until soil moisture reached a critical level (see Chapter 2).

From 13 July to 15 July, the mid-afternoon peak in $T_c - T_a$ increased from 17.0, to 25.5 °C for the 0WR treatment. This period coincides with the SWP at the wilting point when drought stress set in and ET rate dropped considerably (Fig. 2.6). From July 15 on to the end of the study period, mid-afternoon values remained above 20 °C. This data suggests that creeping bentgrass maintained at putting green heights would undergo drought stress when $T_c - T_a$ exceeds 10 °C.

A small increase in mid-afternoon $T_c - T_a$ was also observed for 50WR and 100WR after July 15. This is likely due to drought stress around the edges of the plots in the unirrigated buffer zones as they exhibited symptoms of drought at the same time as the unirrigated 0WR plots. Values of $T_c - T_a$ never exceeded 15 °C for either treatment. Values for 50WR and 100WR were consistently within 2-3 °C of each other with mid-afternoon peaks slightly higher for 50WR.

After the onset of drought stress for 0WR plots, a trend was observed at night where $T_c - T_a$ for 0WR was 1 to 2 °C cooler than other treatments. This could be due to the lack of soil moisture buffering temperature change. This could be of value because weather parameters like SR and WS are less variable at night potentially making it easier to discern changes in temperature caused by drought stress. However, more trials are needed to o make decisive conclusions. ‘

Canopy Temperature Relative to Non-Water Stressed Baseline

In this study, the NWSB is defined using data from the 100WR treatments as they were irrigated to replace all water lost through ET ensuring sufficient soil moisture for full transpiration. A simplified approach to the CWSI is utilized in which a T_c estimated water stressed baselines and NWSB are used to account for current weather conditions. Thus any increase in T_c for 0WR or 50WR relative to the 100WR (representing a NWSB) plots would indicate water stress via reduced ET.

In 2017, ranges of Rel_{NWSB} for 50WR and 0WR were -0.8 to 1.1 °C and -1.9 to 10.4 °C, respectively (Fig. 3.6). Similar to T_c measurements, values were at their maximum in the mid-afternoon and were at their minimum prior to sunrise. On 23 July, one day prior to visible wilt, the mid-afternoon Rel_{NWSB} peaked exceeded 2.0 °C for 0WR. In the following days, the peak in Rel_{NWSB} increased to a maximum value of 8.0 °C with peak values being 4°C or higher through the end of the collection period. Nighttime values for the 0WR treatment plots were consistently greater than -1.0 °C until 23 and 24 July at which point values below -1.0 °C were common. For 50WR treatments, T_c was consistently within 1.1 °C of the 100WR plots which represented the NWSB (Figure 3.6).

In 2018, ranges of Rel_{NWSB} for 50WR and 0WR were -1.4 to 6.2 °C and -2.8 to 13.9 °C, respectively. On 11 July, four days prior to visible drought stress in the 0WR treatment plots, mid-afternoon RelNWSB peak reached 2.0 °C. From 11 July to 15 July, as SWP crossed the critical value of -1501 kPa (Fig. 3.9), the Rel_{NWSB} value increased to 13.9 °C. Similar to 2017, when mid-afternoon Rel_{NWSB} values reached 2.0 °C on July 22, nighttime values dropped below -1.0 °C for the first time in the collection period. The trend is attributed to the unintentional inclusion of drought stressed alleys when images were analyzed. As values for 0WR increased, Rel_{NWSB} temporal trends for 50WR treatment plots mimicked those of the 0WR treatment but to a lesser degree as values were frequently less than half of 0WR values at the mid-afternoon peak.

These results suggest that measuring T_c relative to a NWSB can indicate water stress with a greater signal-to-noise ratio than T_c-T_a. While 2018 data showed signs of drought stress prior to visual detection, due to the subjective nature of visually determining water stress, further research is needed to make the claim that it can be an early indicator of water stress on a consistent basis. Results of this study indicate that creeping bentgrass managed at putting green heights would be at or near drought stress when T_c regularly exceeds 2 °C when compared to a NWSB. Payero *et al.*, (2005) looked at modeling a NWSB in various weather conditions for tall fescue and found that models were improved using near-noon values. Similarly, this study found mid-day values were the most revealing as it relates to measuring water stress. There may be value in investigating the nighttime signature of Rel_{NWSB} as an early indicator of water stress as it responded inversely but to a lesser degree than mid-afternoon measurements.

Standard Deviation of Canopy Temperature

Variation in T_c as measurement of water stress caused by reduced stomatal conductance was suggested by (Fuchs, 1990) and discussed by (Jones, 2004). The standard deviation of Tc (SD_{Tc}) output by the camera system used in this study allowed for the evaluation of variance in T_c as plots transitioned from non-stressed to drought stress conditions (Figure 3.6). Similar to other metrics, maximum values were observed in the mid-afternoon and minimum values were observed at nighttime. Brief, irregular spikes in SD_{Tc} (Fig. 3.7) were images containing non-turf objects such as people or maintenance equipment.

In 2017, two days before visible wilt (22 July), maximum daily SD_{TC} values rarely exceeded 0.50 °C for all treatments. From 22 July through 25 July, maximum daily values for the 0WR treatment increased to 3.70 °C and frequently remained above 3.00 °C for the rest of the 2017 study period, indicating greater variance in temperature in the measured areas. In this same period, daily maximum SD_{TC} values for 50WR and 100WR increased slightly but never exceeded 1.00 °C. The series of thermal images (Fig. 3.8), indicate areas of reduced transpiration increasing in size as the study progresses from a non-stressed to drought stress conditions, corresponding to the increase in SD_{Tc}.

In 2018, similar to 2017, from the beginning of the study period until two days prior to visible wilt (11 July) daily maximum SD_{Tc} values did not exceed 0.50 °C for any treatment. However, from 11 July to 15 July, midday maximum SD_{Tc} values increased for all treatments and remained high from the remainder of the 2018 study period (27 July). The increase in SD_{Tc} maximum values was greatest for the 50WR treatment; a daily peak of 3.54 °C was observed on 15 July and exceeded 4.00 °C on five days from 19 July and the end of the collection period. Daily maximum SD_{Tc} values for the 0WR treated plots increased to n 3.00-3.50 °C. Daily maximum SDTc values for the 100WR treatment were the lowest of the three treatments, reaching values between 1.00 and 2.00 °C.

The increase in SD_{Tc} for 0WR treatment in 2017 corresponds to a drop in SWP, with a noticeable increase occurring two days prior to visible wilt, meaning SD_{Tc} could be used to identify drought stress. However, 2018 results did not support this as T_c variation increased in all treatments while SWP only dropped for 0WR. Unfortunately, this could be a consequence of the drought-stressed buffer zones being unintentionally included in the measurement area within the camera system. As suggested by Fuchs

(1990), variation of T_c did increase with drought stress but inconsistent results between years means more research is necessary to make definitive claims on the value of SD_{Tc} as an early predictor of drought stress.

Modeling Canopy Temperature for Non-Water Stressed Baseline

An accurate estimation of T_c for a NWSB is necessary for a metric like Rel_{NWSB} to be useful in making irrigation decisions. This study applied multiple regression analysis to the 2018 dataset to create a model that would predict T_c of a NWSB for creeping bentgrass putting greens using four weather parameters (T_a, SR, RH, & WS). A total of 3,216 time points from the 2018 data collection period were used. Canopy temperature of three replications of 100WR were averaged to determine T_c of the NWSB. Models were created for the whole dataset and also split into days when plots received irrigation/precipitation and did not receive irrigation/precipitation to evaluate whether water at the surface would affect the model. Models using various combinations of weather parameters were evaluated to test which factors provided the best fit to a regression line.

T_a and SR show the strongest correlations to T_c (Fig. 3.3 and Table 3.1). Models containing these two factors gave the best fit with any number of factors. Model fit increased slightly with number of factors. Models with the best fit were: 4-factor model (R^2=0.971, 3 factor model (T_a, SR, WS) (R^2=0.966), 3-factor model (T_a, SR, RH) (R^2=0.964), and 2-factor model (T_a, SR) (R^2=0.955) for all three datasets

When evaluating No Irrigation and Irrigation models, RH as a single factor shows stronger correlation on days with irrigation (R^2=0.44) compared to days with no irrigation (R^2=0.31). Wind speed as a single factor showed a better fit on days with no irrigation (R^2=0.27) compared to days with irrigation (R^2=0.11). However, only small differences were observed between datasets using 2-, 3-, or 4-factor models including RH or WS. For all 2-, 3-, and 4-factor models, the No Irrigation dataset showed a slightly better fit than the Irrigation dataset.

To test the model with the best fit, the 4-factor model was applied to the 2017-2018 dataset (Fig. 3.10). In 2017 (n=5685), the model predicted T_c to be slightly higher than measured values overall with the median T_Δ of 0.64±2.03 °C with 90% of T_Δ falling between -3.32 and 3.26 °C. In 2018 (n=4435), median T_c was 0.70±2.06 °C with 90% of T_Δ falling between -3.47 and 3.26 °C. While the Rel_{NWSB} metric appeared to be sensitive to drought stress around 2 °C, errors in predictions for the model with best bit frequently exceeded ±3 °C, meaning that a more accurate model would be needed to confidently make irrigation scheduling decisions.

For both 2017 and 2018, the model trended to predict slightly warmer T_c at night and slightly cooler in the day compared to measured values suggesting separate models for these conditions may be valuable. Payero *et al*. (2005), when modeling NWSB for tall fescue maintained at lawn height, found that stratifying regression models according to amount of SR improved results. The models developed in that study were found to be more accurate during the daytime (SR>0), agreeing with results from this study that separate models for day and night would improve predictions of T_c for NWSB. Models with more factors produced a greater adjusted R^2 meaning that including RH and WS improved the fit of the models. However, the improvement was slight so depending on availability of weather data, the 2-factor model could be effective. Error in predictions also appeared to increase at periods of high WS; this error could be minimized if an on-site weather station was used.

Canopy temperature and weather data were available for non-water stressed plots of creeping bentgrass maintained as a putting green over the course of three days in 2016. The best 2-, 3-, and 4-factor models were applied to this dataset (n=369) to evaluate performance (Fig. 3.11). Data was only available between 5:00AM and 10:00PM CDT on these days.

The 2-factor model (T_a, SR) provided the most accurate predictions of T_c for a NWSB in 2016 (Fig. 3.12) with a median T_Δ was 0.90±1.27 °C with 90% of values measuring between -1.21 and 3.39 °C. For the 3-factor model (T_a, SR, WS), median T_Δ was 1.35±1.65 °C with 90% of values measuring between -0.88 and 4.89 °C. For the 4-factor model, median T_Δ was 1.17±1.67 °C with 90% of values measuring between -1.08 and 4.84 °C. The value of the 2-factor model on this dataset could be due to data including mostly times when SR>0. This further supports the idea that separate models for day and night would improve predictions, increasing the likelihood that models could improve irrigation decisions.

3.5 Conclusions

This study shows that thermal imaging can provide valuable information on plant water status of a creeping bentgrass putting green. Measurements such as SD_{Tc} and Rel_{NWSB} showed a clear response to drought stress with the potential to show early indications of drought stress to aid in irrigation scheduling. The Rel_{NWSB} showed the earliest indication of drought stress on the 0WR plots but this requires an accurate estimation of T_c for a NWSB in the existing weather conditions. The SD_{Tc}, which requires no additional measurements or estimations, also increased for 0WR prior to visible drought stress. However, research covering a wider range of conditions and scales would be needed to precisely quantify the values at which irrigation should be triggered to maintain healthy turf and minimize irrigation applied.

In attempting to predict T_c for a NWSB of a creeping bentgrass putting green, this study produced a model with a high goodness-of-fit (R^2=0.971) using T_a, SR, RH, and

WS while a similar fit was also found using only T_a and SR (R^2=0.955). However, differences between T_c predicted by the model and measured values were great enough at times that a more accurate model would be needed to confidently inform irrigation decisions. This model could be improved by developing separate models for daytime and nighttime.

This study shows that thermal imaging can produce various valuable measurements to help turf managers make decisions but more research will be necessary to improve interpretation of these data for different species and management regimes.

3.6 Tables & Figures

Figure 3. 1 Layout of research area and thermal camera.

Hawkeye camera system was mounted on the wooden electrical pole on the right side of the image, facing north. White box on the left side of the image is a datalogger recording soil moisture information from TDR probes buried in each plot.

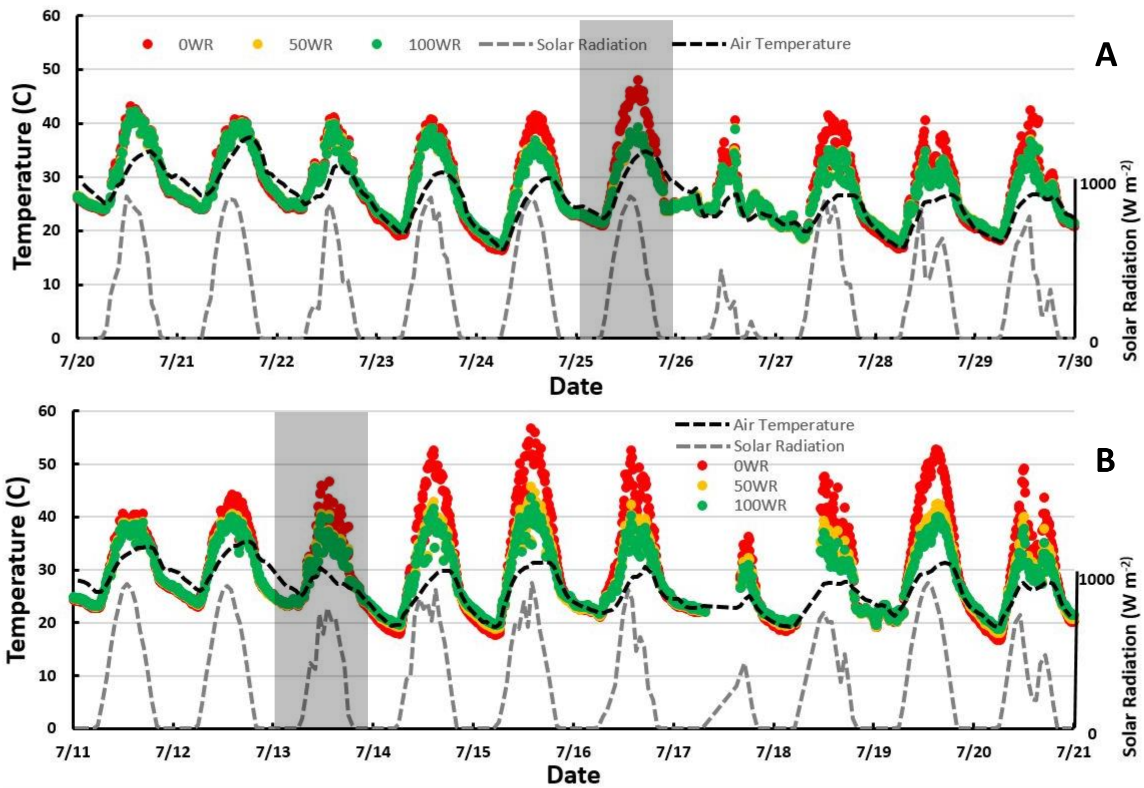

Figure 3. 2 Canopy and air temperature and solar radiation in 2017 and 2018.

Canopy temperature by treatment, air temperature, and solar radiation as a function of time in A) 2017 and B) 2018. Values of T_c are means of three replications at each time point. Visible wilt in turf occurred on 24 July 2017 and 13 July 2018**.** Gray line denotes first day visible wilt was clearly observed.

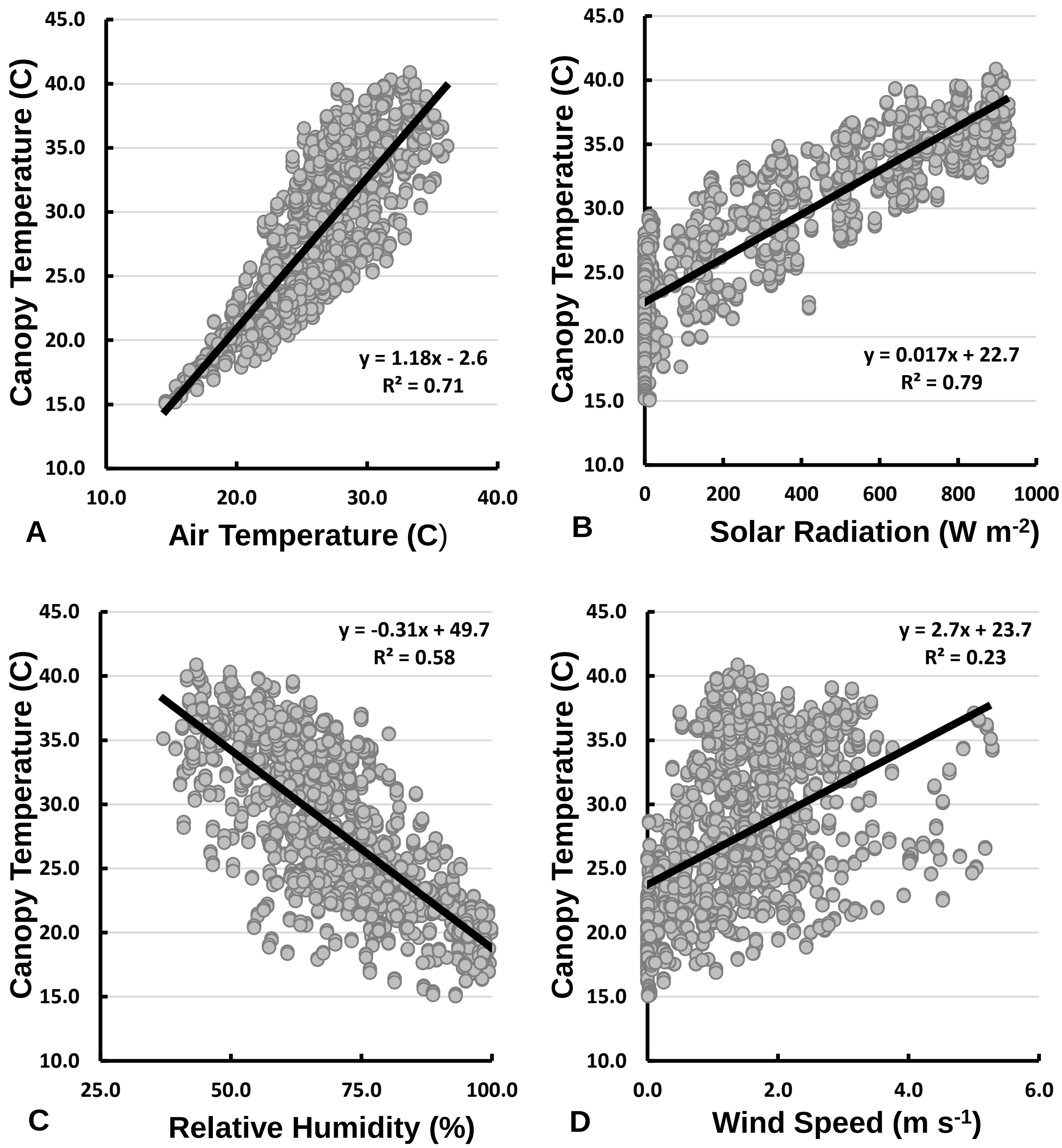

Figure 3. 3 Regression of canopy temperature with weather parameters.

Relationship between canopy temperature and A) air temperature, B) solar radiation, C) relative humidity, and D) wind speed for 100WR plots in 2018. Canopy temperatures were measured every ten minutes and averaged over each hour from 26 June to 27 July 2018. Measurements are mean canopy temperature for each plot of the 100WR treatment, representing the non-water stressed baseline.

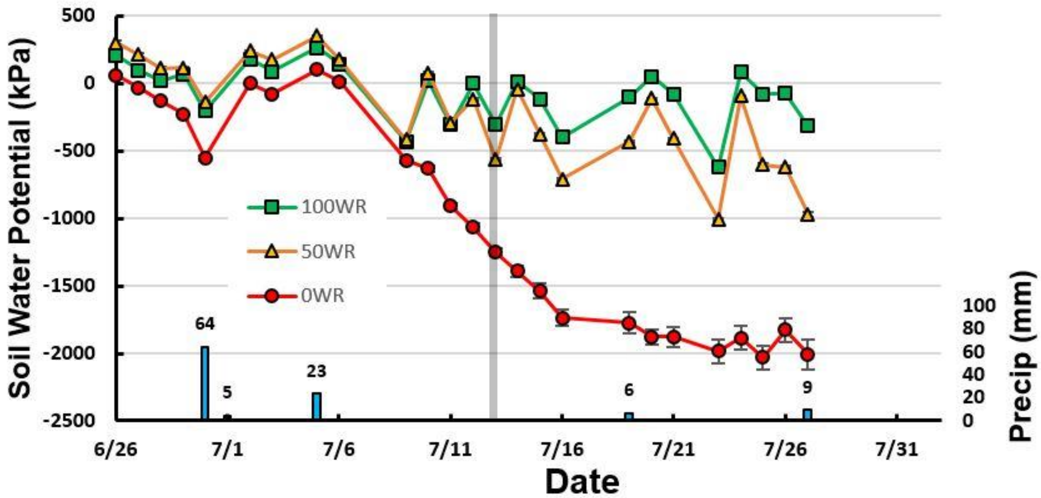

Figure 3. 4 Pattern of soil water potential by date for each treatment in 2018.

Visible wilt was observed on 13 July when soil water potential fell below the wilting point of -1501kPa. As soil moisture decreases, greater force is required to pull water into the plant. The full water replacement (100WR) treatment represents the non-water stressed baseline (NWSB). Rain events are denoted along the x-axis.

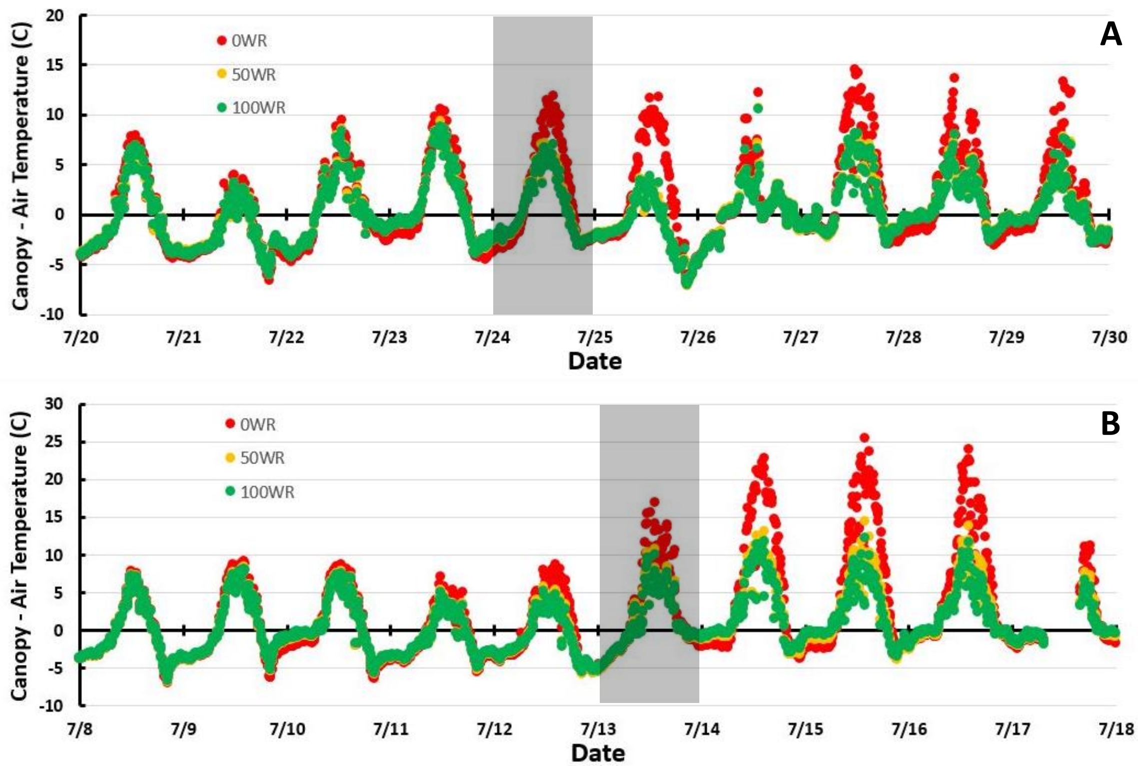

Figure 3. 5 Canopy temperature minus air temperature by date for the 2017 and 2018 study periods.

Canopy temperature minus air temperature (Tc – Ta) for all treatments in A) 2017 and B) 2018. Values of $T_c - T_a$ are means of three replications. Visible wilt in turf occurred on 24 July 2017 and 13 July 2018 indicated by gray box.

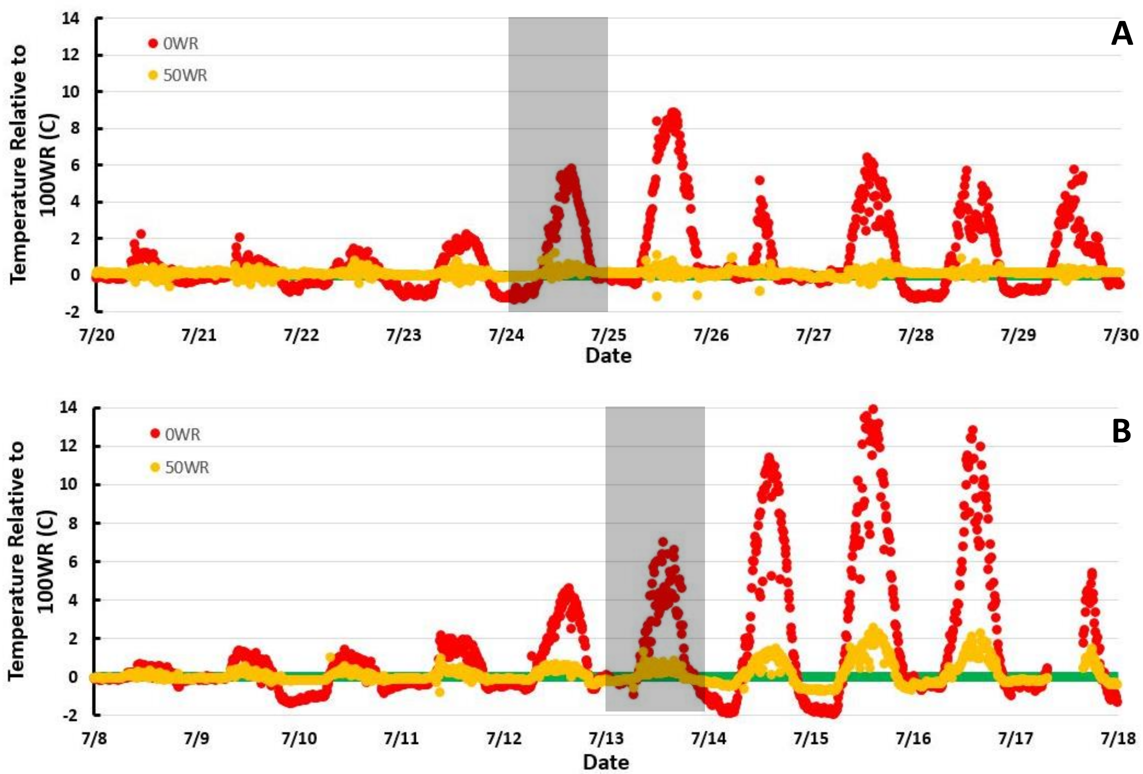

Figure 3. 6 Canopy temperature relative to the non-water stressed baseline by date in both years.

Canopy temperature relative to a non-water stressed baseline (100WR) by treatment for the critical period in a) 2017 and b) 2018. Zero on the x-axis represents the non-water stressed baseline. Values are means of three replications. Visible wilt in turf occurred on 24 July 2017 and 13 July 2018.

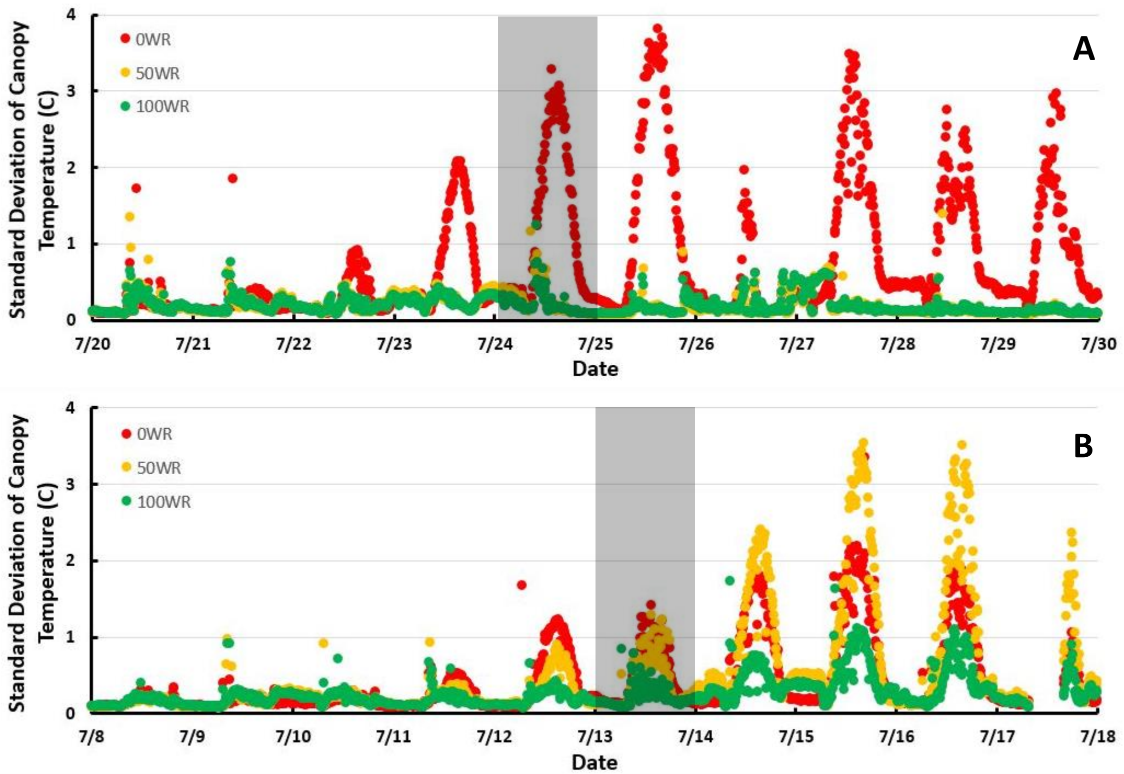

Figure 3. 7 Standard deviation of canopy temperature by date for both years.

Standard deviation of canopy temperature (SD_{Tc}) by treatment for the critical period in A) 2017 and B) 2018. Values are means of three replications. Visible wilt in turf occurred on 24 July 2017 and 13 July 2018.

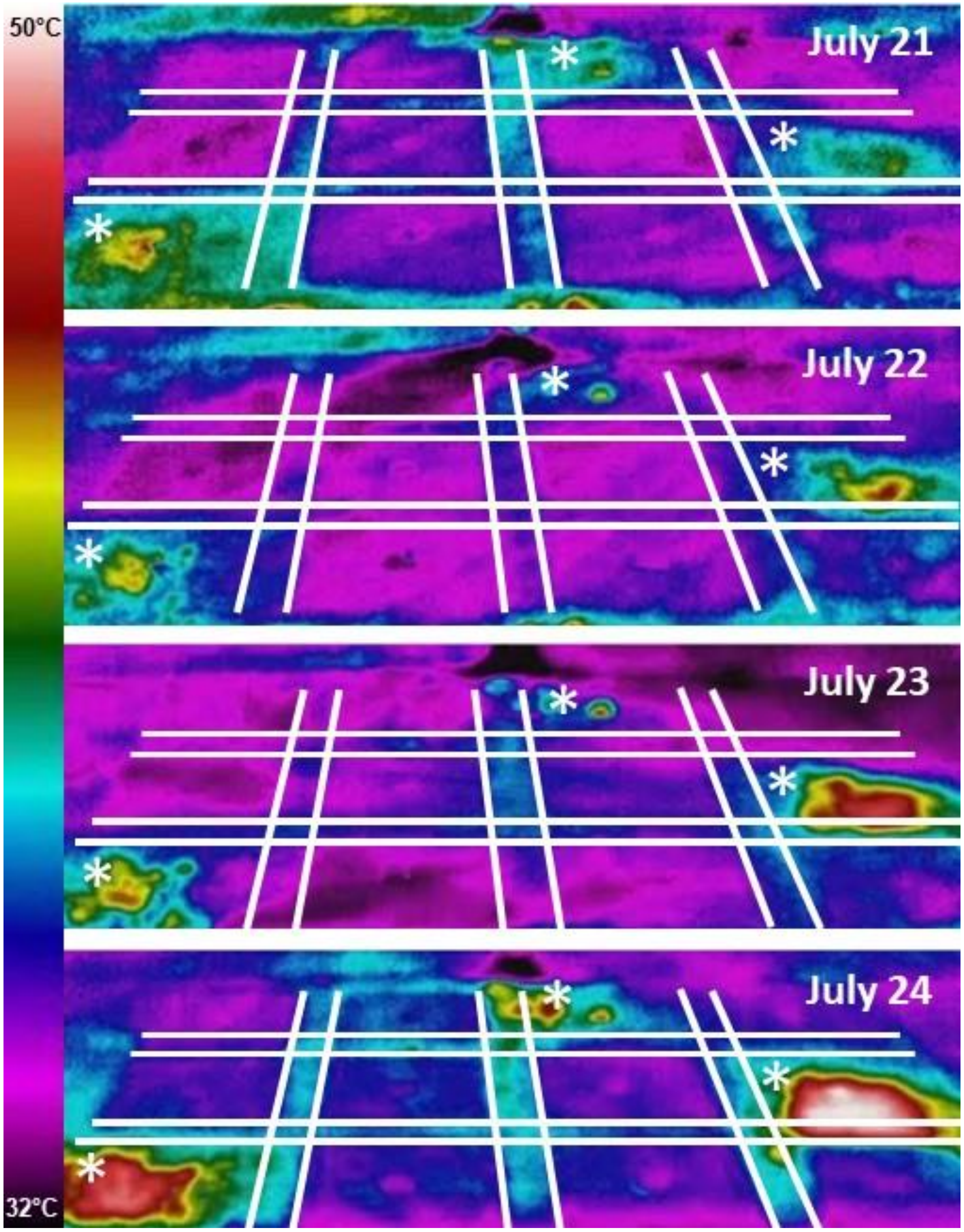

Figure 3. 8 Thermal images of research area as no water replacement plots begin to show visible wilt in 2017.

Plots with an asterisk received the no water replacement treatment. Color scale on left ranges from 50 °C (white) to 32 °C (dark purple). White lines were added to denote plot area from buffer zones.

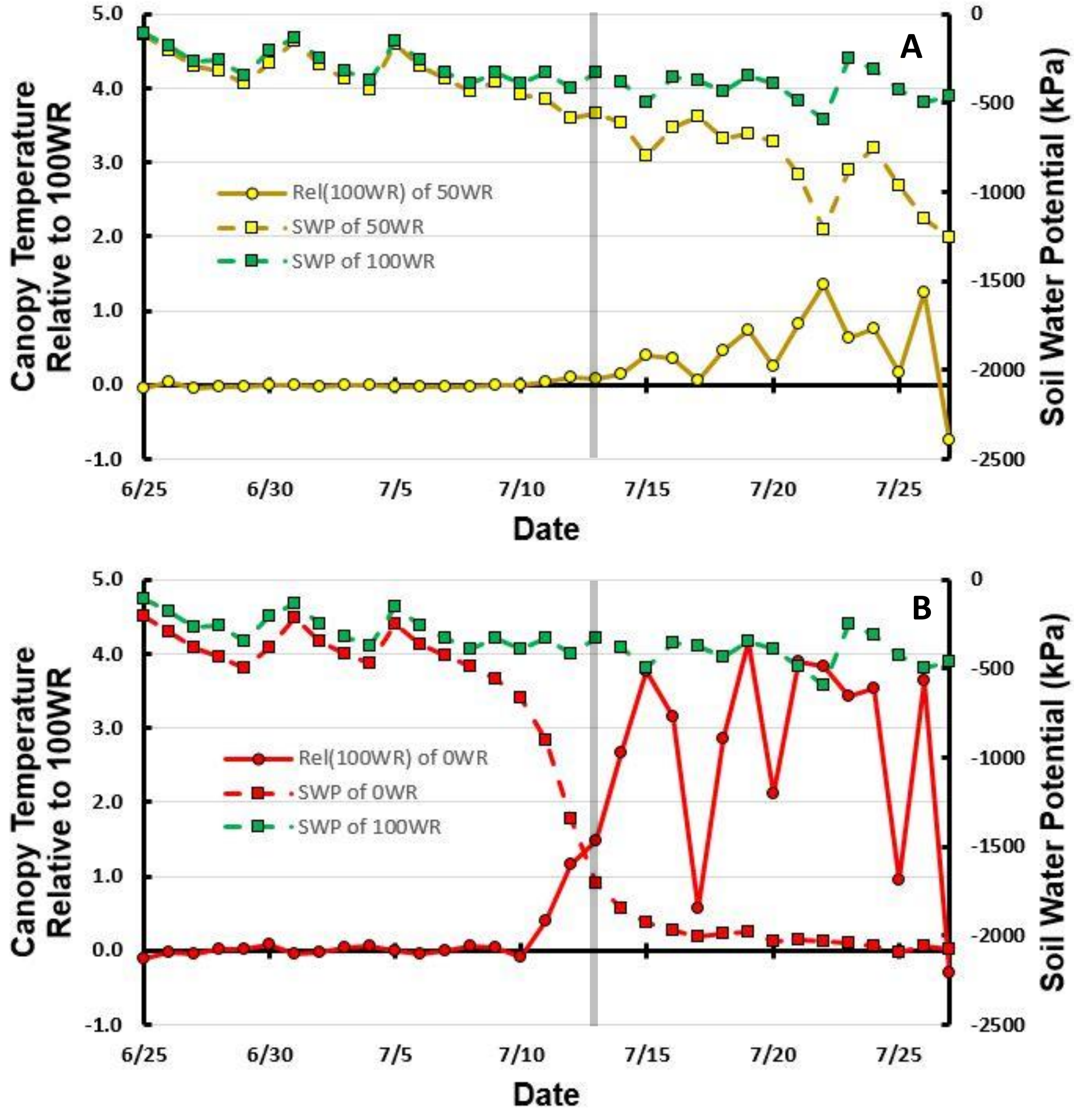

Figure 3. 9 Relationship between canopy temperature relative to non-water stressed baseline metric and soil water potential.

Relationship between Rel_{NWSB} and SWP in 2018 of A) 50WR and B) 0WR. SWP of 100WR is represented in green as a point of comparison. SWP (square points) are plotted on the secondary axis. Gray line denotes first day of visible wilt.

ALL

# of Factors	Model Factors	Multiple R	Adjusted R^2	Y-Intercept	Air Temperature	Solar Radiation	Relative Humidity	Wind Speed
					Coefficients			
1	Air Temperature (T_a)	0.867	0.752	-1.1	1.10			
1	Solar Radiation (SR)	0.817	0.667	22.5		0.016		
1	Relative Humidity (RH)	0.609	0.371	43.9			-0.245	
1	Wind Speed (WS)	0.415	0.172	22.8				2.24
2	T_a, SR	0.977	0.955	4.2	0.78	0.010		
2	T_a, RH	0.870	0.757	3.4	1.03		-0.037	
2	T_a, WS	0.867	0.752	-1.1	1.10			0.00
3	T_a, SR, WS	0.983	0.966	3.9	0.84	0.011		-0.66
3	T_a, SR, RH	0.982	0.964	-1.8	0.86	0.011	0.053	
3	T_a, RH, WS	0.871	0.758	3.7	1.04		-0.041	-0.14
4	T_a, SR, RH, WS	0.986	0.971	-0.8	0.90	0.011	0.042	-0.56
	n=	3216						

NO IRRIGATION

# of Factors	Model Factors	Multiple R	Adjusted R^2	Y-Intercept	Air Temperature	Solar Radiation	Relative Humidity	Wind Speed
					Coefficients			
1	Air Temperature (T_a)	0.870	0.758	-1.7	1.13			
1	Solar Radiation (SR)	0.829	0.688	21.8		0.017		
1	Relative Humidity (RH)	0.555	0.308	41.4			-0.217	
1	Wind Speed (WS)	0.524	0.274	21.7				2.97
2	T_a, SR	0.978	0.957	3.8	0.79	0.011		
2	T_a, RH	0.873	0.762	2.0	1.07		-0.033	
2	T_a, WS	0.871	0.758	-1.9	1.15			-0.13
3	T_a, SR, WS	0.985	0.971	2.6	0.89	0.011		-0.85
3	T_a, SR, RH	0.984	0.967	-1.6	0.85	0.012	0.051	
3	T_a, RH, WS	0.874	0.764	2.2	1.10		-0.039	-0.32
4	T_a, SR, RH, WS	0.988	0.976	-1.3	0.92	0.012	0.038	-0.71
	n=	1332						

IRRIGATION

# of Factors	Model Factors	Multiple R	Adjusted R^2	Y-Intercept	Air Temperature	Solar Radiation	Relative Humidity	Wind Speed
					Coefficients			
1	Air Temperature (T_a)	0.865	0.748	-0.6	1.08			
1	Solar Radiation (SR)	0.811	0.658	23.0		0.016		
1	Relative Humidity (RH)	0.669	0.447	46.6			-0.279	
1	Wind Speed (WS)	0.330	0.108	23.7				1.73
2	T_a, SR	0.977	0.955	4.6	0.77	0.010		
2	T_a, RH	0.868	0.754	5.0	0.98		-0.045	
2	T_a, WS	0.865	0.748	-0.5	1.07			0.05
3	T_a, SR, WS	0.983	0.967	4.8	0.81	0.011		-0.65
3	T_a, SR, RH	0.981	0.962	-1.7	0.87	0.011	0.054	
3	T_a, RH, WS	0.868	0.754	5.4	0.99		-0.048	-0.10
4	T_a, SR, RH, WS	0.985	0.970	0.4	0.87	0.011	0.038	-0.56
	n=	1883						

Table 3. 1 Performance of models to predict canopy temperature of a non-water stressed baseline in various weather conditions.

Models were separated into days with or without rain/irrigation, and combined models to evaluate if recent precipitation affected models. Models with fewer numbers of factors require less data collection to make a prediction. Units are degrees Celsius, watts per meter squared, percent, and meters per second respectively.

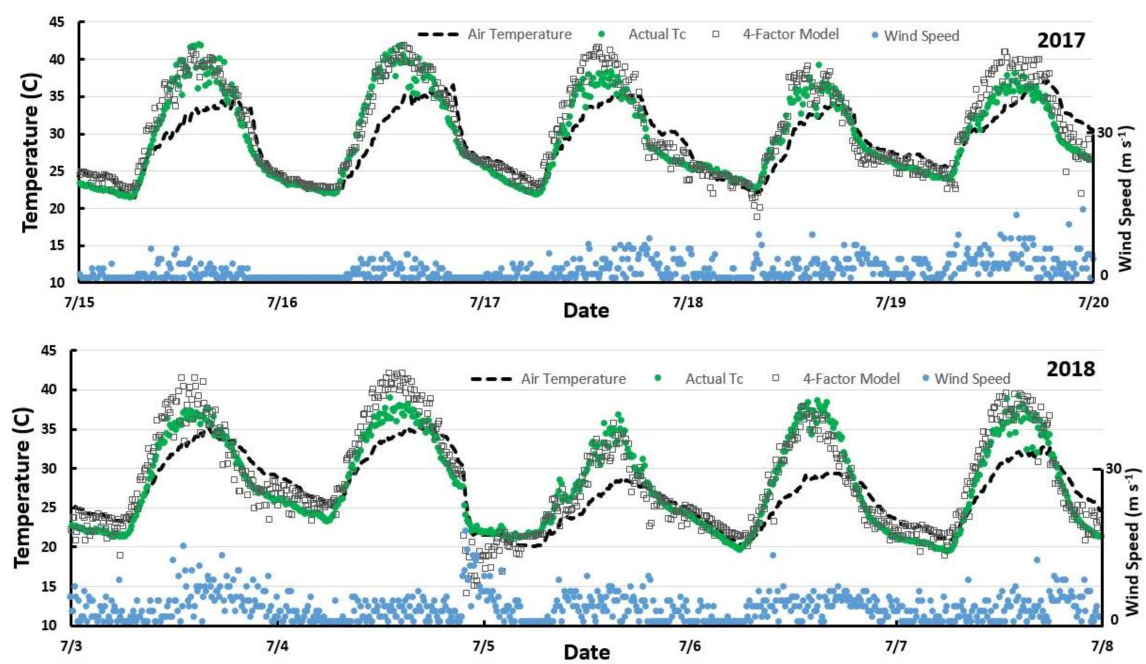

Figure 3. 10 Comparison of predicted and actual canopy temperatures of a non-water stressed baseline using the 4-factor model applied to 2017 and 2018 datasets.

Predicted and actual canopy temperatures of 100WR plots in 2017 (top) and 2018 (bottom) with wind speed on the secondary y-axis. Predictions were calculated using the 4-factor model (air temperature, solar radiation, relative humidity, and wind speed).

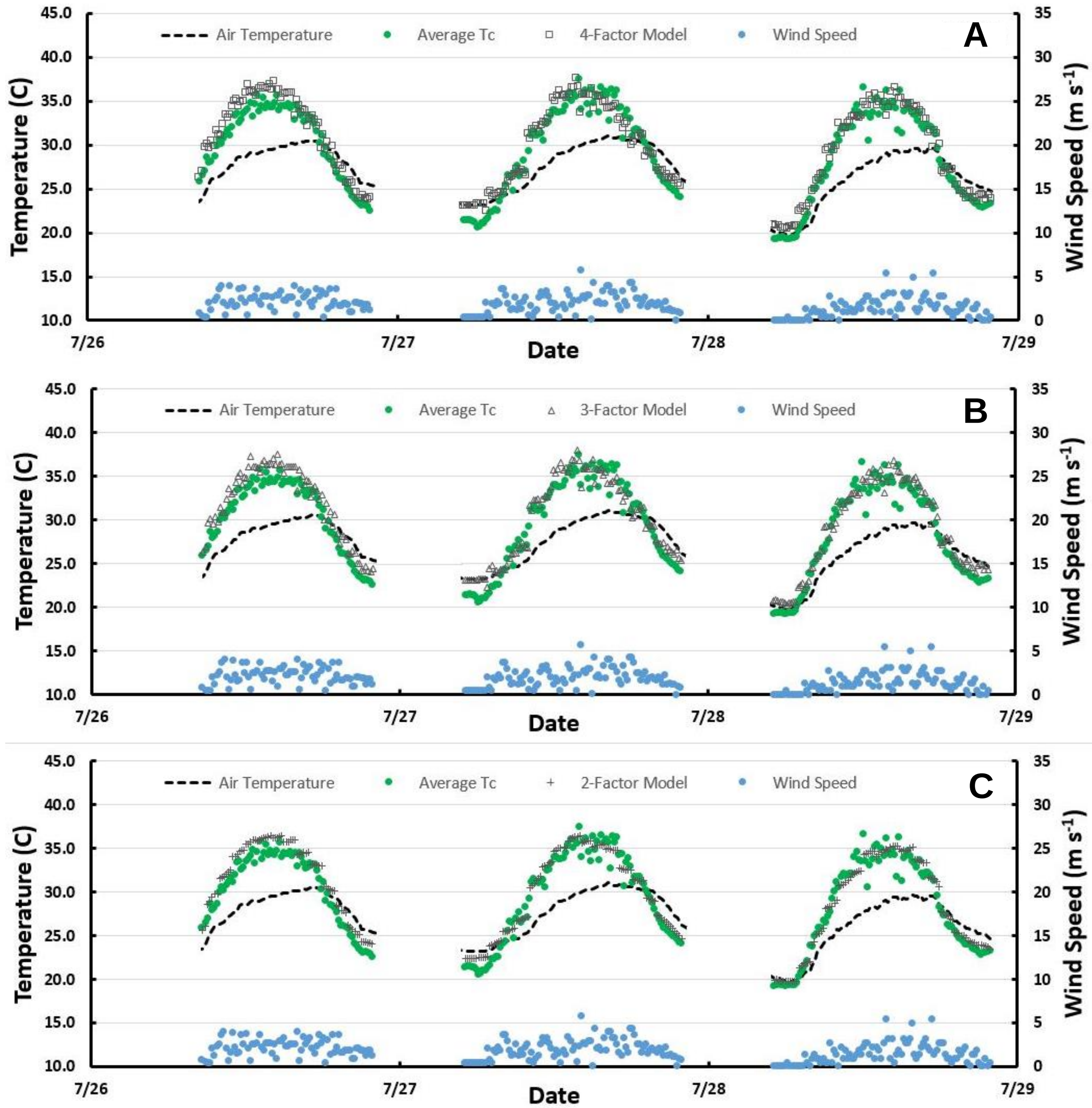

Figure 3. 11 Comparison of predicted and actual canopy temperatures of a non-water stressed baseline using the 2-, 3-, and 4-factor models applied to the 2016 dataset.

Predicted and actual canopy temperatures of well-watered plots from a study conducted in 2016 with wind speed on the secondary y-axis. Most predictive models were used with A) 4-factors [air temperature, solar radiation, relative humidity, and wind speed] B) 3-factors [air temperature, solar radiation, and wind speed] and C) 2-factors [air temperature and solar radiation].

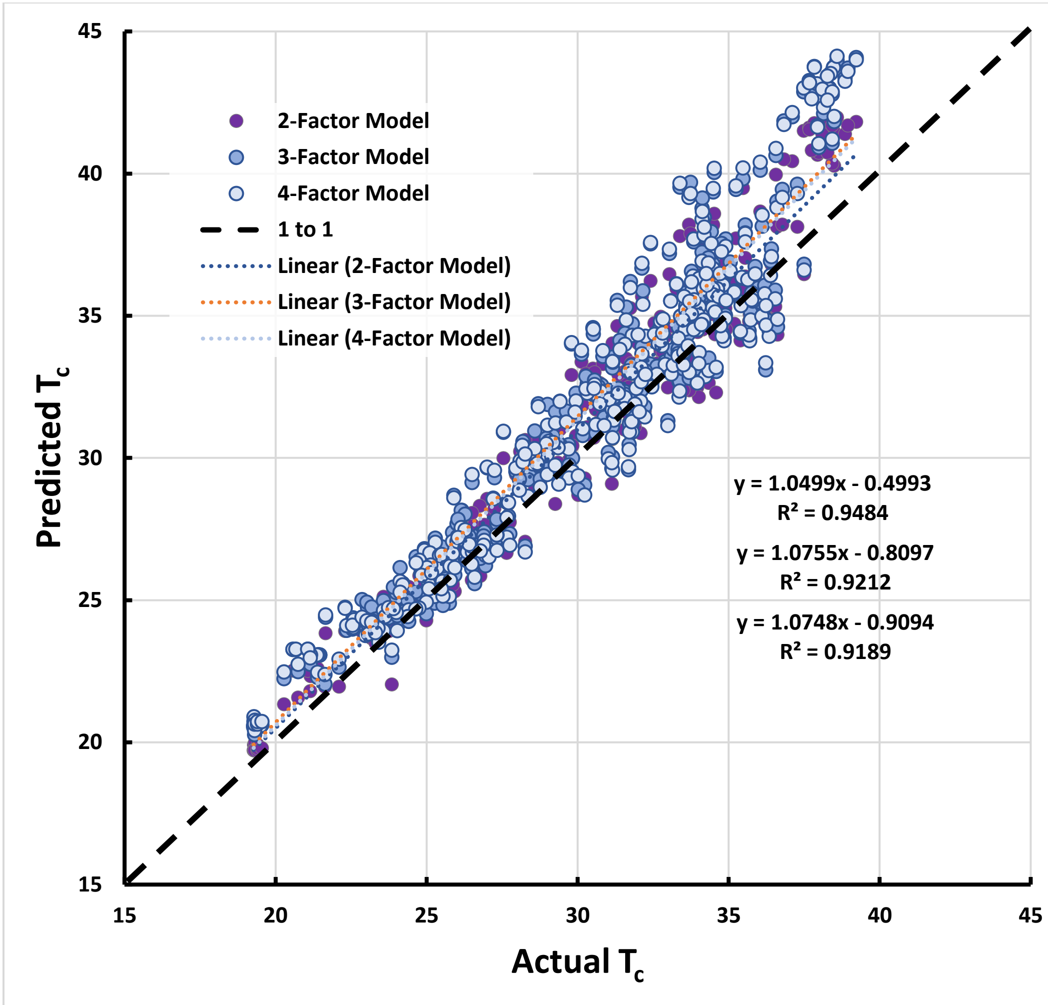

Figure 3. 12 Correlation of predicted and actual canopy temperatures for 2-, 3-, and 4-factor models applied to 2016 dataset.

Trendlines for each model are indicated by dashed lines. Bold dashed line indicates the 1:1 line.

CHAPTER 4: CONCLUSIONS, IMPACTS, AND FUTURE RESEARCH

The need to minimize use of water resources in the golf industry is ever-increasing to reduce irrigation and labor resources costs. One way to reduce water consumption without sacrificing the quality of the playing surface is maximize irrigation scheduling efficiency. As thermal imaging technology advances, it becomes a more practical, affordable tool to remotely monitor areas of turf for hotspots, which gives insight into plant water status. Canopy temperatures can be used to indirectly gauge transpiration rates. While using thermal imagery analysis to identify canopy temperature (Tc) hotspots is relatively simple to understand, an improvement in T_c data interpretation can lead to a greater level of irrigation efficiency, reducing consumption of water resources and labor used to monitor plant water status.

This study used a mounted thermal imaging camera to continuously measure T_c of a creeping bentgrass putting green built to USGA recommendations that was irrigated to three levels of water replacement (100%, 50%, and 0%) in Lincoln, Nebraska. The overall objective was to identify trends in T_c of creeping bentgrass that could be used to predict and measure water stress to allow for deficit irrigation without compromising plant health. To reach that objective, it was important to first understand how water use changed as soil moisture transitioned from field capacity to wilting point and identify patterns as plants approached water stress conditions. From there, correlations of T_c with changes in water use could be used to identify water stress using thermal imagery.

In evaluating water use, we found that K_c, which normalizes ET for weather conditions, were relatively constant when soil water potential (SWP) was above the wilting point (Fig. 2.8). Wilting point was identified as -1501 kPa in this study using segmented regression analysis. When SWP dropped below the wilting point, K_c

approached zero in value and the plant entered dormancy when water stress conditions persisted and the turfgrass transitioned from normal rates of transpiration to little to almost no transpiration. We had hypothesized a gradual decline in ET but this on/off pattern of water use would leave a smaller window than expected to find any changes in T_c data to help predict when a healthy, transpiring plant will cross the wilting point threshold.

A rainout structure would have aided in avoiding the effects of precipitation. This could have allowed for more dry-down runs, adding more evidence to support our findings. No water stress conditions were observed in the100WR or 50WR treatments. With the use of a rain structure, or had the weather provided a long enough stretch without precipitation, it is possible that a more gradual decline in water use could have been observed in the 50WR treatment, which represents a more realistic deficit irrigation strategy than 0WR. This rain structure would have also allowed for more days of lysimeter measurements and improved the accuracy of water use measurements.

Other factors that could have improved the quality of data in this study would be to: i) irrigate the buffer zones between the plots to avoid water stress, ii) not have data collection instruments powered by solar power, and iii) generate the water retention curve after both dry-down periods. Our decision to withhold irrigation in the buffer zones was intended to avoid excess water moving into the plots. However, we found that drought stressed buffer zones affected the data more that irrigated turf would have, specifically in the SD_{Tc} measurement as it proved very sensitive to small hot spots. Also, all of the electricity used at the UNL Turfgrass Research Center was gathered from solar cells attached to the main shed and stored in batteries. There were a handful of times where a cloudy stretch of weather would prevent the batteries from charging fast enough as they were being used to power the camera system, the weather station, and in-ground soil probes. This created a few small gaps in the data set. A more reliable method of powering this data collection equipment would have removed these small gaps. Soil water potentials are appear quite different between 2017 and 2018 data, indicating these years should be evaluated separately. Values in 2018, the year the water retention curve was generated, appear to agree more closely with previous research. Had a retention curve been generated after 2017, values between years may have been more similar.

When evaluating multiple metrics utilizing T_c to detect water stress, the standard deviation of Tc (SD_{Tc}) and the relative difference between Tc and the non-water-stress baseline (NWSB) derived from the 100WR, were used to identify the onset of water stress (Fig. 3.6 & 3.7). Both metrics remove the need for weather data to identify plant-water status. The diurnal pattern of T_c metrics consistently peaked mid-day when air temperature (T_a) and solar radiation (SR) were at their maxima. Due to this, we often refer to the daily peak of metrics as this is when the greatest difference between treatments was observed.

The thermal imaging system used in this study (Hawkeye System® by Itricorp, Haymarket, VA) digitally analyzed each image and extracted a number of measurements including the SD_{Tc} which measures variation in T_c over the target area. A large SD_{Tc} indicated more or larger hotspots within the scene, pointing to increased water stress. During the period in the study prior to a visible observation of plant wilting in the 0WR treatment, maximum daily SD_{Tc} values were small for and exceeded 2 °C one day prior to visible wilt; SD_{Tc} values did not exceed 1 °C in the 100WR plots at any point in 2017. Daily peak of SD_{Tc} increased to >3 °C after visible wilt was observed and remained high for remainder of the collection period. Similarly, SWP reached a minimum value and plateaued for the remainder of the collection period.

The SD_{Tc} data in 2018 seems to be affected by drought stress in the buffer zones. Buffer zones were unintentionally included in the target area of some plots in the camera system that year, leading to an unexpected increase in T_c variation of 50WR plots which showed no symptoms of water stress in the majority of the plot but drought stress around the edges near the buffer zone. However, an increase in SD_{Tc} for 0WR and 50WR in days leading up to visible wilt support the idea that this metric responds to impending drought stress as response was related to visible drought in the measured area.

While development of accurate T_c models for various species under different management conditions would require extensive research, the impact could be significant. Turf managers could apply the model to T_c data from thermal cameras to allow for rapid, remote monitoring of plant-water status while providing precise control of playing conditions in addition to reducing labor and water consumption.

Thermal imaging is growing in popularity as a tool for turf managers. Common current methods to track soil moisture include labor-intensive probing of greens with handheld soil moisture meters or expensive in-ground sensors that can be difficult to install. Both of these methods measure only single point in the area. Thermal imagery can be collected quickly and remotely without disturbing the playing surface and provide spatial relationships of data which can be useful in managing irrigation. Anecdotally, an irrigation issue was identified during the course of this study when a leaky head on a nearby plot was spotted as an area with T_c that was consistently cooler than the surrounding area. Thermal cameras can be mounted on trees or buildings and moved regularly to monitor different areas. The system used in this study wirelessly transmitted data, requiring only a power source.

This technology is becoming increasingly affordable as well. A thermal camera attachment for a cell phone can be purchased for around $200 where handheld systems of the past were thousands of dollars. If cost continues to decrease and data interpretation is improved, thermal imagery analysis could be a standard tool for turf mangers.

This research indicates that it may be possible to identify definitive values and/patterns as early indicators of drought stress in turfgrass. Managers could postpone watering until a threshold for irrigation is identified using the model and metrics described in this study, in turn, reducing water consumption. This would also be useful in highly maintained golf courses looking to push the limits of green speed by drying out the soil as much as possible.

However, these triggers are likely to vary with species, management regime, climate, microclimate, and soil. This study was limited to one research area with a single species and mowing height with limited foot traffic and only two dry-down periods due to lack of a rain shelter. While this study shows that metrics can be used as indicators of drought stress, more situations need to be evaluated to make specific assertions. The size of the target area would likely greatly influence the magnitude of the SD_{Tc} metric. While creeping bentgrass is the most commonly used species in putting greens in the United States, species such bermudagrass (*Cynodon dactylon spp.*) and annual bluegrass (*Poa annua*) also account for a large percentage of putting green area and require significant water inputs because of the climates they are grown in.

Research that would further increase the impact of this study would be to specifically identify the metric thresholds to trigger irrigation and minimize water consumption for additional species, locations, and management. In summation, water use of creeping bentgrass remained consistent until SWP reached the wilting point, when water rapidly slowed down with K_c approaching zero. Observations of T_c combined with water use findings show that metrics utilizing T_c are responsive to water stress. Further research on specific values of these metrics could prove that early indication of water stress could be detected, allowing for precision irrigation scheduling.

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