# Comparative Study on Sensitivity Variations in Three Soil Moisture Sensors to Optimize Water Use Efficiency in IOT-Based Automated Irrigation

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***Abstract:*** *Efficient water management in agriculture is crucial for improving productivity. In this study, Automated irrigation systems using soil moisture sensors for precise water discharge control and Internet of Things (IoT) technology were studied to achieve real-time data monitoring. The sensitivity of different types of soil moisture sensors varies, especially in field conditions. Hence, poses a challenge in optimizing irrigation water, leading to lowered productivity. Therefore, we provided insights into optimizing sensor selection and calibration for more effective water resource management in agriculture through performance evaluation of capacitive, resistive, and Time Domain Reflectometry (TDR) sensors in measuring soil moisture content under different soil types. The correlation between sensor sensitivity and the accuracy of soil moisture measurements under different soil types was studied. The laboratory experiment was conducted to evaluate th-e performance of factory-based calibrated soil moisture sensors. The performance of the soil moisture sensors was evaluated using Root Mean Squared Error (RMSE), Index of Agreement (IA), and Mean Bias Error (MBE). The result shows that the performance of the factory-based calibrated capacitive, resistive, and Time Domain Reflectometry (TDR) did not meet all the* *statistical criteria except the capacitive sensor for sand loamy. There was a strong positive relationship among sensors. The correlation between TDR and resistive moisture readings was 0.96, between TDR and capacitive moisture readings was 0.98, and between resistive and capacitive moisture readings was 0.97. The correction equations were developed using the laboratory experiment and validated in the field. The correction equations for capacitive, resistive, and TDR improved the accuracy in field conditions.*

**Keywords:** *Internet of Things, moisture, microcontroller, real-time monitoring, sensors.*

## 1.0 Introduction

Soil moisture content has been of concern in many fields, especially agricultural engineers, agronomists, and crop scientists. It is a critical parameter in understanding water and solute transport in soil. Monitoring soil moisture content in agriculture is very tedious and time-consuming when done manually. Therefore, using sensors to improve water management through precise irrigation scheduling is essential because of their practicability in providing continuous data. Sensors can be installed at multiple depths, and they are not destructive. The common sensor technologies are Time Domain Reflectometry (TDR) and Frequency Domain Reflectometry (FDR) [1], [2]. The Internet of Things (IoT) has recently attracted growing attention from academia and industry [3], [4]. The development of IoT and the rise of free and open-source technologies have created an ideal environment for scientific and technological innovations [5].

Agriculture has increasingly utilised advanced technology to manage various practices and operations and make informed decisions using sensors based on field monitoring [6]. Irrigation, the largest global consumer of water resources, using more than 75% of freshwater, has been particularly impacted by these advancements [7]. With rapid population growth and climate change, the demand for freshwater is expected to rise, causing water scarcity [8]. Traditionally, irrigation scheduling has depended on the farmer's experience [9]. Still, there is a need to adopt precision monitoring methods based on advanced scientific devices and modern technologies that offer practical solutions.

Effective water management is fundamental to achieving agricultural success and maintaining environmental sustainability [10], [11]. Accurate measurement and control of soil moisture levels are critical, particularly in automated irrigation systems, where soil moisture sensors play an essential role. These sensors provide real-time data that helps farmers optimize water use and enhance crop yields [12]. Field study is important because it will reveal the key factors affecting sensor sensitivity since most sensors are fabricated under laboratory conditions [13].

However, the reliability of automated irrigation systems is highly dependent on the accuracy of these sensors [14]. Inconsistent sensor sensitivity can lead to inaccurate soil moisture measurements, inefficient irrigation practices, and water wastage [15].

[16] reported that the factory-based calibrated TDR, resistive, and capacitive sensors could not meet all statistical criteria except the capacitive sensor in the sand loamy. According to the results of their lab experiment, soil moisture sensors need to be calibrated for specific soil types (site-specific circumstances) to increase accuracy. Prior studies have also examined this [17], [18], [19].

This study addresses the variations in sensitivity among different types of soil moisture sensors, including capacitive, resistive, and Time-Domain Reflectometry (TDR) sensors. It will offer valuable insights into sensor selection and calibration methods for optimizing automated irrigation practices for more effective water management in agriculture.

## 2.0 Materials and Methods

Laboratory and field experiments were conducted to evaluate the performance of factory-based calibrated soil moisture sensors.

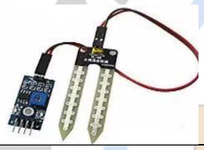
### 2.1 Laboratory Experiment

***Materials***

Materials used during the laboratory experiment were plastic crate containers (80*41*35 cm) and factory-based calibrated soil moisture sensors. The type, specifications and functions of soil moisture sensors are shown in Table 1.

The system also includes an Arduino Uno microcontroller for sensor data collection and transmission, a WiFi module for wireless data transfer, a relay switch to control the irrigation pump, and a toggle switch for power management. An LCD shows real-time sensor readings and system status, with components connected by wires and assembled on a breadboard. In addition, a 3.7V LiPo battery power sensors, a 12V DC pump for irrigation,

Table 1: Type and specifications of soil moisture sensors

| S/N | Type of sensor | Specification | Function |
|---|---|---|---|
| 1 | *Capacitive Soil Moisture Sensor*  | SKU: SEN0193 | Measures the soil moisture by determining the capacitance between its probe and the surrounding soil. Provides a non-destructive way of sensing moisture content. Widely used in agriculture and automated irrigation systems. |
| 2 | *Resistive Soil Moisture Sensor*  | SKU: SEN0114 | Work on the principle of varying resistance with soil moisture. As the soil becomes more conductive with increased moisture, the resistance changes, allowing the sensor to detect moisture levels. |
| 3 | *TDR (Time Domain Reflectometry) Soil Moisture Sensor*  | TDR-310H | Measure soil moisture by sending electromagnetic pulses through the soil and analyzing the reflection time. The moisture content affects the soil's dielectric properties, altering the reflection time and providing accurate moisture readings. |

and pipes for water transport. A 12V power supply powers the pump. The system also includes a DHT22 sensor to measure temperature and humidity and wood materials to construct the framework for the setup.

### 3.0 Soil classification and preparation

Soil samples were collected from the SUA MODEL FARM agricultural fields and analysed for texture classification and bulk density in the soil laboratory at Sokoine University of Agriculture (SUA)(https://www.coa.sua.ac.tz/soil/commercial-laboratory/).

The average result of the soil classification and bulk density is shown in Table 2. The soil samples were oven-dried at $105^0$C for 24 hours for laboratory experiments.

The sensor performance was evaluated at low soil moisture levels for drought conditions.

### 4.0 Sensor calibration and installation

Capacitive, Resistive, and Time-Domain Reflectometry (TDR) sensors were calibrated before the experiment. The calibration was conducted based on the readings in oven-dried and fully saturated soil. The analogue sensor readings on the oven-dried soil were considered 0% moisture level readings of sensors, while analogue sensor readings in fully saturated soil were taken as 100% moisture. The readings were mapped to capture the moisture level between 0% and 100% for both sensors.

Table 2: Soil bulk density and classification

| Class | Bulk Density (g/cm$^3$) | Sand (%) | Silt (%) | Clay (%) |
|---|---|---|---|---|
| Loamy Sand | 1.52 | 78.5 | 9.1 | 12.4 |
| Sandy Clay Loam | 1.31 | 59.3 | 15.6 | 25.1 |


Figure 1: Overview of the laboratory experiment setup.

Figure 2: Circuit and program written respectively

The calibrated sensors were installed in the container with air-dried soil at 15 cm depth from the surface (Figure 1). The sensors were connected to an Advantech-made Arduino Uno microcontroller (Arduino Uno R4). The Arduino Uno microcontroller processed the recorded measurements from moisture sensors at 10-minute intervals (Figure 2).

### *5.0 Data Collection*

During data collection, the soil in each container was wetted using a 12V diaphragm pump sprayer and covered with a plastic liner to minimise evaporation. Wetted soil samples were collected thrice during the experiment using a 61 cm³ size soil ring for volumetric water content (VWC) analysis. At the same time, the sensor's data were sent to the microcontroller every 10 minutes and transmitted to an online ThingSpeak cloud platform via a WiFi module for analysis. The duration of the laboratory experiment was 14 days. The collected data are shown in Table 3.

Table 3: Collected data and their descriptions

| Measurement | Description |
|---|---|
| Timestamp | The exact date and time when the data entry was created. This is crucial for tracking temporal changes in soil moisture and environmental conditions. |
| Entry ID | A unique identifier for each data entry. This ensures data integrity and facilitates easy referencing. |
| ***TDR Sensor Data*** | |
| TDR Analogy | The raw analogy reading from the TDR sensor indicates the relative soil moisture level. |
| TDR Voltage Data | The voltage output from the TDR sensor is proportional to the soil moisture content. |
| TDR Moisture | The calculated soil moisture content is derived from the TDR sensor readings. |
| ***Resistive Sensor*** | |
| Resistive Analogy | The raw analogy reading from the resistive sensor indicates the relative soil moisture level. |
| Resistive Voltage | The resistive sensor's voltage output varies with soil moisture content. |
| Resistive Moisture | The calculated soil moisture content is derived from the resistive sensor readings. |
| ***Capacitive Sensor*** | |
| Capacitive Analog | The capacitive sensor's raw analogy reading indicates the relative soil moisture level. |
| Capacitive | The voltage output from the capacitive sensor is proportional to the soil |

| | |
|---|---|
| Voltage | moisture content. |
| Capacitive Moisture | The calculated soil moisture content is derived from the capacitive sensor readings. |

### *6.0 Statistical Analysis*

The performance of the soil moisture sensors was analysed using the ThingSpeak online cloud platform.

According to [20], the significant difference between the sensor values and soil sample values was evaluated using Root Mean Squared Error (RMSE), Index of Agreement (IA), and Mean Bias Error (MBE).

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{N}(M_i - P_i)^2} \quad \text{i}$$

$$\mathrm{IA} = 1 - \frac{\sum_{i=1}^{N}(M_i - P_i)^2}{\sum_{i=1}^{N}(|P_i - \bar{M}| + |M_i - \bar{M}|)^2} \quad \text{ii}$$

$$\mathrm{MBE} = \frac{1}{N}\sum_{i=1}^{N}(P_i - M_i) \quad \text{Iii}$$

**Where:** $N$ is the sample size, $M_i$ is the measured (soil sampling) value, $P_i$ is the predicted (sensor measurement) value, and $\bar{M}$ is the average measured value.

IA is dimensionless, but RMSE and MBE are expressed in volumetric water content ($cm^3/cm^3$) units. A score of 0 denotes no agreement between measured and anticipated values, while a range of IA falls between 0 and 1. A perfect match between observed and expected values is indicated by a value of 1. A higher IA score indicates better agreement between observed and projected values. According to [21], most agricultural applications require sensor measurement precision of less than 0.02 $cm^3/cm^3$. According to [17], the MBE and RMSE criteria were ± 0.02 and less than 0.035 $cm^3/cm^3$, respectively. Thus, MBE± 0.02 $cm^3/cm^3$ and RMSE < 0.035 $cm^3/cm^3$ were used in this investigation to assess the sensor performance.

### 7.0 Field Experiment

Based on [20], the validation of corrective equations was assessed in agricultural settings. The soil types used in the laboratory experiment, sand loamy and sandy clay loam, are the same in the two chosen agricultural fields. Cabbages were being grown in these fields [22], as shown in Figure 3. Table 2 displays the results of the soil texture categorisation analysis conducted by the SUA soil laboratory. A 3-inch-diameter ring was used to gather soil samples to determine the volumetric water content. A limited number of soil samples were conducted to minimise disturbing the soils around the sensors. This volumetric water content data was compared to factory-based calibrated and corrected soil moisture sensor data [23]. Sensors were installed by digging a shallow trench, inserting the sensors horizontally into the soil, and then backfilling the trench. Capacitive, Resistive, and Time Domain Reflectometry (TDR) sensors were connected to a programmed Arduino Uno microcontroller to record the measurements of soil moisture levels every 10 minutes.

Figure 3: Sensor placement layout

Table 2: Soil classification for field demonstration

| Sensor | Class | Sand (%) | Silt (%) | Clay (%) |
|---|---|---|---|---|
| Capacitive | Sand Loamy | 91.9 | 3.7 | 4.4 |
| | Sandy Clay Loam | 87.9 | 5.8 | 6.3 |
| Resistive | Sand Loamy | 54.8 | 23.6 | 21.6 |
| | Sandy Clay Loam | 92.3 | 1.3 | 6.4 |
| TDR | Sand Loamy | 53.3 | 26.6 | 20.1 |
| | Sandy Clay Loam | 86.8 | 4.8 | 8.4 |

## 8.0 Results and Discussion

### *8.1 Correlation of sensor readings*

Figure 4 shows the correlation matrix of relationships between soil moisture readings from TDR, Resistive, and Capacitive sensors. The results indicate strong positive relationships among sensors. The correlation between TDR and resistive moisture readings was 0.96, between TDR and capacitive moisture readings was 0.98, and between resistive and capacitive moisture readings was 0.97. These high correlations indicate consistency and reliability across different measurement technologies despite the differences in sensor types.

### 8.2 Analysis of skewness and distribution patterns in sensor data

The histograms (Figure 5) reveal several vital insights regarding the skewness of the variables. The TDR analog variable exhibits significant positive skewness (Skewness: 2.26), indicating a concentration of lower values and a long tail of higher values. Conversely, the TDR moisture, resistive moisture, and capacitive moisture variables demonstrate negative skewness (Skewness: -0.75, -0.48, and -0.73, respectively), signifying those higher values are more frequent with tails extending towards lower values. The resistive analogue variable displays significant positive skewness (Skewness: 0.62), while the capacitive analogue variable is virtually symmetrical with mild negative skewness (Skewness: -0.14). Additionally, the capacitive analogue variable is practically symmetrical with a very tiny left skew, indicating a more equal distribution of values around the mean.

Each variable exhibits a distinct concentration of values within particular ranges in terms of distribution patterns (Figure 5). Capacitive moisture values are mainly concentrated around 70–80, but TDR analogue values are mainly clustered between 500 and 700. Notable peaks in these ranges indicate common measurement values, whereas the frequencies of observations vary; for example, TDR _moisture has a high frequency of values between 40 and 60. The TDR_analogue variable, which exhibits a notable decline in frequency over 700 with smaller peaks indicating outliers, makes the existence of outliers clear. More research may be necessary to fully comprehend these outliers' effects on the entire data set.

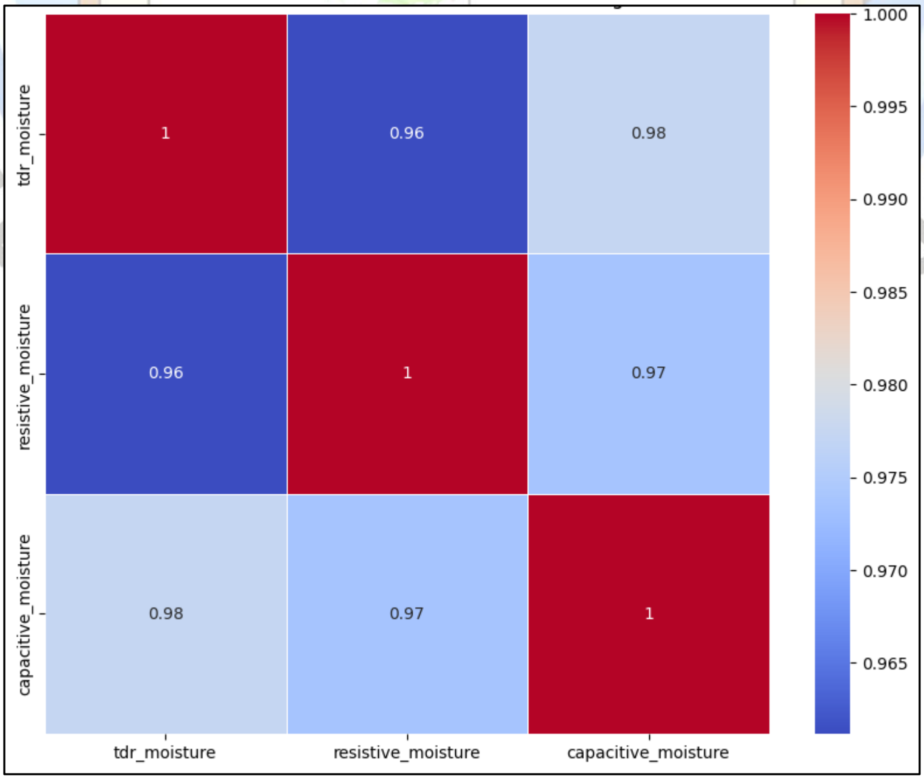


Figure 4: Correlation matrix of three sensors' moisture readings

Furthermore, the distribution of soil moisture readings from TDR, resistive, and capacitive sensors is shown in the box plot (Figure 6). The TDR sensor displays some outliers below 10%, a median of roughly 50%, and an interquartile range (IQR) of roughly 30% to 65%. The resistive sensor exhibits more significant variability due to its more extensive range with an IQR ranging from 40% to 80% and a higher median of roughly 60%. With a narrower IQR from 45% to 75%, the capacitive sensor has a median near the resistive sensor at about 60%, indicating more consistent readings. The range of moisture levels detected is indicated by the whiskers on all sensors, which extend from almost 0% to over 80%. The box plot illustrates the central tendency and variability of the various sensors, demonstrating that resistive and capacitive sensors record more significant and variable moisture levels, whereas TDR readings are lower and more consistent.

### *8.3* Sensor sensitivity

Three sensors, TDR, resistive, and capacitive, provide soil moisture values over time in the graph, which is subject to laboratory testing. Every sensor shows a downward trend, which suggests that the earth is drying off. While the resistive and capacitive sensors hold greater levels for longer before progressively declining, the TDR sensor exhibits a fast fall early on. At first, moisture levels are- high above 80%. In contrast to the resistive and capacitive sensors, which gradually diminish with fluctuations, the TDR sensor always declines sharply. All sensors converge to low moisture levels below 20% by about 4000 minutes, with the TDR sensor recording the lowest moisture and the capacitive sensor typically recording higher than the resistive (Figure 7). These variations emphasise the importance of selecting suitable sensors depending on the particular monitoring needs.

### *8.4* Sensor performance

Laboratory tests were used to evaluate the performance of TDR, resistive, and capacitive sensors in sand loamy and sandy clay loam. The outcome of the statistical analysis is shown in Table 3. Table 3 compares the sensor readings with the volumetric water content determined by sampling soil for sandy clay loam and loamy sand. According to the Capacitive's MBE readings, the sensor's average underestimation of volumetric water content in the sand, loamy sand, and sandy clay loam was 0.01 $cm^3/cm^3$, 0.03 $cm^3/cm^3$, and 0.02 $cm^3/cm^3$, respectively. Sand's RMSE value satisfies the requirements, however sandy clay loam and loamy sand do not. Both the MBE and RMSE standards were met by the capacitive's performance for sand. MBE _ 0.02 $cm^3/cm^3$ and RMSE <0.035 $cm^3/cm^3$ are the requirements. The sensor overestimated the volumetric water content by an average of 0.03 $cm^3/cm^3$ in the sand, underestimated it by 0.03

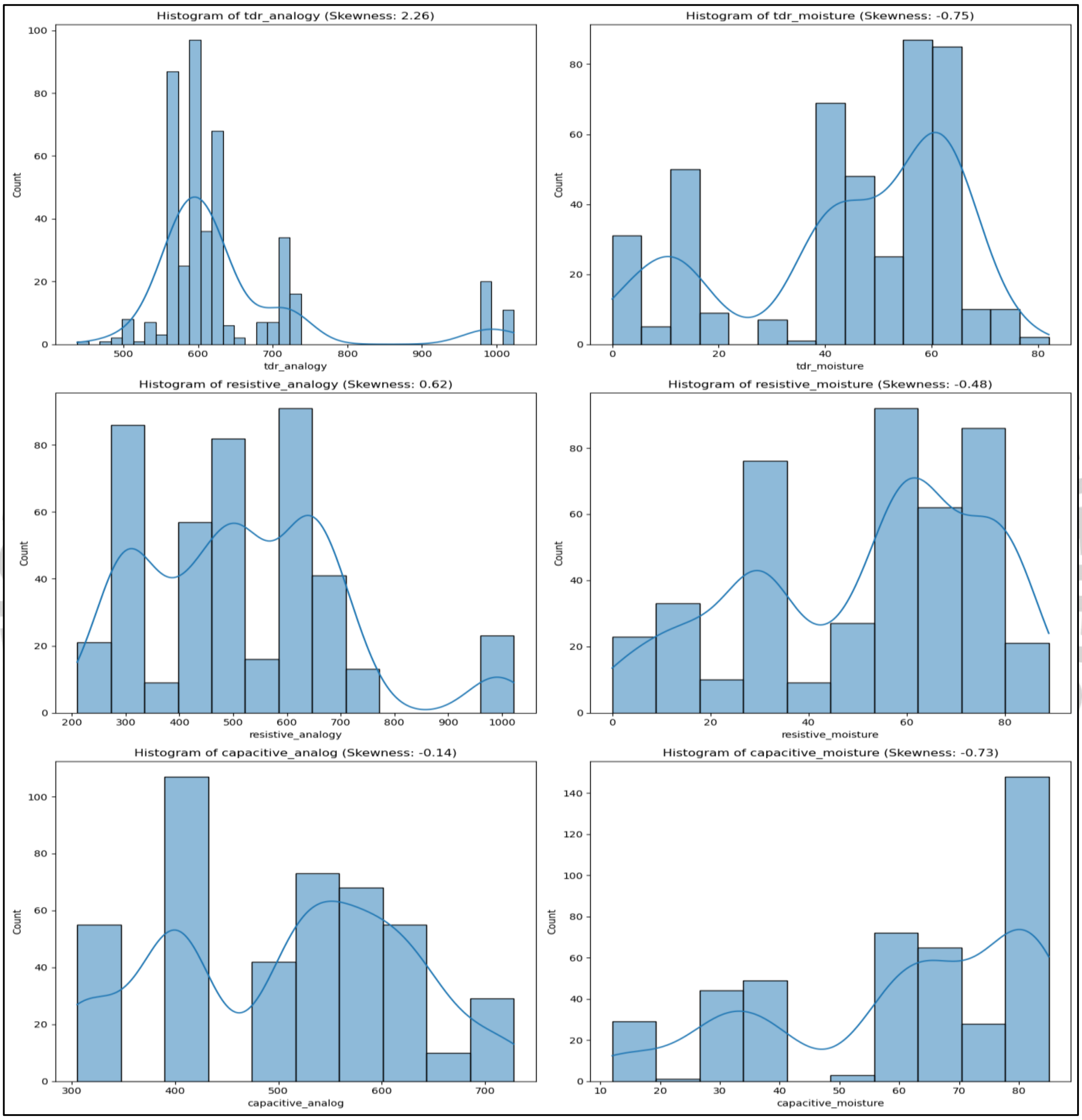



Figure 5: Skewness of different sensor data

$cm^3/cm^3$ in the loamy sand, and underestimated it by 0.05 $cm^3/cm^3$ in the sandy clay loam, according to the statistical values for the resistivity. Furthermore, it was intriguing to note that the resistivity values in Table 3 were negative at the lowest moisture level, suggesting a calibration problem. The RMSE values for sand and loamy sand have satisfied the requirements, except for sandy clay loam.

### 8.5 Significant Variations

The study found significant variations in the sensitivity of capacitive, resistive, and TDR soil moisture sensors. Table 4 shows the performance metrics for each sensor type.

According to the findings, out of the three sensor types,

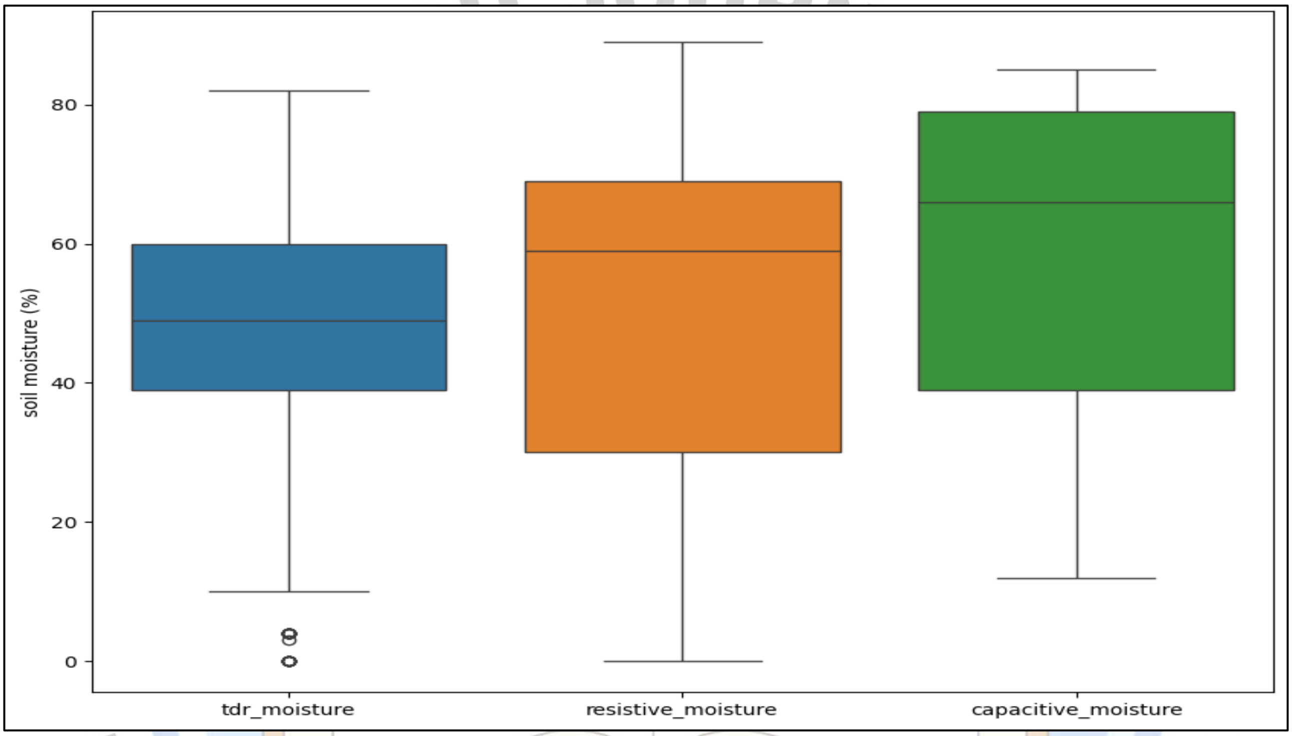



Figure 6: Box plot analysis of soil moisture readings

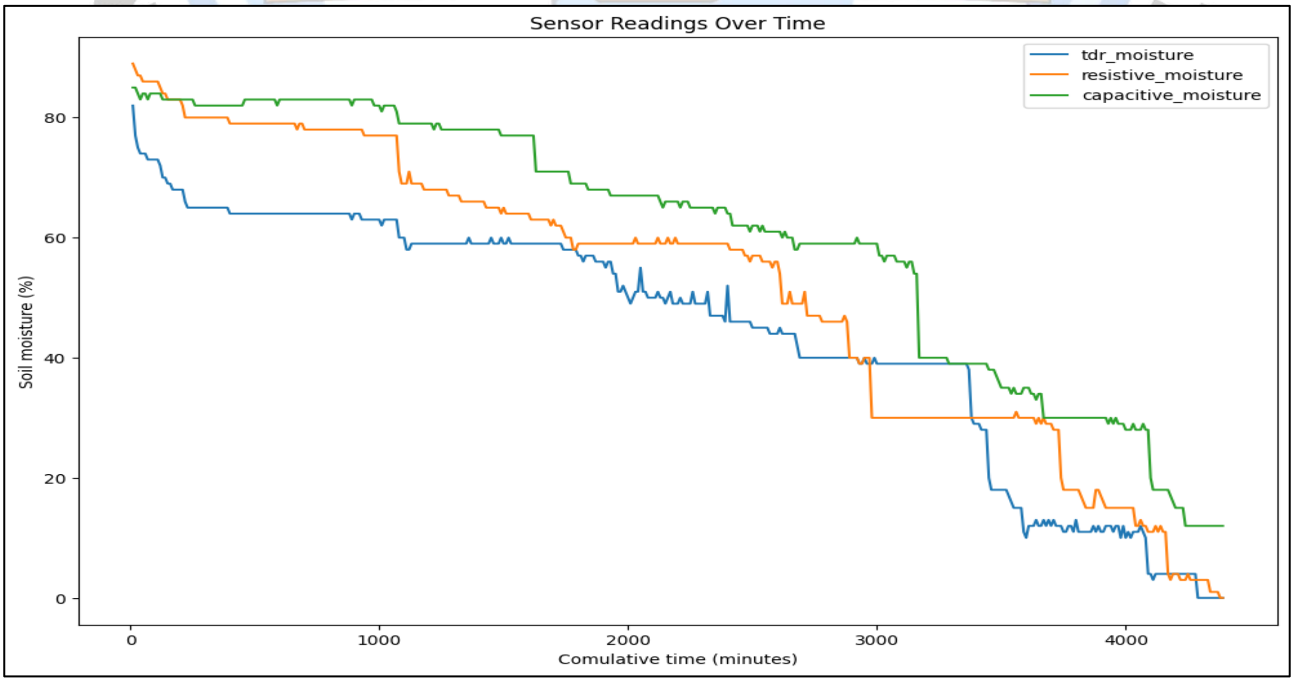



Figure 7: Sensor sensitivity comparison over time

Table 3: Statistical analysis to compare measured values to sensor values

| Moisture levels/ crop type | Sensor | RMSE | IA | MBE |
|---|---|---|---|---|
| Sand Loamy | Resistivity | 0.010 | 0.96 | -0.01 |
| | Capacitive | 0.035 | 0.82 | 0.03 |
| | TDR | 0.046 | 0.74 | -0.03 |
| Sandy Clay Loam | Resistivity | 0.032 | 0.91 | -0.03 |
| | Capacitive | 0.040 | 0.88 | -0.02 |
| | TDR | 0.063 | 0.62 | -0.05 |

Table 4. Table showing significant variations in the sensitivity for each sensor type

| **Statistic** | **TDR** | **Resistive** | **Capacitive** |
|---|---|---|---|
| Count | 439 | 439 | 439 |
| Mean | 44.33 | 51.59 | 60.32 |
| Standard Deviation | 20.87 | 24.16 | 21.73 |
| Minimum | 0 | 0 | 12 |
| 25th Percentile | 39 | 30 | 39 |
| 50th Percentile | 49 | 59 | 66 |

the TDR sensor had the lowest standard deviation the best accuracy and consistency when measuring soil moisture content. According to this, TDR sensors are less impacted by environmental variables including changes in humidity and temperature, making them appropriate for automated irrigation systems in various agricultural contexts.

### *8.6 Correction equations*

Correction equations for the three sensors were created using the laboratory data (Table 5). The value from the factory-calibrated sensor is denoted by θvi. The corrected value is θv. Since the resistivity values at the lowest moisture content measurement were negative, the logarithmic resistivity equations for sand loamy and sand clay loam are unavailable.

Table 5. Correction equations for TDR, Resistive and Capacitive soil moisture sensors

| Soil Type | Sensor | Equation Type | Equation | RMSE | IA | MBE | R2 |
|---|---|---|---|---|---|---|---|
| Sand Loamy | TDR | Linear | $\theta v = 1.4011 * \theta_{vi} - 0.0213$ | 0.005 | 0.99 | 0.001 | 0.97 |
| | | Exponential | $\theta v = 0.0036e^{43.906 * \theta vi}$ | 0.031 | 0.84 | 0.004 | 0.88 |
| | | Logarithmic | $\theta v = 0.0577 * \ln(\theta vi) + 0.2294$ | 0.008 | 0.97 | 0.001 | 0.92 |
| | | Quadratic | $\theta v = -0.5029 * (\theta_{vi})^2 + 1.4532 * \theta_{vi} - 0.0225$ | 0.005 | 0.99 | 0.001 | 0.97 |
| | Resistive | Linear | $\theta v = 0.6055 * \theta vi + 0.0064$ | 0.003 | 0.99 | 0.001 | 0.99 |
| | | Exponential | $\theta v = 0.0083e^{19.316 * \theta vi}$ | 0.020 | 0.92 | 0.002 | 0.93 |
| | | Logarithmic | N/A | N/A | N/A | N/A | N/A |
| | | Quadratic | $\theta v = 1.0217 * (\theta_{vi})^2 + 0.4689 * \theta vi + 0.0083$ | 0.002 | 0.99 | 0.001 | 0.99 |
| | Capacitive | Linear | $\theta v = 2.1154 * \theta_{vi} - 0.0465$ | 0.016 | 0.97 | -0.001 | 0.89 |
| | | Exponential | $\theta v = 0.0032e^{43.918 * \theta vi}$ | 0.061 | 0.78 | 0.006 | 0.85 |
| | | Logarithmic | $\theta v = 0.1157 * \ln(\theta vi) + 0.4187$ | 0.017 | 0.56 | 0.001 | 0.88 |
| | | Quadratic | $\theta v = -12.181 * (\theta_{vi})^2 + 3.6501 * \theta_{vi} - 0.0873$ | 0.016 | 0.97 | -0.001 | 0.89 |
| Sandy Clay Loam | TDR | Linear | $\theta v = 0.9759 * \theta_{vi} - 0.0283$ | 0.059 | 0.76 | −0.057 | 0.89 |
| | | Exponential | $\theta v = 0.0149e^{20.471 * \theta vi}$ | 0.055 | 0.81 | 0.005 | 0.85 |
| | | Logarithmic | N/A | N/A | N/A | N/A | N/A |
| | | Quadratic | $\theta v = -1.7108 * (\theta_{vi})^2 + 1.1702 * \theta vi + 0.028$ | 0.017 | 0.97 | 0.001 | 0.90 |
| | Resistive | Linear | $\theta v = 1.7905 * \theta_{vi} - 0.093$ | 0.011 | 0.99 | 0.001 | 0.97 |
| | | Exponential | $\theta v = 0.0131e^{16.505 * \theta vi}$ | 0.017 | 0.99 | 0.001 | 0.99 |
| | | Logarithmic | $\theta v = 0.2036 * \ln(\theta vi) + 0.5697$ | 0.015 | 0.99 | 0.001 | 0.94 |
| | | Quadratic | $\theta v = 13.837 * (\theta vi)^2 - 1.5894 * \theta vi + 0.0858$ | 0.016 | 0.99 | 0.001 | 0.99 |
| | Capacitive | Linear | $\theta v = 1.2857 * \theta vi + 0.0142$ | 0.037 | 0.88 | -0.001 | 0.65 |
| | | Exponential | $\theta v = 0.0439e^{10.074 * \theta vi}$ | 0.043 | 0.87 | -0.011 | 0.49 |
| | | Logarithmic | $\theta v = 0.1532 * \ln(\theta vi) + 0.5019$ | 0.024 | 0.89 | -0.011 | 0.67 |
| | | Quadratic | $\theta v = -9.1965 * (\theta_{vi})^2 + 3.5828 * \theta_{vi} - 0.1146$ | 0.034 | 0.89 | 0.020 | 0.68 |

Drawing from prior research, this study assessed the sensor's performance using the following standards: $R2 > 0.65$, MBE $+0.02$ $cm^3/cm^3$, $IA > 0.8$, RMSE $< 0.035$ $cm^3/cm^3$, as observed by [21], [24].

According to the statistical analysis results, every kind of equation for TDR and capacitance in the sand loamy has satisfied the requirements. TDR and the factory-calibrated capacitor both satisfied the requirements. Exponential and logarithmic equations did not perform as well as the linear and quadratic type equations of capacitive. All forms of equations have satisfied the requirements in sandy clay loam. The TDR and capacitive linear, exponential, and quadratic equations have satisfied the requirements.

In loamy sand, the quadratic equation satisfied the requirements, while linear and exponential equations did not.

Logarithmic, exponential, and linear equations performed poorly in sandy clay loam. Only the quadratic equation was able to meet the requirements. According to prior research, the quadratic equations often had the highest IA and R2 and the lowest RMSE and MBE [24].

## 8.7 Validation of Correction Equations

The field experiment was performed to validate the correction equations. Figures 8, 9 and 10 show the comparisons of factory-based calibration of soil moisture sensors to corrected values for sand loamy and sandy clay loam, respectively.

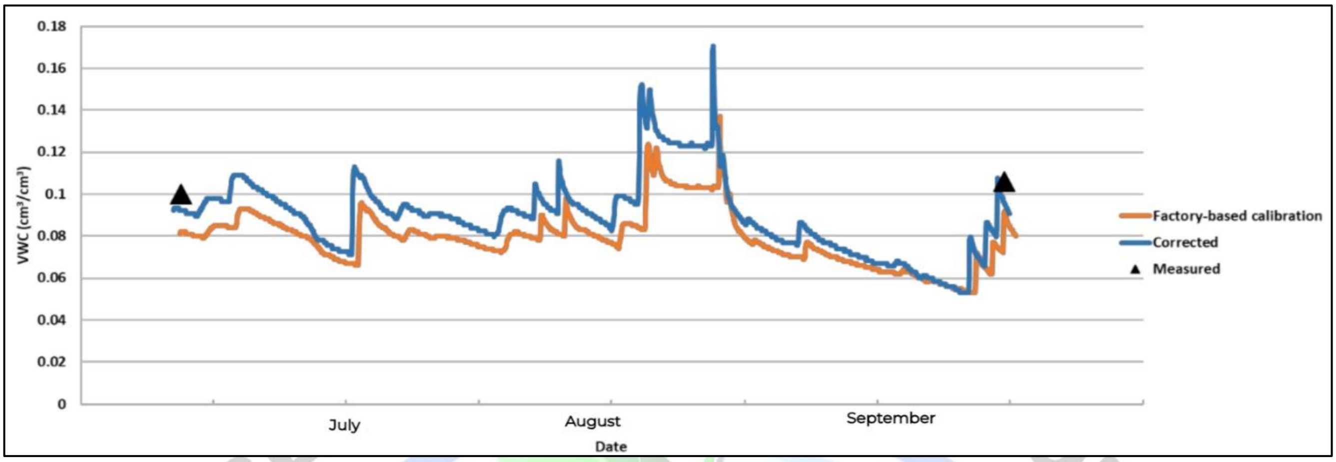



Figure 8: Comparison of factory-based calibration to corrected values for Capacitive in sand loamy

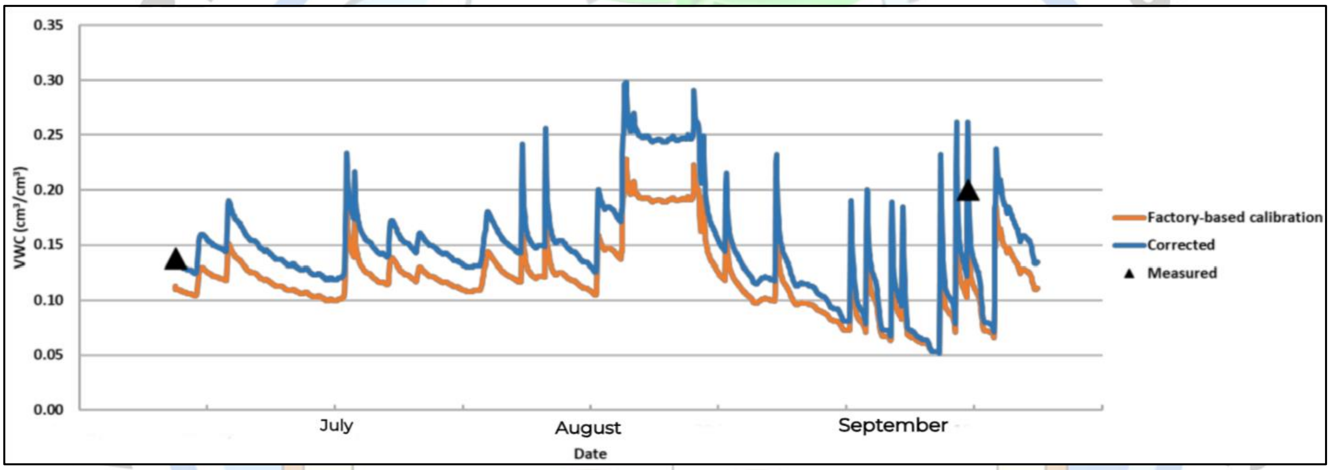



Figure 9: Comparison of factory-based calibration to corrected values for resistivity in sand loamy

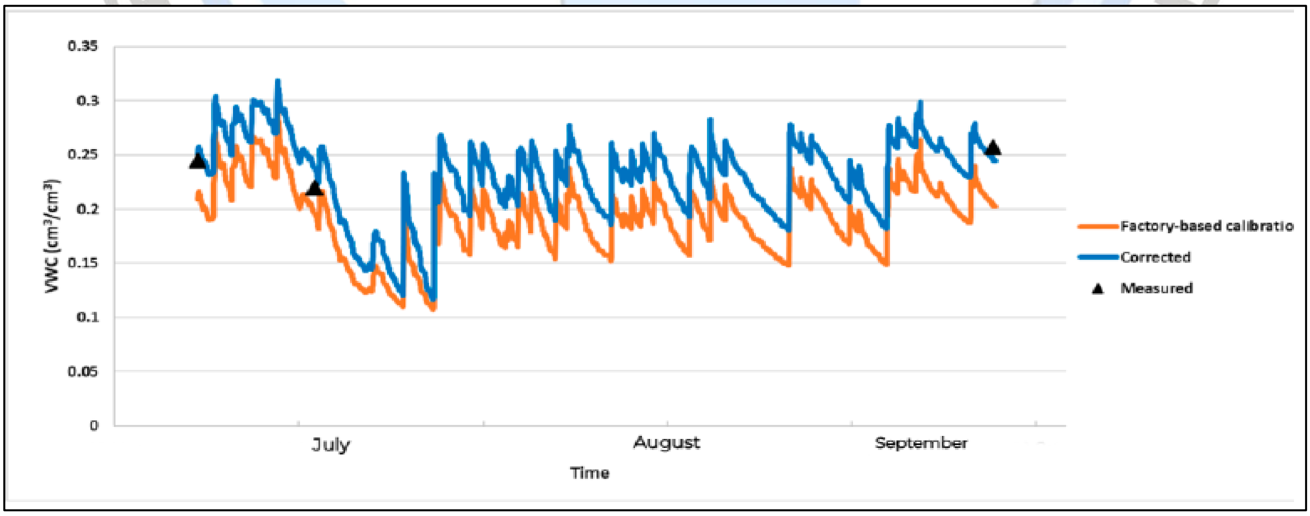



Figure 10: Comparison of factory-based calibration to corrected values for TDR in sand loamy

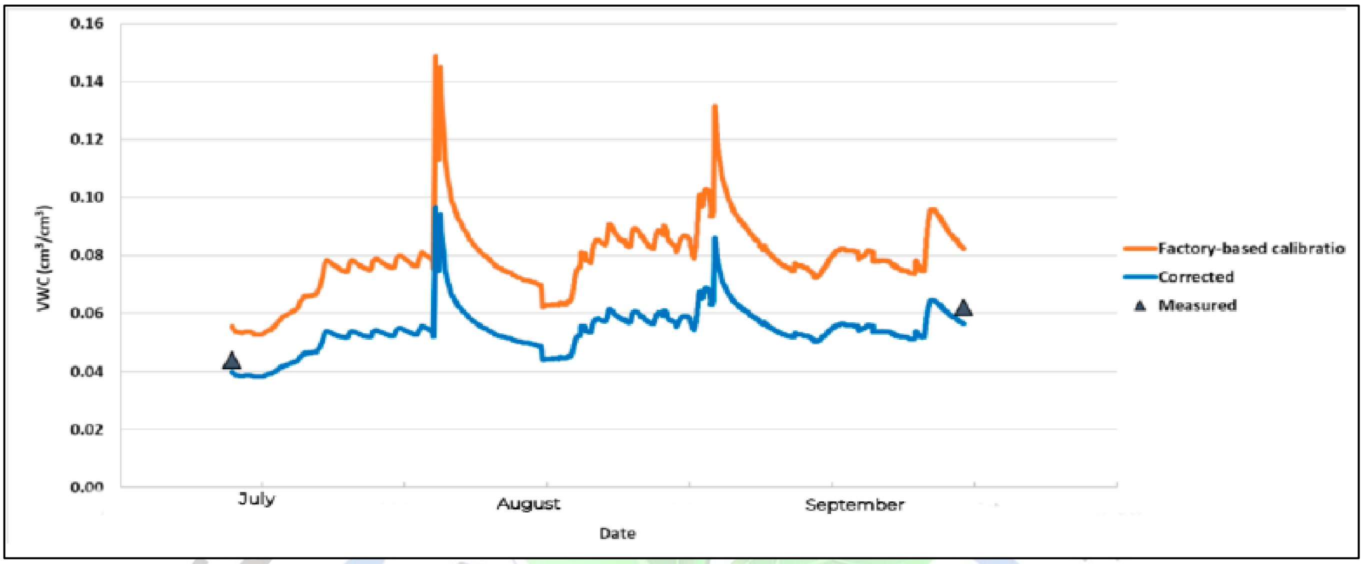



Figure 11: Comparison of factory-based calibration to corrected values for Capacitive in sandy clay loam

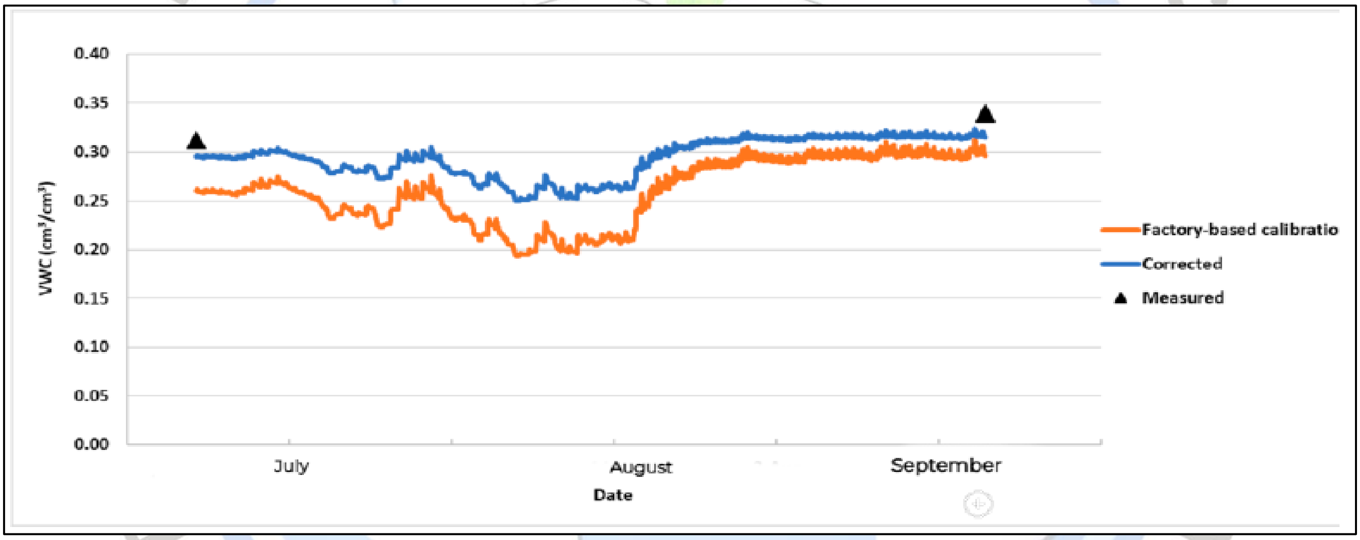



Figure 12: Comparison of factory-based calibration to corrected values for Resistive in sandy clay loam

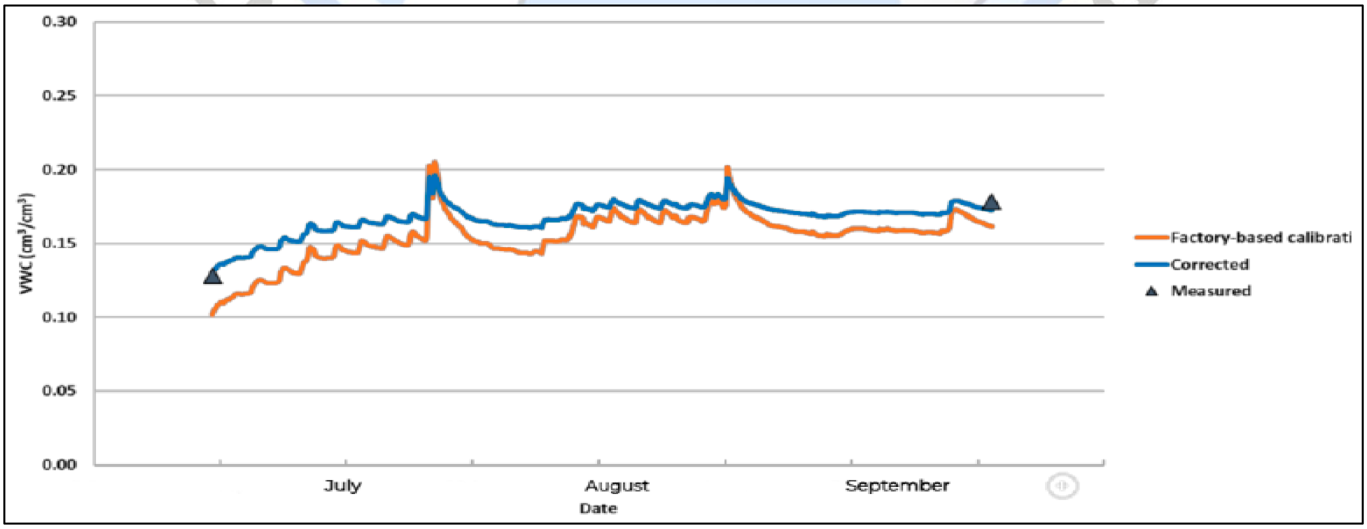



Figure 13: Comparison of factory-based calibration to corrected values for TDR in sandy clay loam

The RMSE values for factory-based calibration and after correction in loamy sand are 0.023 and 0.021 $cm^3/cm^3$, respectively. This result shows that loamy sand slightly improved the correction equation (0.002 $cm^3/cm^3$). Another study also had RMSE values of 0.024, 0.023, and 0.044 $cm^3/cm^3$ in loamy sand [17]. The RMSE values for factory-based calibration and after correction in sandy clay loam are 0.039 and 0.012 $cm^3/cm^3$, respectively. Overall, the moisture sensor performance was improved with the correction equations.

The factory-based calibration of capacitive, resistivity, and TDR soil moisture sensors is compared to corrected values for sand loamy and sandy clay loam, respectively, in Figures 11, 12 and 13. The RMSE values in sand loamy after correction and factory-based calibration are 0.006 and 0.026 $cm^3/cm^3$, respectively. This outcome demonstrates a 0.019 $cm^3/cm^3$ improvement using the sand loamy correction calculation. After correction and factory-based calibration, the RMSE values in sandy clay loam are 0.020 and 0.047 $cm^3/cm^3$, respectively. Overall, the correction equations significantly increased the capacitive sensor's performance.

Mounting the soil moisture sensor dramatically impacts its performance, in addition to fixing the calibration equation. Previous studies have also stressed the need for adequate contact between the sensor and soil to prevent the formation of an air gap [25], [26], [27]. As soil depth grows, variations in soil temperature are reduced.

## 9.0 Conclusions

Through laboratory and field tests, this study assessed the effectiveness of TDR, resistive, and capacitive soil moisture sensors. Except for the capacitor for sand loamy, none of the factory-based calibrated TDR, resistive or capacitive, performed well enough to satisfy the statistical requirements. Last, TDR sensors are highly precise and perfect for in-depth research and large-scale farming. Resistive sensors are cost-effective but require more maintenance and capacitive sensors balance cost and accuracy for widespread application. A precise assessment of soil moisture is necessary to maximise irrigation effectiveness. TDR, high-sensitivity sensors improve water use efficiency by affecting water application rates and irrigation schedules by providing accurate moisture data. Making the most of sensor data for improved irrigation techniques requires careful calibration, thoughtful positioning, and routine maintenance. More sustainable water consumption will result from integrating these sensors with data analytics and IoT platforms, enhancing real-time monitoring and predictive irrigation control.

Consequently, it is advised that TDR, resistive, and capacitive soil moisture sensors be calibrated for each kind of soil. The lab experiment produced the correction calibration equations for each of the three sensors. The field experiment's sensor demonstration verified that the correction equations increased the accuracy of the TDR, resistive, and capacitive sensors.

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