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Effects of Wi-Fi-Enabled Smart Irrigation Controllers on Water Use and Plant Health of Residential Landscapes in the Intermountain West

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EFFECTS OF WI-FI-ENABLED SMART IRRIGATION CONTROLLERS ON WATER USE AND PLANT HEALTH OF RESIDENTIAL LANDSCAPES IN THE INTERMOUNTAIN WEST

by

Shane R. Evans

A thesis submitted in partial fulfillment
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ABSTRACT

Effects of Wi-Fi-Enabled Smart Irrigation Controllers

on Water Use and Plant Health of Residential

Landscapes in the Intermountain West

by

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Utah State University, 2020

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The state of Utah is prone to periodic drought and dry growing seasons. It is also considered one of the fastest growing states in the U.S. As such, concerns regarding water use and the need for water conservation persist. Recent advances in irrigation technologies have led the state of Utah to incentivize residents to save water by providing rebates for the purchase of smart irrigation controllers. The objective of this research was to determine whether Wi-Fi-enabled smart irrigation controllers can reduce the amount of water applied to residential landscapes, while maintaining plant health and aesthetics. To accomplish this objective, the water application allowed by Wi-Fi-enabled irrigation controllers was compared to water application by a manually programmed irrigation controller (Hunter XC-400), and average residential irrigation amounts in the state.

Data collected included total water application, soil volumetric water content, and plant health indicators. Plant health indicators were measured multiple times per week and averaged, while total water application for each experimental treatment was measured monthly. In addition, total water application was compared to actual evapotranspiration (ET_A) measured using on-site lysimeters. The experiment was conducted for 14 weeks during the 2018 and 2019 growing seasons at Utah State University's Greenville Research Farm, Logan Utah, USA. The Wi-Fi-enabled smart irrigation controllers chosen for the experiment were the Orbit B-Hyve Wi-Fi Sprinkler System, Rachio Smart Sprinkler Controller, and Skydrop Halo Smart Sprinkler System. These controllers were chosen because they are included in the state-wide rebate program. Results indicated that Wi-Fi-enabled smart irrigation controllers saved water when compared to average residential irrigation amounts in the state (1200 mm annually) and were comparable to the manually programmed irrigation controller. During the two-year study, the Rachio controller applied an average of 801 mm of irrigation water annually, the B-Hyve controller applied an average of 786 mm of irrigation water annually, and the Skydrop controller applied an average of 507 mm of irrigation water annually. Programmed according to USU Extension recommendations, the manually programmed irrigation controller applied an average of 515 mm of irrigation water annually.

(61 pages)

PUBLIC ABSTRACT

Effects of Wi-Fi-Enabled Smart Irrigation Controllers

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Residential and commercial landscapes provide home and business owners with several benefits. These benefits range from improved air quality and flood control to the reduction of noise and breakdown of organic chemicals. However, these landscapes are routinely overwatered which can lead to plant disease, nutrient pollution, and large amounts of water being wasted. Utah State University, in conjunction with the Center for Water Efficient Landscaping (CWEL), the Utah Division of Natural Resources and Weber Basin Water Conservancy District, conducted an experiment to determine if Wi-Fi-enabled smart irrigation controllers conserve water as compared to average residential irrigation amounts and manually programmed controllers.

A two-year study was completed at the Utah State University Greenville Research Farm in Logan, Utah. The three different Wi-Fi-enabled controllers tested were selected because of their inclusion in a state-wide rebate program to incentivize residents to save water. Average residential irrigation amounts were determined based on thousands of water audits performed by the USU Extension Water Check Program. The manually programmed irrigation controller was selected based on local availability and distributor recommendations.

When compared to the average residential irrigation amounts in the state of Utah, Wi-Fi-enabled irrigation controllers applied significantly less water. When compared to the manually programmed irrigation controllers (programmed according to USU Extension recommendations), the highest performing Wi-Fi-enabled irrigation controller applied similar amounts of water.

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CHAPTER I

INTRODUCTION AND LITERATURE REVIEW

The United States has experienced a growth in population of 5.63% since 2010 (U.S. Census Bureau, 2018). As the population continues to grow and more housing is developed, the amount of turfgrass area is also expected to increase. This increase in turf area has the potential to limit the quality and quantity of freshwater available to consumers if irrigation efficiency is not optimized (Johnson et al., 2013). It is estimated 16.4 million hectare (ha) of land within the continental United States is covered with turfgrass (Milesi et al., 2005). This includes grass used for roadsides, athletic fields, golf courses and various landscapes, including residential landscapes which account for approximately 66% of the area (Breuninger et al., 2013). Though industry and agriculture are also major users of water, the Intergovernmental Panel on Climate Change (IPCC) suggests residential water use, including landscape irrigation, is an important area of focus given population growth in relatively water scarce urban areas. This population growth means that water demands will increase in these areas while water supplies may be reduced (Bates et al., 2008).

The United States uses approximately 1.2 trillion liters (L) of water every day (USGS, 2015), and an audit by the United States Environmental Protection Agency (USEPA) found that as many as 1200 L of water may be used per household per day (USEPA, 2017). Within each household, up to 60% of water may be used outdoors and it is estimated that as much as 50% of that water may be wasted due to evaporation, wind drift, runoff, and inefficient irrigation methods and systems (USEPA, 2017). Previous studies by Hilaire (2008) and

Mayer (1999) found that up to 50% of total water use in homes could be attributed to lawn irrigation. A study by Chavez (1973) found that between 40 and 65% of metered water was used for maintaining plants in landscapes. Though irrigation technologies have improved over time, these findings suggest that irrigation application rates to residential landscapes have stayed nearly the same. As a result landscapes, particularly those containing large areas of turfgrass, may be considered wasteful of water in certain areas of the country, especially when watered with automated irrigation systems (Devitt and Morris, 2008). The "set it and forget" approach is often associated with this type of irrigation because homeowners may program a controller at the beginning of the irrigation season and return to change the program only when they turn off the system as winter approaches. This results in excessive amounts of water being applied to the landscape. In addition, homeowners utilizing manual irrigation systems watered less than those with automated irrigation systems. In both circumstances however, approximately 80% of homeowners did not know how much water their irrigation system applied (Bremer et al., 2012).

Various factors may influence residential water use and several scholars have investigated them. For example, drought caused by higher temperatures and lower precipitation rates, has been found to increase irrigation water application (Campbell, 2004) and evaluating how drought influences water use may help water resource managers and planners develop new strategies to counteract these increases (House-Peters, 2010). In addition to drought, other factors such as income, land use, and water price can influence irrigation decisions (Day, 2003; Domene and Sauri, 2006; Foster and Beattie, 1979).

Another important factor that influences residential water use is human behavior (Wentz and Gober, 2007). Bremer et al. (2013) found that homeowners preferred a green lawn but were not certain how much water was needed to maintain such a lawn. A similar study reported that homeowners placed more importance on maintenance attributes than aesthetic attributes (Hugie et al. 2012). Within the state of Utah, homeowners preferred drought-adapted landscapes to more traditional, high-water use landscapes (McCammon et al., 2009) indicating homeowners are aware of the need for water conservation but may not always know how to find additional information and resources on water conservation techniques.

To educate homeowners, Carrow (2006), recommended teaching best management practices (BMPs) and providing opportunities for interaction with university-based, Cooperative Extension specialists. Carrow (2006) stated that science based BMPs should be taught in order to conserve water, while maintaining optimal turfgrass performance. Best management practices included landscape design improvements, improved irrigation systems and utilization of irrigation controllers with integrated sensors or other forms of advanced software (Carrow, 2000; Carrow, 2006; Irrigation Association, 2014).

Because of periodic drought and rapid population growth, water use challenges are often amplified in the Intermountain Western U.S. (USGS, 2009), which includes the states of Utah, Nevada, Idaho, and portions of the surrounding eight states (NRCS, 2014).

On average, these states use more water per capita than other states in the nation with Idaho and Utah topping the list at 700 L and 640 L of water used per capita per day, respectively (USGS, 2015). Further complicating the situation, Kearney et al. (2014) has shown that states with the lowest average annual precipitation rates (230mm-500mm) (Idaho, Utah, Wyoming, Arizona, Nevada, Colorado, Montana, and New Mexico) are anticipated to grow in population by as much as 45% by the year 2040.

With average annual precipitation rates of 330 mm, Utah is the second most arid state in the U.S. and is subject to periodic drought (USGS, 2009). In addition, the state is highly urbanized and is expected to more than double in population by 2050 (Endter-Wada et al., 2008). Many communities along the highly populated Wasatch Front of Utah could encounter serious water shortages during this period of growth, while attempting to pursue water supply augmentation options (Utah Division of Water Resources, 2007).

Providing communities in the U.S. with a reliable public water supply is a priority of federal and local governments (USEPA, 2016). To support this supply, municipal water conservation programs have historically concentrated on increasing the efficiency of indoor water use by retrofitting plumbing fixtures (faucets, shower heads, toilets), promoting use of water-efficient appliances (washing machines, dishwashers), and encouraging people to utilize water-efficient practices in the home (USEPA, 2016). However, increasing attention is being paid to landscape water use as demographic changes and suburbanization trends in arid regions of the U.S. fuel increasing water demands (Endter-Wada et al., 2008). In the state of Utah, water conservancy districts have increasingly focused efforts on improving the efficiency of outdoor irrigation practices to reduce water use in the state (Kopp et al., 2017). To provide a label for water-saving products and a resource for helping save water, the USEPA created the WaterSense program in 2006. WaterSense is a voluntary program to label water-efficient products in order to help consumers save water and support market change. Products earning the WaterSense label have been certified to use at least 20% less water, save energy, and perform as well or better than regular models (USEPA, 2018). Included in this list of products such as washing machines, faucets, irrigation controllers, and sprinkler heads designed for residential landscapes.

Studies have shown advantages to using smart irrigation controllers (Cardenas-Lailhacar et al., 2010; Davis et al., 2009; Leinauer and Devitt, 2013; Kopp et al., 2017; McCready et al., 2009; Pittenger et al., 2004; Sandor, 2018). Smart irrigation controllers may use technologies such as integrated rain and/or soil moisture sensors or local weather data to calculate evapotranspiration (ET) rates. These rates may then be automatically incorporated into an irrigation controller's programming to allow efficient irrigation application. Controllers utilizing rain sensors have been shown to reduce irrigation by 7-30%, while soil moisture sensor-based controllers may reduce irrigation by as much as 74% (McCready et al., 2009). Other studies of weather-based controllers suggest water savings between 25-62% are possible (Kopp et al., 2017; McCready et al., 2009; Pittenger et al., 2004). However, studies have also shown excess water may also be applied by weather-based smart controllers when compared to manually programmed controllers (Grabow et al., 2013; Pittenger et al., 2004).

This research evaluated three Wi-Fi-enabled smart irrigation controllers, which were connected to the internet through an on-site router. Weather data from a nearby weather station was also accessed by the controllers. Some weather-based smart controllers utilize data from sensors connected directly to the controller, however Wi-Fi-enabled controllers use data from external sources. This feature allows a user to access weather data without the need for on-site weather data collection. The three Wi-Fi-enabled smart irrigation controllers chosen for this study were the Orbit B-Hyve Wi-Fi Sprinkler System (Bountiful, UT, USA), the Rachio Smart Sprinkler (Generation 2, Denver, CO, USA), and the Skydrop Halo Smart Sprinkler System (American Fork, UT, USA). All three controllers were USEPA WaterSense certified as of 2018. The Skydrop Halo Smart Sprinkler System has since been discontinued and removed from the list. In addition to being WaterSense certified, the controllers were chosen because they are rebated as part of the state's Division of Water Resource's water conservation programming. The Division focuses on identifying and implementing water management, conservation and development strategies, with the state's water conservancy districts aiding in the monitoring and maintaining of water facilities.

In cooperation with the Weber Basin Water Conservancy District and the state's Division of Water Resources, this study was conducted to determine if Wi-Fi-enabled smart irrigation controllers could reduce water use as compared to manually programmed irrigation controllers and average residential irrigation amounts in the state of Utah. Additionally, plant health indicators and aesthetics were monitored over the course of the study. A search of the literature has shown no previous research has been conducted using the three Wi-Fi-enabled smart irrigation controllers chosen.

CHAPTER II

METHODOLOGY

Research Site Description

The experiment was conducted during weeks 26 to 39 of 2018 (28 June – 29 September) and weeks 26 to 39 of 2019 (24 June – 30 September) in North Logan, UT, USA at the Utah Agricultural Experiment Station Greenville Research Farm (41°45’53.97’’ N, 111°48’34.10’’ W, 1413 m above sea level) to determine the effects of Wi-Fi-enabled smart irrigation controllers on turfgrass health responses and quality. Total water application was compared between the controllers and average residential irrigation amounts in the state of Utah. To assure plant health uniformity across treatments, the same watering schedule for all treatments was used for four weeks prior to the initiation of the experiment each year.

The soil at the site is a Millville silt loam (coarse-silty, carbonatic, mesic Typic Haploxeroll) and is considered well-drained. Onsite weather data was collected during the weeks of the study by an automated station (Model ET 106, Campbell Scientific, Logan, UT, USA) located approximately 200 m from the study site. Incoming shortwave radiation, wind speed, relative humidity, temperature and dew point, precipitation, soil temperature and soil moisture data were collected. These data were then used to calculate cool-season turfgrass reference ET (ET_o) using the Penman–Monteith equation (Allen et al., 2005).

The research site was originally established in 2009 on a total area of 930 m^2 divided into 20 plots, each measuring 28 m^2. Following irrigation installation in 2009, plots were planted with 21 m^2 of Kentucky bluegrass (*Poa pratensis* L.) and 7 m^2 of other ornamental plants (including *E. alatus*, *F. Glauca*, *B. microphylla*, and *P. lactiflora*) and mulch (Kopp et al., 2017). Plots were designed to be representative of local ornamental landscapes where Kentucky bluegrass is the predominant turfgrass species.

Kentucky bluegrass in the plots was maintained at a mowing height of 7.62 cm (clippings recycled on plots) with one application of ammonium sulfate fertilizer (49 kg N ha^{-1}, 21–0–0 [N–P–K]) applied each spring and one application of ammonium sulfate fertilizer applied each fall (73 kg N ha^{-1}) during each year of the study. Grass areas of the plots were irrigated using overhead spray (1.1 L min^{-1}) with Hunter sprinkler heads (MP Rotator 2000, San Marcos, CA, USA). To reduce weed pressure, a foliar application of 2,4-Dichlorophenoxyacetic acid (2,4-D) was applied each year in addition to periodic hand weeding. In June of 2018, plots were treated with Nufarm Mallet 0.5G insecticide, after the discovery of billbug larvae in the root zone of the turfgrass areas.

The experiment was arranged as a randomized complete block design with five blocks, in which four treatments were randomly assigned to plots within each block (Fig. 1). Experimental treatments included three commercially available Wi-Fi-enabled smart irrigation controllers and one standard, manually programmed irrigation controller.

To determine the actual amount of water utilized by Kentucky bluegrass at the experiment location, four weighing lysimeters were constructed, installed at the site, and hung from precision scales to directly measure ET. Each scale was connected to a Campbell Scientific CR 1000 datalogger which recorded the amount of water lost each day. The following day, the amount of water lost from each lysimeter was replaced using drip irrigation emitters (Fig. 2).

Irrigation Controllers

The Wi-Fi enabled smart controllers utilized in the study were the Orbit B-Hyve Wi-Fi Sprinkler System, the Rachio Smart Sprinkler, and the Skydrop Halo Smart Sprinkler System. The standard manually programmed irrigation controller utilized was a Hunter controller (XC-400, San Marcos, CA, USA), which served as the control for the experiment. The Hunter controller was chosen based on local availability and distributor recommendations. The three commercially available Wi-Fi-enabled smart controllers were selected in consultation with the state's Division of Water Resources and the Weber Basin Water Conservancy District.

The base programming used for all four controllers was the same. However, the site-specific environmental settings programmed into the Wi-Fi-enabled smart controllers differed depending on allowable inputs (Table 1). These inputs were chosen based on questions asked during initial setup of each irrigation zone programmed through each controller's smart phone application. Though the soil at the research site is a silt loam, the closest programmable option for soil choice was loam (Table 1).

The Rachio controller, in addition to requiring input for individual irrigation zones, required the user to choose an irrigation schedule (Fig. 3). The options for the schedule were 'fixed', 'flex monthly', and 'flex daily'. The schedules were described as ranging from "most predictable" to "most water savings", where 'fixed' is the most predictable water application and ‘flex daily’ is the most water-saving. For this experiment, the ‘flex daily’ option was chosen to maximize water savings.

The base programming for the Hunter controller was chosen based on USU Extension recommendations (Kopp et al., 2013). These recommendations are based on a historic (previous 30-yr) ET average and a recommended irrigation depth per application of 12.5 mm. During the months of June and July, irrigation was applied every three days. In August, irrigation was applied every four days, and in September every six days (Kopp et al., 2013). These monthly irrigation frequencies were adjusted to replace 100% of ET as determined from the previous 30-yr average ET.

The length of each irrigation was determined using a catch cup test as described by Irrigation Association (2009). For these tests, catch cups were placed in the turf area of each plot and the sprinkler system was run for 20 minutes. Irrigation depth measurements were then taken from the cups and distribution uniformity was calculated, after which the precipitation rate of the sprinklers was also calculated. After adjustments, an average distribution uniformity of 75% was calculated for the 20 research plots. Based on average sprinkler precipitation rates, it was calculated that 76 minutes were required to apply the recommended irrigation depth of 12.5 mm to each plot.

Data Collection

The experiment was conducted for 14 weeks in 2018 (30 June – 30 September) and 14 weeks in 2019 (28 June – 30 September), a time frame chosen specifically to include the warmest and driest period of each growing season. Total water application for all plots was measured using Sensus iPerl low flow water meters which recorded water use on an hourly basis. Data was downloaded monthly using UniPro v.2.6.2 software. Measurements of soil volumetric water content, normalized difference vegetation index and canopy temperature were taken every 2-3 days between 11:00-13:00 hours.

Soil volumetric water content

Soil volumetric water content (VWC) measurements were taken with a Campbell Scientific HS2P soil moisture meter, a device incorporating two rods measuring 20 cm in length. The HS2P uses time-domain reflectometry (TDR) to measure VWC of the soil. Volumetric water content data from the meter was downloaded using Hydrosense II support software. To account for plot variability, five measurements were taken at random locations within each plot and averaged. Measurements taken each week were also averaged for the duration of the experiment.

The TDR method determines soil bulk density by measuring the time needed for an electromagnetic pulse to travel along a transmission line (two metal rods for the HS2P) surrounded by soil. As the pulse travels along the rods, part of the pulse is reflected when a discontinuity, such as a probe-waveguide surrounded by soil, is found. This reflected pulse causes a change in energy level along the rods wherein the amount of time traveled can be determined and volumetric water content calculated (Muñoz-Carpena et al., 2004).

Normalized difference vegetation index

Normalized difference vegetation index (NDVI), was measured using a Spectrum FieldScout TCM 500. Similar to soil VWC measurements, NDVI measurements for each week were averaged for the duration the experiment. As with soil VWC, five measurements were taken within each plot and averaged daily. Data from the instrument was downloaded weekly using FieldScout support software.

Normalized difference vegetation indices have values between 0 and 1 with values closer to 1 indicating a higher amount of green cover for the area being evaluated. Data recorded by the instrument in this study measured reflected light from a circular section of turfgrass approximately 45.6 cm^2 in area. Normalized difference vegetation indices were calculated as [near infrared (NIR) – Red)]/[NIR + Red]) (Spectrum Technologies, 2013).

Percent green cover

Measurements of percent green cover were taken weekly for the duration of the experiment according to methods described by Karcher and Richardson (2013). Digital photos were taken in each plot using a light box, measuring 0.53m in width, 0.74m in length and 0.58 m in height. A Canon Powershot camera was used to take the digital photos in both years of the experiment. After each session, photos were analyzed using the Turf Analyzer program (Karcher and Richardson, 2005). For the program, inputs of hue, saturation and brightness are required and, in this study, inputs of hue ranged from 76-170, inputs of saturation ranged from 10-100, and inputs of brightness ranged from 0-100.

Turfgrass canopy temperature

Turfgrass canopy temperature was measured and averaged each week using a FLIR E5 infrared camera. The entirety of each 21 m^2 turfgrass plot was evaluated by taking photos from 4 m above the plot. These photos were then downloaded directly to a computer and canopy temperature measurements were recorded manually.

Statistical Methods

The effects of irrigation controller, soil VWC, NDVI, percent green cover, and canopy temperature were analyzed using a linear mixed model with repeated measures for a mixed model. Time of observation was the repeated measure. The fixed effects for the experiment were the controller and the controller × week interaction. The random effects were the block and the block × controller interaction. The SAS procedure GLIMMIX was used for all data analyses (SAS Institute, 2013). Means were separated using the Tukey–Kramer method where ($P \leq 0.05$).

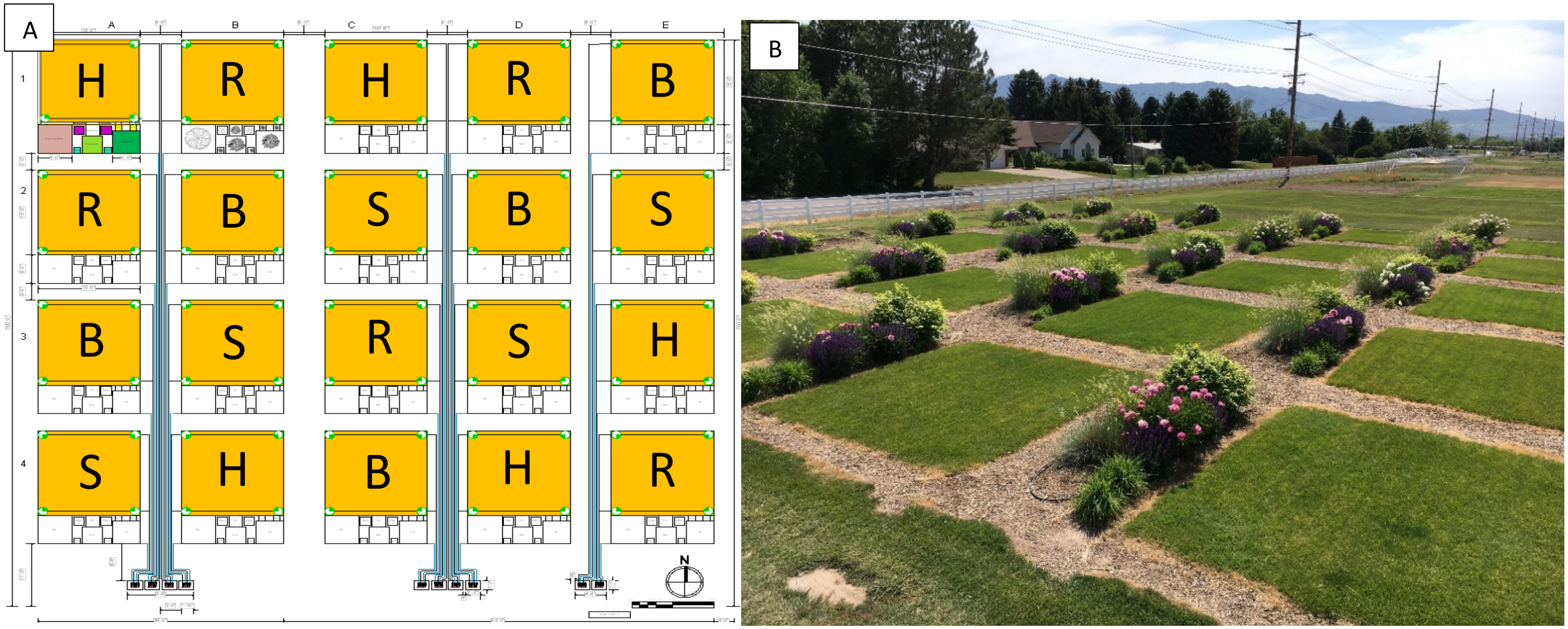

Fig. 1. (A) Plot layout for the 20 individual research plots. "B" indicates an Orbit B-Hyve controller, "H" indicates a Hunter controller, "R" indicates a Rachio controller, and "S" indicates a Skydrop controller. (B) Research plots and plantings.

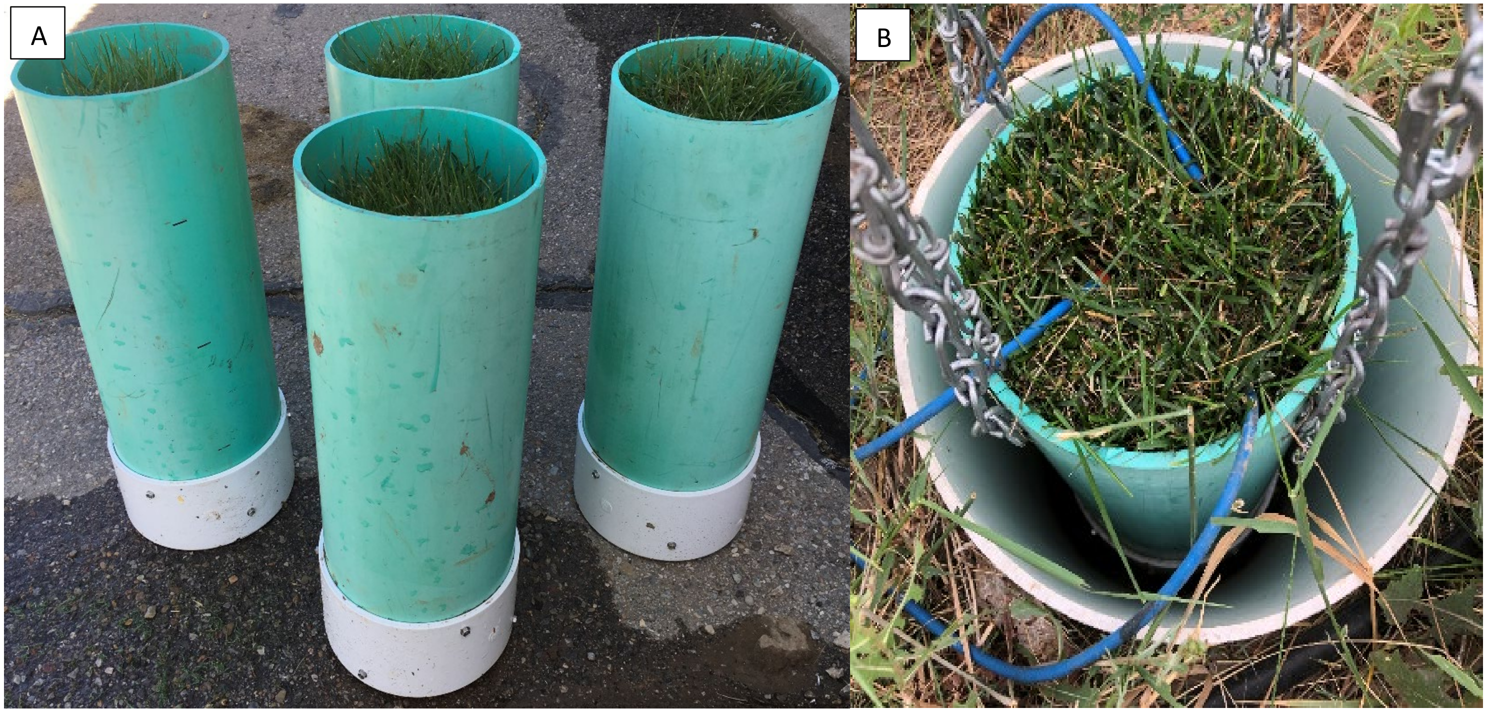

Fig. 2. (A) Four weighing lysimeters, constructed of PVC pipe, before installation at ground level. (B) A weighing lysimeter, hung by chains from a precision scale, installed at ground level with three drip irrigation emitters.

Table 1. Programming questions and inputs entered for each controller tested.

Inputs/Options	Rachio	Skydrop	B*Hyve
Vegetation	Cool-Season Grass	Cool-Season Grass	Cool-Season Grass
Soil Type	Loam	Loam	Loam
Type of Sprinklers	Rotor	Rotor	Rotor
Number of Sprinklers	4	4	4
Choose Weather Station	Greenville	Greenville	Greenvile
Sun Exposure	Full	Full	Full
Slope	None	None	None
Application Rate (mm/hr)	9.91	-	9.91
Efficiency (%)	75	-	75
Plant Factor	0.8	-	0.8
Microclimate Factor	-	-	1
Management Allowed Depletion (%)	50	-	50
Permanent Wilting Point (%)	-	-	12
Area (sq. m.)	20.9	-	-
Root Zone (cm)	15.2	-	15.2
Allowable Surface Accumulation (mm/hr)	-	-	7.62
Basic (Steady) Infiltration Rate (mm/hr)	-	-	8.9

- No response to the question was required for the controller

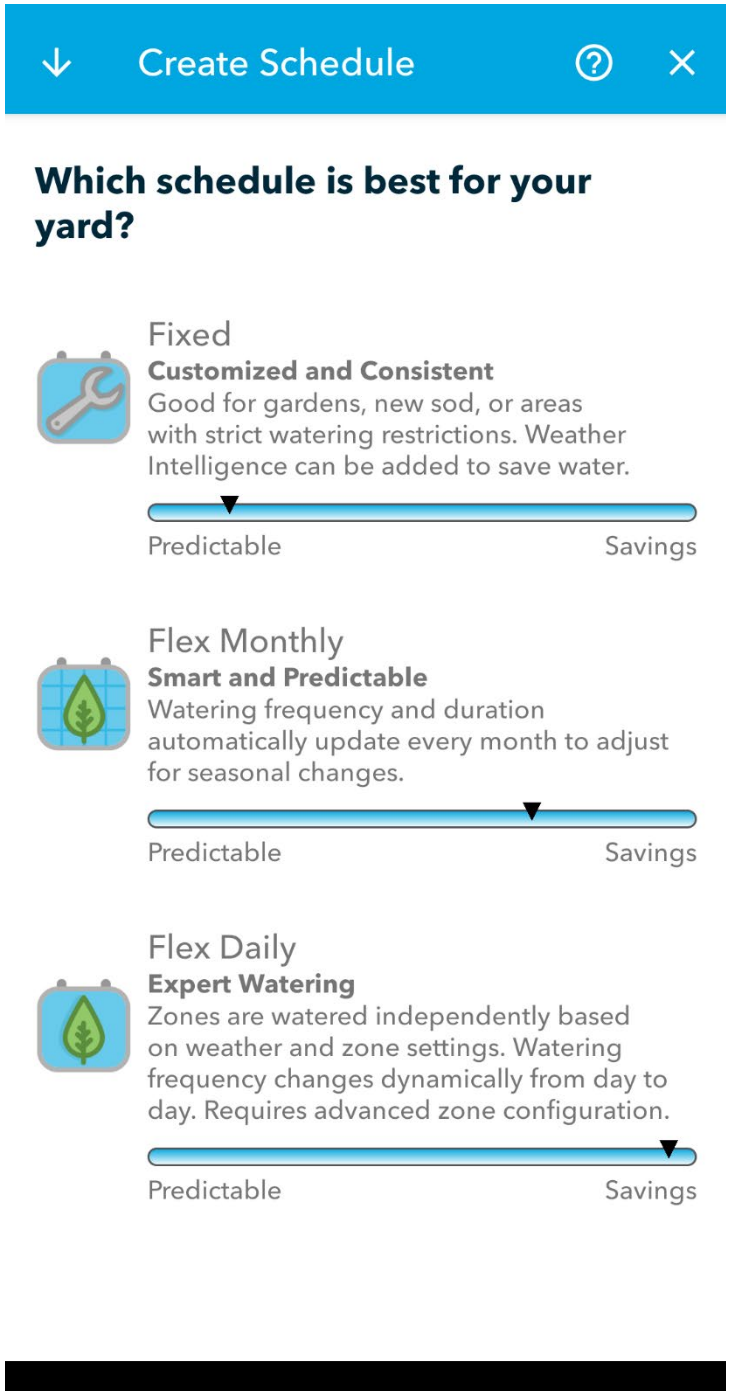

Fig. 3. Scheduling options for the Rachio controller.

CHAPTER III

RESULTS AND DISCUSSION

Weather

Weather was similar during the months of June-August for both years of the study, with the exception of high amounts of rainfall in September 2019 compared to September 2018. Average maximum daily air temperatures were 29.6 °C and 27.3 °C in 2018 and 2019, respectively (Figs. 4 and 5). The warmest month in each year was July with average maximum daily air temperatures of 32.5 °C in 2018 and 31.0 °C in 2019. Precipitation events occurred rarely during both growing seasons, with the exception for September 2019 when 110 mm of rain fell (Fig. 5). Total precipitation, during the study, was 9.9 mm in 2018 and 123.2 mm in 2019.

Data collected by the onsite Campbell Scientific ET 106 weather station (Logan, UT, USA), was used by each of the three Wi-Fi-enabled irrigation controllers and though the same weather data was used by each controller, variations in amounts of water applied were observed. These differences may be attributed to the internal algorithms used by each controller for determining irrigation scheduling in relation to weather data. However, these algorithms are not accessible to users and so differences among them are unknown. In addition to the differences observed in weather from year to year, these algorithms may explain why differences in the amount of irrigation applied each year were observed.

Total Water Application

The amount of applied irrigation water varied significantly across the treatments (Tables 2 and 3). In 2018, total amounts of water applied were 447 mm (Skydrop), 491.5 mm (Hunter-Control), 830.5 mm (Orbit B-Hyve), and 838.5 mm (Rachio). In 2019, total amounts of water applied were 567.8 mm (Skydrop), 539 mm (Hunter-Control), 741.5 mm (Orbit B-Hyve), and 764.2 mm (Rachio), (Figs. 6 and 7).

Daily ET_A measurements were summed to determine weekly ET_A for replacement in lysimeters. These applications were compared to the irrigation depths applied by each controller on a weekly basis (Figs. 6 and 7). Total growing season ET_A values were 539 and 570.1 mm in 2018 and 2019, respectively. The Rachio and Orbit B-Hyve treatments applied 56 and 53% more water than ET_A, while the Hunter-Control treatment applied 4% less and the Skydrop treatment applied 5% less than ET_A.

Utah State University Extension irrigation recommendations, which guided programming of the Hunter-Control in the study, were based on a historic, 30-year average of local climate data. Although the Rachio and Orbit B-Hyve treatments irrigated more than the Hunter-Control during the experiment, they still applied 57% less water than a typical Utah homeowner. Of the four controllers, the Skydrop applied the least water, using 72% less irrigation than a typical Utah homeowner. These percentages were calculated from previous irrigation audits performed through a long-running Utah State University Extension program, finding that homeowners in the state apply on average 1200 mm of water per growing season.

Water application was significantly affected by week, controller and the interaction of week × controller during both years of the study (Tables 2 and 3). Comparing water application across weeks in 2018, there were only four weeks in which significant differences were not observed between the controllers. These were week 26 (earlier in the season) and weeks 36, 38 and 39 (later in the season) (Fig. 6). Similar trends, with minor variations, were observed in 2019 (Fig. 7). In 2019, week 29 was the only week in which significant differences were not observed between the treatments.

Plant Health Indicators

Soil volumetric water content

Soil volumetric water content (VWC) was significantly affected by week, controller, and the interaction of week × controller (Tables 2 and 3). In 2018, average soil VWC was variable across treatment (23.4% Skydrop, 25.7% Hunter-Control, 31% Orbit B-Hyve, and 29.7% Rachio). In 2019, average soil VWC was also variable across treatments (31% Skydrop, 29.8% Hunter-Control, 33.6% Orbit B-Hyve, and 31.9% Rachio) (Figs. 8 and 9). In 2018, significant differences in soil VWC among the treatments were observed beginning in week 27 of the experiment but were not consistent until week 30 (Fig. 8). In 2019, significant differences in soil VWC were observed in every week of the study through week 34 (Fig. 9). These differences ended during weeks 36-38 when very high amounts of natural precipitation occurred.

During both years of the experiment, the soil profiles of the treatments did not exceed 36% or drop below 18% VWC (Figs. 8 and 9). For comparison, the field capacity of the Millville silt loam is 35% and the permanent wilting point is 13%. Only the Orbit B-Hyve treatment exceeded the field capacity of the soil and none of the treatments reached the soil's permanent wilting point during the experiment. Throughout the experiment, and across treatments, soil VWCs remained at levels where moisture was readily available to the turfgrass. This indicates that the reduced amounts of irrigation water application allowed by the controllers in the study did not reduce soil VWC to detrimental levels.

The Rachio treatment applied the most water over the course of the two-year study, but higher soil VWC readings were observed in the B-Hyve treatment. As shown in Figures 8 and 9, the B-Hyve treatment recorded higher values of soil VWC than the Rachio treatment 75% of the time. One possible reason for this finding could be the time at which irrigation was applied. To maintain adequate water pressure for the irrigation systems, timing of application had to be staggered across the plots. When applied, irrigation began at 0000 hours with one irrigation controller scheduled to begin irrigating every 20 minutes thereafter. Under this schedule, a maximum of four irrigation controllers could irrigate concurrently and still maintain adequate system pressure. Irrigation times for the Rachio treatment occurred between 0140 and 0300 hours, while irrigation times for the B-Hyve treatment occurred between 0500 and 0620 hours. The time-of-day difference in water application may account for the differences observed in soil VWC since soil VWC and plant health measurements were taken between 1100 and 1300 hours.

Normalized difference vegetation index

Measurements of NDVI were significantly affected by week, controller and the interaction of week × controller (Tables 2 and 3). In 2018, average values for NDVI of the treatments were 0.67 (Skydrop), 0.66 (Hunter-Control), 0.70 (Orbit B-Hyve), and 0.70 (Rachio) (Fig. 10). In 2019, average values of NDVI of the treatments were 0.64 (Skydrop), 0.63 (Hunter-Control), 0.67 (B-Hyve), and 0.64 (Rachio) (Fig. 11). Lower average NDVI was observed in 2019 than 2018 for all treatments.

During both years of the study, significant differences in NDVI among the treatments were observed. In 2018, the Rachio and Orbit B-Hyve treatments were never significantly different from one another, but both were significantly different from the Hunter-Control and Skydrop treatments for eight consecutive weeks (Fig. 9). In 2019, NDVI for the Orbit B-Hyve treatment was significantly different from all other treatments on four occasions, three of which occurred during July, the hottest month of the 2019 growing season (Figs. 5 and 11).

Though visual quality ratings were not recorded during this study, previous research has found a significant correlation between NDVI and visual quality ratings (Jiang and Carrow, 2007; Bell et al., 2009; Lee et al., 2011). Utilizing a visual quality rating scale of 1-9, with 6 denoting minimal acceptable quality (Morris et al., 1998) and using the pooled models described by Lee et al. (2011), none of the measurements of NDVI in this study were above the minimal acceptable quality rating. Calculations from Lee et al. (2011) pooled models show a turfgrass stand maintained at 7.62 cm should record NDVI values between 0.724 and 0.764 to meet minimal acceptable visual quality levels. During this two-year study, the highest NDVI value recorded was 0.713. However, Lee et al. (2011) also concluded that the 95% confidence interval surrounding predictions of NDVI from visual rating ranged from ±1.34 to 1.81 (on a 1-9 scale) indicating that the models developed are not precise enough to detect small differences between treatments. In addition, Bell et al. (2009) concluded that although high coefficients of correlation have been observed between NDVI and visual quality ratings, sensors alone are not sufficient for specific evaluations of color, texture and density.

Percent green cover

Percent green cover was significantly affected by week, controller and the interaction of week × controller in both years of the study (Tables 2 and 3). The average percentages of green cover for each treatment in 2018 were 77% (Skydrop), 75% (Hunter-Control), 85% (Orbit B-Hyve), and 83% (Rachio) (Fig. 12). In 2019, average values for each treatment were 75% (Skydrop), 72% (Hunter-Control), 83% (Orbit B-Hyve), and 74% (Rachio) (Fig. 13).

Powlen et al. (2019), described a threshold of 70% green cover as acceptable. Using this threshold, percent green cover was unacceptable once in 2018 and 14 times in 2019. The majority of these measurements occurred during the month of July 2019.

Figure 5 shows the average daily maximum temperature for July 2019 was 31 °C. Only July 2018 with an average daily maximum temperature of 32.4 °C maintained higher temperatures during the study.

In 2018, significant differences in percent green cover were not observed between treatments until week 32 of the experiment, after which significant differences continued through the remainder of the growing season (Fig. 12). In 2019, significant differences in percent green cover were observed between experimental treatments in every week but week 39, the last week measurements were taken (Fig. 13).

Measurements of percent green cover and NDVI were compared and were highly correlated (R=0.82) which is similar to previous studies where correlation coefficients ranged from 0.59-0.88 (Leinauer et al., 2017; Jing et al., 2019). The high coefficients of correlation between measurements of NDVI and percent green cover in this experiment, and others, suggest that only one of the measurements is necessary for similar studies.

Turfgrass canopy temperature

Canopy temperature measurements were taken over the course of the study, but no significant differences were observed. Though measurements were taken between 1100-1300 hours each day, high variability caused by sporadic cloud cover may have effected results.

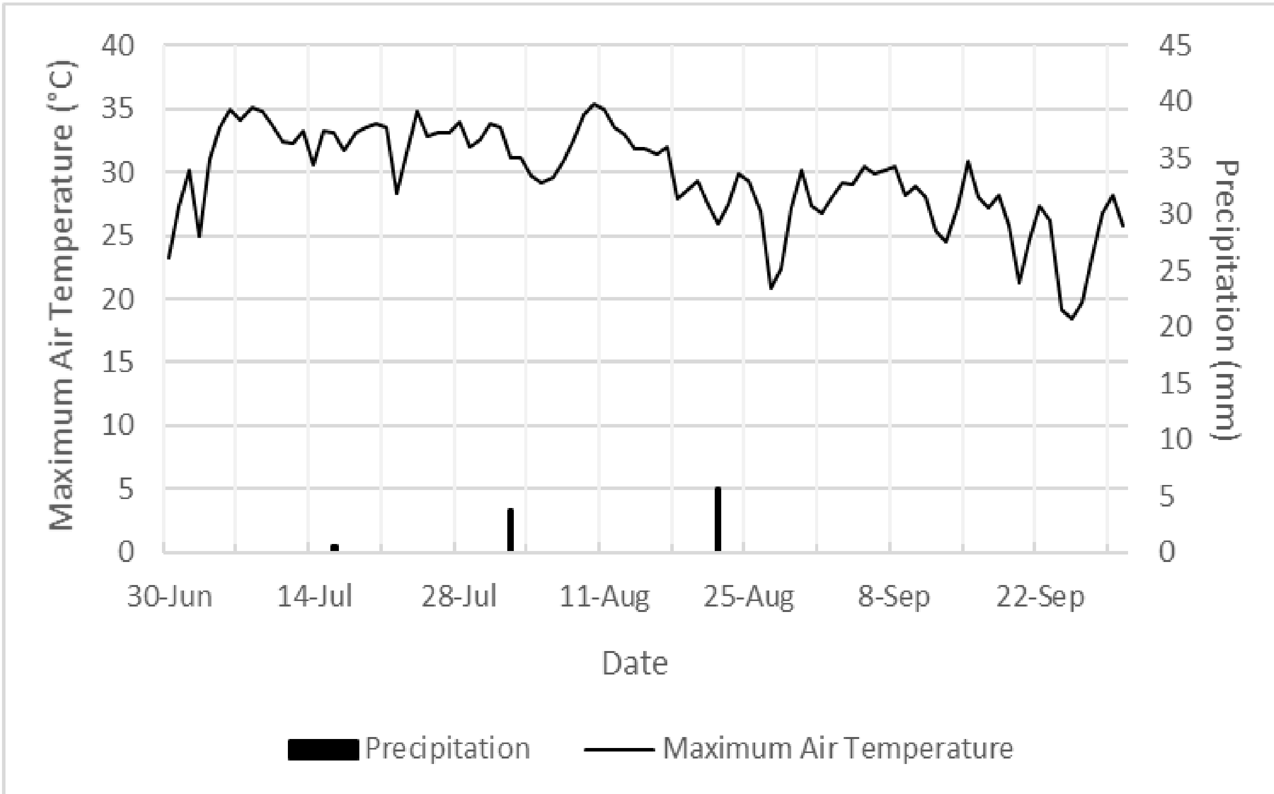

Fig. 4. Maximum daily air temperature (°C) and precipitation (mm) in 2018.

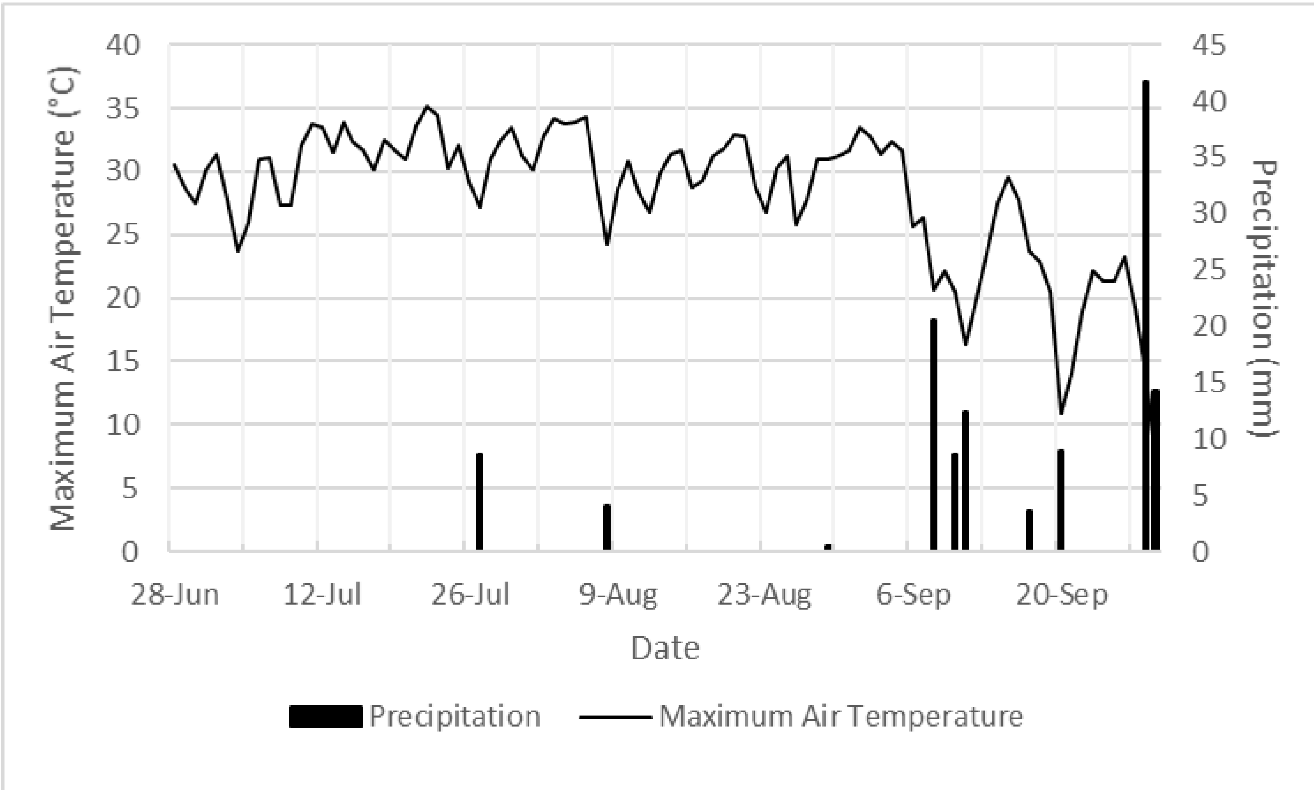

Fig. 5. Maximum daily air temperature (°C) and precipitation in (mm) 2019.

Table 2. Analysis of variance summary of repeated measures analyses for water application, soil volumetric water content, normalized difference vegetation index, canopy temperature, and percent green cover in 2018.

	DF	Water Use	Soil Volumetric Water Content	Normalized Difference Vegetation Index	Canopy Temperature	Percent Green Cover
Controller	3	***	***	***	NS	*
Week	13	***	***	***	NS	***
Controller*Week	38	***	***	*	NS	*

*Significant at the 0.05 probability level
*** Significant at the 0.001 probability level
NS denotes not significant

Table 3. Analysis of variance summary of repeated measures analyses for water application, soil volumetric water content, normalized difference vegetation index, canopy temperature, and percent green cover in 2019.

	DF	Water Use	Soil Volumetric Water Content	Normalized Difference Vegetation Index	Canopy Temperature
Controller	3	***	**	***	NS
Week	16	***	***	***	NS
Controller*Week	48	***	***	**	NS

	DF	Percent Green Cover
Controller	3	**
Week	15	***
Controller*Week	45	**

** Significant at the 0.01 probability level
*** Significant at the 0.001 probability level
NS denotes not significant

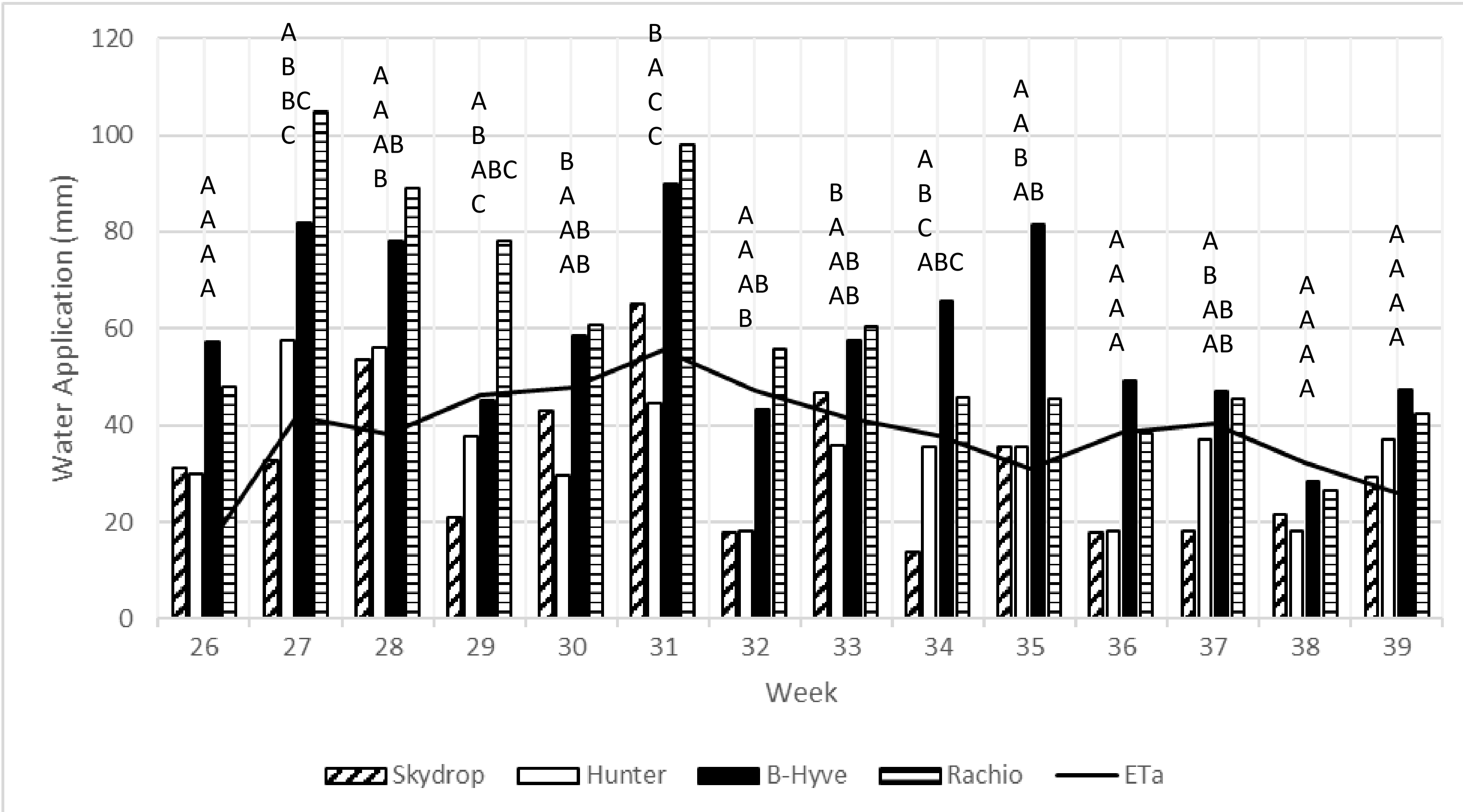

Fig. 6. Depth of irrigation application by week in 2018. Significant differences between controllers are noted by different letters. The top letter represents the Skydrop controller. The second letter represents the Hunter-Control. The third letter represents the Orbit B-Hyve controller and the bottom letter represents the Rachio controller. Weekly actual evapotranspiration (ET_A) is also shown.

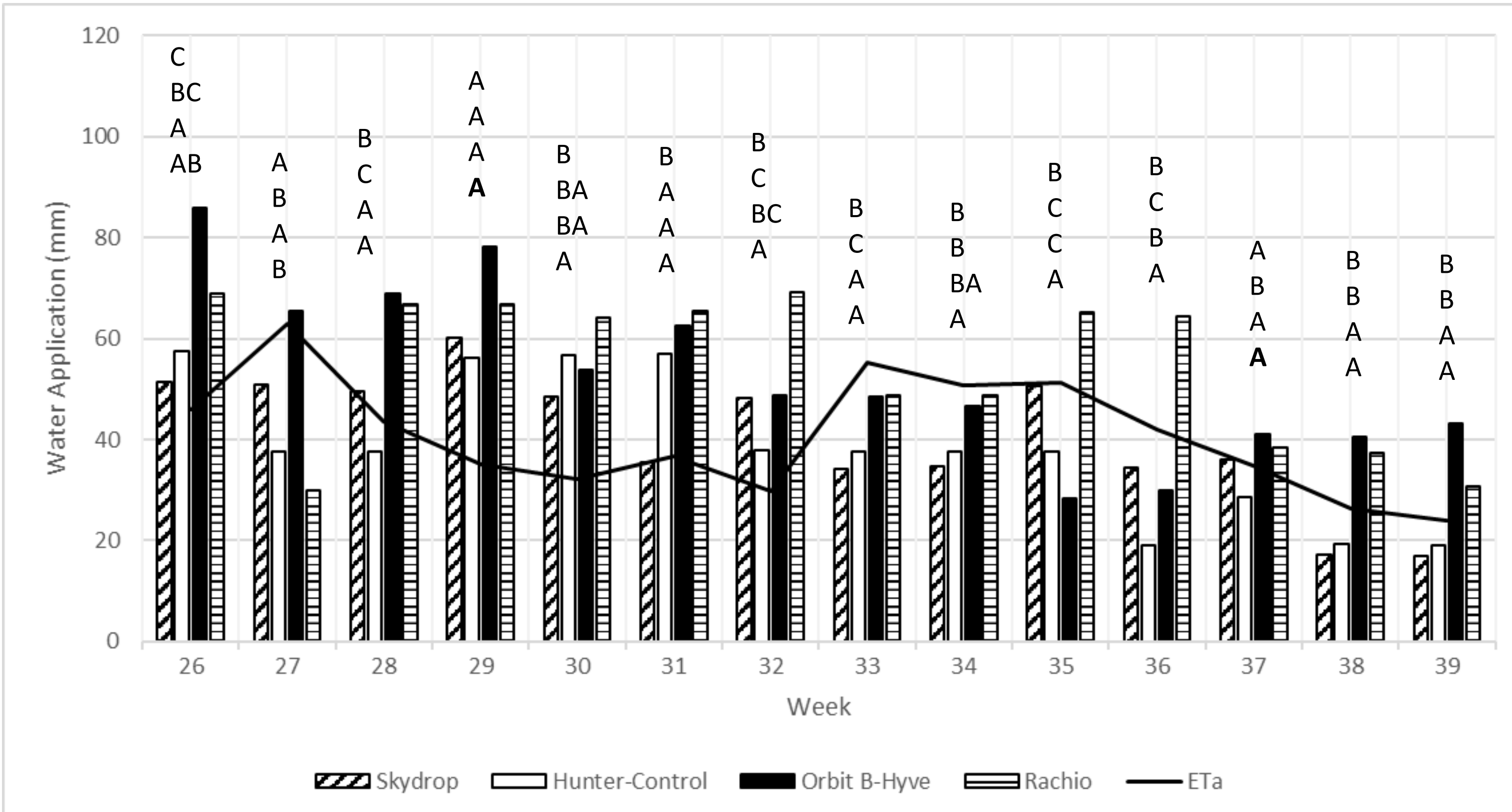

Fig. 7. Depth of irrigation application by week in 2019. Significant differences between controllers are noted by different letters. The top letter represents the Skydrop controller. The second letter represents the Hunter-Control. The third letter represents the Orbit B-Hyve controller and the bottom letter represents the Rachio controller. Weekly actual evapotranspiration (ET_A) is also shown.

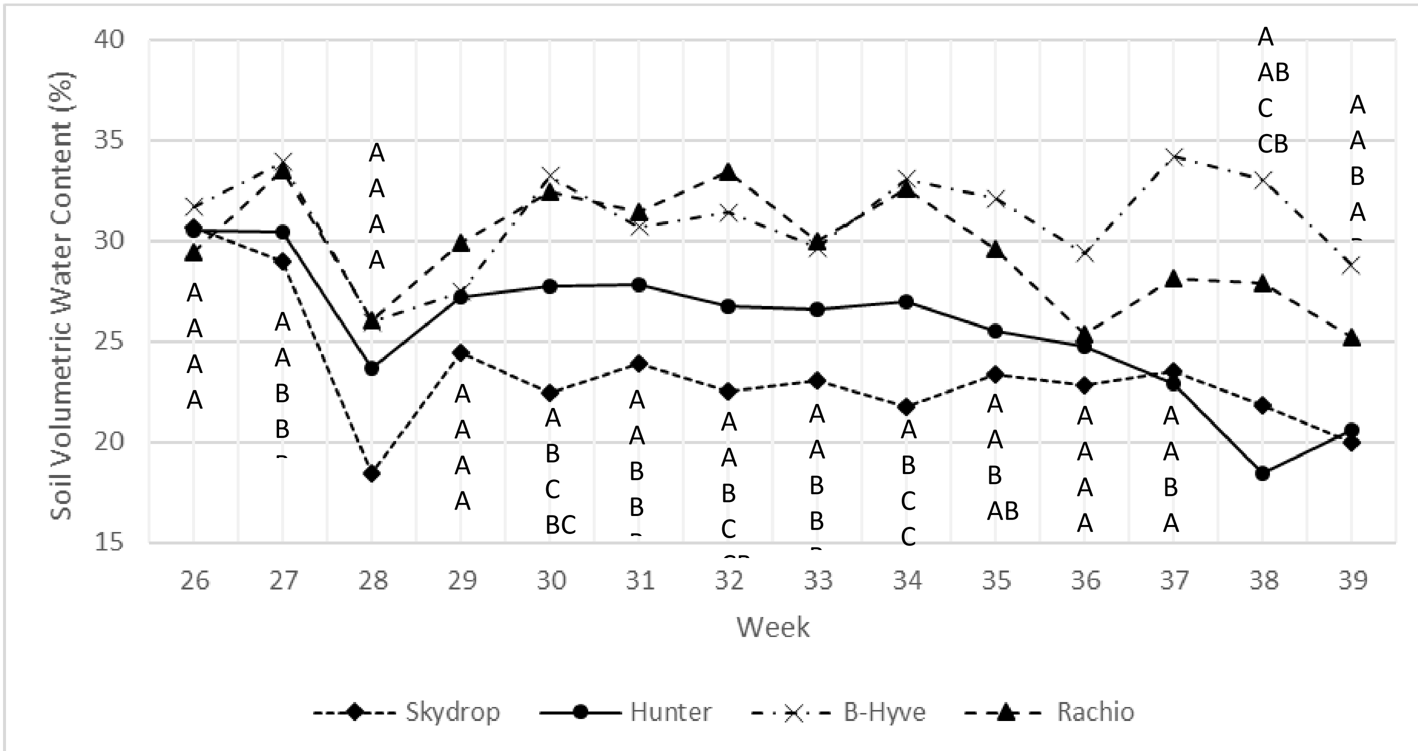

Fig. 8. Soil volumetric water content by week in 2018. Significant differences between controllers are noted by different letters. The top letter represents the Skydrop controller. The second letter represents the Hunter-Control. The third letter represents the Orbit B-Hyve controller and the bottom letter represents the Rachio controller.

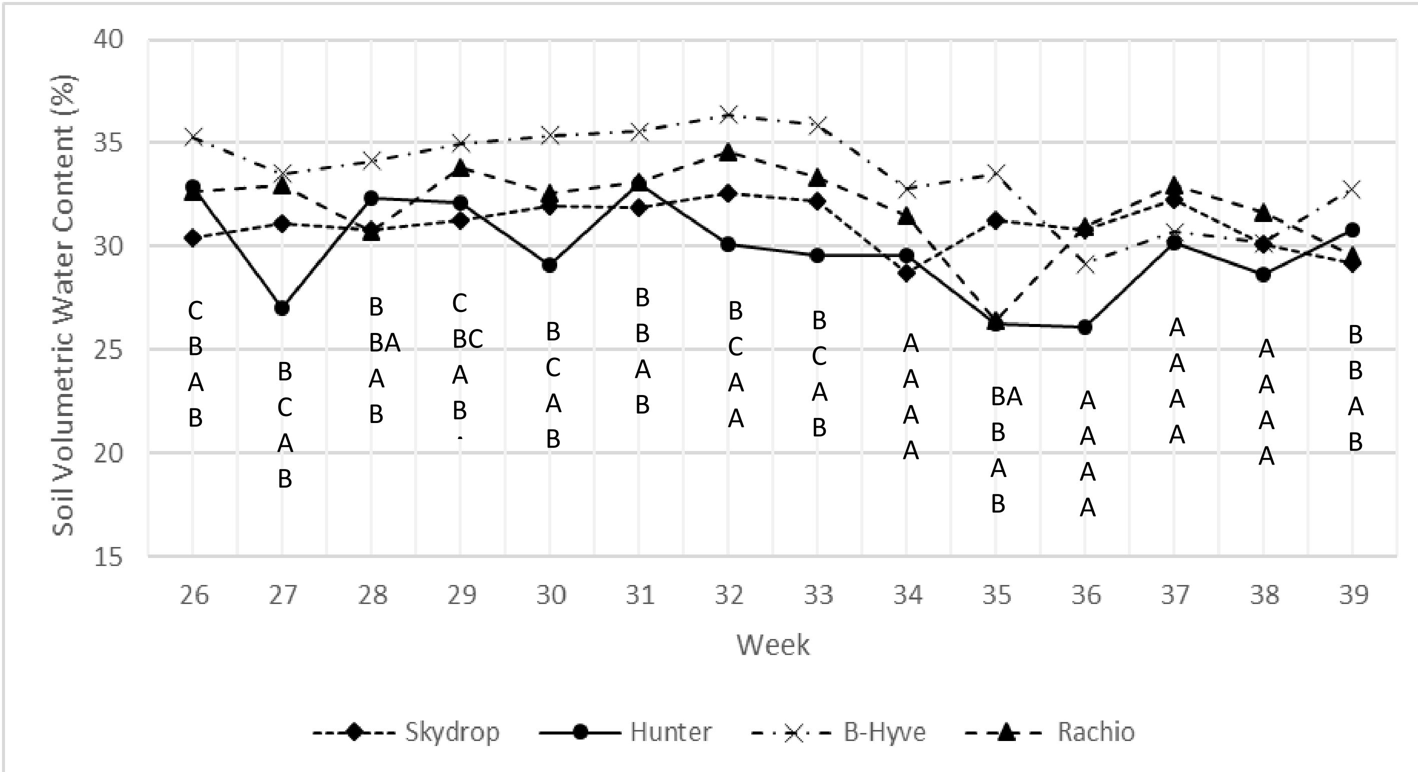

Fig. 9. Soil volumetric water content by week in 2019. Significant differences between controllers are noted by different letters. The top letter represents the Skydrop controller. The second letter represents the Hunter-Control. The third letter represents the Orbit B-Hyve controller and the bottom letter represents the Rachio controller.

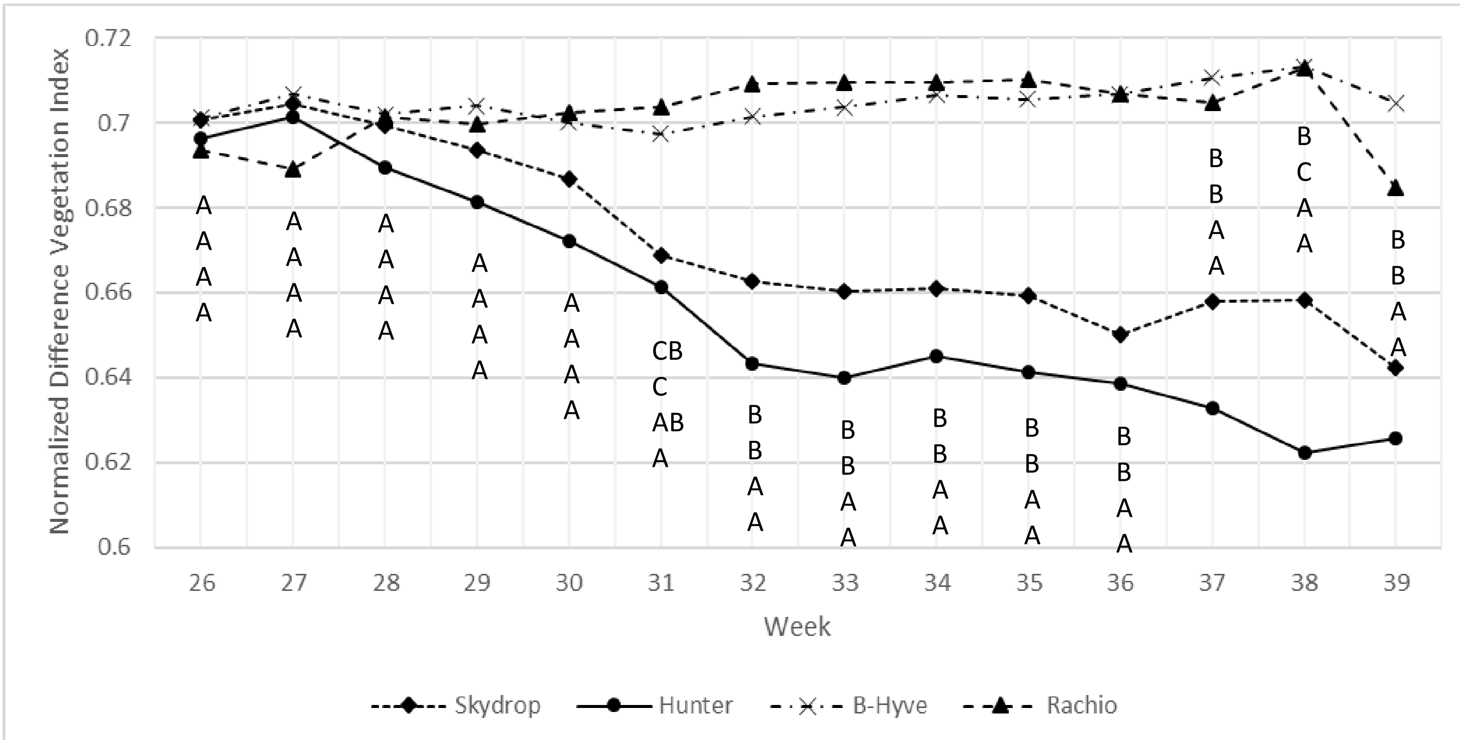

Fig. 10. Normalized difference vegetation index measurements by week in 2018. Significant differences between controllers are noted by different letters. The top letter represents the Skydrop controller. The second letter represents the Hunter-Control. The third letter represents the Orbit B-Hyve controller and the bottom letter represents the Rachio controller.

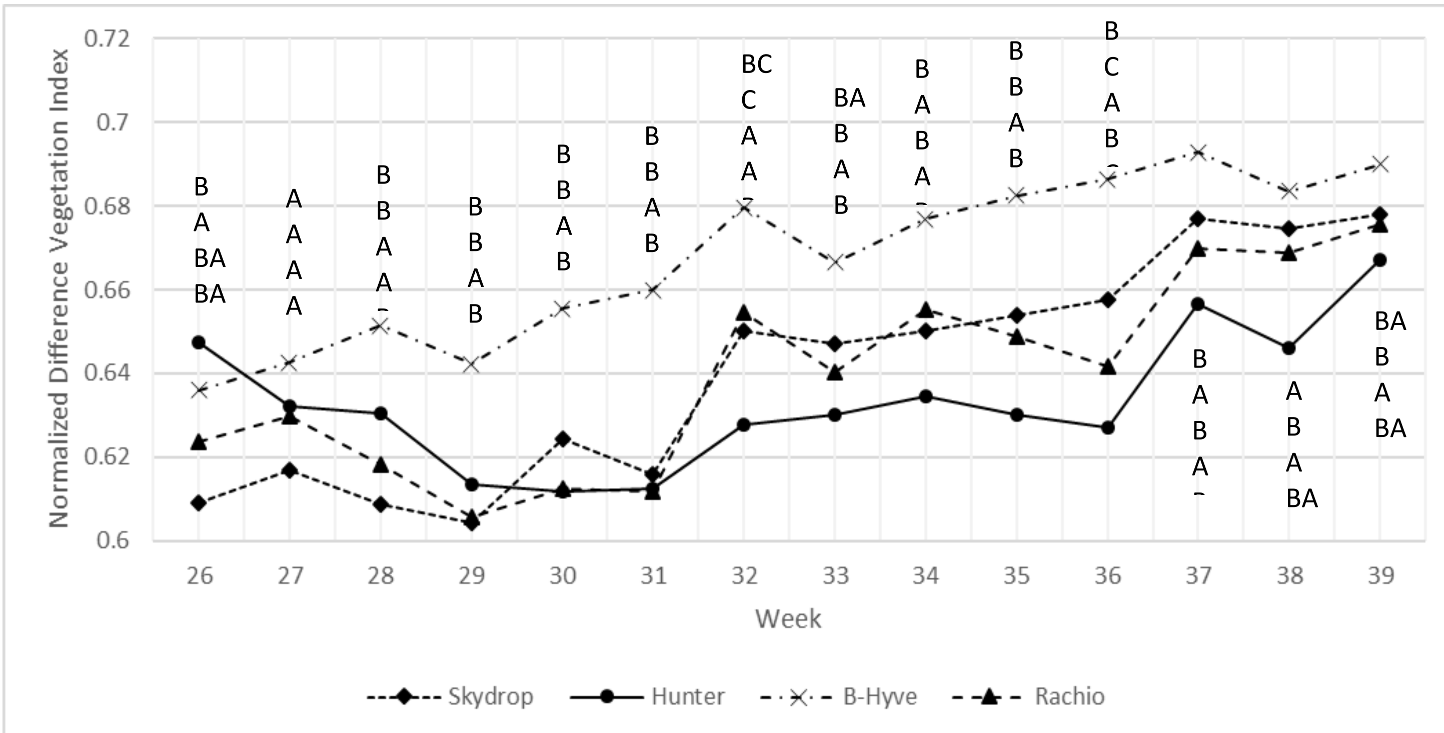

Fig. 11. Normalized difference vegetation index measurements by week in 2019. Significant differences between controllers are noted by different letters. The top letter represents the Skydrop controller. The second letter represents the Hunter-Control. The third letter represents the Orbit B-Hyve controller and the bottom letter represents the Rachio controller.

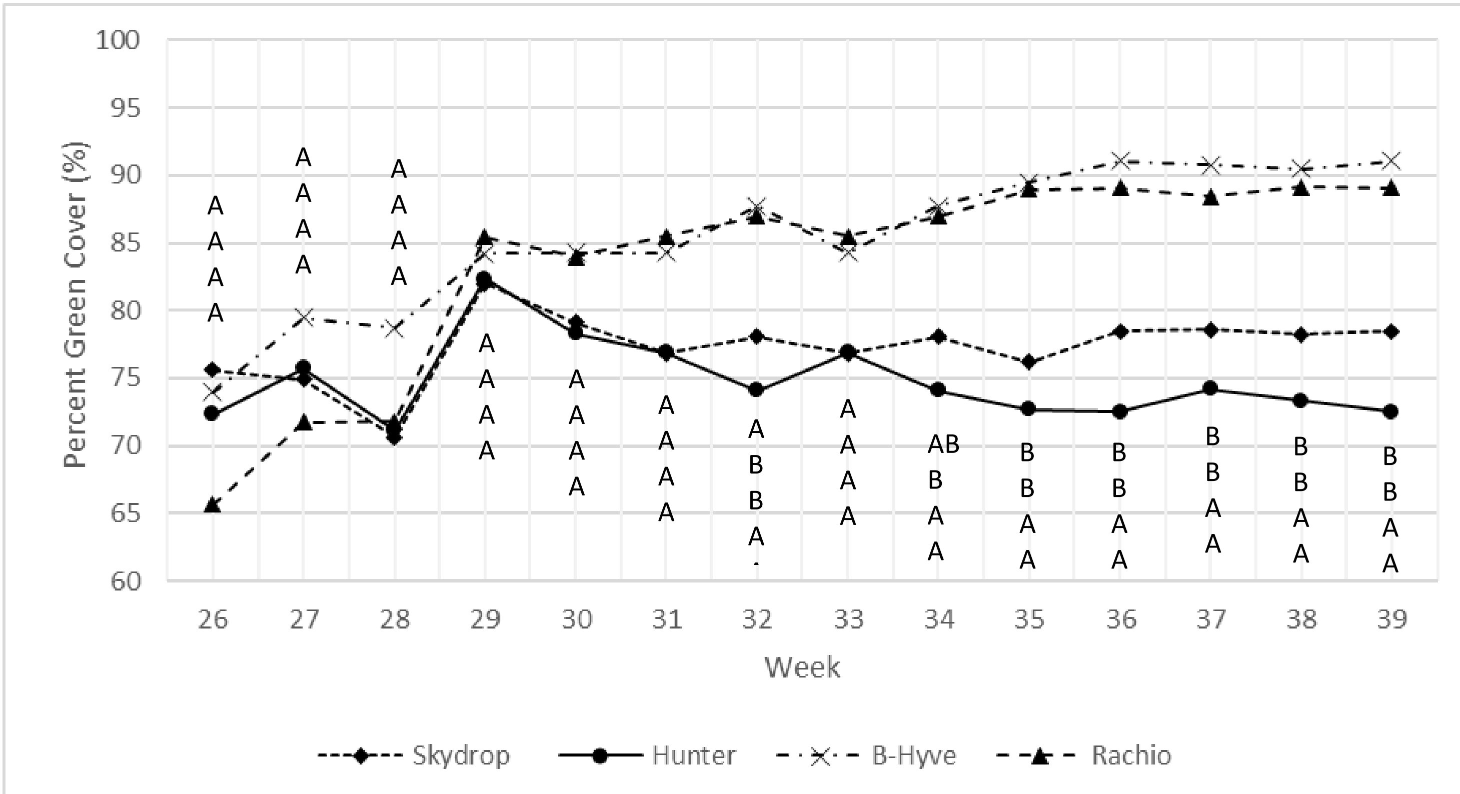

Fig. 12. Measurements of percent green cover by week in 2018. Significant differences between controllers are noted by letters. The top letter represents the Skydrop controller. The second letter represents the Hunter-Control. The third letter represents the Orbit B-Hyve controller and the bottom letter represents the Rachio controller.

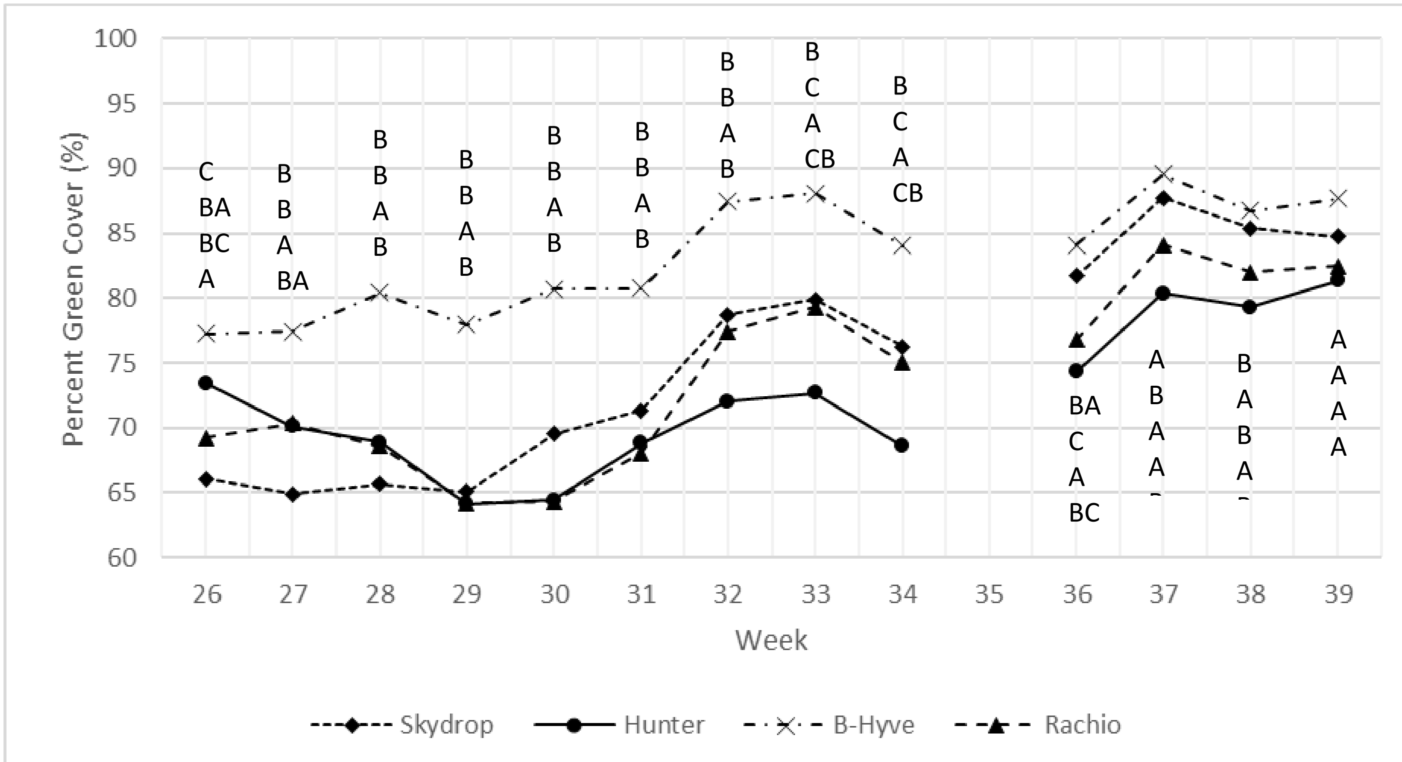

Fig. 13. Measurements of percent green cover by week in 2019. Significant differences between controllers are noted by letters. The top letter represents the Skydrop controller. The second letter represents the Hunter-Control. The third letter represents the Orbit B-Hyve controller and the bottom letter represents the Rachio controller. Measurements were not taken in week 35.

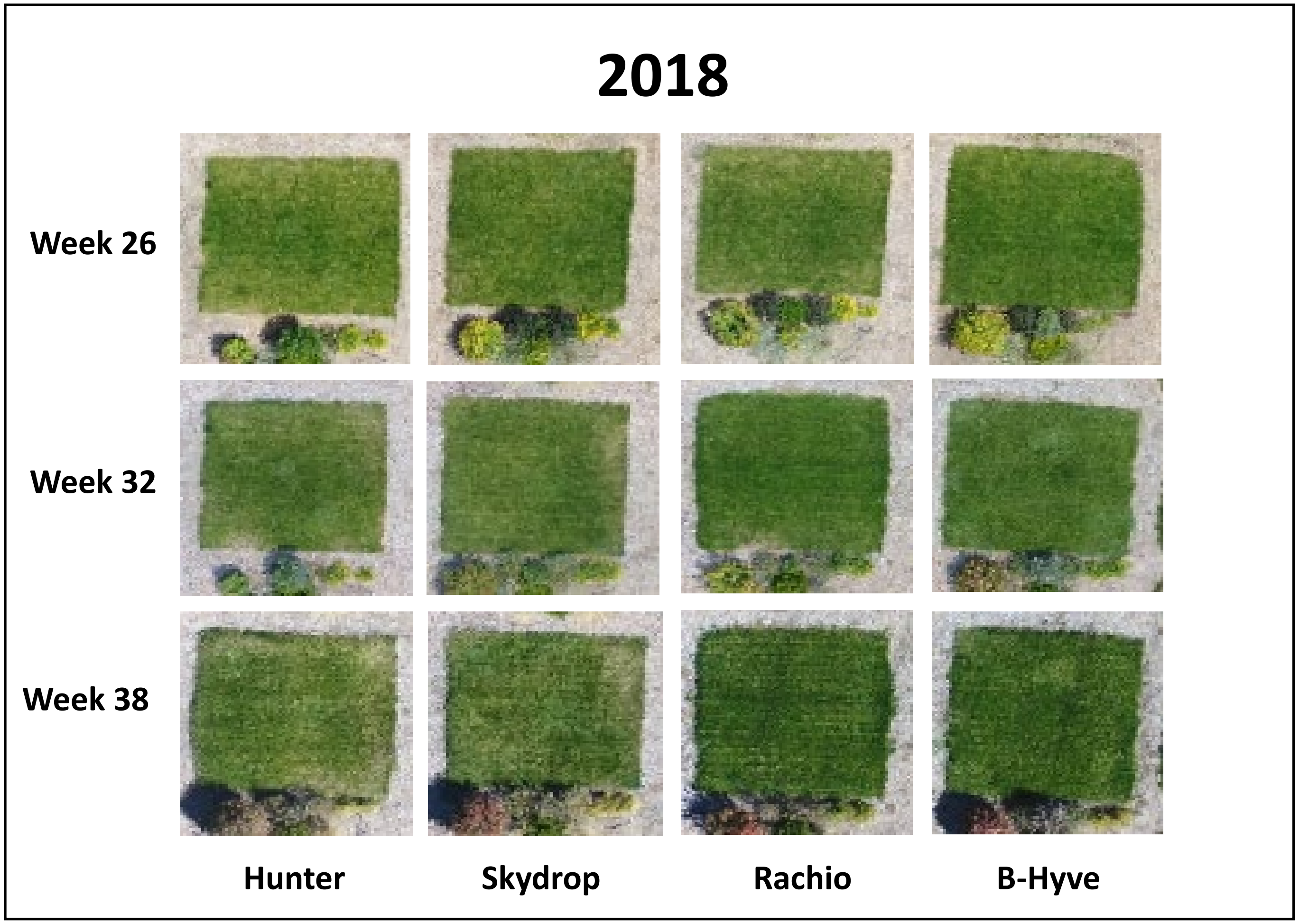

Fig. 14. Aerial images of the plots taken from 30 m at weeks 26, 32 and 38 for visual comparison in 2018.

Fig. 15. Aerial images of the plots taken from 30 m at weeks 26, 32 and 38 for visual comparison in 2019.

CHAPTER IV

CONCLUSIONS

Key Findings

Of the controllers tested, the Skydrop Halo Smart Sprinkler System applied the least amount of water over the two years of the study, followed by the Hunter XC-400 (Control), Orbit B-Hyve Wi-Fi Sprinkler System and the Rachio Smart Sprinkler. In addition, every controller tested, including the Hunter-Control, applied less water than the typical Utah homeowner. The Hunter-Control in the experiment was manually programmed according to USU Extension recommendations and the lower water application achieved by following these recommendations indicates that comparable water savings are achievable between manually programmed irrigation controllers and the highest performing Wi-Fi-enabled smart controller tested. In fact, if homeowners were to implement recommended irrigation schedules, as much as 70% less water could be applied to lawns and landscapes. However, manually programming irrigation controllers may be challenging for some homeowners and landscape managers, and Wi-Fi-enabled smart controllers may help to overcome this challenge.

Because Wi-Fi-enabled smart irrigation controllers allow irrigation zones to be created by answering a variety of questions about the landscape and that information is saved to the controller, changes to the irrigation schedule occur automatically without the need for regular, manual programming changes by the homeowner or landscape manager.

After an irrigation zone and schedule are created, the internal algorithms of these controllers then run continuously and irrigate according to real-time weather conditions.

Concerning plant health, lower measurements of soil moisture, percent green cover and NDVI were observed in the Hunter and Skydrop treatments. This can be attributed to the lower amounts of irrigation applied to these treatments. Though these lower measurements often resulted in significant differences amongst treatments, plant health, in all treatments, was maintained above acceptable levels throughout the study.

Possible Limitations and a Look Ahead

Soil VWC measurements were taken manually during the experiment, but continuous in-situ measurements may have helped to develop a more detailed picture of soil moisture both within and below the root zone. Soil VWC measurements were also taken in the top 20 cm of soil. Placing sensors below 20 cm may have provided insight as to whether irrigation water was moving beyond the root zone. Additionally, soil VWC measurements were taken the same time every day and continuous measurements may have shown whether dryer conditions were reached at different times during the day.

For this experiment the control treatment was programmed according to USU Extension recommendations. In future studies, irrigation schedules taken from surveys of homeowners or more deficit to ET_o could be implemented for comparison.

Wi-Fi-enabled smart irrigation controllers are popular with consumers. But how well do consumers respond to the questions posed by the controller when creating an irrigation zone? Additional research considering common mistakes made during programming could indicate how these mistakes impact potential water savings. For example, how is the amount of water applied affected if a consumer chooses a sandy soil when their property actually has a clay loam soil? Many other programming mistakes are also possible. Additional research, to answer these questions, may provide manufacturers and consumers with more information in order to maximize water savings while maintaining aesthetically pleasing landscapes.

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