ABSTRACT

GHALI, IHAB ELHUSSEINI. Comparing Digital Image Analysis and Other Turf Quality Measurements in the Evaluation of Smart Irrigation Technologies. (Under the direction of Dr. Garry Grabow.)

The objectives of this study were to 1) identify the correlation among digital imagery results, visual quality ratings, a canopy spectral reflectance index, and canopy temperature in evaluating the quality of tall fescue (*Festuca arundinacea* Schreb) irrigated by different irrigation treatments, 2) develop and implement a methodology to use a digital imagery process to provide objective and quantitative estimates of turfgrass quality, 3) evaluate two types of smart irrigation technologies; ET and soil-moisture-based controller systems by evaluating their resulting water application and turf quality with a standard time-based irrigation, and 4) evaluate the effect of three different irrigation frequencies incorporated with these technologies. The experimental study was conducted at the North Carolina State University Lake Wheeler Turf Field Laboratories, Raleigh, North Carolina. A total of 40 plots (4.0 m × 4.0 m each) were established with tall fescue and organized into four blocks of ten plots each. Each block had 9 plots with treatment combinations of controller technology: a timer-based standard controller system (Tim), an add-on (1 setpoint) SMS system (AC1), and an ET-based system (ET); and watering frequency: 1, 2, and 7-days per week plus a tenth plot with an on-demand (2 setpoint) SMS system (AC2). Turf quality (using 4 different techniques) and water application measurements were taken on a weekly basis for all plots during the monitoring season of each year. Dark green color index (DGCI) was strongly and positively correlated with the visual rating (VR) index ($r = 0.67$ and 0.85, for 2008 and 2009, respectively) and spectral reflectance index (NDVI) ($r = 0.79$ and 0.87, for 2008
and 2009, respectively), but negatively and weakly correlated with differentials of canopy and ambient air temperature (ΔT) (r = -0.10 and -0.24, for 2008 and 2009, respectively). A new digital imagery model was developed by using a two-variable (the mean and standard deviation (SD) of DGCI values) multiple linear regression model to predict VR values. The model produced more accurate estimates of VR (R^2 = 0.927 and 0.899 for calibration and validation sets, respectively) than the one-variable model that used only the average value of DGCI (R^2 = 0.879 and 0.843 for calibration and validation sets, respectively). Over a 3-year period, SMS treatments resulted in average water savings of 38% for AC1 treatments and 22% for AC2 treatment compared to the timer-based treatments, whereas the ET treatments applied 13% more water than the timer-based treatments. The AC2 and the ET-based treatments resulted in the best turf quality. All other treatments resulted in turf quality, using visual rating method, at or above the minimum acceptable level across 2 years (2008 and 2009) of study. All three frequencies (once per week, twice per week and daily) tested in this study were not statistically different in terms of turf quality.

Because of their objective measurements, digital imagery analysis, and canopy spectral reflectance techniques can be used to effectively evaluate the variability in turf quality under different irrigation treatments thus helping to identify irrigation management strategies that not only efficiently apply water, but also maintain turf quality. The new digital imagery model, developed by using the DGCI value and its spatial variability across pixels within an image, was found to be more analogous to a visual rating scale and may provide a useful and predictive tool for estimating turf quality.
Comparing Digital Image Analysis and Other Turf Quality Measurements in the Evaluation of Smart Irrigation Technologies

by

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A thesis submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the Degree of Master of Science in Biological and Agricultural Engineering

Raleigh, North Carolina

2011

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BIOGRAPHY

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ACKNOWLEDGEMENTS

First and foremost I would like to express my sincere gratitude to my advisor Dr. Garry Grabow. This thesis would not have been possible without his valuable contributions of time, ideas, guidance, patience, and immense knowledge that make my research experience productive and stimulating.

Besides my advisor, I would like to thank the rest of my thesis committee Dr. Grady Miller and Dr. R.L. Huffman, for their encouragement, and insightful comments.

I would like to thank Carl Tutor and Bobby Vick for their help and support during the first stages of the field work in this research. A special thank for Kyle Briscoe for visual turf ratings. I also appreciate my fellow graduate students especially Mayank, Shiying, and Lamyaa for sharing ideas and their valuable comments.

Lastly, I would like to thank my family for all their love and encouragement. For my beloved mother who’s remembering me in her all prayers and supporting me spiritually throughout my life. And most of all for my loving, supportive, encouraging, and patient wife Lamyaa whose faithful support during the all stages of this Master is so appreciated. Thank you.
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PREFACE

This thesis consists of three chapters. The first chapter serves in part as a detailed literature review of the different methods used to evaluate turf quality. There is an emphasis placed on the use of digital imagery process in evaluating turf quality. This chapter also presents a literature review on the use of smart irrigation controllers in different crop irrigation applications, especially turfgrasses. The second chapter discusses the relationship between the different turf quality evaluation methods used in this study to evaluate the variability in tall fescue (Festuca arundinacea Schreb) under different irrigation treatments, with emphasis on developing a system to use digital imagery to provide objective and quantitative estimates of turf quality. The third chapter describes a study to evaluate three smart controller systems, weather-based (ET) and soil-moisture based controllers, incorporated with three different irrigation frequencies and compares water application and turf with a standard time-base irrigation controller.

Some common parts will be found in chapters 2 and 3 as their data were collected from the same site, and the chapters were written to be independent.
CHAPETR 1: LITERATURE REVIEW

Turfgrass is the major component of most landscapes in United States. In North Carolina, turfgrass acreage encompasses an area equal to 44% of the total state’s harvested crop acreage (NCDA, 2001); larger than the combined acreage of corn, wheat, tobacco, and peanuts. Residential lawns account for 69% of the total turfgrass acreage in the state and have increased in acreage by 21.4% between 1995 and 1999 to a total of 2,135,000 acres in 1999 (NCDA, 2001). The main purpose of using turfgrass is to stabilize soil and to add to the aesthetic value of the landscape.

Benefits and Functions of Turfgrasses

Benefits of turfgrasses can be classified according to their functional, recreational and aesthetic purposes (Beard and Green, 1994).

The functional turfgrasses purposes may include; soil erosion control, dust prevention, reducing pollution and flood control. Turfgrasses reduce water resources contamination by reducing runoff and sediment entry into downstream water bodies. They also work as a filtering layer that prevents nitrates and other chemicals from reaching the ground water. Turgeon (1996) reported that turfgrass on roadsides absorb toxic fumes emitted from vehicles thereby providing an air cleaning effect. Turfgrasses also reduce noise, glare and dust problems on areas surrounding buildings (Beard, 1973).

Turfgrass provides a low-cost recreational surface for both passive and active uses (Beard and Green, 1994). It is commonly used in athletics fields, surrounding offices, parking lots and small urban parks.
The aesthetic functions of turfgrass are to provide highly visual quality lawns and attractive landscapes surrounding homes, parks, and other significant sites. The aesthetic values of turfgrass are significant to the psychological health of modern man especially in densely populated urban areas (Derrick, 2001).

Turf color is a major component of its aesthetic value and a direct indicator of turf water and nutrient status (Beard, 1973). Therefore, turf quality is often evaluated in turfgrass field studies.

**Turf Quality Evaluation Methods**

Traditional methods of determining turf quality have often been based on a visual rating system as explained by the National Turfgrass Evaluation Program (NTEP) (Morris, 2002). The method uses a scale ranging from 1 to 9, with 1 representing the lowest quality and 9 representing the highest quality turf. A rating of 6 or above is generally considered acceptable (Morris, 2002). This scale is mainly a function of color, density, and uniformity (Horst et al., 1984). Although this technique does not require much labor and provides quick quality estimation, it tends to be subjective and non-reproducible and may vary widely among evaluators (Horst et al., 1984). Differences in assessments by humans occur because individuals differ in their capability to perceive various wavelengths of visible light, which can lead to differences in visual estimates of turf quality (Mirik et al., 2006). Therefore, alternative techniques are needed to provide a quick, reliable, objective and non-destructive tool in assessing turf quality.

Various techniques have been developed to objectively evaluate turf quality. Turf color has been measured with a reflectance measurements using a spectrophotometer
(Birth and McVey, 1968), and using chlorophyll and amino acid analysis (Johnson, 1973; Nelson and Sosulski, 1984). These methods are costly (need expensive equipment), time consuming (requires samples to be transported to a laboratory for analysis), and are species or cultivars, dependent.

Colorimeters have been successfully used to quantify the color of creeping bentgrass (Landschoot and Mancino, 2000), to evaluate varying turf color due to seasonal changes (Kimura et al., 1989), and to address differences among cultivars and genetic lines (Thorogood et al., 1993). The disadvantage of using colorimetry is the relatively small turf area that it measured (less than 20 cm²).

Turf canopy temperature is another way used to measure response of turfgrass to water deficiency (Jiang et al., 2009). Turfgrass canopy temperature changes according to the moisture level and transpiration rates with leaf canopy temperature exceeding ambient air temperature under turfgrass drought stress as a result of transpiration reduction (Jiang et al., 2009). Canopy and ambient air temperature differentials (ΔT) have been found to be a good tool for assessing turf quality under water deficit conditions in tall fescue (Fenstermaker-Shaulis et al., 1997) and perennial ryegrass (Jiang et al., 2009).

The problem with measuring ΔT is its sensitivity to weather variation and the complexity of the model required, when sampling under non-ideal weather conditions, for estimating ΔT accurately (Martin et al., 1994).

Multispectral radiometry (MSR) reflectance, that measures light reflectance from turf canopies in visible and infrared ranges, has been found to be associated with water content (Penuelas et al., 1993) and leaf pigment content (Bell et al., 2004; Cater and
Spiering, 2002; Stiegler et al., 2005). Various spectral reflectance wavelengths may be used to determine turf quality and distinguish between stressed and healthy grass (Bell et al., 2002; Jiang and Carrow, 2005). Canopy spectral reflectance has been also used to monitor disease (Raikes and Burpee, 1998) and nitrogen stress (Kruse et al., 2006) in creeping bentgrass. Reflectance at both visible red (R) and near-infrared (NIR) ranges was used to develop the normalized difference vegetation index (NDVI) (Rouse et al., 1973), where NDVI is defined as \((\text{NIR} - \text{R}) / (\text{NIR} + \text{R})\). The NDVI index has been used to evaluate turfgrass canopy characteristics (Sönmez et al., 2008; Xiong et al., 2007; Jiang et al., 2003; Trenholm et al., 1999) and many studies have been conducted using the NDVI index to monitor turfgrass quality (Fitz-Rodriguez and Choi, 2002, Keskin et al., 2003, Jiang et al., 2009). NDVI has also shown to effectively express changes in leaf water content and soil moisture in perennial ryegrass under water deficit conditions (Dettman-Kruse et al., 2008). Although this index shows promise, the area captured by most NDVI meters is relatively small.

Digital image Analysis (DIA) provides an alternative method to measure the reflectance from vegetative surfaces and has become an effective tool for use in agronomic research (De Koeyer et al., 1993). DIA has been used to quantify canopy coverage in wheat (Lukina et al., 1999), soybeans (Purcell, 2000), and turfgrass (Richardson et al., 2001). Also, it has been used to quantify crop damage due to different diseases (Adamsen et al., 1999; Díaz–Lago et al., 2003; Steddom et al., 2005; Mirik et al., 2006). In another study, digital imagery was used to quantify turf canopy color and showed strong agreement between an index using DIA and visual ratings in evaluating
turf color (Karcher and Richardson, 2003). An index known as a dark green color index (DGCI) was developed by Karcher and Richardson (2003) using hue, saturation, and brightness (HSB) levels (See Chapter 2).

There are many benefits of using a digital imagery technique to monitor changes in vegetative surfaces due to various conditions. It provides objective, unbiased, nondestructive, and consistent measurements. This technique is capable of providing rapid, accurate, and precise results as recent digital image collection equipment has the capability to acquire hundreds of images per hour to be stored for subsequent analysis at the researcher’s convenience (Díaz-Lago et al., 2003). The digital imagery process is also a cost-effective technique requiring only a digital camera, computer, and image analysis software. A low-cost digital camera, with white balance adjusting capability, and a light box, that provides a consistent lighting source (Ikemura, 2003), are sufficient for collecting images with low-quality Joint Photographers Expert Group (JPEG) compression format. Steddom et al. (2005) concluded that results from digital image analyses, using low-quality (JPEG) images, have a number of desirable qualities for data quantification and have the same results of those using a lossless format such as TIFF or RAW images. Furthermore, free digital image analysis programs are available online for analyzing data and have functions similar to commercial image analysis programs.

**Turfgrass Irrigation Control**

With a steady increase in using residential irrigation systems in North Carolina by 29.4% between 1994 and 1999 (NCDA, 2001), and recent drought problems, it is essential to use an efficient irrigation system to meet the dual goals of conserving water
and maintaining an acceptable turf quality. Over-irrigation causes water waste and leaching of nutrients, and under-irrigation causes unacceptable turf quality (Cardenas-Lailharcar et al., 2005). For these reasons proper irrigation accounting for turf water demand (landscape) is important.

Landscape water demand can be estimated using either by: 1) soil-moisture measurements; and/or 2) by calculating reference evapotranspiration (ET₀), from weather station data. Controllers that use these measurements to update the water scheduling according to plant water needs are known as smart irrigation controllers.

**Smart Irrigation Controllers**

*a. Soil-moisture based controller studies*

Soil-moisture feedback controllers have been widely used to control irrigation for different agricultural crops. Dukes and Scholberg (2004) recorded irrigation water savings of 23% and 50% while using TDR probes and a commercially available dielectric sensor, respectively, on a sweet corn and bell pepper. Granular matrix sensors (GMS) have been used to control the irrigation by using soil-water feedback on corn and cotton in North Carolina (Grabow et al., 2004). These sensors are widely used for irrigating agricultural crops, but they still limited when used at residential landscape irrigation level (Qualls et al., 2001).

Soil-moisture feedback systems have been used to control irrigation for turfgrass for several years. A monthly water saving range from 42% to 95% was reported by Augustin and Synder (1984) using moisture sensors to control irrigation on bermudagrass. Allen (1997) found an average water savings of 10% compared to control
sites in a study of sensor controlled irrigation in one commercial and 26 residential sites. In Western Australia, use of WaterSmart soil-moisture based irrigation control systems (not available in U.S.) resulted in an reduction of 25% in water use compared to control plots while maintaining acceptable turf quality (Pathan et. al., 2003). In Florida, soil-moisture-sensor (SMS) based systems applied 69% to 92% less irrigation water than a time-based irrigation scheduling system without a rain sensor on bermudagrass (*Cynodon dactylon* L.) during wet weather conditions (Cardenas-Lailhacar et al., 2008). Using TDR probes to manage irrigation of sprinkler irrigated Kentucky bluegrass (*Poa pratensis* L.) reduced water consumption by 16% compared to ET-based irrigation recommendations (Blonquist, Jr. et al., 2006).

\[ b. \text{Weather based (ET) controller studies}\]

Several studies on turf have been conducted to evaluate the performance of weather-based controller systems. One study recorded 59% water savings when using a Toro Intellisense controller compared to a standard time-based scheduling (Shedd et al., 2007), and another recorded water savings of 21% when using a WeatherTRAK ET controller (Aquacraft, Inc., 2003). A weather based Aqua Conserve controller resulted in average water savings ranging from 7 to 25% in three different residential landscape irrigation studies in California (Addink and Rodda, 2002). Pittenger et. al. (2004) found that the Aqua Conserve controller over-irrigated in most cases and the Accurate WeatherSet controller under-irrigated in most cases while the Hydropoint Weather TRAK controller over-irrigated in some cases and under-irrigated in others. In Las Vegas, a mixed landscape study conducted on 27 residential sites showed that an ET
based irrigation controller saved 20% water compared to non-ET based control sites (Devitt et al., 2008). Generally, ET controllers have the potential to reduce water application compared to timer-based controllers while maintaining acceptable turf quality (Davis et al., 2007).

Knowledge of water-use in turfgrasses could improve management strategies and facilitate turfgrass breeding for drought resistance and/or development of low water-use species and cultivars (Huang et al., 1997). Carrow (1991) reported that water-use may vary among turfgrass species. Based on turfgrass species, irrigation amounts should be adjusted based on drought resistance (Baldwin et al., 2006). Differences in drought resistance in warm-season and cool-season turfgrasses have been reported and studied intensively (Hook and Hanna, 1994; Jiang et al., 1998; Karsten and MacAdam, 2001; Kim and Beard, 1998; Schaan et al., 2003). Cool-season turfgrass tolerates hot conditions and gives acceptable turf quality when irrigated (NCDA, 2004) but the challenge is to maintain acceptable quality during summer months while still conserving water.

**Turfgrass Types**

Turfgrasses are classified into warm-season and cool-season turf depending on physiological processes. Warm-season grasses are native to tropical or sub-tropical environments and cool-season grasses are native to cold and temperate environments (Christians, 2006). Figure 1.1 illustrates the shoot growth patterns of both-season grass types.
a. Warm-Season Turfgrass

A warm-season turfgrass is defined as a species adapted to favorable growth during warm portions (26.7 °C to 35.0 °C) of the growing season (Turgeon, 1996) and it goes dormant during winter (especially in the transition zone) turning brown until spring due to chlorophyll loss (Christians, 2006). Warm-season turfgrasses are widely distributed throughout the warm humid, warm sub-humid, and warm semi-arid climates and have been utilized to varying degrees in the transition zones (Beard, 1973). The most common warm-season turfgrasses are bermudagrass (*Cynodon dactylon*), zoysiagrass (*Zoysia japonica*), St Augustinegrass (*Stenotaphrum secundatum*), centipedegrass (*Eremochloa ophiuroides*) and bahiagrass (*Paspalum notatum*) (Beard, 1985).

b. Cool-Season Turfgrass

A cool-season turfgrass is defined as a turfgrass species adapted to favorable growth during cool portions (15.6 °C to 23.9 °C) of the growing season and may become dormant or injured during hot weather (Turgeon, 1996). Cool-season species are widely distributed throughout the cool humid, cool sub-humid, and cool semi-arid climates and also extend into the transition zone. The most common cool-season turfgrasses are tall fescue (*Festuca arundinacea*), Kentucky bluegrass (*Poa pratensis*), perennial ryegrass (*Lolium perenne*) and creeping bentgrass (*Agrostis palustris*) (Beard, 1985).

This study focused on a common cool-season turfgrass tall fescue that is the predominant turfgrass in North Carolina, in the transition zone.
GENERAL OBJECTIVES

The general research objectives were to:

i. Identify the correlation among digital imagery results, visual quality ratings, canopy spectral reflectance, and canopy temperature in evaluating the quality of tall-fescue irrigated by different irrigation treatments (presented in Chapter 2).

ii. Develop and implement a methodology to use digital imagery process to provide objective and quantitative estimates of turfgrass quality (presented in Chapter 2).

iii. Evaluate two types of smart irrigation technologies: ET, and soil-moisture-based controller systems; and to compare water application and turf quality with a standard time-based controller. The effects of three different irrigation frequencies were also evaluated (presented in Chapter 3).
REFERENCES


Figure 1.1 Shoot growth patterns of cool- and warm-season grasses (Christians, 2006)
CHAPTER 2: COMPARING DIGITAL IMAGE ANALYSIS AND OTHER TURF QUALITY MEASUREMENTS IN TALL FESCUE

ABSTRACT

Turf color is a direct indicator of turf water and nutrient status and is a major component of its aesthetic value. Therefore, turf quality is often evaluated in turfgrass experiments. Accurate, nondestructive, rapid and objective assessment of turf quality is essential for experiments that evaluate irrigation management strategies. The main objective of this study was to identify changes in and correlations among turf visual rating, canopy reflectance index, canopy temperature and a turf color index based on digital imagery in evaluating turfgrass quality under different irrigation treatments. A study of ten irrigation treatments on tall fescue (Festuca arundinacea Schreb.) plots combining controller technology (a standard time-based system, two soil-moisture-based systems, and an evapotranspiration based system) and watering frequency (1, 2, and 7-days per week) replicated four times in a randomized complete block design was done at the North Carolina State University Lake Wheeler Turf Field Laboratories. Digital imagery analysis was used to assess turf color quality by using a dark green color index (DGCI), created from hue, saturation, and brightness (HSB) values of each pixel obtained from digital images of the turf canopy. Images were collected under uniform lighting conditions, for direct comparison with a visual rating, a normalized difference vegetation index (NDVI) calculated from the red and near-infrared canopy reflectance, and turf canopy temperature. These measurements were taken on a weekly basis during the summers of
2008 and 2009. DGCI, was strongly and positively correlated with the visual rating index 
(r = 0.67 and 0.85, for 2008 and 2009, respectively) and NDVI (r = 0.79 and 0.87, for 
2008 and 2009, respectively), but negatively and weakly correlated with differentials of 
canopy and ambient air temperature (ΔT) (r = -0.10 and -0.24, for 2008 and 2009, 
respectively). A new model to predict the visual rating (VR) index was developed and 
calibrated using candidate DGCI statistics from 120 images in the calibration data set. 
Candidate DGCI statistics were fitted to different models using a multiple linear 
regression (MLR) procedure. The model using mean and SD was selected as the best 
model. An independent validation dataset of 120 samples was used to validate the VR 
model. Fitness of calibration and validation models was verified using the adjusted 
coefficient of determination (adjusted R^2), root mean square errors (RMSE), and the 
Mallow’s Cp statistic. The results showed that the two-variable (mean and SD) model 
produced more accurate estimates (adjusted R^2 = 0.926 and 0.899) than the model that 
only used one term (the average value of DGCI) in predicting the VR values (adjusted R^2 
= 0.879 and 0.843) for calibration and validation sets, respectively.

Because of their objective measurements and their continuous scales, digital 
imagery analysis, and canopy spectral reflectance techniques allow greater potential 
accuracy and precision in turf quality estimates thus helping to identify irrigation 
management strategies that not only efficiently apply water, but also maintain turf 
quality. Based on the new digital imagery model results, using the two-variable model 
may provide a useful tool for estimating the turf quality of tall fescue.
INTRODUCTION

More than 2.1 million acres of turfgrass add to the functional, recreational and aesthetic value of North Carolina. With a steady increase in the number of residential irrigation systems in North Carolina (29.4% between 1994 and 1999 (NCDA, 2001)), and recent serious droughts, managing irrigation water is essential for enhancing turf performance under limited water supply conditions and for conserving water. In addition, both over-irrigation and under-irrigation can have negative impacts on turf quality (Cardenas-Lailhacar et al., 2005). Therefore, rapid and accurate estimates of turf soil moisture conditions and turf quality are necessary for timely and proper irrigation.

Turf Quality

Traditional methods of determining turf quality have often been based on a visual rating system that uses a scale ranging from 1 to 9, with 1 representing the lowest quality and 9 representing the highest quality turf. A rating of 6 or above is considered minimally acceptable (Morris, 2002). This scale is mainly a function of color, density, and uniformity (Horst et al., 1984). The technique requires little labor and provides quick quality estimation. Horst et al. (1984) studied the results of 10 trained researchers, who individually evaluated the same turfgrass stands for quality and density to find how their ratings compared. Results showed the variation between the individual raters was greater than between the turfgrass stands rated. Differences in assessments by humans occur because individuals differ in their capability to perceive various wavelengths of visible light, which can lead to differences in visual estimates of turf quality (Mirik et al., 2006). This rating system is biased due to subjectivities of the raters and difference in rater
experience resulting in inaccurate estimation of turf quality (Keskin et al., 2003). Keskin et al. (2003) concluded that spectral reflectance analysis was superior to the visual rating system.

Spectral reflectance analysis has been introduced as an alternative to visual ratings for assessment of turf quality as a quick, reliable, and non-destructive tool. Vegetative physiological indicators such as leaf water content and chlorophyll concentration are affected by water deficiency in turfgrass (DaCosta et al., 2004; Jiang and Huang, 2000) and were found to be related to various spectral reflectance measurements in the near-infrared (NIR) region (Moran et al., 1994; Fenstermaker-Shaulis et al., 1997). Canopy spectral reflectance measurements have been used to estimate plant quality under several different irrigation and/or fertilization levels (Fernandez et al., 1994; Fenstermaker-Shaulis et al., 1997; Rollin and Milton, 1998; Osborne et al., 2002b; Baghzouz et al., 2007). Spectral reflectance analysis requires measurement of the spectral radiation reflected by the plant canopy at different light wavelengths in both the visible and near-infrared (R and NIR, respectively) ranges (Trenholm et al., 1999; Keskin et al., 2003). Trenholm et al. (1999) showed that the light reflectance technique has the potential to quantify grass health and results are highly correlated with visual ratings. Various spectral reflectance wavelengths may be defined to determine turf quality and distinguish between stressed and healthy grass (Bell et al., 2002; Jiang and Carrow, 2005). Reflectance at both visible red and near-infrared NIR ranges was used to develop the normalized difference vegetation index (NDVI) (Rouse et al., 1973), where NDVI is defined as (NIR – R) / (NIR + R). NDVI is commonly used to
evaluate turfgrass canopy characteristics (Sönmez et al., 2008; Xiong et al., 2007; Jiang et al., 2003; Trenholm et al., 1999). Many studies have been conducted using the NDVI index to monitor turfgrass quality (Fitz-Rodriguez and Choi, 2002, Keskin et. al., 2003, Jiang et al, 2009). Common results of these studies showed that NDVI is highly correlated with visual rating ($r = 0.70$ to $0.97$). NDVI has also shown to effectively express changes in leaf water content and soil moisture in perennial ryegrass under water deficit conditions (Dettman-Kruse et al., 2008). Other spectral indices have had different results depending on the wavelength used, but still have shown good correlation with visual ratings. Dettman-Kruse et al. (2008) used spectral data to distinguish between wear-treated and untreated plots.

Turf canopy temperature is another tool used to measure responses of turfgrass to water deficiency (Jiang et al., 2009). Turfgrass canopy temperature changes according to the moisture level and transpiration rates with leaf canopy temperature exceeding ambient air temperature under turfgrass drought stress as a result of transpiration reduction (Jiang et al., 2009). Canopy temperatures for well-watered crops have been found to be lower (2-3°C) than a stressed plant under water deficit in a study using peas (Clark and Hiller, 1973). The difference between plant canopy temperature and ambient air temperature ($\Delta T$) has been studied as a tool to manage irrigation scheduling in Kentucky bluegrass (Poa pratensis L.) because it relates to the water potential in turf leaves (Throssell et al., 1987). Canopy and ambient air temperature differentials ($\Delta T$) were found to be significantly correlated with NDVI ($r = -0.54$) when studying the quality of tall fescue [Festuca arundinacea Schreb] under water deficit conditions.
Jiang et al. (2009) concluded that changes in (ΔT) are a useful tool to predict the leaf water and soil water content of perennial ryegrass (Lolium perenne L.) under water deficit conditions.

Digital image Analysis (DIA) provides an alternative method to measure the reflectance from vegetative surfaces and has become an effective tool for use in agronomic research (De Koeyer et al., 1993). DIA has been used to quantify canopy coverage in wheat (Lukina et al., 1999), soybeans (Purcell, 2000), and turfgrass (Richardson et al., 2001). It has also been used to quantify crop damage due to different diseases (Adamsen et al., 1999; Díaz-Lago et al., 2003; Steddom et al., 2004; Mirik et al., 2006). Digital imagery was used by Karcher and Richardson (2003) to quantify turf canopy color and showed strong agreement between an index derived from DIA and visual ratings in evaluating turf color. According to their research, that used independent color information on the amount of red, green, and blue (RGB) light emitted for each pixel, the intensity of red and blue tends to confound how green an image appears. To simplify the interpretation of digital color data, RGB values are converted directly to hue, saturation, and brightness (HSB) values that are based on human perception of color (Karcher and Richardson, 2003). In the basic color system (Figure 2.1), hue refers to an angle on a continuous circular scale from 0° to 360° to describe the color itself (0° = red, 60° = yellow, 120° = green, 180° = cyan, 240° = blue, 300° = magenta). Saturation refers to color pureness, from the maximum value of 100% (fully saturated color) through paler colors all the way down to gray (0%). Brightness refers to color intensity from maximum brightness or white (100%) to black (0%) (Adobe Systems, 2002). The hue, saturation
and brightness (HSB) values, according to Adobe Systems (2002), are calculated by converting the absolute RGB levels (on a scale of 0 to 255) to percentage RGB levels by dividing each level by 255 and using these percentage levels in the equations below:

\[
Hue = \begin{cases} 
\text{undefined,} & \text{if } \Delta = 0 \\
60 \times \frac{G-B}{\Delta} + 0, & \text{if } M = R \\
60 \times \frac{B-R}{\Delta} + 120, & \text{if } M = G \\
60 \times \frac{R-G}{\Delta} + 240, & \text{if } M = B 
\end{cases}
\]  

(2.1)

\[
Saturation = \begin{cases} 
0, & \text{if } M = 0 \\
\frac{M-m}{M}, & \text{if } M \neq 0 \\
1, & \text{if } m = 0 
\end{cases}
\]  

(2.2)

\[
Brightness = M
\]  

(2.3)

Where:

- R, G, and B = Red, Green, and Blue percentage levels, respectively,
- \( M = \max (R, G, B) \),
- \( m = \min (R, G, B) \) and,
- \( \Delta = M - m \)
An index developed using HSB levels known as a dark green color index (DGCI) was developed by Karcher and Richardson (2003) who found a strong agreement between DGCI and visual rating. DGCI is computed as:

\[
DGCI = \frac{\left(\frac{H - 60}{60} + (1 - S) + (1 - B)\right)}{3}
\]  

(2.4)

Where:

\(H, S, B\) = hue, saturation, and brightness levels, respectively.

There are many benefits of using a digital imagery technique to monitor changes in vegetative surfaces due to various conditions. It provides objective, unbiased, nondestructive, and consistent measurements. This technique is capable of providing rapid, accurate, and precise results as recent digital image collection equipment and image analysis software have the capability to acquire hundreds of images per hour to be stored for subsequent analysis at the researcher’s convenience (Díaz-Lago et al., 2003). The digital imagery process is also a cost-effective technique requiring only a digital camera, computer, and image analysis software. A low-cost digital camera, with white balance adjusting capability, and a light box that provides a consistent lighting source (Ikermura, 2003), are sufficient for collecting images with low-quality Joint Photographers Expert Group (JPEG) compression format. Steddom et al. (2005) concluded that results from digital image analyses, using low-quality (JPEG) images, have a number of desirable qualities for data quantification and have the same results of those using a lossless format such as TIFF or RAW images. Furthermore, free digital image analysis programs are available online for analyzing data and have functions similar to commercial image analysis programs.
The objectives of this research were to identify the correlation among digital imagery results, visual quality ratings, canopy spectral reflectance, and canopy temperature in evaluating the quality of tall fescue under different levels of stress due to different irrigation treatments and to develop a system to use digital imagery to provide objective and quantitative estimates of turfgrass quality.

**MATERIALS AND METHODS**

**Site description for water-use treatments study**

This study was conducted at the North Carolina State University Lake Wheeler Turf Field Laboratory, Raleigh, North Carolina, from 15 May to 18 September 2008 and from 7 May to 11 August 2009. The soil at the research site is classified as a Cecil sandy loam (fine kaolinitic, thermic, Typic Kanhapludults) although particle size distribution of samples obtained from soil cores from the site placed it in the clay category (USDA system).

This study was within a larger study which primary goal was to evaluate ten different water-use treatments with respect to applied water and turf quality. Three controller technologies (a standard time-based controller, ET-based controller, and soil water sensor-based system) with three irrigation frequencies (once per week, twice per week and daily irrigation scheduling) produced nine treatment combinations and the tenth treatment was a water on-demand soil-water feedback system that was allowed to irrigate daily using two soil-water content setpoints to start and terminate irrigation instead of using a specific irrigation frequency. An Intellisense TIS-240 series (Toro, Inc., Riverside, Calif.) controller was used for the ET-based system. The Acclima Digital TDT...
RS-500 “add-on” system and Acclima CS-3500 “water on-demand” system (Acclima Inc., Meridian, Idaho) were used to evaluate soil-water sensor-based systems. Rain sensors (Irritrol Systems Inc., Riverside, Calif.) were added to the time-based and ET-based system to override irrigation in case of rainfall events.

Before installation, the study area was graded into two separate terraces and established to ‘Confederate’ tall fescue (*Festuca arundinacea* Schreb) using sod. Each terrace was divided into two replications of ten plots each representing the ten different irrigation treatments. Each irrigation treatment was replicated four times in a randomized complete block experimental design. Each 16 m² (4.0 m x 4.0 m) plot was irrigated independently using four quarter circle pop-up spray head sprinklers (Toro 570 3.7 m series with 23º trajectory), with a discharge rate of 0.315 L s⁻¹ at 210 kPa. (Figure 2.2).

**Turf quality measurements**

Turf quality was monitored on weekly basis during the monitoring seasons of 2008 and 2009 using four different techniques. In 2008, digital images were collected for a period of six weeks (14 August through 19 September), turf was visually rated for a period of twelve weeks (5 June through 21 August), NDVI values were taken for a period of nineteen weeks (15 May through 19 September), and ΔT was measured for a period of seventeen weeks over the same period as NDVI measurements, except no readings were taken the ninth and the eighteenth week (10 July and 11 September, respectively) as weather conditions were not favorable. In 2009, all turf quality measurements were taken for a period of fifteen weeks (7 May through 11 August). Turf was not visually rated for the last week.
a. **Visual Rating:**

Turf quality was visually assessed for all plots by an experienced turf evaluator and rated on a scale of 1 to 9 representing poor to excellent quality respectively (Morris and Shearman, 1997).

b. **Spectral Reflectance:**

Canopy spectral reflectance was taken using a Field Scout TCM 500 Turf Color Meter (Spectrum Technologies Inc., Plainfield, Ill.) to assess turf quality by a “normalized difference vegetation index” (NDVI). The Field Scout meter has its own internal light source that emits visible red (R) and near infrared (NIR) lights from a single light-emitting diode light source. Reflectance at these different wave lengths was used to develop the normalized difference vegetation index (NDVI) as follows:

\[
\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}}
\]

Where:

- NDVI = Normalized Difference Vegetation Index
- NIR = Reflectance in the band of 850 ± 5 nm
- R = Reflectance in the band of 660 ± 5 nm

A T-handle extension was attached to the TCM500 meter to allow measurements while standing (Figure 2.3). One reading per plot was taken on a weekly basis during the 2008 sampling season and five readings were taken per plot during the 2009 sampling season to increase the total sampled area because of the relatively small area sampled by the Field Scout meter. Each sample represented about 0.03% of the plot area. The five values taken within each plot were averaged to represent the whole plot.
c. **Canopy Temperature:**

Turf canopy temperature was measured weekly between 12:00 and 15:00 EST (Eastern Standard Time) using a handheld infrared thermometer (Spectrum Technologies Inc., Plainfield, Ill.) (Figure 2.4). Differential temperatures (ΔT) were obtained by subtracting ambient air temperature from canopy temperature. Turf canopy temperature was measured by taking one reading per plot in full sun while avoiding shadows and windy conditions. Sampling was done holding the thermometer at 1.0 m above the turf at an angle of 45° from horizontal as proposed by Throssell et al. (1987).

d. **Digital Image Analysis:**

Turf quality was evaluated by using digital image analysis process that included; (1) acquiring digital images by a digital camera in jpeg (joint photo graphic experts group, “.jpg”) format under consistent lighting, (2) extracting the red, green and blue (RGB) levels for all pixels in the acquired images using ImageJ software (National Institutes of Health, Bethesda, Md.), (3) converting the RGB levels into Hue, Saturation and Brightness (HSB) parameters, and (4) creating a turf color index, known as the dark green color index (DGCI), from the HSB values (Karcher and Richardson. 2003).

Turf images were taken using a Nikon Coolpix 4300 digital camera (Nikon Inc., Melville, N.Y.). The images were collected in JPEG format, with a color depth of 16.7 million colors, an image size of 640 x 480 pixels (about 150 kilobytes per image), and an image quality of “fine” that is equivalent to an image quality (Q) of ≈65 according to Adobe Systems (2002). The compressed level of JPEG images ranged from 8:1 to 5:1 representing more and less uniform turf color respectively without noticeable visible loss,
bringing the effective storage requirement down to about 4-bits/pixel. Camera settings were adjusted manually to guarantee the same captured conditions for all images and were set to a shutter speed of 1/8 sec, an aperture setting of f/2.8, and a focal length of 80 mm. All images were collected from the plots using a uniform light source (Ikemura, 2003) from a light box (Figure 2.5) to prevent any changes in light due to shadows or clouds. The camera was adjusted manually for white balance by using a grey piece of paper to adjust the camera's color sensitivity to preserve natural colors under the fluorescent lighting inside the box.

Images were collected weekly for all forty plots for a period of six weeks in 2008 (14 August through 19 September) by taking one mid-plot image per plot, and for a period of fifteen weeks in 2009 (7 May through 11 August) by taking five images per plot. The number of images was increased in 2009 to increase the area sampled from each plot as each image captures only about 0.6% of whole plot area. Images were taken in the area located at the center of plot that received water from all four sprinklers (Figure 2.6).

Images were downloaded to a personal computer for subsequent analysis. A macro was developed in ImageJ software (National Institutes of Health, Bethesda, Md.) to quantify turfgrass color for 200 digital images (5 per plot x 40 plots), taken each week in 2009, by determining red, green, and blue levels (RGB) for each pixel and exporting the digital values of RGB with pixel location, to a text file for further analysis. Code written in the R language version 2.7.0 (R Development Core Team, 2008) was used to; (a) convert RGB levels on a scale of 0 – 255 to percentages by dividing each value by 255; (b) convert the percent RGB values into hue, saturation, and brightness (HSB) levels
for each pixel; (c) develop a color index, by using the calculated HSB levels to calculate a dark green color index (DGCI) for each pixel; and (d) develop statistical tables and charts for HSB levels and DGCI values calculated from all pixels in each image. This is contrasted to the method of Karcher and Richardson (2003) who calculated one DGCI value for each image using the average HSB levels obtained using SigmaScan Pro version 5.0 software (SPSS, 1998). Basically, the process using SigmaScan Pro version 5.0 software is to; (a) calculate and export the average RGB values to a MS Excel spreadsheet (Microsoft Corporation, 1999); (b) convert the average RGB values to percentages by dividing each value by 255; and (c) convert the percent RGB values to HSB values based on an Adobe Systems (2002) algorithm, described previously. One color index (DGCI) was calculated from the average of transformed HSB levels, for each image, using equation (2.4).

Six digital images, in JPEG format, taken in the middle of the 2009 monitoring season (July 2), representing six different levels of visual turf quality (8, 7, 6, 5, 3, and 2) were used to check the effect of different compressed image qualities on DGCI. Each image was saved in a lossless TIFF format (Tagged Image File Format) with an uncompressed 24-bit RGB image (307200 pixels, 900 kilobytes). Each lossless image was subsequently used to generate five JPEG images at five different image quality levels of Q=100, 75, 50, 25, and 0 according to Adobe Systems (2002). The average of DGCI was calculated for uncompressed and compressed images by using SigmaScan Pro version 5.0 software (SPSS, 1998) with a macro developed by Karcher and Richardson (2005).
Ten image samples (Figure 2.7) were chosen among 200 images taken in the ninth week of monitoring data in 2009 (02 July) to be analyzed in detail. These ten images were selected to represent all treatments in the middle of the irrigation season and to represent a range in turf quality. Histograms and statistics of H, S, B, and DGCI were developed for all ten images, using R-2.7.0 software (R Development Core Team, 2008) to show their variation within an image. The average of DGCI calculated previously for the ten image samples were compared with the average of DGCI calculated by using SigmaScan Pro version 5.0 software (SPSS, 1998) with a macro developed by Karcher and Richardson (2005) to identify any differences between the two methods.

**Statistical Analysis**

Two statistical procedures; correlation and linear regression analysis, were used to judge the performance of DGCI against the other turf quality measures used in this study. Pearson’s correlation coefficients ($r$) were determined by constructing a correlation matrix using the PROC CORR procedure of the Statistical Analysis System (9.1 edition; SAS Institute, Cary, N.C., 2006) using separate data sets for 2008, and 2009. Linear regression analyses were performed on all turf quality data collected across all water treatments and replications (i.e. forty data pairs per week for each combination) during 2008 and 2009 to determine the relationships between other turf quality measurements and DGCI.

Linear regression analysis was performed between DGCI calculated using ImageJ and R software (H, S, and B from all pixels) and DGCI calculated using SigmaScan
software averaged (H,S,B) to determine the relationship and identify any discrepancies between the two methods in calculating the DGCI index.

Pixel data (RGB values) sampled using a 10 × 10 pixel grid in both x and y directions were used to calculate DGCI values for four different images (representing 2 good, one poor, and one median turf quality index). Four semi-variograms were derived from these four digital images (out of the ten images illustrated in Figure 2.7) by using the spatial correlation of DGCI. Variogram calculations were developed to determine at what distance in pixels DGCI values are independent.

The semi-variogram is a geostatistical tool used to fit a model of the spatial correlation of a random variable to infer maximum distances of spatial autocorrelation (ranges).

In mathematical terms, the empirical variogram \( \hat{\gamma}(h) \) according to Cressie (1993) is:

\[
\hat{\gamma}(h) = \frac{1}{2n(h)} \sum_{(i,j)}^{n(h)} [z(x_i) - z(x_j)]^2
\]  

(2.6)

Where:

\( n(h) \) = the number of pairs of observations \( i, j \), at a specified distance (lag) of \( h \)

Some parameters used to describe semi-variogram (Figure 2.23) are defined as (Van Groenigen, 2000):

- **nugget** = the height (intercept) of the semi-variogram at the discontinuity at the origin.
- **sill** = limit of the variogram tending to infinity lag distances.
range = the distance in which the difference of the variogram from the sill becomes negligible or the distance \( h \) at which \( z(x_i) \) and \( z(x_j) \) are no longer correlated (see figure 2.23, right).

**Developing a digital imagery model**

Using a digital imagery process to produce a color index (DGCI) may fairly express turf quality and correlate well to the traditional visual rating technique, but weighting this index with a measure of color uniformity may add more strength to the relationship as the turf quality visual rating scale is a function not only of color and density, but also of uniformity.

To develop and test a new digital imagery model, six weeks (starting from week no. 8 [June 25\textsuperscript{th}] to week no. 13 [July 30\textsuperscript{th}], in the middle of the 2009 monitoring season) of DGCI statistics (mean, standard deviation, skewness, and kurtosis) were used as candidate variables to a statistical model used to predict visual ratings. The data set was split into subset for calibration (\( n=120 \), using a dataset comprised of even numbered weeks) and validation (\( n=120 \), using a dataset comprised of odd numbered weeks). Each week’s dataset had 40 values of VR (as a dependent variable), and DGCI statistics (as independent variables); including mean, standard deviation (SD), skewness (skew), and kurtosis (kurt). Table 2.1 shows the descriptive statistics of both dependent and independent variables in the calibration and validation datasets.

Calibration models were generated using the multiple linear regression (MLR) procedure (SAS Institute, 2006). The MLR analysis was performed with the PROC REG procedure in SAS software using stepwise regression to select the best combination of
independent variables (DGCI mean, SD, skew, and kurt) to predict the dependent variable (VR turf quality). The performance of the various calibration regression models were ranked based on the adjusted coefficient of determination (adjusted $R^2$), the root mean squared error (RMSE), and the Mallow’s Cp statistic. Better performing models are indicated by a higher $R^2$ value and smaller values of RMSE and Cp. Models with fewer predictors (simpler models) are preferable because they minimize problems that occur with over-fitting of the calibration dataset. All explanatory variables used in the calibration regression models were tested for collinearity by using the variance inflation factor (VIF) option in the PROC REG procedure in SAS software. A large VIF (>10) indicates that collinearity may be influencing the estimates, and suggests that variables causing the collinearity should be dropped from the model. The chosen MLR calibration equation was then used to predict the VR values from the DGCI statistics data of the validation dataset. Goodness of fit was evaluated based on adjusted $R^2$ value and RMSE.

RESULTS AND DISCUSSION

Correlation Analysis

Correlation analyses showed significant relationships among visual rating, dark green color index (DGCI), normalized difference vegetation index (NDVI), and canopy-air temperature differential ($\Delta T$) in both monitoring seasons (Table 2.2 and 2.3). Those correlations were stronger in 2009 compared to 2008, particularly for DGCI with NDVI and visual rating. This is probably due to the limitation in DGCI data in 2008. Two weeks of DGCI data were available to compare with VR results in 2008 versus 14 weeks in
2009. Also, only six weeks of DGCI data coincided with NDVI results in 2008 versus 15 weeks in 2009. In addition, DGCI data were only taken during the last weeks of the data collection season in 2008 (lower water stress period). Quality (VR) for all turf plots were nearly the same during these weeks and it was difficult to differentiate between methods used to evaluate the turf. Table 2.4 shows summary statistics by year for the quality rating measures.

Visual rating was positively correlated with DGCI and NDVI but negatively correlated with ΔT (Table 2.2 and 2.3). In 2008, visual rating was strongly correlated with NDVI (r = 0.75, P < 0.0001) and DGCI (r = 0.67, P < 0.0001); the weakest correlation was with ΔT (r = -0.26) although the correlation was still statistically significant (P < 0.0001). Results were similar for 2009 data, with visual rating strongly correlated with DGCI (r = 0.85, P < 0.0001) and NDVI (r = 0.8, P < 0.0001) and weakly correlated with ΔT (r = -0.25, P < 0.0001). DGCI was strongly correlated with NDVI in both years (r = 0.79 and 0.87, P < 0.0001 for 2008 and 2009 respectively). Canopy and air temperature differential (ΔT) was significantly correlated with visual rating but not as high as DGCI and NDVI. ΔT was not significantly correlated with DGCI in 2008 (r = -0.10, P = 0.48).

Correlation coefficients between DGCI and other turf quality indicators calculated for each week in 2009 are plotted in figure 2.8, to show the degree of correlation over the 2009 sampling season. Strong correlations are shown between visual rating and DGCI for all weeks in 2009 (r ≥ 0.85, P < 0.0001). Good correlation was also found between NDVI and DGCI in the first four weeks in 2009 (r ranging from 0.72 to 0.89, P < 0.0001) and
their relationship strengthened in subsequent weeks (r ranging from 0.91 to 0.95, \( P < 0.0001 \)). DGCI and canopy-air temperature differential (\( \Delta T \)) was strongly correlated (\( r \geq -0.70, \ P < 0.0001 \)) most of the time (9 weeks out of 15 weeks) but still not as strong as the correlation between visual rating and NDVI (Figure 2.7). Other weeks showed poor correlation between DGCI and \( \Delta T \). There were a couple of weeks with positive correlation (2 and 6) that resulted in poor overall correlation between the two variables (\( r = -0.24 \)) as shown in Table 2.3.

The slight variability in the weekly relationship between visual ratings and both digital imagery and canopy spectral reflectance may be due to the subjective nature of visual ratings and its discrete scale that is used for rating turf quality (discrete scale from 1 to 9) versus a continuous scale used in digital imagery and canopy spectral reflectance processes, which allows for higher resolution of DGCI and NDVI measurements.

The weakness in the weekly relationship between digital imagery results and turf canopy temperature measurement results is likely caused by fluctuations in turf canopy temperature due to changes in weather conditions, such as solar radiation (cloud interception), humidity, and wind speed (advection of energy), during the measuring period. A weather station (Watchdog 700, Spectrum Technologies, Plainfield, Ill.) was installed at the site to record solar radiation, air temperature, relative humidity, wind speed, and rainfall measurements every 15 minutes. Table 2.5 shows weather parameters during the period of turf canopy sampling for all fifteen weeks in 2009. Two adjacent weeks (5 and 6 in 2009) were taken as examples of strong and weak correlation between DGCI and \( \Delta T \), respectively (Figure 2.8) and compared in terms of weather data statistics.
(Table 2.6) at the time of the canopy temperature measurements. Strong correlation \( r = -0.78, \ P < 0.0001 \) was found between DGCI and \( \Delta T \) in week 5 of the 2009 monitoring season (Figure 2.7) where weather data showed relatively small coefficients of variation (CV %) across the range of weather variables: solar radiation (CV% = 1.8); ambient air temperature (CV% = 0); humidity (CV% = 1.3); and wind speed (CV% = 8.3) (Table 2.6). The following week (week 6), showed weak correlation \( r = 0.11, \ P = 0.51 \) between DGCI and \( \Delta T \) (Figure 2.8), and was found to have much higher coefficients of variation for the same weather variables: solar radiation (CV% = 63.8); ambient air temperature (CV% = 2.8); humidity (CV% = 4.2); and wind speed (CV% = 20.0) (Table 2.7).

Fluctuation in solar radiation may be the greatest cause of inaccurate turf canopy temperature measurements, as grass canopy temperatures will increase linearly with solar radiation intensity (Feldhake et al., 1985). Feldhake and Edwards (1992) found that for a 1 kPa increase in vapor pressure deficit, turf canopy temperature decreased 2.1°C and each 100 W/m² increase in net radiation caused an increase of 0.6°C in canopy temperature. Fluctuation in wind speed did not have a significant effect on turf canopy temperature measurements during sampling, since measurements were taken with wind speed less than 1.6 kph and thermometer readings remained stable. Canopy temperature measurements should be taken under stable weather conditions or the turf canopy-air temperature deferential (\( \Delta T \)) should be adjusted for the variation in weather conditions (Feldhake and Edwards, 1992).
Linear Regression Analysis

Linear regression analysis results of turf quality measurement data pairs showed significant regressions except for DGCI and ΔT in 2008. Table 2.8 and Figures 2.9 to 2.20 show regression results and plots, respectively. Digital imagery and spectral reflectance measurements, DGCI and NDVI, are reported on a continuous scale whereas visual rating measurements were reported on a discrete scale. The relationships of these two measurements with visual rating were significant. These relationships were stronger in 2009 \( (r^2 = 0.71, \text{Figure 2.15 and 0.65, Figure 2.16, respectively}) \) than 2008 \( (r^2 = 0.45, \text{Figure 2.9 and 0.56, Figure 2.10, respectively}) \). The strongest relationship was between DGCI and NDVI \( (r^2 = 0.62, \text{Figure 2.12 and 0.75, Figure 2.18, for 2008 and 2009, respectively}) \). Canopy and air temperature differential (ΔT) had the weakest relationship with the other turf quality measurements; visual rating \( (r^2 = 0.07, \text{Figure 2.11 and 0.06, Figure 2.17, for 2008 and 2009, respectively}) \); DGCI \( (r^2 = 0.01, \text{Figure 2.13 and 0.06, Figure 2.19, for 2008 and 2009, respectively}) \); and NDVI \( (r^2 = 0.04, \text{Figure 2.14 and 0.08, Figure 2.20, for 2008 and 2009, respectively}) \).

DGCI Analysis

DGCI did not show significant variation \( (\approx 1\%) \) when it was developed from a TIFF format image of 900 kb size or a low quality \( (Q=0) \) JPEG format image of \( \approx 30 \) kb size (Table 2.8). Using a higher JPEG quality level \( (Q=75) \) with a size of \( \approx 150 \) kb showed lower variation of DGCI values \( (< 0.3\%) \) when compared to those with TIFF format. With images of lower turf quality \( (VR=3 \) and less) the variation among DGCI values was greater \( (0.5\% \) to \( 1.5\%) \) but still not large (Table 2.8).
Histograms of DGCI, for the ten images shown in Figure 2.7, and statistics are shown in Figures 2.21 and 2.22. Images 1 and 4 representing daily and weekly ET irrigation treatments respectively, have the lowest variance in DGCI. Their low DGCI variance indicates more color uniformity than the other images regardless of their different mean values of DGCI (0.432 and 0.405, respectively). On the other hand, image 7 of a weekly timer-based system plot has the highest variance in DGCI. Although image 4 and 6 having the same mean value of DGCI (0.405 and 0.406, respectively), image 4 has significantly (P <0.0001) lower DGCI variance than image 6 (Figure 2.21).

Variogram parameters, for the four images, were estimated from fitting DGCI data with a spherical model (Cressie, 1993) as representing in Figures 2.23, and 2.24. The spherical model ranges are 159, 75, 34 and 54 pixels for images 1, 2, 3, and 8, respectively. With a pixel size of 0.5 mm, the distances to which DGCI is spatially correlated are 8, 3.7, 1.7, and 2.7 cm (for images 1, 2, 3, and 8 respectively) with no spatial dependence in DGCI values at distances further apart than this.

Using the ten digital images illustrated in Figure 2.7, Figure 2.25 shows the linear regression and correlation between the ten average values of DGCI calculated via SigmaScan software (Karcher and Richardson, 2003) i.e., DGCI calculated using average values of HSB, and the ten means of DGCI calculated via R software that used imageJ text files of RGB values extracted from the same digital images i.e., DGCI calculated for each pixel, then averaged.
Digital Imagery Model

Calibration:

Table 2.9 shows statistics indicating the performance of eight calibration models based on several linear combinations of the candidate independent variables (mean, SD, skew, and kurt of DGCI).

The explanatory variables and regression coefficients for the best calibration models generated by the stepwise regression procedure are given in Table 2.10. Collinearity indices (VIF) are also given for all independent variables in each model of two variables or more.

The MLR model number 8 produced the best performance criteria as $R^2$ and adjusted $R^2$ were highest, the RMSE was the lowest, and Mallow’s Cp values were found to be next to the lowest. This model contains the most variables (4) and thus may be difficult to compute with some datasets. Although, model number 2 did not perform as well as the other two models with more variables (models no. 6 and 8) with a slightly lower $R^2$ and adjusted $R^2$, and a slightly higher RMSE (Table 2.9), it had fewer terms (mean and SD of DGCI) than models 6 and 8 that had three and four variable, respectively. Although all explanatory variables in all calibration models passed the collinearity test with VIF values much less than ten, model number 2 showed the least VIF value ($\approx 1.0$) for its two independent variables (Table 2.10).

Calibration model number 2 performed better than model number 1, which uses only the DGCI mean to estimate the VR value. The two-variable model had a noticeably
higher adjusted $R^2$ of 0.926 and lower RMSE of 0.302 compared to an adjusted $R^2$ of 0.879 and RMSE of 0.385 produced by the one-variable calibration model (Table 2.9).

Model number 2 was selected for testing with the validation dataset. The model was expressed as:

$$\hat{VR} = \beta_0 + \beta_1 \text{(Mean)} + \beta_2 \text{(SD)}$$

(2.7)

where:

$\hat{VR} =$ the predicting visual rating value of turf quality,

Mean = the mean of DGCI values within an image,

SD = the standard deviation of DGCI values within an image,

$\beta_0, \beta_1, \beta_2 =$ linear regression coefficients of the model (given in Table 2.10).

Model testing and validation:

To check the performance of the selected calibrated model, the MLR equation constructed from the calibration data was applied to the validation set of 120 digital image samples. The adjusted $R^2$ and RMSE for the validation set are summarized in Table 2.11 and compared against the base one-variable model. The results using the validation dataset showed that the two-variable model had a noticeably higher adjusted $R^2$ of 0.899 and lower RMSE of 0.397 compared to the one-variable model that had an adjusted $R^2$ and RMSE of 0.843 and 0.495, respectively (Table 2.11). Furthermore, a comparison of scatter plots, with the estimated regression line and 95% confidence interval bands of the mean and predicted responses for calibration (Figure 2.26) and validation (Figure 2.27) sets, showed that the CLM (confidence interval of mean predicted value) and CLI (confidence interval of individual predicted value) had narrower
ranges (better performance) for the two-variable model compared to the one-variable model.

SUMMARY AND CONCLUSIONS

Four rating techniques were used to evaluate turf quality in a study designed to evaluate the effects of different turf irrigation treatments on tall fescue. The significance of the relationship between one of the techniques (digital imagery) and the other three turf quality measurement results used in this study was investigated.

In 2008, weaker correlations were reported between DGCI and other turf quality measurements. This is probably due to the limitation of DGCI data availability in 2008 (Only 6 weeks out of 19 weeks of data). Also, DGCI data in 2008 were available in last 6 weeks when turf quality for all plots were nearly the same (irrigation treatments had a lesser effect due to moderate weather conditions during this period) therefore it was hard to differentiate the difference in turf quality measurements. In 2009, this study revealed strong correlations between DGCI, and NDVI and visual ratings ($r = 0.87$ and $0.85$, respectively). On the other hand, oscillatory correlation (from strong to week and vice versa) occurred in weekly measurements between canopy-air temperature differential ($\Delta T$), and DGCI, NDVI and visual ratings ($r = 0.27$ to -0.88). This fluctuation in correlation may be caused by the fluctuation in weather, especially solar radiation, during turf canopy temperature sampling. Feldhake and Edwards (1992) mentioned that the canopy-air temperature differential should be adjusted for the variation in weather data, especially for solar radiation and vapor pressure deficit. Strongest correlation was found between DGCI index developed from digital imagery and canopy spectral reflectance.
index (NDVI) \( r = 0.83 \) and 0.87, for 2008 and 2009 respectively). Both, DGCI and NDVI provide objective, quantitative turf quality evaluation and no experience is needed. On the other hand, the visual rating technique requires some training, may vary from day to day for the same evaluator (Trenholm et al., 1999), and different values may be reported between evaluators because of its subjectivity. Furthermore, visual ratings are reported on a discrete scale, but DGCI and NDVI are measured on a continuous scale which allows greater potential precision in turf quality estimates. Results from this study illustrate that changes in DGCI (calculated using ImageJ and R software, HSB from all pixels) effectively described the variability in tall fescue turf quality due to various irrigation treatments.

Using a lossless image format or different degrees of JPEG compression for the same image did not significantly affect the calculated DGCI values \( \approx 1\% \) difference). More variation in DGCI values was associated with using lower turf quality (VR of 3 or less) images; however the difference in DGCI was not large. Medium image quality \( (Q=50 \text{ according to the Adobe Systems, 2002}) \) is preferable for use in developing the DGCI in tall fescue as it results in smaller file size and processes faster during image analysis yet still yields essentially the same results of those using a lossless format.

Compared to using just one DGCI value, the distribution of DGCI values presents a clearer and more understandable view not only for how green the turf is (the mean value of DGCI) but also the uniformity of color in the image pixels (variance of DGCI values).
Multiple linear regression was used to develop calibration models for predicting the visual rating of turf quality using DGCI statistics (mean, SD, skew, and kurt), developed from all pixels within an image. Similar outcomes were obtained with two, three, and four term calibration models. Much better calibration results ($R^2 \approx 0.93$) were obtained with the multiple term models compared to the calibration model that only used one term (the average value of DGCI) to evaluate the turf quality ($R^2 = 0.88$). The two-variable calibration model, that used mean and SD values to predict the VR, was selected for testing with a validation dataset ($n=120$). The two-variable variable model had better results using the validation dataset (adjusted $R^2 = 0.899$, RMSE= 0.397) than the one-variable model that used only the average value of DGCI to evaluate turf quality (adjusted $R^2 = 0.843$, RMSE= 0.495). Based on these results, using the two-variable model is suggested for use in predicting VR values in tall fescue under different irrigation treatments over a one-term model that uses only the mean of DGCI values to predict VR values. Other models may need to be developed for other turf species.

For variogram analyses, it was noticed that the spherical model range could be used as an indication for turf color uniformity with increasing variogram range indicating more turf color uniformity and vice versa. A wide range of the distance between two independent DGCI values was observed in tall fescue (longer distance associated with higher DGCI and vice versa).

The correlation coefficient obtained between the two methods in evaluating DGCI (using ImageJ software, and SigmaScan software) indicated strong positive correlation ($r$
= 0.998, \( P < 0.0001 \), the slight difference between their outcomes was due to the method of how each technique obtained a value of average DGCI.
REFERENCES


SPSS. 1999. Sigma Scan Pro v. 5.0. SPSS Science Marketing Dept., Chicago, Ill.


Table 2.1 Descriptive statistics of dependent and independent variables that were used in developing a new digital imagery index, for both calibration and validation sets.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Calibration Set (n = 120)</th>
<th>Validation Set (n = 120)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min.</td>
<td>Max.</td>
</tr>
<tr>
<td>Y</td>
<td>VR</td>
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</tr>
<tr>
<td></td>
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<td>8.0</td>
</tr>
<tr>
<td>X_i</td>
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<td></td>
</tr>
<tr>
<td>DGCI (Mean)</td>
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</tr>
<tr>
<td>DGCI (SD)</td>
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<td>0.067</td>
</tr>
<tr>
<td>DGCI (Skew.)</td>
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<td>0.648</td>
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<tr>
<td>DGCI (Kurt.)</td>
<td>-0.471</td>
<td>2.370</td>
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DGCI = dark green color index, SD = standard deviation, and CV = coefficient of variation.

Table 2.2 Pearson correlation coefficients among normalized difference vegetative index, canopy and air temperature differential, dark green color index, and visual turf ratings across all 40 plots in 2008.

<table>
<thead>
<tr>
<th></th>
<th>NDVI</th>
<th>ΔT</th>
<th>DGCI</th>
<th>VR</th>
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<tr>
<td>NDVI</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correlation</td>
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<td>0.79&lt;sup&gt;(d)&lt;/sup&gt;</td>
<td>0.75&lt;sup&gt;(b)&lt;/sup&gt;</td>
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<td>&lt; 0.0001</td>
<td>&lt; 0.0001</td>
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</tr>
<tr>
<td>ΔT</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correlation</td>
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<td>-0.26&lt;sup&gt;(c)&lt;/sup&gt;</td>
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<td></td>
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<tr>
<td>P-Value</td>
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</tr>
<tr>
<td>DGCI</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correlation</td>
<td>0.67&lt;sup&gt;(f)&lt;/sup&gt;</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>P-Value</td>
<td>&lt; 0.0001</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

NDVI = normalized difference vegetative index, ΔT = canopy-air temperature differential, DGCI = dark green color index, and VR = visual turf ratings.

(a) n = 680
(b) n = 480
(c) n = 440
(d) n = 240
(e) n = 200
(f) n = 80
Table 2.3 Pearson correlation coefficients among normalized difference vegetative index, canopy and air temperature differential, dark green color index, and visual turf ratings across all 40 plots in 2009.

<table>
<thead>
<tr>
<th></th>
<th>NDVI</th>
<th>ΔT</th>
<th>DGCI</th>
<th>VR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation</td>
<td>-0.29 (a)</td>
<td>0.87 (a)</td>
<td>0.80 (b)</td>
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<td>P-Value</td>
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<td>&lt; 0.0001</td>
<td>&lt; 0.0001</td>
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<tr>
<td>ΔT</td>
<td>Correlation</td>
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<td>-0.25 (b)</td>
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<tr>
<td>P-Value</td>
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<td>&lt; 0.0001</td>
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<td></td>
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<tr>
<td>DGCI</td>
<td>Correlation</td>
<td>0.85 (b)</td>
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<td>P-Value</td>
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</tr>
</tbody>
</table>

NDVI = normalized difference vegetative index, ΔT = canopy-air temperature differential, DGCI = dark green color index, and VR = visual turf ratings.

(a) n = 600
(b) n = 560

Table 2.4 Turf quality measurement summary statistics for 2008 and 2009.

<table>
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<tr>
<th>Statistic</th>
<th>2008 experiment</th>
<th>2009 experiment</th>
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<td>ΔT</td>
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<tr>
<td>N</td>
<td>760</td>
<td>680</td>
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<td>Max.</td>
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<td>Mean</td>
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<td>STDEV</td>
<td>0.036</td>
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NDVI = normalized difference vegetative index, ΔT = canopy-air temperature differential, DGCI = dark green color index, VR = visual turf ratings, and STDEV = standard deviation.
Table 2.5 Weather data during turf canopy temperature sampling in 2009.

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SRD = solar radiation, TMP = air temperature, HMD = humidity, WNS = wind speed, and RNF = rain fall
Table 2.6 Statistics for weather data reported during canopy turf temperature measurements (Table 2.5) in monitoring weeks 5 and 6 of 2009 monitoring season.

<table>
<thead>
<tr>
<th>Week</th>
<th>Date - Time</th>
<th>wat/m²</th>
<th>°C</th>
<th>%</th>
<th>kph</th>
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<tr>
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<td>10.8</td>
</tr>
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<td>0.00</td>
<td>0.5</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>CV (%)</td>
<td>1.8</td>
<td>0.00</td>
<td>1.3</td>
<td>8.3</td>
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</table>

<table>
<thead>
<tr>
<th>Week</th>
<th>Date - Time</th>
<th>wat/m²</th>
<th>°C</th>
<th>%</th>
<th>kph</th>
</tr>
</thead>
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<td>63.8</td>
<td>2.8</td>
<td>4.2</td>
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SRD = solar radiation, TMP = air temperature, HMD = humidity, and WNS = wind speed
Table 2.7 Linear regression results between different turf quality indicators.

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<tr>
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<td>y</td>
<td>x</td>
<td>n</td>
<td>$\beta_1$</td>
<td>$p$</td>
<td>$\beta_0$</td>
<td>$p$</td>
<td>$r^2$</td>
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<td>VR</td>
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<td>0.223</td>
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<td>-0.070</td>
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<td>0.48</td>
<td>0.406</td>
<td>$\leq 0.0001$</td>
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<td>VR</td>
<td>480</td>
<td>0.032</td>
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<td>0.487</td>
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<td>VR</td>
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<td>$\leq 0.0001$</td>
<td>17.09</td>
<td>$\leq 0.0001$</td>
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<td>$\leq 0.0001$</td>
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<td>17.65</td>
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<td>0.06</td>
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</table>

VR = visual turf ratings, DGCI = dark green color index, NDVI = normalized difference vegetative index, and $\Delta T$ = canopy-air temperature differential. Linear regression equation form: $y = \beta_0 + \beta_1 x$
Table 2.8 DGCI values calculated using uncompressed (lossless format) and compressed (lossy format) digital images at different image qualities.

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<th>Image Quality</th>
<th>Size (kb)</th>
<th>comp. ratio</th>
<th>bit/color pixel</th>
<th>DGCI</th>
<th>VR</th>
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<th>comp. ratio</th>
<th>bit/color pixel</th>
<th>DGCI</th>
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<th>Size (kb)</th>
<th>comp. ratio</th>
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<th>VR</th>
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<th>Image Quality</th>
<th>Size (kb)</th>
<th>comp. ratio</th>
<th>bit/color pixel</th>
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DGCI = dark green color index, VR = visual rating, TIFF = tagged image file format, JPEG = joint photographic experts group, kb = kilobytes, and comp. ratio = compression ratio.
Table 2.9 Calibration regression results: Visual turf rating versus DGCI model statistics.

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<th>No. of Vars.</th>
<th>R²</th>
<th>Adj. R²</th>
<th>Mallow's Cp</th>
<th>RMSE</th>
<th>Predictors (Xᵢ)</th>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>0.880</td>
<td>0.879</td>
<td>97.34</td>
<td>0.385</td>
<td>x</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>0.927</td>
<td>0.926</td>
<td>16.04</td>
<td>0.302</td>
<td>x ×</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>0.880</td>
<td>0.878</td>
<td>99.30</td>
<td>0.386</td>
<td>x ×</td>
</tr>
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<td>4</td>
<td>2</td>
<td>0.885</td>
<td>0.883</td>
<td>90.62</td>
<td>0.378</td>
<td>x ×</td>
</tr>
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<td>5</td>
<td>3</td>
<td>0.928</td>
<td>0.926</td>
<td>16.93</td>
<td>0.302</td>
<td>x × ×</td>
</tr>
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<td>3</td>
<td>0.934</td>
<td>0.933</td>
<td>4.82</td>
<td>0.287</td>
<td>x ×</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>0.885</td>
<td>0.882</td>
<td>92.62</td>
<td>0.380</td>
<td>x × ×</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
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<td>0.933</td>
<td>5.00</td>
<td>0.286</td>
<td>x × × ×</td>
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DGCI = dark green color index, R² = coefficient of determination, RMSE = root mean square error, SD = standard deviation, and No. of Vars. = number of variables.

Table 2.10 Calibration model parameters developed using MLR and collinearity index (VIF) for explanatory variables in each model.

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<th>Regression Coefficient</th>
<th>Explanatory variables (VIF)</th>
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<td>0.203</td>
<td>26.349</td>
</tr>
<tr>
<td>6</td>
<td>0.078</td>
<td>27.480</td>
</tr>
<tr>
<td>8</td>
<td>0.460</td>
<td>26.671</td>
</tr>
</tbody>
</table>

DGCI = dark green color index, VIF = variance inflation factor, and SD = standard deviation.

Table 2.11: Results of model evaluation with validation dataset (n=120).

<table>
<thead>
<tr>
<th>Mod. No.</th>
<th>calibration model</th>
<th>Adj. R²</th>
<th>RMSE</th>
<th>F(β₀)=0.0</th>
<th>F(β₁)=1.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>^VR₁= -3.883+ 26.928(Mean)</td>
<td>0.843</td>
<td>0.4951</td>
<td>-0.0254</td>
<td>1.0053</td>
</tr>
<tr>
<td>2</td>
<td>^VR₂= 0.203+ 26.349(Mean)-69.96(SD)</td>
<td>0.899</td>
<td>0.3972</td>
<td>0.0321</td>
<td>0.9953</td>
</tr>
</tbody>
</table>

VR = visual rating, R² = coefficient of determination, RMSE = root mean square error, and SD = standard deviation.
Figure 2.1 The hue, saturation, and brightness (HSB) color space.

Image available at:
westone.wa.gov.au/toolboxes/surveying/toolbox12_02/resources/images/content/pre_colour_hsbmodel.jpg
Figure 2.2 Site schematic showing plot layout and irrigation treatments.
Figure 2.3 TCM500 Turf Color Meter.

Figure 2.4 Crop Mini IR Thermometer.
Figure 2.5 Details of light box used to obtain digital image.
Figure 2.6 Plot schematic showing digital imagery sampling region.
Figure 2.7 Digital images of randomly chosen 10 turfgrass plots taken in 2 July 2009.

1 Upper text on each image represents (left to right); plot#, irrigation treatment, image location, and image#.
2 Lower text on each image represents (left to right); Hue angle°, Saturation%, Brightness%, and DGCI level.
Figure 2.8 Correlation coefficients between DGCI and other turf quality indicators for all monitored weeks in 2009.

*, **, *** Significance at 0.1, 0.01 and 0.001 level, respectively.
Figure 2.9 Relationship between dark green color index DGCI and turf visual ratings during 2008 monitoring season.

$y = 0.025x + 0.223$

$R^2 = 0.446$

$n=80, \ P<0.0001$

Figure 2.10 Relationship between normalized difference vegetation index NDVI and turf visual ratings during 2008 monitoring season.

$y = 0.032x + 0.487$

$R^2 = 0.557$

$n=480, \ P<0.001$
Figure 2.11 Relationship between canopy-air temperature differential (ΔT) and turf visual ratings during 2008 monitoring season.

\[ y = -1.061x + 17.09 \]
\[ R^2 = 0.069 \]
\[ n=440, \ P<0.001 \]

Figure 2.12 Relationship between dark green color index DGCI and normalized difference vegetation index NDVI during 2008 monitoring season.

\[ y = 0.659x - 0.070 \]
\[ R^2 = 0.622 \]
\[ n=240, \ P<0.001 \]
Figure 2.13 Relationship between DGCI and canopy-air temperature differential (ΔT) during 2008 monitoring season.

\[ y = -0.001x + 0.406 \]
\[ R^2 = 0.009 \]
\[ n=200, P=0.48 \]

Figure 2.14 Relationship between NDVI and canopy-air temperature differential (ΔT) during 2008 monitoring season.

\[ y = -0.002x + 0.730 \]
\[ R^2 = 0.035 \]
\[ n=680, P<0.0001 \]
Figure 2.15 Relationship between dark green color index DGCI and turf visual ratings during 2009 monitoring season.

Figure 2.16 Relationship between normalized difference vegetation index NDVI and turf visual ratings during 2009 monitoring season.
Figure 2.17 Relationship between canopy-air temperature differential (ΔT) and turf visual ratings during 2009 monitoring season.

Figure 2.18 Relationship between dark green color index DGCI and normalized difference vegetation index NDVI during 2009 monitoring season.
Figure 2.19 Relationship between DGCI and canopy-air temperature differential (ΔT) during 2009 monitoring season.

Figure 2.20 Relationship between NDVI and canopy-air temperature differential (ΔT) during 2009 monitoring season.
<table>
<thead>
<tr>
<th>Image #</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plot #</td>
<td>401</td>
<td>408</td>
<td>306</td>
<td>201</td>
<td>206</td>
</tr>
<tr>
<td>Irri. Treatment</td>
<td>ET-7</td>
<td>AC2</td>
<td>ET-2</td>
<td>ET-1</td>
<td>AC1-2</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.094</td>
<td>0.129</td>
<td>0.031</td>
<td>0.088</td>
<td>0.070</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.732</td>
<td>0.838</td>
<td>0.573</td>
<td>0.718</td>
<td>0.641</td>
</tr>
<tr>
<td>Mean</td>
<td>0.432</td>
<td>0.415</td>
<td>0.305</td>
<td>0.405</td>
<td>0.366</td>
</tr>
<tr>
<td>Variance</td>
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<td>0.0029</td>
<td>0.0029</td>
<td>0.0027</td>
<td>0.0031</td>
</tr>
<tr>
<td>Stdev</td>
<td>0.0518</td>
<td>0.0540</td>
<td>0.0543</td>
<td>0.0515</td>
<td>0.0561</td>
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<tr>
<td>Skewness</td>
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<td>0.2671</td>
<td>-0.3428</td>
<td>0.0323</td>
<td>-0.3956</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.706</td>
<td>0.832</td>
<td>0.368</td>
<td>0.697</td>
<td>0.795</td>
</tr>
</tbody>
</table>

Figure 2.21 Statistics for DGCI values for all image pixels (n=307200) for images (1, 2, 3, 4, and 5) illustrated in Figure 2.7
<table>
<thead>
<tr>
<th>Image #</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
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<tbody>
<tr>
<td>Plot #</td>
<td>207</td>
<td>101</td>
<td>104</td>
<td>106</td>
<td>108</td>
</tr>
<tr>
<td>Irri. Treatment</td>
<td>Tim-2</td>
<td>Tim-1</td>
<td>AC1-1</td>
<td>AC1-7</td>
<td>Tim-7</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.126</td>
<td>0.010</td>
<td>0.101</td>
<td>0.000</td>
<td>0.061</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.792</td>
<td>0.897</td>
<td>0.821</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Mean</td>
<td>0.406</td>
<td>0.257</td>
<td>0.399</td>
<td>0.216</td>
<td>0.352</td>
</tr>
<tr>
<td>Variance</td>
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<td>Stdev</td>
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<td>Skewness</td>
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<td>0.0503</td>
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<tr>
<td>Kurtosis</td>
<td>0.715</td>
<td>-0.025</td>
<td>0.659</td>
<td>13.332</td>
<td>3.837</td>
</tr>
</tbody>
</table>

Figure 2.22 Statistics for DGCI values for all image pixels (n=307200) for images (6, 7, 8, 9, and 10) illustrated in Figure 2.7.
Figure 2.23 DGCI semi-variograms for images 1 (left) and 2 (right) (Figure 2.7), respectively.
Figure 2.24 DGCI semi-variograms for images 3 (left) and 8 (right) (Figure 2.7), respectively.
Figure 2.25 Relationship between the average DGCI calculated by the average of HSB levels (using all pixels) computed via SigmaScan software and the average DGCI calculated by the R software code using RGB levels for each pixel developed by imageJ. The deviation of the two points from the regression line at lower levels of DGCI is due to an increasing number of pixels dominated by the red (R) level.
Figure 2.26 Scatter plots with regression line and 95% confidence interval for mean and predicted response (VR) for calibration models 1(a.) and 2 (b.).

\[
\hat{VR}_1 = -3.883 + 26.928\text{(Mean)}
\]

\[
\hat{VR}_2 = 0.203 + 26.349\text{(Mean)} - 69.96\text{(SD)}
\]

Figure 2.27 Scatter plots with regression line and 95% confidence interval for mean and predicted response (VR) for validation models 1(a.) and 2 (b.).

\[
\hat{VR}_1 = -3.883 + 26.928\text{(Mean)}
\]

\[
\hat{VR}_2 = 0.203 + 26.349\text{(Mean)} - 69.96\text{(SD)}
\]

Mean = the mean of DGCI values for all pixels in an image, and SD = the standard deviation of DGCI values for all pixels in an image.
CHAPTER 3: EVALUATION OF SMART IRRIGATION TECHNOLOGIES
USED TO CONTROL IRRIGATION ON TALL FESCUE

ABSTRACT

With increasing competition for water and the desire for high turfgrass quality, appropriate water management strategies should be accorded high priority to maintain acceptable turf quality and conserve water. The main objective of this study was to evaluate two types of commercially available irrigation control technologies; one based on evapotranspiration (ET) estimates and the other based on feedback from a soil-moisture sensor (SMS), and to compare water application and turfgrass quality resulting from these technologies with that using a standard time-based controller. A total of 40 plots (4.0 m × 4.0 m, each) were established with tall fescue (Festuca arundinacea Schreb) at the North Carolina State University Lake Wheeler Turf Field Laboratories and organized into four blocks of ten plots each. Each block had 9 plots with treatment combinations of controller technology: a timer-based standard controller system (Tim); an add-on (1 setpoint) SMS system (AC1); and an ET-based system (ET), and watering frequency: weekly; twice per week; and daily (1, 2, and 7 days per week, respectively) plus at tenth plot with an on-demand (2 setpoint) SMS system (AC2). Four different methods: visual rating, canopy spectral reflectance, canopy turf temperature, and digital imagery were used to evaluate turf quality. Over a 3 year period, SMS treatments resulted in average water savings of 38% in AC1 treatments, and 22% in AC2 treatment compared to the timer-based treatments, whereas the ET treatments applied 13% more
water, on average, than the timer-based treatments. The weekly AC1 treatment applied the least amount of water (10mm/week), whereas the twice per week ET treatment applied the most water (25mm/week). The AC2 treatment and the ET-based treatments resulted in the best turf quality. Other treatments resulted in turf quality at or above the minimum acceptable level.

INTRODUCTION

Irrigation withdrawals account for 40 percent of total fresh water withdrawals in the United States (USGS, 2005). Thus, investing in technologies and water management strategies that reduce agricultural water is the best means for freeing water for other purposes (FAO, 2003). In the last three centuries, fresh water demand has increased more than 35 fold to meet agricultural, municipal and industrial needs (Kird and Kanber, 1999). Increasing fresh water demand has decreased the allocation of water for irrigation, especially for non-food crops (Hanks, 1983). Drought stress due to water rationing is the most important environmental factor limiting growth of these non-food commodities, especially ornamental plantings such as turfgrass (Beard, 1973). Thus, developing appropriate water management strategies for turfgrass should be accorded high priority (Githinji, 2007). In the last decade, developing strategies to maintain an acceptable turf quality with considerably less water use have been a primary goal of turfgrass researchers and managers (Ervin and Koski, 1998).

In North Carolina, turfgrass acreage encompasses an area equal to 44% of the total state’s harvested crop acreage (NCDA, 2001), larger than the combined acreage of corn, wheat, tobacco, and peanuts. Residential lawns account for 69% of the total
turfgrass acreage in the state and have increased in acreage by 21.4% between 1995 and 1999 to a total of 2,135,000 acres in 1999 (NCDA, 2001).

In North Carolina, a recent study of five communities within the Neuse River Basin showed that the percentage of homeowners that irrigate turf ranged from 54% in Kinston to 89% in New Bern (Osmond and Hardy, 2004). Applying routine amounts of water at regular intervals in humid regions such as North Carolina, where irrigation must be managed in conjunction with prevailing rainfall conditions will almost result in over-irrigation and the needless waste of water and energy (Evans et al., 1991). To achieve healthy and acceptable turf quality needed for residential, industrial and commercial purposes, applied water must match changing irrigation water demand as under-irrigation and over-irrigation can affect turfgrass quality negatively (Cardenas - Laiharcar et al., 2005). Using irrigation control technologies may lead to water conservation and acceptable turf quality.

**Water Conservation Strategies**

Several water management strategies have been suggested to optimize the water use in irrigation of turfgrasses, as reducing irrigation may enhance water use efficiency in turfgrass (DaCosta and Huang, 2005). Chalmers et al. (1981) mentioned that a slight water deficit could enhance the distribution of carbohydrate to the reproductive structures and also control excessive vegetative growth. Previous water management studies have aimed to achieve water conserving management practices such as; precision irrigation through which turfgrass is allowed to deplete soil water to the point of incipient water stress within its root zone before irrigation (Stewart et al., 2004), incorporating water-use
efficient turfgrasses into the landscape (Wade et al., 1992), using soil-water feedback in controlling irrigation (Grabow et al., 2004), and development of drought resistant and drought avoidance turfgrasses (Kenna and Horst, 1993). These water conservation strategies for turfgrass practice are becoming increasingly needed, both in arid or humid regions (Carrow, 1996).

**Irrigation Scheduling**

With a steady increase in the number of residential irrigation systems in North Carolina and recent droughts during 2007 and 2008, it is essential to use an efficient irrigation scheduling strategy to achieve both goals of conserving water and maintaining acceptable turf quality.

Irrigation scheduling aims to make the most efficient use of water and energy by applying the right amount of water to cropland at the right time (Evans et al., 1991). Proper irrigation scheduling also has environmental benefits such as minimizing the risks of salinization and nutrient leaching (Githinji, 2007). Effective irrigation scheduling requires consideration of several factors including soil-water holding capacity, root depth, effective rainfall, and weather conditions as water-use varies with soil moisture content and environmental factors including solar radiation, wind speed and temperature (Cary and Wright, 1971).

Irrigation scheduling strategies to optimize water use and maximize crop yield have been studied extensively. Irrigation should be applied when the metric potential is high enough that the soil can supply water fast enough to meet the crop-water need, hence avoiding drought stress that may affect yield and quality of the crop (Taylor,
1965). Using soil-water feedback systems to schedule irrigations have proven to reduce water consumption, as well maintain acceptable turf quality (Vasanth, 2008). Irrigation frequency may have major effects on yield and quality of the crop as well.

Less frequent irrigation has been recommended to improve deep rooting and subsequently drought avoidance (Youngner, 1985) and to foster better root development on both cool-season grass and warm-season grasses (Bennett and Doss, 1960; Doss et al., 1960). Turf quality, shoot density, root length and root length density can be improved by increasing the time interval between irrigation events (Jordan et al., 2003).

All irrigation scheduling methods consist of monitoring parameters that determine the need for irrigation (Githinji, 2007). The main purpose of these systems is to determine the irrigation amount and timing. “Time-based” irrigation controller technology is a system that uses irrigation controller clocks to control irrigation duration and frequency. Rainfall sensors have been used with a time-based irrigation schedules to enhance the efficiency of this scheduling method, and have shown to reduce in water usage by 45% compared to time-based irrigation systems without rainfall sensors (Cardenas - Laiharcar et al., 2005).

Several irrigation controller systems have been developed that can be categorized as those use feedback from a sensor monitoring the amount of moisture in the root zone, and those that use weather data to estimate the amount of water needed by the turf to irrigate. These controllers that use feedback technologies show promise for improved water management and they are known as smart irrigation technologies.
Smart Irrigation Technologies

Irrigation scheduling in these smart systems are mainly controlled by monitoring either soil-water content or atmospheric conditions used to estimate plant evapotranspiration (ET).

a. Soil-water based systems

These systems use sensors placed in the soil within the crop’s root zone, as feedback to control irrigation. Most of these systems prohibit irrigation when volumetric soil moisture is above a pre-determined level.

There are two main types of soil moisture based systems. The simplest types are “add-on” systems that are connected to a standard irrigation control clock. An adjustable setpoint level prevents irrigation when the soil-water content exceeds this level. This setpoint is usually set to 75% of the soil water content at field capacity (Grabow, 2008). A more complex type of soil-senor-based system is an “on-demand” system, in which two setpoints are used; one (the lower) to initiate irrigation and another (the higher) to terminate irrigation.

b. ET controller based systems

ET-controllers are irrigation controllers that use weather data to adjust watering amounts and times. A variety of input information is required by the controller, such as irrigation system performance specifications, site conditions, and type of turf or landscape for set-up. Weather data is used to calculate reference evapotranspiration \((ET_o)\), which used to estimate plant water requirements.
Several empirical equations have been proposed for estimating reference ET due to the complexity of directly measuring it. Some examples are the Blaney-Criddle equation, the Penman equation, and the Penman-Monteith equation (Allen et al., 1998). The Penman-Monteith equation is the most accurate equation to estimate the reference ET due to its inclusion of the climatic variables that affect crop evapotranspiration (Githinji, 2007).

The Penman-Monteith equation is:

$$ET_o = \frac{0.408 \Delta (R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)} \quad (3.1)$$

where,

$R_n =$ net radiation at the crop surface, MJ m$^{-2}$ d$^{-1}$

$G =$ soil heat flux, MJ m$^{-2}$ d$^{-1}$

$\gamma =$ the psychrometric constant, kPa °C$^{-1}$

$e_s =$ the saturation vapor pressure, kPa

$e_a =$ the actual vapor pressure, kPa

$u_2 =$ the mean daily wind speed at 2 m, m s$^{-1}$

$\Delta =$ the slope of the saturation vapor pressure curve, kPa °C$^{-1}$

$T =$ the average daily air temperature, °C

Crop evapotranspiration ($ET_c$) is the amount of water that plant should be received to meet its water use demands and is given by:

$$ET_c = ET_o \times K_c \quad (3.2)$$

where,
\[ ET_c = \text{crop ET, mm d}^{-1} \]

\[ ET_o = \text{reference evapotranspiration, mm d}^{-1} \]

\[ K_c = \text{the crop coefficient} \]

The crop coefficient, \( K_c \), depends upon plant type, the growth stage of plant, and climatic conditions (Allen et al., 1998) and has been suggested to be 0.8 for cool season grasses (Allen et al., 1998).

Two approaches are used to obtain the weather data needed for ET-controllers. One approach uses on-site weather collected from simple weather instruments. A variation of the approach uses long term water requirements, adjusted by on site temperature. The second approach uses data collected off site that is processed and sent via paging technologies to the controller at an hourly to daily frequency.

**Turf Quality**

In North Carolina, turf quality is a very important as more than 2.1 million acres of turfgrass add to the functional, recreational, and aesthetic value of the state (NCDA, 2001). There are several ways to evaluate turf quality including visual rating, canopy temperature, canopy spectral reflectance, and digital imagery analysis.

A visual rating system has been promoted by the National Turfgrass Evaluation Program. This scale ranges from 1 to 9; 1 means “poor quality” and 9 means “excellent quality”. A rating of 6 or above is considered to be acceptable quality (Morris, 2002). This scale is mainly function in turf quality, color, density, and uniformity (Horst et al., 1984).
Turfgrass canopy temperature is another tool to measure turf quality. Canopy temperature changes according to turf moisture stress; therefore, it may be a good measure of turf quality.

Spectral reflectance analysis is an alternative to visual ratings and is an unbiased method to assess turf quality. It is based on measuring reflected light from turfgrass in both red and near-infrared spectral bands (Trenholm et al., 1999; Keskin et al., 2003). Depending on these measurements, different reflectance and stress indices may be defined to determine the turf quality and distinguish between stressed and healthy grass.

Recently, Digital image Analysis (DIA) has become a common tool used in scientific studies and was effectively been used to measure turfgrass cover (Richard et al., 2001) and quantify turfgrass color (Karcher et al., 2003).

The main objectives of this research were to evaluate two types of smart irrigation technologies: ET and soil-moisture-based controller systems; and to compare water application and turf quality with a standard time-based controller. Another objective was to evaluate the effect of three different irrigation frequencies incorporated with these technologies.

MATERIALS AND METHODS

Site and Experimental Set-up

This study was conducted at the North Carolina State University Lake Wheeler Turf Field Laboratory (35° 44’ 28” N, 78° 40’ 50” W) in Raleigh, North Carolina. The soil at the research site is classified as a Cecil sandy loam (fine kaolinitic, thermic, Typic Kanhapludults).
A total of forty 4 m × 4 m plots were established to ‘Confederate’ tall fescue (*Festuca arundinacea* Schreb) using sod. The plots were organized into two terraces, both terraces having two replications containing ten plots each. Each plot presented a different irrigation treatment. Nine different irrigation treatments were created by combining three controller technologies including a standard timer-based controller, ET-based controller, and soil water sensor-based (“add-on” system), with three irrigation frequencies (once per week, twice per week, and daily) and the tenth treatment was an “on-demand” soil-water feedback system that uses two soil-water content setpoints to start and terminate irrigation allowed to water any day as required. Each irrigation treatment was replicated four times in a randomized complete block experimental design (Figure 3.1).

A soil water retention curve was developed for replications 1 and 2 (Figure 3.2) to help characterize the soil at the site. Soil cores from the site were analyzed for particle size distribution and fell into the clay category (USDA system). Van Genuchten’s equation was fit to soil core data to identify the θ - h relationship (Van Genuchten, 1980):

\[
\theta_h = \frac{\theta_{sat}}{[1 + \alpha h^n]^{(1-1/n)}}
\]

Where:

- \(\theta_h\) = volumetric water content at applied pressure head \(h\),
- \(\theta_{sat}\) = volumetric water content at saturation,
- \(h\) = applied pressure head, kPa
- \(\alpha\), \(n\) = curve fitting parameters.

Parameters from the curve fitting can be found in Figure 3.2.
The irrigation system (Figure 3.3) of the study area was supplied by water pumped from a nearby pond that serves other turf facilities at Lake Wheeler Turf Field Laboratory. A 50-mm class 200 PVC mainline was used to deliver the water to the terraces where it was filtered via a 60 mesh filter (Figure 3.4). A 50-mm ball valve located upstream of the water filter isolated the system during maintenance. Two 38-mm class 200 PVC sub-main lines served twenty plots on each terrace. Both sub-mains had a 38-mm pressure regulator to regulate the water pressure to about 210-kPa upstream of the solenoid valves serving each plot. Five water meters (AMCO Water Metering System Inc., Ocala, Fla.) were connected to each sub-main line in parallel. Each water meter logged irrigation amounts for four plots on a common manifold with separate solenoid valves. Each plot was equipped with four quarter circle pop-up spray head sprinklers (Toro 570 3.7-m series with 23º trajectory), with a discharge rate of 0.315 L s⁻¹ at 210-kPa. All four spray heads were connected to transitional poly pipes to a 25-mm PVC pipe served by a solenoid valve. This arrangement provided independent irrigation control of each plot. Details of turf cultural practices may be found in Vasanth (2008).

**Irrigation Controllers**

a. *Standard timer-based controller (Tim)*

Irrigation events in this system were set by using a Toro irrigation controller (Custom Command Series, Toro Inc., Riverside, Calif. - Figure 3.5). This system was programmed to apply the long-term gross irrigation requirement (GIR) at three irrigation frequencies (once per week, twice per week, and daily). Controller run times were adjusted monthly to reflect changes in GIR. A rain sensor (Irritrol Systems Inc.,
Riverside, Calif. - Figure 3.6) was attached to the timer-based controller to skip watering when rainfall event occurred.

b. **ET-based controller (ET)**

An Intellisense TIS-240 series (Toro, Inc., Riverside, Calif. - Figure 3.7) controller was used to control irrigation for the ET-based plots according to daily downloaded reference ET values and a soil-water budget maintained in the controller. Three irrigation programs were used to set the three irrigation frequencies.

c. **Soil moisture-based controller (“add-on” system, AC1)**

The Acclima Digital TDT RS-500 system (Acclima Inc., Meridian, Idaho) was used to evaluate a soil-water sensor-based “add-on” system. Soil-water feedback sensors were planted in the three plots in replication 2 to control irrigation. The other replications were “slaved” to the control replication. A user interface module for each irrigation frequency was connected to a standard irrigation controller (same make and model as the controller used for the standard timer-based treatment) that was programmed exactly as timer-based treatments. A separate program on one controller was used for each irrigation frequency.

d. **Soil moisture-based controller (“on-demand” system, AC2)**

An Acclima CS-3500 system (Acclima Inc., Meridian, Idaho) was used to control irrigation scheduling for evaluation of an “on-demand” system. A soil-water feedback sensor identical to that used in the “add-on” system was used in this system but the system was programmed for two threshold values; the lower one to initiate watering, and the upper one to terminate watering (Figure 3.8). Watering was allowed each day
between 12:30 a.m. and 1:30 a.m. but only occurred if the soil water level was below the lower setpoint. Irrigation cycle time and soak cycle time were both set at 10 minutes. The soak cycle was meant to prevent over-irrigation due to irrigation cycles occurring prior to the wetting front arriving at the sensor depth.

The experimental site was equipped with a data logger (Campbell Scientific Inc., Logan, Utah) (Figure 3.9). Wind speed was measured by an anemometer that was connected to the datalogger programmed to terminate irrigation if wind speed exceeded 4.5 m s\(^{-1}\) to ensure that water from one treatment did not drift to an adjacent treatment. A logging atmometer with a #30 canvas cover (ET gage Co., Loveland, Colo.) was used to simulate on-site reference ET (Figure 3.10). Weather data was collected by an automated weather station (Watchdog 700, Spectrum Technologies, Plainfield, Ill.) (Figure 3.11) located on the site to estimate reference ET by using the Penman-Monteith equation (see Equation 1.1). Solar radiation, air temperature, relative humidity, wind speed, wind direction and rainfall depth were recorded at 15 minute intervals. All irrigation controllers and the data logger were housed inside a shelter located between the two terraces. The weather station and the atmometer were located immediately adjacent to the shelter.

**Irrigation Scheduling**

Field capacity of the soil in the study area was determined prior to the start of the experiment. Figure 3.12 (Vasanth, 2008) shows volumetric soil water content at a depth of 13 cm measured by monitoring sensors located in the 10 plots of replication two over
a period of two days. All ten plots were saturated using a watering hose to determine field capacity. There was a rapid drainage of soil water due to gravitational forces followed by a noticeable decrease in drainage after about 24 hours. At this time, field capacity was assumed and the average soil-water content was about 32%.

The setpoint for the “add-on” controller was set at 24% volumetric soil water content (75% of field capacity). The setpoints for the “on-demand” watering system were 21% volumetric soil-water for the lower setpoint (initiate watering) and 30% volumetric soil-water content (94% of the field capacity to allow some soil storage for rainfall) for the upper setpoint (terminate watering). In this case the lower setpoint was set at an allowable depletion of 67% of plant available water.

Weekly irrigation treatments were scheduled on Tuesdays, and twice per week irrigations were scheduled for Mondays and Thursdays (Vasanth, 2008). Irrigation was applied between 12:00 am and 6:00 am to reduce evaporative losses and to reduce drift as wind speed is normally low during this period. The study periods were 31 May to 4 September 2007, 15 May to 4 September 2008, and 7 May to 11 August 2009.

Thirty years of weather and effective rainfall data were used to establish the net irrigation requirement (NIR), effective rainfall (ER), and the gross irrigation requirement (GIR) given in Table 3.1 (adapted from Vasanth, 2008, Table 2.1) for both “add-on” and standard timer-based watering systems.

Effective (ER) rainfall amount is the portion of total rainfall used by a crop, e.g., turfgrass and serves to reduce the irrigation requirement. ER can be determined empirically by using the equation given in SCS TR-21 (USDA, 1970) as shown below:
\[
ER = SF \times (0.70917 \times P_m^{0.82416} - 0.11556) \times 10^{0.02426 \, ET_c} \tag{3.4}
\]

where

ER = the effective rainfall, mm

SF = soil water storage factor,

\[P_m\] = precipitation, mm

\[ET_c\] = crop evapotranspiration, mm day\(^{-1}\)

The soil water storage factor was calculated from:

\[
SF = 0.531747 + 0.295164 \times D - 0.057697 \times D^2 + 0.003804 \times D^3 \tag{3.5}
\]

where D is usable soil water storage in the crop root zone which is a fraction of the available water holding capacity of the soil. D was assumed to be 0.66 of the AWHC within the root zone in this study (Vasanth, 2008).

The net irrigation requirement (NIR) was calculated by using the following equation:

\[
NIR = ET_c - ER \tag{3.6}
\]

The gross irrigation requirement (GIR) was calculated as follows:

\[
GIR = NIR / \text{(Irrigation system uniformity)} \tag{3.7}
\]

where irrigation system uniformity was taken to be DU\(_{\text{LH}}\) (Fangmeier et al., 2006), that was determined to be 80% through field auditing (Vasanth, 2008).

Gross irrigation requirements and sprinkler irrigation rates were used to calculate monthly runtime settings as shown in Table 3.2 (adapted from Vasanth, 2008, Table 2.2). Sprinkler filters were cleaned prior to the 2008 and 2009 study seasons and sprinkler irrigation rates were tested manually to ensure that they met proper runtimes and application rates were programmed in the controllers.
Data Collection

a. Water-use

Water use data were obtained from April 28 to September 8 of 2007, from April 26 to September 27 of 2008, and from May 2 to August 15 of 2009. Water application for each plot (including 10 minute, hourly, and daily data) were collected weekly with LoggerNet software (Campbell Scientific Inc., Logan, Utah). In addition, water meter readings for each manifold (serving 4 plots) were manually recorded each week to verify the automatically acquired data.

Weather data were downloaded each week from the automated weather station (Watchdog 700, Spectrum Technologies, Plainfield, Ill.) located on the site.

Soil moisture data were downloaded each week from the Acclima CS3500 controller (Acclima Inc., Meridian, Idaho). Soil moisture was sampled every 10 minutes, by the Acclima TDT monitoring sensors located in all plots in replication 2, and logged by the Acclima CS3500 controller.

b. Turf quality

Turfgrass quality was rated weekly during irrigation treatments for all plots by using four techniques: visual rating, canopy spectral analysis (using NDVI readings), canopy temperature, and digital imagery (using DGCI measurements). More details of turf quality monitoring may be found in Chapter 2.

Data Analysis

Mixed models as implemented in PROC MIXED of SAS Version 9.13 (SAS Institute, Cary, N.C., 2006) were used to analyze weekly water use and turf quality data.
The technology, frequency and their interaction were treated as fixed effects, and week, replication and the interaction term (week × technology × frequency) were treated as random effects. The least square means (lsmeans) procedure was used to identify differences in treatment means in water use and turf quality data. A repeated statement including the AR(1) option was used in the model for turfgrass quality data to model the residuals and thus make the statistical model free of correlated errors. Plot number was treated as the subject in the repeated statement.

RESULTS AND DISCUSSION

Water Application

Average weekly applied water, over all experimental years, were calculated for all irrigation treatments by using least square means (lsmeans) estimates and are given in Table 3.3. Figure 3.13 shows cumulative applied water (averaged of all replications) for all irrigation treatments during the experimental periods by all three study years. Cumulative applied water was not computed for any of the Acclima add-on (AC1) treatments in 2009 due to damage of the user interface module from lightning storms that resulted in some periods without irrigation control. Water use for weeks in which these units were non-functional were treated as missing data. Average weekly water applied over the 3 year period was significantly ($P<0.0001$) affected by technology and the interaction between technology and frequency; however, the effect of irrigation frequency was not significant ($P=0.1182$).
a. **Comparison among technologies:**

When averaged across frequencies, the Acclima add-on system (AC1) applied the least amount of water followed by the water on-demand system (AC2) and the timer-based system (13 mm, 16 mm, and 20 mm per week, respectively). The ET system applied the most irrigation water (23 mm per week). On average, both soil moisture systems (AC1 and AC2) applied less water than the timer-based and ET systems (Table 3.3, Comparison B). Over the entire 3-yr period, the AC1 system applied 38% less water when compared to the timer-based system followed by the AC2 system with 22% water savings ($P<0.001$), while the ET system applied 13% more water, on average, than the timer-based system ($P=0.0041$). On average, more water was applied in 2007 than the other experimental years (Table 3.13 and Figure 3.13). This probably was due to the drought conditions that increased turf irrigation requirements.

Standard time-based systems applied nearly same average weekly water depth in all years of the experimental period. The timer-based systems applied 21 mm, 20 mm, and 20 mm per week for 2007, 2008, and 2009 respectively. This was probably due to their fixed watering schedule that was set to apply the same amount of water for each irrigation frequency for a given month instead of using weather data or a soil-water budget to schedule watering.

b. **Comparison among frequencies:**

Table 3.3 (Comparison A) shows that the Acclima on-demand system (AC2) applied less water ($P < 0.001$) when compared with the other irrigation frequencies in 2008 while there were no statistically significant differences between the AC2 system
and the other irrigation frequencies in 2009. Over all years the AC2 treatment applied statistically significant less water compared to daily and twice per week irrigation treatments across all other technologies. The AC2 treatment applied less water than weekly irrigation treatments across all other technologies (16 mm vs. 18 mm per week, respectively) however the difference was not significant (P=0.164).

c. Comparison among different technologies and frequencies:

Table 3.3 (comparison C) shows that over the entire 3-yr period, the weekly add-on (AC1-1) treatment applied the least amount of water (10 mm per week) followed by the twice per week add-on (AC1-2), the daily add-on (AC1-7), and AC2 treatments (14 mm, 14 mm, and 16 mm per week, respectively). The ET systems, at twice per week and daily frequencies (ET-2, and ET-7, respectively), applied the most amount of water (25 mm and 24 mm per week, respectively).

Turf Quality

Visual Rating

a. Comparison among technologies:

Table 3.4 shows statistical comparisons (at $\alpha =0.05$) between treatments for average weekly visual turf quality ratings in 2008, 2009, and over both years. The AC2 treatment and the ET treatments, across all frequencies, had higher turf quality indices (7.1 and 6.9, respectively) than the timer-based treatments (6.7) while the AC1 treatments had the lowest turf quality index of 6.5 across all years (Comparison B), yet the AC1 treatment average index was above the minimum acceptable turf quality rating of 6.0. Figures 3.14 and 3.15 show the turf quality measurements (average of replications) on a
weekly basis for all technologies in 2008 and 2009, respectively. The water on-demand treatment had the highest turf quality, for most weeks in both years. In 2009, the average turf quality of the add-on treatments dropped suddenly (indicated by bold line in figure 3.15) starting from week 7 of study period (18 June) till it reached the lowest value of 5.5 (less than the minimum acceptable turf quality) during the 9th week (2 July). AC1 treatments were compromised by failure of the RS500 units due to electrical storms in 2009. On June 9th, a severe lightning storm disabled the AC2 and AC1-7 RS500 units and also the Toro Custom command controller they were attached to disabling the AC1 treatment. The controller was replaced on June 11th, and the AC1-1 treatment was placed back in operation. The AC1-7 treatment was back in operation June 23, while the AC1-2 treatment was not functional until July 8th. From June 27th to July 8th, the AC1-2 treatment was wired to bypass the damaged RS500 module to allow scheduled irrigations, effectively putting the system into sensor bypass mode. A second lightning storm on August 3rd damaged the AC1-7 RS500 unit and sensor, and blew the Toro Custom Command fuse thus disabling the AC1 and AC2 treatments. The fuse was replaced on August 7th (last week of data collection season) and the AC1 and AC2 treatments placed back into operation. On August 10, the AC1-7 treatment was wired to bypass the RS500 system and allow irrigation to preserve the turf.

b. Comparison among frequencies:

The water on-demand system (AC2) resulted in significantly higher turf quality compared to the once per week, twice per week, and daily treatments; however no
significant differences in turf quality between these three frequencies were detected when averaged across the different technologies (Comparison A, Table 3.4).

c. **Comparison among different technologies and frequencies:**

The AC2 treatment had the highest turf quality index (7.3) followed by ET-7, daily Tim (Tim-7), and AC1-1 (7.1, each) while the lowest turf quality index was found on AC1-7 plots (5.8, less than the minimum acceptable turf quality) in 2009 (Comparison C, Table 3.4). When combined over both years, the overall trend was an increase in turf quality with an increase in irrigation frequency for the ET treatments (6.8, 7, and 7.1, respectively) and the timer-based treatments (6.5, 6.7, and 7, respectively) while the quality declined with increasing irrigation frequency for AC1 treatments (6.9, 6.7, and 6, respectively) (Table 3.4).

Average visual rating turf qualities of (6.2 and 6.3 in 2008), and (6.3 and 6.1 in 2009) were reported for plots in replications 1 and 3, respectively; which were significantly lower than replications 2 and 4 averages (7.0 and 7.3 in 2008) and (7.4 and 7.6 in 2009), respectively. This is probably due to substantial soil cuts that occurred during construction and leveling of the two terraces that may have affected infiltration rate and water holding capacity (Vasanth, 2008).

**Spectral Reflectance Index (NDVI)**

a. **Comparison among technologies:**

Table 3.5 shows average weekly NDVI for 2008 and 2009 and the combined years. The average NDVI was highest for the AC2 treatment compared to the other technologies averaged across frequencies in 2008 and 2009 (Comparison B). Figures 3.16
and 3.17 show the NDVI measurements (average of replications) on a weekly basis for all technologies in 2008 and 2009, respectively.

b. \textit{Comparison among frequencies:}

The AC2 system resulted in a higher index ($p = 0.031$) compared to the average of weekly, twice per week, and daily treatments averaged across the different technologies (Comparison A, Table 3.5).

c. \textit{Comparison among different technologies and frequencies:}

The averages of NDVI turf quality were not significantly different between technologies and frequencies except for the AC1-7 treatment that had the lowest turf quality index when combined over both years (Comparison C, Table 3.5).

\textbf{Digital Imagery Index (DGCI)}

a. \textit{Comparison among technologies:}

Table 3.6 shows average weekly DGCI for 2008, 2009, and over both years. Findings were similar to the NDVI results. The AC2 system resulted in a significant higher index compared to the other technologies in 2008, 2009, and when combined over both years (comparison B). Figures 3.18 and 3.19 show the DGCI measurements (average of replications) on a weekly basis for all technologies in 2008 and 2009, respectively.

b. \textit{Comparison among frequencies:}

The average DGCI was highest for the AC2 system compared to the weekly, twice per week, and daily treatments; however no significant differences in turf quality
between these three frequencies were detected when averaged across the different technologies in all years (Comparison A, Table 3.6).

c. *Comparison among different technologies and frequencies:*

Combined over both years, the AC2 treatment had the best DGCI index (0.414) followed by AC1-1, AC1-2, and ET-7 (0.411, 0.401, and 0.400, respectively) while the AC1-7 treatment had the lowest index compared to the other treatments (Comparison C, Table 3.6).

**Canopy-air temperature differential (ΔT)**

a. *Comparison among technologies:*

Table 3.7 shows average weekly ΔT (°C) for 2008 and 2009 and pooled over both years. There was no difference in ΔT among the water on-demand system, the timer-based system, and the ET system when data were pooled across years. The add-on system plots had the highest ΔT among technologies (Comparison B) when pooled across frequencies. Figures 3.20 and 3.21 show the ΔT (°C) measurements (average of replications) on a weekly basis for all technologies in 2008 and 2009, respectively.

b. *Comparison among frequencies:*

There was no difference in ΔT among any of frequencies when averaged across technologies for all years (Comparison A, Table 3.7).

c. *Comparison among different technologies and frequencies:*

The AC1-7 treatment had the highest ΔT in all years while the ET-7 treatments had the lowest ΔT among treatments (Comparison C, Table 3.7).
SUMMARY AND CONCLUSIONS

The AC1 treatments (one setpoint) applied the least average weekly amount of water. A general trend of increasing applied water with increasing irrigation frequency was noticed for AC1 treatments in 2007 and 2008; however, in 2009, the AC1-7 treatment applied less water than the AC1-2 treatment. On average, the AC1-1 treatment applied the least amount of water and resulted in turf quality that was at or above the minimum acceptable limit. The most effective irrigation schedule was achieved by using the AC2 system (two setpoint) as it resulted in substantial water savings while maintaining good turf quality.

On average, soil-water feedback systems, either using one or two setpoints (AC1 and AC2 system, respectively), applied less water than either the timer-based or the ET treatments. Over all years, the AC1 treatments resulted in average water savings of 38% compared to the timer-based system, while the AC2 treatment applied 22% less average water than the timer-based system. Both soil-water feedback treatments resulted in average acceptable VR turf quality over the monitoring periods, with the exception of the AC1-7 treatment that resulted in VR turf quality at or below the minimum acceptable level (in 2008 and 2009, respectively).

Although the AC2 treatment resulted in average water savings of 22 and 31% (compared to the timer-based and the ET systems, respectively) over all years, it had the best turf quality compared to the other technology treatments. This is probably due to the settings that keep the soil-water content above the wilting point (avoiding drought stress
that leads to a decline in turf quality) and at or below field capacity (avoiding unneeded applied water).

The ET treatments resulted in good turf quality but applied 13% more water, on average, than the timer-based system. This probably was due to its overestimation of reference ET that is used to schedule watering for this system.

The average weekly applied water amounts for the timer-based system were nearly the same (21, 20, and 20 mm per week in 2007, 2008, and 2009, respectively) as its treatments were scheduled to apply the same amount of water at the same time intervals instead of using real-time weather data or soil-water status to schedule watering.

All three frequencies (once per week, twice per week, and daily) tested in this study were not significantly different in terms of turf quality. However, these different water frequencies applied significantly more water and resulted in lower turf quality when compared to the AC2 treatment.

Turf quality as measured using either NDVI or DGCI resulted in nearly the same findings. This is probably due to the strong correlation between both measurements (see Chapter 2).
REFERENCES


Table 3.1 Monthly long-term reference ET (ET$_o$), turf ET (ET$_c$), precipitation, effective precipitation (ER), net irrigation requirement (NIR) and gross irrigation requirement (GIR) (adapted from Vasanth, 2008, Table 2.1).

<table>
<thead>
<tr>
<th>Month</th>
<th>ET$_o$</th>
<th>ET$_c$</th>
<th>Precipitation</th>
<th>ER</th>
<th>NIR</th>
<th>GIR</th>
</tr>
</thead>
<tbody>
<tr>
<td>April</td>
<td>150.0</td>
<td>120.0</td>
<td>65.8</td>
<td>39.5</td>
<td>80.5</td>
<td>100.6</td>
</tr>
<tr>
<td>May</td>
<td>176.4</td>
<td>141.1</td>
<td>99.6</td>
<td>59.0</td>
<td>82.1</td>
<td>102.6</td>
</tr>
<tr>
<td>June</td>
<td>169.5</td>
<td>135.6</td>
<td>93.5</td>
<td>52.7</td>
<td>82.9</td>
<td>103.6</td>
</tr>
<tr>
<td>July</td>
<td>188.8</td>
<td>151.0</td>
<td>101.8</td>
<td>62.4</td>
<td>88.6</td>
<td>110.7</td>
</tr>
<tr>
<td>August</td>
<td>174.5</td>
<td>139.6</td>
<td>102.1</td>
<td>60.0</td>
<td>79.6</td>
<td>99.6</td>
</tr>
<tr>
<td>September</td>
<td>140.7</td>
<td>112.6</td>
<td>81.0</td>
<td>44.3</td>
<td>68.3</td>
<td>85.3</td>
</tr>
</tbody>
</table>

Table 3.2 Gross irrigation depth (mm) and runtime settings (minutes) for the Acclima add-on and time-based irrigation systems (adapted from Vasanth, 2008, Table 2.2).

<table>
<thead>
<tr>
<th>Frq/Technology</th>
<th>Gross Irrigation Depth(mm)</th>
<th>Runtimes (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>April</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Once per week</td>
<td>25.15</td>
<td>17 – 3x</td>
</tr>
<tr>
<td>Twice per week</td>
<td>12.7</td>
<td>13 – 2x</td>
</tr>
<tr>
<td>Daily</td>
<td>3.56</td>
<td>7 – 1x</td>
</tr>
<tr>
<td><strong>May</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Once per week</td>
<td>25.65</td>
<td>18 – 3x</td>
</tr>
<tr>
<td>Twice per week</td>
<td>12.7</td>
<td>13 – 2x</td>
</tr>
<tr>
<td>Daily</td>
<td>3.56</td>
<td>7 – 1x</td>
</tr>
<tr>
<td><strong>June</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Once per week</td>
<td>25.91</td>
<td>17 – 3x</td>
</tr>
<tr>
<td>Twice per week</td>
<td>12.95</td>
<td>13 – 2x</td>
</tr>
<tr>
<td>Daily</td>
<td>3.81</td>
<td>8 – 1x</td>
</tr>
<tr>
<td><strong>July</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Once per week</td>
<td>27.69</td>
<td>19 – 3x</td>
</tr>
<tr>
<td>Twice per week</td>
<td>13.97</td>
<td>14 – 2x</td>
</tr>
<tr>
<td>Daily</td>
<td>4.06</td>
<td>8 – 1x</td>
</tr>
<tr>
<td><strong>August</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Once per week</td>
<td>24.89</td>
<td>17 – 3x</td>
</tr>
<tr>
<td>Twice per week</td>
<td>12.45</td>
<td>13 – 2x</td>
</tr>
<tr>
<td>Daily</td>
<td>3.56</td>
<td>7 – 1x</td>
</tr>
<tr>
<td><strong>September</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Once per week</td>
<td>21.34</td>
<td>15 – 3x</td>
</tr>
<tr>
<td>Twice per week</td>
<td>10.67</td>
<td>11 – 2x</td>
</tr>
<tr>
<td>Daily</td>
<td>3.05</td>
<td>6 – 1x</td>
</tr>
</tbody>
</table>

1x = one cycle, 2x = two cycles, 3x = three cycles
Table 3.3 Average weekly applied water (mm) and statistical comparison between technologies and frequencies at \( \alpha = 0.05 \).

<table>
<thead>
<tr>
<th>Treatment</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>All years (2007 - 2009)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Comparisons(^a)</td>
<td>Comparisons</td>
<td>Comparisons</td>
<td>Comparisons</td>
</tr>
<tr>
<td></td>
<td>lsmeans</td>
<td>A ( \neq ) B ( \neq ) C</td>
<td>lsmeans</td>
<td>A ( \neq ) B ( \neq ) C</td>
</tr>
<tr>
<td>AC 2(^c)</td>
<td>22.4</td>
<td>a ( \neq ) b ( \neq ) b</td>
<td>10.3</td>
<td>c ( \neq ) b ( \neq ) e</td>
</tr>
<tr>
<td>AC1-1</td>
<td>10.5</td>
<td>e ( \neq )</td>
<td>10.1</td>
<td>e ( \neq )</td>
</tr>
<tr>
<td>AC1-2</td>
<td>16.3</td>
<td>d ( \neq )</td>
<td>10.5</td>
<td>e ( \neq )</td>
</tr>
<tr>
<td>AC1-7</td>
<td>17.6</td>
<td>cd ( \neq )</td>
<td>12.6</td>
<td>de ( \neq )</td>
</tr>
<tr>
<td>Average AC1(^d)</td>
<td>14.8</td>
<td>c ( \neq )</td>
<td>11.1</td>
<td>b ( \neq )</td>
</tr>
<tr>
<td>ET-1</td>
<td>20.5</td>
<td>bcd ( \neq )</td>
<td>21.6</td>
<td>ab ( \neq )</td>
</tr>
<tr>
<td>ET-2</td>
<td>31.2</td>
<td>a ( \neq )</td>
<td>21.5</td>
<td>ab ( \neq )</td>
</tr>
<tr>
<td>ET-7</td>
<td>32.1</td>
<td>a ( \neq )</td>
<td>20.0</td>
<td>bc ( \neq )</td>
</tr>
<tr>
<td>Average ET(^e)</td>
<td>27.9</td>
<td>a ( \neq )</td>
<td>21.0</td>
<td>a ( \neq )</td>
</tr>
<tr>
<td>Tim-1</td>
<td>21.6</td>
<td>bcd ( \neq )</td>
<td>25.1</td>
<td>a ( \neq )</td>
</tr>
<tr>
<td>Tim-2</td>
<td>22.5</td>
<td>b ( \neq )</td>
<td>16.5</td>
<td>cd ( \neq )</td>
</tr>
<tr>
<td>Tim-7</td>
<td>19.8</td>
<td>bcd ( \neq )</td>
<td>17.7</td>
<td>bc ( \neq )</td>
</tr>
<tr>
<td>Average Tim(^f)</td>
<td>21.3</td>
<td>b ( \neq )</td>
<td>19.8</td>
<td>a ( \neq )</td>
</tr>
</tbody>
</table>

**Average of frequency across treatments**

| Weekly             | 17.5     | b \( \neq \)        | 18.9     | a \( \neq \)        | 15.8     | NS \( \neq \)        | 17.6     | bc \( \neq \)        |
| Twice per week     | 23.3     | a \( \neq \)        | 16.2     | b \( \neq \)        | 19.8     | NS \( \neq \)        | 19.4     | a \( \neq \)        |
| Daily              | 23.2     | a \( \neq \)        | 16.8     | ab \( \neq \)       | 15.5     | NS \( \neq \)       | 18.7     | ab \( \neq \)       |

\(^a\) A = Comparison among frequencies across technologies, B= Comparison among technologies across frequencies, C= comparison among different technologies and frequencies.

\(^b\) NS = no statistical difference between any effect (column) at \( \alpha = 0.05 \).

\(^c\) Acclima CS3500 (on-demand sensor controller).

\(^d\) Acclima RS500 (add-on sensor controller).

\(^e\) Toro TIS-240 Intellisense controller.

\(^f\) Standard timer based controller.
Table 3.4 Average weekly VR\textsuperscript{a} and statistical comparison between technologies and frequencies at $\alpha = 0.05$.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>2008 Ismeans</th>
<th>Comparisons\textsuperscript{b}</th>
<th>2009 Ismeans</th>
<th>Comparisons</th>
<th>Both years (2008/2009) Ismeans</th>
<th>Comparisons</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>AC 2\textsuperscript{c}</td>
<td>6.96</td>
<td>a</td>
<td>a</td>
<td>ab</td>
<td>7.29</td>
<td>a</td>
</tr>
<tr>
<td>AC1-1</td>
<td>6.60</td>
<td>c</td>
<td></td>
<td></td>
<td>7.07</td>
<td>a</td>
</tr>
<tr>
<td>AC1-2</td>
<td>6.42</td>
<td>de</td>
<td></td>
<td></td>
<td>6.93</td>
<td>bc</td>
</tr>
<tr>
<td>AC1-7</td>
<td>6.25</td>
<td>e</td>
<td></td>
<td></td>
<td>5.82</td>
<td>e</td>
</tr>
<tr>
<td>Average AC1\textsuperscript{d}</td>
<td>6.42</td>
<td>c</td>
<td></td>
<td></td>
<td>6.61</td>
<td>d</td>
</tr>
<tr>
<td>ET-1</td>
<td>6.71</td>
<td>bc</td>
<td></td>
<td></td>
<td>6.80</td>
<td>c</td>
</tr>
<tr>
<td>ET-2</td>
<td>7.02</td>
<td>a</td>
<td></td>
<td></td>
<td>6.95</td>
<td>bc</td>
</tr>
<tr>
<td>ET-7</td>
<td>7.15</td>
<td>a</td>
<td></td>
<td></td>
<td>7.09</td>
<td>ab</td>
</tr>
<tr>
<td>Average ET\textsuperscript{e}</td>
<td>6.96</td>
<td>a</td>
<td></td>
<td></td>
<td>6.95</td>
<td>b</td>
</tr>
<tr>
<td>Tim-1</td>
<td>6.46</td>
<td>cde</td>
<td></td>
<td></td>
<td>6.55</td>
<td>d</td>
</tr>
<tr>
<td>Tim-2</td>
<td>6.56</td>
<td>cd</td>
<td></td>
<td></td>
<td>6.77</td>
<td>cd</td>
</tr>
<tr>
<td>Tim-7</td>
<td>6.94</td>
<td>ab</td>
<td></td>
<td></td>
<td>7.09</td>
<td>ab</td>
</tr>
<tr>
<td>Average Tim\textsuperscript{f}</td>
<td>6.65</td>
<td>b</td>
<td></td>
<td></td>
<td>6.80</td>
<td>c</td>
</tr>
<tr>
<td><strong>Average of frequency across treatments</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekly</td>
<td>6.59</td>
<td>c</td>
<td></td>
<td></td>
<td>6.81</td>
<td>b</td>
</tr>
<tr>
<td>Twice per week</td>
<td>6.67</td>
<td>bc</td>
<td></td>
<td></td>
<td>6.88</td>
<td>b</td>
</tr>
<tr>
<td>Daily</td>
<td>6.78</td>
<td>ab</td>
<td></td>
<td></td>
<td>6.67</td>
<td>c</td>
</tr>
</tbody>
</table>

\textsuperscript{a} VR = Visual turf quality ratings on a scale of 1 to 9

\textsuperscript{b} A = Comparison among frequencies across technologies, B= Comparison among technologies across frequencies, C= comparison among different technologies and frequencies.

\textsuperscript{c} Acclima CS3500 (on-demand sensor controller).

\textsuperscript{d} Acclima RS500 (add-on sensor controller).

\textsuperscript{e} Toro TIS-240 Intellisense controller.

\textsuperscript{f} Standard timer based controller.
Table 3.5 Average weekly NDVI\(^a\) and statistical comparison between technologies and frequencies at \(\alpha = 0.05\).

<table>
<thead>
<tr>
<th>Treatment</th>
<th>2008 Ismeans (\bar{\text{X}})</th>
<th>2009 Ismeans (\bar{\text{X}})</th>
<th>Both years (2008/2009) Ismeans (\bar{\text{X}})</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>AC 2(^c)</td>
<td>0.722</td>
<td>a</td>
<td>a</td>
</tr>
<tr>
<td>AC1-1</td>
<td>0.708</td>
<td>cd</td>
<td></td>
</tr>
<tr>
<td>AC1-2</td>
<td>0.701</td>
<td>de</td>
<td></td>
</tr>
<tr>
<td>AC1-7</td>
<td>0.680</td>
<td>f</td>
<td></td>
</tr>
<tr>
<td>Average AC1(^d)</td>
<td>0.696</td>
<td>d</td>
<td></td>
</tr>
<tr>
<td>ET-1</td>
<td>0.708</td>
<td>bc</td>
<td></td>
</tr>
<tr>
<td>ET-2</td>
<td>0.715</td>
<td>b</td>
<td></td>
</tr>
<tr>
<td>ET-7</td>
<td>0.714</td>
<td>bc</td>
<td></td>
</tr>
<tr>
<td>Average ET(^e)</td>
<td>0.712</td>
<td>b</td>
<td></td>
</tr>
<tr>
<td>Tim-1</td>
<td>0.700</td>
<td>e</td>
<td></td>
</tr>
<tr>
<td>Tim-2</td>
<td>0.707</td>
<td>cd</td>
<td></td>
</tr>
<tr>
<td>Tim-7</td>
<td>0.711</td>
<td>c</td>
<td></td>
</tr>
<tr>
<td>Average Tim(^f)</td>
<td>0.706</td>
<td>c</td>
<td></td>
</tr>
</tbody>
</table>

Average of frequency across treatments

<table>
<thead>
<tr>
<th>Frequency</th>
<th>2008 Ismeans (\bar{\text{X}})</th>
<th>2009 Ismeans (\bar{\text{X}})</th>
<th>Both years (2008/2009) Ismeans (\bar{\text{X}})</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>Weekly</td>
<td>0.705</td>
<td>b</td>
<td></td>
</tr>
<tr>
<td>Twice per week</td>
<td>0.708</td>
<td>b</td>
<td></td>
</tr>
<tr>
<td>Daily</td>
<td>0.701</td>
<td>c</td>
<td></td>
</tr>
</tbody>
</table>

\(\text{NDVI} = \) Normalized difference vegetative index

\(^a\) A = Comparison among frequencies across technologies, B = Comparison among technologies across frequencies, C = comparison among different technologies and frequencies.

Acclima CS3500 (on-demand sensor controller).

Acclima RS500 (add-on sensor controller).

Toro TIS-240 Intellisense controller.

Standard timer based controller.
Table 3.6 Average weekly DGCI\textsuperscript{a} and statistical comparison between technologies and frequencies at $\alpha = 0.05$.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>2008 Ismeans</th>
<th>Comparisons</th>
<th>2009 Ismeans</th>
<th>Comparisons</th>
<th>Both years (2008/2009) Ismeans</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>AC 2\textsuperscript{c}</td>
<td>0.415</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>0.413</td>
</tr>
<tr>
<td>AC1-1</td>
<td>0.408</td>
<td>ab</td>
<td></td>
<td>0.411</td>
<td>b</td>
</tr>
<tr>
<td>AC1-2</td>
<td>0.397</td>
<td>bc</td>
<td></td>
<td>0.403</td>
<td>c</td>
</tr>
<tr>
<td>AC1-7</td>
<td>0.379</td>
<td>d</td>
<td></td>
<td>0.366</td>
<td>g</td>
</tr>
<tr>
<td>Average AC1\textsuperscript{d}</td>
<td>0.395</td>
<td>b</td>
<td></td>
<td>0.393</td>
<td>c</td>
</tr>
<tr>
<td>ET-1</td>
<td>0.398</td>
<td>bc</td>
<td></td>
<td>0.394</td>
<td>ef</td>
</tr>
<tr>
<td>ET-2</td>
<td>0.398</td>
<td>bc</td>
<td></td>
<td>0.394</td>
<td>ef</td>
</tr>
<tr>
<td>ET-7</td>
<td>0.390</td>
<td>c</td>
<td></td>
<td>0.401</td>
<td>cd</td>
</tr>
<tr>
<td>Average ET\textsuperscript{e}</td>
<td>0.395</td>
<td>b</td>
<td></td>
<td>0.396</td>
<td>b</td>
</tr>
<tr>
<td>Tim-1</td>
<td>0.393</td>
<td>c</td>
<td></td>
<td>0.390</td>
<td>ef</td>
</tr>
<tr>
<td>Tim-2</td>
<td>0.403</td>
<td>bc</td>
<td></td>
<td>0.391</td>
<td>f</td>
</tr>
<tr>
<td>Tim-7</td>
<td>0.394</td>
<td>c</td>
<td></td>
<td>0.398</td>
<td>de</td>
</tr>
<tr>
<td>Average Tim\textsuperscript{f}</td>
<td>0.396</td>
<td>b</td>
<td></td>
<td>0.393</td>
<td>c</td>
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<td><strong>Average of frequency across treatments</strong></td>
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<td></td>
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<tr>
<td>Weekly</td>
<td>0.400</td>
<td>b</td>
<td></td>
<td>0.398</td>
<td>b</td>
</tr>
<tr>
<td>Twice per week</td>
<td>0.399</td>
<td>b</td>
<td></td>
<td>0.396</td>
<td>b</td>
</tr>
<tr>
<td>Daily</td>
<td>0.389</td>
<td>c</td>
<td></td>
<td>0.388</td>
<td>c</td>
</tr>
</tbody>
</table>

\textsuperscript{a}DGCI = Dark green color index

\textsuperscript{b}A = Comparison among frequencies across technologies, B= Comparison among technologies across frequencies, C= comparison among different technologies and frequencies.

\textsuperscript{c}Acclima CS3500 (on-demand sensor controller).

\textsuperscript{d}Acclima RS500 (add-on sensor controller).

\textsuperscript{e}Toro TIS-240 Intellisense controller.

\textsuperscript{f}Standard timer based controller.
Table 3.7 Average weekly ΔT\(^a\) (°C) and statistical comparison between technologies and frequencies at \(\alpha = 0.05\).

<table>
<thead>
<tr>
<th>Treatment</th>
<th>2008 Ismeans</th>
<th>Comparisons</th>
<th>2009 Ismeans</th>
<th>Comparisons</th>
<th>Both years (2008/2009) Ismeans</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>AC 2(^c)</td>
<td>9.50</td>
<td>b</td>
<td>b</td>
<td>cd</td>
<td>11.94</td>
</tr>
<tr>
<td>AC1-1</td>
<td>10.11</td>
<td>b</td>
<td></td>
<td></td>
<td>12.00</td>
</tr>
<tr>
<td>AC1-2</td>
<td>10.10</td>
<td>b</td>
<td></td>
<td></td>
<td>12.20</td>
</tr>
<tr>
<td>AC1-7</td>
<td>10.97</td>
<td>a</td>
<td></td>
<td></td>
<td>13.65</td>
</tr>
<tr>
<td>Average AC1(^d)</td>
<td>10.39</td>
<td>a</td>
<td></td>
<td></td>
<td>12.61</td>
</tr>
<tr>
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<td>bcd</td>
<td></td>
<td></td>
<td>12.45</td>
</tr>
<tr>
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<td>9.67</td>
<td>bcd</td>
<td></td>
<td></td>
<td>12.11</td>
</tr>
<tr>
<td>ET-7</td>
<td>9.34</td>
<td>d</td>
<td></td>
<td></td>
<td>11.46</td>
</tr>
<tr>
<td>Average ET(^e)</td>
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<td>b</td>
<td></td>
<td></td>
<td>12.00</td>
</tr>
<tr>
<td>Tim-1</td>
<td>9.93</td>
<td>bcd</td>
<td></td>
<td></td>
<td>12.64</td>
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<td>9.37</td>
<td>d</td>
<td></td>
<td></td>
<td>12.03</td>
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<td>9.36</td>
<td>d</td>
<td></td>
<td></td>
<td>11.90</td>
</tr>
<tr>
<td>Average Tim(^f)</td>
<td>9.55</td>
<td>b</td>
<td></td>
<td></td>
<td>12.19</td>
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</table>

**Average of frequency across treatments**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>Weekly</td>
<td>9.92</td>
<td>a</td>
<td></td>
</tr>
<tr>
<td>Twice per week</td>
<td>9.71</td>
<td>ab</td>
<td></td>
</tr>
<tr>
<td>Daily</td>
<td>9.89</td>
<td>a</td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) ΔT = Canopy-air temperature differential

\(^b\) A = Comparison among frequencies across technologies, B = Comparison among technologies across frequencies, C = comparison among different technologies and frequencies.

\(^c\) Acclima CS3500 (on-demand sensor controller).

\(^d\) Acclima RS500 (add-on sensor controller).

\(^e\) Toro TIS-240 Intellisense controller.

\(^f\) Standard timer based controller.
Figure 3.1 Site schematic showing plot layout and irrigation treatments.
Figure 3.2 Soil-water retention curve for soil in replication 1 (a.) and 2 (b.). Van Genuchten equation (van Genuchten, 1980) used to fit the model to the given data.
Figure 3.3 Site schematic showing irrigation system layout.
Figure 3.4 Mainline 60 mesh filter at the site.

Figure 3.5 Toro irrigation controller used for standard timer-based (Tim) and “add-on” (AC1) soil moisture sensor systems.
Figure 3.6 Rain sensors.

Figure 3.7 Intellisense TIS240 ET-based controller.
Figure 3.8 On-demand irrigation schedule process.
Figure 3.9 Campbell Scientific datalogger.

Figure 3.10 ET Atmometer with #30 Canvas Cover.
Figure 3.11 Watchdog 700 Weather Station.

Figure 3.12 Soil-water content of ten plots in replication 2 after saturating (adapted from Vasanth, 2008, Figure 2.1).
Figure 3.13 Cumulative applied water for various irrigation treatments in 2007, 2008, and 2009, average of replications.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC 2</td>
<td>4</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>AC1-1</td>
<td>4</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>AC1-2</td>
<td>4</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>AC1-7</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>ET-1</td>
<td>4</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>ET-2</td>
<td>4</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>ET-7</td>
<td>4</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Tim-1</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Tim-2</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Tim-7</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

- **20 weeks of data in 2007** Total rain = 290.3 mm
- **23 weeks of data in 2008** Total rain = 630.4 mm
- **13 weeks of data in 2009** Total rain = 250.7 mm

2 Average of two replications  
3 Average of three replications  
4 Average of four replications
Figure 3.14 Visual rating for irrigation technologies across frequencies in 2008.

Figure 3.15 Visual rating for irrigation technologies across frequencies in 2009.
Figure 3.16 NDVI for irrigation technologies across frequencies in 2008.

Figure 3.17 NDVI for irrigation technologies across frequencies in 2009.
Figure 3.18 DGCI for irrigation technologies across frequencies in 2008.

Figure 3.19 DGCI for irrigation technologies across frequencies in 2009.
Figure 3.20 $\Delta T$ (°C) for irrigation technologies across frequencies in 2008.

Figure 3.21 $\Delta T$ (°C) for irrigation technologies across frequencies in 2009.