Abstract

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Two current challenges with watering in a commercial greenhouse are differences in watering styles by employees and the amount of time required for employees to monitor crops. Substrate moisture sensing allows for continuous monitoring and greater irrigation control by measuring the volumetric water content (VWC). While sensors have been used in automated irrigation, there is still the question of how and when to trigger watering events. For large-scale deployment, an open-source low-cost substrate moisture sensor was conceptualized, manufactured, and tested against commercial sensors. The prototype, called the Precision Agriculture Wireless Water Sensor (WolfPAWWS), was manufactured for roughly $25 (Updated: March 2020) per unit, including component overage. For this study, there was an investigation into the number of sensors required to accurately trigger a watering event and development of a new slope method for determining when to trigger a watering event. The moderate agreement of the Cohen kappa coefficient suggested that the number of sensors could be reduced from 8 to 6 sensors per zone, but further examination using the proposed method may be needed to fully test this hypothesis. Most of the linear regression models for the new slope method explained at least 83% of the variability in the median VWC, but the slope required to trigger a watering would need to be altered when plants experience faster water uptake during reproductive stages. In addition to evaluating the method for triggering, sensor-based irrigation was compared to expert-based irrigation for the effect on maize performance. There was not found to be significant differences between the two methods, which is promising for future implementation of automated control for sensing. The WolfPAWWS were more reliable than the
commercial sensor, but the sensing approach must be improved before irrigation control implementation. Since this slope method was only applied to one experimental dataset, additional application to additional data will determine the robustness of method implementation. Based on the issues associated with scaling up sensor-based irrigation control, expert insight and monitoring will be required when initially implementing sensors in a commercial greenhouse. This work on substrate moisture sensing and the decision-making methods has the potential for future use in commercial greenhouse applications.
Decision Making Methodology for Substrate Sensing in Controlled Environments

by
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Dedication

I would like to dedicate this work to Jim Llewellyn for asking the hard questions and forcing me to think more critically about my project. I hope my work on this project helps to make your life easier in the future.

I would like to dedicate this work to Amelia Saul - my sister, my best friend, my motivator, my inspiration to keep moving forward. To my parents, Geoff and Brenda Saul, for instilling in me the value of education and always learning.
Biography

Kaelin Saul graduated from North Carolina State University with her bachelor’s degree in Biological and Agricultural Engineering in 2014. She completed her master’s degree in Biological and Agricultural Engineering with a bioprocessing concentration from Kansas State University in 2016. Her master’s research focus was on the development of starch content and fermentation efficiency predictive models for mutant grain sorghum. After graduating, Kaelin worked at a small vineyard for a year before pursuing her PhD from North Carolina State University in Biological and Agricultural Engineering with a focus in precision agriculture.
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Chapter 1 - Introduction

Overview

Commercial greenhouses have a high throughput of various plants and crops that require constant monitoring and maintenance for high quality. According to Boada et al. (2018), greenhouses were looking for low-cost irrigation management solutions by examining soil or substrate moisture to meet their plant watering needs and improve their watering practices. This finding was supported by contacts in the plant industry who were seeking to develop a low-cost, wireless sensor to be used in their greenhouses. Their challenge was to create a $10.00 sensor which could be used to sense moisture content in potted plants and to assist in automating their irrigation systems. Beyond the sensor, additional questions were identified related to implementation of sensor-based irrigation management at scale and the potential plant performance impacts of automated irrigation systems as compared to traditional management methods. Therefore, the overall goal of this dissertation was to assess the tools, methods, and outcomes associated with sensor-based irrigation in a commercial greenhouse setting. In Chapter 2, specific objectives were 1.) to design and assess a new open-source sensor for potted plants, 2.) to determine variability among sensors, and 3.) to ascertain how the prototype compared to commercial sensors in accuracy and reliability. The specific objectives for Chapter 3 were 1.) to evaluate how many uncalibrated sensors in a zone are necessary for irrigation decision-making and 2.) to conceptualize a potential alternative to triggering irrigation based on a threshold value using uncalibrated sensors. In Chapter 4, the specific objective was to compare sensor- and expert-based irrigation scheduling as it relates to 1.) discrete and continuous sensor measurements, 2.) water delivery and leaching, and 3.) plant performance metrics, including kernel counts, dry mass, plant height, and root rot ratings.
**Dissertation Organization**

This document is organized as a paper-style dissertation. Each of the primary chapters are formatted as individual manuscripts for submission to peer-review. Chapter 1 is a general introduction to the research and provides overarching context. Chapter 2 is a manuscript that developed and tested an open-source wireless capacitive sensor with a target price of $10 per unit. Chapter 3 is a manuscript that investigated irrigation methodology to provide management techniques for future studies. Chapter 4 is a manuscript that compared how sensor- and expert-based irrigation scheduling affected plant performance. Chapter 5 is a summary of key findings and closing remarks.

**Sensing Technologies and Methods**

The most common method for describing soil moisture is to use the volumetric water content (VWC). VWC, which is the volume of water within a known volume of soil, serves as the basis for determining the amount of water available within the soil (Pardossi et al., 2009). There are several types of technology used to measure the VWC of soil or substrate *in situ*. The first type is time domain reflectometry (TDR) sensors, which are based on the propagation velocity and the amount of time needed to exit from and return to a known length of probe (Dobriyal et al., 2012). TDR has been accepted as being more accurate than resistive and capacitive technologies, but the devices were more expensive (Kargas & Soulis, 2012). A low-cost sensor was required for large-scale implementation of irrigation control. Capacitive soil moisture sensors can provide a low-cost method for large-scale irrigation control (Fares & Polyakov, 2006).

Calibration, placement, and number of sensors are important factors that must be investigated prior to large-scale deployment of sensing technology (van Iersel et al., 2013).
Calibration on a large-scale would be difficult, which led to the investigation of irrigation scheduling methods that used uncalibrated low-cost capacitive sensors. Alhammadi et al. (2017) described good irrigation scheduling as the time when water availability in the soil is low, which can be based on a sensor-based threshold value. With uncalibrated sensors, a single threshold value would not be appropriate and could lead to under- or overwatering (Pardossi et al., 2009). Accounting for microclimate variability can make irrigation control difficult (Ferentinos et al., 2017). Henderson et al. (2018) concluded that feedback sensor-based irrigation could be used in greenhouses, but factors, such as microclimate variability, must still be taken into consideration. One way to account for this form of variation in a greenhouse room is to use sensor-based irrigation on a zone-specific basis, as opposed to a room-by-room basis with timer-based irrigation.

Sensors undergo calibration to ensure greater accuracy, generally by comparing to a known standard. Numerical experiments using a mathematical model found that soil specific calibration was necessary for sensor-based irrigation scheduling (Soulis et al., 2015). A study by Kizito et al. (2008) applied a generalized calibration curve across soil properties. A different study claimed that relatively accurate readings from sensors could be sufficient for large-scale implementation if measurement repeatability and resolution high enough. (van Iersel et al., 2013). In total, previous studies raise a question around the need for individual high accuracy, explicitly calibrated sensors versus multiple lower accuracy sensors which can identify aggregated trends in soil moisture response.

**Irrigation Decision-making Methodology**

One important consideration prior to implementing automated irrigation is the number of sensors for decision-making. Application of sensor technology in the greenhouse requires greater
understanding of the number of sensors to avoid deficit or excessive watering on a large scale. A study done by Daniels et al. (2012) investigated the number of sensors responsible for watering different tree species. This study concluded that six to ten sensors were needed among species, which represents 2-4% of the 250 trees per species. Our study determined how many substrate moisture sensors would be required for irrigating wild-type maize (Zea mays sp) on a zone-specific basis. Additionally, this study used low-cost capacitive sensors that were not calibrated to simulate scaling up in a commercial greenhouse, which might not have the capacity to calibrate all individual sensors.

A pre-determined threshold, or set point, can be used to trigger irrigation. Peters and Evett (2008) developed a method that used a temperature-time threshold that used the canopy temperature as the threshold value used to trigger irrigation. Aside from using the plant canopy, another approach is to use soil, or substrate, water content. Dabach et al. (2016) used automated irrigation that use soil moisture sensors to trigger irrigation based on a threshold value. In one study, the threshold value was set based on the water consumption and reduced water usage up to 33% for greenhouse rooms at different temperature set-points (Rodriguez-Ortega et al., 2017). However, while the threshold can lead to lower water consumption, an inaccurate threshold could lead to under- and overwatering.

Pardossi et al. (2009) emphasized the importance of setting the proper threshold for triggering watering events. One study found that the lowest frequency of watering events was observed for the lowest set-point treatment (Montesano et al., 2018). There is a sacrifice in accuracy when using low-cost sensors, which could lead to delays in triggering. Ideally, confidence in the sensor output would mean that the sensors would trigger a watering event at the right time regardless of the threshold. Romero et al. (2012) used the same threshold value for
consistent watering. The threshold value can be arbitrary with uncalibrated sensors and the lower cost of capacitive sensors can lead to lower reliability on raw readings, which was why this study investigated a new method for controlling irrigation.

Predictive models can use different watering parameters to control irrigation. Prenger et al. (2005) used the crop water stress index in combination with evapotranspiration to create a model for irrigation control. Another study by Pawlowski et al. (2017) developed a predictive model used crop transpiration and water content to determine how much and when to water tomatoes. The combination of sensors and expert observation are needed to ensure that not only are the sensors reflecting changes in substrate moisture, but also, triggering reflects the changes in plant stages as well.

**Irrigation Scheduling**

Substrate moisture sensors are used to control irrigation scheduling, but how does sensor-based technology impact plant growth and development? Different methods led to conflicting results of the impact of irrigation scheduling on yield and growth of different crops. There was a significant difference between grain yields with lower yields for deficit irrigation methods but concluded that partial root zone irrigation produced greater root biomass for genotypes with the highest yields (Kaman et al., 2011). El-Wahed & Ali (2013) found that irrigation system, water applied during single irrigation event and mulching positively influenced grain properties, including grain yield. However, another study concluded that quality and growth of basil and bellflowers was not affected by variations in substrate water content due to microclimate differences (Henderson et al., 2018). A comparison of sensor- and timer-based irrigation scheduling in the greenhouse discovered that there was not a significant difference in the quality
of plants between the two methods (Wheeler et al., 2018). The contradicting literature led to the evaluation of sensor-based and expert-based irrigation scheduling in this study.

There have been studies that have investigated full automation of irrigation. Nawandar & Satpute (2019) proposed a fully automatic irrigation control system by using evapotranspiration estimates and a parameter-based conditions, including soil water content, based on a neural network. Field studies used water-balance algorithm and feedback from 15 Decagon 10HS real-time soil moisture sensors and expert insight over two years to develop a fully automated irrigation scheduling system (Millán et al., 2019). However, despite full automation, an expert must ensure the irrigation system and substrate moisture sensors are operating properly. The aim of this research was to provide ways to control irrigation in a commercial greenhouse with limited human intervention.

A two-year case study of sensor-based irrigation implementation was done by Wheeler et al. (2018). The greenhouse increased sensor-based irrigation scheduling for up to 1800 poinsettias and 900 geraniums by the end of the second year. The authors acknowledged that there was higher water usage for sensor-based irrigation based on the irrigation threshold set by the employees resulting in higher substrate water contents. As opposed to setting the threshold initially, the employees tended to increase the sensor threshold over time, which is normally how the employees approach timer-based irrigation control. The authors interviewed greenhouse owners and found that cost is a limiting factor for adoption of sensor technologies and reallocation of labor is one of the main benefits for sensor-based irrigation control. The proposed work focuses on the use of low-cost sensors, which will require initial installation cost, but labor costs should be able to be reduced long-term (Wheeler et al., 2018). Development of decision-making methods for determining the threshold value and irrigation timing would be useful for
training of employees, which could lead to widespread adoption of substrate sensing technology in the future.

In summary, there is a need for execution of low-cost sensing technology in commercial greenhouses. There are open questions on how to reliably identify how many sensors are needed in a zone and how watering events should be triggered for large-scale irrigation control. Comprehensive impacts of automated scheduling with sensors and traditional timer scheduling with expert insight need to be compared to fully understand the effectiveness prior to large-scale implementation.
References


Chapter 2 - Design and implementation of low-cost open-source soil moisture sensor for controlled environments

Introduction

The act of watering a potted plant seems like a trivial task. At scale, however, watering has been identified as one of the most complex and time-consuming activities in a high-throughput greenhouse setting. While overwatering is detrimental to plant growth and development, greenhouse employees were taught or have incorrectly learned this practice.

Teaching timing and technique for watering has been identified as the most important training need for greenhouse employees (Raudales, 2019). Greenhouses have been implementing automatic irrigation control systems, which have the potential to produce higher quality plants and to avoid wasting water (Ferrarezi et al., 2015; Rowe, 2010). Soil, or substrate, moisture sensing is an enabling technology necessary to automate irrigation systems. Soil moisture sensors provide non-destructive, accurate, real-time data for determining plant watering needs (Dobriyal et al., 2012; Kargas & Soulis, 2012). Due to the potential movement of plants in a greenhouse room and the number of sensors needed for large-scale production, wired sensors are not always practical for automatic irrigation control. For scalability, sensors need to be to inexpensive and work within the greenhouse infrastructure.

The main difference between resistive and capacitive soil moisture sensors are the method for converting substrate dielectric properties into proxy values to estimate VWC. Resistive sensors consisted of two probes that were inserted into the soil profile. Soil between the probes functioned as a variable resistive load value across which an analog voltage was measured. Measured voltage drop across the soil was correlated to substrate VWC (Saleh et al., 2016). Capacitive sensors measure the capacitance, instead of the resistance, within the soil.
These sensors have a pair of electrodes that measure changes in the oscillating frequency to find the dielectric of the soil and the amount time required to charge the capacitor. The change in charge time directly correlates to change in soil water content (Dobriyal et al., 2012). In comparison to resistive sensors, the insulation of the capacitive probe reduces the effect of ionic concentration on the measurement (Oates et al., 2017). In both cases, the soil, or substrate, acts as the dielectric constant, which is based on ratio of electric permeability between a material and air. Resistive and capacitive soil moisture sensors required additional soil-specific and temperature-specific calibrations (Kargas & Soulis, 2012; S.U., et al., 2014). Some advantages of capacitive sensors are simple installation, soil-specific accuracy, and increased sensitivity (Chakraborty et al., 2019). However, there are still challenges associated with using capacitive sensors to control irrigation.

Capacitive substrate moisture sensors are one type of low-cost sensor that could be used for greenhouse applications due to its low cost. Capacitive sensors measure the apparent dielectric permittivity, instead of apparent resistance, within the soil. Topp et al. (1980) found that an increase in volumetric water content led to an increase in the dielectric constant. Thus, a higher raw output would indicate a higher dielectric constant. There have been many prototypes that have been developed and tested to determine accuracy and reliability of measurements. Another prototype developed by Nagahage et al. (2019) also found sensor-to-sensor variability based on the coefficient of variation values. Jorapur et al. (2015) developed a low-cost heat-pulse dual-probe soil moisture sensor that used solar and lithium batteries to power the sensor, which survived 3.6 days on solar power before needing to be recharged. However, another study using wireless sensor networks discovered that solar radiation affected the reliability of their sensors (Ferentinos et al., 2017). One field-scale study used solar-powered technology with sensors,
including soil water content sensor, communication module, and datalogger to control irrigation (Sun et al., 2009). Aside from solar-powered systems, there are some considerations that could affect sensor measurement. Some of the conditions that can impact sensor use in identical soils are weather, irrigation method, vegetation, and calibration (Alhammadi et al., 2017). Andrade-Sanchez et al. (2004) concluded that their device was influenced by changes in soil moisture, salinity, texture, and temperature.

In addition to the type of soil, soil temperature and salinity within the soil was found to affect the measurement of capacitive soil moisture sensors (Zhang et al., 2011). Comparison of two capacitive-type Hydra SDI-12 and Decagon 5TM sensors to a CS616 TDR sensor concluded that Hydra capacitive probes were preferred due to lower RMSE and higher $R^2$ values between actual and sensor-based VWC (Sharma et al., 2017). An accuracy comparison of TiendaTec E-Best YL-69 prototype to Decagon 5TE and EC-5 soil moisture sensors concluded that there was a similar performance between the different sensors (Jiménez et al., 2019). After developing a prototype, the sensor was compared to other commercial capacitive sensors to determine its accuracy and reliability.

The complexity of the accounting for all the variables affecting sensor measurement can make it difficult to capture real-world, in-situ accuracy. A study by van Iersel et al. (2013) described that sensor accuracy in large-scale applications was sufficient if there was measurement repeatability and resolution. Newly developed sensors can be compared against existing widely adopted commercial sensors to determine accuracy. Millán et al. (2019) defined sensor reliability based on the reported data’s quality. Reliability in the proposed study determined the quality by evaluating the number of missing data for two types of substrate
moisture sensors. Before increasing manufacturing, testing of accuracy and reliability will be required to ensure prototype performance.

The objectives of this study was to (1) develop a low-cost open-source wireless substrate moisture sensor, (2) evaluate sensor-to-sensor variability, and (3) compare the accuracy and reliability of the prototype to an off-the-shelf sensors. The sensor prototype was conceptualized, designed, and fabricated before undergoing performance testing. Two initial testing experiments were performed with the sensor prototype to evaluate the differences in sensor readings based on the incremental addition of water to substrate and the comparison of sensor outputs using a more practical in-situ greenhouse implementation. The accuracy experiment compared the newly developed prototype to the commercial Decagon EC-5 sensor based on the percentage of the maximum sensor measurement. For reliability, an experimental dataset was analyzed to ascertain the percentage of missing readings for the sensor prototype and commercial Miflora low-cost sensors.

Methods

WolfPAWWS Prototype Design

A prototype sensor, called the Wolf Precision Agriculture Wireless Water Sensor (WolfPAWWS), seen in Figure 2.1, was created by combining a printed circuit board (PCB)-based capacitive volumetric water content (VWC) sensor and a commercial ESP8266 Wi-Fi-enabled communications module (multiple manufacturers, ESP8266). The probe was incorporated within the PCB with a single prong containing three coplanar plates. This design was similar arrangement to open-source and commercial capacitive sensors, such as the DFRobot sensor (Shanghai, China). An electronic design consultant was hired to facilitate hardware design. Prototypes were manufactured by MacroFab, Inc. (Houston, TX). The target
price per device was $10, but the price of a single sensor was $25 (Updated: March 2020), including component overage. A charging and programming dock was created and manufactured in addition to the sensor (Figure 2.1). The charging dock connected to the sensor platform in any orientation, which prevented damage to the sensor. The dock featured status indicator LEDs for diagnostic functions, including battery charge. A single dock serviced multiple sensors, which minimized the number of expensive connectors.

![Figure 2.1. Capacitive soil moisture sensor prototype, called the Wolf Precision Agriculture Water Wireless Sensor (PAWWS) attached to a custom charging and programming dock.](image)

The prototype sensors featured a hardware deep sleep circuit, which automatically triggered sampling at a fixed interval of 15 minutes. The deep sleep function maximized battery life by eliminating background microprocessor processes. The sensor prototypes used a rechargeable battery, which eliminated the need to stock and dispose of single-use batteries. Lithium iron phosphate battery chemistry was selected to reduce cost but expected to still provide a 4-8 week battery life. A clear conformal coating spray (Swift Response, Weston, FL)
was used twice on each sensor, which protected electrical components. The sensing portion was covered to prevent measurement errors due to the coating.

**Figure 2.2** describes the basic circuit design for the measurement. R1 and R2 formed a reference voltage (VREF) for the comparator circuit by creating a voltage divider between the supply voltage and ground. The operational amplifier, seen as U2 in **Figure 2.2** acted as a linear comparator, which recorded the charge time required for the soil moisture sensor capacitor to reach half of the supply voltage. Since the linear comparator used the supply voltage as a reference, the measurement was not influenced by the battery life. With a higher dielectric constant, the charge time would be longer for the capacitor, ideally a linear relationship. A lower dielectric would be associated with a drier substrate. The code developed for measuring the raw output of the sensors was based on the number of loop counts that were required to charge the capacitor. For additional information about the prototype, see Appendix.

![Diagram of the soil moisture measurement circuit for the WolfPAWWS (Precision Agriculture Water Wireless Sensor) capacitive prototype. The operational amplifier acted as a linear comparator between the supply voltage and the charge time required to reach half of the supply voltage.](image)

Figure 2.2. Diagram of the soil moisture measurement circuit for the WolfPAWWS (Precision Agriculture Water Wireless Sensor) capacitive prototype. The operational amplifier acted as a linear comparator between the supply voltage and the charge time required to reach half of the supply voltage.
WolfPAWWS Prototype Design Assessment

Benchtop Calibration. This experiment was meant to establish the relationship between the raw readings of the WolfPAWWS and VWC. The goal was to create a range of raw reading values that could allow for a VWC calibration across the entire range of expected values.

A custom peat:perlite substrate, like Farfard 3B (Sun Gro Horticulture, Agawam, MA), was separated into tins and oven-dried overnight at 105 °F. The substrate was re-equilibrated by combining the dried substrate together. A compaction process was used to fill in PVC columns. Substrate was loosely added to the substrate and a straight edge was used to remove excess. Tapping the column filled the void space and substrate was repeatedly added until the compacted substrate was flush with the column edge. This compaction process was repeated for the initial calculations and benchtop calibration. After substrate compaction, water was slowly added to the column to allow time for substrate uptake until saturation. There was a five-minute acclimation time, which ensured full saturation before the drainage of excess water. At this point, the substrate was at holding capacity with no free water in the substrate-water matrix. The recorded weights for the oven-dried substrate represented 0 % moisture and the substrate at holding capacity represented 100 % moisture. These substrate weights were converted to volume (1 g = 1 mL assumption) to calculate the total water needed to reach field capacity in the column. With this known volume, another experiment was designed to determine the amount of variability between individual WolfPAWWS.

After calculating the incremental water to be added to each sample, substrate was oven-dried and re-equilibrated according to the same procedure previously mentioned. Oven-dried substrate, by weight, was put into clear sealable bags. Water was added to each bag, from 10 – 90 %, according to the volume conversion found in the initial calculations. The substrate
was able to acclimate overnight within the bags. Substrate was compacted into the columns and two pieces of Parafilm were placed over the top of each column immediately due to evaporation. Three sensors were randomly assigned to each column (Figure 2.3). The first few readings were neglected to allow for the sensor to acclimate to the substrate. There were three sensors for each increment and 48-49 datapoints per sensor, except for one sensor in the 10% group with 38 points, which was roughly 12 h of reading values.

![Figure 2.3. Incremental benchtop calibration experimental setup for water addition from 10 to 90% with 3 WolfPAWWS in each column.](image)

**Greenhouse in-situ Relative Wetness.** Wild-type maize (*Zea mays* sp) was grown in a commercial greenhouse room at Corteva Agriscience, formerly DuPont Pioneer, in Johnston, Iowa. The orientation of the zones was East-West and the greenhouse room was around 232 m² (2500 ft²). The commercial monitoring system used sensors to measure relative humidity, air temperature, and photosynthetic active radiation (PAR). Two zones next to the cooling cell were used for the experiment.

Sensor-based irrigation scheduling was determined by VWC data generated by a capacitive soil moisture sensor Flower Power (Parrot Inc., China, Model no. PF900001), referred to as Parrot in this study. Each zone contained 50 pots with one WolfPAWWS and Parrot sensor randomly assigned to alternating pots for a total of 25 of each sensor type per zone. Pots were
watered to field capacity at the beginning of the study. The VWC of the substrate naturally decreased over time due to plant uptake and environmental evaporation loss. The sensors estimated VWC, expressed as a percentage, every 30 minutes. The facility pre-determined threshold value was set at 17% VWC for both zones. The threshold value was based on the median of five Parrot sensors spatially distributed in each zone. The data analysis only included the first dry-down cycle, which ended once the substrate level reached the lowest point, or threshold, before a subsequent watering event.

**Commercial Sensor Comparison.** WolfPAWWS prototypes were compared to the higher accuracy EC-5 sensors (Decagon Devices Inc., Pullman, WA). A peat:perlite substrate (Fafard 3B, Sun Gro Horticulture, Agawam, MA) mixture was used in 20 cm (8 in) diameter pots. All pots were mounded until there was excess over the lip of the pot. A straight edge removed excess substrate to be flush with the top of the pot. All pots were equally compacted using a press to a depth of 0.025 m (1 in) from the top of the pot.

The EC-5 sensors were placed in the center of each pot, for a total of five pots. Then, water was slowly added to each pot. For the initial watering, each pot received 300 ml water in 15-min intervals for 4 cycles. The saturated pots equilibrated for 12 hours before the second watering. Each pot received an additional 500 ml water in 10-min intervals for 3 cycles. It is assumed that pots were at field capacity after the second watering, which was represented by drainage. WolfPAWWS were added after water addition since they are water-resistant. Two WolfPAWWS were added to four of the pots, with the last pot only containing the EC-5 sensor. Decagon specified that the diameter of influence for the EC-5 sensors was 2.5 in. WolfPAWWS were placed in roughly the same place on either side of pot (Figure 2.4).
Data collection took place from 04 to 11 February 2020. For comparison between the two raw outputs for the sensor types, there was a comparison of the coefficient of variation. Analysis of variance and Tukey multiple comparison determined statistical significance (p < 0.05).

**Reliability**

The WolfPAWWS were compared to Parrots and Miflora (Xiaomi, China, Model no. HHCCJCY01HHCC), referenced as Miflora for this study, off-the-shelf sensors, with all sensors measuring substrate moisture based on capacitance.

Sensors were spatially distributed for two zones in the center of a greenhouse room. Using the three sensor types and two positions, either left or right of the corn stalk seen in Figure 2.5, there were six total sensor combinations. For each zone, these six combinations were randomly assigned without replacement for each block. This study used a randomized block design with spatial location acting as the treatment.
Each zone contained 16 of each sensor type, with half of the sensors to the left and the other half to the right of the plant. For example, the WolfPAWWS sensor is on the left and the Parrot sensor is on the right of the plant stalk as seen in Figure 2.5. All Miflora sensors to the left of the plant were responsible for the watering decision to serve as a point of comparison to sensors to the right of the plant. Since WolfPAWWS send measurements at 15-min increments and Miflora at 30-min increments, the analysis compared the percentage of daily missing readings from each sensor type for both zones.

![Figure 2.5. Location of sensors in relation to the corn stalk: WolfPAWWS (left) and Parrot sensor (right).](image)

For all experiments, data was imported and analyzed with R statistical software (R Foundation for Statistical Computing, Vienna, Austria) for tabular and graphical visualization.

**Results & Discussion**

**WolfPAWWS Prototype Design Assessment**

**Benchtop Calibration.** The expected outcome was for there to be a linear relationship between the mean of the raw output readings and the amount of water added to each column (Figure 2.6).
Range of raw readings was highly variable among sensors. The largest spread was for sensors in the 10%, 50%, and 80% groups, but a closer look at the data showed that the three sensors with the highest average raw outputs were from each of these groups. These results demonstrated that all sensors would need to be individually calibrated, or an equation would need to be developed, before being deployed in the greenhouse (Bogena et al., 2017). According to Dabach et al. (2016), higher measurement variability means more devices are needed for quantitative evaluation. However, if sensors still followed the same relative trend, there could be a way to compare various raw sensor readings to each other by normalizing the values. This 12-h study demonstrated low standard deviation between the raw readings for each individual sensor with 21 out of the 24 sensors with standard deviations below 80 counts. This small variability between individual sensor raw readings led to the implementation of a greenhouse *in situ*
experiment, which attempted to normalize the raw reading outputs without individual sensor calibration.

**Greenhouse in-situ Relative Wetness.** Since individual sensor calibration would not be easily scalable for large-scale production, this experiment was meant to evaluate whether the sensors could be standardized directly in the greenhouse based on the two extremes (before irrigation and field capacity), similar to the incremental calibration (Figure 2.7 & Figure 2.8). Both figures represent spatial distribution of sensors across two zones, A and B. Some of the sensors did not respond due to battery issues. Some of the sensors exhibited faulty measurements and were excluded from the figures. The raw reading output values from the WolfPAWWS for both zones generally follow two distinct trends with values either around 15000 or around 45000 counts. This clustering could be due to two different batches of sensors, which could have slightly different components or manufacturing. The groupings of raw outputs are promising since instead of calibrating individual sensors, two calibration curves could be used based on the raw output.
Figure 2.7. WolfPAWWS raw output in zone A for *in-situ* greenhouse experiment on 27-28 June 2019.

Figure 2.8. WolfPAWWS raw output in zone B for *in-situ* greenhouse experiment on 27-28 June 2019.
All sensors demonstrated an increase in output reading after the watering event, followed by a mostly stagnant line. The trend is expected to stay static since the time shown in the figures is so short. WolfPAWWS sensor 58 slowly continues to increase after the watering event, which could be due to slow, continual amount of water reaching the probe over time. Nawandar & Satpute (2019) described how positioning is important to avoid under- and over-estimation of soil water moisture. The measurement direction of the sensor probe within the pots potentially influenced some of these trends since the greenhouse operated with drip irrigation. The WolfPAWWS measurement plates are on one side of the sensor probe. The positioning of the sensors in this study had the capacitance-measuring side of the probe faced away from the drip tape, which meant the plates were only in contact with the drier substrate. By shifting the probe to be inserted perpendicular to the drip tape, the capacitance plates may more rapidly reflect changes in the substrate water content. Over time, the raw outputs for the sensors tend to increase as opposed to decrease, which could be due to the PCB insulating material absorbing water leading to a drift in the readings, which has been documented in some materials. Harris and Stonard (2018) designed a similar prototype and identified that the prototype had reduced sensitivity between the permanent wilting point and before field capacity. Greater investigation will be required to determine which of these factors impacted the raw sensor measurements.

**Commercial Sensor Comparison.** ANOVA results demonstrated that there were significant differences (p < 0.05) in reading values between the EC-5 sensors. This analysis was supported by looking at the differences among the EC-5 sensors (Figure 2.9). Ideally, all pots would have similar moisture contents due to the addition of the same amount of water and the drainage of the substrate. While the EC-5 sensors follow similar trends over time, there was still measurement variability among individual sensors with 520 considerably lower than the others.
Rosenbaum et al. (2009) found that variability between sensors between EC-5 sensors was very large in comparison to measurement noise. The sensors could have become loose, which would have limited the contact of the sensors with the substrate leading to differences in measurement. Since the control (517C) was statistically different from the others, there is a lower likelihood that the addition of the WolfPAWWS impacted the EC-5 measurements. Since compaction could have been problematic, additional testing will be needed to determine if the sensors can be more standardized for comparison to the WolfPAWWS.

Figure 2.9. Measurement variability in raw sensor output among the EC-5 sensors in different pots for accuracy comparison study.
The differences in the EC-5 sensors led to consideration of sensors within individual pots. All percent of the maximum readings for EC-5 and WolfPAWWS were significantly different, except for EC-5 516 and WolfPAWWS 58. The WolfPAWWS dry-down curves were not as linear and experienced greater measurement noise than the EC-5 sensors. Qu et al. (2014) compared a prototype to Decagon EC-5 sensors and found that the sensor output voltage was linear for both sensor types and that the proposed sensor was more sensitive in various soils. In addition to the significant differences in the sensor-sensor variability, there is roughly 10% range between the EC-5 sensors and the WolfPAWWS based on the percent of the maximum reading. González-Teruel et al. (2019) compared a soil moisture sensor prototype to Decagon ECH2O commercial sensors and found that the accuracy was lower, but the authors described how the sacrifice in accuracy was related to lower cost components of the prototype. Additional testing using a more precise built-in counter for measuring time to charge the capacitor could reduce the amount of sensor-sensor variability.

For individual sensors, the coefficient of variation (CV) of the repeated raw outputs was similar within each sensor type. CV values for the EC-5 sensors was around 3% and 6%. The CV of raw outputs for the WolfPAWWS were around 29-30% with one outlier (sensor 21) at 54%. The higher CV values for the WolfPAWWS raw sensor output suggested that there was greater variability than for the EC-5 sensors. A similar study by Nagahage et al. (2019) calculated CV values for a low-cost prototype and found under 0.1% difference in raw output, and a significant difference between the individual raw outputs for all the sensors in the same treatment group. Another study found average CV values of 4.6% and 5.9% for Decagon 10HS and 5TE when varying VWC (Vaz et al., 2013). The authors suggested that one of the reasons for differences in
the CV values was due to sensor type sensitivity to air pockets within the soil. Fine-tuning the sensor design could improve the sensor-to-sensor variability for future studies.

Reliability

Due to battery issues for the WolfPAWWS, the reliability data analysis only explores one week (17 – 26 August 2019) of the experiment duration. One aspect of reliability for this study was to determine the number of missing readings for each type of sensor (Table 2.1). For both zones, the WolfPAWWS had the lowest daily average percentages of missing data points with 0.3% and 0.6% in zone A and B, respectively. The Miflora sensors in zone B had the highest daily average percentage with 24% missing data points while zone A only had roughly 9% missing data points, on average. The highest percentage of missing data points for both Miflora zones was on 21 August 2019. Aside from 17 August 2019, the second highest day for both WolfPAWWS zones was on 23 August 2019, which could potentially be related to connecting to Wi-Fi.

Table 2.1. Comparison of daily total percentage of missing readings for Miflora and WolfPAWWS prototype sensors

<table>
<thead>
<tr>
<th>Date</th>
<th>Zone A Miflora % Missing</th>
<th>Zone A PAWWS % Missing</th>
<th>Zone B Miflora % Missing</th>
<th>Zone B PAWWS % Missing</th>
</tr>
</thead>
<tbody>
<tr>
<td>8/17/2019</td>
<td>12.50</td>
<td>2.98</td>
<td>17.19</td>
<td>9.72</td>
</tr>
<tr>
<td>8/18/2019</td>
<td>8.07</td>
<td>0.00</td>
<td>16.41</td>
<td>0.11</td>
</tr>
<tr>
<td>8/19/2019</td>
<td>7.42</td>
<td>0.15</td>
<td>22.01</td>
<td>0.00</td>
</tr>
<tr>
<td>8/20/2019</td>
<td>6.38</td>
<td>0.00</td>
<td>22.79</td>
<td>0.69</td>
</tr>
<tr>
<td>8/21/2019</td>
<td>26.30</td>
<td>0.00</td>
<td>38.15</td>
<td>0.00</td>
</tr>
<tr>
<td>8/22/2019</td>
<td>6.74</td>
<td>0.17</td>
<td>23.56</td>
<td>0.00</td>
</tr>
<tr>
<td>8/23/2019</td>
<td>8.19</td>
<td>1.89</td>
<td>23.29</td>
<td>1.87</td>
</tr>
<tr>
<td>8/24/2019</td>
<td>6.77</td>
<td>0.17</td>
<td>23.44</td>
<td>0.17</td>
</tr>
<tr>
<td>8/25/2019</td>
<td>6.87</td>
<td>0.00</td>
<td>22.19</td>
<td>0.00</td>
</tr>
<tr>
<td>8/26/2019</td>
<td>5.86</td>
<td>0.00</td>
<td>25.78</td>
<td>0.00</td>
</tr>
<tr>
<td>Average</td>
<td><strong>9.27</strong></td>
<td><strong>0.34</strong></td>
<td><strong>23.99</strong></td>
<td><strong>0.60</strong></td>
</tr>
</tbody>
</table>
While both sensor types had short timeframes where none of the sensors were responsive, one possible reason for the difference is the type of connection. The Miflora sensors connect to Bluetooth while the WolfPAWWS connect to Wi-Fi to send measurements. Bluetooth is a short-distance technology, which can be a limiting factor in the greenhouse. Ruiz-Garcia et al. (2009) stated that Bluetooth would not be useful in low power situations due to the amount of energy it takes to turn off and on. Also, the sensors only have a certain amount of time to send a measurement before the Raspberry Pi continues to the next sensor. The hard-wired deep sleep circuit for the WolfPAWWS makes it more difficult to miss measurements unless Wi-Fi connection is lost.

This reliability study found that the WolfPAWWS had a lower amount of missing readings in comparison to the Miflora sensors. However, both the Miflora and PAWWS generally missed 1-2 readings at a time, which meant 1-1.5 h and 0.5-0.75 h between measurements, respectively. One of the patterns with the Miflora sensors was missing one reading, sending a reading, and then, missing another reading, which means 1 h in between readings over a 2 h timeframe. Depending on when the sensor types miss sending readings, the effect of the reliability should be minimal, but the irrigation controller would be delayed in watering with many consecutive missing readings or excessive erroneous measurements. Most of the Miflora sensors in both zones for this dataset triggered watering events between 2 – 9 pm, which would be critical times for missing data. For the Miflora sensors that were delayed in sending measurements from 9 am – 1 pm on the 21 August, the controller could have been affected in delaying triggering due to missing data. In future analysis, determination of critical irrigation times would be necessary to ensure closer monitoring of sensors during initial scale up of sensor-based irrigation. Reliability should be considered when determining how many sensors
are required for triggering watering events. Before scaling up sensor implementation, one important consideration would be to ensure the number of sensors and the decision-making method are sufficient for triggering a watering during critical times prior to the permanent wilting point for the crop.

**Conclusion**

A new low-cost wireless sensor prototype, called WolfPAWWS, was developed to measure changes in substrate moisture content within the greenhouse. WolfPAWWS used Wi-Fi while the Miflora and Parrot sensors worked on Bluetooth. Manufacturing of Parrots was discontinued so this analysis only used data from Miflora sensors. Incremental benchtop calibration demonstrated that there was a large amount of variability in raw output readings, which could be due to measurement sensitivity. The small variability among individual sensors led to the *in-situ* greenhouse experiment that would use lowest and highest raw readings to normalize the differences in measurement among sensors. The *in-situ* results found that there were two groupings of raw outputs, but similar trends, which could be due to the sensors coming from different manufacturing batches. It was later discovered that the code could be improved but was not able to be implemented in experimentation. The new method would use the internal clock counter built-in to the ESP8266 Wi-Fi chip. The orientation of the sensor probe potentially contributed to the raw output for the WolfPAWWS, which requires more investigation in the future.

There was a significant difference between individual EC-5 sensors. Further analysis discovered that the EC-5 measurements followed a similar trend but there was variability in actual values. Comparison of percent of the maximum readings for the two sensor types in individual pots found that all sensors were significantly different from each other, apart from 516
and 58 in pot 5. Lower compaction rates and the void space in the mixture could have contributed to this variation in measurement. CV values of the repeated raw outputs was similar within each sensor type with EC-5 sensors around 3 or 6% and WolfPAWWS (except 21) roughly 29-30%. Refining the sensor design and improving the measurement using the built-in counter could potentially increase the accuracy of the sensor. Aside from battery issues with the WolfPAWWS due to the charger indicator LEDs, the WolfPAWWS were more reliable in sending measurements than the Miflora. The total missing readings from WolfPAWWS was 0.3 and 0.6% while Miflora were missing 9 and 24% for zones A and B, respectively. The hardwired WolfPAWWS deep sleep circuit led to the reliability of the WolfPAWWS. Miflora sensors operated on Bluetooth and only had a limited timeframe to send measurements, which contributed to lower reliability. While additional design modifications and testing is required for the WolfPAWWS, this device is an economically viable option for potential greenhouse implementation in the future.
References


Chapter 3 - Decision making methodology for irrigation scheduling in controlled environments

Introduction

Large-scale implementation of sensor-based irrigation is a high initial investment, but increased control of watering with sensors can enhance plant quality while reducing water usage (Evett et al., 2012). Sensors provide more individualized control of zones within a greenhouse, which could account for microclimate variability and changes in plant water demand by growth stage, which would allow for more specialized irrigation control. When implementing sensors to assist in irrigation decision making, there is a balance that must be struck between the quality of data that can be generated and then become actionable versus management of the sheer volume of extra information from adding more sensors (van Iersel et al., 2013). Management of sensors on a large-scale can be challenging due to the logistics for the number of sensors required to provide power and connectivity along with the technical issues associated with scale-up. Therefore, an informed methodology for selecting the number of sensors needed and how to best trigger irrigation from those sensors is needed.

While there have been multiple studies on predictive modeling and irrigation control systems using sensors, there is still the question of defining what a good watering decision looks like and what are the metrics used to find optimal watering (Autovino et al., 2018; Goumopoulos et al., 2014; Millán et al., 2019; Nawandar & Satpute, 2019; Pawlowski et al., 2017; Prenger et al., 2005; Romero et al., 2012; Wheeler et al., 2018). Most previously published studies do not explain why the number of sensors were chosen or the method for setting the threshold set-point for irrigation. The number of sensors used in previous work are most likely limited for economic reasons to smaller scale experiments.
Low-cost sensors can be used to increase data volume for irrigation control. With low-cost typically comes lower sensor performance which could contribute to incorrect triggering due to measurement variability and error. Calibration can potentially improve sensors performance, but calibration at scale is challenging and may be time or cost prohibitive at commercial scale. Calibration is one of the most important factors that must be investigated before scaling up sensor-based irrigation (van Iersel et al., 2013). According to Kizito et al. (2008), large-scale use of soil moisture sensors must find a way to simplify calibration. Methods to implement low-cost sensors with minimal formal calibration could bridge the gap to allow more wide-spread sensor-based irrigation control.

The main reasons for setting a proper trigger threshold is to optimize irrigation. Rodriguez-Ortega et al. (2017) established threshold values based on water consumption which reduced water usage by 16% - 33% at 32°C and 1% - 20% at 26°C for tomato plants. Identification of an optimal threshold could not only prevent overwatering, but help to produce healthier plants (Pardossi et al., 2009). When methods for setting a threshold are discussed, the typical approach is a weighted average of normalized soil water content sensor values to determine the daily irrigation scheduling (Millán et al., 2019). To address challenges associated with large-scale sensor implementation, the goal of this study was to evaluate management techniques using uncalibrated low-cost substrate moisture sensors to improve automated irrigation. The objectives of this study were to (1) find the number of uncalibrated sensors needed in one zone for irrigation control and (2) provide an alternative solution to using a threshold value with uncalibrated sensors.
Material and Methods

Experimental Setup

This experiment took place from 31 July to 27 August 2019 in a commercial greenhouse (Corteva Agrisciences, Johnston, IA). Wild-type maize (*Zea mays* sp.) was grown in a custom peat-perlite mixture, like Fafard 3B (Sun Gro Horticulture, Agawam, MA) in 20 cm (8 in) diameter containers. Plants were moved to the greenhouse room and arranged in zones of 50 pots. Two of the zones in the center of the room, referred to as zone A and B, were instrumented. Eight Miflora (Xiaomi, China, Model no. HHCCJCY01HHCC), called Miflora in this study, soil moisture sensors were responsible for triggering watering based on measured volumetric water content (VWC). Measurements were taken in 30-min increments.

At the beginning of the experiment, plants were not watered until symptoms of mild drought stress were identified by greenhouse staff. A threshold value based on the median of the most recent eight readings before the room manager decided to water was recorded and used as the minimum VWC value for each zone. Setting the threshold value based on eight readings meant that the watering decision was based on one reading from each sensor in the target zone. Based on this method, the resulting VWC threshold value was set at 21% for zone A and 17% for zone B.

Sensors were installed in the pots on 31 July and the irrigation controller was activated at the first watering event. The dataset timeframe was from 01-27 August. The original date and time were padded to the nearest 30-m interval to align timepoints for analysis. This experimental dataset was used for both analyses described below.
**Number of Sensors Analysis**

Zones A and B were limited to a maximum number of eight available VWC sensors per zone. An analysis was performed on each zone to determine if reducing the number of sensors would result in a different watering decision compared to eight sensors. The median VWC was calculated using all eight sensors at each 30-min time step served as a baseline. The calculated median VWC was compared to the threshold VWC for each zone. When the median VWC was at or below the threshold VWC, the timestep was assigned a value of 1 as an indication of the occurrence of a watering event. If the median VWC was above threshold VWC, then the timestep was assigned a value of 0 to indicate that a watering event would not occur. The same calculation process was repeated, but there was a reduction in the number of sensors used to calculate the median VWC. For example, at each timestep, seven sensors were randomly selected to calculate the median, compared to the zone’s threshold VWC, and assigned the binary indicator for its watering status. The random selection and watering decision process was repeated for one to seven sensors. For each sensor count, 100 iterations were performed for all data points during the study period. Binary contingency tables compared the agreement between the eight-sensor baseline and the simulated reduced number of sensors to calculate the kappa coefficient (Cohen, 1960).

**Threshold Method Analysis**

The dataset was divided into watering cycles, which started one hour after the previous watering event and stopped at the subsequent trigger event. Due to a software update in the irrigation controller which led to over-target watering, the first few cycles were excluded from the analysis. Median VWC values calculated for the waterlogs during the experiment were used to determine the timeframes for the cycles. Zone A had nine watering cycles from 9-25 August
2019 and zone B had eight watering cycles from 9-27 August 2019. Linear regression models were used to determine the amount of variation between consecutive watering cycles in each zone. The explanatory variable was the timepoint, in 30-min increments, starting at 0 min for each cycle. The response variable was the median VWC (%) value, which was based on the most recent eight VWC readings.

**Results & Discussion**

**Number of Sensors Analysis**

The kappa coefficient was used to determine if the number of sensors per zone could be reduced for large-scale irrigation management while still having similar irrigation trigger events (Figure 3.1). Eight sensors were chosen as the baseline in the commercial environment because it was twice the amount currently used by the facility. The number of simulations for calculating the kappa coefficient was based on computing power and analysis run time. There was a noticeable difference between how zone A and zone B reacted to modifying the number of sensors. The agreement between all sensor counts and the eight-sensor baseline for both zones was statistically different from chance agreement at a 0.05 significance level. All kappa coefficients were positive, suggesting the likelihood for agreement was greater than random chance, but there was variability among reduced sensor counts and the baseline of eight sensors (Cohen, 1960).
Zone B exhibited the expected response in the kappa coefficient. A linear, incremental increase in agreement with the baseline of eight sensors with an increased sensor count. Zone A did, generally, experience greater agreement as the number of sensors increased toward eight sensors. The linear trend was not as strong as seen in Zone B. Landis & Koch (1977) suggested that a kappa coefficient in the range of 0.41 – 0.60 demonstrated moderate agreement and 0.61 – 0.80 demonstrated substantial agreement between the two raters. Another study found that kappa coefficients between 0.40 and 0.75 were fair agreement and exceeded random chance (Fleiss et al., 2003). With the Landis & Koch (1977) classification, six and seven sensors fall in the moderate agreement range in zone A whereas six and seven sensors fall in between moderate and substantial agreement in zone B. The relative decrease in agreement between eight and six sensors, even for zone A in the moderate agreement range, would not be expected to produce a meaningful reduction in sensor outcomes. Thus, for the number of sensors that were tested during this study, six should perform as well as eight sensors. The pertinence of these kappa
coefficient classifications should be evaluated based on the field of study. The kappa coefficient is contextual as demonstrated by the different classification ranges, so interpretation of hard values may not hold in all situations.

Daniels et al. (2012) found that six to ten Decagon 5TM sensors sufficed for different tree species, which represented 2-4% of the 250 trees per species involved in their study. This difference in the number of sensors could be related to the different watering needs of tree species as opposed to crops in a greenhouse or the total system errors of the sensors involved. The number of sensors could be potentially reduced from eight to six sensors (representing 12% of the zone population) based on the kappa coefficient results for drought-resistant crops, such as corn. However, corn is a harder crop, which means that a different sensor count could be required for other crops that are more susceptible to small changes in substrate water content. The described analysis technique has value as an approach to assess the impact of reduced numbers of low-cost sensors, but greater numbers of sensors than those available for testing may be needed to fully test the hypothesis.

**Threshold Method Analysis**

**Cyclical Irrigation.** Linear regression resulted in all cycles for both zones demonstrated how the rate of change in VWC varied between watering cycles (Table 3.1). The watering cycle durations became shorter over time, which indicated an increase in water uptake. Cycle 8 in zone A had the shortest cycle duration and the lowest $R^2$ value. Initial measurements from sensors during cycle 8 were lower, which could mean that the sensors did not reflect VWC or less water was delivered to plants, leading to lower readings. The $R^2$ values for both zones demonstrated that at least 83% of the variance in VWC was explained by the linear regression models. The high $R^2$ values indicated that linear regression was a good fit for the VWC data. The residual
error was higher for the watering cycles with faster water uptake, which was due to the greater
deviance of the steeper observed data from the linear prediction.

Table 3.1. Comparison of Linear Regression Models for Irrigation Watering Cycles

<table>
<thead>
<tr>
<th>Watering Cycle</th>
<th>Number of Timepoints</th>
<th>Cycle Duration (min)</th>
<th>Slope Coefficient Estimate (% Point)</th>
<th>(R^2)</th>
<th>Residual Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>104</td>
<td>3090</td>
<td>-0.41</td>
<td>0.92</td>
<td>1.13</td>
</tr>
<tr>
<td>2</td>
<td>100</td>
<td>2970</td>
<td>-0.36</td>
<td>0.94</td>
<td>0.83</td>
</tr>
<tr>
<td>3</td>
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<td>0.96</td>
<td>0.75</td>
</tr>
<tr>
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<td>0.94</td>
<td>0.84</td>
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<td>Zone B</td>
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<td>75</td>
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<td>-0.60</td>
<td>0.89</td>
<td>1.43</td>
</tr>
<tr>
<td>6</td>
<td>87</td>
<td>2580</td>
<td>-0.53</td>
<td>0.84</td>
<td>1.86</td>
</tr>
<tr>
<td>7</td>
<td>60</td>
<td>1770</td>
<td>-0.56</td>
<td>0.87</td>
<td>1.17</td>
</tr>
<tr>
<td>8</td>
<td>100</td>
<td>2970</td>
<td>-0.37</td>
<td>0.96</td>
<td>0.68</td>
</tr>
</tbody>
</table>

Despite the high model-fit for most of the watering cycles, the focus of this analysis was
to examine how the slopes change over time. Overall, the slopes were lower before cycle 6 in
zone A and cycle 5 in zone B, which indicated a slower rate of change in VWC. Over time, the
VWC drops at a quicker rate, which indicated the faster water uptake during the corn
reproductive stages. The initial thought was that the threshold value would only be initially set
since the threshold would account for faster uptake. However, due to the uncalibrated nature of
the raw sensor values, the threshold might have to be altered to reflect changes in growth stage
(Harris & Mapp, 1988). This threshold method might better account for changes in the substrate
moisture since the current method has a heavy reliance on the threshold value set by the
uncalibrated VWC sensor readings. The higher residual errors associated with zone B demonstrated the individualized difference between the two zones and how there was greater variability in sensor output for that zone. This zone-specific variability was one of the reasons for implementing sensor use in the greenhouse, which will account for microclimate changes in the greenhouse. More data collection for various zones will hopefully help to determine an overall slope value to ascertain the optimal time for triggering a watering event.

**Conclusion**

There are many challenges associated with scaling up the implementation of sensors for automatic triggering in commercial greenhouses. Regular individual calibration of substrate moisture sensors might not be plausible, which is why this study aimed to create a methodology framework for how and when to trigger watering events. The highest range of kappa coefficients in zone A were for six sensors from ~0.4 – 0.58 and ranged from ~0.6 – 0.66 for seven sensors in zone B. According to the Landis & Koch classification, these kappa coefficients coincided with the 40 – 60% range for moderate agreement with eight sensors. Further experimentation could test this hypothesis to validate whether the number of sensors could be reduced for large-scale greenhouse application. Daily monitoring of sensor performance will ensure sensors are replaced if they are sending erroneous measurements. Other types of plants could require a different number of sensors, but this analysis method could serve as a baseline for future studies.

Another challenge in setting up automated irrigation control related to the threshold, which triggers watering. However, aside from these cycles, the linear regression models explained at least 83% of the variability of median VWC values for the remaining watering cycles. Each zone exhibited changes in the slopes between subsequent watering cycles with the largest percentage drop happening when plants were taking in more water, which led to higher
frequency of watering or shorter durations between successive cycles. Based on this initial analysis, the use of the slope to trigger a watering event would need to be altered as plants approach the reproductive stages with a steeper slope to account for greater water uptake. While these results were promising, additional machine learning applications and more data collection will be needed prior to implementation of this method in a commercial greenhouse.
References


Introduction

Commercial greenhouses have been specifically designed to produce large quantities of crops that meet target quality goals, which are defined differently for each crop. Optimizing commercial greenhouse systems may result in more predictable, consistent production, which allows known production capacity and better resources planning. One greenhouse process which could benefit from optimization is watering.

Irrigation scheduling using sensors has been shown to improve plant quality and reduce water usage (Rodriguez-Ortega et al., 2017, Montesano et al., 2018). Automated irrigation control has demonstrated potential to prevent permanent damage to plants, which could affect yield and other plant performance measures (Autovino et al., 2018). Drought stress caused by under-watering has been well documented, but both under- and overwatering will affect crop performance. Overwatering has led to increased disease susceptibility and nutrient leaching (Pardossi et al., 2009).

There have been multiple studies on sensor-based irrigation control, but primary focus has been upon agricultural field implementation (Evett et al., 2012; Romero et al., 2012; El-Wahed & Ali, 2013). Sensor-based irrigation helped to manage unpredictable field conditions, but weather and environmental conditions still played a role in causing production environment variability within greenhouses (Ferentinos et al., 2017; Henderson et al., 2018). Sensor-measured substrate conditions within a greenhouse were shown to vary enough to influence irrigation needs (Rodriguez-Ortega et al., 2017). Soil moisture sensors have been used to account
for spatial variability, which allowed irrigation to address the watering needs for individual zones in a greenhouse (Hedley & Yule, 2009).

Broad implementation of substrate sensors in a commercial greenhouse could help manage variability and allow targeted water application - especially if correlated to environmental sensors or robust measures of plant health and their physiological responses. One of the most accessible ways to assess water available to a containerized plant in substrate is to leverage soil moisture sensing technologies to describe the local environment within the substrate media. Accurate irrigation management requires metrics to determine when to irrigate and how much water to apply. There are two typical measurement modes found in soil moisture sensors: instantaneous and continuous. Instantaneous sensors are usually hand-held and provide discrete readings when requested by the user. Continuous sensors record multiple readings without user interaction. Continuous, near real-time data is vital for accurate automated irrigation management. High-frequency measurements reflect rapid changes in the relationship between the substrate, plant, and its environment. Thus, continuous measurements have helped to account for temporal variability better than a coarse instantaneous measurement (Birgand et al., 2016).

There are multiple soil moisture sensing technologies which could be implemented in a commercial greenhouse setting. Most notable are sensors which measure soil moisture tension or apparent dielectric permittivity. Tensiometers measure matric water potential within soil and have been used to provide information about water availability for irrigation control. In previous studies cost prevented wide implementation and the intensive management requirements of the devices led to incorrect readings and overwatering (Debach et al., 2016). Dielectric sensing such as capacitive and time-domain reflectometry (TDR) may be well suited to the greenhouse
environment. Both capacitive and TDR relate electromagnetic soil or substrate properties to volumetric water content (VWC). Capacitive sensors estimate the apparent dielectric permittivity of the substrate, mostly influenced by the presence of water, by measuring the amount of time required to discharge a fixed capacitor. TDR sensors measure the amount of time required for an electromagnetic pulse to be reflected to the sensor. Evett et al. (2012) suggested that TDR sensors were well suited for field research, but acknowledged the high cost associated with installing multiple sensors. The cost of TDR sensors and the lack of wireless options make this sensing technology not plausible for large-scale greenhouse installations that require multiple sensors for irrigation management. Capacitive sensors are the most likely candidate greenhouse watering management since they are robust, affordable, generate small data volumes, and are easily connectable to wireless networks. Once sensors have been identified, their management, performance, and plant outcomes need to be compared against traditional methods of irrigation management – trained human experts.

The overall objective of this study was to compare sensor- and expert-based irrigation scheduling. Specific objectives were to compare: (1) discrete & continuous sensing of substrate VWC under sensor- and expert-based watering, (2) water delivery and leaching under the two systems, and (3) plant performance measures of kernel counts, dry mass, plant height, and root rot ratings.

Materials & Methods

Two irrigation scheduling methods were compared: expert-based and sensor-based. Expert-based irrigation scheduling depended on daily observations by an experienced employee. Before 10:00AM each morning the trained employee assessed leaf canopy appearance, picked up selected pots, or felt the substrate of 2-3 pots within each zone to determine the level of moisture.
Based on observations, weather conditions, and plant stage, the employee decided on appropriate irrigation scheduling required for that day. Sensor-based irrigation scheduling was determined by data generated by a commercial off-the-shelf capacitive soil moisture sensor (Mi Flora, Xiaomi, China, Model no. HHCCJCY01HHCC). The sensors reported VWC, expressed as a percentage, every 30 minutes. All watering decisions were made on an individual zone basis.

All experiments occurred in a commercial greenhouse at Corteva Agriscience, formerly DuPont Pioneer, in Johnston, Iowa. The greenhouse room for this study was roughly 232 m² (2500 ft²) and the zones were oriented East-West. The greenhouse room contained sensors to measure relative humidity, air temperature, and photosynthetic active radiation (PAR). Artificial lights were used to supplement natural sunlight when PAR fell below a certain threshold. A commercial control system monitored and regulated all environmental sensors. The crop under production was a wild-type maize (Zea mays sp). The experiment was conducted from 26 September to 23 October 2019.

Each zone in the production room contained 50 plants. Four zones in the greenhouse room were dedicated to this study. Two zones were watered with expert-based irrigation scheduling and two according to sensor-based irrigation scheduling. The greenhouse room used drip-tape irrigation; each pot was positioned with five emitters spanning 19 cm (7.5 in). The two zones assigned each irrigation scheduling treatment were treated as replicates. Due to limited space in the room, there were no border plants for the duration of the experiment. Seven sensors per zone were assigned to monitor the four study zones in this greenhouse room. A random number generator constrained between one and seven was used to determine the first plant in each observed zone to receive a sensor. Every seventh plant after the initial sensor position received a sensor until all sensors were placed.
At study initiation all pots were watered until the substrate reached holding capacity and were then observed for substrate conditions and plant response. Once the plants started to exhibit mild drought stress based on the expert’s observation, the median of the last seven readings served as the initial VWC watering threshold for the sensor-based zones. The set-point value determined the occurrence of subsequent watering events for the sensor-based zones. Using observation, rather than a fixed VWC, as the initial trigger allowed variability in plant performance, greenhouse room conditions, and ambient weather to be incorporated within the target set-point. Each Miflora substrate moisture sensor connected via Bluetooth to a Raspberry Pi 2 Zero (Raspberry Pi Foundation, Cambridge, UK), which sent data readings to an internal, cloud-based Internet of Things (IoT) platform. A watering event was triggered when the median of the last seven VWC readings for a zone, ideally one reading from each sensor in that zone, was at or below the threshold VWC. When this set-point condition was met, the Raspberry Pi triggered the irrigation controller to open the solenoid valve for the specific zone. Nutrient solution, water containing fertilizer, was delivered to the plants using drip irrigation. A sensor-based watering event consisted of three cycles when water was applied for four minutes with 20 minutes in between each repetition. Before pots were moved for any reason, the drip tape was labelled to ensure accurate repositioning of the pot after daily measurements.

**Discrete Moisture Content & Water Delivery Measurements**

Discrete VWC data and water delivery measurements were taken daily prior to 10:30 AM local time and additionally after each watering event. VWC readings were collected with a HH2 Moisture Meter connected to a Theta Probe (Delta-T Devices, Cambridge, UK). The average VWC was calculated if there was more than one measurement taken on that date. Two empty buckets were placed in each study zone, aligned like a planted pot, to measure the amount of
water delivered to that zone. Trays were placed under each instrumented pot to capture the volume of water leached from each pot. Total water and leaching volumes were measured with a graduated cylinder. Water delivery was calculated by subtracting average leached water volume from the average total water input to each zone.

**Pollination & Kernel Counts**

Manual pollination occurred for each plant immediately after first silk, all plants were pollinated by the same person. All plants, except one that was prematurely de-tasseled, were self-pollinated. Kernel counts were collected ten days after pollination. Kernel counts were estimated by taking the average number of kernels of six rows and multiplying by the total number of rows on the ear. A picture was taken at harvest of each individual ear and as group for each pollination date.

**Root Rot Rating**

A root rot rating score was assigned to each plant in the study. Root rot scores indicated plant health on a 1-5 scale with 1 having exhibited poor root structure while 5 indicated a healthy root structure. Some of the symptoms associated with a score of 1 were the absence of roots, root thinning, root browning, and the smell of root decay. The characteristics associated with a score of 5 were no discoloration of the roots and the presence of thick roots throughout the substrate. The same person assigned a root rot rating to each pot.

**Above Ground Biomass**

After harvest and kernel counts, each stalk was cut at 76 – 100 mm from the substrate surface and sectioned into approximately 0.3 m (1 ft) pieces. Stalk pieces and the ear from each plant were immediately placed in a mesh bag to oven-dry for 14 days at 70°C and was weighed on a scale (Mettler Toledo, Model: ML4002E/03).
**Stalk Height Measurements**

Height was measured from the room floor to the top-most leaf with a meter stick. Initial height was taken on the first day plants were in the room and final height was taken on the last day that plants were in the room. Initial height was subtracted from final height to measure vertical growth of the plant over the duration of the study.

**Data Analysis**

Initial data tidying was done in Excel (2016, Microsoft, Redmond, WA). Data was imported into R statistical software (R Core Team, 2018, Vienna, Austria) for tabular and graphical visualization. Analysis of variance (ANOVA) and repeated measures mixed model statistical analysis was completed in R. All ANOVA analysis was conducted at a significance level of 0.05. For the expert-based method, sensor data was individually averaged prior to averaging the two zones together.

**Results & Discussion**

There was a failure with an automated irrigation valve on 30 September 2019, which caused severe overwatering of one of the sensor-based zones. The overwatered zone data were included in VWC and water delivery visualizations but was omitted from plant performance analysis. Elimination of one of the sensor-based zones means there were no replicate values for data from the sensor-based irrigation treatment. On 18 October, there were repeated IoT communication issues, which led to large timeframes of missing data. Data from 18 – 23 October were omitted from VWC data analysis.

**Substrate Moisture Content**

**Discrete Handheld Sensor Readings.** Discrete daily VWC readings for both irrigation regimes were plotted in Figure 4.1. Readings were collected after initial substrate saturation with
the sensor-based zones reporting approximately 25% VWC while the expert zone reported 22.5% VWC. After initial dry-down from container capacity, VWC of the sensor-based method zone maintained higher VWC when compared with the other zones. The expert initially delayed irrigation compared to the sensor-based zone. The expert maintained higher VWC later in the growing season based on an expectation for increased water demand during pollination as opposed to the fixed threshold maintained by sensor-based irrigation.

Figure 4.1. Daily temporal substrate moisture content averages based on discrete measurements from HH2 meter connected to Theta probe sensor for expert- and sensor-based irrigation scheduling methods.

**Continuous Sensor Readings.** Real-time moisture content readings were compared for sensor and expert irrigation scheduling (Figure 4.2). The expert set the minimum median VWC at 17% for the sensor-based rows. Due to the previously discussed IoT issues, the real-time data
from 18-23 October were excluded due to the number of missing data readings. For both methods, there were small fluctuations in VWC readings from the sensors. Small variations like these were expected in electromagnetically noisy environments where there were multiple fans, pumps, and lighting systems which could have created interference.

![Figure 4.2. Temporal substrate moisture content averages based on continuous measurements from Miflora sensors for expert- and sensor-based irrigation scheduling methods.](image)

Consistent general trends were evident between discrete and continuous VWC measurements, but there were key differences (Figure 4.1 & Figure 4.2). Numerical values for VWC differed by up to 10 percentage points between continuous and discrete measurements. This difference was likely caused by an offset in internal calibration values between the two sensor types – since the data was recorded as reported from each sensor. Additionally, there were
watering events recorded with the high-frequency measurements that were not captured with the daily readings. Without continuous sensor data, a general increasing trend in VWC could appear without knowing when the watering event took place and how the substrate dried out over time. The increasing VWC values seen in the daily readings toward the end of the study were describing conditions at near their maximum daily VWC, which was not indicative of the actual dynamic substrate conditions. Thus, daily moisture content with a handheld sensor by itself would not be an accurate decision-making tool for sensor-based watering. Regularly inserting and removing the sensor probe disturbed the substrate. As the crown roots grew, there were limited locations for taking the measurements. Both substrate disturbance and root interference could impact reading accuracy. Substrate contact and positioning of sensors influenced irrigation scheduling efficiency in the study by Soulis et al. (2015). A dry-down curve from the initial watering was apparent for both irrigation control methods, but VWC for the expert irrigation method was lower than the sensor irrigation method before triggering the first watering event. One of the expert-based zones were near the outer edge of the production room and received additional sunlight exposure, which may have led to increased water usage or lower VWC. These environmental conditions could have accounted for improved plant performance metrics discussed later. The first two watering events for the expert-based method were lower in comparison to the sensor-based method.

Repeated measures ANOVA were used to determine if there were differences in continuous VWC readings between methods over time. All observations with missing soil moisture readings were omitted for the analysis. The effect of scheduling method and the interaction between the scheduling method and time were significant ($p < 2.0 \times 10^{-16}$), but the effect of the time was not significant ($p = 0.13$). The significant interaction effect meant that the
rates of change in substrate VWC over time were different depending on the type of irrigation scheduling. Analysis of the other metrics will determine whether there were meaningful differences in plant performance between the two irrigation methods.

**Water Delivery**

Daily water delivery consisted of the difference between average total water applied and leaching volumes (Figure 4.3). There were two timeframes with noticeable discrepancies between the two methods. The first discrepancy was the substantially higher water delivery on 30 September 30 for sensor-based irrigation scheduling due to the valve failure. The second discrepancy was 14-21 October when there was at least ~250 ml difference between the two methods. For this timeframe, expert-based irrigation had greater water delivery than the sensor-based method. Peak substrate VWC was higher and the dry-down rate was greater for the expert-based method during this same timeframe. Increased expert-based water delivery corresponded to the timeframe when the maize was silking and tasseling. Human observation of plant conditions provided insight on plant needs. Algorithmic development will be required to build in setpoint modifications if desired.
Figure 4.3. Daily temporal water delivery (difference between average total water delivered and average leaching volume) averages for expert- and sensor-based irrigation scheduling methods.

Overall, the sensor-based zone consumed 28% less water. Goumopoulos et al. (2014) found that their newly developed wireless sensor network with zone-specific irrigation led to a 20% reduction in water usage in comparison to traditional irrigation for strawberries. Event-based irrigation control also reduced water usage by 20% in the greenhouse (Pawlowski et al., 2017). While the sensor-based method was more sustainable for water delivery, there are other metrics related to plant development that must also be accounted for in determining the feasibility of sensor-based irrigation within the greenhouse.

The daily average leaching volumes, shown in Figure 4.4, demonstrated the varying degree of water uptake based on the irrigation scheduling method. As shown with water delivery, the overwatering event at the beginning of the study was depicted with leaching volume. On
average, each pot in the sensor-based zone on 01 October had 300 ml of excessive water that was
not taken up by the substrate or the plant. The results also revealed that the expert-based
irrigation method, on watering days, had a greater average leaching volume in comparison to
sensor-based after 01 October.

Figure 4.4. Daily temporal leaching volume averages for expert- and sensor-based
irrigation scheduling methods.

Decreased leaching in sensor-based scheduling was identified as a potential advantage of
automated irrigation. Increased water delivery and subsequent leaching in expert-based
irrigation after 12 October was an intentional reaction to plant growth stage during pollination.
During pollination, plants require additional water (Rink et al., 2010). Field-based surface drip
irrigation has been adjusted in previous studies to account for the increased water demand
(Eugenio Coelho & Or, 1996). The expert knew the plants would need more water to carry out these physiological processes and wanted to ensure that the plants had ample water available for uptake. As common to other agricultural management decisions, without actionable data the risk to crop production drove over application of inputs. The combination of sensor technology and expert knowledge has the potential to guide watering decision-making and reduce excessive watering in the greenhouse.

**Kernel Counts**

For seed production, a lower kernel count meant that there were less kernels available that could be potentially viable for genetic purposes. There was not a significant difference (p = 0.16) in kernel counts between the two irrigation scheduling methods (Table 4.1). The similarities in kernel count for the two irrigation methods could be partly due to the time of year. The experiment was conducted between seasons so the difference between treatments was more subtle. There was less variability in counts for the expert-based irrigation treatment. Genetic transformations at this facility scale required a minimum of 200 kernels per ear for ample selection of embryos. Both methods produced ears with an average greater than 200 kernels, but both also had ears with less than 200 kernels. Water stress has been correlated to lower kernel counts per ear (Payero et al., 2009).

<table>
<thead>
<tr>
<th>Method</th>
<th>Kernel Count</th>
<th>Dry Biomass (g)</th>
<th>Plant Height gain (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>SD</td>
<td>p-value</td>
</tr>
<tr>
<td>Expert</td>
<td>436</td>
<td>207</td>
<td>0.16</td>
</tr>
<tr>
<td>Sensor</td>
<td>506</td>
<td>112</td>
<td></td>
</tr>
</tbody>
</table>

*p < 0.05

*Note.* SD represents standard deviation.
The sensor-based irrigation scheduling approach with less daily labor input and less water usage produced a similar number of kernels, on average. This result was surprising since the differences in watering for the two methods was expected to contribute to higher kernel count yields for the expert-based scheduling. Peters & Evett (2008) described a beneficial outcome where less time and energy for management and decision-making was necessary for automated center pivot irrigation control even though there was not a significant difference in yield between the automated and manual irrigation treatments. Due to the seasonal differences, Payero et al. (2009) recommended irrigation scheduling that was adaptable, not fixed, to account for variability. While higher average kernel count was promising, there must be more experimentation with sensor-based irrigation scheduling before implementation on a larger scale.

**Dry Biomass**

Expert-based irrigation produced greater dry biomass than sensor-based irrigation (Table 4.1). In comparison to the other variables, there was found to be a significant difference between the two methods. Dry biomass was related to growth, which meant that there was probably more evapotranspiration and greater energy available for developmental processes for the expert-based irrigation (Payero et al., 2008). However, the increased vegetative growth did not translate into additional reproductive performance, as indicated by kernel counts. In comparison to the expert-based scheduling with overwatering, sensor-based scheduling only watered when plants began to exhibit water stress. Payero et al. (2009) described how water stress influenced the growth and development of maize, which in turn, could lower biomass and kernel count. Watering frequency and fertilizer was correlated to total shoot dry weight in a study done by Muhumed et al. (2014), which could have contributed to the higher dry biomass for the expert-based irrigation scheduling. The sensor-based zones originally set at a threshold value with mild water stress
meant that the plants could have experienced water stress during the vegetative stage, which led to lower dry biomass (Shanahan & Nielsen, 1987).

**Plant Height**

There was no significant difference (p-value = 0.428) in plant height between the two irrigation methods (Table 4.1). There was high standard deviation for both methods with roughly 9 and 12 cm for expert- and sensor-based scheduling, respectively. This variability could be due to both methods experiencing under- and over-watering, which can affect plant quality (Chen et al., 2019). Denmead & Shaw (1960) found that water stress during the corn vegetative stage led to shorter stalks in comparison to plants that did not undergo water stress, which could have contributed to the shorter sensor-based irrigation plants. Another study by Mellors et al. (1984) discovered that a greater watering rate correlated with greater plant heights for soybeans. While there was not a significant difference, the expert-based method exhibited a greater change in plant height, which had a higher water delivery than the sensor-based method.

**Root Rot Rating**

Due to the exclusion of one of the sensor-based zones, Table 4.2 describes the percentage, based on frequency, for the different root rot ratings of each method.

<table>
<thead>
<tr>
<th>Method</th>
<th>Root Rot Rating (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Sensor</td>
<td>0</td>
</tr>
<tr>
<td>Expert</td>
<td>0</td>
</tr>
</tbody>
</table>

Expert-based irrigation scheduling had a higher percentage of plants at root rating score of 3, but sensor-based irrigation had a greater percentage of plants rated greater than 3. Expert-
based irrigation had 64% of plants greater than 3 and sensor-based had 72% of plants rated greater than 3. A higher rating score indicated that sensor-based irrigation resulted in a healthier root system. One study described how overwatering has the potential to cause nitrogen leaching and decreased oxygen within the root zone (Payero et al., 2008). The higher water delivery of the expert-based method towards the end of the experiment likely resulted in lower root rot score. Moderate water stress, like sensor-based scheduling in this study, was found to be correlated with higher corn root length (Newell & Wilhelm, 1987).

**Conclusion**

Substrate VWC is dynamic which can make it difficult to capture how much water within the substrate is available for uptake by the plant. By using sensors to measure the water content in the substrate, continuous data can aid in irrigation decision-making with expert monitoring. Handheld daily VWC readings failed to reflect changes in VWC between watering events, and potential measurement accuracy issues over time supported the use of real-time sensors. Real-time, as opposed to daily, data created a more holistic view of substrate water availability. VWC as measured by continuous sensors were significantly different between sensor- and expert-based irrigation methods. Sensor-based irrigation resulted in reduced substrate VWC. Sensor-based irrigation reduced both water application and leaching. Water application was reduced by 28%.

There was no significant difference between the irrigation methods in kernel counts and plant height. Kernel counts met minimum threshold for preservation of genetic purity for both methods, which is one of the purposes for growing wild-type cultivars in a commercial greenhouse. There was a significant difference in dry biomass between the two irrigation methods. The difference in dry biomass was less than four grams, which may not reflect a meaningful difference even if statistically significant. Sensor-based irrigation improved root rot
ratings with 72% compared to 64% of plants receiving positive root rot ratings. The higher water delivery associated with the expert-based irrigation may have caused additional root rot.

Implementation of sensor-based irrigation scheduling with individualized zone-specific control can provide reduced water usage and similar plant outcomes within a commercial greenhouse. As indicated by the valve failure which led to overwatering and the exclusion of one of the study zones, sensor-based irrigation is not foolproof. Technical insight and supervision by a trained employee would be necessary for greater confidence before implementing sensors on a commercial scale.
References


Chapter 5 - Concluding Remarks

Large-scale deployment of sensors for automatic irrigation management in commercial greenhouses will be costly and challenging. A new low-cost wireless sensor prototype, called WolfPAWWS, was developed to measure changes in substrate moisture content and to account for zone-to-zone variability within a greenhouse. The WolfPAWWS exhibited sensor-to-sensor variation in the raw readings with respect to changes in volumetric water content (VWC). However, individual WolfPAWWS experienced less variability in the raw output in the incremental water experiment. The in-situ greenhouse experiment identified two clusters for the WolfPAWWS following the same general trend, which could be due to differences in manufacturing for two batches of sensors. The direction and position of the WolfPAWWS probe in the substrate was important to the sensor performance. Additional experimentation will be needed to determine whether the manufacturing batch impacted the accuracy of the measurement. There were significant differences in the raw measurements from the EC-5 sensors. Further analysis discovered that the EC-5 measurements followed a similar trend but there was variability in actual values, which demonstrated there is substantial differences in measurement, even in commercial sensors. The high porosity or initial compaction of the substrate used in the experiment could have contributed to this variation in measurement. In the future, using a higher level of substrate compaction and adding water to the substrate prior to adding the sensors could narrow the variability among the EC-5 sensors.

Design improvements and using the built-in counter for coding could lead to higher accuracy of the sensor in the future. However, the battery issues greatly reduced the amount of data available for this data analysis. The reliability of the WolfPAWWS was higher than the Miflora after resolving the battery charge issue. The advanced engineering of the WolfPAWWS
sensor contributed to the increased reliability due to the hard-wired deep sleep functionality that requires it to stay on Wi-Fi until the measurement is sent to the controller. The diagnostic LEDs were useful for indicating the charging, but it was difficult to determine when the batteries were fully charged leading to missing data. There was an increase in sensor performance by switching to a commercial lithium battery charger. Power management is always an issue and requires sensor monitoring to avoid missing data, which could cause incorrect irrigation triggering. After implementing design changes, the WolfPAWWS could be useful as a low-cost wireless sensor for future studies. At the time of writing, the sensor is being refined for deployment in a commercial greenhouse.

Singular sensor calibration on a large-scale would not be practical. For this reason, a new decision-making method was conceptualized to study how to trigger irrigation. The range in Cohen kappa coefficients for 100 simulations suggested that the number of sensors per zone could be decreased from eight to six sensors with moderate agreement. The development of this method for determining the number of sensors needed per zone has value in providing a way for researchers to test this hypothesis further in the future. This analysis is only meant to provide guidance for future studies using capacitive sensors, but other crops might need a different number of sensors per zone. The low cost associated with the commercial capacitive sensors requires monitoring of sensor measurements but could decrease the amount labor and time spent watering. Thus, the analytical effort would increase while the manual effort required for watering would decrease with the adoption of a hybrid expert-sensor irrigation management strategy.

When using uncalibrated sensors on a large scale, there needs to be a different method for triggering irrigation. This study compared individual irrigation events to determine if there was a similarity among the slopes that could be used for triggering irrigation in the future. The shorter
irrigation cycles had high $R^2$ values, but also, higher residual errors because of the physiological changes resulted in faster water uptake. All linear regression models explained at least 83% of the variability of median values for the irrigation cycles in both zones, with exception of the two cycles with the shortest duration. The largest percent decrease for both zones was before the shortest irrigation cycles, which indicated that the plants were taking in more water. The slopes between consecutive cycles are similar, but the threshold slope would need to be changed when prior to the reproductive stages of corn growth. While these initial results are promising, more testing is needed prior to utilizing this method for triggering irrigation. In the future, more data could allow for the development of machine learning algorithms that would predict when to trigger irrigation events.

This study compared sensor-based to expert-based irrigation scheduling and how these methods affected the health of corn plants. The use of soil moisture sensors measuring in real-time along with expert monitoring can determine irrigation scheduling by depicting the cyclical changes in substrate moisture. On the other hand, daily handheld soil moisture sensor readings were destructive to the substrate and did not depict all changes in substrate moisture. There was a significant difference between the real-time VWC readings and the type of irrigation scheduling. Apart from a few ears, the kernel counts for both methods was high enough for genetic transformation purposes. For kernel counts and plant height, the irrigation methods were not significantly different, but there was a significant difference between method for dry biomass. For root rot ratings, 72% of the plants from the sensor-based method had a score higher than 3 (healthier roots) compared to 64% of the plants from the expert-based method. Greater water usage by the expert possibly impacted the root rot ratings.
In both sensor-based irrigation zones, there was an overwatering event due to an error in setting the controller parameters, which led to significantly lower plant performance in one of the zones excluded from the analysis. To avoid this issue in the future, proper protocols need to be created before scaling up use of sensors. There was a stipulation in effect to prevent the controller from prematurely triggering an additional watering. This fail-safe does not allow the controller to trigger another watering until an hour after the initial decision to water. However, the sensors did not reflect the change in substrate moisture within the hour after the first watering. Thus, the median of the readings was at the set-point, which triggered a second watering event. Due to this error, there needs to be a reassessment of the reaction time of the sensors to changes in substrate water content. Irrigation scheduling with real-time soil moisture sensing would be an alternative that would reduce human labor and provide greater control of specific zones within a commercial greenhouse. A combination of real-time sensors and expert knowledge could lead to more precise irrigation scheduling, which could contribute to reduced water usage.
Appendix
Appendix: Substrate Moisture Sensor Prototype Supplemental Materials

Below are the supplemental materials and bill of materials for designing the substrate moisture sensor prototype.

Supplemental Materials

Additional documentation, including the computer coding, gerber files, and schematic files, for both the substrate moisture sensor prototype and charger has been added to a GitHub, Inc. (San Francisco, CA) public repository (https://github.com/wufpack/WolfPAWWS-sensor-prototype).

Bill of Materials

Table A.1 was broken down for each component: part number, description, numerical value (if applicable), quantity, cost for one component, and total cost. The unit cost for the rechargeable lithium iron phosphate batteries were $3.18 as of March 2020.

Table A.1. Bill of materials for Precision Agriculture Wireless Water Sensor (WolfPAWWS) substrate moisture sensor prototype (Updated: March 2020)

<table>
<thead>
<tr>
<th>Name</th>
<th>Part Number</th>
<th>Description</th>
<th>Value</th>
<th>Quantity</th>
<th>Unit Cost</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>C3 - C5, C8, C11</td>
<td>MF-CAP-0603-0.1uF AVX TAJC10 7K010RNJ Samsung CL10 A475KQ8NN NC</td>
<td>Capacitor MLCC0603 0.1uF 10% 25V In a Pack of 25, AVX Tantalum Capacitor</td>
<td>100 nF 100 uF</td>
<td>5 2</td>
<td>$0.06 $0.87</td>
<td>$0.30 $1.73</td>
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<tr>
<td>C6, C7</td>
<td>Samsung CL10 A475KQ8NN NC</td>
<td>Cap Ceramic 4.7uF 6.3V x5R 10% SMD</td>
<td>4.7 uF</td>
<td>13</td>
<td>$0.12</td>
<td>$1.59</td>
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<tr>
<td>D2</td>
<td>MCC 1N4448 WX-TP</td>
<td>1N4448X Series 100V 500mA 4ns SMT</td>
<td>1N4448 8WX-TP</td>
<td>12</td>
<td>$0.13</td>
<td>$1.61</td>
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<tr>
<td>P2, P3</td>
<td>Keystone 54 Diodes Inc. DMG2305 UX-13</td>
<td>Cylindrical Battery Contacts, Clips</td>
<td>NA</td>
<td>2</td>
<td>$0.38</td>
<td>$0.76</td>
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<tr>
<td>Q1, Q3</td>
<td>Diodes Inc. DMG2305 UX-13</td>
<td>P-Channel 20V 65 Ohms Surface Mount</td>
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<td>3</td>
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<tr>
<td>Name</td>
<td>Part Number</td>
<td>Description</td>
<td>Value</td>
<td>Quantity</td>
<td>Unit</td>
<td>Total Cost</td>
</tr>
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<tr>
<td>Q2</td>
<td>Diodes Inc. DMMT39 06W-7-F Diodes Inc. MMBT39 04-7-F</td>
<td>Trans GP BJT PNP 40V 0.2A 200mW Transistor General Purpose BJT NPN 40V</td>
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<td>2</td>
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<td>Q4 - Q6,Q8</td>
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<tr>
<td>R1,R2,R8 - R10,R18</td>
<td>Stackpole Electronics R MCF0603FT100K</td>
<td>Res Thick Film 0603 100K Ohm 1% 0.1W</td>
<td>100k</td>
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<td></td>
<td>$2.07</td>
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<td>R4,R7,R11 - R17,R19, R20,R22, R25</td>
<td>MF-RES-0603-10K</td>
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<td>R21</td>
<td>Yageo RC0603 FR-0739KL Susum RL08 16T-R010-F</td>
<td>Res Thick Film 0603 39K Ohm 1% 0.1W RL Series 0603 0.01 Ohm 0.25 W ± 1%</td>
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<td>R26</td>
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<td>R3</td>
<td>Yageo RC0603 FR-0710ML</td>
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<td>R5,R6</td>
<td>Yageo RC0603 FR-0768K1L</td>
<td>Res Thick Film 0603 68.1K Ohm 1% 0.1W</td>
<td>68.1k</td>
<td>13</td>
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<td>$1.59</td>
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<td>U1</td>
<td>Espressif Systems ESP-WROOM-02</td>
<td>ESP Module 802.11 b/g/n 2.4835GHz 72200Kbps</td>
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<td>U2</td>
<td>Texas Instruments TP L5111DDCR</td>
<td>Comparator Dual ± 3.5V/7V 5-Pin SSOP</td>
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<tr>
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<td>Diodes Inc. AP7365-30WG-7</td>
<td>LDO Regulator Pos 3 V 0.6A 5-Pin SOT-25 T/R</td>
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<td>Tvs Diode 5V 10.8V SOT23</td>
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<td>U5,U7</td>
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</table>

Total $25.72