THESIS

DEVELOPING INTERNET-OF-THINGS SOIL MOISTURE SENSOR NETWORKS FOR IMPROVING IRRIGATION MANAGEMENT IN TURFGRASS

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Ian Brazil Aksland

Department of Soil and Crop Sciences

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Master's Committee:

Advisor: Jay Ham

Raj Khosla
Yaling Qian

ABSTRACT

DEVELOPING INTERNET-OF-THINGS SOIL MOISTURE SENSOR NETWORKS FOR IMPROVING IRRGATION MANAGEMENT IN TURFGRASS

The importance of efficient irrigation in turfgrass management is underscored by substantial water usage in urban landscapes. In many western U.S. cities, over 50% of the total annual residential water use is allocated to turfgrass and landscape irrigation. Unfortunately, 30 to 60% of this urban irrigation water is wasted due to improper irrigation scheduling. This research focuses on the development and testing of innovative Internet-of-Things (IoT)-based soil moisture sensor networks designed to help optimize irrigation management in turfgrass. Golf course fairways served as a test bed for the research. A second phase of the research focused on how spatial variability in soil type and other landscape properties might impact soil sensor sampling plans, including the number of sensors and their installation locations. The overarching goal was to explore technologies that could promote more widespread use of soil sensors in irrigation decision-making to control golf courses and other turf areas like parks, green spaces, and residential lawns.

The first phase of the project involved the design and calibration of custom-made capacitive soil moisture sensors, termed DP7T, which measure both soil moisture and temperature. A custom IoT cellular datalogger and innovative below-ground housing were also developed to read the sensors and transmit the information to the cloud via a cellular modem. Detailed laboratory calibrations were performed in various soil types using temperature-controlled chambers. After calibration, the systems were field-tested on three golf courses. Calibration results highlighted the importance of including temperature corrections, and necessity to include a built-in temperature transducer in each soil sensor. After temperature correction, excellent soil-specific linear calibrations were obtained on the log transform

of volumetric water content vs sensor millivolt output, but soil specific calibrations were required. Extensive field tests validated the reliability of both the sensors and IoT dataloggers under field conditions. Cellular IoT connectivity facilitated real-time data transmission and analysis to online user dashboards, providing real-time information for improved irrigation management. However, results indicated significant micro and macro-scale spatial variation in sensor output when three measurement stations were deployed along fairways at each course. The large variation in soil moisture on a fairway suggests that this degree of spatial variation will confound the use of proximal soil sensors as a tool for irrigation management in these systems.

To better understand how spatial variability in soils and landscape features affected sensor readings, spatial soil variation along the fairways was mapped using electromagnetic induction (EM38). The electromagnetic EM38 data showed a positive relationship with soil moisture content across all three golf courses, and literature has pointed to a strong correlation between topography and soil variability. More research is needed to fully understand how to successfully merge EM38 mapping layers and live soil moisture data to precisely recommend which sprinklers need adjustment for optimal irrigation, but this project suggests a model for further studies.

The integration of low-cost sensors with IoT systems in this study demonstrated the potential of this technology. However, more research is needed on how proximal soil sensors should be deployed to characterize spatial variability in soil moisture across the landscape effectively. This will likely involve optimizing the number and deployment locations of soil sensors to capture the most information with the fewest sensors and at the lowest cost, while still meeting the day-to-day needs of turfgrass water managers.

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Rationale

The state of Colorado consumes over five million acre-feet of fresh water a year for Agriculture, Municipal, Industrial, and Self-Supplied Industrial applications (State of Colorado, 2015). Like most of the surrounding western states, Colorado withdraws over 80% of its consumptive water use for irrigation according to United States Geological Survey (USGS) estimates (Dieter et al., 2015). Water management is crucial in making sure that irrigation and other facets of a functioning society can continue to thrive not only in Colorado but across the United States and abroad. Changing climate exacerbates water scarcity concerns emphasizing the need to monitor and better manage limited freshwater resources. Water resource issues like those surrounding the Colorado River also highlight the importance of water management; irrigation accounts for 70% of the withdraws from the river (Richter et al. 2024). While agricultural water use accounts for the majority of the state's irrigation budget, urban water use for lawns and landscapes is on the rise and competes for regional water resources. In most western US cities, landscape irrigation accounts for 40 to 70% of total annual municipal water use (Yue et al., 2022). As freshwater costs increase, it is crucial to ensure that water in both rural and urban areas is being used appropriately and that improved irrigation management is the most important first step in meeting Colorado's water challenge.

The Importance of Irrigation Scheduling in Turfgrass

The total area of turfgrass in the United States accounts for roughly 16 to 20 million ha (Milesi et al., 2005). Turfgrass water consumption varies significantly based on grass type, climate, and location. Determining water requirements for turfgrass or any plant is complex, with United States Golf Association USGA reporting typical ranges from 3-8mm per day for most cool season grass's and 2-5mm per day for warm season grass's (Huang, 2008). Combining turfgrass's estimated land cover with water intake of turfgrass would suggest it has comparable water consumption to some of the largest irrigated crops like corn and soybean (Milesi et al., 2005). It's crucial to acknowledge that these estimates might be overestimated, yet the extent of irrigated turfgrass remains substantial. The rising cost of water reflects the challenge of balancing water supply with growing demand, underscoring the imperative for conservation efforts wherever feasible (USDA, 2004, 2006). This trend is observable across various regions. For example, municipal water rights in Fort Collins, CO have increased from $5.27 per cubic meter to $55.29 per cubic meter between 2017 and 2024 with a forecasted 4-6% increase annually for the following decade (Fort Collins Area Chamber, 2024). Turfgrass is especially concentrated in urban spaces and uses a significant amount of water, amplifying the urgency of conservation measures.

Turfgrass irrigation is often mismanaged by homeowners, amateurs, and even experienced irrigators. The United States Environmental Protection Agency (EPA) (2002) estimate up to 50% of the irrigation water applied gets wasted due to overwatering caused by the method and system used. This fact was also supported in research done in Florida, stating "Irrigation efficiency tended to be less than 50% on homes and on plot-based studies where 'typical' time clock schedules were used" (Dukes, 2011). Given an irrigation system is operating within its recommended specifications, most often research points to the culprit being calendar or time-based controllers. Time-based irrigation does not account for important variables such as an upcoming precipitation event, localized weather, soil variation, rootzone size, or seasonal trends in plant water consumption. When adjusting their timers, people have often displayed a, "set it and forget it" mentality for their irrigation scheduling (Dobbs et al, 2013). In Colorado's climate, this tendency usually leads to overwatering during early spring and late fall.

Model-based methods for irrigation scheduling that use weather data to estimate evapotranspiration show improvement over the calendar-based controllers. However, like all modeling approaches, they exhibited issues with rainfall calculations and other input errors not being properly accounted for (Pittenger et al., 2004). This is because water balance models often use the Penman-

Monteith or an adapted version of the equation for predicting evapotranspiration (Monteith, 1965; Penman, 1948). These types of models rely heavily on the accuracy of measured meteorological inputs and various assumptions. A critical limitation of water balance models is their lack of self-correction mechanisms. If the model's calculations deviate from actual soil moisture conditions due to inaccurate inputs, faulty assumptions, or unexpected environmental changes, there is no built-in way to automatically realign the model with real-world conditions. This discrepancy can compound overtime, leading to increasingly inaccurate irrigation recommendations. Without external intervention or recalibration, the model may continue to operate based on flawed calculations, potentially resulting in improper watering of landscapes. Despite these issues, model-based methods can reduce water use by 30 to 40% compared to calendar-based controllers, especially in the fall and spring (Serena et al., 2020). Smart controllers, leveraging internet connectivity and water balance modeling, are becoming more popular and are often incentivized through rebate programs. While many research studies show weather-based controllers increase in irrigation efficiency anywhere from 15% to more than 40% (Lunstad and Sowby, 2024), EPA estimates that most residential homes with sprinklers still use timer-based watering systems. Water balance approaches to urban irrigation scheduling is an improvement, but the next step is to add real-time soil moisture information that provides feedback to water balance models and helps optimize irrigation timing.

The Value of Using Internet of Things Technology and Soil Moisture Sensors

Emerging advancements on the Internet of Things (IoT), wireless connectivity, low-cost sensing, cloud computing, machine learning, and new avenues of technology fabrication have the potential to dramatically transform soil moisture sensing systems and revolutionize irrigation management (García et al., 2020). Leveraging these technologies in urban applications addresses many of the soil sensor issues being experienced and unlocks modern tools such as live data updates, notifications, cloud storage, application programming interface (API) calls, mobile apps, big-data analytics, and deep learning.

Combining these tools or technologies like machine learning with IoT further enhances the potential for improvement (Nsoh et al., 2024). Getting devices into the environment for irrigation management with these capabilities requires an advanced infrastructure of multiple components (Fig. 1). This ensures that all necessary information is collected and utilized before making an irrigation decision. In the end, time and cost investments must be considered to make a realistic solution that fulfills desired real-world applications.

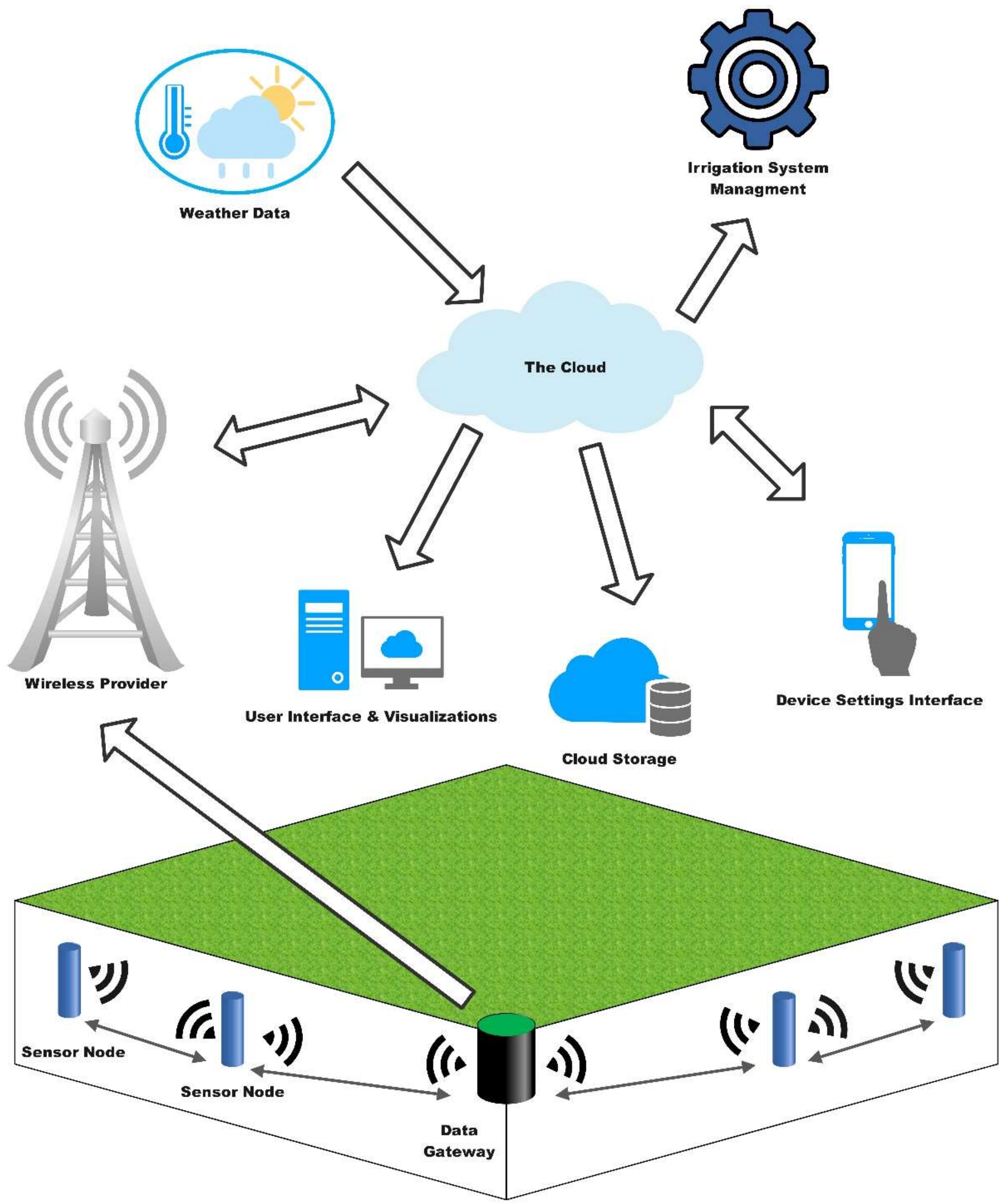

Figure 1. A concept diagram of how data from the Internet of Things can be used for irrigating turfgrass.

Researchers use soil sensor networks in turfgrass management in golf courses, sports fields, and other green spaces. Although this technology has the potential to conserve water, its adoption is slow (Taghvaeian, 2021). During the study, interviews with golf course professionals and other irrigators across the country were performed; these completed customer discovery projects were part of two programs I was enrolled in, the CSU Ventures Research to Market Cohort in 2020 and the Innosphere Ventures' Commercialization Program in 2021. Conversations with golf course managers, superintendents, and other turf professionals uncovered some reasons why current solutions are still inadequate. Common issues include high cost, implementation challenges and poor reliability, limited spatial coverage, poor integration with irrigation controllers, inadequately configured user interfaces. Consequently, currently available soil sensor systems fall short of providing the anticipated solutions (Khachatryan et al., 2020).

Predictably, irrigation controllers for turfgrass that utilize soil moisture sensors are seldom used, with our discovery interviews pointing to almost all irrigation decisions being based on timers, models, intuition, or water availability. Though a shift may be happening; a Florida survey showed that 49% of respondents preferred controllers with soil moisture sensors (Khachatryan et al., 2020). A small number of control systems make use of soil moisture sensors to automate irrigations; limited research papers on this subject indicate potential savings of 42%-72% over timer irrigation (Cardenas-Lailhacar and Dukes, 2012; Haghverdi et al., 2021; Singh et al., 2024) compared with model-based methods that have demonstrated a 30%-59% savings (Shedd et al., 2007; Serena et al., 2020). Despite the water savings shown as a benefit, problems remain in practical applications, including overall cost, reliability, installation, and implementation of environmental sensors.

Companies offering turf irrigation sensors on the market include HydroPoint (Petaluma, CA, United States), Hunter Industries (San Marcos, CA, United States), and The Toro Company (Bloomington, MN, United States). However, their offerings range in the thousands of dollars to implement a handful of units and often are thousands more to have wireless data transmission. Most digital soil moisture sensors available output relative moisture reading, necessitating several direct samples over time around each sensor to correlate its raw output with the surrounding soil's volumetric water content. Additionally, many of the sensors in use have some degree of temperature and salinity response that require calibrations or specialized hardware to counteract. Volumetric water content, temperature, and salinity calibrations can be achieved, but doing so adds more complexity to the soil sensor implementation.

Golf courses serve as ideal testing grounds for advances in irrigation technology due to their consistent vegetative cover, uniform cutting height, and overall easy access. Additionally, golf courses benefit from the expertise of turf professionals and their support networks, which facilitate the implementation and monitoring of new technologies (Wang et al., 2024). The unique irrigation system control and layout of golf courses, along with their willingness to implement advanced technologies like soil moisture sensors and individually programmable sprinklers, further enhance their suitability for testing. These systems allow superintendents to manage water usage with precision, ensuring optimal turf health and playing conditions while conserving water resources (Straw et al., 2019). However, the diverse environmental conditions also present a challenge, requiring the technology to accommodate various microclimates.

Addressing Spatial Variability and Sampling Challenges when Using Soil Moisture Sensors

Even when irrigators decide to use soil moisture sensors as part of their irrigation management scheme, questions regarding optimum number and spatial sampling configuration (density and distribution) always arise. Two things must be considered to address these concerns. First, understanding the soil and environmental spatial and temporal variability, and second, weighing that variability with the user’s ultimate needs or limitations. Placement of soil moisture sensors requires knowledge of the area’s soil variability to make sure the space is being accurately sectioned into its uniquely managed irrigation zones. Soil scientists have studied the sources of temporal, spatial, and extrinsic soil variability (Heuvelink and Webster, 2001). In a chapter of Methods of Soil Analysis, these sources of variability were compared to the slope of the soil-water retention curve, finding Soil Type (CV 23.00%) to have the largest coefficient of variation, followed by Extrinsic Random (CV 21.8%), Tillage (CV 14.5%), and temporal week-to-week variability (CV 9.3%) (Dane and Topp, 2020). This data supports the concept that soil water differences are highly dispersed across time and space, implying that to properly represent a location's water retention capabilities and account for its many contributing mechanisms requires a high measurement density. The physical and chemical traits of soil have a direct impact on where the water can go and how much can be stored.

While sensor placement is crucial, the effective use of the collected data is equally important in irrigation management. As Pierra et al. (2002) noted, irrigation management ultimately comes down to two critical decisions: when to irrigate and how much water to apply (Campbell et al., 1982). To address these questions, the data from soil moisture sensors must be integrated into a decision support algorithm or system. This integration can take various forms, depending on the complexity of the irrigation needs and available resources. One approach is the use of a water balance model, which incorporates sensor data along with other factors such as crop type, growth stage, and weather conditions to estimate crop water requirements. Alternatively, a more direct method involves setting a soil moisture threshold, where irrigation is triggered when the sensor readings drop below this predetermined "trigger point". Regardless of the chosen method, the key is that sensor technology must be integrated with some form of data science to reach actionable outcomes. This integration process must consider various factors, including sensor accuracy, location (both across the landscape and with depth), data collection frequency, and numerous other variables. Among these considerations, determining the optimal number of sensors and their placement within the irrigated system remains a particularly challenging aspect, requiring a balance between comprehensive data collection and practical implementation.

To enhance our understanding of soil moisture variability across landscapes, it is beneficial to focus on metrics that remain relatively stable over time and exert a significant influence on soil water content. These key factors include soil physical properties, topography (Neupane et al., 2024), and irrigation system layout. The irrigation system layout, while not always directly affecting below-ground moisture distribution variability, remains a critical factor in regulating overall soil water content. Research has demonstrated that above-ground sprinkler uniformity has a limited effect on below-ground moisture distribution (Dukes et al., 2006). Interestingly, studies have shown that the initial soil moisture uniformity may have a more substantial impact on subsequent moisture patterns (Osman et al., 2019). Despite arguments suggesting minimal influence of irrigation systems on below-ground soil water variability, these systems still play a vital role in regulating soil moisture. This is particularly evident in settings like golf courses, where individual control of sprinkler heads allows for precise water application across the landscape. Without considering the irrigation system layer, it becomes challenging to strike a balance between ideal watering scenarios and the practical limitations imposed by the irrigation system's capabilities.

Management zones are defined areas within a field that share similar characteristics, such as soil type, topography, or nutrient levels. The process of creating zones is crucial for implementing precision agriculture techniques. In this context, determining management zones remains complex and solutions can differ greatly depending on the location of interest. Traditionally, labor-intensive direct grid sampling is performed to map a location’s uniquely similar regions. Other options to measure soil variability have become available that use indirect methods like remote sensing on satellites and drones, as well as electromagnetic induction techniques that quantify magnetic properties of the soil. These indirect measurements decrease labor requirements and are utilized to more quickly understand an area of interest’s management zones; thus, resulting in improved recommendations on the total number of soil sensors and where to install them. Lowering the cost of IoT systems offers more dense coverage of these zones, providing options for higher granularity and redundancy.

Objectives

This study addresses several knowledge gaps and technical needs for using IoT soil moisture sensors to improve irrigation scheduling in turfgrass and golf courses. Firstly, the research focused on creating a novel IoT soil sensor system to minimize disruptions in active golf fairways. The design was installed below ground, so it was essentially "invisible" and didn't interfere with golfers' play. Another innovation was the development of a low-cost capacitive soil sensor, priced at approximately $10 to ensure affordability. This sensor not only provided soil moisture measurements but also incorporated soil temperature readings, a feature typically found in high-end research sensors, offering both functionality and cost-effectiveness. An essential aspect of this study was the field testing of these IoT systems and sensors in their intended environment, providing proof of concept and validating their functionality on golf courses. The research also aimed to understand spatial variability on golf course fairways and its relationship to soil water content requirements across different areas. While electromagnetic induction and other geographic layers have been utilized in agronomic settings, their application and documentation for golf course fairways remained limited. This study explored spatial analysis tools to optimize sensor deployment and improve overall irrigation management on fairways.

In summary, the objectives of this project were to:

- Develop an IoT soil measurement datalogger with an accompanying online user interface for golf course fairways and similar turfgrass sites.
- Test a new low-cost dielectric capacitive soil moisture sensor, calibrate it in multiple soils, and develop a temperature correction for the calibration.
- Conduct field trials of the IoT soil moisture system at multiple golf course locations, assessing the overall system viability, soil sensor lab temperature correction and VWC calibration function.
- Use electromagnetic induction with soil samples, high resolution topography, and irrigation system layers to better delineate management zones on a golf course fairway and determine optimal locations for the deployment of the IoT soil moisture stations.

Resources

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Chapter 2: Development of IoT Soil Moisture Measurement System for Turfgrass

Introduction

Low-cost soil sensor systems that integrate IoT, cloud computing, and machine learning are promising technologies for optimizing turfgrass irrigation (Chapter 1). These new tools have the potential to revolutionize irrigation scheduling and soil management (Tadda et al., 2018). The use of proximal soil sensing to determine precise irrigation timing and calculate optimal irrigation amounts is particularly promising. Several research papers have compared soil-sensor-based irrigation scheduling to more traditional timer-based approaches. They found that using sensor-based smart turfgrass controllers resulted in a potential water savings of 30%-70% (Cardenas-Lailhacar and Dukes, 2012; Haghverdi et al., 2021; Singh et al., 2024) However, installing soil sensor systems in real-world applications is complicated by additional challenges like soil variability, human and vehicle traffic, the physical system footprint, maintenance of components, wireless connectivity, sensor reliability, and managing the resulting data in a way that benefits the user. These issues often cause irrigators to question the return on investment when considering soil sensors, resulting in low adoption rates for both agricultural and urban irrigation—typically less than 12% (Taghvaeian, 2021). Clearly, further research on soil sensors and IoT is needed to enhance their appeal and promote more widespread adoption.

As discussed in Chapter 1, golf courses provide an excellent testbed for doing research on turfgrass irrigation. A 18-hole course may have between 50 and 150 individual irrigation management zones spread over 40 to 80 Hectares (100 to 200 acres). An obvious challenge in using soil moisture sensors in these systems is the sheer number of sensors required and the considerable expense to purchase, install, and maintain the instrumentation. Even if one only installed a single IoT sensor per zone, the course is required to buy and install over 100 units – and if you selected three locations per zone you would be well over 300 measurement stations. While there are multiple IoT soil moisture systems on the market, most of these are designed for agricultural applications that are not suitable for turfgrass and golf because they have solar panels, masts, and other infrastructure installed above ground. Clearly these would not be suitable on golf courses or sports fields because they would interfere with play and be aesthetically unappealing. There are a few IoT soil moisture systems that are targeted for turfgrass management, like Toro's Turf Guard System that measures moisture at two depths (2 and 8 inches) near the surface at a single location (The Toro Company, Bloomington, MN). These sensors are installed just below the surface, allowing them to be placed on fairways and greens without interfering with play. However, each sensor costs over $550 and requires additional wireless nodes for connectivity. This means that even a modest installation of 100 sensors across a golf course could exceed $75,000 when factoring in the cost of the wireless infrastructure. Given the significant spatial variation in soil properties and the lack of uniformity in irrigation application within a sprinkler-irrigated zone, a practical solution would have multiple sensors per zone. As a result, instrumenting an 18-hole golf course with commercial IoT soil sensors could easily cost over $250,000. This level of economic investment poses a barrier to adoption, even for golf courses with substantial budgets. For parks, sports fields, and residential landscapes, where budgets are smaller, the cost barrier is even greater. A lower-cost, and perhaps open-source option for using IoT soil moisture sensors is needed for widespread adoption in turfgrass.

The field deployment of an IoT sensor node for measuring soil moisture requires three key technological components: 1) the soil moisture sensors themselves, 2) the IoT system that reads data from the sensors and transmits it to the cloud via a wireless link, and 3) the supporting infrastructure, including a reliable power source and a protective enclosure. There are multiple ways to measure soil moisture with proximal sensors, including capacitance, frequency domain reflectometry (FDR), and time domain reflectometry (TDR). Of the three, capacitance-based sensors are the logical choice when trying to reduce cost because the electrodes can be fabricated directly into the printed circuit board (PCB) material

(S.U. et al., 2014; Placidi et al., 2020; Okasga et al., 2021). Many popular research-grade soil sensors like METER Group's Ech2o EC-5 sensor (METER Group, Pullman, WA), use this measurement principle and rely on PCB fabricated electrodes. However, even these instruments, which are one of the most economical research grade sensors, cost $120 each. More recently, researchers have been testing much lower-cost versions of capacitor-based sensors that cost under $10 (Placidi et al., 2020, Schwamback et al., 2023). The problem with these lower-cost capacitance sensors is that they operate at much lower frequencies compared to research grade sensors, and are thus more sensitive to soil salinity and temperature (Robinson et al., 1999; Kizito et al., 2008) Furthermore, the commercially-available versions of this low-cost sensor are not waterproof (i.e., have exposed electronics), are difficult to inserted into firm or hard soil because of probe geometry, are subject to electrode damage during insertion, have no temperature measurement, and are not configured for easy interface with IoT data systems. So while these very inexpensive sensors have shown promise for irrigation scheduling (Okasha et al., 2021), research is needed to develop hardened more accurate version, with improved electrode geometry for easy soil insertion, waterproofing for below surface installations, and well-documented calibration curves that include temperature effects.

In addition to soil sensors, field hardware for a low-cost IoT measurement node requires a microcontroller to read the sensors and a wireless internet connection for real time data transmission. WiFi is a popular option for IoT devices indoors, but is rarely available in urban spaces like golf courses, parks, and sports fields. This has led many commercially-available IoT soil sensor companies to use proprietary wireless systems built around LoRa or LoRaWan. However, these systems add complexity to both hardware and software infrastructure. Fortunately, rapid advancements in cellular IoT, especially 5G, are making it the preferred choice when developing IoT irrigation control systems and soil monitoring (Payero, 2024, Tang et al., 2024). Cellular based interfaces allow flexibility on where sensor nodes because they can connect to the nearest cell tower without the need for and supporting wireless infrastructure (routers, repeaters, LoRa base stations/hubs, etc.). Fortunately, companies like particle.io (Particle Industries, Inc., San Francisco, California) and Blues wireless (Blues Inc., Boston, MA) offer low-cost hardware options that are idea for reading soil sensors and sending data to the cloud over cellular networks.

The final step in building a fully functional IoT measurement node is the all-important environmental housing and power supply. This is especially challenging in turfgrass systems like golf courses and sports fields because any above-ground structure is undesirable. This disallows using antenna masts, solar panels for charging, and other infrastructure. Ideally, the entire system would be installed below ground and be essentially "invisible" to passers-by or anyone using the golf course or sports field. This is also desirable in parks and other public areas to prevent vandalism or theft of the equipment. Additionally, the IoT electronics must be designed to consume very little power and be paired with robust battery packs, enabling the system to operate autonomously for extended periods—ideally several months—without requiring maintenance.

There is a clear need for the development of low-cost IoT technology to measure soil moisture that meets the specific requirements of managing irrigation in turfgrass systems. The objective of this study was to address this need by focusing on three key goals: 1) developing an affordable soil moisture sensor, 2) integrating the sensor with an innovative IoT cellular-based data acquisition system, and 3) designing a underground housing and deployment approach to enclose and power the system, making it suitable for use on golf courses, parks, and sports fields. Once completed, multiple measurement systems were deployed and tested on three golf course fairways across Fort Collins, CO, during the summer of 2020.

Soil Moisture Sensor Design, Construction, and Calibration

Soil Sensor Design and Construction

To achieve the goal of having both a low-cost and functional soil moisture sensor, a custom capacitance probe was designed, hereafter referred to as DP7T (dual probe version 7, with temperature) (Fig. 2 and 3). The sensor's internal frame, that includes the sensing electrodes and electronics circuit traces, is fabricated from printed circuit board material (PCB). This is a common strategy when trying to make a low-cost capacitance sensor (Dean et al., 2011), because the design is created in a CAD program and then made in bulk at a commercial PCB fabrication company for under $1 each. The sensor uses a dual probe geometry (i.e., two-pronged), based on the research of (Gonzalez-Teruel et al., 2017), and is similar to commercially-available sensors like the Echo EC-5 sensor (Meter, Pullman, WA). Each 'prong' of the sensor contains two linear copper traces embedded in the PCB, functioning as the plates of a capacitor (add figure from Eagle, sent via email). These sensors detect soil moisture by sensing changes in the soil's dielectric permittivity induced by change in soil water content. Rather than measuring the average water content between the probes, the sensor measures a small volume of soil around each probe and integrates these measurements into a single reading. Fringe capacitance soil sensors have a very small sampling volume (Goswami et al., 2018), so using two probes per sensor reduces errors by doubling the sampling volume, but still gives a thin probe cross section for easier insertion into the soil.

The circuit used to measure the capacitance of sensed by the probe electrodes is strongly based on circuit published or an open-source circuit by DFrobot (SEN0193, DFRobot, Shanghai, China). This circuit has been widely used and copied for both commercial and research applications (e.g., Abdelmoneim et al., 2025). In the DP7T Soil Moisture and Temperature- Probe, there are four main parts to the circuit (Fig. 3). The voltage regulator makes sure the probe can take a 3V-5V excitation and still operate the onboard chips at the required voltage. The second part is the 555-timing circuit (500 kHz osciallator) that determines the reading of the analog output in this case controlled by what the capacitor probe traces are experiencing. The third component is the high pass filter and peak detector circuit that converts waveform from the 555-timer to a dc-analog-signal for signal processing by the analog to digital converter (ADC) on the microcontroller. With this type of circuit, voltage output decreases as soil water content increases. Last was the thermistor circuit that measures sensors temperature. The raw voltage signal from the thermistor circuit is converted to Celsius using a third-order Steinhart-Hart equation. Each sensor generated two voltage outputs: one for water content and another for temperature. Additionally, a power (3.3V) and ground connection were required, so each required a four-conductor cable. Research has shown that many capacitive sensors are susceptible to temperature changes and high soil salinity levels (Kizito et al., 2008); a lab experiment found statistically different responses from sensors put in soil with a salinity level of 5 dSm^{-1} compared to 0.7 dSm^{-1} and 0.0 dSm^{-1} concentrations (Cardenas-Lailhacar & Dukes, 2015). Temperature also affects the readings of soil moisture sensors; sensors with added temperature compensations showed improved results (Oates et al., 2017). To combat the temperature issues, a thermistor was integrated into the DP7T sensor circuit to help correct the impact of temperature on the dielectric permittivity of water and the direct impacts of temperature on the electronics. This was particularly important for installations near the soil surface that see high soil temperature fluctuations. The golf courses had annual testing done for salinity that showed numbers below 0.7 dSm^{-1} so it was assumed that the soil salinity levels in these locations would have a negligible effect on the sensor's readings.

After sensor circuit boards assembly, the last step was making sure they were properly encapsulated and ready for outdoor installation. Before weatherproofing, a two-meter cable with a 1.0mm mini-micro JST PH connector was attached for interfacing to a data logger. Using the OpenSCAD software, custom designed 3D modeled enclosure hubs were modeled. Material was printed using Polyethylene terephthalate glycol (PETG), a thermoplastic polyester. To finish ruggedizing the sensors, ultimately, the printed enclosure hubs were sealed with epoxy. Additionally, a custom-designed install tool was 3D printed that made the process of installing sensors easier and more consistent (Fig. 2). Each sensor costs under $5 in parts. However, added labor costs are associated with assembling the printed circuit boards (PCB) and a final assembly before they are ready for outdoor use, putting the final cost closer to $10.

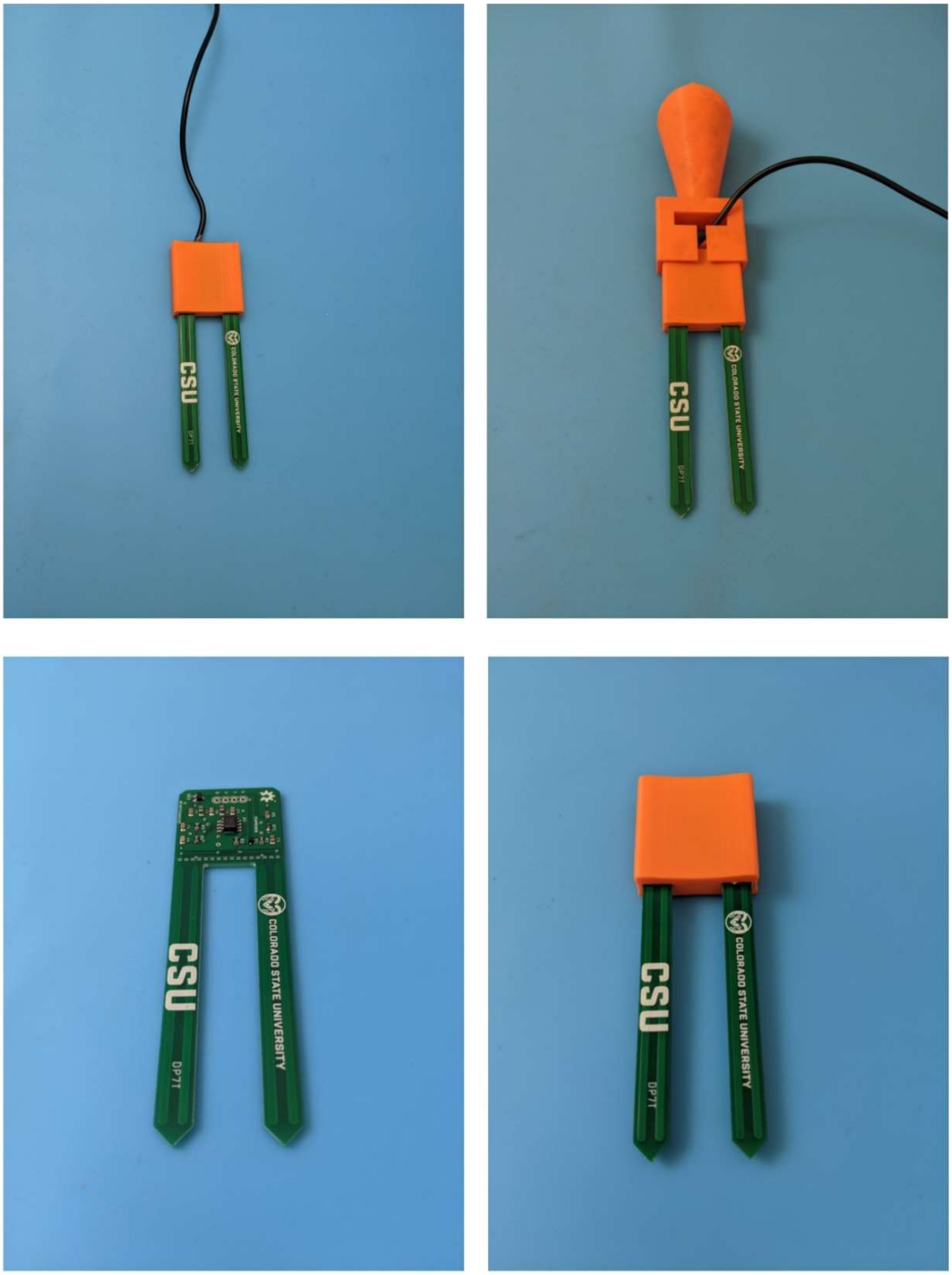

Figure 2. Images of a DP7T sensor with and without a waterproof shell as well as an installation tool (upper right) used to increase ease of use and accuracy when inserting the probe.

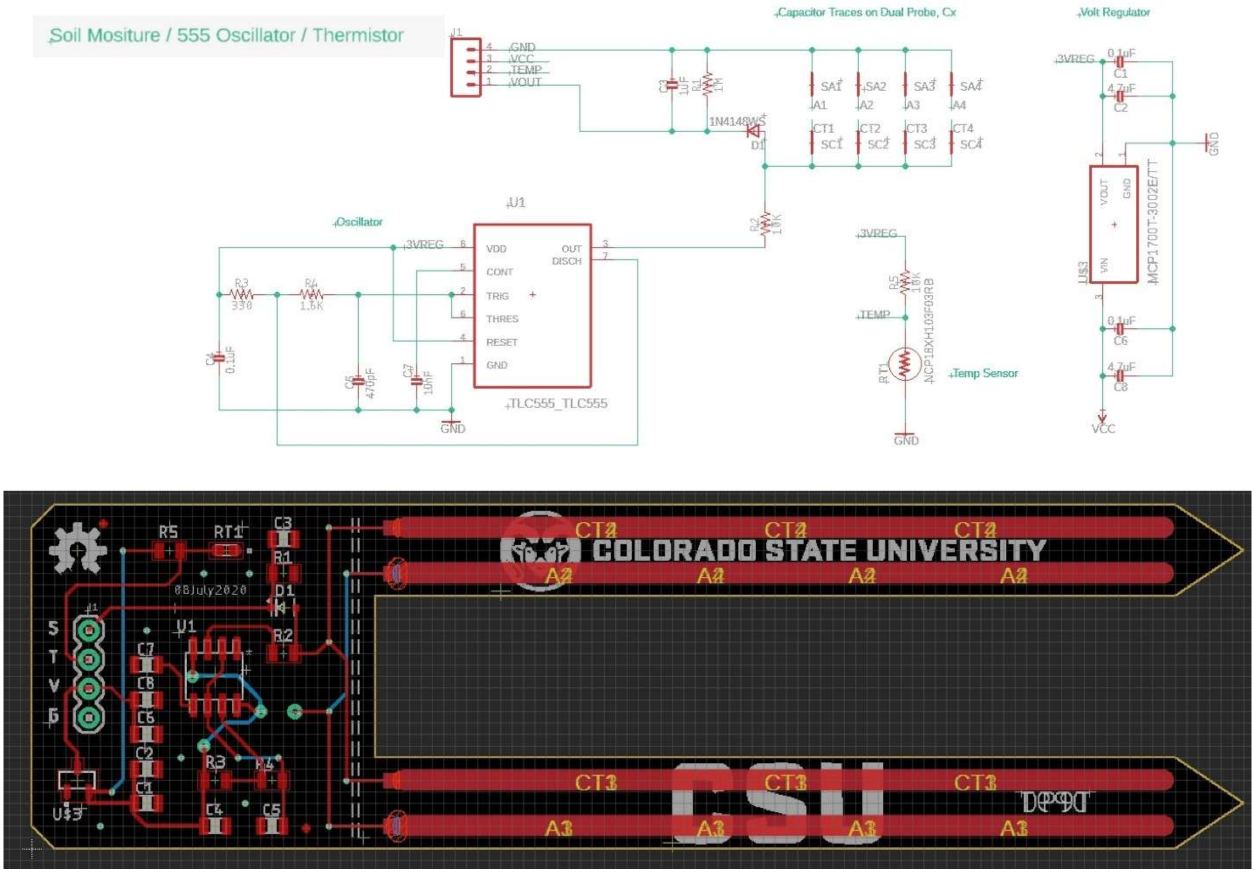

Figure 3. An electrical schematic (upper) and PCB board diagram (lower) of the DP7T probe.

Calibration methods

The sensors were calibrated in the lab using several soil types over a full range of water contents. All calibration work was done in temperature-controlled chambers to also quantify the temperature effect on the calibration curves.

Temperature Chambers Design and Specifications

To test the temperature response of the sensors, temperature-controlled units were fabricated by modifying an off-the-shelf adjustable temperature controlled cooler box (P27 Unit, Koolatron, Ontario, Canada) with a Peltier thermoelectric heat pump module. A circuit consisting of four relays permitted proper cooling or heating inside the insulated chamber; this was maintained by controlling the fans, Peltier Plate power, and the polarity of current going through the plate. An ESP32 microcontroller unit was used to send information to an onboard SD card, managing the cooler data while also transmitting information via Wi-Fi over a 2.4 GHz frequency to a cloud server. A mobile user interface was developed using the Blynk.io platform to control the settings and show live conditions inside the chamber.

The control system could run within a dead band of half a degree Celsius to any temperature between 10°C-35°C in a 20°C room. The software also includes an autocycle mode to run from two set temperatures in intervals determined by the user, staying at each temperature step for a defined time. For the temperature corrections of the moisture sensors, the complete range was selected between 10°C-35°C in increment steps of five degrees Celsius every four hours (Fig. 4). The four-hour time per step was determined by tracking the temperature of a 2000ml bottle of water in the chambers to see how long it took to reach equilibrium with the set temperatures.

Two temperature sensors (MCP9808) with an accuracy +/- 0.25°C were installed near the top and bottom of the chambers to detect any vertical gradients that might be present. The average of the two measurements was used for thermostat control, although the difference between the two sensors was also recorded. One extra MCP9808 was added to monitor a chosen sample and did not affect the chamber's temperature management system.

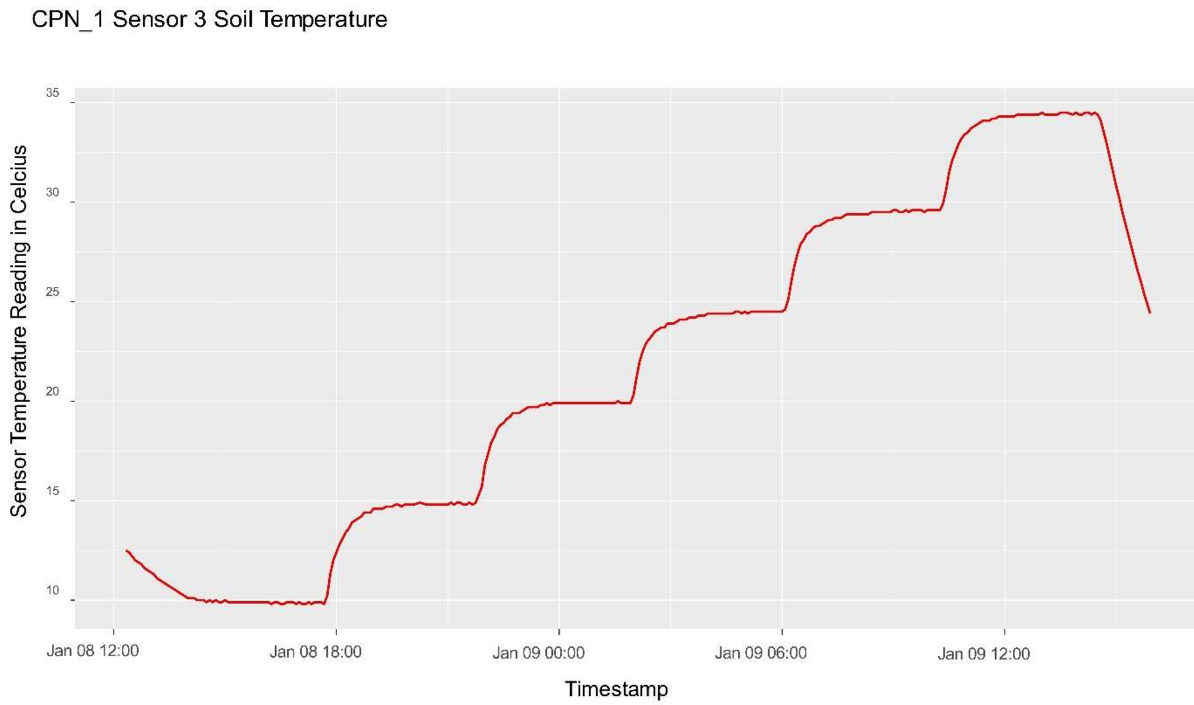

Figure 4. Data from the custom temperature chamber. An example of one of the containers' temperature data after being put through a full-range cycle from 10 to 35 C over 24 hours.

Soil Selection, Mixing, Packing, and Sensor Installation

Experiments were run on three distinct soils utilizing the temperature chambers: a Nunn clay loam (City Park Nine Golf Course, CO), Heldt clay loam (Southridge Golf Course, CO), and an Ascalon sandy loam (Carr, CO). Two samples were retrieved from golf courses used during the field testing phase of the study (see Field Testing). City Park Nine being the oldest course in the city had a much darker profile indicating higher soil organic matter while Southridge had a more traditional non-weathered clay soil with lower organic matter and higher bicarbonates. The third soil was collected from a location in Carr Colorado that provided soil with higher sand content.

Each of the three soil types was sent through four cycles at different water contents. Every cycle had five custom 3D printed containers (radius = 30.5 mm; soil depth = 110 mm; soil volume 321.471 cm^3) with lids to make sure moisture leaving was limited (Fig. 5A). Sensors were inserted into each of the five containers that were targeting the same water content and same soil type (i.e., five replications). The soil samples were wetted to four different volumetric water contents for the test: air-dry soil; saturated soil; a 50-50 mix of air-dry soil and saturated soil, herein referred to as 50_dry; and a 25-75 mix of air-dry soil and saturated soil, herein referred to as 75_dry. These mixing combinations were purposely chosen to target data points within the range you would typically see for an agronomic soil from field saturation to wilting point. The dry runs were performed to get the sensor's complete theoretical response range in the soils. After each experiment, every container had its VWC individually calculated using gravimetric moisture and oven-dried samples (Fig. 5B).

Packing and sensor insertion involve a series of precise steps to ensure proper setup and functionality. Before packing, it is crucial to break up any large clogs and add layers incrementally, applying medium pressure with a packing tool (Fig. 5C). This process typically requires five to seven batches to reach the desired height, marked by a line slightly recessed from the container's lip. Once packed, a thin cover lid is applied, followed by the insertion of a soil sensor, and then another cap equipped with an airtight gland to route the cable out to the data logger. During sensor insertion, careful handling is essential to avoid errors. The sensor should be inserted into the thin recessed cover (has pre-cut slots for the probe legs) in one smooth motion without wiggling, as this minimizes the risk of contact errors that could compromise readings (Fig. 5D). The airtight gland not only ensures cable integrity but also helps reduce water loss during testing. Adhering to these steps with precision is critical for achieving accurate and reliable sensor performance.

Figure 5. Four pictures demonstrate a run with: (A) five soil samples inside the custom temperature control chamber, (B) tins with three distinct soil water contents ready for the oven after a calibration run, (C) a 3D printed sensor container with a saturated sample alongside a packing tool, (D) and a sensor inserted with the container top-cap removed to see inside.

Soil Sensor Default Response

Soil moisture sensor data were collected in five-minute intervals with the same IoT datalogger setup used on the fairways (see IoT Datalogger Section). Data was sent live to a server that eventually was combined with the gravimetric samples measured from the containers. Each sensor has a thermistor not just to determine soil temperature, but also to provide the ability to carry out a temperature correction. Every sensor provided a time series graph at a constant soil water content; temperature being the independent variable as it relates to the sensor reading. Figure 6 shows the raw sensor voltages from sensors for the three soil types between 10 and 35 C). Points from an individual sample tend to group in a horizontal line because of the temperature effect that will be discussed in the next section.

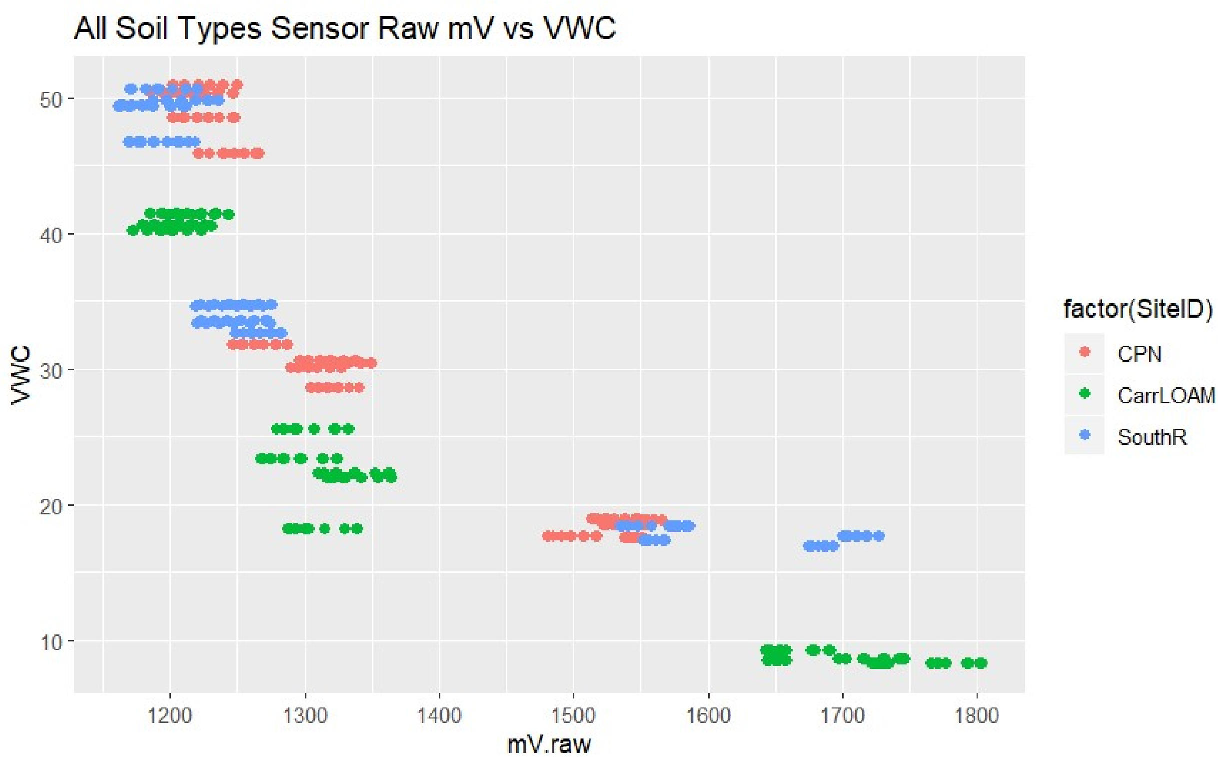

Figure 6. Displayed is raw millivolt sensor output at multiple water contents between 10 and 35 C collected from three soil types without any temperature corrections. Shown are data from City Park Nine golf course (CPN, clay loam), Southridge golf course (SouthR, clay loam), and the Carr location (Sandy loam).

Sensor Calibration: Volumetric Water Content with a Temperature Correction

Improving the Soil Sensor Calibration Equation

Capacitive sensors' temperature response has been observed by many researchers, and this was confirmed to be true for the DP7T sensor as well. Before moving forward with the correction, it was important to quantify how much accounting for temperature would improve our calibration. An AIC (Akaike information criterion) test was performed on the three soil types with temperature and raw millivolts predicting each unique soil's VWC (Table 1). Two of the three results showed that using temp and raw millivolts gave the lowest AIC values; with City Park Nine's soil being the only one that didn't, preferring solely raw millivolts. It outranked the combined temperature and raw-millivolts model by a small 0.368 difference. The previous research on these types of sensors and the AIC results support that the DP7T has a temperature response and that if corrected for should improve the Volumetric water content model precision.

Table 1. Relationship between raw mV output of DP7T sensor and the measured temperature as it relates to the measured VWC.

City Park Nine Soil Moisture and Temperature Sensor Model AIC Table

	(Intercept)	mV.raw	Temperature.in.C	mV.raw:Temperature.in.C	df	logLik	AIC	delta	weight
2	76.08023	-0.0314373	NA	NA	3	-2104.072	4214.144	0.0000000	4.618609e-01
4	75.01683	-0.0314646	0.0503308	NA	4	-2103.256	4214.512	0.3681247	3.842147e-01
8	76.19327	-0.0321855	-0.0030771	3.26e-05	5	-2103.171	4216.342	2.1976041	1.539244e-01
1	24.70090	NA	NA	NA	2	-2571.789	5147.578	933.4339744	9.373441e-204
3	24.92632	NA	-0.0102383	NA	3	-2571.782	5149.564	935.4197755	3.472864e-204

Carr Loam Soil Moisture and Temperature Sensor Model AIC Table

	(Intercept)	mV.raw	Temperature.in.C	mV.raw:Temperature.in.C	df	logLik	AIC	delta	weight
4	65.29388	-0.0292558	0.0518668	NA	4	-2039.797	4087.594	0.000000	4.345764e-01
2	66.36569	-0.0292078	NA	NA	3	-2040.868	4087.737	0.142819	4.046256e-01
8	65.59809	-0.0294406	0.0381018	8.3e-06	5	-2039.791	4089.582	1.988446	1.607980e-01
1	18.16869	NA	NA	NA	2	-2483.138	4970.277	882.682764	9.245687e-193
3	18.80194	NA	-0.0285362	NA	3	-2483.064	4972.128	884.534126	3.663710e-193

SouthRidge Soil Moisture and Temperature Sensor Model AIC Table

	(Intercept)	mV.raw	Temperature.in.C	mV.raw:Temperature.in.C	df	logLik	AIC	delta	weight
4	81.20081	-0.0356732	0.0667281	NA	4	-1974.101	3956.201	0.000000	5.560535e-01
8	83.10070	-0.0368604	-0.0180164	5.27e-05	5	-1973.793	3957.586	1.385133	2.781882e-01
2	82.62053	-0.0356290	NA	NA	3	-1976.311	3958.622	2.420667	1.657583e-01
1	25.41543	NA	NA	NA	2	-2584.135	5172.269	1216.068150	4.778294e-265
3	25.58238	NA	-0.0074738	NA	3	-2584.131	5174.262	1218.060855	1.764260e-265

Sensor Temperature Correction

A clear pattern emerged with the sensor analog moisture readings increasing with temperature (Fig. 7). In shallow installations for turf and other applications that see high-temperature swings, having a temperature correction can prove to be a necessity to get the quality of data expected. It becomes even more essential if the location's soil moisture content is high due to this sensor's lower sensitivity at higher water contents; this lower sensitivity in the wet end is caused by the non-linear sensor response.

In the temperature chamber runs, a sensor sent its soil moisture and thermistor readings live every five minutes. By looking at the data of the temperature response test runs, a clear positive relationship between the analog millivolts reading and soil temperature was observed (Fig. 7). However, the effect is small; in Fig. 7 for example voltage increasing from 1290 mV at 10C to 1327 at 35C, or about 1.5 mV/C. A common approach to removing the temperature effect from sensors raw output voltage (Vraw) takes the form

$$V_{corrected} = V_{raw} + CF \times (T - T_{ref}) \quad (1)$$

Where $V_{corrected}$ is the corrected voltage, T is sensor temperature, C; T_{ref} is a reference temperature (e.g., 25C), and CF is the correction factor determined experimentally, mV/C.

A statistical temperature correction was developed using this approach using 25 Celcius as a reference temperarue (Eq. 2) and pooling data from all three soil types. The correction factor was calculated using a second-order polynomial correction factor Eq. (3) instead of using a constant as well as a delta-temperature argument Eq. (2). Thus, equation 1 was to apply a temperature correct to all sensor data going forward, normalizing all data to the reference temperature.

$$\Delta\mathrm{T} = \mathrm{Tsensor} - 25 \quad (2)$$

$$\mathrm{CF} = 0.00000484 \times \mathrm{mVraw}^2 - 0.015 \times \mathrm{mVraw} + 14 \quad (3)$$

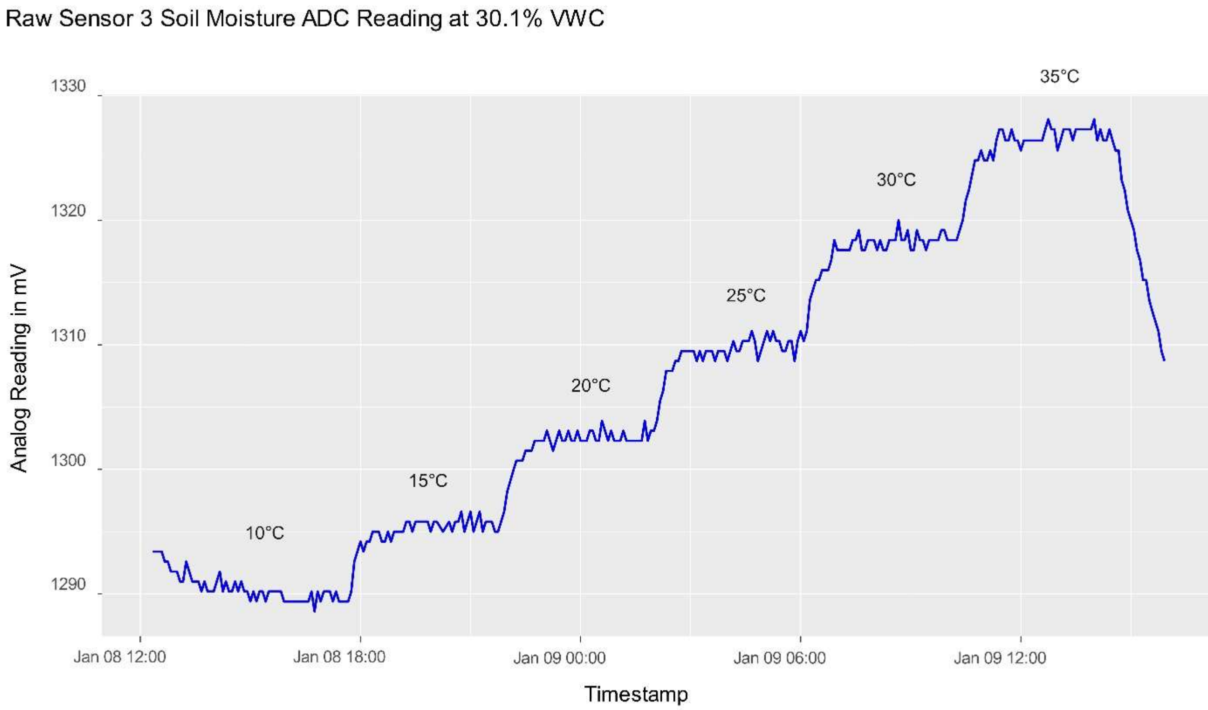

Figure 7. A single DP7T sensor's raw millivolt readings of a Nunn clay loam soil at 30.1% VWC throughout a temperature chamber cycle from 10°C to 35°C in steps of 5°C.

Final Sensor Calibration

Because these sensors had a non-linear response to water content (Fig. 8), a logarithmic transformation was applied and substantially improved the linear models fit (Fig. 9). R software utilizing a linear model "lm" function produced a coefficient of determination that was .9953 for City Park Nines Soil, .9895 for the Carr Sandy Loam, and an R^2 of .978 for Southridge (Fig. 9). Each of the three linear models applied to the temperature corrected data had a total of 600 points, with five readings taken for each container's unique temperature and VWC combinations. Although the result improved when doing lines of fit individually, combining the three soil's readings to create one curve provided a lower but still very strong R^2 value of .8617 (Fig. 10). If it's acceptable to use a more generic function, this is advantageous. It will allow one function to represent multiple soil types and circumvent the time required to individually calibrate each sensor to its unique soil. It's important to remember that even with a well-formulated generic equation, to get the best results when calibrating to VWC, it's advised to individually calibrate each sensor being installed and ideally get at least a few calibration points ranging across the dry and wet ends of the soil moisture spectrum. The results in this study were promising, but the agronomic soils tested did not have extreme differences from one another; lab experimentation on more soil types would be desirable.

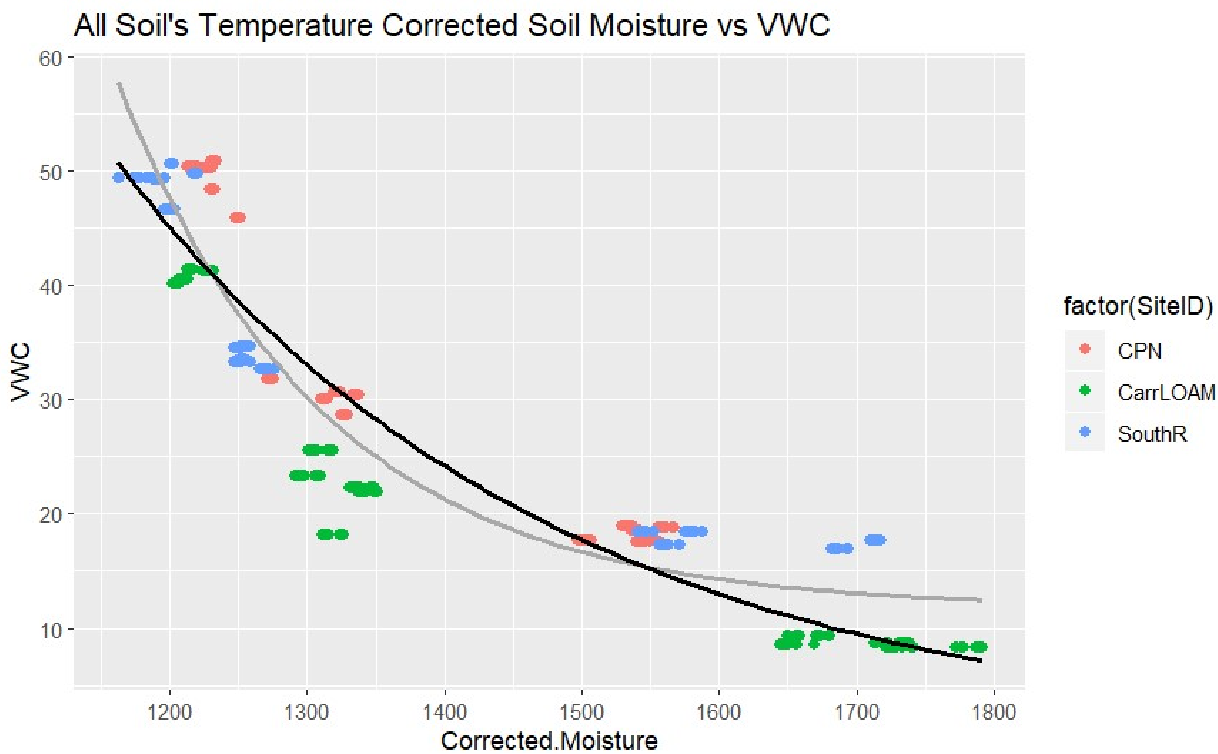

Figure 8. Temperature corrected soil moisture in millivolts (x-axis) compared to VWC (y-axis) using all three soil types and a asymptotic (grey line) and exponential decay (black line) fit. Here corrected moisture on the X-axis is the sensor mV output corrected for temperature (Eq, 3).

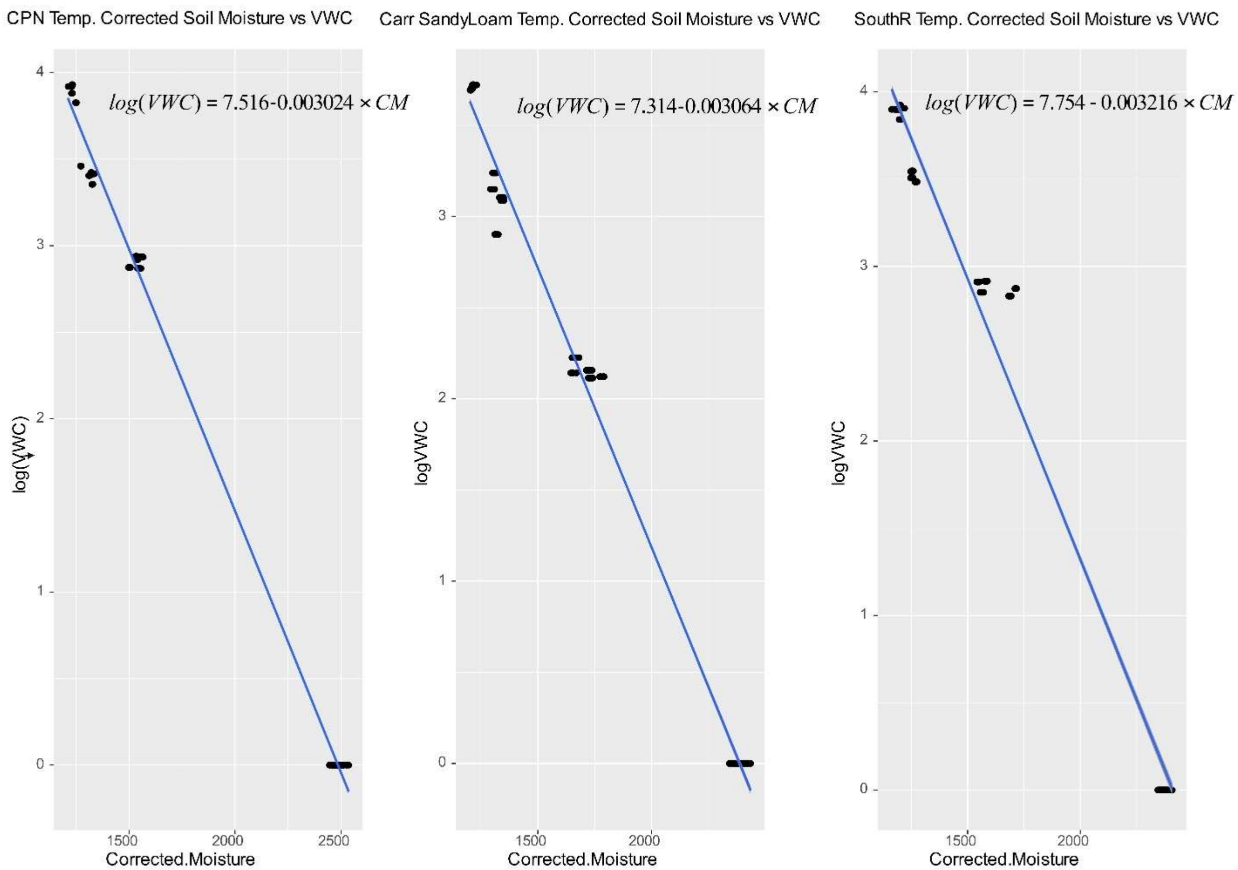

Figure 9. Individual lines of fit for each soil type using a linear model with a natural log transform on the response variable. The x-axis in this case is the mV output from the sensor that has been corrected for temperature (Eq. 3).

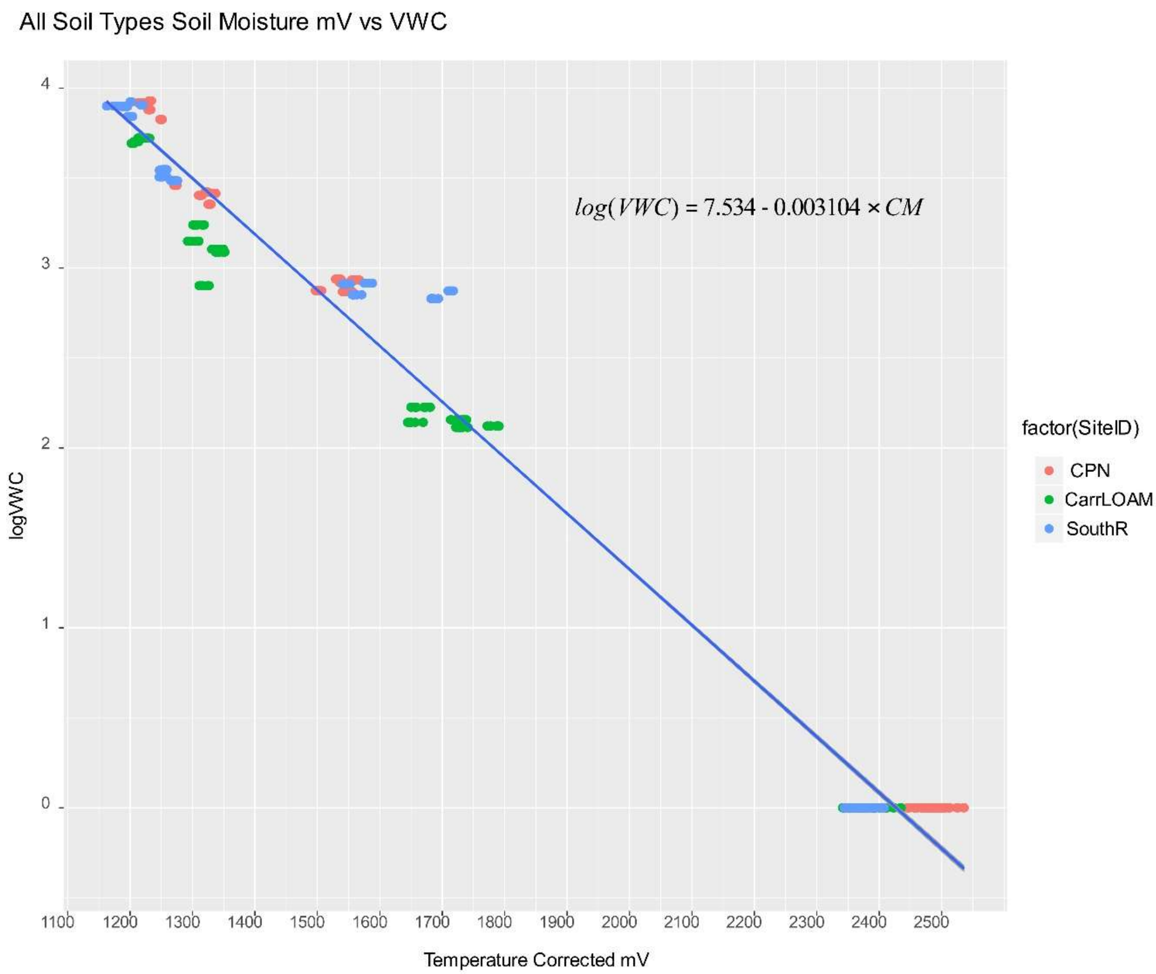

Figure 10. This graph combines all three soil types to make a single linear line of fit with a log transform on the measured VWC.

IoT Cellular Datalogger and Field Design

The soils sensors described in the previous section each generate two voltages that represent changes in soil water content and temperature. To read voltage from multiple sensors and send data to the internet over a wireless link, requires an IoT datalogger, enclosure, power, and supporting field hardware and firmware – hereafter called an IoT measurement station (IMS) - analogous to a weather station. The design used in this study has four low-cost soil sensors at each IMS location. Figure 11 shows the data flow from the soil sensors, to the IoT datalogger, and into the larger IoT cloud infrastructure using a cellular connection. The main goal was to design and fabricate an IMS that could be used in golf course fairways, parks, and other public turfgrass locations.

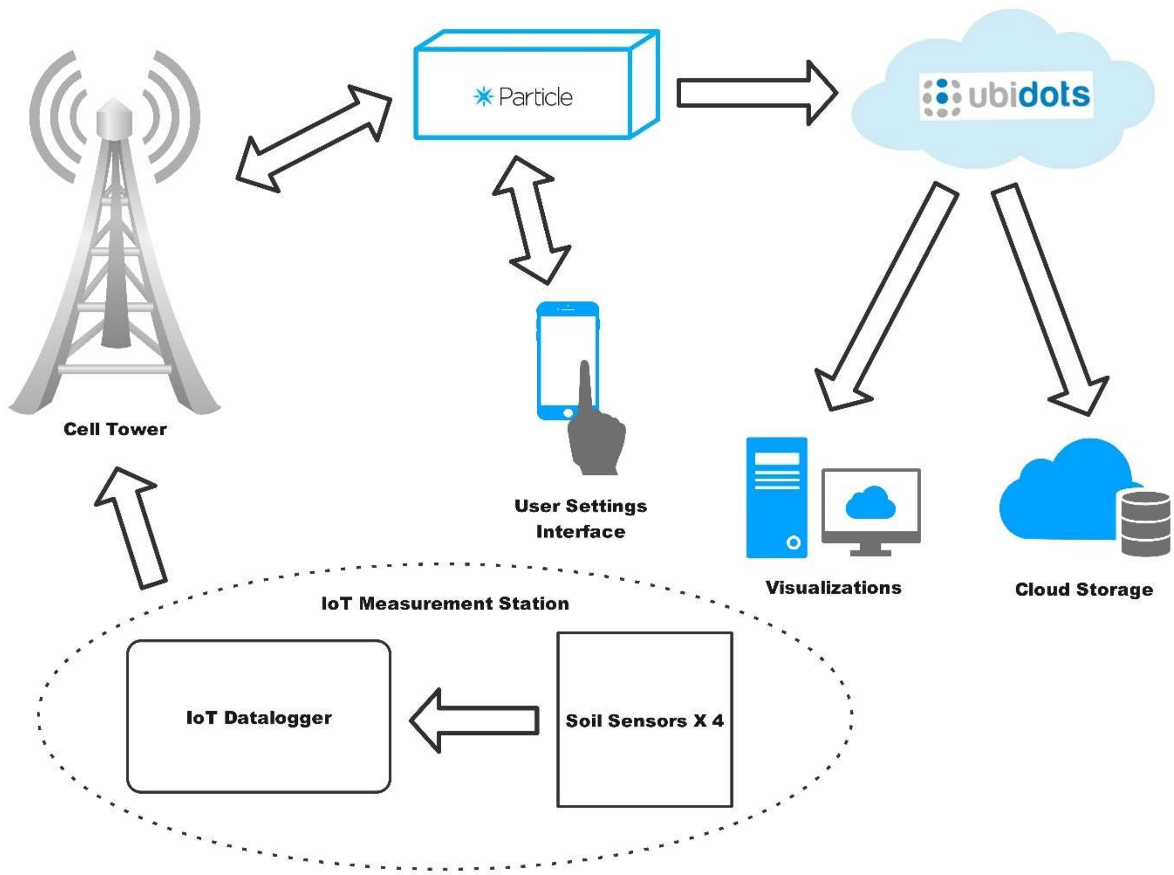

Figure 11. An Illustration of the data flow and communications diagram.

IoT Cellular Datalogger

The voltages from the soil sensors were read with a Particle Boron development board (Particle IO) attached to a custom PCB carrier board developed for this study. The Boron includes a Nordic Semiconductor nRF52840 microcontroller paired with a u-blox SARA R510S-01B LTE cellular modem. So, for only about $45 one gets a powerful IoT device that can read sensors and transmit data to Particles IoT cloud platform over cellular networks. It also includes 20 GPIO, UART, I2C, and SPI connections. The analog to digital converter equipped uses a differential successive approximation register recorded at a 12-bit resolution.

To expand its functionality, the Boron board was plugged into a custom PCB carrier board developed for this study (Fig. 12A). The carrier board design is comprised of surface mount devices (SMD) and other connections that allow for added features and a more reliable user experience. These benefits include power regulation, power conservation, peripheral connections, user switches, as well as memory, and onboard sensor chips. The carrier board furnishes two rows of female headers to accommodate microcontroller boards with a Adafruit Feather pinout footprint – including the Boron. The feather layout was chosen because it has universal specifications, and many companies offer feather breakouts of their products.

The carrier board has 14 key components (Fig. 13), most of which handle power in a variety of ways. The load switch is used to limit current draw from sensors when they're not being used. The voltage regulator makes sure the voltage going into the onboard parts is appropriate, while a fuse is located for safety in case of power errors. A user switch cuts power to the board and paired with the button gives the user some choices when physically located at the board. One of the most important power components is the RTC chip which also operates as a deep sleep timer. To make the power consumption low enough to operate on only a battery, it was essential to improve on the software sleep available at the time. The RTC can be set and will connect the microcontroller's enable pin LOW for the desired duration. This essentially is like unplugging the board, so all the power draw remaining is from the quiescent current of any remaining live parts. Besides power, the carrier also provides usable sensor input plugs and expands the abilities of what the system can sense. The Boron has several ADC channels, but more are needed to read a group of soil sensors which generate two voltages per sensor. To address the issue a multiplexing chip was added to allow for more analog inputs. This granted the user the ability to read 10 analog signals. Hence, permitting 5 soil moisture and 5 soil temperature data lines to be collected. More conductor connections were added for I2C communication and to plug in a battery. A relative humidity and air temperature sensor was included to track climate conditions around the board. In addition to dealing with power and sensors, the board was also equipped with a FRAM chip for extra nonvolatile memory storage.

Battery power for the IoT datalogger was provided by a 3x18650 pack design was used in this study. Its parts consisted of 3D printed legs, PCB tracks, and a three-slot 18650 battery pack. Using a cut piece of expanded PVC board, the custom legs were fastened to it using flathead screws and acorn nuts. The legs secured the battery pack while also permitting a location for the Carrier 2.1 to be screwed in at (Fig. 12B). To prevent the pack from moving around when inside the enclosure, two pieces of one sided-Velcro were required.

The battery design was made to be installed easily and offer flexibility for multiple use cases. Any three of the same 18650 battery sizes could be used, giving options to the different voltages and Amp-hours desired. Depending on the cost and manufacturer, the range of mAh per 18560 battery cell usually falls between 1100mAh-3600mAh. The custom PCB tracks also offer the option to cut the necessary traces and solder wire to switch the pack to a series connection increasing the voltage instead of capacity. For this study, a 3.7 nominal voltage was well above the minimum 3.3 volts required, so putting them in parallel was favored. Two different companies' products were used going with Samsung's 29E and LG's M36 cells. Based on their datasheets this gave about 31.64 Wh and 38.30 Wh respectively per pack. At that time the Samsung 29E cost about $1.07 per Ah while the LG M36 was $1.59 per Ah. Both worked to advertised specs and had no trouble charging. They functioned without issues over the duration of the field season. During prototyping, if the system's batteries ran out of charge, they could be replenished by replacing the entire pack or by putting newly charged batteries in. A pack can be recharged through their common connection with a lithium-ion charger that takes a two position 2.0mm JST connection. Furthermore, with a compatible feather microcontroller and solar panel, photo voltaic charging is possible. In this case, 6-volt solar panels with the correct max current could be attached by connecting a USB micro type B connection to the Particle Boron's integrated battery charging circuit.

The IoT datalogger was placed in an environmental enclosure made of resistant ABS plastic with four screws that fasten the lipped lid on top. The box incorporates a gasket in the lid to offer an enhanced water-tight seal. Rated to IP65 with total dimensions of 158mmX90mmX60mm, it was affordable, and it fit well into the valve box. Additionally, a larger ½ inch hole was drilled on top for the omnidirectional antenna. Five NPT ¼ inch glands were drilled and tapped in a triangular pattern along the bottom for sensor cable passthrough. If installed properly they have an IP68 rating and are made of Nylon making them extremely resistant to almost any corrosion. A piece of one-sided Velcro was put just above where the glands were installed to give the carrier and battery brick a place to fasten to (Fig. 12C).

The Particle Boron requires an external antenna and a Taoglas G30.B.108111 omnidirectional antenna with a waterproof design was used. A wideband design allowed it to be compatible with standard Cellular and WiFi radio frequencies ranging from 698MHz ~ 960MHz and 1.71GHz ~ 2.7GHz. The highest strength of each band is at 829MHz and 2.4GHz. The smallest coaxial cable version offered was used to reduce losses, delivering peak Gains of 1.2dBi for 829MHz and 3.2dBi at 2.4GHz. The antenna was mounted at the end of the enclosure making for a very compact design (Fig. 12C).

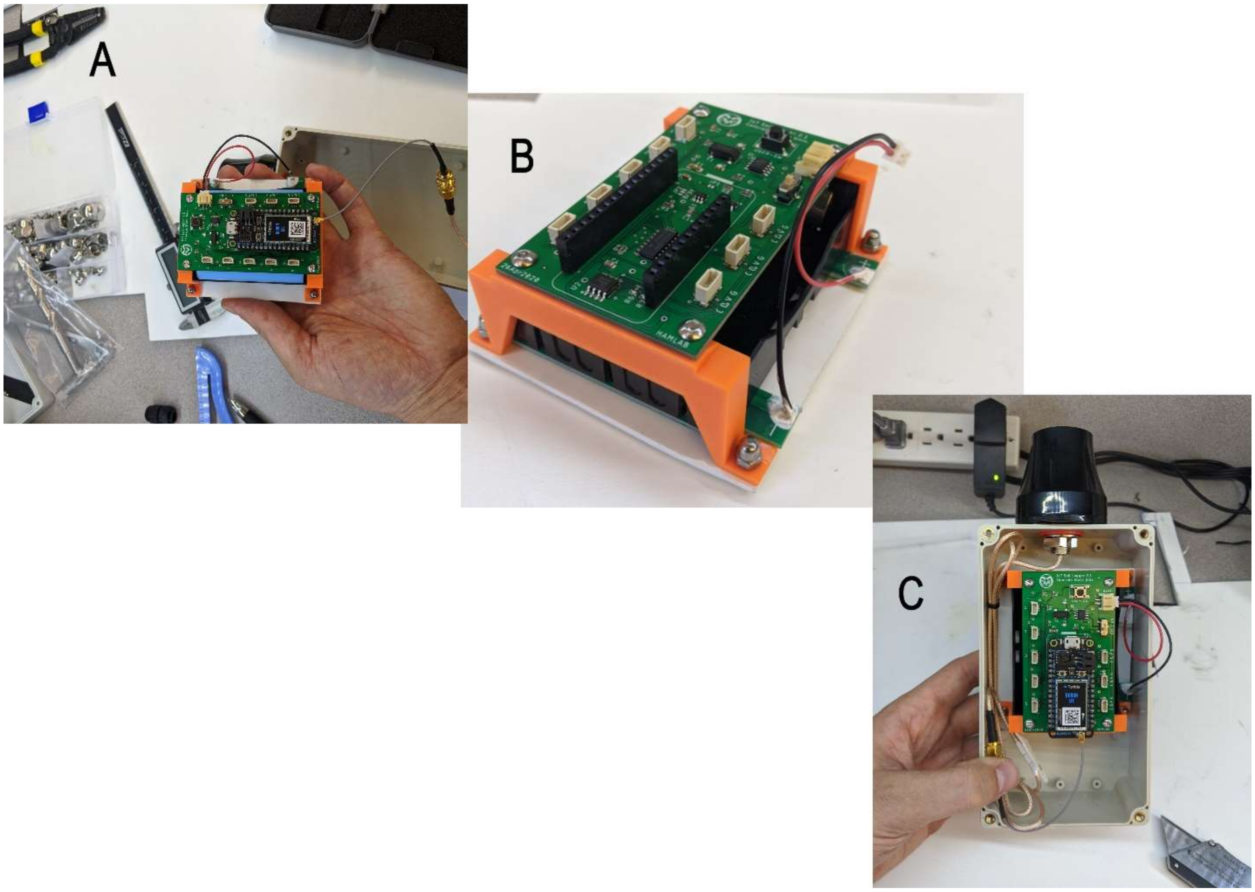

Figure 12. Pictures demonstrate: (A) the IoT Cellular Datalogger, (B) carrier-battery block, (C) field ready IoT datalogger showing the antenna and the enclosure lid is removed to show internals.

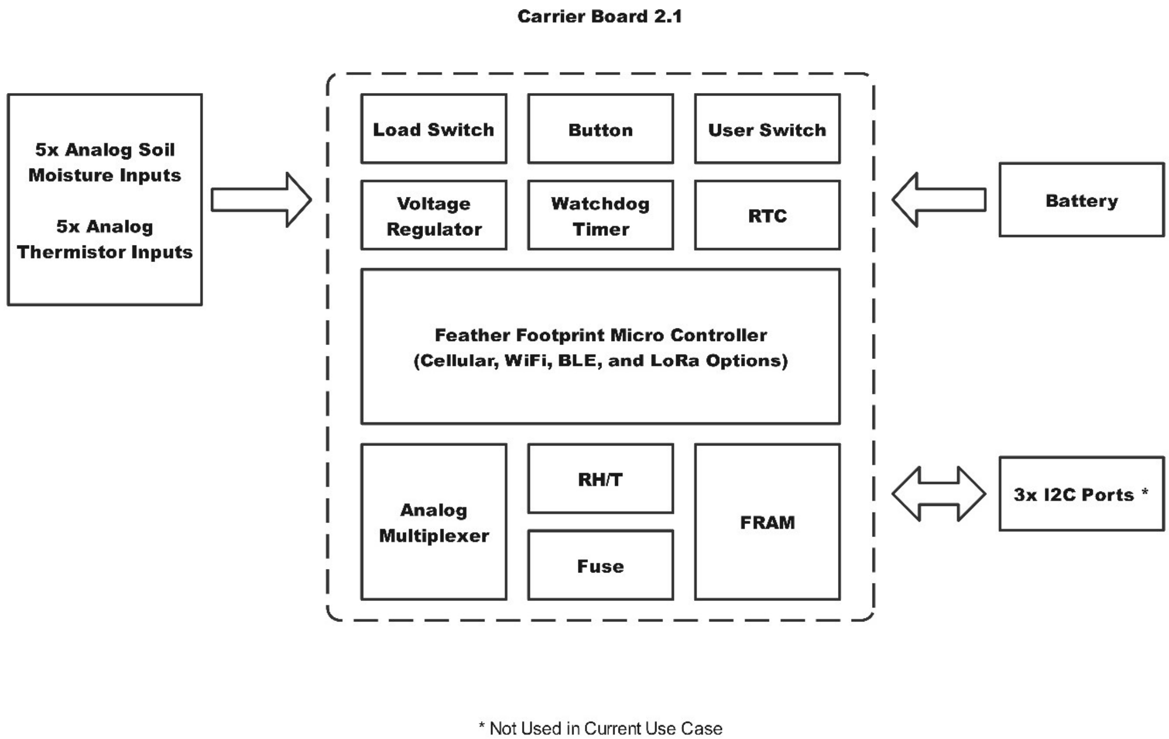

Figure 13. Block diagram symbolizing the carrier board 2.1 printed circuit board design.

Valve Box

For golf courses or open spaces, avoiding above-ground towers is almost a necessity. Interviewed state officials and workers have expressed that theft or tampering are a concern, further demonstrating above-ground devices and enclosures are impractical for urban public settings. The systems needed to meet a couple of criteria; the footprint had to run at or below surface level, integrate naturally into the environment, and offer access when they needed to be retrieved or physically modified. The valve box met many of the desired criteria, and the versions were adapted from a 10” to 6” diameter (Fig. 14). The smaller diameter allowed for on-fairway placement due to the size and appearance, which was similar to a golf course irrigation valve enclosure.

The installation required a hole to be dug a bit deeper than the height of the box. Using pea gravel to backfill, the valve box is negotiated to sit level and flush with the soil-turf surface. The pea gravel also allows water that builds up to quickly drain down and out of the main compartment. At times the systems can still get flooded, but this reduces the chance of failures. Located at the bottom of the valve box, two cut-outs are on either side; typically, they're utilized for pipe access into the box. For the valve box system, the cutouts were used as conductor access points where wires could be run through the holes situated 180 degrees from each other. At the end of the installation, a ring of grass needs to be cut so the valve box can be properly surrounded and camouflaged (Fig 15).

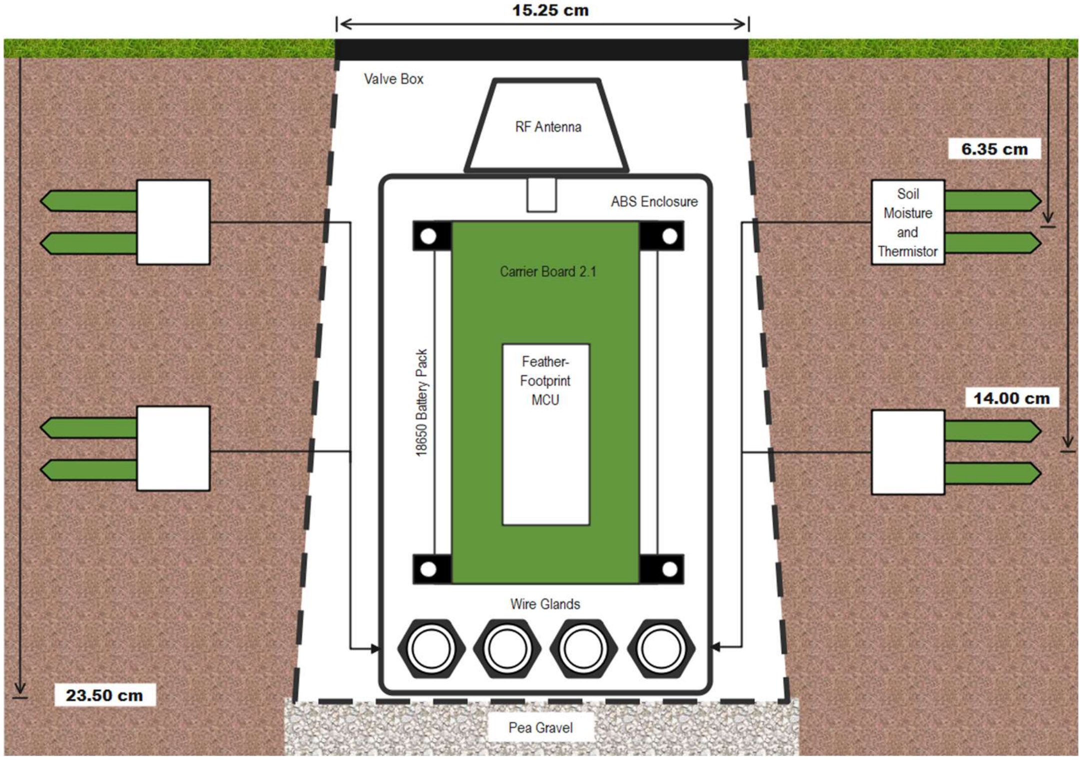

Figure 14. Complete IoT Measurement Station diagram to view the design and parts.

Figure 15. Demonstration of IoT Measurement Station before being covered up in the Fairway and side-view showing valve-box placement.

Hardware Cost

The bill of materials for the IoT Measurement Station showcases a cost-effective solution for soil monitoring, purchased in 2020 with a total hardware cost of $152.04 (Table 2). This custom-built system combines soil sensors and an IoT datalogger, utilizing components such as a Particle Boron LTE microcontroller, Taoglas antenna, and custom DP7T soil sensors. The breakdown includes protective elements like an ABS enclosure and a valve box, as well as a battery pack with lithium-ion batteries for power. Notably, this total cost is more than 10 times less than comparable commercial options currently available. However, it's important to emphasize that this figure represents only the material costs and does not include labor expenses for assembly or installation. This cost-efficient approach demonstrates the potential for creating accessible and scalable IoT solutions for environmental monitoring.

Table 2. A complete bill of materials purchased in early 2020 for the IoT datalogger installation, including both the 2020 IoT Cellular Datalogger and four DP7T sensors.

ItemName	CompanyOrGroup	Function	Count	UnitCost	Total
G30.B.108111	Taoglas	Antenna	1	$26.53	$26.53
Junction Box	Zulkit	ABS Enclosure	1	$7.51	$7.51
3x18650 Battery Pack V1	Ham Lab CSU	Hold Parts Together	1	$4.04	$4.04
18650 Lithium Ion Battery	Samsung 29E	18650 Battery	3	$3.00	$9.00
Nylon Cable Glands	Kable Kontrol	Watertight Inputs	5	$0.24	$1.19
Carrier 2.1	Ham Lab CSU	Special Functions	1	$19.00	$19.00
DP7T Soil Sensor	Ham Lab CSU	Sense Soil Enviornment	4	$3.77	$15.08
Hook and Loop Tape	Strenco	Secure Battery Brick	1	$0.25	$0.25
Boron LTE	Particle	MCU and Cellular Conection	1	$59.37	$59.37
6-inch Valve Box	NDS	Protection	1	$9.18	$9.18
Pea Gravel	Vigoro	High Drainage Medium	0.2	$4.45	$0.89
			TOTAL	SUM	$152.04

Firmware and Software

Custom firmware was developed for the particle Boron, the development board used to read the sensor and transfer data to the cloud via a cellular (Fig. 16). The organizational method of the code used a structure called a finite state machine (FSM) that switches from state to state based on if certain criteria are met or not (Fig. 16). The device will begin in the Setup STATE. There it initializes the sensors, Carrier SMD's, and RF connectivity. This is also when the system checks to see if either of the optional modes is set to true. Verbose mode, if on, will communicate the system's every move as it jumps to the next tasks. If diagnostic mode is on, then the device will stay on and perform a cycle every two minutes. These two settings are to help the user troubleshoot any issues. After the Setup STATE finishes, next is the Idle STATE, where the system waits for commands. Once the proper time is reached the case switches to the Measuring STATE. As the name suggests, the sensors and other important variables are then updated. After Measuring there are two possible options. If the system detects something went wrong in the measuring loop the software instead of reporting the results will enter an Error STATE. If measurement is successful, the program transitions to the Reporting STATE. The data is then sent out, and once complete will enter the sleeping STATE to save power. The same is true after the Error state. Instead of sending bad data, reporting STATE is skipped and goes straight to Sleeping STATE.

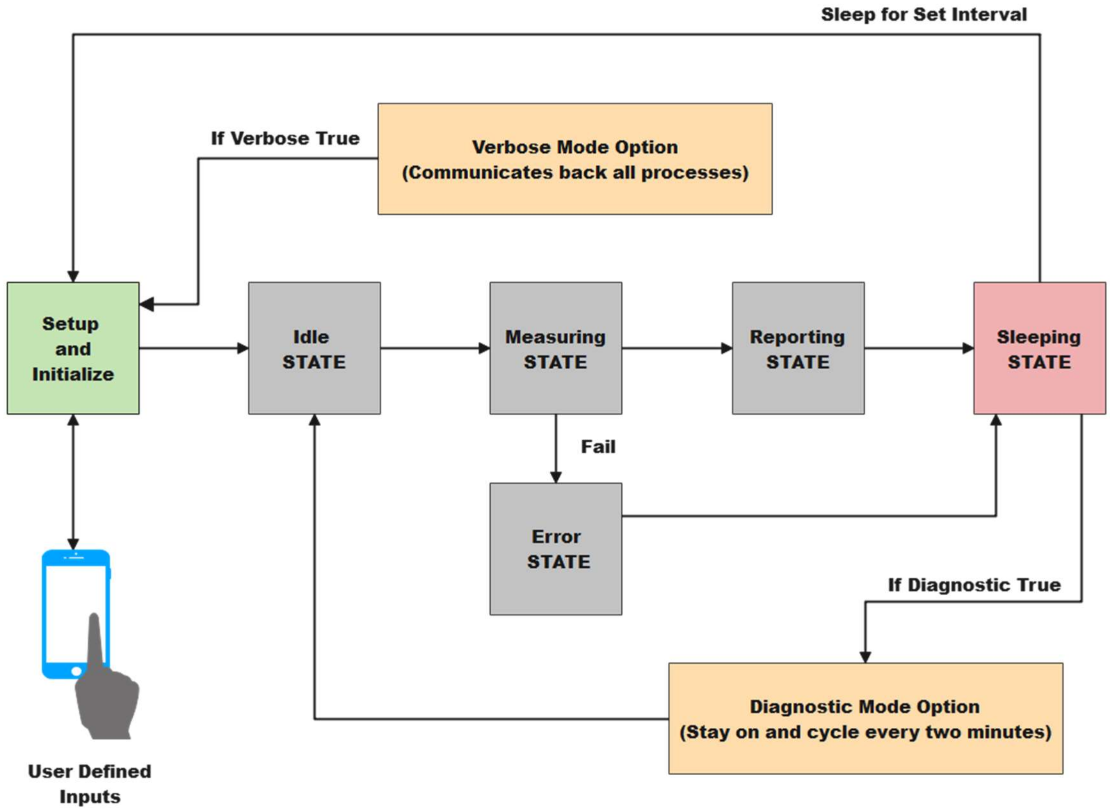

Figure 16. Flowchart of firmware on the Particle Boron used in the IoT datalogger. A state machine code structure is shown as a block diagram.

IoT Networking

A fundamental component of the systems was wireless connectivity and cloud storage. Once data is delivered to the cloud, it is backed up and, after a few missed sample intervals, one could know if a system stopped working. A 4G LTE cellular option was used to achieve wireless connectivity. This is done by purchasing devices and SIMs through the Particle system. As a result, a monthly charge ($3/mo/device) was issued based on a combination of your data usage and the total number of active

SIMs. The plans could be started and canceled at any point making a commonly complex cellular connection much easier to achieve. Most of the work between the cell towers and the Particle Boron is handled in the background, so the majority of the coding effort can be put into designing the data flow and user interfaces. Furthermore, Particle offers particularly helpful device management tools and product creation that gives added organization and over-the-air programming capabilities to your device fleet.

This project's design utilizes one data storage service and two user interfaces that allow for numerous control features. Particle functions within the Particle App give the user the ability to view live data feeds of all variables as well as the freedom to change desired parameters like sample interval, set the time zone, and turn diagnostic and verbose modes on or off over a mobile. For data collection, storage and data analysis the Ubidots IoT platform (Ubidots, Medellín, Colombia) was used; achieved by particle integrations that sent data to Ubidots via webhook. More specifically this was completed by using the HTTP protocol and formatting the JSON script so that Ubidots servers accepted the data strings sent in.

Once the connection was tested and successfully sent to Ubidots there were two separate actions performed following the data's arrival. First, each device's data is stored and backed up in their cloud. In addition to the data storage, the second part includes the user features offered such as customizable interfaces, visualizations, and data analysis tools. By creating organizations, users can sign into their accounts through an app-portal and see only the devices that are meant for them. Dashboards can also be created that display live data in ways best suited for the client. Creating alerts and synthetic variables are also options for use cases that find them important.

Field Testing

Locations

Field testing was completed on three different city-owned golf courses across the city of Fort Collins, U.S.A. in the summer of 2020. We collaborated with the superintendents and other city leaders to install IoT soil measurement systems and monitor them over the season. Three IoT measurement stations (value-box style configuration) were installed on a chosen fairway at each golf course - nine total (Fig 17). The three measurement locations on each fairway were chosen to capture the anticipated variability in moisture content so that the average of all three stations would represent overall conditions. More on how spatial variability affects soil moisture measurement is discussed in Chapter 3. All courses used sprinkler irrigation with weather-based scheduling programmed and monitored by the superintendent.

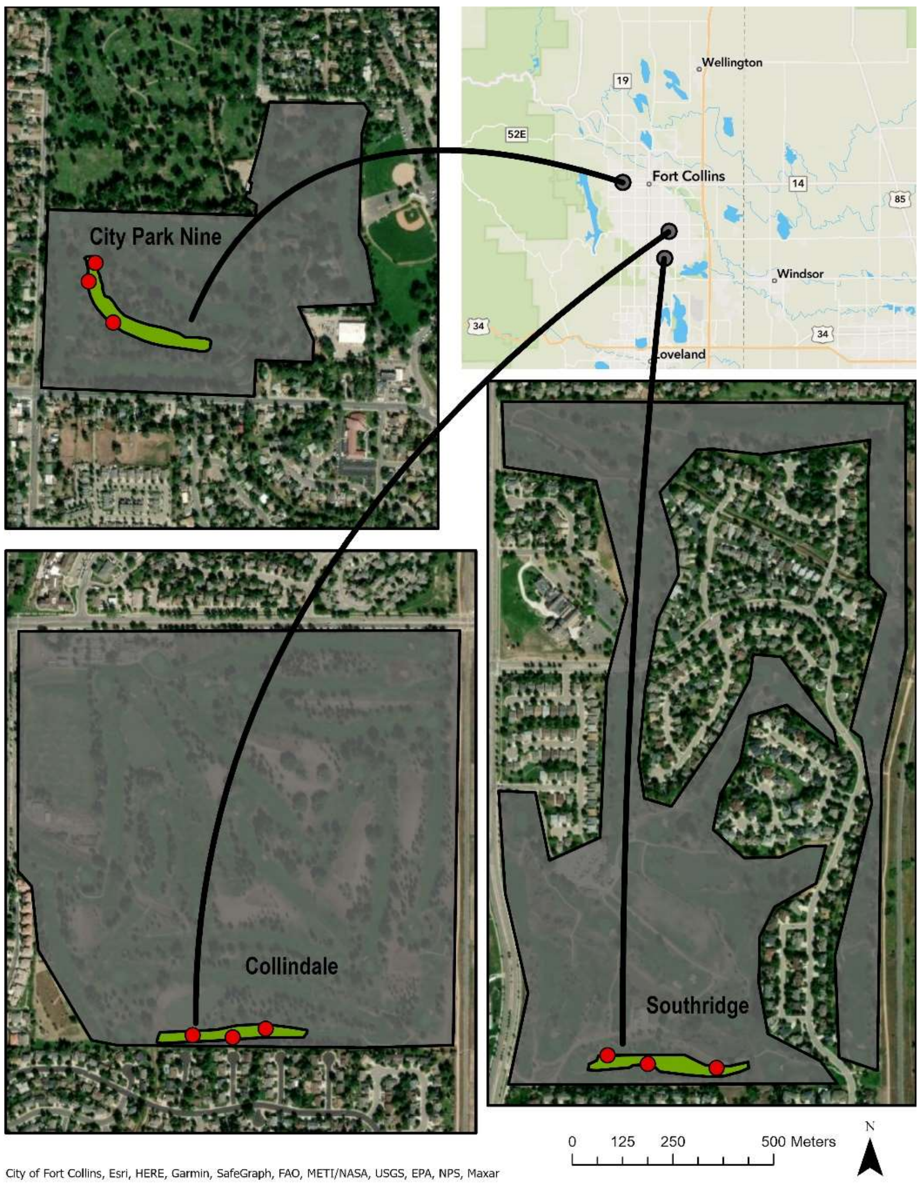

Figure 17. Three red test locations are shown for each fairway at 1:10,000 scale and their golf courses at a 1:500,000 scale.

Southridge

Southridge Golf Course is in south Fort Collins at 40.5071° N, 105.0535° W. The course's fairways were mostly comprised of creeping bent grass (Agrostis stolonifera). Fairway 15 was chosen, having a long straight run with an incline leading up to the hole. Near the tee, there was a low spot that had large trees shading it, while the other half sloped up towards the hole that was positioned on a hill in full sun.

City Park Nine

The oldest course in Fort Collins offered a very much darker soil profile (carbon sequestration over time) than the other courses and was located at 39.7528° N, 104.9504° W. There was a turf mix of creeping bent grass (Agrostis stolonifera) and annual bluegrass (Poa annua) on the fairways. City Park Nine Golf Course is located right off City Park close to the university campus. Jim, the superintendent recommended we outfit Fairway 7 due to the variability it experiences along its bend. The hole was a Par five and had a curve leading to the flag. At the tee mound and along the first straight there were many large trees, but once around the bend, the turf was in more direct sun. The fairway was almost entirely flat.

Collindale

The City of Fort Collins Collindale Golf Course is an 18-hole course located in the center of the city at 40.5375° N, 105.0509° W. The turfgrass on the fairways was a majority creeping bent grass (Agrostis stolonifera). This was the longest fairway tested, a Par five with a long straight run. A river dividing the green was the only obstruction in the way. The south side of the fairway had heavy tree coverage, while most other areas did not, driving more variation in the soil. This was one main reason the superintendent, Brent, encouraged Fairway 6 for installation.

IoT Measurement Station installation

The sensor pairs were installed at depths of 2 inches (5 cm) and 6 inches (15 cm), positioned approximately 3 feet (1 meter) away from the logger (Fig. 18A). Care was taken to ensure proper installation by avoiding preferential flow paths or unnatural ponding around the sensors. During backfilling, the soil was carefully packed to eliminate air gaps while avoiding excessive movement or jiggling of the sensors to maintain accurate placement and reliable data collection. Pieces of turf removed during installation were saved and carefully replanted over the trench and holes to promote quick regrowth (Fig. 18B). Thanks to frequent watering on the golf course, the turf healed rapidly and was fully restored to normal within one week after replanting.

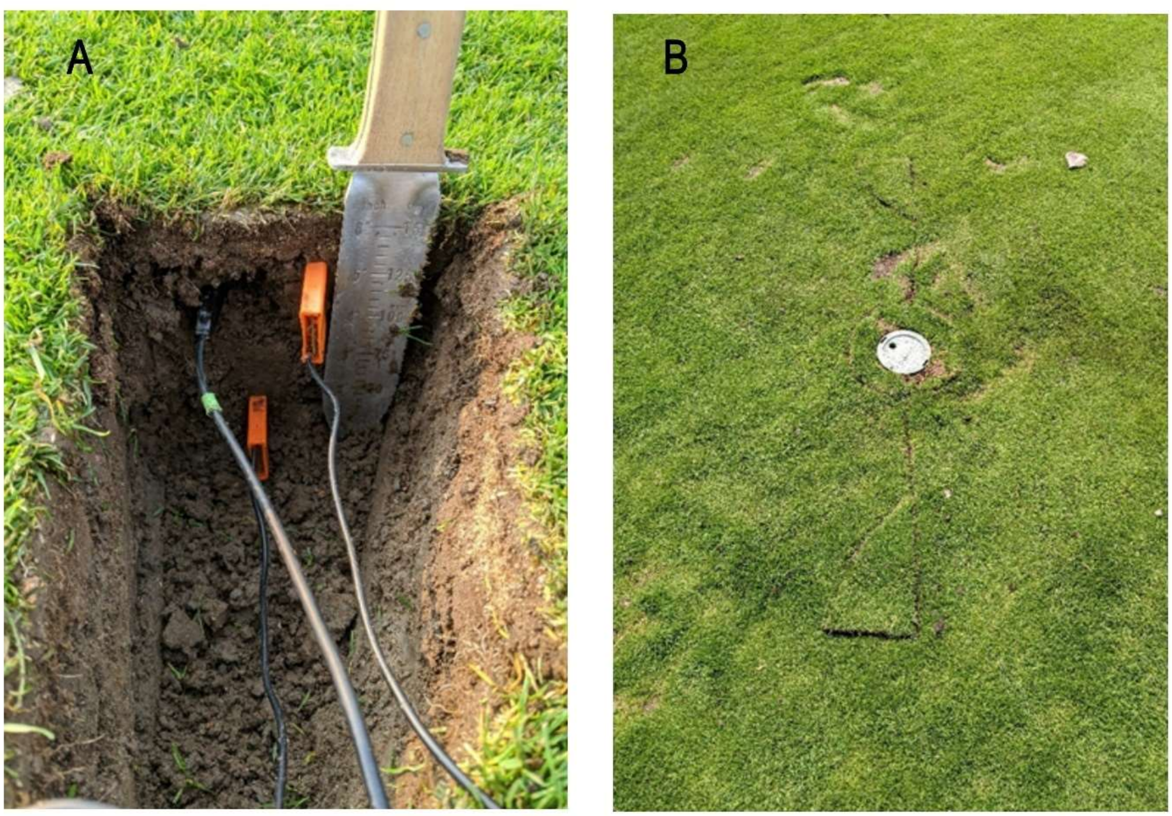

Figure 18. Two photos show a fairway soil sensor installation at 2 and 6 inch depths (A), and an after-shot directly following an installation giving an idea of the overall footprint (B).

Power Consumption

Battery consumption is a key feature of any IoT system designed to operate discreetly and, in this case also underground. Solar panels should be avoided if possible, furthering the need for a low-power system. Ideally, battery life would exceed one year on a single charge, but for irrigation management an easier goal is to have the battery last several months during the summer season when peak evapotranspiration occurs. That is about three to four months in Fort Collins, CO, between June and September). Although Cellular LTE technology has progressed from the power-hungry 3G and 2G variations, it still uses a relatively large amount of power when connecting and communicating with the cellular towers. For this reason, quality large capacity batteries were desired with adequate current discharge and energy density.

When the cellular modem and components are turned off and the board is waiting for its next measurement it is critical to use as little power during this stage as possible. Carrier 2.1 has a watchdog timer, load switch, and RTC circuit that offer a lower power state. When using 30-minute measurement intervals the 8.5 Ah battery pack could last 12 weeks on a single charge. The battery life could be extended for a few more weeks by using batteries with a higher combined capacity of 9.9 Ah, or by reducing the sampling frequency (e.g., uploading data every 2 hours).

In-Field Soil Sensor Temperature Correction and Comparison to Gravimetric Samples

Throughout October 2020 direct gravimetric samples were taken from two of the golf fairways; the Southridge and City Park Nine locations. Using an Oakfield-style probe, soil samples were collected weekly about 1 meter from each DP7T sensor and at the same depth as the sensor. Water content and bulk density were calculated using standard gravimetric methods from moist and oven-dry samples. Errors were anticipated based on direct sampling in such a small area around the probes because of spatial variability in soils and non-uniform irrigation patterns. Given the commercial course was in use all day, the direct sampling method was the best perceived way to get volumetric data as consistently as possible. Although options exist that could be more reliable like a neutron probe or time domain reflectometry, they proved to be either too expensive or complex for these commercial golf settings.

Comparisons were made between the gravimetric volumetric water content and DP7T sensor's data feed. The lab-developed calibration was used to convert the voltages from the sensors to VWC. Overall, the comparison of sensor-based VWC and gravimetric VWC showed mixed results (Fig. 19). The calculations showed decent correlation, but the two methods would often disagree by 5%-10% or more and accuracy wasn't consistent. This comparison was problematic due to a few reasons. The golf courses keep the fairways well-watered, so dry soil conditions were rare and the range of moisture levels to sample is limited. The samples were taken once weekly over 5 weeks. Looking at the time range the measured samples of VWC were taken, most of the locations were always near field capacity (within 5% VWC) over those five weeks. This is not ideal for calibration, because having a larger range of VWC values helps minimize sampling errors. The sensor data and gravimetric samples seemed to both show a strong response with large irrigation or rain events. However, the high degree of uncertainty caused by sampling around such a small measurement area and the golf fairways irrigation environment made it difficult to calculate sensor accuracy using the gravimetric data.

In addition to testing if the systems could track water content in the field, the temperature correction developed in the lab chambers needed to be verified in a real-world environment. This is demonstrated in the three and a half month time series graphs of four different soil moisture sensors; with two lines representing before and after the temperature correction was applied (Fig. 20). The significance of temperature on the sensor output will always depend on the location and sensor design. A location that experiences a large range of soil moisture contents or a more sensitive sensor can help diminish the temperature effect, becoming dwarfed by a much larger soil moisture response.

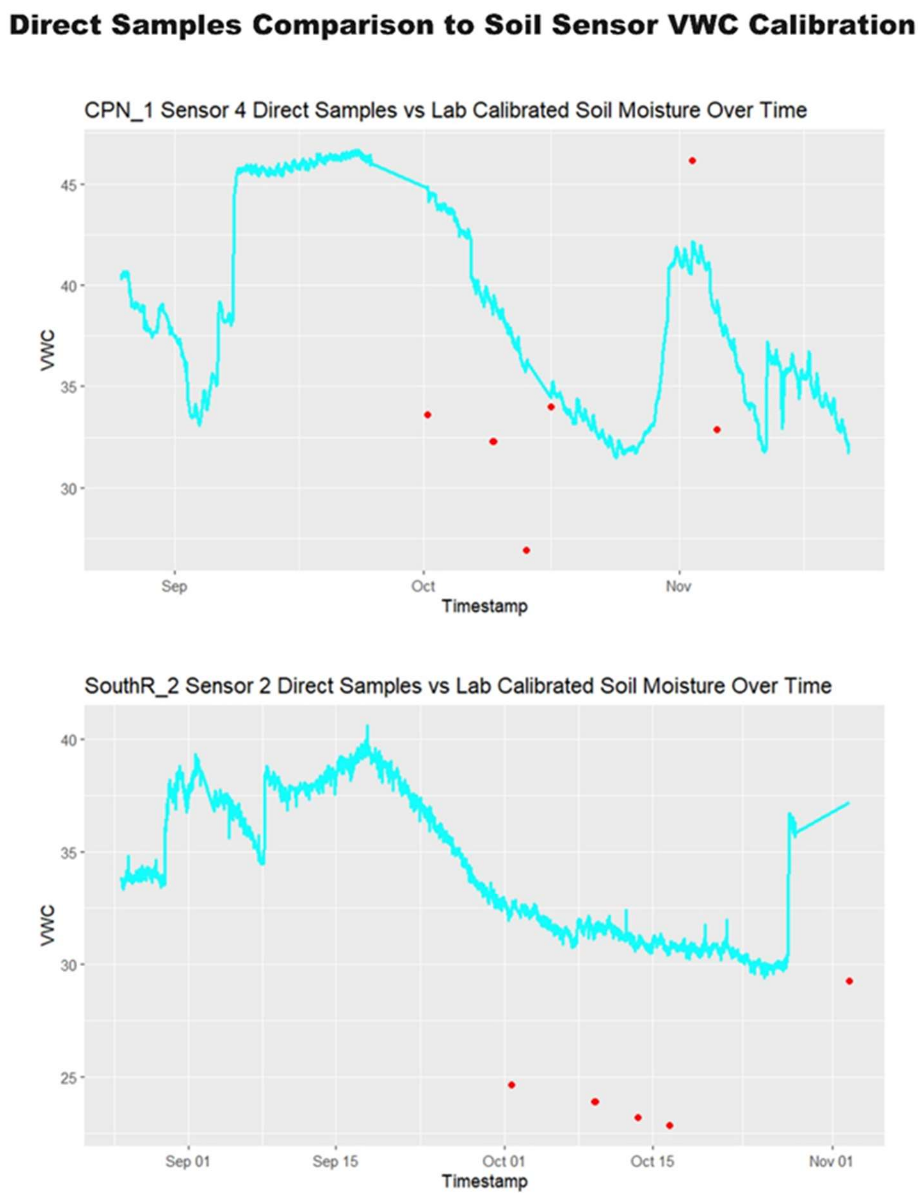

Figure 19. Direct samples taken weekly overlayed with the temperature corrected VWC from the corresponding soil sensors.

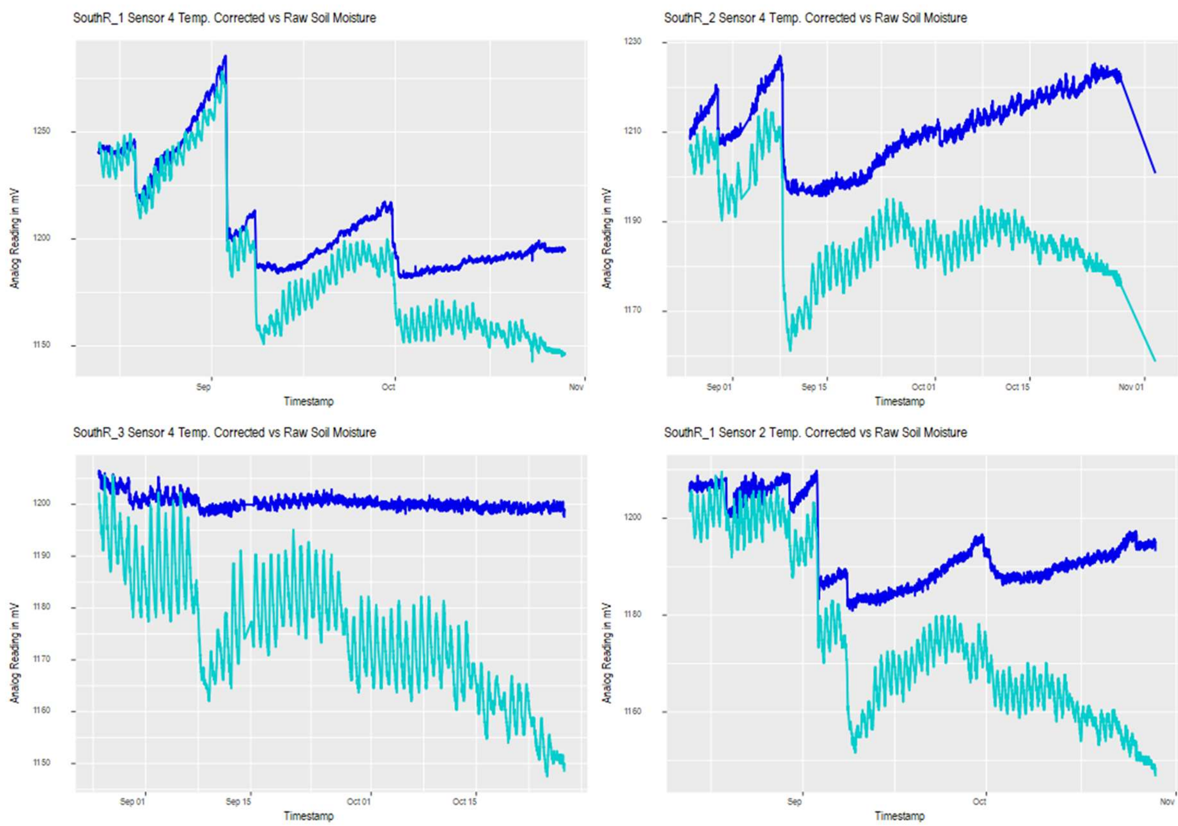

Figure 20. Before and after graphs of fairway soil moisture sensor readings with the dark blue being temperature corrected data and light blue lines representing non-corrected raw data.

Data Management

Every installed IoT measurement system had a device and data feed associated with it that sent data to the Ubidots IoT cloud platform. Using a login portal each user could sign in and see the devices linked with their profile. For this study's purposes having time-series graphs of the data was most convenient, but user interfaces can be adjusted to individual needs. In the 2020 study, an IoT dashboard displaying the near real-time sensor data was created. See figure 21 for an example screenshot of a dashboard for a Southridge IoT measurement system. The sensor pairs installed at the two different depths are shown in the time-series graphs, distinguished by the light and dark blue colors. The payload sent to the cloud had both soil moisture and temperature for each sensor in addition to the box's overall connection, enclosure environment, and power variables. All sent data were backed up, ready to be visualized, integrated, or downloaded from a cloud-based server. These dashboards provided a way for any approved user to view or download the data, while simultaneously proving that the systems could deliver and store data wirelessly.

Soil moisture variability is evident at both microscale and macroscale levels, as demonstrated in Figures 22 and 23. Although these terms are subjective, for this analysis the microscale variability is defined as sensors attached to the same IoT measurement station (soil sensors installed within 2 meters). Macroscale variability in this case is represented by the variability across the fairway; with spacing between IoT measurement stations ranging from 50-100 meters.

Figure 22 highlights microscale variability by comparing soil moisture sensor readings within a 1-meter radius of an IoT measurement station. Intuitively, sensors installed at the same depth and in close proximity (within 2 meters) would be expected to produce similar readings. However, the data reveal differences, likely due to factors such as uneven irrigation coverage from sprinklers, shading effects from nearby vegetation or structures, potential sensor errors, soil-sensor contact changing over time, and small-scale variations in soil properties or microtopography. These localized influences contribute to distinct micro-variations in soil moisture, even within what is considered a uniform irrigation zone.

Figure 23 illustrates macroscale variability by comparing soil moisture readings at a single depth across three IoT measurement stations distributed along a golf fairway. At this larger scale, variability is driven by broader factors such as differences in irrigation zone programming, variations in soil type and compaction, and the spatial distribution of plant water use. While achieving uniform soil moisture across the fairway is ideal for consistent turf health and efficient water management, the data show significant differences between stations during peak growing seasons. Interestingly, as the season transitions into fall and plant water uptake decreases, soil moisture levels across the fairway begin to converge toward field capacity. This seasonal trend underscores how plant activity amplifies macroscale variability during periods of high water demand while allowing for greater uniformity as growth slows later in the year. Together, these figures highlight the complexity of managing soil moisture at both small and large spatial scales on a golf course.

Figure 21. An example of a user dashboard for a Southridge system to view and download collected data.

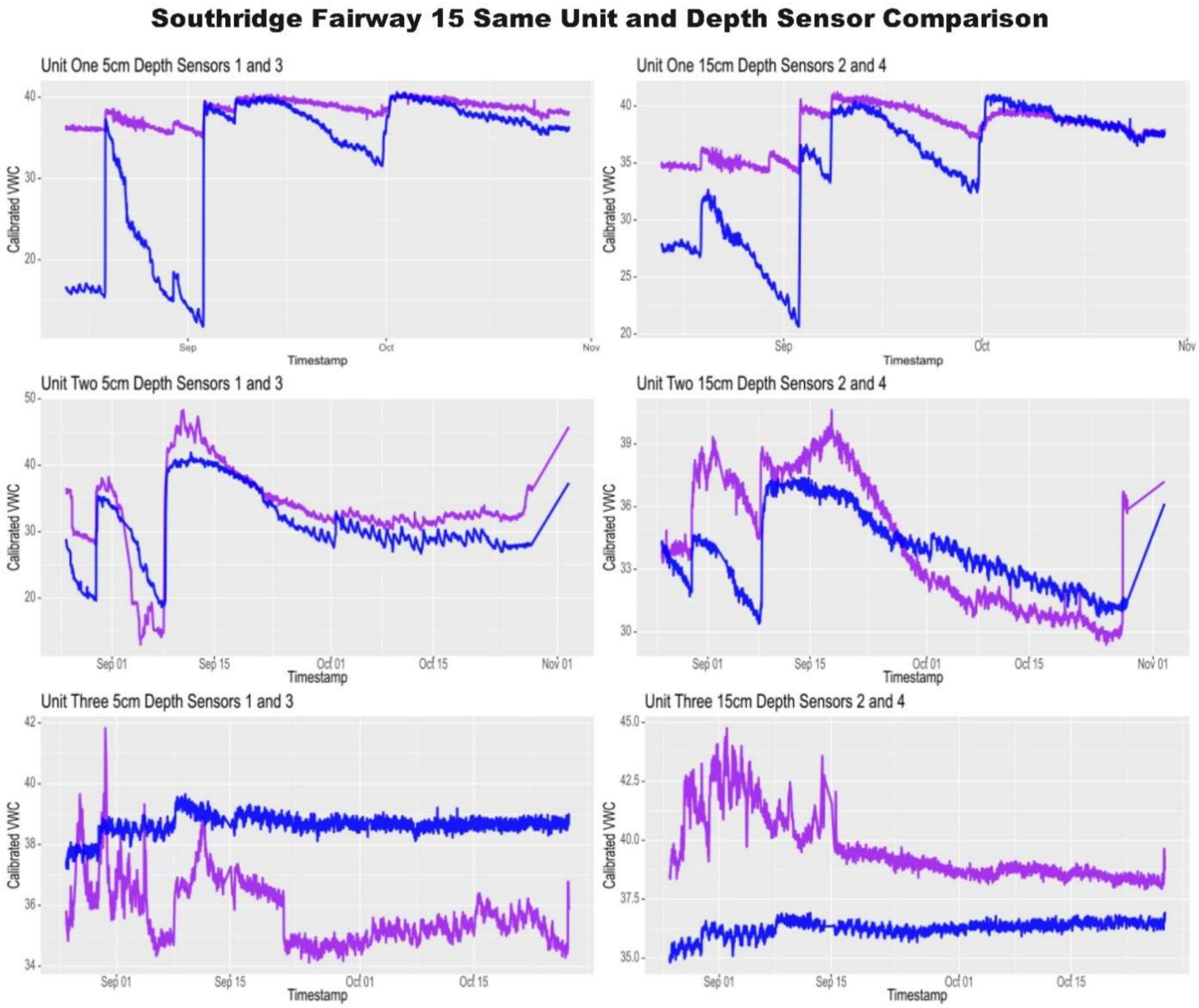

Figure 22. Data from three measurements stations on the Southridge golf course fairway. Shown are volumetric water content data collected from the two 5-cm-depth sensors and two 15-cm-depth sensors at each station.

Figure 23. Variation in soil water content among three stations positioned along the full length of a fair (Southridge). Shown are data from the 5-cm sampling depth (top) and 15-cm depth (bottom).

Summary and Conclusions

This study successfully demonstrates the initial development and validation of a low-cost wireless soil moisture sensor system tailored for turfgrass applications. The research represents a significant achievement, combining the creation of innovative hardware, firmware, and extensive in-field IoT testing—an accomplishment that required overcoming numerous technical challenges. The system's ability to provide real-time soil moisture data at an affordable price highlights its potential to revolutionize irrigation practices in turfgrass management, particularly in high-value environments such as golf courses.

While the system has shown promise, the findings also underscore areas for refinement to enhance its real-world efficacy. A critical improvement lies in addressing sensor sensitivity at high soil moisture levels, which are common in golf course conditions. Proposed design modifications, such as expanding the response range, improving linearity, or inverting the voltage-water content relationship, offer clear pathways to achieving greater accuracy under these conditions. Importantly, these enhancements must be balanced with the need to maintain the system's cost-effectiveness, ensuring its accessibility for widespread adoption.

Another key contribution of this research is its emphasis on improving calibration strategies. Expanding the calibration dataset to include a broader range of soil compositions—such as growing mixes with higher sand content—will enhance the sensor's accuracy and applicability across diverse environments. A practical approach to streamline this process involves grouping similar-performing soil types, which can reduce the need for extensive direct calibrations without compromising measurement precision.

The field test results showed the significant impact of micro and macroscale spatial variability when attempting to quantify soil water content on golf courses using proximal sensors. The high variability in water content observed across fairways suggests that large numbers of sensors may be required. However, Clearly, more research is needed on optimizing sampling strategies and developing data processing techniques before IoT soil sensors can be economically deployed for irrigation management on golf courses. Additional research on spatial variability is covered in Chapter 3.

The study also highlights the importance of establishing dedicated testing sites that replicate real-world golf course conditions. These sites would enable rigorous verification testing under controlled yet realistic scenarios, capturing the full range of sensor responses. Additionally, they could serve as platforms for future automated irrigation studies, advancing both sensor technology and water management strategies while mitigating risks associated with field testing.

Beyond technical advancements, this research emphasizes the value of user-centric design. By integrating user feedback through shared dashboards and fostering collaboration with turf managers, the study ensures that the tools developed are practical, intuitive, and aligned with end-user needs. This approach not only enhances usability but also increases adoption potential by addressing real-world challenges faced by turfgrass professionals.

In conclusion, this research makes significant contributions to the field of soil moisture sensing technology and turfgrass management. By identifying challenges and proposing actionable solutions, it lays a strong foundation for future advancements in this domain. The findings provide a clear roadmap for optimizing soil moisture strategies, ultimately leading to improved turf health, enhanced water conservation, and better playing conditions. Furthermore, this work underscores the importance of balancing technological innovation with cost-effectiveness and user-centric design principles. By addressing these critical factors, this study contributes meaningfully to the development of sustainable and practical solutions for optimized turfgrass management practices while advancing the broader field of soil moisture monitoring technologies.

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Chapter 3: EM38 Mapping and Geographic Data to Optimize Soil Moisture Sensor Deployment on Golf Course Fairways

Introduction to Chapter 3

In both agricultural and urban irrigation, soil sensors can help quantify the dynamics of soil moisture over time and space, and increase irrigation efficiencies (Blonquist et al., 2006). To increase the irrigation water use efficiency, it requires a profound knowledge of many variables that can impact variations in soil water content across a landscape (Famiglietti et al., 2008). Soil physical traits including structure and texture impact soil moisture variability, but other physical and biological factors also play a role (Albertson & Montaldo, 2003). A complex interaction between vegetation, topography, isolated weather, and the irrigation system has an impact on how the soil moisture content is distributed across an area of interest (Teuling & Troch, 2005). Given a limited number of soil sensors for each field or urban landscape, it is challenging to optimize the placement of the sensors to address spatial variability. The user must deliberately target zones that have similar irrigation management requirements (Schneider et al., 2009). Historically, quantifying spatial variability in soil properties has required a lot of labor-intensive soil sampling, but modern technologies such as electromagnetic induction, yield maps, topography, and remote sensing allow us to identify 'management zones' while minimizing the number of soil samples (Shaner et al, 2008).

Emerging tools that have been used to help understand geospatial dynamics include satellites, drones, electromagnetic induction techniques, and other sensing technologies. These tools are used to better understand variability in agronomic factors such as volumetric water content, salinity, and vegetation condition (e.g., Normalized Difference Vegetation Index). However, soil moisture and crop stress indices change on a daily or even hourly basis, so logistically mapping fields with drones and other equipment can become impractical on the scale and frequency desired for making real-time decisions throughout a growing season (Moran et al., 1997). Alternatively, internet-connected soil moisture sensors can provide real-time data and be installed at multiple depths and locations. The most optimal solutions may arise from combining these types of sensors with geographic information inputs; studies using multi-layered approaches have indicated improvements over conventional methods (Mahmood et al., 2012). Potentially, before courses are constructed, layered approaches could also assist in irrigation system designs.

Mapping soil electrical conductivity with an electromagnetic instrument (e.g., EM38-MK2 (Geonics, Ltd., Mississauga, Ontario, Canada) towed over the soil surface is a commonly used tool in precision agriculture. Corwin et al. (2003) has reported that EM38 electrical conductivity readings relate well to horizontal soil variability. The apparent Electrical Conductivity (ECa) output of the soil, discounting air because of its low electrical conductivity, is represented by three main pathways: solid, liquid, and solid-liquid (Corwin & Yemoto, 2017). These pathways contribute to how easily the electrical signals can be received through the soil once the magnet(s) have been introduced, and ultimately determine the perceived uncalibrated electrical conductivity. Many agricultural studies using this instrument focus on particular contributors to the EC_a readings in the soil, demonstrating a relationship to salinity, soil type, depth to clay pan, and soil moisture (Heil & Schmidhalter, 2019). Because EC_a is affected by many soil factors, measuring it and direct sampling after taking readings grants insight into the soil's spatial variability on a field scale. By methodical direct sampling, specific soil variables that contribute to EC_a's variability like soil salinity, clay content, depth to clay rich layers, soil water content, the depth of flood deposited sands, organic matter, leaching fraction, irrigation patterns, drainage behavior, and compaction patterns due to farm machinery can be separated out and visualized independently (Corwin & Lesch, 2005). Once establishing an area's soil variability, the next steps involve grouping homogeneous soils together, intended to create zones with unique and similar management requirements. EM38 survey data has been used to identify optimal management zones in agricultural fields, introducing a potentially cost-effective way of creating quasi-homogeneous regions for zone-specific irrigation applications (Chiericati et al., 2007). More modern techniques using weighted multivariate spatial clustering, take many data layers and create a set number of clusters that weigh all the inputs based on the response variables measured outcome (Ohana-Levi et al., 2019).

While techniques for defining and using management zones have been developed for conventional agriculture, it is rare to see these methods applied to turfgrass irrigation in the urban landscape. In turf irrigation, uniformity issues exist, with one golf course study suggesting the variability in the soil was mostly a result of permanent soil features and not the irrigation systems application distribution (Kieffer & Huck, 2008). Regardless of the quality of the soil moisture maps or management zones created for turf, there is still no streamlined approach linking the zones to their uniquely prescribed irrigation. Golf courses present a unique opportunity by having individually controllable sprinkler heads. This makes it possible to fine-tune water applications to meet the specific needs of each distinct section of the fairway. The objective of this project was to map multiple golf course fairways with an EM38 and see if management zones could be discerned and possibly be used to assist in the deployment of soil moisture sensors. This data could then be theoretically applied to make decisions on irrigation scheduling and connect the management zones to real-world actions in the future.

Material and Methods

The research was conducted on three public golf courses in Fort Collins, CO, USA (Latitude 40.585258N, Longitude -105.084419W). A single fairway (par 4 or larger) was selected for study at each course after consultation with the superintendent: City Park Nine Golf Course, hole 7, 480 yards (439 meters); Southridge Golf Course, hole 15, 403 yards (369 meters), and Collindale Golf Course hole 6, 550 yards (503 meters). The courses are comprised of grass species composition dominated by creeping bentgrass (*Agrostis stolonifera)* on the newer courses while City Park Nine had decent coverage from annual bluegrass (*Poa annua*) and creeping bentgrass intermixed. pH levels from soil tests ranged from

7.2-7.7 over the three fairways. Benefiting from the golf course manager's soil texture tests (surface horizon 0-10 cm) taken on or near the fairways, results were accumulated and ranged from loam (24% clay) to clay loam (30% clay). Soil survey data of each location's typical soil layer profile helped verify the soil types, showing City Park Nine as a Nunn clay loam (clay loam 0-9 inches). Southridge's fairway had three soil distinctions with the west most section being labeled as a Stoneham loam; further specified as loam (0-3 inches) and clay loam (3-9 inches). The two other sections going east were named Nunn Clay Loam (clay loam classification from 0-9 inches) and Heldt clay loam (clay loam classification at 0-4 inches and clay for 4-15 inches). Colindale's site was listed as a Nunn Clay Loam (designated as a clay loam in the top 0-9 inches).

To quantify potential spatial variation on each fairway, different strategies were employed to collect geographic data. An EM38-MK2 was utilized to measure and visualize the apparent electrical conductivity of the soil. Elevation and topography were mapped using high-resolution LiDAR data provided by the Natural Resources Conservation Service. In addition to the EM38 and Elevation information, GPS locations of every sprinkler head and radius of throw were also recorded.

Recommendations on individual sensor placement in the cross section of soil and the broader sensor system installation across an area are both reliant on natural factors and the irrigation system. For example, research for soil sensor placement on a drip irrigation system shows a significant moisture gradient as you get farther away from the driplines (Soulis & Dercas, 2015). In this case if soil sensors are not positioned in fairly precise locations from the drip line the results would become hard to interpret. Their models showed that a soil moisture error of +-.03 cm^3/cm^3 reduced the irrigation efficiency by 10.2%-18.7% while errors of +-.01 cm^3/cm^3 affected irrigation efficiency by 2.5%-6.4% (Soulis & Dercas, 2015). In their tests they concluded that the most suitable soil moisture sensor position for irrigation scheduling in this scenario was 11 cm from the drip line and 10 cm below the soil surface (Soulis & Dercas, 2015). Soil moisture sensors used on furrow irrigated Potato mounds also found unique optimal ranges for sensor depth placements used for irrigation timing (Stieber & Shock, 1995). Even with proper depths determined, sensor positioning across the landscape is less obvious.

Soil sampling and other methods that quantify soil variability provide crucial insights for optimizing soil sensor placements. Soil parameters directly influence water holding capacity and plant interactions. In this study, the goal was to relate soil variability differences to unique water management zones measurable by soil sensor systems. Quantity constraints limited the deployment to three soil sensor systems (4-5 sensors per system) for each fairway. While numerous studies have examined sensor depth and positioning in relation to irrigation output (furrow), research on optimizing sensor placements to capture soil water variability on larger scales remains limited, highlighting a key gap that requires further investigation (Muñoz-Carpena et al., 2024). Several studies have acknowledged the difficulty of selecting soil moisture sensor locations and proposed guidelines for placement. These guidelines consider factors such as field location, crop condition, sensor proximity to plants or irrigation outlets, and position on raised seedbeds (Bryant et al., 2023). One approach recommends selecting areas representative of the majority of crop growing conditions, installing sensors equidistant from two plants, avoiding damage to nearby plants during installation, ensuring good sensor-to-soil contact, avoiding installation in waterways, adhering to manufacturer's instructions, and installing soil sensors several weeks after planting (Lena et al., 2021). Given the difficulties of determining and verifying optimum soil sensor installations across complex landscapes, this study's in-situ sensor deployment leveraged similar methods to determine optimal locations but adapted them to golf course fairways. A couple advantages of the fairways over traditional agriculture were the uniformity of the vegetation height and small gaps between plants; this simplified some of the process.

Although a lot of work has been done on management zones, not much research has been done to verify optimal field scale soil moisture sensor distribution for improved irrigation efficiency, particularly for sprinkler irrigated turfgrass. Selecting install locations has commonly been done with customer intuition, but new clustering and evaluation techniques allow for new quantitative insights (Rossini et al., 2021). All the golf fairways that were instrumented used individually controlled, variable rate, sprinkler-head irrigation systems. Only having three sensor systems per fairway put limitations on what could be measured; covering every sprinkler head with a unit was not feasible. The data layers were used to help understand soil variability, with ultimately the super intendent of each course having final say of where systems were fitted. To get an improved representation of the soil moisture content in a particular area, efforts were made to install 2 meters outside of any sprinkler head and avoid edges of throw.

Data Collection

To evaluate the potential management zones in each fairway, three GIS layers were collected: 1) EM38-MK2 mapping, 2) topography from an existing LIDAR database, and 3) map of sprinkler heads and throw.

EM38-MK2

Description

An EM38-MK2 is a meter-long electromagnetic induction device that excites the soil as it is slid across the ground to measure the soil's apparent electrical conductivity (EC_a). Keeping undesired objects away from the sensor, the user ideally pulls the device with a sled taking readings on a consistent time interval and tagging the location via a Global Positioning System. Benefiting from spatial statistics, sample locations are output to best represent the variability in the EC_a readings. EC_a changes as a function of soil variables like salinity, compaction, organic matter content, soil moisture, and soil structure (Doolittle & Brevik, 2014).

The EC_a output from the EM38 generated stands for the bulk apparent soil electrical conductivity; a measurement that is sensitive to several soil characteristics requiring ground sampling if the intension is to separate the various components causing the changes in the EC_a readings (Padhi & Misra, 2011). The dual pathway parallel Conductance generated from the EM38-MK2 outputs an EC_a value according to Eq.

(4) (Rhoades et. al., 1989). θ is the volumetric water content and EC is the electrical conductivity. The subscript ss shown as $(X)_{ss}$ implies surface conductance, $(X)_{ws}$ indicates the water-soil pathway, and $(X)_{wc}$ denotes the continuous liquid pathway.

$$EC_a = \frac{(\theta_{ss} + \theta_{ws})^2 EC_{ws} EC_{ss}}{\theta_{ss} EC_{ws} + \theta_{ws} EC_{ss}} + (\theta_w - \theta_{ws}) EC_{wc} \tag{4}$$

The EM38-MK2 has two different depth options that are determined by its orientation (referred to as “dipole orientation”). It is equipped with one transceiver (Tx) and two receiver (Rx) coils that measure two separate depths simultaneously. Exciting the soil with a magnetic field reads back both the soil conductivity and magnetic susceptibility at the two depths. A precise determination of the reading depth for the EM38-MK2 is difficult to acquire. Theory would indicate an unlimited depth of measurement, but used in soil, the contributions to EC_a get reduced as the magnetic pulse penetrates deeper; the relationship of this depth to EC_a is nonlinear and dependent on the device orientation (Heil & Schmidhalter, 2017). Common designations of measurement depths are listed for the two orientations. In horizontal dipole mode, the two Rx coils measure two bulk average EC_a values, a deep and shallow reading, over the 0 - 75 cm and 0 - 37.5 cm depths, respectively. In vertical dipole mode, the deep and shallow measurement depths increase to 0-150 cm and 0-75 cm, respectively. Because the study was concentrating on soil moisture variability for these turfgrass applications (i.e., root zone depth < 20 cm), the focus was primarily on the shallowest 0 – 37.5 cm measurement.

Preparation

When the EM38 device is paired with a GPS unit via Bluetooth or RS-232 communication it combines the datasets automatically. At each golf course fairway, plastic flags were used at every 50 meters to outline transects that were spaced apart four meters; minimizing the spacing between them while still allowing clearance for the towing vehicle to drive through. Because the fairway maps can bend and have imperfect geometry, it worked well to have the lines marked from the middle out to avoid crossing lines. During this process, it is crucial to make sure to have no metal near the EM38. It is also required to warm up the device for calibration by leaving it on for 30 minutes before use. On a couple of occasions, sporadic values would arise during calibration; changing the way the magnetic coils were oriented and interacting with the surrounding metal or radiofrequency interference helped stabilize the readings in these cases.

Field Sampling

The EM38 setup utilized a custom plastic sled with a one-meter-long rope to tow the device behind a golf utility cart. All efforts were made to limit the amount of metal close to the EM38 while also keeping the distance between the instrument and the soil surface constant. Readings were taken every half-second from the backpack GPS unit (Trimble, Sunnyvale, CA, United States) and EM38 while the cart drove between the flagged lanes (Fig. 24).

Figure 24. Live-action images were taken in the summer of 2020 at City Park Nine, Fort Collins, CO using an electric cart, EM38-MK2, plastic sled, Global Positioning System backpack module, and plastic flags to collect soil data.

Software

Completing the data collection with the EM38 yields a raw N38 file, which is uploaded to DAT38MK2 and converted to an M38 file. Then the M38 file is loaded into ESAP sigDPA to make sure the data is separated by each transect and any edge effects or known places of metal are ideally cropped out before analysis. After saving the text file created from sigDPA, it was loaded into ESAP-RSSD to verify and decorrelate. When determining outliers, anything outside three standard deviations was ignored. Next, the weight of how distance or EC affects the simple random sampling (SRS) sample algorithm was adjusted, slowly altering the values until achieving the smallest final opt-criteria. In the ESAP-RSSD software, there are three sample number options: 6 (limited design), 12 (standard design), and 20 (full design). For these tests, the standard design was chosen. By saving the sample locations, text files are output containing twelve point-IDs with corresponding GPS coordinates and transect number. These files were used to find the direct sample locations aimed at calibrating the EM38-MK2's readings.

Sample Collection

After receiving the file of sample locations, a GPS was utilized to locate the 12 positions. Each location had a bulk density measurement taken from the top 10cm of soil surface. Two additional bags of 0-20cm and 20-40cm depths were collected and later combined for soil analysis. These bags were packed with samples comprised of five cores taken in a pentagon shape around each of the twelve location points. Samples were stored in airtight bags and cooled on-site. Soil water content and bulk density were determined on the following day gravimetrically and after oven-drying. Other parameters such as salinity, soil texture, organic matter percentage, and NPK tests may also be required to separate the various soil parameters that affect the EC readings from the EM38 sensor. However, for this study, the focus was on identifying management zones for soil moisture content, so the soil samples were only processed to determine soil water content.

Topography: NRCS Light Detection and Ranging Dataset

The topographic data for each fairway was provided by Natural Resource Conservation Service. Digital elevation data was captured and stored in Light Detection and Ranging (LiDAR) rasters utilizing the Geospatial Data Gateway (NAIP Staff). Once downloaded, data were imported to the proper geographic coordinate system. The LiDAR one-meter data is generated with a Universal Transverse Mercator projection (UTM). These data provide smaller slices of data maps that have a submeter accuracy on the true size and orientation of the land. Larger projections must sacrifice at least one property related to the true area, distance, direction, shape, or scale of the world due to a round 3D planet being unable to be perfectly drawn on a flat surface. UTM projection minimizes these errors by slicing the world into 60 zones and a determination at the equator for a North or South label. Fortunately, a golf course is small compared to one of these zones and didn't require any stitching of images to get a highly accurate projection. Most of Colorado falls within UTM Zone North-13 with the western side of the state being the only part not within the zone.

Digital Elevation Maps and other visualizations like hill shade tools can be generated on the ArcGIS Pro software after inputting an elevation raster. Using the visualization options, the viewer can see how the topography of the fairway looks and have a high-resolution digital layer that likely has an influence on soil moisture (e.g., low spots, hills) and other agronomic components (Hedley, et al., 2013). An area more prone to drier conditions may be a sloped surface that experiences smaller infiltration amounts than if it was flat (Fox, et al., 1997). To varying degrees, the bottom of a hill or low spot could see higher levels of moisture when water runs off towards lower and more level areas. Additionally, sun exposure on the aspect of a particular location could cause a lower soil moisture level and higher evapotranspiration rate than places that don't receive as much radiation. Although not as impactful as slope, some studies have shown aspect to be a significant factor in determining management zones (Helman et al., 2017). A group studying soil moisture as it relates to topography in China, showed slope to have the largest significant relationship to moisture content; other smaller influencing topographic factors such as aspect and elevation were also shown to have a link to soil water content (Guo et al., 2020). Note that papers studying the same topographic factors in different settings can calculate varying degrees of significance and this is not uncommon. It depends on the specific site being studied and what range of values are detected for each variable observed.

Valve location and sprinkler throw

For the three fairways, it was important to document the sprinkler heads and radius of throw. Collecting this data provides the ability to see how a fairway irrigation system is organized and what limitations may exist when deciding to water for each setup. To create this dataset every sprinkler head was marked using a standard hand-held Global Positioning System (GPS) app found on most smartphones. The GPS statistics app included the latitude, longitude, max error, and other GPS data. The maximum error was no more than 3.2 meters providing a point dataset within a 10-foot tolerance of accuracy. The superintendents supplied the radius of throw for the sprinkler heads, and a buffer was applied to the point location data on ArcGIS pro software to generate a map for each of the three courses (Fig. 25). In most cases, golf courses have complete control of every head and as a result, each is treated as its own zone. Having this layer gives information on the irrigator's level of control along with the distribution uniformity and overall structure of the irrigation system. Each sprinkler head on these golf courses has settings with options to set the application rates and timings individually.

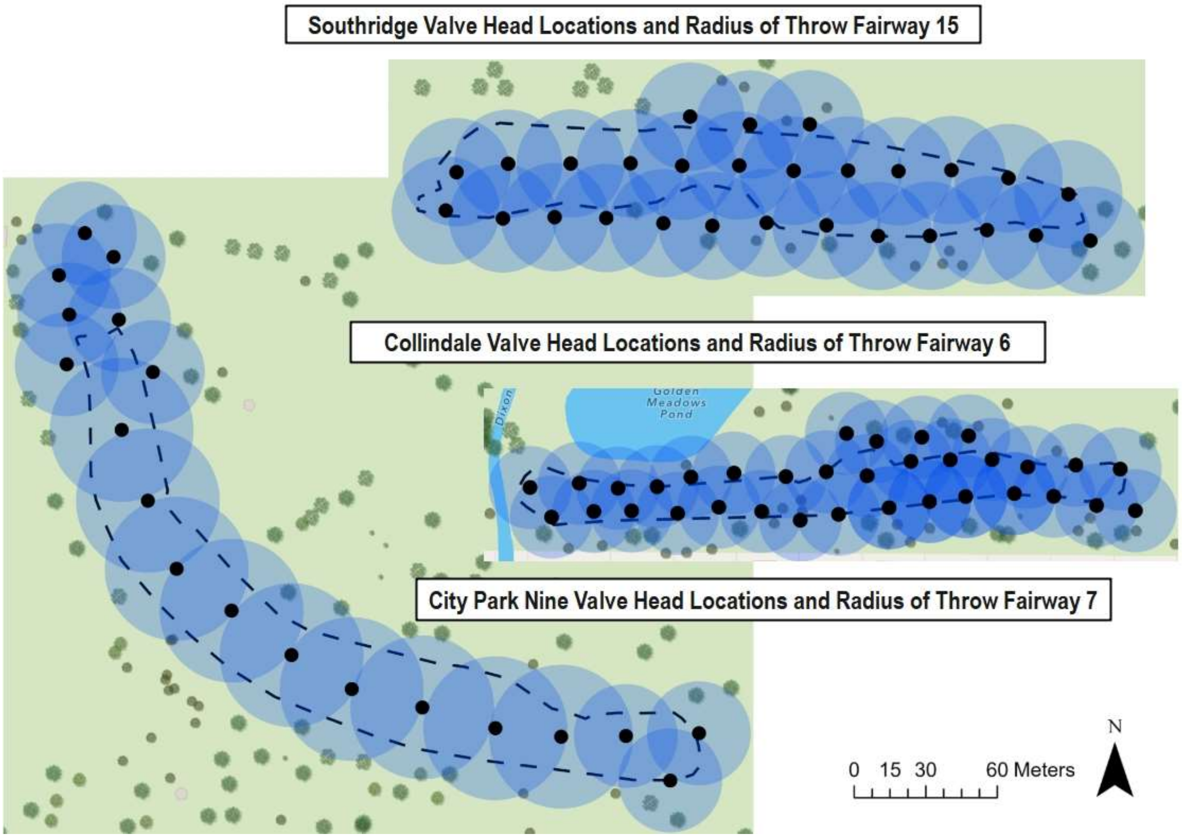

Figure 25. Visuals of three city golf course fairway locations; fairway perimeters with dotted lines, each sprinkler heads positions (black dots), and radius of throw marked out with transparent blue circles.

Results and Discussion

EM38-MK2 EC_a Map

Although overlaying multiple layers to analyze zones has been shown to be effective (Ohana-Levi et al., 2019), in this study that was not realistic. Collecting a larger sample size is conceivable, but to adequately train a model on how various input layers decide irrigation zones would require far more than three fairways; in addition, temporal data collection would be required to see how these generated zones may change over time and detect any repercussions caused from irrigations. To complicate things further, it has been shown that having more data layers is not always better for determining management solutions (Hornung et al., 2006). Sometimes a layer added may be unnecessary; having a minimal effect on the variable of concern or is inaccurate, overcomplicating, and ultimately negatively influencing the result. That being said, encouraging outcomes have been found using a multi-layered approach. In Denmark, a positive result was observed using electrical conductivity data combined with remote sensing to map large areas at a high spatial resolution; able to deliver a finer detail and generally more accurate assessment than the courser soil maps provided from the country (Møller et al., 2021).

For this project attention and effort were put towards collecting key layers that contribute to soil moisture content given it was logistically feasible. When selecting for layers, to avoid overcomplicating the process a concerted effort should be made to only include data that is understood to affect soil water content and is realistic to collect for the situation. The EM38-MK2's EC_a readings operated as a baseline, showing much of what the general soil moisture variability looks like. The goal by the end of this study was to have a dataset that outlines and prepares for a multilayered approach solution to soil moisture mapping. Although the EM38-MK2 was used only once per fairway, it still yielded valuable data that could motivate more extensive temporal studies on turfgrass soil variability in the future. Even if only during a moment in time, the project offered examples of how golf course fairways soils vary across space.

This study relied on the EM38-MK2 to provide an output that determined sample locations representative of the soil variability over the measured area. In theory, if the EC_a readings show a relationship to VWC for these scenarios, this should give data on the water content range of the golf course fairways and demonstrate potential management sectors that may need to be accounted for to increase the irrigation efficiency. Knowing what the range could potentially be on any given day shows that soil moisture differences not only exist but are also large enough to warrant different management practices. For Collindale the VWC ranged from 19%-40% at the time of measurement. Having a large range in water content shows a need for management zones. However, if the areas they occupy aren't large enough to be managed easily by the irrigation system, then it would be good to know that too.

The point data generated from the EM38 and coordinates from the GPS backpack were used as the file input to create the maps. On ArcGIS Pro, the Kriging Exponential Semivariogram tool was applied on the shallow EC_a reading, making sure to run the analysis within the fairway shape feature. Color cells were classified into four equally spaced sections determined by the 0-40cm EC_a readings. Presetting's were kept and determined by the ArcGIS Pro software for cell and lag size. All maps were set to a 1:1500 scale for display purposes (Fig. 26). The maps offer a visual interpretation of the spatial correlation between all the raw EC_a points taken in the field.

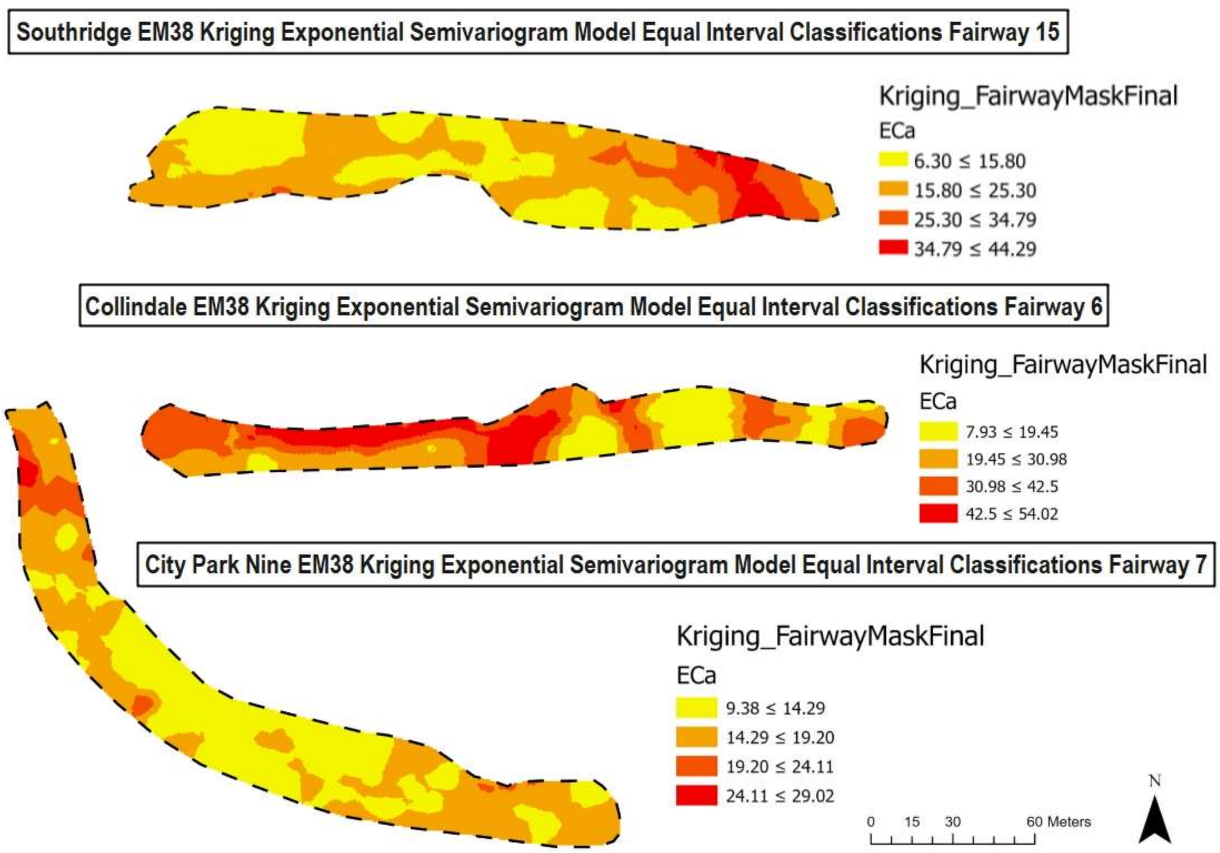

Figure 26. EM38-MK2 Maps made in ArcGIS Pro software utilizing the spatial analysis package to interpolate between measured points weighing distance and variation of the raw EC_a readings.

EM38-MK2 data correlation with gravimetric water content

A critical step in the process for this study's goals was to investigate how well the EM38 EC_a readings correlated with soil water content. These golf courses cut and manage their turf surfaces carefully, performing semi-annual soils tests that revealed low salinity levels and similar bulk densities (With measurements averaging 1.30 g/cm^2 ranging between 1.19 g/cm^2 – 1.38 g/cm^2) for the three courses. With soil structure being somewhat homogeneous and salinity concentrations being relatively low, produced a preferred environment for raw EC_a readings that track well with soil moisture differences. Each fairways linear model was calculated from the VWC and EM38 readings that were taken from the twelve direct gravimetric samples. The linear model output for Southridge had an intercept of 0.2786 VWC and slope of 0.0014 VWC per EC_a; Collindale's intercept was 0.2336 VWC with a corresponding slope of 0.0022 VWC/EC_a. Lastly, the intercept calculated for City Park Nine was 0.2404 VWC and a slope of 0.0011 VWC/ EC_a.

Analyzing the results, although weak, indicated a correlation between the EM38 readings and gravimetric measurements of soil water content. Using R software to create a linear model between volumetric water content from 0cm - 40cm vs shallow EC_a (fig. 27) gave p-values of 0.094, 0.013, and 0.121 for Southridge, Collindale, and City Park in that order. Although City Park Nine and Southridge had p-values above the .05 threshold of significance, as expected they were all showing an upward trend between EC_a and VWC (Fig. 27). One reason for the lower significance of the two courses could be a result of the volumetric water content range being much smaller than Collindale and being unable to eliminate metal pipes from old farming operations at City Park Nine causing bias in EC_a readings.

Finding weak correlations among EM38 readings and gravimetric water content on a golf course fairway is not surprising. Research using EM38's showed lower quality outcomes when samples were taken in isolated instances instead of with a neutron probe, collected over shallower depths, or when applied on smaller spatial scales (Hossain et al., 2010). Sources of error include measuring the shallowest 0-40cm depth, selecting a transect spacing of four meters, and using standard three-meter GPS accuracy instead of differential GPS.

From previous literature demonstrating the relationship between soil water content and EC_a (Padhi & Misra, 2011) and looking at the three fairways linear model results gives an elevated level of confidence that the soil water content in the top 40 cm is related to the Ec_2 (EC_a at the shallow depth) readings that were taken. The result demonstrates the EC_a maps generated, although not perfect, have valid insight into soil water content variability across the three fairways at a single moment in time. Root Mean Squared Error (RSME) was used to evaluate the quality of the model fit. It is designed to calculate the tolerance on average that the model can predict Volumetric Water Content (VWC) given an EC_a Value. The Southridge model had an RMSE ± 0.01613 $cm^3\ cm^{-3}$, Collindales RSME ± 0 .03807 $cm^3\ cm^{-3}$, and City Park Nine an RSME ±0.01991 $cm^3\ cm^{-3}$. Comparing the range of VWC values observed on the courses to the size of the corresponding RSME did not produce the best results. Nevertheless, they are still small enough to fit between the total range and differentiate between water contents at an adequate level to create differentiated zones. Being able to create these zones is a critical step for setting up a soil sensing network, letting more informed decisions on sensor placement, and providing a glimpse at what potential management zones could look like on a particular day.

The EM38 and sample data was collected to determine areas on the fairways that may benefit from different water management prescriptions. Although additional factors affecting the instrument readings can be sought after, in this study, the primary focus was on soil moisture variability. From previous use of this sensor, Bennett and George (1995) indicated a high sensitivity to salt content with saline soils dominating over other factors that affect EC_a. Fortunately, the golf courses have soil samples annually taken; all of which showed salinity levels between 0.4 and 0.7 dSm^{-1}, much lower than studies using the device for salt mapping. These courses, unlike some other irrigated turf have the luxury of relatively clean irrigation water and professional turfgrass management, so spatial variation in salinity likely had minimal impact on the EM38 readings.

EM38-MK2 Direct Samples vs ECa 0cm-40cm depth with Linear Line of Fit and 95% Confidence Interval

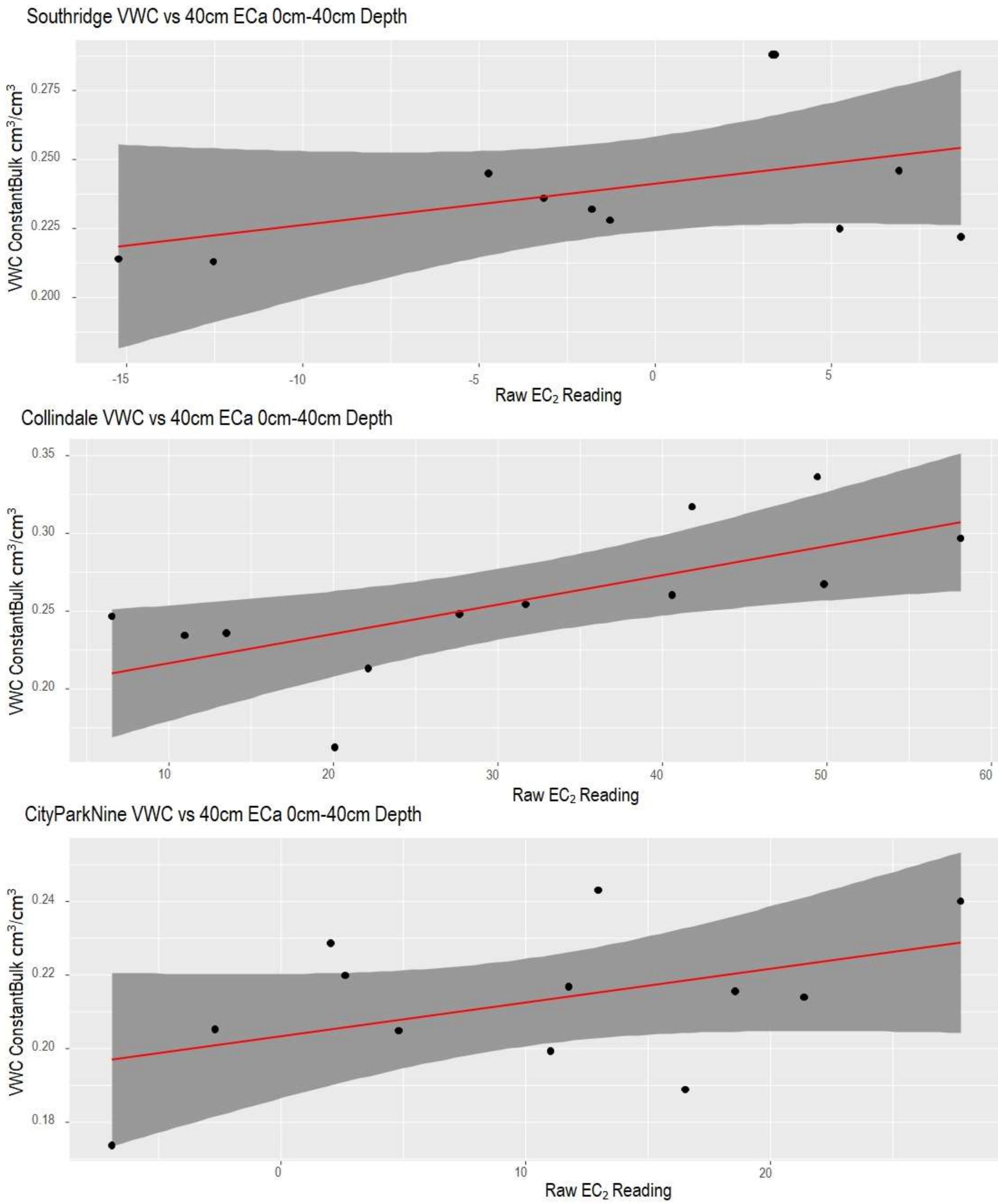

Figure 27. Three linear models with ECa shallow depth (EC_2) readings at the direct sample locations as the x and the measured VWC of samples taken from the fairway as y.

Demonstration of potential irrigation management zones based on EM38-MK2 data

EM38-MK2 data provides a general understanding of soil variability for irrigation management, but not specifically soil water content. To relate the raw readings to a soil water metric, a volumetric water content (VWC) line-of-fit column was created and filled with each of the fairways' unique linear models linking the EC_a readings to an estimate of VWC. More studies will need to be performed to realize the true accuracy potential of using EC_a readings on golf courses to estimate VWC. However, this offers an example of how this could be achieved given a more extensive experiment.

Transforming the EC_a readings to volumetric water content generated cells with values closer connected to irrigation and plant stress, at least for the time they were taken at. To get a better idea of the seasonal variability pattern it's recommended that multiple measurements be taken at different times throughout the year. VWC is more relevant to an irrigator and makes classifications easier to justify. When deciding VWC thresholds for management zones, it seemed more practical to select cutoffs that would influence someone's actions. The concept is like a contour map, but instead of cutoffs being based on elevation they correspond to the soil moisture content. In the case of irrigation application, approaching wilting point or overwatering has an impact on deciding when to water. Research has found turf stress to be complex, impacted by the soil's total available water, genetic traits, and root development factors (Huang & Gao, 1999). That said, it's common to see soil water content thresholds divided into three categories. Soil samples were not taken to verify the accuracy or precision of the generated VWC map, so it can't be authenticated.

Research testing the number of zones to use has shown two zones can perform better than the more common three-zone differentiation (De Lara et al., 2018). Selecting a specific number of zones to use can be a challenge and is not always clear. For these maps they were created with a conventional approach using three divisions; finding inspiration from an athletic turf study that categorized the soil moisture by wet, dry, and acceptable levels (Dickson et al., 2018). With the irrigation manager in mind, three ranges were chosen, labeled “Close to Plant Stress”, “Acceptable”, and “Watered”.

The topsoil’s found on the three courses were determined to be almost entirely clay loam based on soil tests sent in by the superintendents and national soil survey maps. To run these tests, it was assumed the three fairways had similar total available water. For this reason, cutoffs were kept the same between the three fairways. Determining what water content the plant will get stressed at is challenging. To be more precise it would be ideal to get the plant stress data for each specific fairway. Not having collected the necessary data to do on-site plant stress calibrations, a North Dakota study on sugarbeets water stress in a clay loam soil was used to determine the field capacity and wilting point estimates for the turfgrass fairways. 17% VWC was defined as the permanent wilting point and field capacity was specified at 35% VWC (Jabro et al., 2020). Although not always the most optimal, the general rule of thumb for irrigation timing is to not let the profile deplete past 50% of its available water, in this case, inferring anything lower than 26% VWC should be watered. The rationale behind the yellow-colored cutoff range going up to 30% was to signify to the irrigator that they have at least a day or two of high ET before they will want to water. The volumetric water content cutoffs in reference to the labels were 0%-26% VWC, 26%-30%VWC, and 30%-Saturation VWC. Colors for each were assigned in order of Red, Yellow, and Green correspondingly (Fig. 28). The average bulk density samples of each course being between 1.19-1.38 g/ cm^3 and assuming a 2.7g/cm^3 particle density gave a theoretical absolute max around .51 cm^3 /cm^3 for field saturated volumetric water content. This also matched well with the temp-controlled lab calibrations in Chapter 2.

To be clear, although these maps were calibrated against gravimetric samples, they were not properly tested for accuracy after being generated. They are intended to be an example of how to create relevant irrigation management zones. Looking at these maps shows sections that may be of concern, and areas that may not need water for a few more days. Ideally having multiple layers feeding into the recommendation would be ideal; with evidence indicating the potential of combining EC_a and other datasets to achieve a better solution than any one of the parts could have (Rallo et al., 2018).

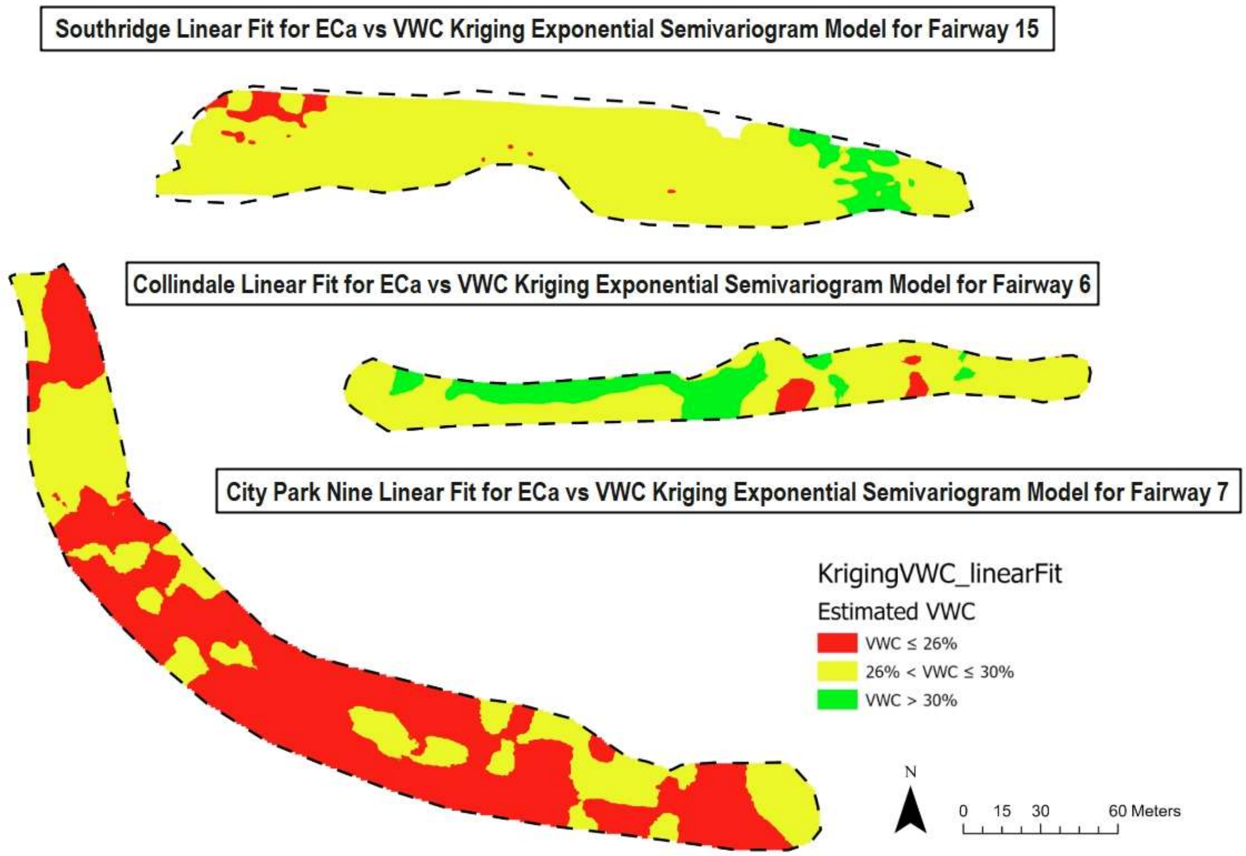

Figure 28. Using raw EM38 data to estimate VWC and create maps based on plant-soil relationships.

Digital elevation map

By utilizing the high-resolution LIDAR data, the elevation raster was clipped to the surrounding fairway of interest. Colors were determined by classifications sectioning the elevation into equal intervals. This offers a visual to see how the elevation changes across the landscape in and around the fairway (Fig. 29). Different maps can be generated to view elevation data. Toolsets are provided that can generate slope, aspect, hill shade, and area solar radiation (WH/m^2) from an elevation raster input. For tools that require additional information like the solar radiation analysis, assumptions are made by the ArcGIS software as it accounts for atmospheric effects (allow you to simulate real-world lighting for example by using ambient occultation), site latitude and elevation, steepness (slope) and compass direction (aspect), daily and seasonal shifts of the sun angle, and effects of shadows cast by surrounding topography to predict solar radiation for each cell over a set unit of time. Research done by other groups on these topographic features in the past has produced significant results when used as factors to determine soil moisture and evapotranspiration distribution across an area of interest; thus, indicating the indirect consequences the lands' geography has on management outcomes too (Helman et al., 2017). Changes in topography, especially elevation and slope can become primary considerations in determining soil variability and give a sense of how excess water moves across the soil surface (Fraisse et al., 2001). Working on the courses and looking at the elevation maps shows these three locations each have very different surfaces. Southridge has by far the largest range of elevation, with a steep incline leading to the hole. The others had more consistent grades.

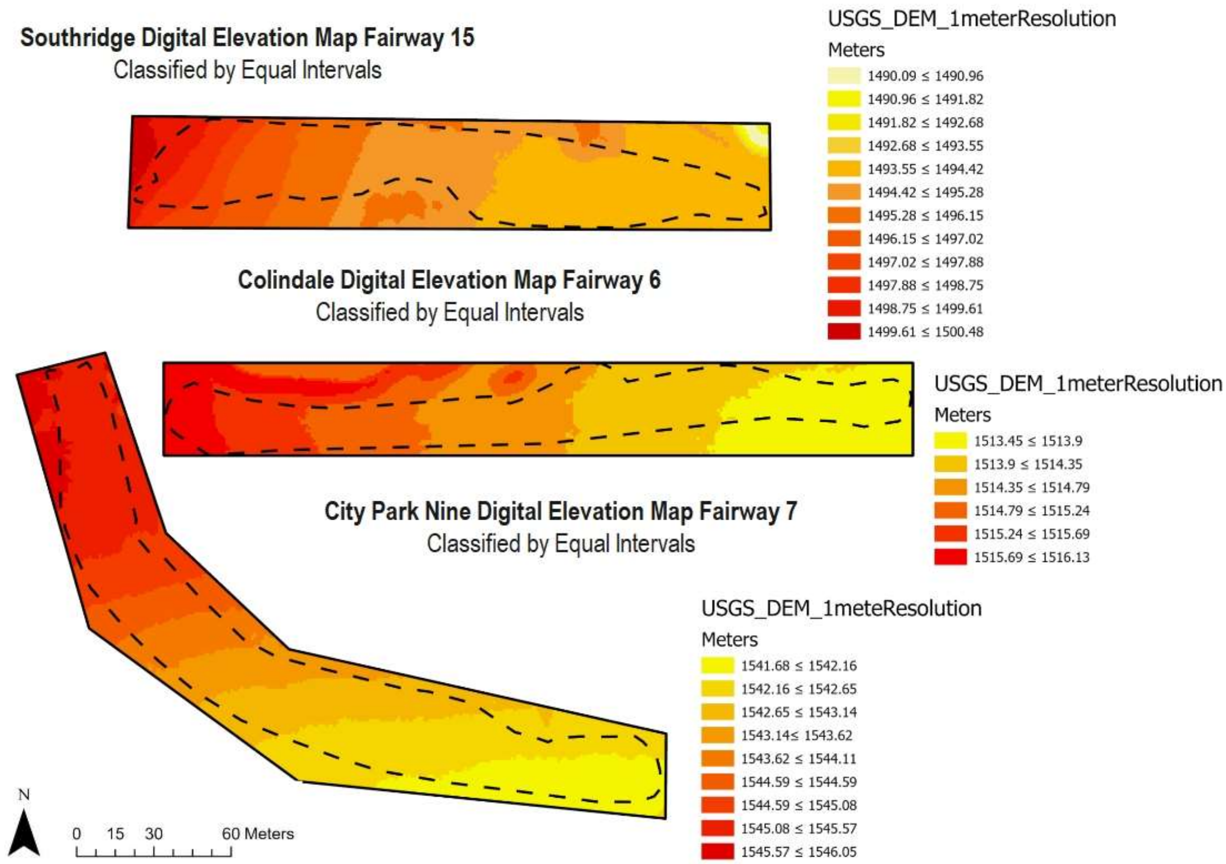

Figure 29. Although at different scales, the three golf course fairways elevation maps are classified by equal interval sizes.

Superintendent Input and Install Location Selections

Although each superintendent wanted to have a better understanding of the water content on any fairway, each offered their unique challenges. To finalize the sensor box installs, the map layers collected from these various sources were analyzed and visually displayed through maps on ArcGIS pro. Without having a program designed for golf to automatically use collected layers to determine soil moisture sensor locations, the superintendent was tasked to make any final recommendations. Qualitatively making use of both the layers created and their experience to verify locations, final soil sensor box install locations were selected on the three fairways as described: 1) Southridge 15 started near trees and ended on an incline towards the hole. As a result, the decision was made to put valve box systems in areas targeting these very different microenvironments including the shaded region on the east and the hill on the west side. 2)

City Park Nine Fairway 7 had an irrigation system that was the oldest out of the three. It was the only course that had two different sprinkler head types with both a 65-foot and 95-foot radius of throw. Due to this, two boxes were chosen to monitor this transition between small and large radius valve heads. An additional location was selected around the bend, a place that the superintendent expressed he had issues with. 3) Collindale had two of the three locations selected to monitor the tree coverage along the southwest side of the fairway and the sunny side just outside of it. A third location was selected based on the EM38-MK2 and superintendent giving insight into a trouble spot about 80 meters in from the east-side edge (Fig. 30).

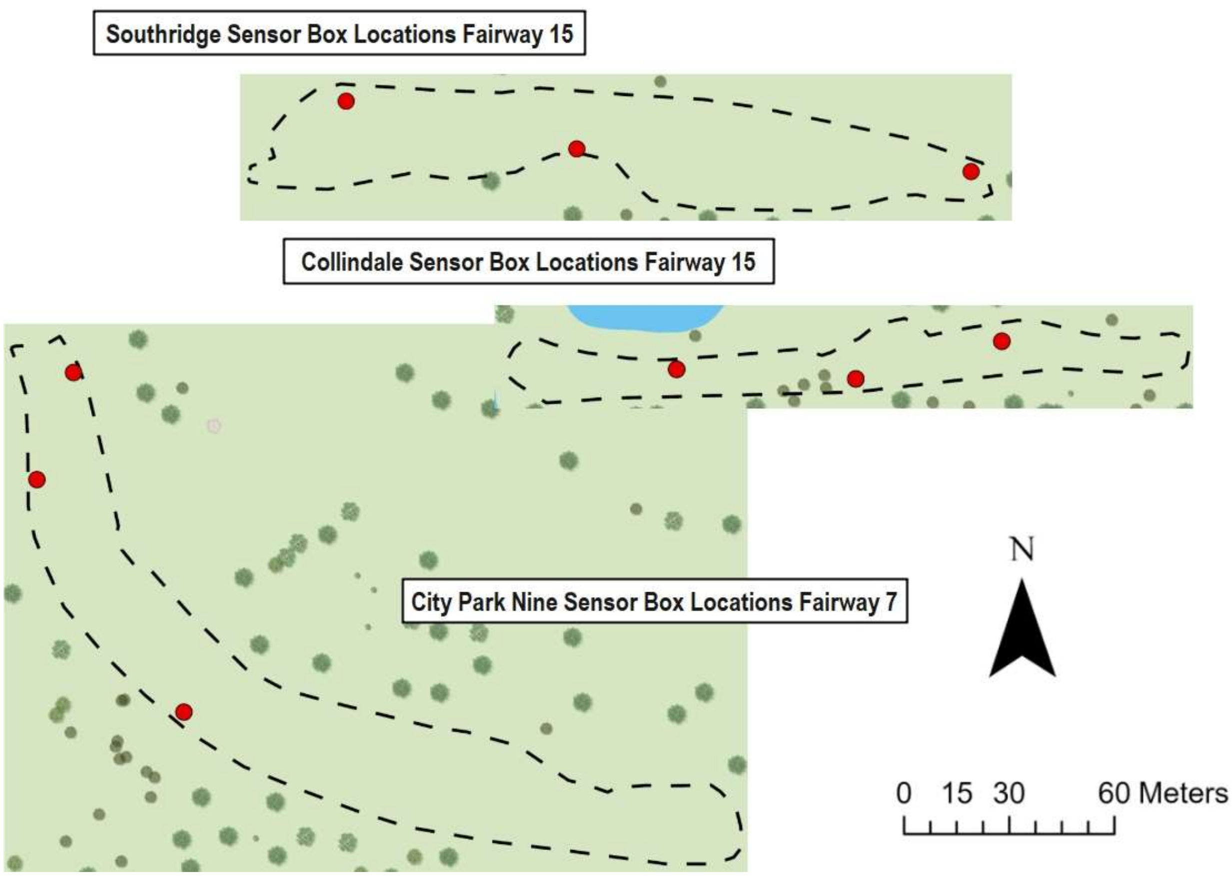

Figure 30. Red dots symbolize the locations of the final 3 sensor valve box installed at the three fairway locations; ultimately determined by numerous maps and manager experience.

Sensor System Install Procedure and Sensor Depths

Once all these components were collected, analyzed, and shared with the superintendent, the final soil moisture system install locations were qualitatively determined based on their experience of the fairway and the various data layers. Each valve-box soil sensing system had two sets of sensors installed a meter from the box in pairs at two and six inch depths. These depths were chosen weighing knowledge of how grass rootzones form and change throughout the year, with many factors contributing (Jordan et al., 2003). The shallow two inch depth was chosen to target the majority of the root biomass, while the six inch depth aimed for an area corresponding to the end of the root zone. A face was excavated to install the sensors perpendicular to the soil surface and carefully backfilled to prevent preferential flow or minimize any probe movement. In total each fairway had 12 soil moisture sensors reading back real-time soil moisture and temperature data at 30-minute intervals.

Summary and Conclusions

The objective of the study was to create management zones around soil moisture variability to aid in where real-time soil moisture sensor systems were installed. Three fairways were examined for topography, EC_a, and irrigation system configurations before they were outfitted with soil moisture sensor valve boxes. EC_a was shown in these scenarios to have a reasonable linear relationship to soil volumetric water content, and literature has pointed to a strong correlation between topography and soil variability. More research will need to be completed to fully understand how to successfully merge the layers and live soil moisture data to recommend precisely which sprinkler valves need to be adjusted, but this project suggests a model for other studies to continue further. Improvements and future steps include taking temporal measurements, testing real-time data and map layers to modify valve head scheduling, and increasing the sensor density on the fairways; in the end to understand how to better manage water content for varying irrigation demands. First a connection needs to be drawn between the water content and the agronomic decision to irrigate. After data collection and a map of soil water content has been prepared, one more step needs to be formed between the model's optimal recommendation and the limits of the irrigation system. To achieve an automated solution three connections should be understood between the water content, soil-plant relationship, and irrigation system.

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Chapter 4: Conclusion

This study aimed to design and implement an innovative soil sensing system for golf courses, integrating multiple disciplines and leveraging connections with the City of Fort Collins. From 2019 to 2021, tests conducted in the lab and on three fairways provided significant insights into the application of Internet of Things (IoT) technology in turf management.

The research achieved key objectives by creating and installing a valve box datalogger, calibrating and trialing a low-cost capacitive soil sensor design, and exploring sensor placement through spatial layer collection. Critical factors identified for golf applications included fairway soil water variability, the need for sensor temperature corrections at shallow depths, and the importance of high sensor sensitivity in wet soil conditions. These findings highlighted the complexity of implementing such systems in the varied environmental conditions of golf course fairways.

One of the study's most promising outcomes was the potential for combining near real-time soil data from irrigation zones with golf courses' high-precision irrigation systems. This integration could revolutionize golf course management by providing superintendents with improved irrigation tools and offering deeper insights into course playability, terrain mapping, and golf ball rolling dynamics. The implications extend beyond water management, potentially enhancing the understanding of the game itself.

The research also uncovered significant challenges for future work. Optimal sensor placement and management zone mapping emerged as crucial areas for exploration. Additionally, technological constraints were revealed, including limited battery life, exposure to damage, lower signal strength below ground, and the absence of automatic detection for malfunctioning sensors. These issues point to clear directions for future technological improvements.

Future innovation requires addressing several key areas. Research should focus on testing management zone methods and their connection to irrigation systems, using soil moisture sensors for ground-truthing and automation (Chapter 3). This process must consider diverse watering scenarios, spatial variability, and the integration of software control and irrigation hardware constraints. Technological advances should target battery efficiency, signal strength, sensor sensitivity, system durability, and low-cost electrical conductivity measurements.

As technology evolves, automation in golf course management appears increasingly promising. Advancements in machine learning, neural networks, low orbit satellites, and wireless communication infrastructure will likely facilitate comprehensive sensor integration. This progression may allow staff to redirect focus from routine irrigation tasks to critical operational responsibilities. With worker shortages and declining birth rates, the need for increased productivity in affected sectors makes automation more appealing, addressing labor challenges while improving operational performance.

In conclusion, this study established a foundational framework for IoT soil sensor technology in golf course management. Despite existing challenges, the potential benefits in water conservation, turf quality, and operational efficiency are substantial. As research progresses, this work promises not only to improve golf course management but also to contribute to broader advancements in precision agriculture and sustainable land management.