# Data Acquisition and Analysis for Improving the Utility of Low Cost Soil Moisture Sensors

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***Abstract*—To cultivate healthy plants and high crop yields, growers must be able to measure soil moisture and irrigate accordingly. Errors in soil moisture measurements can lead to irrigation mismanagement with costly consequences. In this paper, we present a new approach to smart computing for irrigation management to address these challenges at a lower cost. We calibrate low cost, low precision soil moisture sensors to more accurately distinguish wet from dry soils using high cost, high precision Davis Instrument sensors. We investigate different modeling techniques including the natural log of the odds ratio (Log-odds), Monte Carlo simulation, and linear regression to distinguish between wet and moist soils and to establish a trustworthy threshold between these two moisture states. We have also developed a new smartphone application that simplifies the process of data collection and implements our analysis approach. The application is extensible by others and provides growers with low cost, data-driven decision support for irrigation. We implement our approach for UCSB's Edible Campus student farm and empirically evaluate it using multiple test beds. Our results show an accuracy rate of 91% and lowers costs by 4x per deployment, making it useful for gardeners and farmers alike.**

***Index Terms*—Soil Moisture Sensors, Calibration, Log-Odds, Monte Carlo, Linear Regression**

## I. Introduction

### A. Modern Agriculture

It is projected that as much as 4.4 billion acres of irrigated land will be required to meet the needs of our growing population [4]. This new land, which is roughly equivalent to twice the size of the continental United States, will need to be irrigated to cultivate crops and accelerate agricultural productivity. [4] However, global climate change and ecological crises are damaging the many natural processes that make modern irrigation systems possible. For example, variations in rainfall patterns and more extreme weather conditions have impacted the availability and quality of ground water, the main source of water for modern irrigation systems [9]. These challenges present significant obstacles to improving agricultural productivity.

The farmers who do manage to successfully navigate these challenges may inadvertently contribute to further ecological problems. Large-scale irrigation projects, which divert significant amounts of freshwater, can deplete downstream river systems and potentially damage delicate ecosystems. The increased evaporation of water into the atmosphere caused by irrigation can also alter rainfall patterns, not just over the irrigated area, but also thousands of miles away [7]. Additionally, irrigation mismanagement has been linked to further erosion of coast lines, resulting in habitat loss for endangered species [8]. These widespread ecological issues are further exacerbated in the state of California, which is currently experiencing the driest three year period in its history [5]. This makes Californian farms particularly vulnerable to the negative consequences of wasteful irrigation practices.

### B. Soil Moisture Sensors

Ensuring proper moisture content is essential when supporting plant growth and survival. Soil moisture content that is too wet or too dry can negatively impact a plant's photosynthetic capacity and ability to survive. Under watering leads to decreasing biomass, wilting stems, and browning leaves. Over watering prevents roots from absorbing the oxygen they need to function, increasing the risk of root disease and crop failure. It is therefore vital that farmers integrate soil moisture sensors to correctly irrigate their plants, detect leaks in irrigation systems, and optimize for high crop yields. An effective way to take this measurement is to install soil moisture sensors. However, not all soil moisture sensors are created equal.

There are currently two main kinds of soil moisture sensors on the market: high quality and low quality sensors. Each type has its own set of unique advantages and disadvantages. High quality sensors are more accurate and often come equipped with sensors that measure soil temperature, leaf temperature, leaf wetness, and dew point. They also are able to periodically upload the data they record to the cloud, allowing for the creation of dashboards that can be accessed through mobile and web applications. While these additional features make high quality sensors expensive and potentially more complex to deploy and maintain, they provide valuable data and connectivity. Low quality sensors on the other hand, are generally less expensive and easier to deploy, but they come at the cost of accuracy and lack internet connectivity to upload data to the cloud.

The low quality sensor explored in this paper is the Blumat Digital tensiometer soil moisture sensor. Tensiometer soil moisture sensors operate by measuring the increase in soil moisture tension as roots absorb water from the soil [6]. As the surrounding soil dries, the ability of the soil to withdraw water from the sensor increases and the sensor displays a higher

| | How data is collected | Data sensor provided | Price |
|---|---|---|---|
| **Blumat Digital** (tensometer)  | Manually | ❑ Soil Moisture (0 - 300 mBar) | $88 |
| **Davis Weather Station** (electrical resistance)  | Automatically uploaded to the cloud every 5 minutes | ❑ Soil Moisture (0 - 2000 mBar)<br>❑ Soil Temperature<br>❑ Humidity<br>❑ UV-level<br>❑ Rain rate<br>❑ Wind chill<br>❑ ... | $1425 |

Fig. 1. Comparing the features of the Blumat Digital tensiometer soil moisture sensor with the Davis Instruments electrical resistance sensor. The additional features and data contributes to Davis' higher cost.

value [6]. Irrigation of the soil reverses this process and the tensiometer draws water back from the soil. This decreases the pressure on the sensor and it displays a lower value. For the high quality sensor, we use the Vantage Pro2 electrical resistance soil moisture sensor from Davis Instruments. Electrical resistance sensors measure the resistance to the passage of current through soil. The wetter the soil, the less resistance to the passage of current. The Davis Instruments sensor uses a function to transform this resistance into units of pressure [3]. Blumat sensors are stand-alone and are read manually; each one costs $88 (cf Amazon.com) as of this writing. Davis soil moisture sensors are part of a soil moisture station that connect to a Vantage Pro2 base station which collects the data and forwards it to the cloud. The Davis system measures a number of other environmental characteristics in four adjacent locations (connected by wires) and this station combination costs a minimum of $1425 today (cf Amazon.com). Thus, for each 4-sensor deployment, Davis costs 4x more than Blumat. Figure 1 above compares the data acquisition capabilities of the Davis and Blumat soil moisture sensors. The additional data provided by Davis contributes to its significantly higher deployment cost.

### C. Calibration Between Sensors

The range of values and suggested irrigation periods differ between high and low precision sensors. The Blumat Digital sensor reliably measures up to 300 mBar and recommends watering when the sensor reads 120 to 190 millibar (mBar) [2]. In contrast, the Davis sensor can measure up to 2000 mBar (20 cBar) and suggests watering between 300 to 600 mBar. In cooler climates with high water-holding capacity soils, the Davis sensor suggests watering between 400 to 600 mBar [3]. This discrepancy between the Blumat sensor and the Davis sensor, as visualized in figure 2, can result in farmers following drastically different irrigation practices. For example, soil considered moist by the Davis sensor may be deemed dry by the Blumat sensor. This paper aims to reconcile this by introducing a calibration step between the two that allows growers to adjust the range of the low-quality sensor to match that of the high-quality sensor. In doing so, we

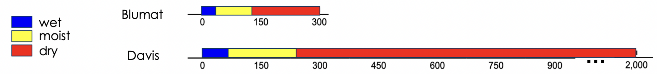


Fig. 2. Visualizing the different calibration and suggested irrigation ranges between the Blumat and Davis soil moisture sensors.

Fig. 3. A picture of the beds at Edible Campus. In addition to serving as a food source, the program promotes sustainable food systems and environmental stewardship at the University of California, Santa Barbara.

hope to enable farmers lower their costs while still achieving successful and sustainable irrigation practices.

## II. Related Work

Many studies have been conducted on the use of low-cost soil moisture sensors in precision agriculture. For instance, researchers from ETH Zurich evaluated the performance between three low-cost soil moisture sensors and a high-accuracy time domain reflectometry (TDR) sensor [10]. They concluded that the low-cost sensors could not reliability measure the soil moisture and that site-specific calibration was crucial for more accurate measurements [10]. However, their work was conducted in a sparsely populated research catchment, while our study was carried out on an active farm in Santa Barbara. Our mobile application also presents more simple visualizations of data, particularly from the Blumat Digital, to enable easy interpretation of soil moisture measurements. Moreover, we focused specifically on establishing a reliable cutoff between wet and moist soil, which can aid in preventing over or under watering and boost crop yields.

The Gravimetric technique is another commonly used research method for calibrating soil moisture sensors.This technique involves comparing the weight of soil samples before and after drying in an oven to accurately determine the amount of water present in the soil. The resulting weight difference is then calibrated against data obtained from soil moisture sensors to establish a precise measurement of soil water content. [11]. A drawback to this method is that it is time-consuming, labor-intensive, and only provides a snapshot of the moisture content at the time of sampling. Moreover, this method is infeasible for many small-scale farms as gravimetric techniques require access to a well-equipped laboratory. Prior studies also indicate that while gravimetric sampling techniques offer high levels of accuracy, it is quality of individual calibration of soil moisture sensors that minimizes the error [11]. Our work aids in decreasing the time and resources required by gravimetric sampling while also presenting calibrations method specific to the the affordable Blumat Digital sensor deployed under real-world conditions. Our proposed method can be quickly replicated by farmers and gardeners and has the potential to improve water-use efficiency and crop yields.

There are several existing mobile applications that help farmers more accurately determine soil moisture content. For example, the MySoil app uses publicly available and crowd sourced soil data to generate watering schedules and provide soil moisture readings. Similarly, the SoilWeb app provides users with soil data from the Soil Survey Geographic dataset, which is published by the USDA Natural Resources Conservation Service. Although such existing apps have been developed to assist with soil moisture sensing, they are often associated with various limitations. These limitations include a dependence on supplementary measuring equipment, inflexibility in calibration and data analysis, and user-unfriendly interfaces for on-site data collection and visualization. To overcome some of these challenges, our study introduces a new mobile application that is custom-built for use with the Blumat Digital soil moisture sensor and targeted towards everyday farmers. This app streamlines the data collection process and offers clear and easily comprehensible visualizations of soil moisture data, making it suitable for both seasoned and novice farmers.

## III. Edible Campus

Prior to our research, our team recognized that in order to preserve water at larger scale farms, we must first begin by working with our local communities. We partnered with Edible Campus, a farming initiative at the University of California, Santa Barbara that provides for food-insecure students. As photographed in figure 3, the farm plants in raised beds and is managed by student farmers, many of whom who work part-time. Due to this part-time status, watering schedules at the farm were often roughly estimated, leading to instances of over watering and unnecessary watering of empty beds. In addition, smaller scale farms such as Edible campus often have limited budgets, which restricts them to purchasing cheaper, low-quality soil moisture sensors. These considerations made Edible Campus an ideal setting and test bed for our research.

## IV. Data Acquisition

### A. Deployment Setup

To gather data for our analysis, we deployed six Blumat Digital and four Davis Instrument soil moisture sensors in two of the beds at Edible Campus as shown in figure 4. Initially, we asked student farmers to periodically input readings from the Blumat sensor into a shared excel spreadsheet - as readings from the Blumat sensor had to be recorded manually. However, we encountered two main limitations with this approach. First, the data recorded by students was often incorrectly time stamped or placed in the wrong column of the spreadsheet. Second, students frequently forgot to record data daily, as there was no immediate incentive for them to do so. These issues led us to explore alternative methods for data collection.

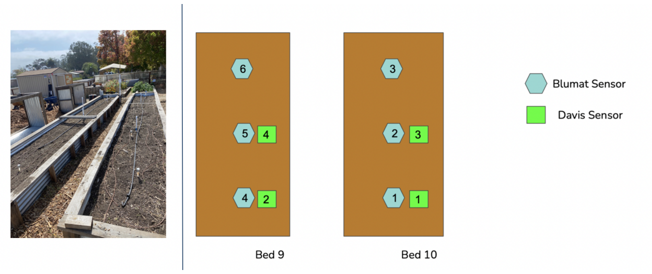


Fig. 4. The deployment of Blumat and Davis soil moisture sensors at Edible Campus. Sensors were evenly spaced out in beds 9 and 10.

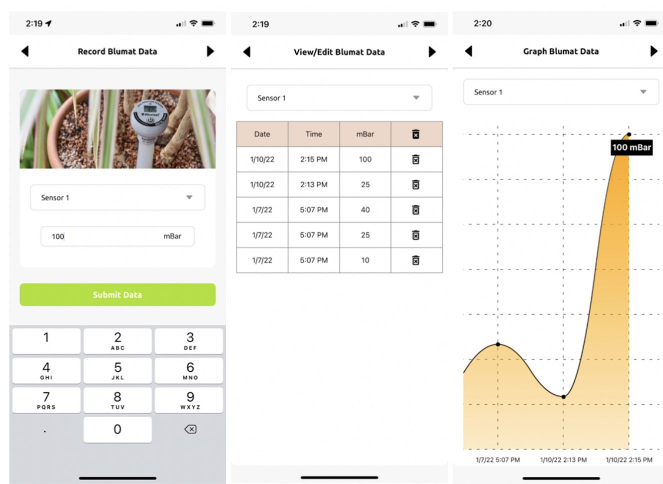


Fig. 5. The first, second, and third page of our mobile application that enabled student farmers at Edible Campus to more accurately collect and visualize Blumat data.

### B. Mobile Application

To address these challenges, our team developed a mobile application that allows students that to more easily collect Blumat data. As presented in figure 5, the app was divided into three pages, each focusing on a core feature. The first page was an input data page that allowed farmers to select a specific Blumat sensor number and input the mBar value. The second page let farmers view and edit all of the data for a specific sensor. The final page displayed a graph visualizing changes in soil moisture readings. Students at Edible Campus used this mobile application to understand trends in moisture levels and collect data that enabled our calibration.

### C. Time Matching Data

The Davis Instrument soil moisture sensor periodically uploads its data to the cloud every five minutes. To match the Blumat data collected from our mobile application with Davis

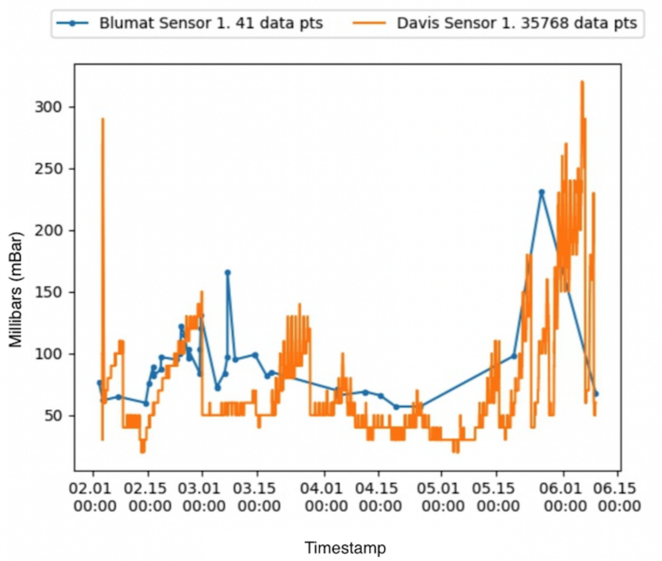


Fig. 6. The graph on the above draws a line through all of the data collected for one of the four Blumat-Davis sensor pairs (w/out outliers). Notice that there exists a correlation between the two sensors.

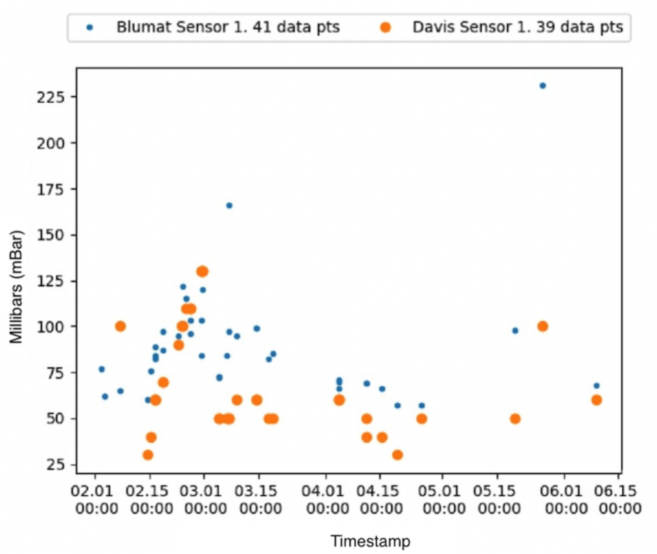


Fig. 7. The graph above displays the raw data for all of the data collected for one of the four Blumat-Davis sensor pairs (w/out outliers). Notice that the data is skewed towards the wet/moist region for both sensors.

data, we paired datapoints that had the closest timestamps to each other. For both figure 7 and 6 the x-axis is the timestamp and the y-axis records the readings from the Blumat and Davis sensors in mBar. By connecting the data points, as shown in Figure 6, it becomes apparent that there is a correlation between the two sensors. This suggests that there is some relationship between the Blumat and Davis sensors, and that additional calibration could be performed to enhance the accuracy of the Blumat sensor in comparison to the Davis sensor. Furthermore, examining the time-matched data depicted in figure 7, it is clear that the soil moisture

| C | ln[P(■)/P(■)] |
|---|---|
| 101 | 0.0222 |
| 102 | 0.0008 |
| 103 | -0.021 |
| 104 | -0.0433 |

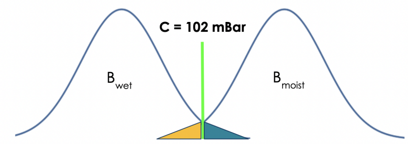


Fig. 8. Finding the cutoff C where the area under the curves in orange and blue are equivalent. This is the mBar the Blumat sensor reads when the soil is at the wet/moist cutoff according to the Davis sensor. The cutoff C is found when the natural log odds is 0. This occurs when C = 102 mBar.

measurements from Edible Campus tend to fall within the wet/moist range for both Davis and Blumat sensors. This is primarily due to the soil management practices employed by the farmers at Edible Campus, who maintain the soil at this level to support optimal plant growth.

### *D. Outlier Removal*

To address outliers, we first eliminated all Blumat readings lower than 50 mBar, as they were accompanied by highly variable Davis mBar values. We also removed Blumat readings above 300 mBar, as the Blumat soil moisture sensor is not accurate in measuring values above 300 mBar. We observed several instances where the water inside the Blumat soil moisture sensors had not been replenished, which provides an explanation for these high mBar readings. Additionally, due to equipment malfunctions of Davis sensor 4, we removed its data from further analysis. It should be noted that the variability of our data is inherent to the fact that our sensors perform data collection on-site. On-site deployment offers the benefit of delivering highly accurate results tailored to the specific deployment. Nonetheless, the approach is not without its drawbacks, as we are unable to maintain constant surveillance over the sensors, leaving them susceptible to damage or longer periods of inaccurate data collection.

## V. Data Analysis

We next investigated multiple popular techniques for performing calibration. We considered the log-odds ratio, Monte Carlo simulation, and linear regressions. We summarize our analysis for each in the following subsections.

### *A. Log-Odds Ratio*

The log-odds ratio is a statistical measure use to compare the likelihood or probability of two events occurring [1]. It is defined as the logarithm of the odds ratio, which is the probability of one event occurring over the probability of the other event occurring. We applied this methodology to determine a more accurate cutoff between wet and moist soil around the Blumat Digital soil moisture sensor using data from the Davis sensor.

According to documentation from Davis instruments, the sensor records less than or equal to 100 mBar in wet soil and greater than 100 mBar in moist soil [3]. Based on this information, our team divided our Blumat data into two sets: $B_{wet}$, containing all Blumat values when the adjacent Davis sensor recorded wet soil and $B_{moist}$, containing all Blumat values when the adjacent Davis sensor recorded moist soil.

Next, we generated two normal distributions by calculating the mean and standard deviation of our two sets of Blumat data. We then calculated the value C such that $P(B_{wet} > C) = P(B_{moist} < C)$ and found that C = 102. In other words, if the Blumat sensor recorded soil moisture levels below 102 mBar, a Davis sensor is more likely to classify the soil as wet. If the Blumat sensor recorded a soil moisture levels above 102 mBar, a Davis sensor is more likely to classify the soil as moist. Thus, the cutoff between wet and moist for the Davis sensor is when the Blumat sensor reads 102 mBar. Figure 8 shows this analysis.

### *B. Monte Carlo*

One limitation of the Log-Odds methodology is that it assumes the distribution of $B_{wet}$ and $B_{moist}$ follows a normal distribution. To further verify our conclusions from our Log-Odds calibration, our team employed Monte Carlo random sampling. This method involves generating a large number of random samples and does not assume any particular distribution of the data. Our goal was to find the cutoff C that most accurately split the Blumat–Davis data pairs.

For each possible cutoff C, our team sampled 50 data points 200 times and calculated the average rate of errors and successes. An error occurred when the Blumat and Davis mBar values were on opposite sides of the cutoff $C$. A success occurred when both values were on the same side of the cutoff $C$.

Through our Monte Carlo experiments, we determined that the optimal cutoff value (C) for the Blumat sensor to attain 9% accuracy was 100 mBar. Notably, this value aligns with the high-precision Davis sensor documentation, which indicates that 100 mBar serves as the threshold between wet and moist soils. Hence, our results corroborate the conclusions reached through the Log-Odds approach, specifically that if a Blumat sensor records below 100 mBar, an adjacent Davis sensor would classify the soil as wet, and if a Blumat sensor records above 100 mBar, an adjacent Davis sensor would classify the soil as moist. Although the Log-Odds cutoff was slightly higher at 102, we assert that the discrepancy is negligible and that the outcomes are consistent

### *C. Linear Regression*

To further analyze the relationship between Blumat and Davis soil moisture sensors and verify the results from our Log-Odds and Monte Carlo experiments, we used Least Squares Linear Regression. The result of our linear regression yielded a line of best fit of:

$$D = .28 * B + 38 \tag{1}$$

Where $D$ is the reading from the Davis sensor in mBar and $B$ is the reading from the Blumat sensor also in mBar. This line of best fit correctly classifies Blumat data as either wet ($D < 100$) or moist ($D > 100$) 91% of the time, which is consistent with the accuracy obtained in our Monte Carlo experiments. This further supports that the cutoff between wet and moist soil is 100 mBar for the Blumat soil moisture sensor.

## VI. Future Work

Moving forward, our research will focus on exploring the amount of water required to attain a specific mBar value, beginning from a known starting mBar value, for the Blumat Digital soil moisture sensor. This will be especially useful for farmers, on both large scale and small scale farms, who want to maintain optimal soil moisture levels. Additionally, we plan to explore the impacts of humidity, pressure, wind speed, and soil temperature on soil moisture at Edible Campus. This data can be collected by our mobile app when student farmers input readings for a Blumat sensor. Finally, we plan to investigate the degree to which the calibration threshold value changes across different locations and soil types.

We also shared our findings with the team at Edible Campus, and as a result, they have started watering their crops at 100 mBar in order to keep the soil in the moist/wet range. To evaluate the impact of this calibration on crop yield, we plan to work in collaboration with the growers to compare yield of the coming summer with that of the previous summer.

## VII. Conclusions

Our research investigates the use of a cutoff value to guide irrigation decisions by growers. We show that we are able to determine this threshold with high accuracy (>90%) using low cost, low accuracy soil moisture sensors coupled with a calibration step. Calibration entails using a high cost, high accuracy sensor system for a short period of time to detect the statistical relationship between the two sensor systems. We then can remove the high cost sensor system (and use it for calibration at other growing areas or farms) and maintain accurate decision support using only low-cost soil moisture sensors. We investigate multiple approaches to identifying this relationship and the combination confirmed the validity of our threshold between moist and wet soils. Our freely available mobile app makes it easy for growers to record data from sensors, visualize their data, and receive decision support as to when to irrigate. By improving the accuracy of low-cost sensors our mobile app gives growers a way to lower their costs but achieve trustworthy and higher accuracy support for their irrigation decisions.

## VIII. Acknowledgments

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## References


[1] J Martin Bland and Douglas G Altman. 2000. The odds ratio. Bmj 320, 7247 (2000), 1468.

[2] Tropf Blumat. 2019. Blumat Digital Soil Moisture User Manual.

[3] Davis Instruments Corp. 2019. Wireless Leaf and Soil Moisture/Temperature Station Installation Manual.

[4] Morgan Kelly. 2020. Expansion, environmental impacts of irrigation by 2050 greatly underestimated. Princeton Environmental Institute (May 2020).

[5] State of California. 2022. New water year begins amid preparations for continued drought.

[6] Resource Conservation District of Monterey County. 2012. How to use a Tensiometer.

[7] Sergi Sabater, Francesco Bregoli, Vicenç Acuña, Damià Barceló, Arturo Elosegi, Antoni Ginebreda, Rafael Marcé, Isabel Muñoz, Laia Sabater-Liesa, and Verónica Ferreira. 2018. Effects of human-driven water stress on river ecosystems: a meta-analysis.

[8] National Geographic Society. 2022. Environmental Impacts of Agricultural Modifications.

[9] Dawei Wang, Yuanyuan Chen, Mourin Jarin, and Xing Xie. 2022. Increasingly frequent extreme weather events urge the development of point-of-use water treatment systems. npj Clean Water 5, 1 (2022), 1–7.

[10] Heidi Mittelbach, Irene Lehner, Sonia I. Seneviratne, Comparison of four soil moisture sensor types under field conditions in Switzerland, Journal of Hydrology, 2012.

[11] Tracy L. Rowlandson, Aaron A. Berg, Paul R. Bullock, E. RoTimi Ojo, Heather McNairn, Grant Wiseman, Michael H. Cosh, Evaluation of several calibration procedures for a portable soil moisture sensor, 2013