Czech University of Life Sciences Prague

Faculty of Agrobiology, Food, and Natural Resources

Department of Water Resources

Czech University of Life Sciences Prague

Calibration of the TMS-4 Datalogger to Determine the Influence of Organic Matter on Measurements of Soil Moisture Content

Master´s Thesis

Samantha Nadine Yamamoto

Natural Resource Management and Ecological Engineering

Ing. Markéta Miháliková, Ph.D.

Declaration

I hereby declare that I have authored this master's thesis carrying the name "Calibration of the TMS-4 Datalogger to Determine the Influence of Organic Matter on Measurements of Soil Moisture Content" independently under the guidance of my supervisor. Furthermore, I confirm that I have used only professional literature and other information sources that have been indicated in the thesis and listed in the bibliography at the end of the thesis. As the author of the master's thesis, I further state that I have not infringed the copyrights of third parties in connection with its creation.

In Prague on April 19, 2024

Samantha Nadine Yamamoto

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Calibration of the TMS-4 Datalogger to Determine the Influence of Organic Matter on Measurements of Soil Moisture Content

Summary:

The TMS-4 Datalogger (TMS-4) is an emerging device that can be used to record important climate data relevant to ecosystems and agriculture, such as temperature and Soil Water Content (SWC). However, the sensor's performance when measuring SWC can be influenced by the presence of Soil Organic Matter (SOM), present in Compost-Amended Soil (CAS), potentially needing calibration to accommodate this influence. Thus the study aimed to calibrate the TMS-4 sensor under controlled laboratory conditions in soils from four different localities (Blatnice u Jaroměřic – loam; Jevíčko – silty clay loam; Velké Hostěrádky – silty clay loam; Uhříněves – silt loam) with consideration of compost treatment of the soil. The method of homogenised soil column was conducted with the calibration tanks of volume 24 L, able to accommodate 4 TMS-4 dataloggers at once. Eight targeted VWC were used for the calibrations: 0, 5, 10, 15, 20, 25, 30, and 35 %. Sensor outputs of SWC were compared to direct measurements of SWC from undisturbed soil samples' gravimetric analysis either for control soil (CON), which was not amended by compost, and CAS, for each targeted VWC. Linear, Polynomial, and Logarithmic equations were derived for each calibration tank. Derived calibration equations differed from Factory Calibration (FC), with FC using Polynomial equations. While results differed between experimental localities and individual sensors, TMS-4 outputs were influenced by compost admixture. Although the SOM of the CON and CAS only differed by 1.5%, there was a considerable difference noted in TMS-4 measurements. Results between soil localities varied, and for this reason, no specific calibration equation can be recommended, however, soil-specific calibration should be considered a necessary step in research using the TMS-4. Although polynomial equations are typically used for indirect measurement calibration, the statistical fitness of polynomial equations contradicted results found with extrapolated values and directly contradicted the reality of SWC measurements for multiple localities. Logarithmic equations had lower statistical fitness but tended to be more reliable in reflecting the real behavior of measurements with changes in SWC. Linear functions had lower suitability to data owing to a change in curvature that occurred in experiments once the SWC reached Transition Water Content, a range of Water Content where the type of soil water influencing DP changes, changing DP measurements and affecting calibration. Substantial sensor-to-sensor variation was found in TMS-4 measurements, and for this reason, sensor-specific calibration is strongly recommended.

Keywords: Calibration, Time Domain Transmission, Soil Organic Matter, Soil Water Content, TMS-4 Datalogger, Dielectric Permittivity

Content

1 Introduction

Soil Water Content (SWC) is a property of soil that varies in time and space and is immensely important to many scientific disciplines. There are many ways of determining SWC, however they vary in feasibility, cost, and accuracy. The TMS-4 Datalogger (TMS-4) is a device developed in recent years that continuously measures temperature and SWC in the field, with three temperature sensors, and one soil moisture sensor. This device allows scientists to gather temperature and soil moisture data close to the soil surface and can reflect the climate conditions experienced by plants and animals in this part of the ecosystem (Wild et al. 2019). Environmental factors, such as temperature, salinity, and soil type, can influence the accuracy of most soil moisture sensors (Bircher et al. 2016). The soil moisture sensor in the TMS-4 determines volumetric water content (VWC) through Time Domain Transmissometry (TDT), a method that estimates soil moisture by measuring Dielectric Permittivity (DP), an electrical property of the soil matrix that is directly proportional to SWC. DP sensing methods operating at high frequencies can determine SWC without being heavily influenced by these factors, which can influence the accuracy of other moisture determination methods (Bircher et al. 2016; Wild et al. 2019; Yu et al. 2021). Another environmental factor that influences the accuracy of the soil moisture sensor is Soil Organic Matter (SOM), which is known to influence moisture content determination methods using soil DP (Fares et al. 2016; Szypłowska et al. 2021). When a property besides what is being directly measured by a sensor influences measurements, the difference between what is measured and the reality of the experiment can be addressed with calibration (Mane et al. 2024). There are several types of calibrations, and it is becoming more popular among scientists to perform multiple types of calibrations to improve the accuracy of their measurements (Rosenbaum et al. 2010). SWC measuring devices typically come with a suggested Factory Calibration (FC), which can work for certain soil applications. However, these calibration equations do not account for many influencing factors in SWC measurements, and often underperform and produce high error when applied as a universal calibration equation compared to derived calibration methods. Scientists can employ soil-specific calibration, which accounts for the properties of each individual soil type used in the experiment, including factors such as soil texture or bulk density. Accounting for soil-specific factors which can be overlooked in FC greatly reduces error in experiments (Lekshmi et al. 2014; Sharma et al. 2018; Singh et al. 2018; Mane et al. 2024). At the same time, the devices used in calibration may have varied levels of performance, in which case sensor-specific calibration can be applied, where all the sensors in a single experiment are tested for their measurements on substances with known DP, such as pure water, to check for deviation in a batch of sensors. Performing this sensor-specific calibration also greatly reduces error (Rosenbaum et al. 2010).

The influence of Soil Organic Matter (SOM) on TDT sensor accuracy has not been explored in literature as thoroughly as other DP-based methods to determine SWC, such as Time Domain Reflectometry (TDR) or Frequency Domain Reflectometry (FDR) (Bircher et al. 2016). The experiment attempts to isolate the influence of SOM in measurements of DP with calibration experiments carried out on multiple soil localities.

2 Scientific Hypothesis and Aims of the Thesis

Hypotheses:

1. The TMS-4 individual sensors will determine the soil water content with an acceptable sensor-to-sensor variation.

2. Sensor measuring accuracy (the resulting water content) will be affected by the soil organic matter content.

Aims:

1. To calibrate the TMS-4 sensor under controlled laboratory conditions in order to evaluate the individual sensor precision for use at specific localities with consideration of compost treatment of the soil.

2. To test the TMS-4 in the field experiments with different compost treatments and evaluate the obtained results.

3 Literature Review

The literature review was divided into four main sections, to review relevant background knowledge for available technology and methods to measure Soil Water Content (SWC), the concept and influencing factors for Dielectric Permittivity (DP), the properties and effects of Soil Organic Matter (SOM), and existing calibration experiments relevant to the work. Relevant background knowledge consisted of several reviews of the current methods for measuring and monitoring SWC. This background knowledge was necessary to understand the needs in SWC measuring that are addressed by the TMS-4 Datalogger (TMS-4), and to provide examples of how different soil properties affect these methods. The influencing factors were explored to better understand DP and SOM, including their relationship to SWC, and each other. Understanding these properties as individual characteristics and as properties that influenced each other throughout the experiment was essential to understanding the experimental results. Existing calibration experiments were reviewed during the calibration testing, and served as models for necessary components and considerations for the experiment.

3.1 Soil Water Content

SWC is a measurement of the amount of water in the soil, which is a fundamental property for agriculture and plant biophysical processes (Bittelli 2011). It is a component of the three-phase soil system, which includes dry soil as the solid phase, water as the liquid phase, and air as the gaseous phase. In a given mass of soil, the amount of water fluctuates and determines the amount of the liquid and gaseous phase in the soil matrix, which determines a number of other physical and chemical properties of soil (Lekshmi et al. 2014). Figure 1 depicts different distributions of soil, water, and air in the soil matrix.

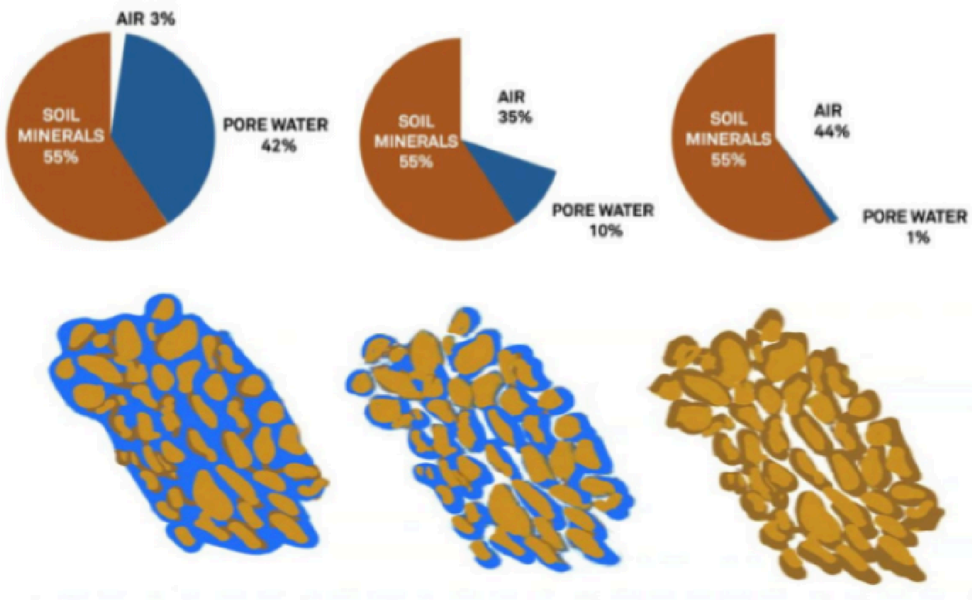


Figure 1 The Distribution of Soil, Water, and Air in the Soil Matrix at Different Levels of Saturation (Source: Adjusted from METER Group. Accessed 2024).

Accurate monitoring of SWC can assist farmers with applying irrigation to optimise plant growth and has a vital role in mineral transformation and nutrition of plants in soil (Bittelli 2011). The SWC of an area is an important consideration for disciplines such as hydrology (Guillod et al. 2015; McColl et al. 2017) agriculture, crop yield, climate (Seneviratne et al. 2010; Holzman et al. 2014; Massari et al. 2014; Zawilski et al. 2023), ecology, and engineering research (Lekshmi et al. 2014).

The moisture in the soil can be affected by different forces, and thus have different behaviour and implications for soil sciences. The three soil water types are gravitational, capillary, and hygroscopic water. Each of these types are named by the force that acts on them in the soil matrix, with hygroscopic water also being referred to as adsorption water. Figure 2 depicts these three soil water types and their interactions with soil particles. Gravitational water moves due to the force of gravity, is lost through soil drainage, and fills the largest spaces, or macropores, in soil. Capillary water is held with capillary forces in soil pores, made from adhesion and cohesion within the smaller channels, or micropores, in soil. Capillary water is an essential component of the ecosystem of soil organisms, as this water is the type most available for plants, and is removed from the soil with interactions within this part of the ecosystem. Adsorption water is held by the adsorption force of solid soil and exists in a thin layer on the surface of soil particles. The adsorption force of soil acts very strongly on water, so adsorbed water cannot be removed under natural conditions, it is unavailable to plants, and requires a heat of at least 105°C to remove in a laboratory setting (Lekshmi et al. 2014).

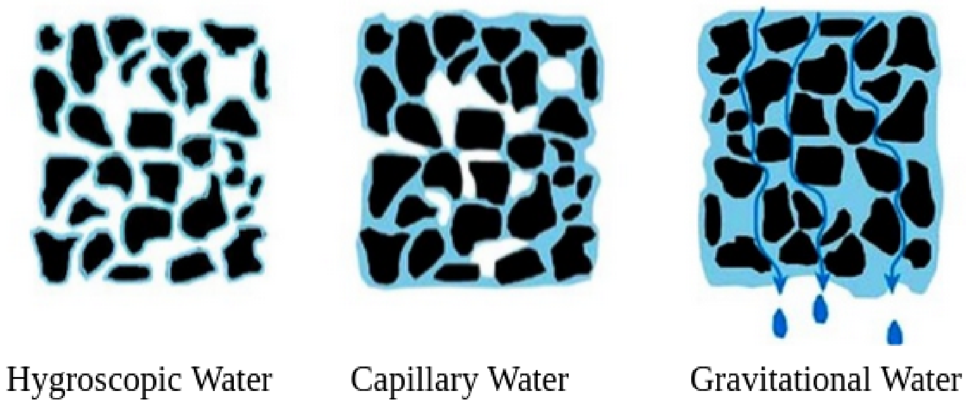


Figure 2 Diagram of the Different Types of Soil Water (Source: TerraGIS. Accessed 2024).

Water availability in soil is affected by environmental factors such as climate, vegetation, topography, and land use, but also intrinsic factors in the soil such as texture and Organic Matter (OM). Soil texture refers to the proportion of soil particles of different sizes, such as clay, silt, and sand. A diagram visualising the particle differences and their size range is depicted in Figure 3. Soil texture determines the soil pores, which hold air and water in the soil. Soils with a high amount of clay have a higher surface area and more micropores compared to other soils, which allows for a high amount of adsorbed and capillary water to remain in the soil, and these soils do not drain or hold air well. At the same time, soils with a high amount of sand have abundant macropores that hold gravitational water and air, these soils do not hold capillary water well and can drain too readily in the context of supporting plant life. Loam soils have a more balanced amount of sand and clay allowing for a supply of water and air in the soil which is more advantageous to plant growth (Amooh & Bonsu 2015).

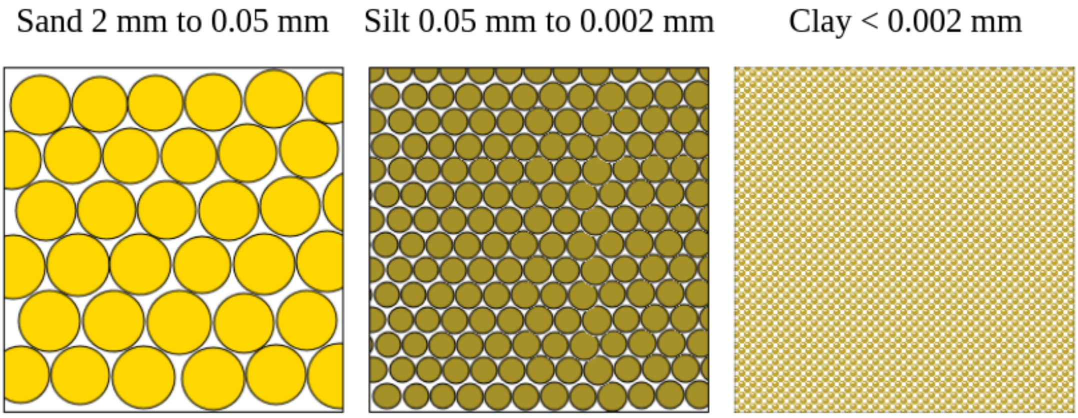


Figure 3 Diagram and Size Range of Sand, Silt, and Clay (Source: Adjusted from Eliades A 2022. Accessed 2024).

3.1.1 **Soil Water Content Monitoring Technology**

SWC is a dynamic property that fluctuates by time and space, as climate and evaporation can change SWC within minutes, and spatial variability of SWC is influenced by soil texture, terrain, and vegetation (Mane et al. 2024). This fluctuation needs to be accounted for in accurate, long-term soil monitoring and is highly sought after in soil-related research.

Research of SWC technology included information related to the current and potential progress made in measuring technology, the advantages and disadvantages of different devices, and factors that influence each method. Methods to measure SWC include direct methods and indirect methods, where direct is the actual measurement of the amount of water in the soil, while indirect methods measure a property of the soil that is dependent on SWC. In the case of indirect measuring, the value of the related soil property is usually calibrated to give a measurement of SWC (Bittelli 2011). SWC can be estimated indirectly with point (in situ) measurements or remote sensing, and only a few of these methods offer continuous monitoring. The currently available methods include the Gravimetric method, as a direct measurement, and many indirect methods (Sharma et al. 2018) which can measure a property of the soil that is dependent on water, such as electrical properties like capacitance, or DP, which are converted to estimate SWC (Czarnomski et al. 2005).

The TMS-4 was developed for sensing SWC using the Time Domain Transmissometry (TDT) method, which is one of several types of sensing methods that measure Dielectric Permittivity (DP) to estimate SWC (Wild et al. 2019). Unfortunately, there was not extensive literature available for the TDT method, because the use of TDT for SWC monitoring is a newer method that has not been heavily studied (Will & Rolfes 2013). Papers involving the TMS-4 were reviewed, but the TMS-4 was not included in most of the discussions of current monitoring technology, such as the advantages, disadvantages, or influencing environmental factors related to SWC measurement. However several of the reviews did elaborate on other, more widely used DP-based methods, such as Time Domain Reflectometry (TDR), Frequency Domain Reflectometry (FDR), and Capacitance methods. Although this information did not directly address the TMS-4 or TDT, it gave insight into the overall advantages of the TMS-4 as a new technology, DP as a property for measuring SWC, and related considerations to SWC testing.

The papers reviewed established studies and experiments of SWC technology and were considered reliable. The only disadvantage was that almost none of them included as much information about TDT as the other methods.

3.1.2 The Direct Method of Measuring Soil Water Content

There is only one method that directly measures SWC, the Gravimetric method, also known as the thermogravimetric method, or the drying method (Seneviratne et al. 2010). This method measures the mass of water in soil by weighing wet soil before and after drying. The drying must be at a heat of 105°C, to ensure the evaporation of adsorption water in the sample. The resulting mass of water is divided by the mass of dry soil to give a SWC by mass. Or, considering the mass of water to be equal to the volume of water, the amount of water can be divided by total volume of the soil sample to obtain the VWC directly. If not available, the SWC by mass can be converted to VWC by multiplying the result by the soil dry bulk density. For this reason, VWC calculations can be variable, and measurements are more accurate when dry bulk density is measured from the volume and mass of each unique sample, as bulk density can vary spatially throughout soil. Gravimetric analysis is used as a reference method for calibrating indirect SWC measurements, and most indirect methods convert to VWC, rather than WC by mass (Bittelli 2011). The Gravimetric method is considered the most accurate but has the disadvantages of being destructive, slow, and not repeatable for a single soil sample (Sharma et al. 2018). The equations for the determination of VWC from gravimetric analysis and a known volume of a soil sample are demonstrated in Equations 1–4.

Determination of SWC by mass is calculated with Equation 1

$$w = \frac{M_W}{M_S} \tag{1}$$

Where:

w ..……………………Water Content by Mass (g/g)

M_W ………………….Mass of Water (g)

M_S …………………..Mass of the Dry Soil (g)

Bulk Density of soil, which can be used in converting Water Content (WC) by Mass to VWC, is calculated with Equation 2

$$\rho_b = \frac{M_S}{V_T} \qquad (2)$$

Where:

ρ_b …………………..Dry Bulk Density of Soil (g/cm^3)
M_S…………………..Mass of the Dry Soil (g)
V_T…………………..Total Volume of the Undisturbed Soil Sample (cm^3)

VWC can be determined from gravimetric measurements in g/g when dry bulk density is available. This conversion is calculated with Equation 3

$$\theta = \frac{w\rho_b}{\rho_w} \qquad (3)$$

Where:

θ …………………..Volumetric Water Content (cm^3/cm^3)
w..…………………..Water Content by Mass (g/g)
ρ_b …………………..Dry Bulk Density of Soil (g/cm^3)
ρ_w …………………..Density of Water (g/cm^3)

The proof of Equation 3 is visible in Equation 4, where the components of Equation 3 are broken down into step-by-step expressions of mass and volume measurements.

$$\theta = \frac{V_W}{V_T} = \left(\frac{M_W}{M_S}\right)\left(\frac{M_S}{V_T}\right)\left(\frac{V_W}{M_W}\right) = \frac{\left(\frac{M_W}{M_S}\right)\left(\frac{M_S}{V_T}\right)}{\left(\frac{M_W}{V_W}\right)} = \frac{w\rho_b}{\rho_w} \qquad (4)$$

Where:

θ …………………..Volumetric Water Content (cm^3/cm^3)
w..…………………..Water Content by Mass (g/g)
M_W…………………Mass of water (g)
M_S…………………..Mass of the dry soil (g)
V_T…………………..Total volume of the soil sample (cm^3)
V_W…………………Volume of water in the soil sample (cm^3)
ρ_b …………………..Dry Bulk Density of Soil (g/cm^3)
ρ_w …………………..Density of Water (g/cm^3)

3.1.3 Indirect Methods of Measuring Soil Water Content

Indirect techniques to measure SWC can involve measuring the electrical properties of soil such as capacitance or DP, or using methods such as radioactive methods, and remote sensing methods (Lekshmi et al. 2014).

Radioactive methods for detecting SWC include the Neutron Scattering and the Gamma Ray Attenuation methods. The Neutron Scattering method disperses fast-moving neutrons into wet soil, which slow when they collide with hydrogen atoms, this speed is measured and determines the presence of hydrogen atoms (Lekshmi et al. 2014; Sharma et al. 2018). The amount of hydrogen atoms in the soil increases directly with the amount of water in the soil, allowing for the determination of SWC. In a review of measuring techniques by Lekshmi et al. (2014), Neutron Scattering is stated to be one of the most accurate measuring methods, and advantageous because it is non-destructive, and can measure a wide area of soil, including different depths, giving SWC for a soil profile (Lekshmi et al. 2014; Sharma et al. 2018). Unfortunately, the disadvantages of the method such as the expensive equipment, variable resolution, and health risks associated with radiation exposure, limit the use of this method. The Gamma Ray Attenuation method transmits gamma rays into the soil, which detects the saturated density of the soil, which is directly related to moisture content, and is used to determine SWC (Lekshmi et al. 2014). This method is non-destructive, fast, and more accurate than Neutron Scattering for the surface areas of soil. However, it can be affected by bulk density in soil, has limitations with calibration (Sharma et al. 2018), and suffers similar disadvantages to the Neutron Scattering method, such as high cost and health risks (Lekshmi et al. 2014).

Remote Sensing methods are designed to measure SWC over large areas that are beyond the range of in-situ sensors. These methods measure properties such as reflectance, thermal inertia, DP, and brightness to determine SWC over vast land areas. While the spatial range of remote methods is undeniably larger than in-situ methods, most of these methods have limitations when measuring areas with vegetation cover, and varied resolution over their areas. Beyond these considerations, they also need in-situ calibration from soil sampling, or indirect sensor measurements (Sharma et al. 2018).

3.2 Dielectric Permittivity

Dielectric methods measure the DP of soils, with DP defined as the capacity of a substance to hold or store an electrical charge (Lekshmi et al. 2014). Dielectric methods are considered advantageous for their accuracy, and convenience for in situ measurements, giving them the advantages of the Gravimetric method, and with the added aspects of safety and repeatability in field measurements (Mane et al. 2024).

3.2.1 Background on Dielectric Permittivity-Based Sensors

Widely used DP methods include Time Domain Reflectometry (TDR), Frequency Domain Reflectometry (FDR), and Time Domain Transmission (TDT). Each involves propagating Electromagnetic (EM) waves through the soil and measuring the time delay or impedance generated from the soil-water mixture (Mane et al. 2024). Each method has a different configuration to propagate an electrical pulse into the soil to determine DP, which can then be converted to SWC with a calibration equation or a Dielectric Mixing Model (DMM) (Bircher et al. 2016). Sensors using TDR or TDT record the velocity of EM waves propagated along open and closed transmission lines (Bogena et al. 2017). All of the devices come with a suggested Factory Calibration (FC) by the manufacturer, but this calibration may not be reliable when applied to soil conditions differing from the manufacturer's experimental conditions (Bircher et al. 2016).

Sensors measuring DP rely on the large difference between the DP of water and solids such as soil, organic matter, and air. DP is generally low in dry soil, generally ranging between 2-6, while the DP of water is around 80, making the DP of soil directly proportional to the amount of water present (Lekshmi et al. 2014). The principle of DP as a measured quality of a substance is shown in Figure 4, where the DP of different pure materials is given. The application of this principle is depicted in Figure 5, which demonstrates how the proportion of water in soil can be interpreted from the DP of a mixed substance containing water, such as partially saturated soil.

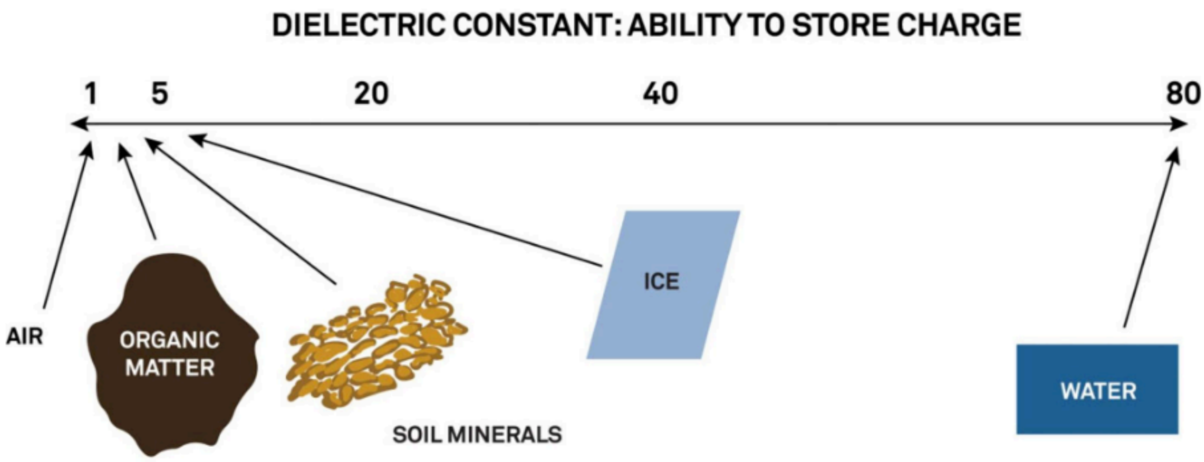


Figure 4 The Dielectric Constant of Water and Other Materials (Source: METER Group. Accessed 2024).

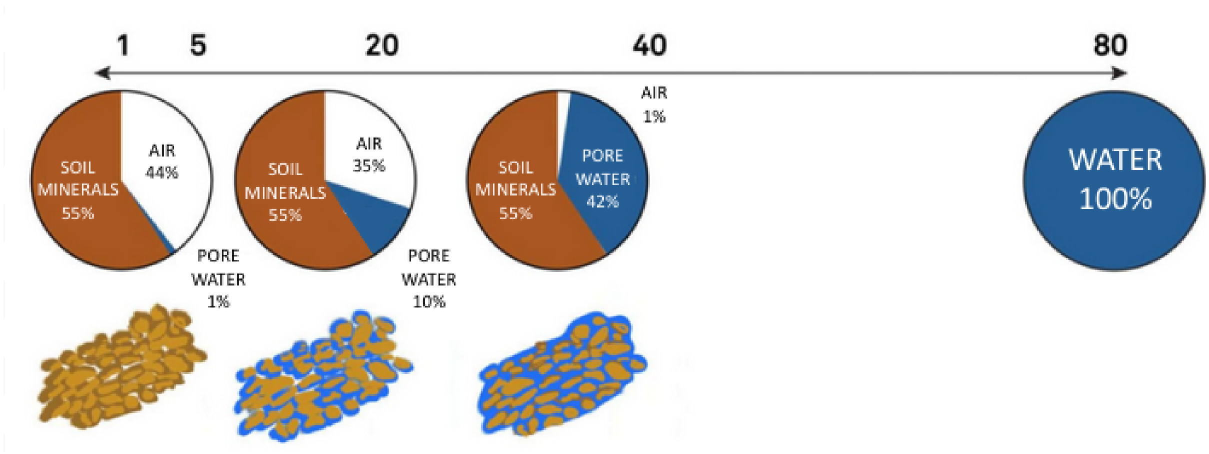


Figure 5 The Dielectric Constant of Soil with Different Amounts of Water (Source: METER Group. Accessed 2024).

Research conducted in the work of Topp et al. (1980), further developed the relationship between the dielectric constant of a substance and WC. This equation accounted for the influence of soil properties measured at a specific frequency range when measuring with TDR. The discussed influence on this property in soil includes soil texture, salinity, WC, temperature, density, and measuring frequency. The frequency range in Topp et al. (1980) was within the frequency range where the influencing factors were of very little influence except for WC and noted that measuring frequency was one of the most important factors influencing DP measurements.

3.2.1.1 Influences on Dielectric Permittivity

There is some conflicting information available about DP sensing methods, and most of the available information is for TDR and FDR sensors. These methods can be influenced by environmental conditions such as temperature and salinity, and characteristics within the sensor, such as operational frequency (Mane et al. 2024). Salinity, conductivity, and mineral content have been observed to influence TDR measurements and Capacitance methods (Baumhardt et al. 2000; Blonquist et al. 2005; Kameyama et al. 2014). In the experiment conducted by Robinson et al. (1998) indirect methods like TDR and Capacitance were found to overestimate relative permittivity in materials with an increasing ionic conductivity. FDR is especially known for its temperature sensitivity, while TDR is considered less sensitive, there is still some temperature drift, and low temperatures can also hide the influence of salinity in sensor performance (Yu et al. 2021).

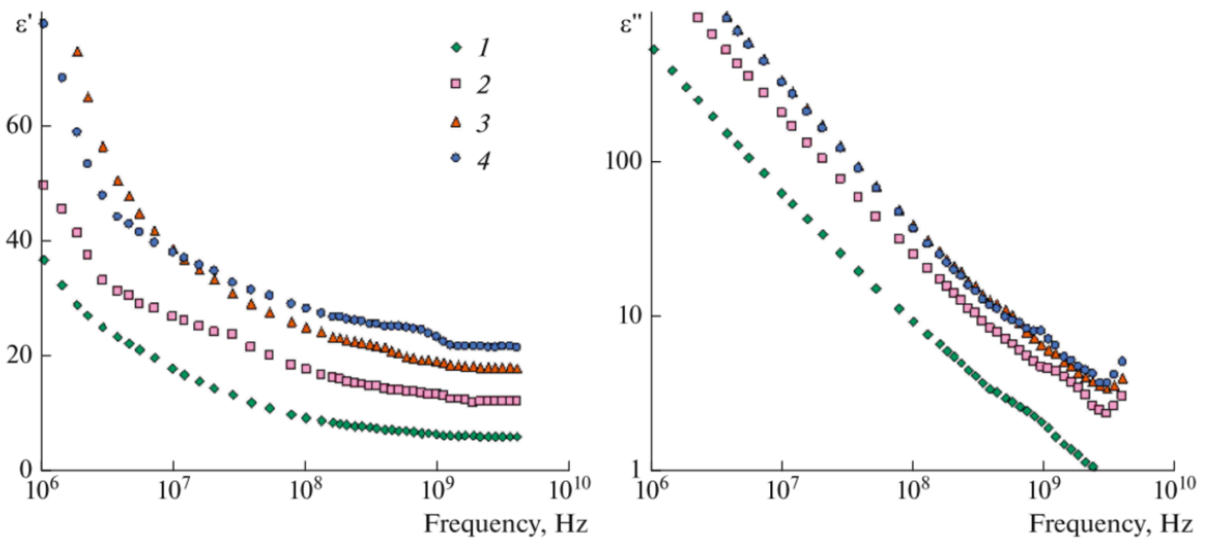
Some explored factors that can influence DP are the ratio of bound water to total SWC, surface area, bulk density, and form of moisture content (Yu et al. 2021). Bound water is related to soil adsorption forces, and dielectric loss from the imaginary part of DP has even been described as related to conductivity and the adsorption forces acting on water (Bircher et al. 2016). TDR requires soil-specific calibration when used in soils with high amounts of organic matter, because the water adsorbed to the surface of SOM measures as a lower value than free water, and SOM has a higher specific area, leading to more adsorbed water and lower values from sensors (Sharma et al. 2018). This phenomenon was noted in the work by Topp et al. (1980), where the active surface area was discussed as a controlling factor in DP, as the layers interacting with the soil surface had a lower DP measurement that was described as similar to water bound as ice, which measures as low as 3 compared to the dielectric constant of free water measuring as 80. Bulk density can influence the amount of contact a sensor maintains with soil during measurement, and higher bulk density can directly affect the accuracy of measurements due to increased contact with sensors (Matula et al. 2016).

3.2.1.2 Sensor Frequency and Dielectric Permittivity

Different DP-based sensors operate at different frequencies, and there is a widely observed difference between low and high-frequency sensors (Wobschall 1978; Bircher et al. 2016; Nasta et al. 2024). The frequency of a DP sensor can amplify the influence of environmental factors on sensor readings, as low-frequency sensors can be influenced by salinity, temperature, and soil texture (Blonquist et al. 2005; Kizito et al. 2008; Nasta et al. 2024). The frequencies of DP-based sensors can range from MHz to GHz. The range of frequencies for FDR sensors is between 10–500 MHz, however, most sensors are below 300 MHz (Szypłowska et al. 2021). Capacitance sensors operate from below 100 MHz. TDR sensors typically operate between 0.1–1.5 GHz and are in the highest frequency range of the DP-based sensors (Mane et al. 2024).

In a study conducted by Seyfried & Murdock (2004), TDR sensors operating at 50 MHz were compared with TDR sensors operating at 1 GHz were used to measure DP in sand and other types of soils. The measured DP of the soil water in sand was similar to pure water, and did not measure differently between the different frequency sensors, but found that in other soils, the soil water had dielectric properties differing from soil water in sand or pure water and that measurements had an observable dependency on frequency (Seyfried & Murdock 2004).

For DP-based sensors which measure Complex Dielectric Permittivity (CDP), in soil includes two parts: the real part and the imaginary part, typically written as ε' and ε''. The imaginary part, noted as ε'' is considered an energy loss which can come from dielectric relaxation, ionic conductivity (Bobrov et al. 2019), and water releasing heat as energy loss when it is exposed to an electromagnetic field (Wang & Schmugge 1980; Mohamed & Paleologos 2018), and several studies suggest that there is an influence of imaginary permittivity on sensor readings of permittivity (Vaz et al. 2013; Szypłowska et al. 2021). FDR sensors typically operate at lower frequencies, which makes measurements more receptive to the influence of imaginary permittivity (Szypłowska et al. 2021), whereas TDR and TDT devices usually operate at higher frequencies, in the GHz range (Vaz et al. 2013). The impact of sensor frequency is demonstrated by the visible change in the value of real and imaginary permittivity shown in Figure 6 when plotted against frequency.



(a) *(b)*

Figure 6 Real (a) and Imaginary (b) Permittivity Measurements at Different Frequencies (Source: Bobrov et al. 2019).

In saline soils, the increased presence of ions, and increased conductivity, contribute to an increase in the conductive loss as the imaginary part of DP, which affects the accuracy of sensors at various frequencies in the MHz range. When sensors operating below 500 MHz are applied to saline soils, the dielectric loss due to conductivity can be greater than the real part of DP. In clay saline soils, sensors operating between 100–500 MHz can have significant increases in the imaginary and real parts of DP, affecting the propagation of the EM pulses involved in sensor reading, and the recording of the pulse time delay, which directly affects the accuracy of determining SWC for TDR methods (Bobrov et al. 2019). One depiction of the range of sensor frequency and sensitivity to salinity is depicted in Figure 7.

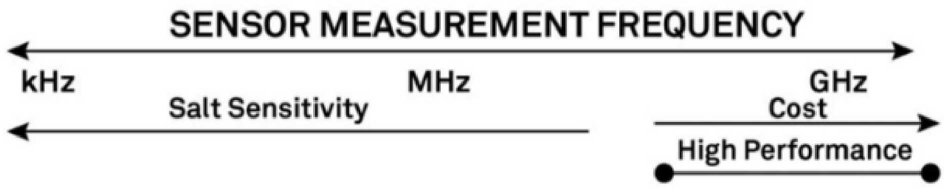


Figure 7 Diagram of Sensor Performance, Sensitivities, and Cost at Different Frequencies (Source: METER Group. Accessed 2024).

Soil texture and composition are known to be an influencing factor in sensor readings, and Bobrov et al. (2019) takes this observation further when stating that there is no suitable calibration equation for all soil types. The influence of clay content in soil can be linked to the effect of saline soils on sensor readings and needs to be considered when evaluating sensor performance. For capacitance sensors, clay and loam soils can influence sensor readings from dielectric relaxation occurring in lower frequencies such as 200–500 MHz (Bobrov et al. 2019). Soil texture was also observed to be influential for sensors measuring at a frequency below 150 MHz in the study conducted by Mane et al. (2024). There is evidence that the influence of soil clay content is lower for sensors operating in the GHz range (Bobrov et al. 2019).

Temperature changes can cause changes in soil conductivity, directly influencing DP and the performance of DP-based sensors (Mane et al. 2024). In a study by Nasta et al. (2024), it was observed that fluctuations in soil temperature affect the performance of low-cost and low-frequency sensors, and that temperature influence on bound water in soil can affect permittivity measurements. This influence on sensor performance is especially potent in fine soils, with higher amounts of clay, thus having more mineral surface area. Unfortunately, the influence of temperature was not accounted for in the Factory Calibration. Calibration equations derived in the experiments that accounted for soil temperature did improve the RMSE (Root Mean Squared Error), however, the authors note that although sensor-specific calibration was not applied, sensor-to-sensor variability can be significant in low-cost sensors and contribute to a higher RMSE, and would be explored in further experiments (Nasta et al. 2024).

One solution to issues with such influence in DP sensors is the development of sensors that operate at higher frequencies, since they are not as influenced by the imaginary part of DP (Bogena et al. 2017). Sensors operating above 100 MHz are considered potentially more accurate for measuring DP with less sensitivity to conductivity and temperature. However, there are cases of low-frequency sensors, such as the FDR Hydra Probe, which operates below 100 MHz, being less affected by temperature changes, because it takes multiple voltage recordings which account for temperature changes when calculating DP (Mane et al. 2024).

Sensors operating at higher frequencies are considered more accurate because sensor measurements are known to not be as influenced by the conductivity and the imaginary part of DP (Bogena et al. 2017).

3.2.2 **Time Domain Reflectometry**

TDR measures DP by sending an electromagnetic wave along a probe inserted in the soil. The wave is propagated along the probe, and once reaching the end of the probe, reflects back and reflected along the probe, and the speed of the wave is influenced by the DP of the soil. The time delay between the initial and reflected pulse is measured to determine DP, which is directly related to SWC (Noborio 2001). A slower pulse movement, and a longer time delay between the initial and reflected pulses, indicate a higher SWC (Báťková et al. 2013).

One developing aspect of the newer sensor methods was the use of sensor-specific calibration, which was sometimes considered a possible step for some soil applications, while more recent papers, involving a wider range of soil properties, deemed the step necessary for accurate measurements. The review of SWC measurement methods by Sharma et al. (2018) described soil-specific calibration as unnecessary for the TDR method (except for soils with high amounts of bound water), and a noted disadvantage for other methods where it is considered necessary, as it adds to the time and procedures required for analysis. Still, many studies have found that soil-specific calibration is becoming an essential component of TDR measurements, as these methods are used on a wider variety of soils with very different properties (Lekshmi et al. 2014).

A calibration equation for the conversion of TDR measurements to SWC was derived in the experiment conducted by Topp et al. (1980). This equation is described in Equation 5, and was derived from measurements in soil conditions where dielectric loss did not heavily influence DP measurements, typically when measuring with a higher frequency (Cosenza et al. 2003).

The VWC of soil can be calculated from measured Relative Permittivity under certain conditions described in Topp's Equation, shown in Equation 5

$$\theta = 4.3\ 10^{-6}\kappa^3 - 5.5\ 10^{-4}\kappa^2 + 2.92\ 10^{-2}\kappa - 5.3\ 10^{-2} \quad (5)$$

Where:

θ …………………..VWC (cm^3/cm^3)

κ..…………………High-Frequency Relative Permittivity

This equation is used widely in calibration experiments in applicable frequency ranges, is applicable for mineral soils using TDR, and is advantageous for being independent of many environmental factors such as temperature, bulk density, salinity, and soil texture.

3.2.3 Time Domain Transmissometry

TDT is not a widely used measurement method, but among the DP-based sensing methods, TDT is considered more accurate because it does not suffer the same limitations or complications as FDR and TDR sensors. TDR and TDT are similar methods that measure a time delay response from an electrical pulse along a transmission line (Wilczek et al. 2020), but differ in that TDR measures from a pulse reflected from their transmission line, while TDT uses a single transmitted signal. Soil heterogeneities, such as air pockets, particles, and water, can cause multiple reflections and interference in the measuring signal, which can influence the TDR-measured signal, but does not interfere with the TDT-measured signal (Will & Rolfes 2013). TDT sensors are considered more accurate than TDR as the measuring pulse is not influenced by multiple reflections (Pérez et al. 2023). The TDT automated measurements are noted to be more easily analysed, giving their measurements stability that is not available in TDR sensing (Kojima et al. 2023). This lack of stability is demonstrated in Figure 8, where there is a visible change in measured permittivity when measuring with TDR, deviating due to the influence of multiple reflections, as opposed to the more consistent TDT measurement (Will & Rolfes 2014).

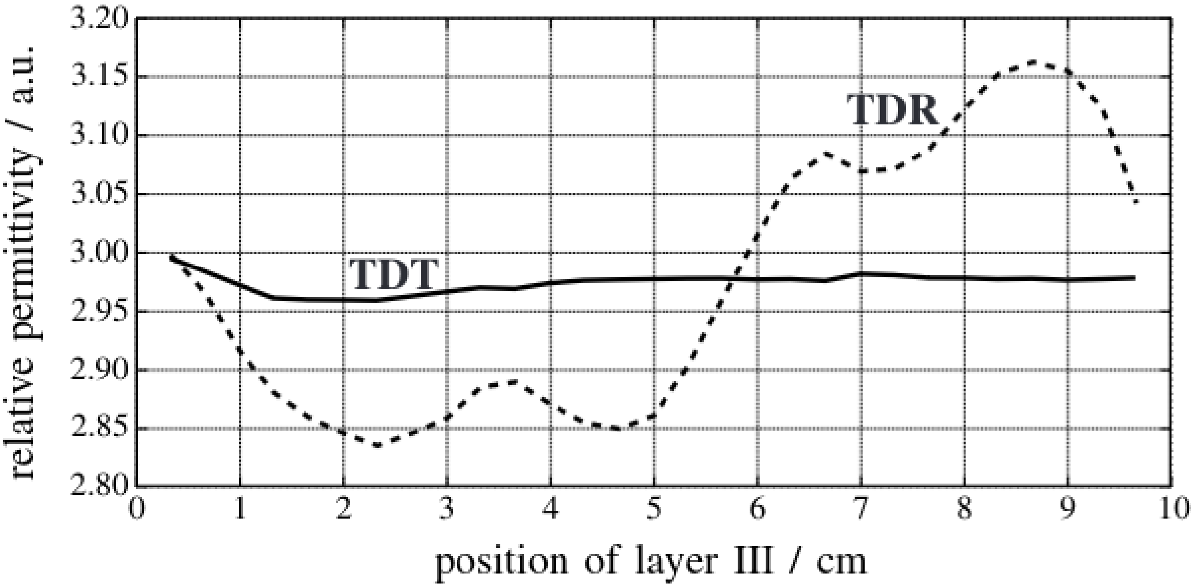


Figure 8 Relative Permittivity Detected by TDR and TDT at Different Soil Depths (Source: Will & Rolfes 2014).

TDT methods were considered expensive or required large equipment in the past, showing a need for a cheaper and field-applicable TDT sensor (Nagahage et al. 2019; Pérez et al. 2023). However, within recent years, small-scale devices were developed, such as the TMS-4, which employ TDT methods at a considerably lower cost (Wild et al. 2019). Recently developed TDT sensors are considered easier to operate, making them accessible for other professionals, however, low-cost sensors are also associated with sensor-to-sensor variability (Bogena et al. 2017). TDT sensors are growing in popularity for their accuracy, low cost, and usability, however, sensor variability and soil-specific considerations may be necessary for a wider range of applications.

3.2.4 **The TMS-4 Datalogger**

The TMS-4 (manufactured by TOMST s.r.o., the Czech Republic) is a newer device developed in recent years that uses TDT to offer continuous SWC and Temperature monitoring for long-term, in situ measurement applications. The device is designed to record microclimate data to observe the environmental conditions of the habitat in the space immediately above and below the soil surface. The size and sensor placement of the TMS-4, depicted in Figure 9 is designed to observe conditions relevant to the different areas of a small herbaceous plant (Wild et al. 2019).

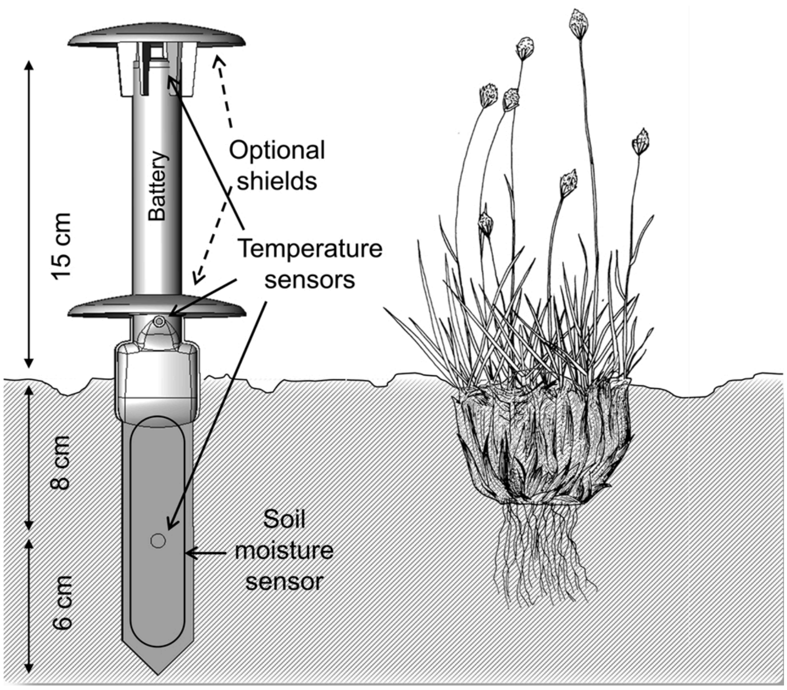


Figure 9 Diagram of TMS-4 Device, Components, and Sensors (Source: Wild et al. 2019).

To measure SWC the TMS-4 propagates an EM pulse at a frequency of 2.5 GHz (Wild et al. 2019), giving it a high enough frequency to avoid the influence of dielectric loss (Bogena et al. 2017), as the range of 0.5–3 GHz is noted as ideal to avoid the effect of imaginary permittivity on DP (Bobrov et al. 2019). The sensor measures the amount of electromagnetic pulses sent along its transmission line, and a reading is calibrated and inverted from a raw number of pulses, appearing as a unitless number from sensor readings, and this number then can be converted to SWC. The pulse values are displayed in the data table generated by the sensor reading software and range from 1–4095, with air measuring 100 and distilled water measuring 3500 pulses (Wild et al. 2019). The transmission wire is configured as a loop sensor, which is considered advantageous for in-situ measurements because it has only 1 port, and measurements have a larger sampling area than other configurations because of a wider cross-sectional area in the blade of the sensor (Will & Rolfes 2014). A full diagram of the TDT measurement components is depicted in Figure 10.

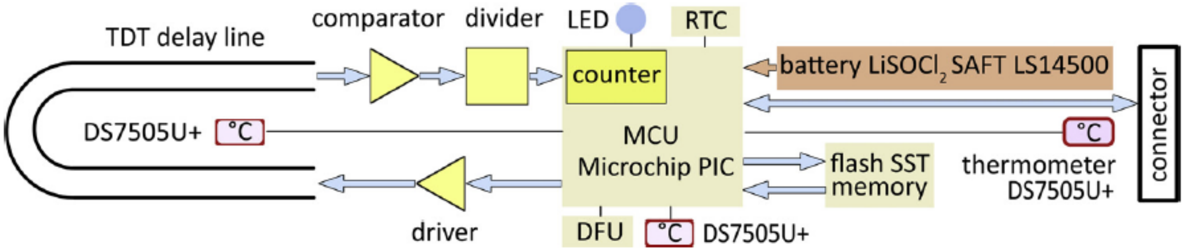


Figure 10 Diagram of the SWC Sensing Equipment in the TMS-4 (Source: Wild et al. 2019).

The manufacturer offers multiple FC equations that account for different soil textures and has been tested for the influence of salinity and temperature, although the article by Wild et al. (2019) detailing the features of the device, suggests soil-specific calibration and notes that measurements taken during periods with frozen soil are not reliable. The TMS-4 Manual offers FC equations for different soil types. The article does note that the TDT method is sensitive to contact with the soil, which can be influenced by shrinking of soil, giving lower than actual SWC values, and that limitations with the sensor included frequent cases of interference and damage from animals in field experiments (Wild et al. 2019).

3.3 Soil Organic Matter

SOM is a component of soils that has an immense influence on soil properties and agricultural productivity. SOM is made of dead plant and animal matter of different levels of decomposition, soil microorganisms, and living organisms such as plant parts and animals which contribute to the formation and transformation of SOM. Living soil microbes determine processes including the decomposition of organic matter, mineralization of nutrients, respiration of carbon dioxide, and carbon transfer. Non-living SOM has three types: active, slow, and passive, which are categorised by how readily they decompose. Active SOM is the most easily decomposed and available of residues, and directly fuels microbial activity. During decomposition by soil organisms, it also contributes to physical soil properties by stabilising aggregates and mineralizing soil nutrients. The proportion of active SOM to total SOM is a metric used to determine soil health and quality (Grubinger n.d.).

SOM influences aggregate stability, cation exchange capacity, nutrient soil processes, and water-holding capacity. SOM is typically more abundant in soils with a finer texture, such as silty and clayey soils, and areas with poor drainage, which encourages SOM accumulation. (Grubinger n.d.).

SOM influences bulk density, with the study by Szypłowska et al. (2021) depicting the inverse relationship between the bulk density of soil and organic matter (OM) content demonstrated in Figure 11.

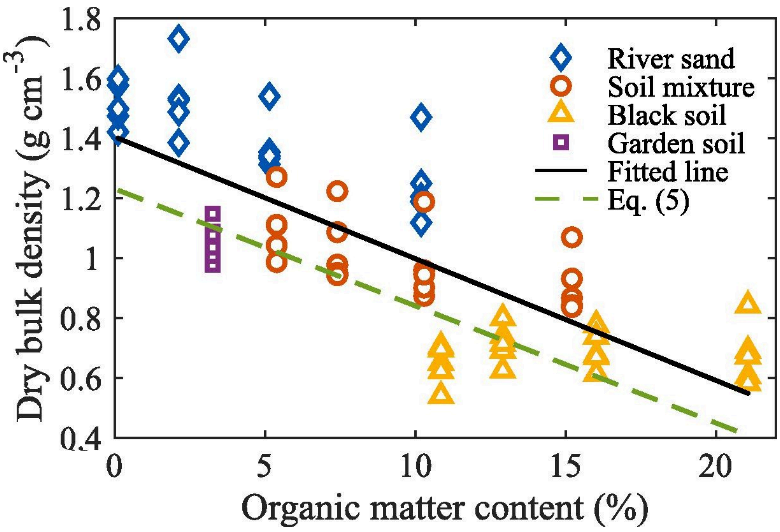


Figure 11 Organic Matter Content Effect on the Dry Bulk Density of Different Soils (Source: Szypłowska et al. 2021).

The influence of SOM in soil and SWC has been thoroughly studied, as SOM influences the texture and water-holding capacity of the soil, which both have a direct influence on SWC. The relationship between SOM and SWC is determined from measurements of Dielectric Permittivity (DP). These influences can come from a change in water retention, resistance to evaporation in soil, or the changing of bulk density, thus directly impacting the calculation of VWC. SOM is known to increase soil water retention (SWR), which can reduce water loss due to evaporation in higher temperatures (Lal 2020). Organic Matter (OM) can change soil texture, pore size, and surface area, depending on the existing characteristics of the soil. In soils with a high proportion of smaller pores, the addition of OM can increase the amount of larger pores, increase the surface area in the soil, and lower bulk density, as depicted in Figure 12 (Park et al. 2019).

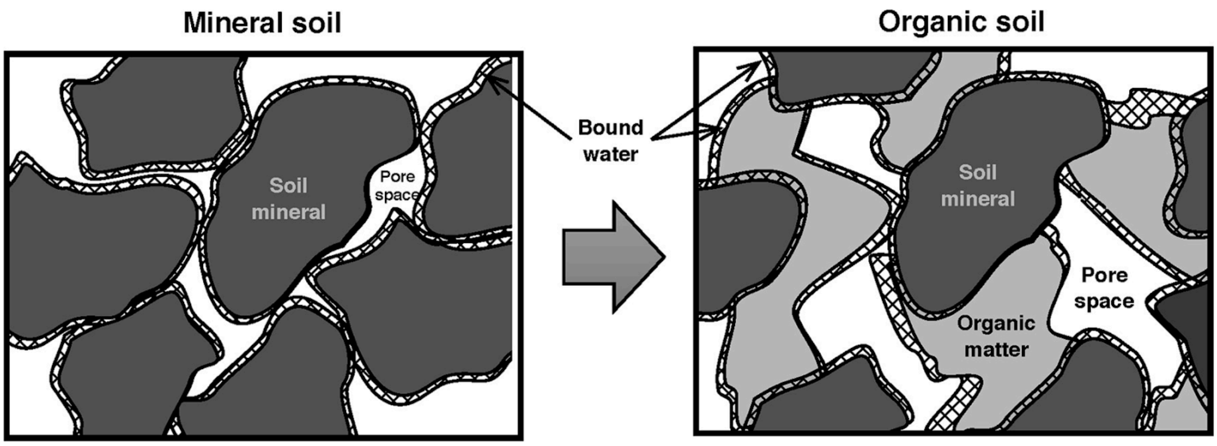


Figure 12 Organic Matter Effect on the Pore Space and Bound Water in Soil (Source: Park et al. 2019).

3.3.1 Soil Organic Matter and Dielectric Permittivity

Unfortunately, very few studies are available that explore the influence of SOM on the TDT method for measuring SWC. However, there are studies available on the influence of

SOM on DP, which has only recently been considered as an environmental factor influencing SWC measurements (Bircher et al. 2016). It was considered in the experiments conducted by Topp et al. (1980) in the context of comparing DP measurements in organic soils with the DP of glass beads with increasing WC, with a limited range of frequency for the TDR method. In their study, organic soils yielded very little change in DP with increasing SWC until the VWC value reached above 10%, but above this level, the response of DP to SWC behaved more like the other measured soils (Topp et al. 1980).

One method of converting indirect sensor values to SWC is the use of a Dielectric Mixing Model (DMM), which accounts for multiple soil-related factors when calibrating values. There are very few models which account for the effect of SOM on DP and the available ones apply to specific ranges of SOM, but may not apply to a wider range of SOM found in field conditions (Bircher et al. 2016; Park et al. 2019). Calibration models and equations have been developed for mineral soils, and the definition of mineral soils in some studies is soils with as high as 10% SOM (Vaz et al. 2013; Mane et al. 2024).

For TDR, soil-specific calibration for organic or humus-rich soils is necessary, as OM has a higher specific area, lower bulk density, and contributes to higher bound water which can alter DP measurements (Bircher et al. 2016). The influence of SOM is known for having a higher specific area, and an increased amount of bound water in the soil. The water being bound directly reduces its movement and thus detection in TDR sensing, resulting in artificially lower measurements for soils with higher SOM. TDR typically operates in the GHz frequency range, and in the GHz range, bound water is measured at a lower DP than free water (Szypłowska et al. 2021). The DP of bound water has even been compared to ice, due to its restricted movement and difference from free water (Bircher et al. 2016). SOM is also directly related to soil bulk density, with an inverse relationship, and the lowering of the bulk density with increased SOM is also associated with a lower DP (Szypłowska et al. 2021).

SOM influences several soil properties that are related to DP, such as bulk density, adsorption forces, and porosity. However these properties are also heavily influenced by soil texture, and SOM has not been studied heavily as a distinct parameter that can influence DP measurements. In the study conducted by Liu et al. (2013), two soils were analysed to isolate the effect of SOM on DP, as the two had a similar clay content, ranging from 16–17%, and different SOM contents, ranging from 4–18%. This study agrees with previous statements that lower bulk density from SOM, and the increase in bound water compared to free water contributes to a lower measured DP in soil, and elaborates that this trend occurs in soils measured at the same frequency and with similar texture and clay content (Liu et al. 2013).

3.4 Calibration Experiments

Calibration is carried out on experimental data to reconcile influencing factors on measurements with the reality of experimental conditions. Deriving a calibration method involves the consideration of several factors surrounding a single variable, these considerations are depicted in Figure 13.

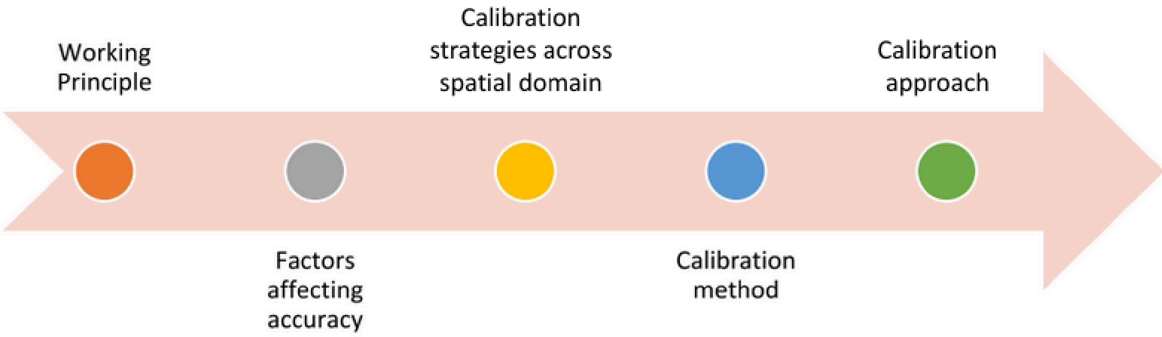


Figure 13 Steps of Calibration (Source: Adjusted from Mane et al. 2024).

In the case of isolating the influence of SOM on Sensor performance of measuring DP, calibration experiments were reviewed to consider the following categories: the working principle of calibration was considered as DP variation in soil, factors affecting accuracy to be salinity, temperature, bulk density, SOM, and soil surface area, calibration strategies to be FC or derived calibration, the calibration method to be laboratory or field, and the calibration approach of linear and nonlinear.

3.4.1 Soil-Specific Calibration and Factory Calibration

Indirect SWC Measuring devices can come with a suggested FC, and the Topp equation (Topp et al. 1980; Equation 5) is considered a universal calibration equation in the context of mineral soils. The equation was considered widely applicable because it was suitable for mineral soils and was not heavily influenced by bulk density, temperature, or salinity, but with a noted limitation for reliability with organic and clayey soil (Cosenza et al. 2003). While these calibration equations are suitable for a range of soil conditions, many studies have noted that they are not reliable for the wide range of soil properties that apply to soil experiments. The FC equation is typically applicable for a range of soil characteristics to improve application and has been successfully used for certain applications. Bircher et al. (2016) explored the performance of soil sensors in soils of varying amounts of SOM, where the given FC equation was found to be reliable when SOM was below 10%, but was much less reliable in organic-rich soil. A study conducted by Bartosz et al. (2023) with FDR reported error and overestimation in FC, especially in clayey and cropland soils. The study went on to conclude that FC didn't account for soil-specific factors, and was found to have high error (Bartosz et al. 2023). In a review of DP-based SWC sensing methods, it is stated that FC is prone to high error and that soil-specific calibrations are necessary, particularly for soils with high clay content and SOM. The study continues by noting that despite contradictory results from authors experimenting with DP sensors, one commonality is the method of deriving individual calibration curves for different types of sensors and different types of soil, rather than relying on FC (Bobrov et al. 2019).

A study conducted by Zawilski et al. (2023) reviewed the reliability of FC on DP-based sensors such as FDR, TDR, capacitance, and remote techniques, and experimented with FDR sensors, to conclude that not only is the FC unable to accurately determine SWC in many different types of soils, but the error in experiments to be unacceptably high.

Soil-specific calibration improved their relative error to varying amounts in different types of soil, an experiment with TDR sensors demonstrated a Nonlinear relationship with gravimetric samples, and the FC was found to have a low reliability below 20% SWC (Walker et al. 2004). In an experiment conducted by Domínguez-Niño et al. (2019), which evaluated the FC for low-cost TDR sensors, the FC was found to overestimate SWC and had significantly high RMSE.

Multiple reviews of SWC measuring devices and methods agree and recommend that soil-specific calibration be carried out for the sake of more accurate measurements for different soil conditions and an overall improvement from FC (Lekshmi et al. 2014; Sharma et al. 2018; Singh et al. 2018; Mane et al. 2024).

Soil-specific calibration has been determined as a necessity for more accurate measurements of SWC, due to the wide range of soil characteristics that affect measurement techniques, and a growing awareness of the high error resulting from FC equations (Dominguez-Niño et al. 2019). In some cases, the FC was considered reliable, but usually for a limited range of soil properties, such as SOM below 10%, and show significant deviation in different soil conditions, and in more extreme levels of SOM, up to and above 30%, a significant deviation of DP measurements were observed (Bircher et al. 2014; Li et al. 2022). The differences between sensor performance and the measurements of DP in pure water, soil water in sand, and soil water in other soils in the experiment performed by Seyfried & Murdock (2014) is considered an indicator that the soil-specific calibration is necessary to address the soil properties which influence DP measurements.

The experiment conducted by Bircher et al. (2016) ran tests with TDR sensors on mineral soils with higher than 10% SOM, however, at these levels, the sensor results followed a different trend than the mineral soils with lower SOM. Mineral soils with higher SOM showed a decrease in relative permittivity and a decreased response with increased Water Content (WC). Sensors demonstrate more scattered data with SOM, which was attributed to the SOM having a more complex structure, and producing more variation in results. Multiple types of sensors were used and applied with different possible calibration equations, such as Linear, Polynomial, and Logarithmic. Logarithmic fit data well for having a more pronounced curve up to 20% SWC, then increasing with a lower response to increased WC (Bircher et al. 2016). Other experiments seeking a calibration equation for SOM and SWC were typically Polynomial, but the studies were related to TDR and FDR with no mention of TDT (Fares et al. 2016; Karim et al. 2018; Songara & Patel 2022).

A review of low-cost TDR sensors conducted by Mittelbach et al. (2012) concluded that none of the sensors in their experiment performed according to the specifications of the manufacturer, and for this reason, site-specific calibration was determined to be necessary for accurate interpretation of sensor measurements.

In the reviewed calibration experiments, different DP-based measuring methods were applied to observe SWC, and equations were derived from the analysis of the indirect measuring methods with direct gravimetric analysis. Typically, the best fit derived equation was Polynomial (Fares et al. 2016; Karim et al. 2018; Bobrov et al. 2019; Sangara & Patel 2022) and in the unique case of Bircher et al. (2016), both Polynomial and Logarithmic equations were considered well suited to their experiment. For the TMS-4, the suggested calibration equations were Polynomial equations with varying parameters depending on texture (Wild et al. 2019).

Linear functions were used in multiple calibration tests to evaluate sensor response to DP in sensor-specific calibrations, and Linearity between sensor measurements and Actual Water Content (AWC) was associated with the accuracy of a measuring technique (Rosenbaum et al. 2010).

3.4.2 Sensor-Specific Calibration

Calibration methods beyond soil-specific calibration may be necessary for precise and accurate SWC measurement; multiple studies have described the importance of calibrations that are not only soil-specific but also sensor-specific. These studies suggest that there can be considerable variability between sensors in a single test, despite conditions in the laboratory experiments being extremely controlled for soil calibration tests. Some noted uncertainties in measurements also came from experimental procedures, such as heterogeneity in the soil from manual packing and compaction, heterogeneities resulting from packing imperfections and compaction introduced some uncertainties to the measurements (Ilie et al. 2020). These considerations extend to large field experiments, which are certain to have heterogeneity in soil and can suffer from variability due to sensor variation. This variation is compounded when cheaper sensors are used in large numbers to account for wide-scale field monitoring (Rosenbaum et al. 2010).

The experiment performed by Rosenbaum et al. (2010) used a two-step calibration to account for sensor variation and soil properties. The calibration for sensor variation used multiple reference liquids with a known DP, to develop a 'reference permittivity,' and evaluate the Linear response of each sensor to multiple DPs. For experiments with a very high amount of sensors in the field, the soil-specific calibration can be performed with a subset of sensors, after a known sensor response to DP has been established with the sensor-specific calibration. Measurements with not only a soil-specific but a sensor-specific calibration applied showed a significantly reduced RMSE compared to their single calibration measurements (Rosenbaum et al. 2010).

In one study using the two-step calibration reduced the RMSE of results by 70% compared to the one-step calibration (Bogena et al. 2017). Further benefits of the two-step calibration system were found in reducing or avoiding variation related to air gaps and soil density, the ability to separate variation arising from sensor intrinsic properties and experimental procedures or environmental impacts, and the procedure allowing for the quick calibration of sensors to a wide range of DP (Dominguez-Niño et al. 2019).

In a review of SWC measurement methods by DP-based sensors conducted by Mane et al. (2024), linear and nonlinear approaches were compared with different calibration types, as depicted in Figure 14. The researchers were surprised that linear and nonlinear values were close together in some calibrations, as they assumed that Linear would have a drastically higher error than the Nonlinear approach in all calibration types. The study aimed to demonstrate the importance of calibration types and influences in SWC measurements by DP-based sensors. The study asserted that general calibrations are prone to high error and that performing site-specific, soil-specific, and even point-specific calibration can reduce RMSE and improve experimental accuracy. The assertion was supported when they compared the RMSE of different calibration types and elaborated that although in types with higher error, the linear and nonlinear calibration have a similar error when accuracy is more favourable in the point and site-specific calibrations, the difference in linear and nonlinear calibration methods became more important. At the same time, overall RMSE was lowest in the point-specific calibration for linear and nonlinear methods, demonstrating that the calibration type has a profound effect on experimental accuracy (Mane et al. 2024).

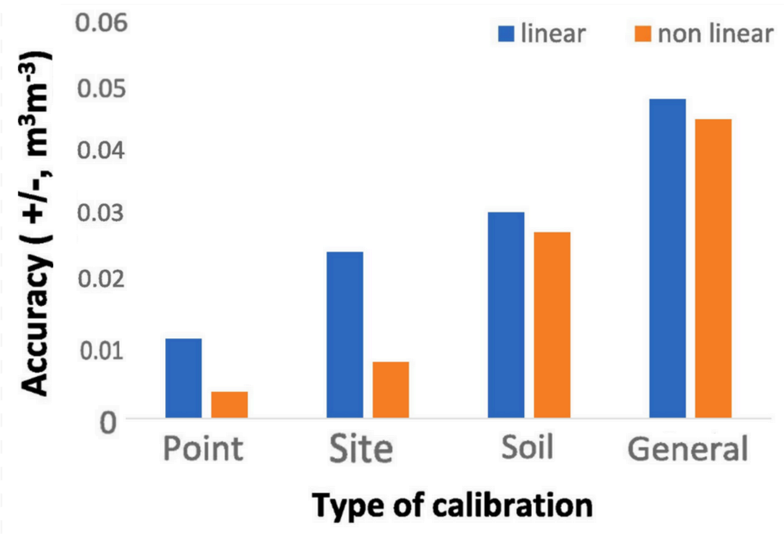


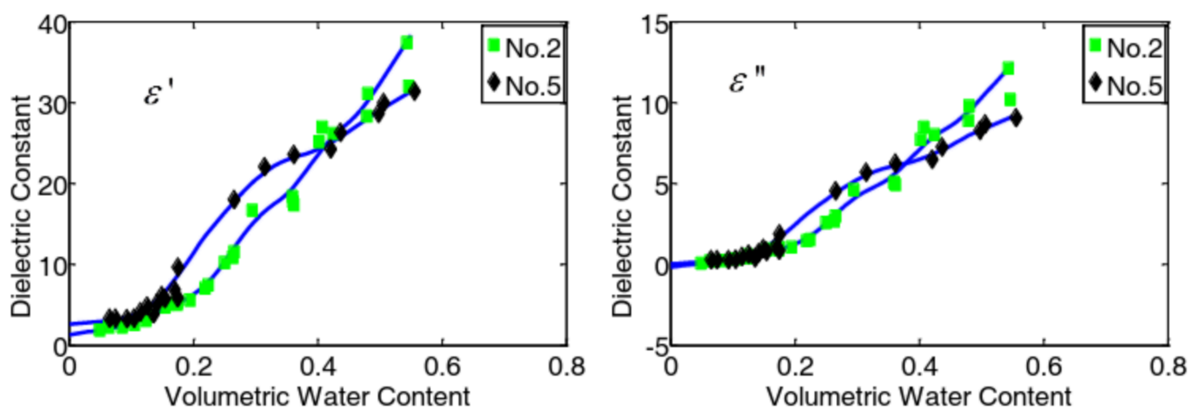
Figure 14 RMSE of Linear and Nonlinear Calibration for Different Calibration Types (Source: Adjusted from Mane et al. 2024).

In the study conducted by Mittelbach et al. (2012), TDR and several types of low-cost sensors were compared in measurements of field data and their respective FC. The study found that none of the sensors performed in congruence with the FC and specifications when applied to field conditions, and concluded that site-specific calibrations are necessary for accurate interpretation of SWC measurements. The study also urges that future experiments, even when using more expensive sensors, evaluate a need for temperature correction for sensors, and depending on the type of sensor, evaluate the influence of soil texture, temperature, bulk density, and salinity (Mittelbach et al. 2012).

3.4.3 Transition Water Content

Several calibration experiments working with different sensing methods have reported a turning point in measurements when the response of sensors to SWC drastically changes. This point is Transition Water Content, and separates two stages of water saturation in soil: when the SWC is below the Transition Water Content, the water in the soil is adsorbed, or bound water, and when SWC is above the Transition Water Content, there is both bound and free water in the system Liu et al. (2013). Because bound water measures at a lower DP than free water (Bircher et al. 2016; Sharma et al. 2018; Szypłowska et al. 2021), DP increases slowly with VWC below the Transition Water Content of a given soil and increases at a higher rate with VWC after passing Transition Water Content (Liu et al. 2013). In a study conducted by Liu et al. (2013) which measured the increasing SWC for soils with similar texture, but different amounts of SOM, the soil with higher SOM was found to have a higher Transition Water Content, adding to the behavioural differences of soil with higher SOM. The study measured SWC with sensors of a wide range of frequencies, from 0.5–40 GHz, and noted that the decreased bulk density and increased adsorption force of the soil that results from increased SOM also contributed to a lower DP at the same SWC and frequency. The Transition Water Content of the soil with higher SOM was around 20% VWC, while the lower SOM soil was around 10–15% VWC (Liu et al. 2013).

Multiple studies have indicated a turning point around 20% SWC where results shifted in behaviour or reliability, even though the studies were testing for different influencing factors for different sensors using the TDR method (Walker et al. 2004; Bircher et al. 2016; Pérez et al. 2023). A TDT prototype was developed by Pérez et al. (2023) for a smaller TDT sensor, which was able to reliably detect SWC in drier soils, but data reflected a turning point above 20% where the results became less reliable. It is also observed in the review of Mane et al. (2024) that the established calibration equation for converting DP to SWC, Topp's calibration equation, becomes less reliable at VWC above 15%. This is especially true in clay or saline soils, and consideration of the imaginary part of DP is then necessary as well as soil-specific calibration for soils with high SOM or clay (Mane et al. 2024). In the study conducted by Liu et al. (2013) mentioned previously, the two soils with similar texture showed the occurrence of Transition Water Content in DP measurements, depicted in Figure 15, with the data trends changing at roughly 20% VWC and 40% VWC.



(a) *(b)*

Figure 15 Measured Real (a) and Imaginary (b) (Source: Liu et al. 2013).

4 Materials and Methods

4.1 Study Area and Soil Samples

The TMS-4 Dataloggers by TOMST s.r.o. (TMS-4) were evaluated in field and lab conditions. The field-based sensors (16-18 pc) were placed in four agricultural fields for the growing seasons of 2022 and 2023. The localities were Blatnice u Jaroměřice (Locality A), Jevíčko (Locality B), Velké Hostěrádky (Locality C) and Uhříněves (Locality U). At each locality, experimental plots amended by compost and control plots without any amendment were designated and their Soil Water Content (SWC) was monitored by the TMS-4. There were always two TMS-4 sensors at the Control Soil (CON) and two at the Compost-Amended Soil (CAS) plots at each locality. The investigation of the possible influence of the higher Organic Matter (OM) content on sensor performance was carried out in the laboratory in the current study. In all localities, topsoil from the control plots was taken for the calibration experiment. While in the field the compost was only applied to the soil surface, the compost in the dosage of 20 t/ha was thoroughly mixed with the soil for the laboratory calibration experiment. Figure 16 depicts the locations of each of the soil localities, and Figure 17 depicts photos of each of the experimental fields, including localities A, B, C, and U.

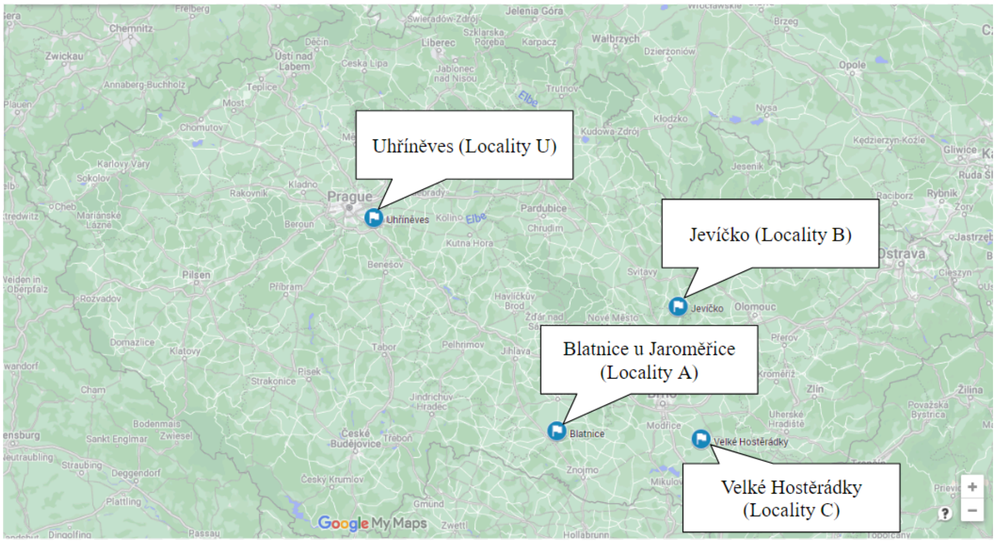


Figure 16 Locations of Sampling Sites in the Czech Republic (Source: Plots google.com).

(a) *(b)* *(c)* *(d)*

Figure 17 Localities (a) A, (b) B, (c) C, and (d) U (Sources: Author and Plots google.com).

Properties of each locality such as climate, land use, crops, and soil type are depicted in Table 1. Soils were classified according to the Systematic Soil Survey of Agricultural Soils utilised in eKatalog BPEJ (RISWC 2022).

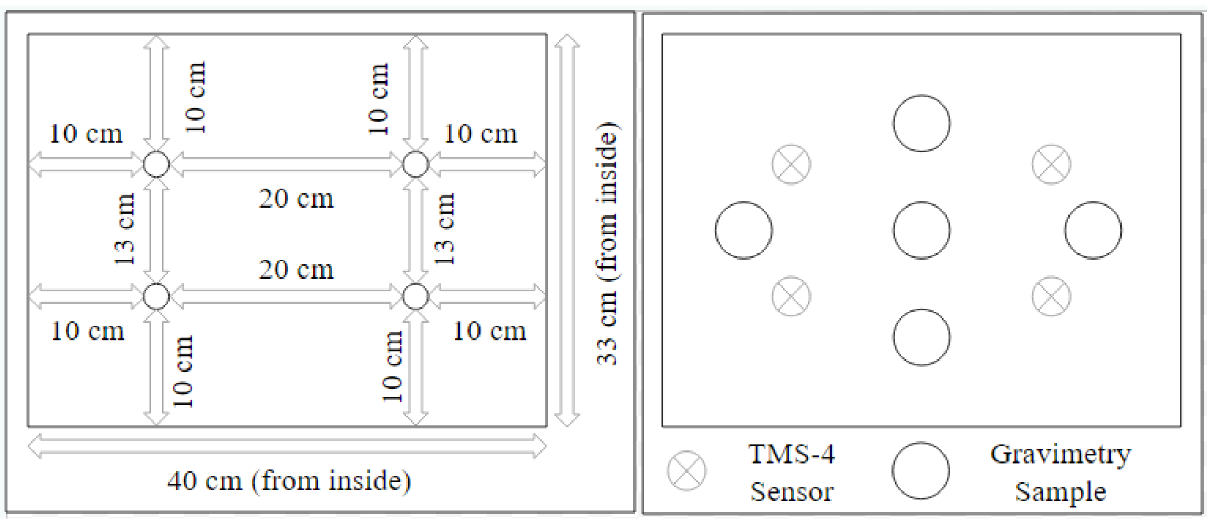
Table 1 Site Properties (Sources: Krejčířová et al. 2007 and Badalíková et al. 2022, 2023).

Locality	Blatnice u Jaroměřice (A)	Jevíčko (B)	Velké Hostěrádky (C)	Uhříněves (U)
Type of Farming	Conventional	Conventional	Organic	Organic
Crop 2022	Cover Crop, Winter Wheat	Corn	Oat, Cover Crop	Spring Wheat
Crop 2023	Winter Wheat	Corn	Cover Crop, Fagopyrum	Spring Wheat
Av. Annual Temp.	7 – 8 °C	7 – 8 °C	8 – 9 °C	8.4 °C
Av. Annual Precip.	550 – 650 mm	550 – 650 mm	550 – 650 mm	575 mm
Soil Type	Cambisol modal carbonate	Cambisol modal eubasic	Chernozem modal	Haplic Luvisol

4.2 TMS-4 Datalogger Calibration Experiment

4.2.1 Calibration Tank Preparation

The method of homogenised soil column was used in this experiment (Kara et al. 2021). It involves preparation of the soil by artificial packing into a tank while maintaining the constant water content and dry bulk density. The calibration tank needed the dimensions to accommodate four TMS-4 sensors with adequate space and to allow the insertion of five small rings (see Figure 18). The usage of multiple sensors in a single test allowed for multiple measurements to be taken in a single replication, yielding more results for overall data analysis. One consideration was maintaining an appropriate distance between the sensors and the walls and floor of the tank, to avoid any interference for the sensors.

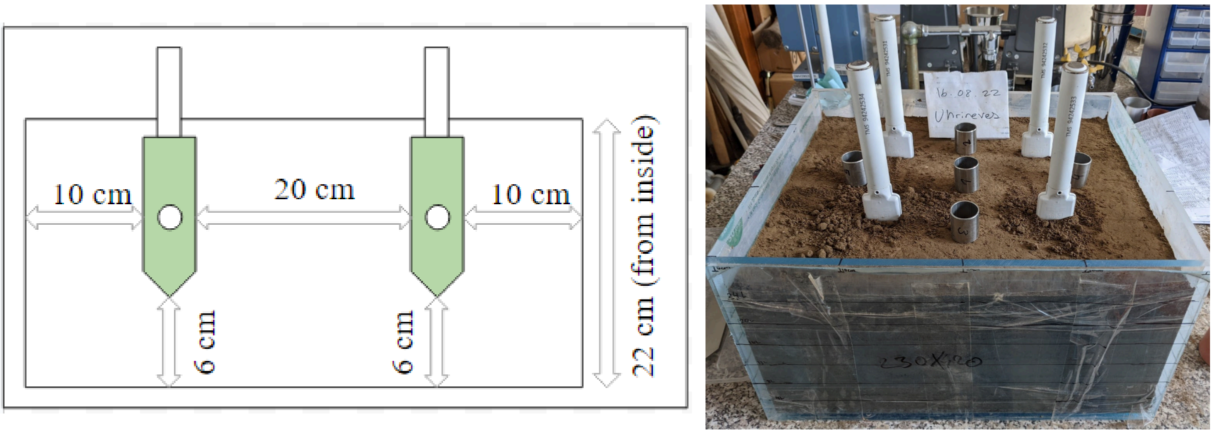


(a) *(b)*

Figure 18 (a) Tank Dimensions and Sensor Spacing (b) Sensor Placement, and Sample Placement (Source: Author).

We contacted the manufacturer to address the proper dimensions of the tank. The recommendation from the manufacturer was to have at least 10 cm in between the sensor and any obstructions. Marks were made on the sides of the tank to ensure that the sensors would be placed in appropriate spots during each replication, having adequate distance from the other sensors, each of the walls of the tank, and the floor of the tank. The dimensions of the calibration tank and the spacing of each TMS-4 in the tank are depicted in Figure 18(a). The positions of each TMS-4 and the gravimetric soil samples are depicted in Figure 18(b).

Figure 19(a) depicts the spacing of each TMS-4 from the side of the calibration tank to demonstrate the depth of the sensors in the tank, and Figure 19(b) depicts a photo of each TMS-4 in use during the actual experiment with sampling rings placed on the surface of their sampling positions, where the marks of the layers used to ensure the uniformity of the soil packing are visible.



(a) *(b)*

Figure 19 (a) Tank Dimensions Side View and (b) Photo of Tank with Sensors and Sampling Rings (Source: Author).

The tank was filled with water at intervals of 4 L, repeated up to 24 L, and marked at the water level at each volume interval. This level was used as the desired volume of soil for each layer and was used as a mark for packing the soil as each layer was added to the tank.

4.2.2 Soil Preparation for Control Experiments

The desired soil characteristics for the Control test were a bulk density of 1.37 g/cm^3 with a mass of 32.88 kg, evenly distributed within a 24 L calibration tank; this value for dry bulk density was determined from the average of actual measured bulk density at the localities. As a precaution, more than 35 kg of soil from each locality was procured for experiments.

First, the soil was laid out to air dry in plastic trays or on parchment paper. The soil was spread out along as much surface area as possible, and larger aggregates were broken by hand to accelerate drying. Matter such as plant debris, rocks, and worms were removed by hand. Drying took anywhere from two days to two weeks depending on the availability of desk space to dry soil, temperature, and sunlight. Once fully dried, the soil was put into a grinder, bringing the soil aggregate size to roughly 6 mm.

The first test performed on each soil was the air-dried test. The soil was packed into the calibration tank one layer at a time, without any additional water. To prepare one soil layer in the calibration tank, 5.48 kg of dry soil was weighed out for the air-dried test. The soil was added to the calibration tank and pounded with a rubber mallet to compress it within a volume of 4 L. Figure 20(a) depicts the soil compression procedure. The dimension marks on the tank were used as an indicator for the desired height of each layer of soil. This procedure was repeated until all six layers of soil were compressed into the calibration tank. The soil was handled slowly for each step of preparation, such as pouring the soil into the calibration tank and pounding it with a mallet, as handling dry soil too fast caused soil particles to fly up and spread around the lab, which risked a loss of soil mass in the experiment. After six layers of soil had been prepared in the calibration tank, measuring with the TMS-4 and gravimetric sampling was performed before beginning the next soil test.

The Targeted Water Content (TWC) for the air-dried soil was 0%, and for every test after the initial air-dried test, water was added to prepare the soil of a certain TWC, which were: 5%, 10%, 15%, 20%, 25%, 30%, 35%. For example, when preparing one layer of soil for the calibration tank in the 5% TWC test, 200 mL of water was mixed in with the soil. The soil was mixed thoroughly by gloved hands, to distribute the water evenly throughout the soil. The required mass of soil per layer increased by 200 g for each test to account for the added water. The volume of soil in the tank was kept constant by pounding the soil into the marked dimensions. 200 mL of water per layer in each of the six layers totaled in 1.2 L of water added to the 24 L calibration tank, increasing the Volumetric Water Content (VWC) of the soil by 5% for each test. Procedures were repeated for a full set of eight total soil tests until the soil was tested at a TWC of 35%. For a full set of TWC tests, the following amounts of water were added in total for each layer: 200 mL for 5%, 400 mL for 10%, 600 mL for 15%, 800 mL for 20%, 1000 mL for 25%, 1200 mL for 30%, and 1400 mL for 35% TWC test. Testing above 35% TWC was not possible because the soil subjected to artificial packing became muddy. A full set of CON (Control Soil) tests and Compost-Amended Soil (CAS) tests for TWC were run for each locality. The Actual Water Content (AWC) was calculated for each test by taking gravimetric samples, which will be described later in the text in section 4.2.5.

4.2.3 **Soil Preparation for Compost Experiments**

Testing for CAS was only possible after CON testing was complete since the same soil was used for both sets of tests. To prepare CON for compost treatment, the CON was dried and put in the grinder like the initial procedures, however, the removal of debris was not repeated. Figure 20(b) depicts the soil mixture, with 32.88 kg of CON mixed with 500 g of compost. This amount of compost in the soil was determined from the compost application rate for the localities of 20 t/ha.

The procedures for adding soil to the calibration tank were repeated, and the properties such as volume and mass of soil in the calibration tank were the same as the CON test. The Compost from Locality C was used in our laboratory calibration experiments. The combined amount of soil tests run between the three localities, CON and CAS, and increasing TWC totaled in 48 TWC tests.

(a) *(b)*

Figure 20 (a) Soil in the Calibration Tank and (b) Preparation of CAS (Source: Author).

Properties of the compost used for field tests and laboratory tests are described in Tables 2, 3, and 4, corresponding with Localities A, B, and C. Compost used for Localities A and C were also used in the field test conducted in Locality U, and the compost used in Locality C was also used for laboratory testing. In each table, the properties are described in total percent (%), a ratio, or a portion in Dry Matter (DM).

Table 2 Compost Parameters for Locality A (Source: Badalíková et al. 2023).

		Date	12.08.2022	26.04.2023	20.11.2023	Requirements
Locality A	Dose t/ha	in matter	31.3	29.5		
		in DM	19	16.8		
	Humidity	%	33.92	43.84	28.22	30-65
	Combustible Substances (%)		39.4	31.5	25.1	min. 20
	N_{tot}	%	1.61	1.42	1.19	min 0.6
		mg/kg DM	16.1	14.2	11.9	x
	C:N	Ratio	12	11	11	10-15
	pH		8.5	8.4	8.6	6-10
	N min from N_{tot}	%	20.55	2.37	7.84	x
		mg/kg DM	3308	336	933	x
	$N\text{-}NH_4^+$	% DM	0.04	0.02	0.05	0.05-0.075
		mg/kg DM	398	202	506	x
	$N\text{-}NO_3^-$	mg/kg DM	2910	134	427	
	Ratio	NH_4^+/NO_3^-	0.14	1.51	1.19	0.5-3.0
	Index Stability	degree	6.9	8.2	7.5	min 6

Table 3 Compost Parameters for Locality B (Source: Badalíková et al. 2023)

		Date	28.02.2022	Requirements
Locality B	Dose t/ha	in matter	174	
		in DM	8.5	
	Humidity	%	51.45	30-65
	Combustible Substances (%)		47.1	min. 20
	N_{tot}	%	1.88	min 0.6
		mg/kg DM	18.8	x
	C:N	Ratio	13	10-15
	pH		9	6-10
	N min from N_{tot}	%	2.89	x
		mg/kg DM	543	x
	$N\text{-}NH_4^+$	% DM	0.03	0.05-0.075
		mg/kg DM	304	x
	$N\text{-}NO_3^-$	mg/kg DM	239	
	Ratio	NH_4^+/NO_3^-	1.27	0.5-3.0
	Index Stability	degree	4.1	min 6

Table 4 Compost Parameters for Locality U and C (Source: Expert Report Project 2023).

		Date	24.03.2022	24.06.2023	26.04.2023	Requirements
Locality C	Dose t/ha	in matter	30	30		
		in DM	21.9	22.8		
	Humidity	%	27.45	24.42	39.29	30-65
	Combustible Substances (%)		20.5	33.9	35.3	min. 20
	N_{tot}	%	1.83	1.66	1.5	min 0.6
		mg/kg DM	18.3	16.6	15	x
	C:N	Ratio	6	10	12	10-15
	pH		6	7.6	8.7	6-10
	N min from N_{tot}	%	7.13	22.76	6.45	x
		mg/kg DM	1305	3778	967	x
	$N\text{-}NH_4^+$	% DM	0.06	0.02	0.07	0.05-0.075
		mg/kg DM	641	238	798	x
	$N\text{-}NO_3^-$	mg/kg DM	664	3540	169	
	Ratio	NH_4^+/NO_3^-	0.96	0.07	4.72	0.5-3.0
	Index Stability	degree	6.6	7.8	8	min 6

4.2.4 TMS-4 Datalogger Setup, Placement, and Operation

Before using the TMS-4, it was necessary to install the corresponding software that serves as a control panel for the TMS-4 settings. The desktop application for viewing TMS-4 data is called the Lolly Manager. The TMS-4 connects to the computer with a TMD Adapter which connects to the computer via a USB port, and to the sensor by connecting the other end of the adapter to the Data Connector located at the top of the sensor, where the Radiation Shield goes. These TMS-4 components are visible in Figure 21, with Figure 21(a) depicting the TMS-4 and the ‘TMD Adapter,’ Figure 21(b) depicting the procedure for wireless connection between the TMS-4 and the adapter when uploading data, and Figure 21(c) depicting the TMS-4 with the radiation shields affixed to the sensor, typically applied during field experiments.

(a) *(b)* *(c)*

Figure 21 TMS-4 Components (a) TMS-4 and TMD Adapter, (b) Data Connector part of Adapter with TMS-4, (c) TMS-4 with Removable Radiation Shields.

Once connected, the Manager application appeared, and the setting of the sensor was switched from Basic Mode to Experimental Mode. The Basic Mode setting is depicted in Figure 22 and makes the sensor take measurements once every 15 minutes. Basic Mode had the longest time interval available between measurements in the TMS-4 settings, so it was used throughout the experiment as the default setting when the sensors were not in use, to conserve memory and battery usage. Experimental Mode recorded measurements once per minute, as the shortest possible time interval between measurements, and was used to record temperature and Soil Water Content (SWC) in the experiment.

The four sensors have a corresponding number, and each sensor was placed in the same designated position for each test, across CON and CAS experiments in localities B, C, and U. The positions were marked to ensure the appropriate distance between the sensors and the calibration tank walls. Sensors were inserted gently and by hand to avoid damage. When having difficulty inserting the sensor in the soil, a metal installation probe provided by the manufacturer was used to ease insertion. This procedure was avoided as much as possible to refrain from further compacting the soil and risk influencing the sensor reading. The probe is typically recommended for use in the field to avoid damaging the sensor blade in rocky soil.

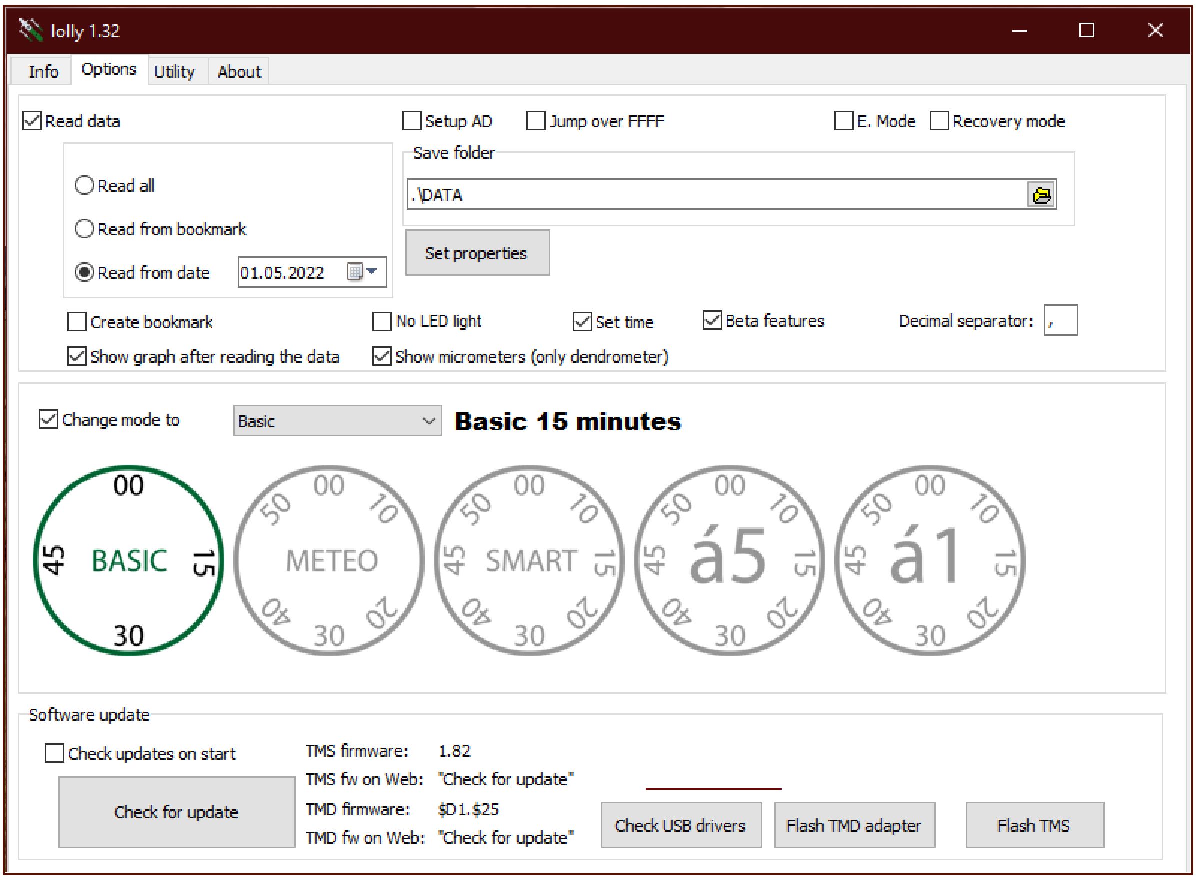


Figure 22 Options Page for the Lolly Application in Basic Mode (Source: Wild et al. 2019).

To perform the calibration experiment, the four sensors were run in soil and recorded a minimum of 10 measurements each. With four sensors in each TWC test, a minimum of 40 measurements were taken per TWC test, with eight TWC tests beginning with air-dried soil, increasing by 5% VWC until 35% TWC, and a minimum of 240 measurements were taken from one complete soil test. One complete soil test was run in CON and then CAS, so a minimum of 480 TMS-4 measurements of SWC were recorded from each locality.

The artificially packed soil needs some time for homogenisation, and the sensor after insertion needs some time to create good contact with the soil. The TMS-4 was found to give lower readings for soil moisture that would climb in the first few minutes of data collection, meaning that the first five or so readings of the device in Experimental Mode would gradually increase before stabilising around a smaller range of readings. For this reason, the sensors were kept in the soil and run in Experimental Mode for around 15–20 minutes in a single test, and the final ten stabilised readings from each replication were used in data analysis, meaning each TWC test was analysed using the ten measurements from the most stable range. Figure 23 depicts the TMS-4 measurement data from the TMS-4 Lolly Application for all measurements in the Locality B CAS calibration test, the stabilisation of the measurements is visible in the curve of the data for each test, and the drastic difference in Dielectric Permittivity (DP) between the open air and wet soil.

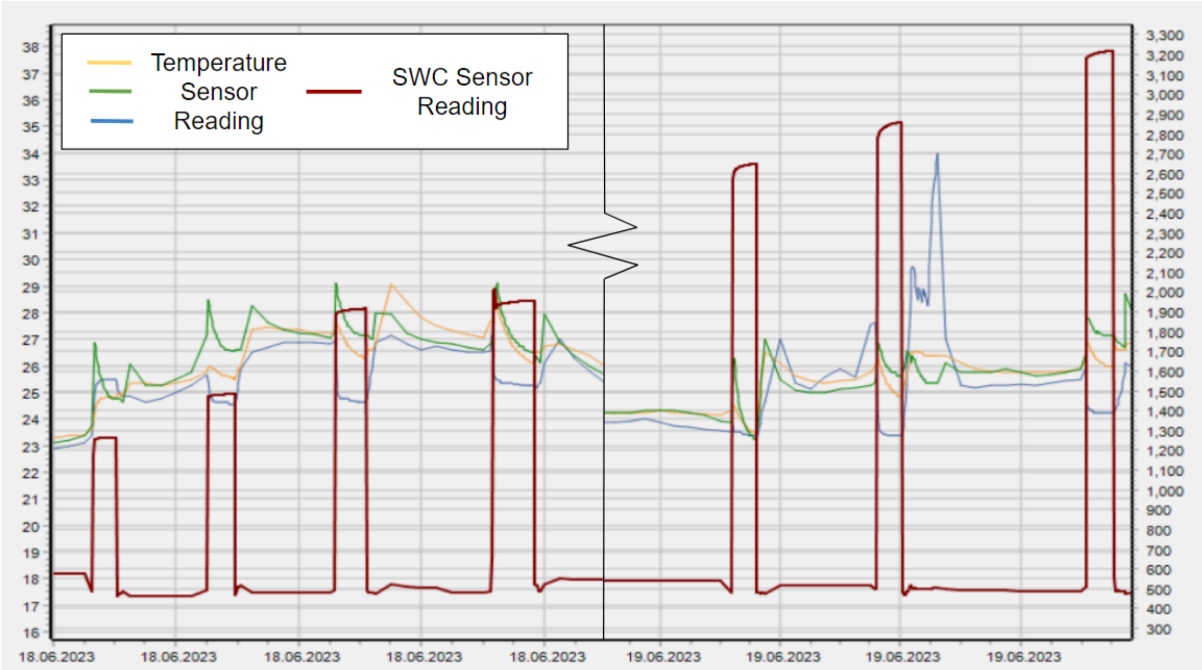


Figure 23 Data from Lolly Application from Calibration Test (Source: Yamamoto et al. 2023).

Because the TMS-4 measurements could be viewed instantly on the Lolly Manager application, we were able to review the results of each test before taking gravimetric samples. The immediate results gave insight into possible errors in sensor readings, as they provided a sensor average for each test and made outlying data replications obvious after sampling and simple to address. In cases where the TMS-4 test was unsuccessful (such as the TMS-4 measuring a lower SWC in the experimental soil after it had been mixed with more water), the TMS-4 could be reinserted and stay in Experimental Mode for replication of the test. This error happened twice in the experiment, and was attributed to unevenly distributed water from soil mixing, or user error in orienting the sensor properly in the soil, and was solved by repositioning and reinserting the sensor in an undisturbed part of the calibration tank. The size of the calibration tank allowed for some freedom in moving the sensor to a different position in the soil without coming too close to the calibration tank walls or the other sensors. Another possible method was to connect the sensors to a laptop with the Lolly Manager software via the adapter while the sensors were in the soil so that data could be reviewed without removing sensors from the calibration tank. If the measurement was unsuccessful the sensor would have to be removed and repositioned in undisturbed soil.

4.2.5 Sampling to Obtain the Actual Water Content by the Gravimetric Method

After the TMS-4 results were reviewed, the sensors were removed, and five undisturbed soil samples were immediately taken from positions in between the sensor positions. The samples were taken from areas as far as possible from the impressions left by the sensors to ensure the sample was undisturbed. Samples were taken with five 15.7 cm^3 sampling rings and always taken from a few centimeters below the soil surface, to avoid sampling soil affected by evaporation. During the sampling of the air-dried soil, the soil was too loose to hold in a sampling ring, so disturbed samples were taken. When water was added, the soil could be taken in an undisturbed sample from the calibration tank. The ring was driven into the soil by hand or with a rubber mallet, to avoid damaging the ring or disturbing the soil. Rings were weighed before and after sampling to measure the mass of the wet soil, and placed in the oven for 105°C to dry till the constant mass. Figure 24 depicts the first batch of samples in the oven.

Figure 24 Sampling Rings with Watch Glass in the Oven (Source: Author).

Due to the high number of samples required for gravimetric analysis, procedures were added to the gravimetric sampling process to accommodate the number of sampling rings available and optimise energy use from the oven. After the mass of the sample and ring were recorded, the soil was removed from the rings and quantitatively placed into corresponding labeled metal tins before going into the oven. Figure 25 depicts the metal tins with soil in the oven. The assumption was that because the volume of the sample is known from the sampling ring and the mass is known from weighing, removing the sample from the ring would not compromise the results of the gravimetric analysis. The mass of the metal tins was recorded to get the mass of the dry soil after drying, and the rings and tins were documented and labeled to prevent further error. This procedure allowed for all samples in one CON or CAS test to be dried at once, saving energy.

Figure 25 Soil from Sampling Rings in Metal Tins for Oven Drying (Source: Author).

After drying, sample dry weights were recorded, allowing the calculation of Water Content (WC) by mass, dry bulk density, and Volumetric Water Content (VWC).

Each TWC test yielded five samples, and eight TWC tests were performed in one full set of soil tests, totaling 40 samples. A full set of soil tests was performed on CON, and another full set on CAS, meaning that each locality required 80 gravimetric samples for analysis.

4.2.6 Training Tests

The experiment involved training tests, where the experimental procedures were carried out for the first time by the student and learned during testing. The experimental procedure required the handling and uniform artificial packing of a relatively large volume of soil (24 L). The initial CAS test was carried out for the Locality Uhrineves (U) and was conducted as a training test. Because this test was carried out as a training test, experimental procedures may have been executed poorly in comparison with later tests. It is for this reason that the data for the CAS Uhrineves test was included for transparency, but should not be considered as reliable as the other tests, which were conducted after more experience was gained with the method, and should not be used for further research or as a standard for experimental results or speculation.

4.3 Calibration and Statistical Methods

Datasets were obtained from gravimetric analysis and TMS-4 measurements, these values were graphed together for calibration. Results were compiled for each soil locality, with the progression of SWC from air dry to 35% TWC for CON and CAS. Average values were taken from the datasets for each SWC test and graphed together with the TMS-4 readings as the x-axis and the gravimetric values as the y-axis. A trendline, equation, and R^2 value were generated from each of the soil test sets for Linear, Logarithmic, and Polynomial equations. The generated equations were then applied to the TMS-4 measurements to generate fitted values for SWC in cm^3/cm^3. The fitted values were then compared with the actual values from gravimetric analysis with Root Mean Squared Error (RMSE). Higher TMS-4 values were applied to each equation to project possible situations of higher SWC to evaluate the equation performance in possibly extreme field situations.

The RMSE calculation is visible in Equation 6 (Matula et al. 2016).

$$RMSE = \sqrt{\frac{1}{n}\sum(\theta_{real} - \theta_{measured})^2} \qquad (6)$$

Where:
θ_{real} …………………..Directly Measured VWC (cm^3/cm^3)
$\theta_{measured}$ ………………Indirectly Measured VWC (cm^3/cm^3)
n...……………………Number of Measurement Points

Calibration equations were evaluated for fitness with the coefficient of determination R^2, RMSE, the application of extrapolated WC values above the range of experimental procedures, and Analysis of Variance (ANOVA). Possible variations between sensor-to-sensor performance and variation between gravimetric samples were evaluated with Standard Deviation (SD).

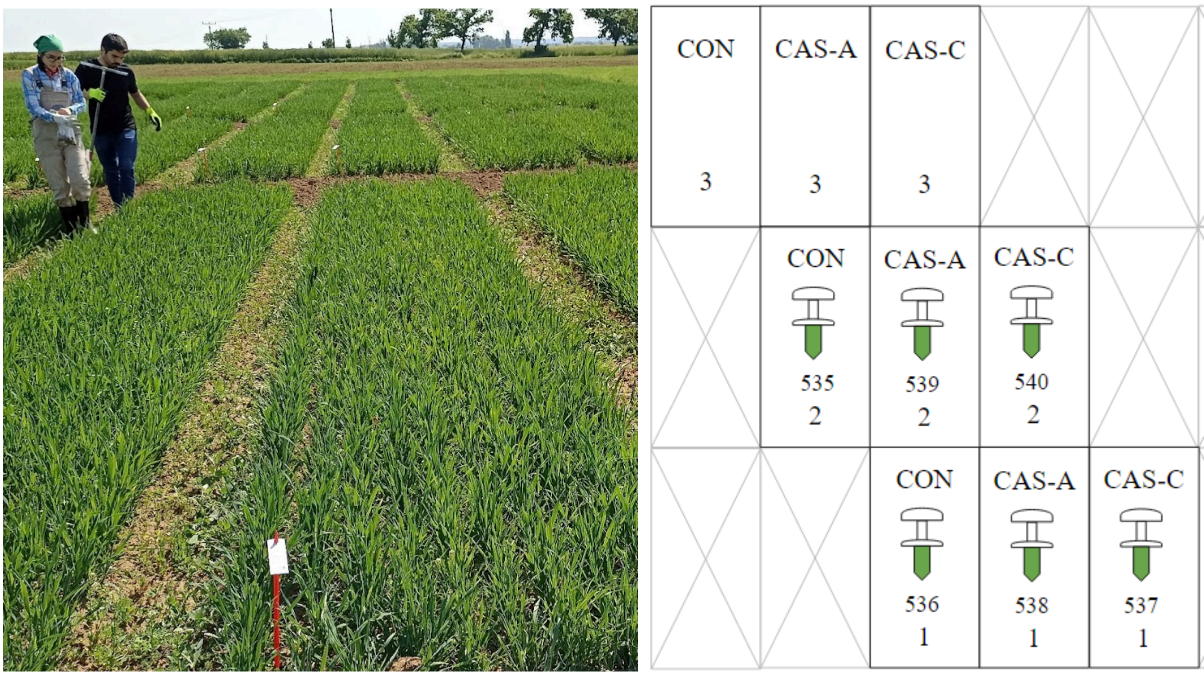
Factory Calibration (FC) equations were used in comparison with derived calibration equations and were generated from the soil type assumed for the soil localities. The TMS-4 has recommended Polynomial FC which includes different inputs based on soil texture and includes a range of soil types from inorganic, such as sand, to high OM such as peat. The soil types with recommended calibration parameters are depicted in Table 5.

Table 5 Calibration Parameters for TMS-4 in Different Soil Types (Source: Wild et al. 2019).

Soil Class	Location (CZ)	Clay (%)	Silt (%)	Sand (%)	ρ(g/cm^3)	Parameters for Calibration Quadratic Curve		
						a	b	c
Sand	Střeleč	0.00	0.00	100.00	1.52	-3.00E-09	1.61E-04	-1.10E-01
Loamy Sand A	Uhlířská A	3.20	24.90	71.90	0.52	-1.90E-08	2.66E-04	-1.54E-01
Loamy Sand B	Uhlířská B	5.30	28.20	66.50	0.97	-2.30E-08	2.82E-04	-1.67E-01
Sandy Loam A	Kopaninsky	5.10	33.70	61.20	1.32	-3.80E-08	3.39E-04	-2.15E-01
Sandy Loam B	Liz	7.60	35.70	56.80	1.07	-9.00E-10	2.62E-04	-1.59E-01
Loam	Podolí	24.10	28.50	47.40	1.55	-5.10E-08	3.98E-04	-2.91E-01
Silt Loam	Nučice	13.00	66.00	21.00	1.29	-1.70E-08	1.18E-04	-1.01E-01
Peat	Jizera Mountains				0.10	-1.23E-07	-1.45E-04	2.03E-01

4.4 Field Monitoring

Experimental fields in each locality were marked for CON and CAS areas. These fields were sampled for soil properties such as average dry bulk density, and porosity, while known farming practices were used to model our laboratory experiment, such as the application rate of compost. While the other experimental fields were operated as semi-field trials in active farmland with the area of each field about 3000 m^2, Locality U was operated as a small-plot field experiment of randomised organisation, with the area of each plot at 10 m^2, as depicted in Figure 26(a).



(a) (b)

Figure 26 Locality U Experimental Field Layout in the season 2023 (a) Photo and (b) Figure (Source: Author).

The experiment in Locality U was carried out in both vegetation seasons 2022 and 2023 using spring wheat as the experimental crop. In 2022, four sensors were installed, two in CON and two in CAS plots. The compost used for CAS plots originated from Velké Hostěrádky (Locality C). In 2023, two different composts were applied to different variations of CAS, the compost used for localities A and C was used on Locality U in separate plots (CAS-A and CAS-C, respectively).

The distribution of CON and CAS plots and the distribution of compost types for CAS plots as well as the position of the six sensors and their numbers are depicted in Figure 26(b). Only six sensors were available, so three plots were not monitored by the TMS-4.

4.5 Other Soil Properties

In order to characterise the experimental soils, additional soil properties were determined such as Particle Size Distribution (PSD) by the Hydrometer method (Gee & Bauder 1986), organic matter content (Nelson & Sommers 1982), pH and Electrical Conductivity (EC) measured in the filtrate (ratio 1:2.5) and analysis of the undisturbed soil samples. The analyses were conducted by other members of the team in the frame of the project, and the author's contribution to these specific analyses was minor. The experimental setup for the PSD test is visible in Figure 27. The properties of soil from each locality taken at different times throughout the growing season in 2023 were determined in various soil tests conducted by the research team, and are visible in Table 6.

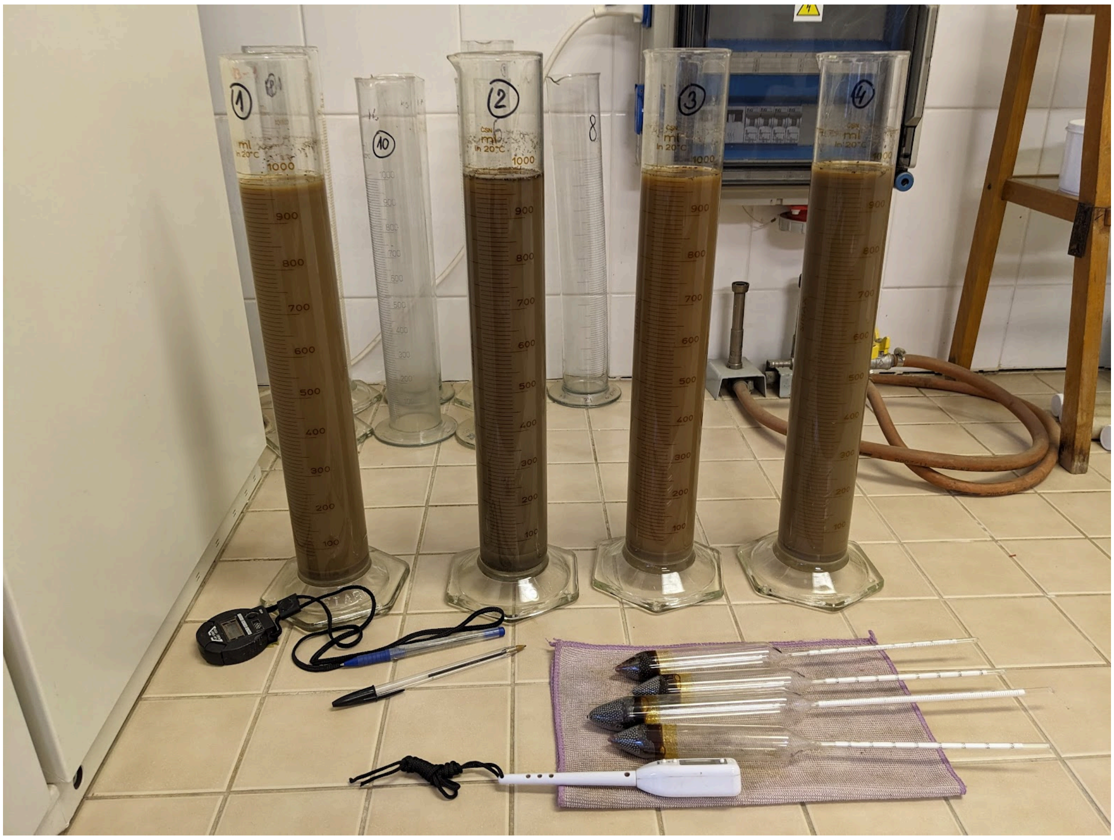


Figure 27 Experimental Setup of PSD Analysis (Source: Author).

Table 6 Soil Properties of Experimental Localities from Samples in 2023 (Source: Data Provided by Thesis Supervisor and Processed by Author).

Locality	Sampling date (2023)	Treatment	Saturated WC (cm^3/cm^3)	BD (g/cm^3)	Organic Matter (%)	EC(μS/cm)	pH
A	April	CAS	53.74	1.15	3.25	180.56	7.12
		CON	51.2	1.18	2.5	149.56	6.54
	Jul	CAS	53.37	1.13	4.28	467	7
		CON	53.33	1.13	3.33	245.05	6.65
B	May	CAS	53.04	1.07	3.7	234.1	7
		CON	44.14	1.43	2.7	157.85	6.26
	Jul	CAS	50.12	1.21	5.24	x	x
		CON	44.18	1.4	2.59		
C	Apr	CAS	50.24	1.2	2.82	254.6	7.65
		CON	48.41	1.28	2.33	129.55	7.57
U	May	CAS-A	x	x	2.2	163.16	6.9
		CAS-C			2.56	162.04	6.99
		CON			2.48	137.68	6.87
	Aug	CAS-A	x	x	x	150.56	6.94
		CAS-C				170.8	6.81
		CON				124.72	6.73

5 Results

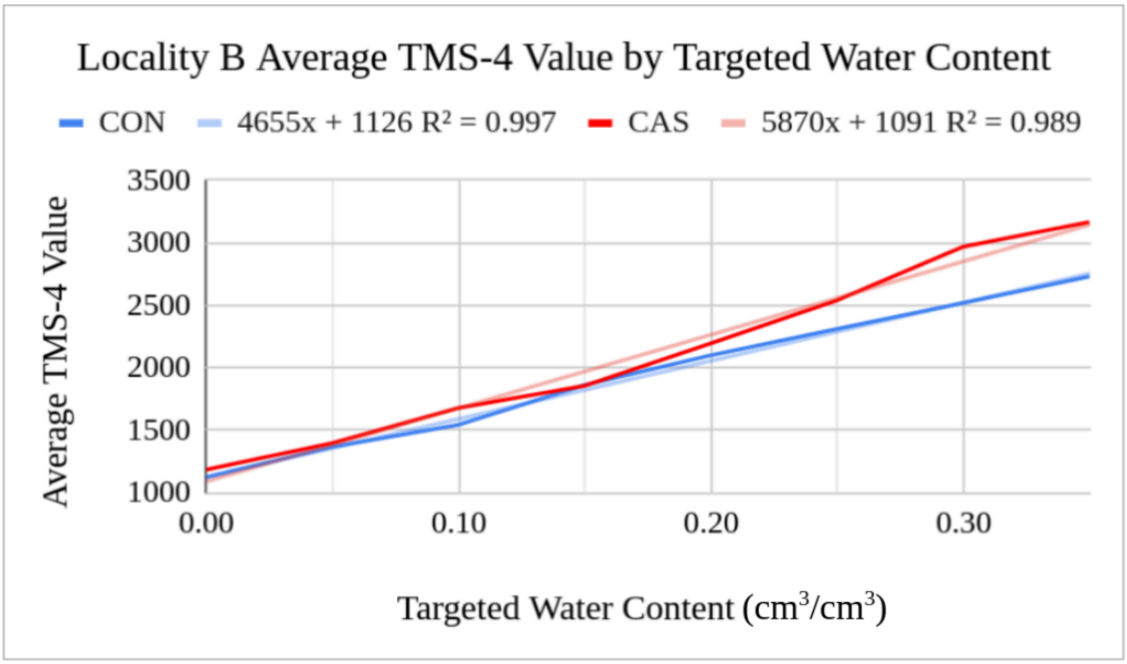
Results were analysed as directly and indirectly measured Soil Water Content (SWC), as the TMS-4 Datalogger (TMS-4) serves as the indirect measurement and the gravimetric analysis of samples gives direct measurements of WC from undisturbed soil samples. All sensor and sample results were reviewed as individual sample trends and overall averages. The results for the TMS-4 and gravimetric analysis were individually reviewed along the Targeted Water Content (TWC) tests to reflect the success of experimental methods, which had high potential for experimental error, as the TMS-4 is a relatively new technology and the gravimetric analysis requires precision in procuring, drying, and measuring 80 undisturbed samples. Homogenising such a large amount of soil could be another source of experimental error. The two measured quantities were then analysed together, with the TMS-4 Measured WC and the gravimetric WC as the standard actual WC, to reflect the performance of the TMS-4 in Control Soil (CON) and Compost-Amended Soil (CAS). Each series was fitted to a Linear trendline to assess the slope as a rate of change of increasing WC and the coefficient of determination R^2 to assess the fit of the Actual Water Content (AWC) test to the desired gradual increase of WC.

The relationship between the AWC and the TMS-4 measurement was then applied with different equations to assess the best fit for a calibration equation, and the suitability of the Factory Calibration (FC) given with the TMS-4.

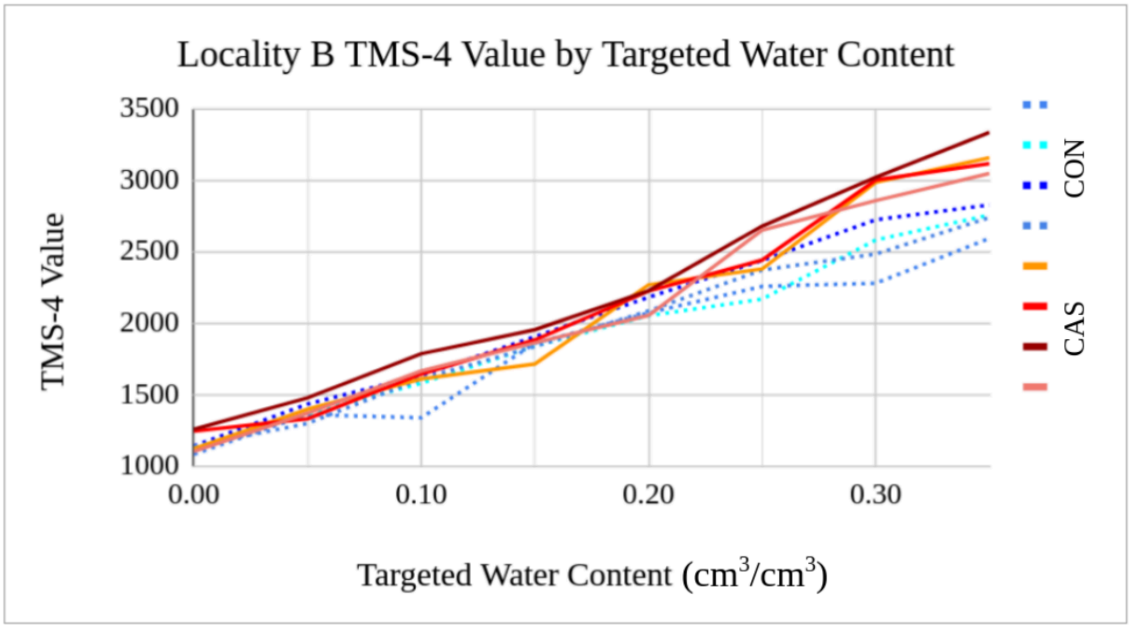
5.1 Linearity Measurements

5.1.1 **TMS-4 Measurements**

TMS-4 measurements were given as unitless numbers from 1–4095, further referred to as TMS-4 values or sensor readings. The values were reviewed among the sensors individually and also combined into an average for calibration and data analysis. Each data series was fitted to a Linear trendline against TWC. Figures 28, 29, and 30 display the TMS-4 measurements taken during each soil test for Localities B, C, and U, with an average TMS-4 value depicted in Figures 28(a), 29(a), and 30(a) for their respective localities, and each sensor in a series along TWC in Figures 28(b), 29(b), and 30(b). The Linearity of the data was used to validate the experiment.

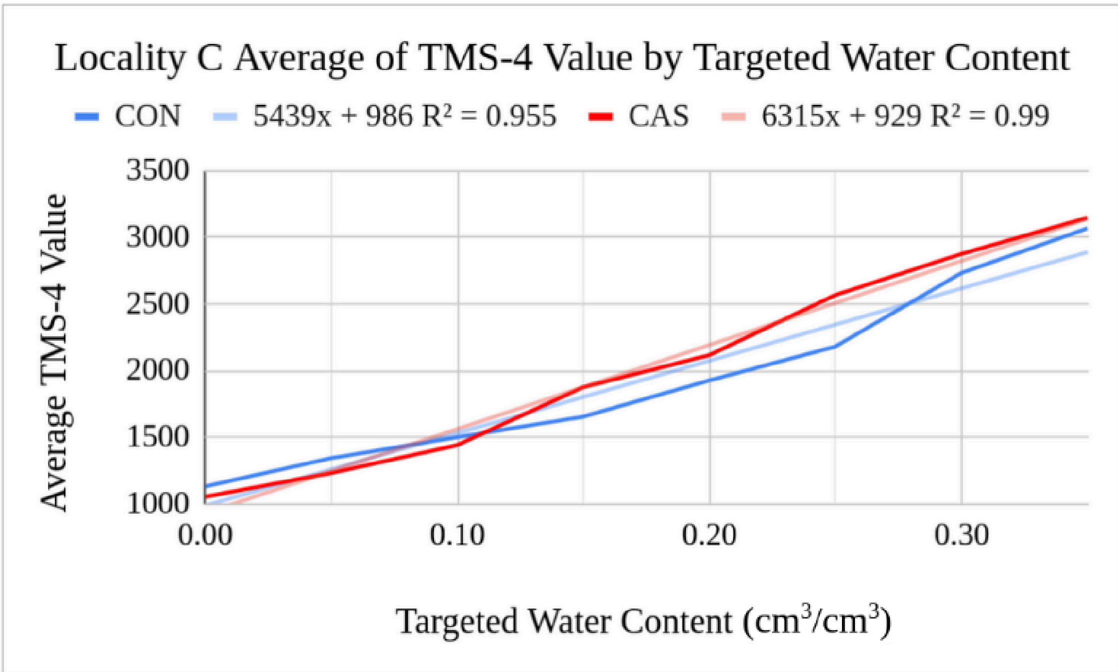


(a)

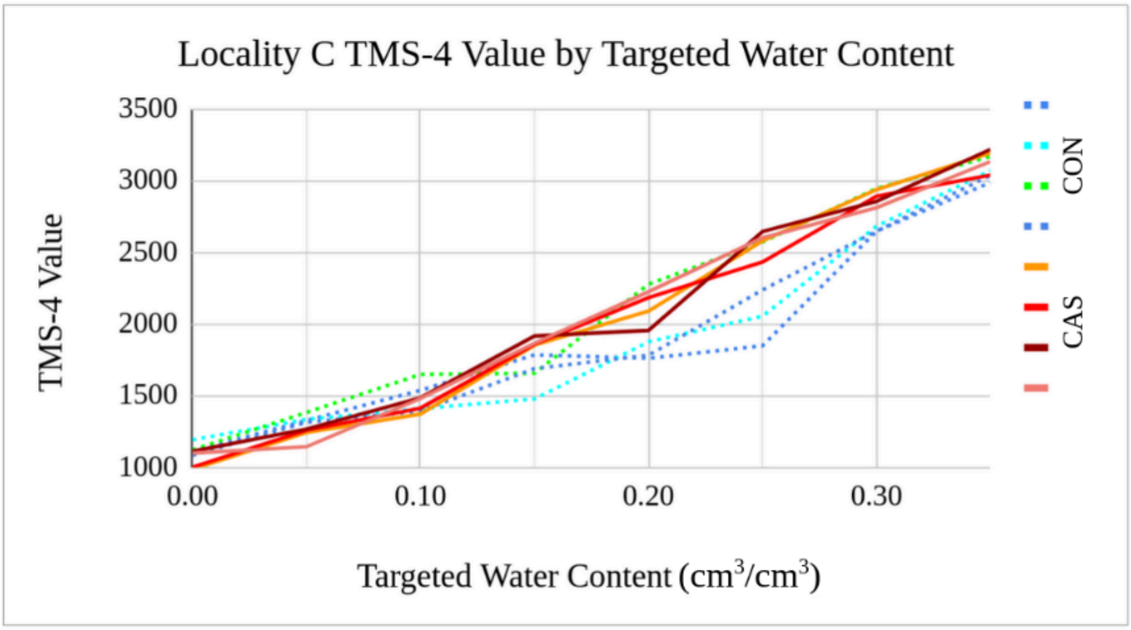


(b)

Figure 28 (a) TMS-4 Average by TWC, and (b) TMS-4 Value by TWC for soil from Locality B.

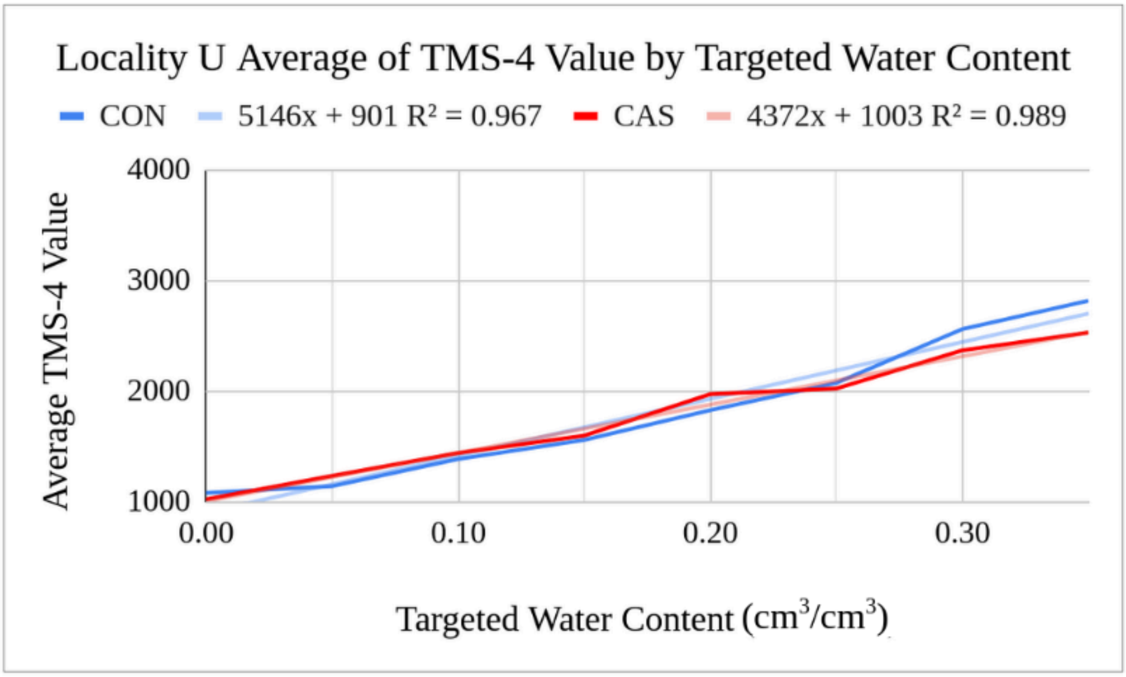


(a)

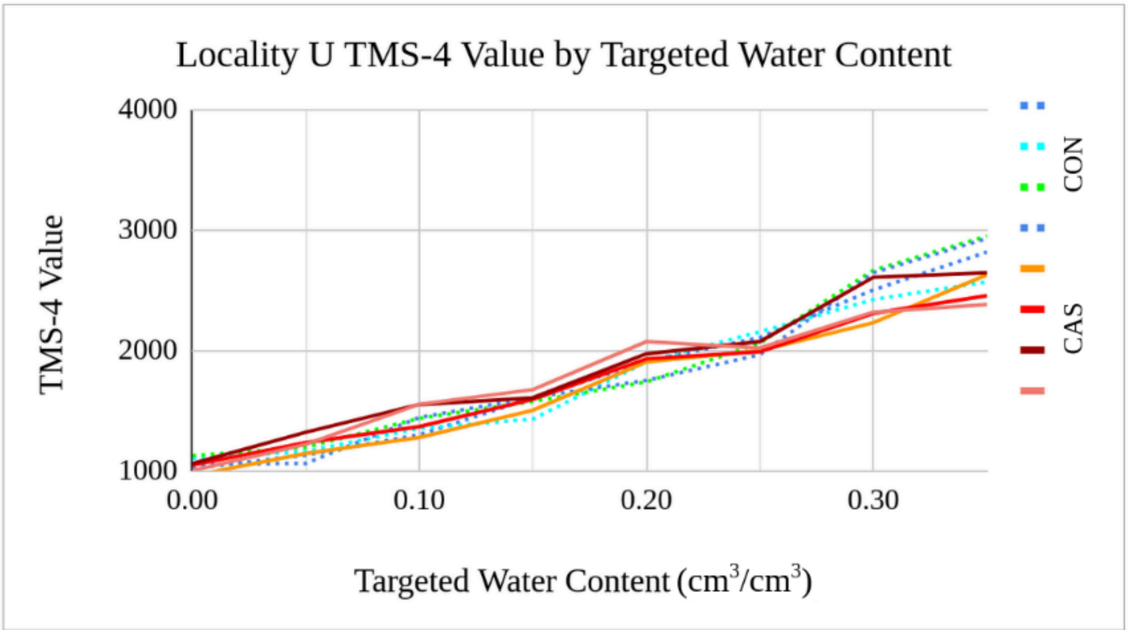


(b)

Figure 29 (a) TMS-4 Average by TWC, and (b) TMS-4 Value by TWC for soil from Locality C.



(a)

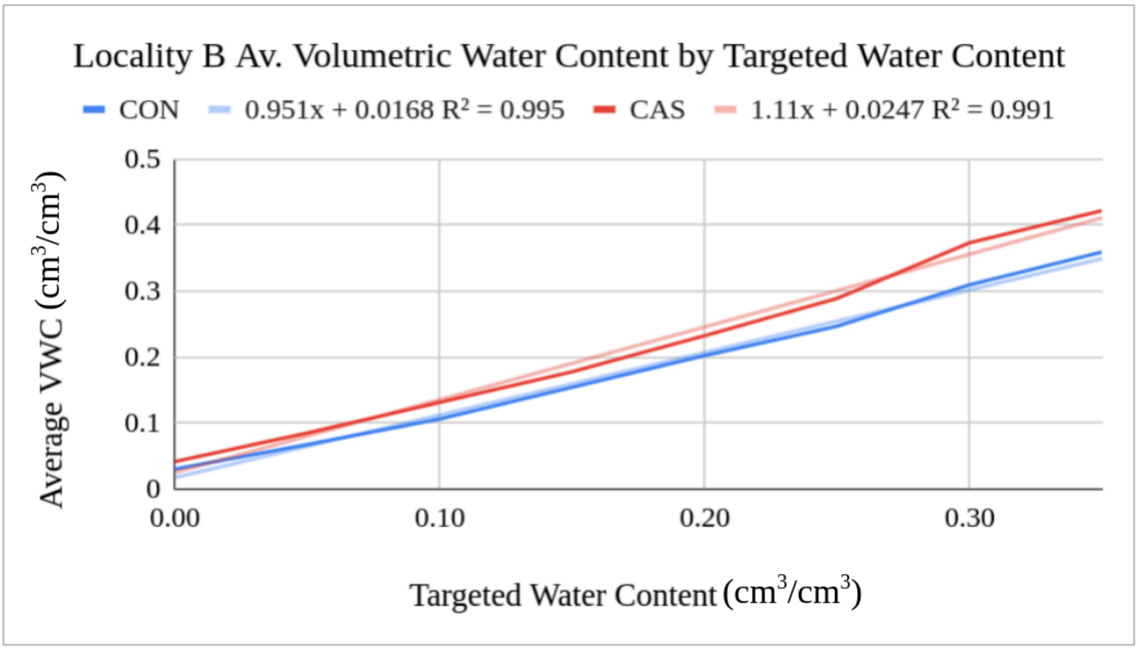


(b)

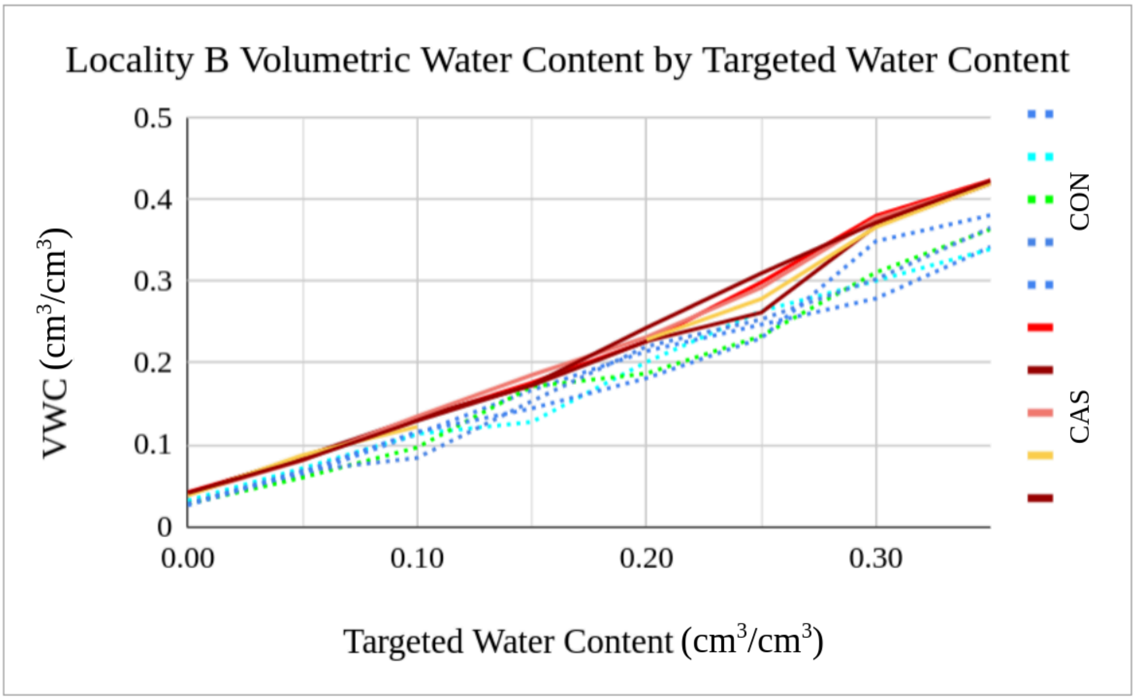
Figure 30 (a) TMS-4 Average by TWC, and (b) TMS-4 Value by TWC for soil from Locality U.

5.1.2 **Undisturbed Samples Analysis**

Undisturbed soil samples were weighed for Water Content (WC) by mass, and the known volume of the sampling ring was used to obtain dry bulk density, which was used to calculate Volumetric Water Content (VWC). Each data series was fitted to a Linear trendline against TWC. Figures 31(a), 32(a), and 33(a) for their respective localities display the VWC during each soil test for soils from Localities B, C, and U, with an average VWC, and each sampling position in a series along TWC depicted in Figures 31(b), 32(b), and 33(b). The Linearity of the data was used to validate the experiment.

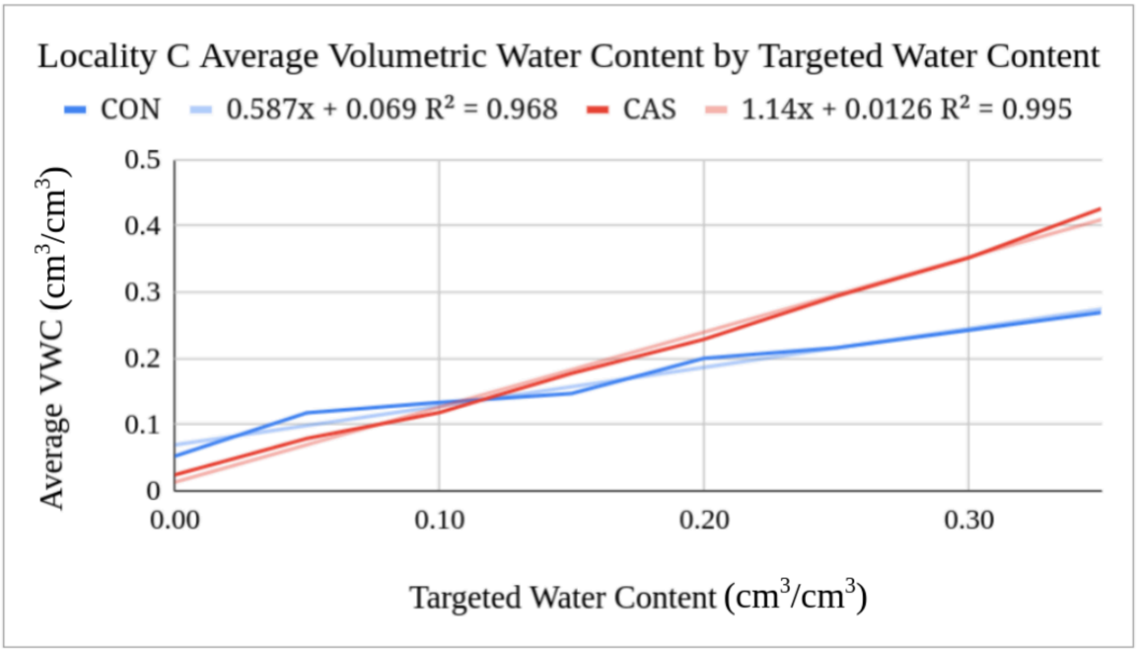


(a)

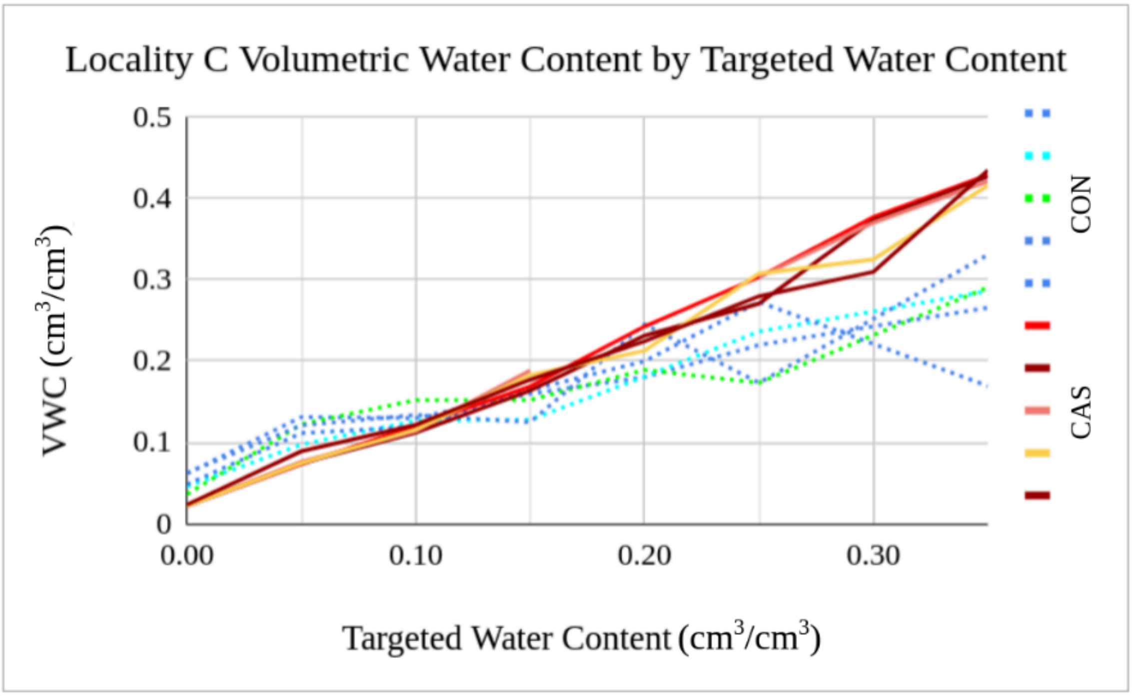


(b)

Figure 31 (a) VWC Average by TWC, and (b) VWC Sample Value by TWC for Locality B.

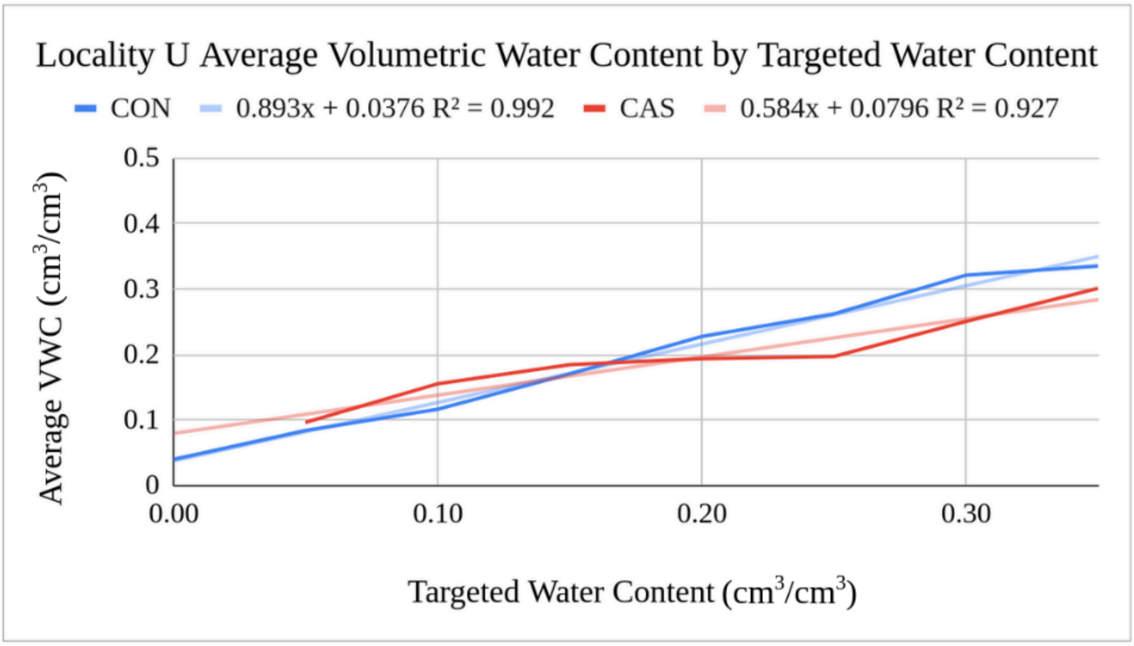


(a)

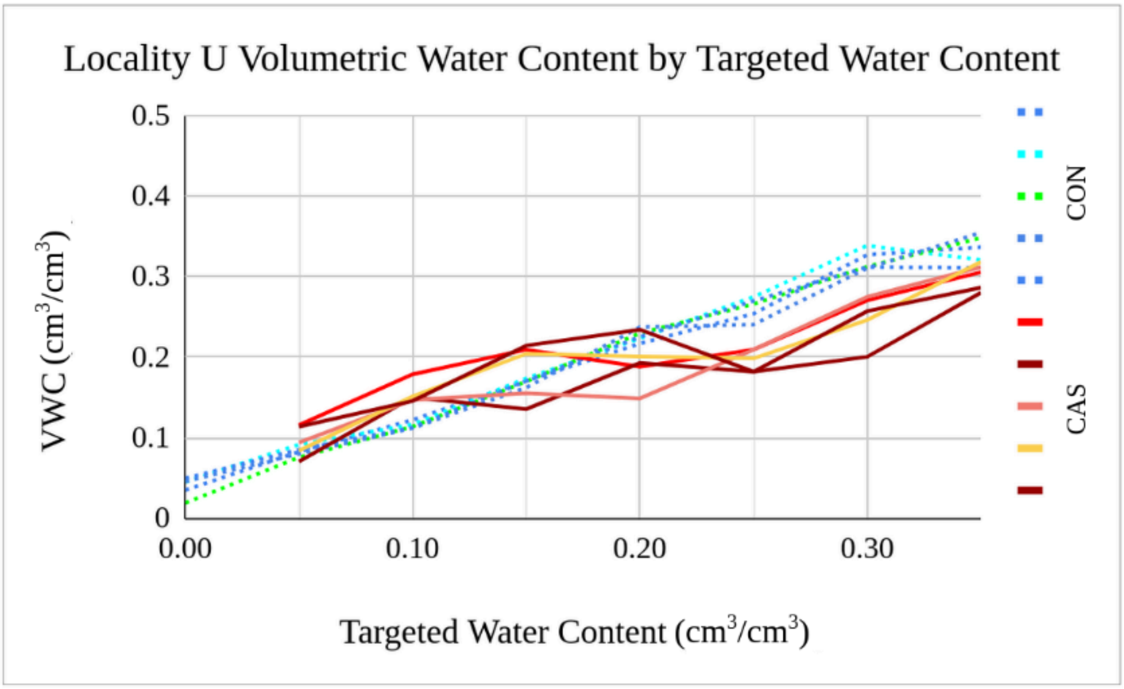


(b)

Figure 32 (a) VWC Average by TWC, and (b) VWC Sample Value by TWC for Locality C.



(a)



(b)

Figure 33 (a) VWC Average by TWC, and (b) VWC Sample Value by TWC for Locality U.

5.2 Calibration Data

Calibration was performed by graphing the average TMS-4 values along the x-axis (independent variable) with the average values of AWC along the y-axis (dependent variable), with one data series for CON and one data series for CAS. The CON results were used as a standard, to evaluate the performance of the TMS-4 on CAS.

5.2.1 Calibration Locality B

Figure 34 depicts the calibration data for Locality B, where the average TMS-4 values are graphed against the average VWC. These data series were used to derive the calibration equations depicted in Figure 35 with trendlines such as 35(a) Linear 35(b) Polynomial and 35(c) Logarithmic. Figure 36 depicts these same 36(a) Linear, 36(b) Polynomial, and 36(c) Logarithmic Equations with extrapolated TMS-4 values to assess the performance of the Calibration Equation. The derived equations, their R^2, and their RMSE are included in Table 7 along with the parameters of the Factory Calibration (FC) equation.

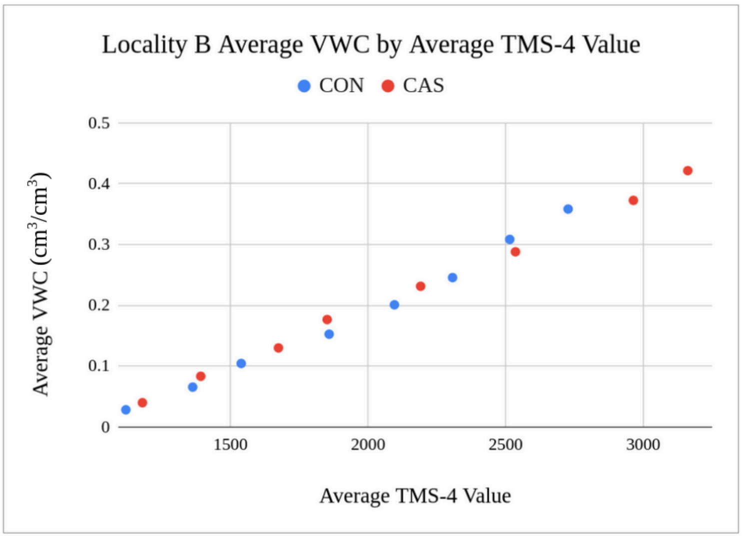
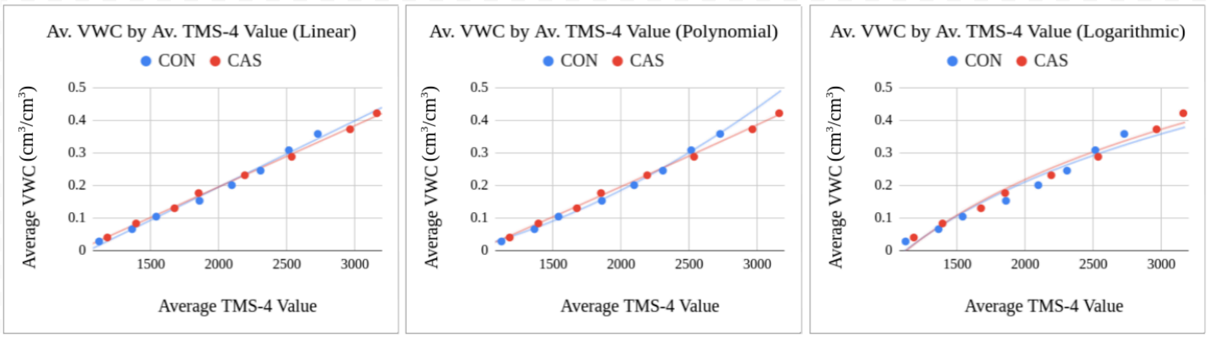
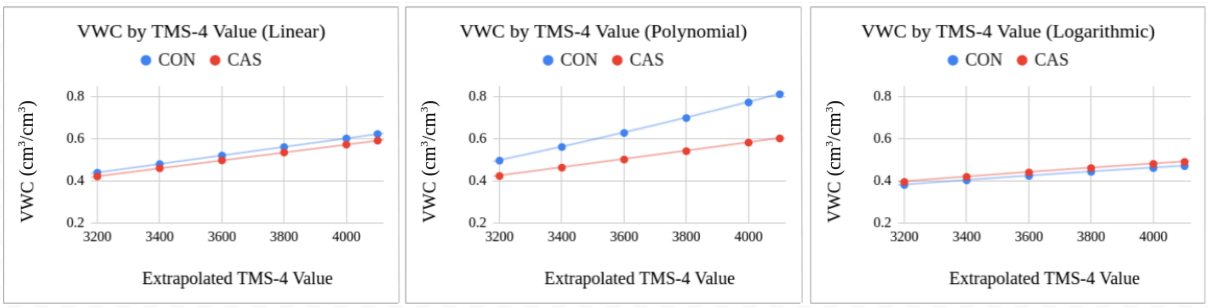


Figure 34 VWC Average by TMS-4 Average for Locality B.



(a) *(b)* *(c)*

Figure 35 Derived (a) Linear, (b) Polynomial, and (c) Logarithmic Equations for Figure 34.



(a) *(b)* *(c)*

Figure 36 Extrapolated Values for Derived (a) Linear, (b) Polynomial, and (c) Logarithmic Equations from Figure 35.

Table 7 Locality B Equation, Formula, R^2, and RMSE for CON and CAS.

	Control Soil			Compost Soil		
Equation Type	Formula	R^2	RMSE	Formula	R^2	RMSE
Linear	2.03E-04x + -0.211	0.990	0.011	1.88E-04x + -0.18	0.998	0.006
Polynomial	-0.0661 + 4.01E-05x + 4.23E-08x^2	0.998	0.005	-0.166 + 1.74E-04x + 3.26E-09x^2	0.998	0.005
Logarithmic	-2.55 + 0.363 ln x	0.955	0.023	-2.67 + 0.38 ln x	0.978	0.019
Factory Calibration	1.7E-08x^2 + 1.2E04x - 0.10		0.019	1.7E-08x^2 + 1.2E04x - 0.10		0.017

5.2.2 Calibration Locality C

Figure 37 depicts the calibration data for Locality C, where the average TMS-4 values are graphed against the average VWC. These data series were used to derive the calibration equations depicted in Figure 38 with trendlines such as 38(a) Linear 38(b) Polynomial and 38(c) Logarithmic. Figure 39 depicts these same 39(a) Linear, 39(b) Polynomial, and 39(c) Logarithmic Equations with extrapolated TMS-4 values to assess the performance of the Calibration Equation. The derived equations, their R^2, and their RMSE are included in Table 8 along with the parameters of the FC equation.

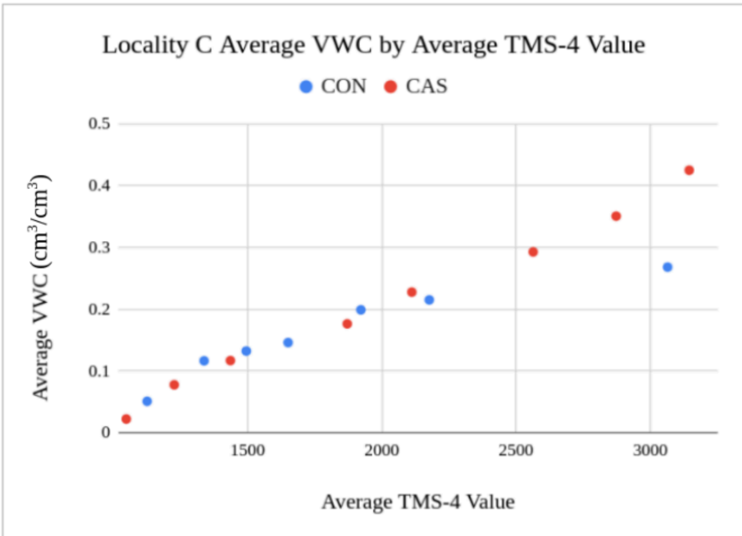
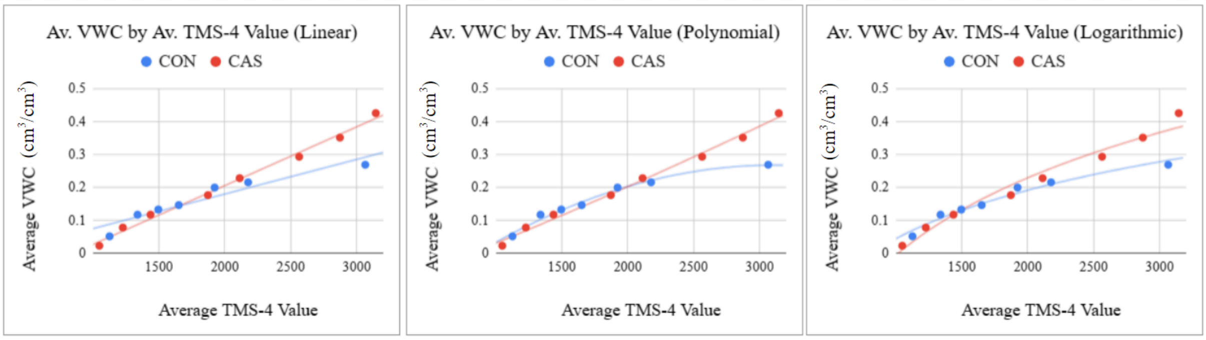
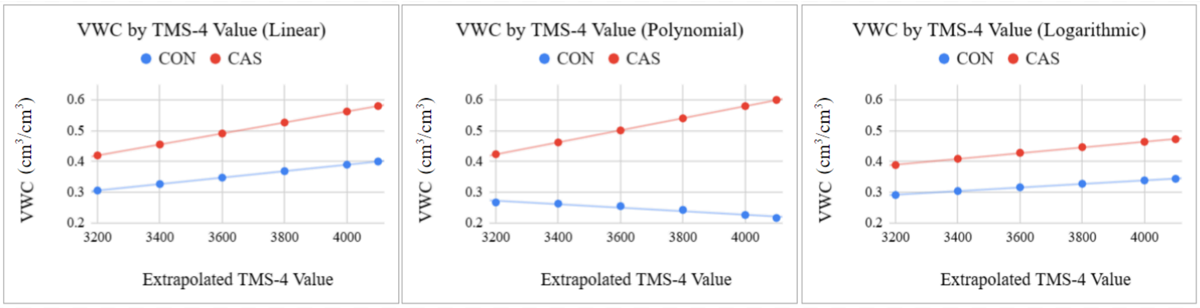


Figure 37 VWC Average by TMS-4 Average for Locality C.



(a) *(b)* *(c)*

Figure 38 Derived (a) Linear, (b) Polynomial, and (c) Logarithmic Equations for Figure 37.



(a) *(b)* *(c)*

Figure 39 Extrapolated Values for Derived (a) Linear, (b) Polynomial, and (c) Logarithmic Equations from Figure 38.

Table 8 Locality C Calibration Equation Type, Formula, R^2, and RMSE for CON and CAS.

	Control Soil			Compost Soil		
Equation Type	Formula	R^2	RMSE	Formula	R^2	RMSE
Linear	1.05E-04x + -0.0302	0.902	0.021	1.79E-04x + -0.152	0.993	0.011
Polynomial	-0.24 + 3.26E-04x + -5.23E-08x²	0.985	0.008	-0.13 + 1.55E-04x + 5.58E-09x²	0.993	0.011
Logarithmic	-1.43 + 0.212 ln x	0.969	0.012	-2.35 + 0.339 ln x	0.971	0.022
Factory Calibration	1.7E-08x² + 1.2E04x - 0.10		0.060	1.7E-08x² + 1.2E04x - 0.10		0.016

5.2.3 **Calibration Locality U**

Figure 40 depicts the calibration data for Locality U, where the average TMS-4 values are graphed against the average VWC. These data series were used to derive the calibration equations depicted in Figure 41 with trendlines such as 41(a) Linear 41(b) Polynomial and 41(c) Logarithmic. Figure 42 depicts these same 42(a) Linear, 42(b) Polynomial, and 42(c) Logarithmic Equations with extrapolated TMS-4 values to assess the performance of the Calibration Equation. The derived equations, their R^2, and their RMSE are included in Table 9 along with the parameters of the FC equation.

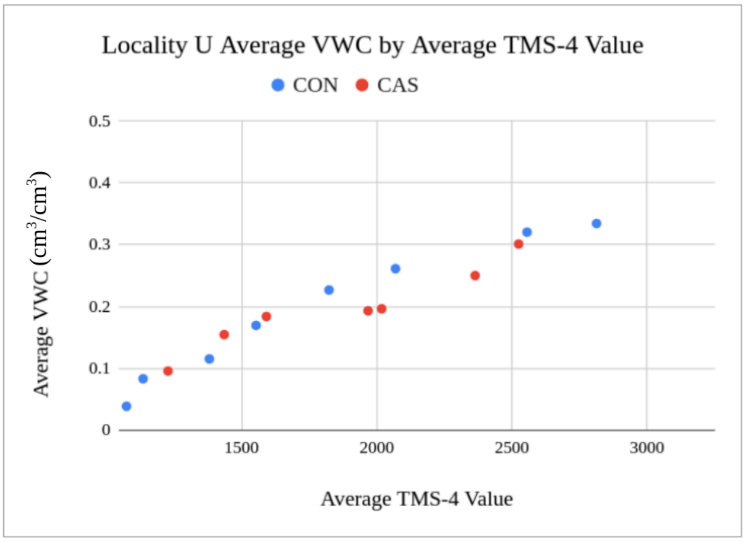
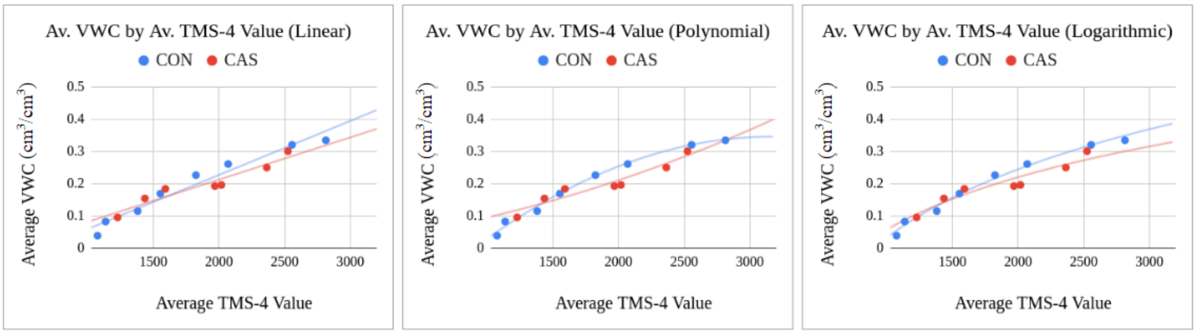
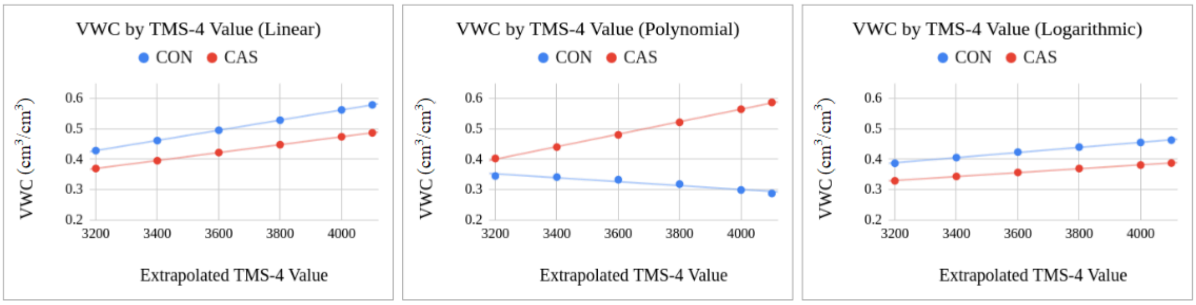


Figure 40 VWC Average by TMS-4 Average for Locality U.



(a) (b) (c)

Figure 41 Derived (a) Linear, (b) Polynomial, and (c) Logarithmic Equations for Figure 40.



(a) (b) (c)

Figure 42 Extrapolated Values for Derived (a) Linear, (b) Polynomial, and (c) Logarithmic Equations from Figure 41.

Table 9 Locality U Calibration Equation Type, Formula, R^2, and RMSE for CON and CAS.

	Control Soil			Compost Soil		
Equation Type	Formula	R^2	RMSE	Formula	R^2	RMSE
Linear	1.68E-04x + -0.108	0.957	0.021	1.31E-04x + -0.049	0.914	0.018
Polynomial	-0.332 + 4.26E-04x + -6.71E-08x²	0.993	0.009	0.022 + 5.08E-05x + 2.12E-08x²	0.917	0.017
Logarithmic	-2.09 + 0.306 ln x	0.989	0.011	-1.57 + 0.235 ln x	0.901	0.019
Factory Calibration	1.7E-08x² + 1.2E04x - 0.10		0.035	1.7E-08x² + 1.2E04x - 0.10		0.031

5.2.4 Calibration Locality A

Figure 43 depicts the calibration data for Locality A, where the average TMS-4 values are graphed against the average VWC. These data series were used to derive the calibration equations depicted in Figure 44 with trendlines such as 44(a) Linear 44(b) Polynomial and 44(c) Logarithmic. Figure 45 depicts these same 45(a) Linear, 45(b) Polynomial, and 45(c) Logarithmic Equations with extrapolated TMS-4 values to assess the performance of the Calibration Equation. The derived equations, their R^2, and their RMSE are shown in Table 10, along with the parameters of the FC equation. Due to time constraints and the laborious nature of the experiment, only CON was evaluated for Locality A. The analysis was conducted by other members of the team in the frame of the project, and the author's contribution to this specific analysis was minor.

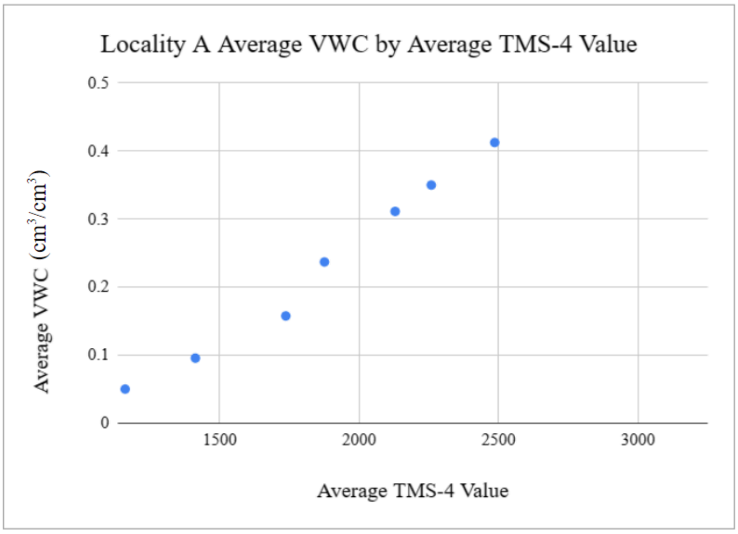
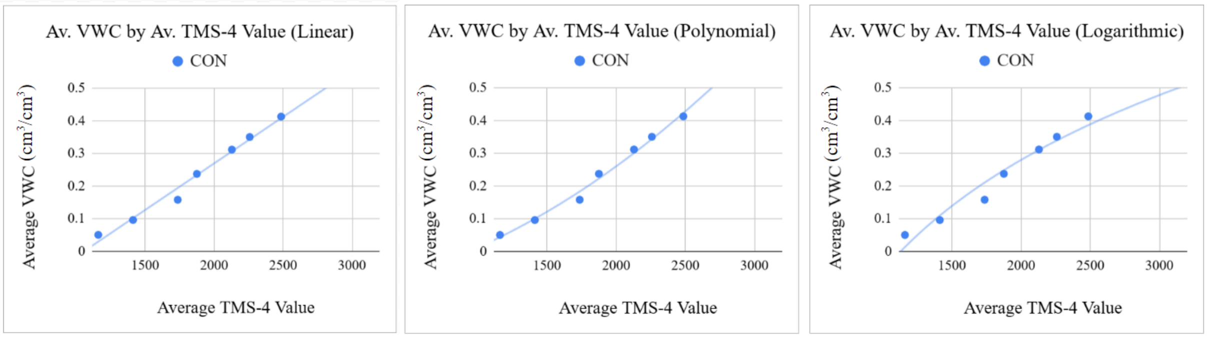
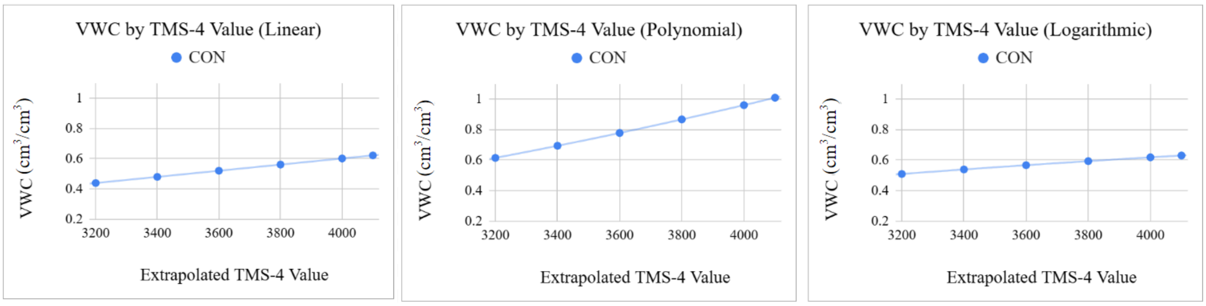


Figure 43 VWC Average by TMS-4 Average for Locality A.



(a) (b) (c)
Figure 44 Derived (a) Linear, (b) Polynomial, and (c) Logarithmic Equations for Figure 43.



(a) (b) (c)
Figure 45 Extrapolated Values for Derived (a) Linear, (b) Polynomial, and (c) Logarithmic Equations from Figure 44.

Table 10 Locality A Calibration Equation Type, Formula, R^2, and RMSE for CON.

	Control Soil		
Equation Type	Formula	R^2	RMSE
Linear	0.0003x - 0.3017	0.983	0.074
Polynomial	6E-8x² + 7E-05x + 0.1199	0.989	0.079
Logarithmic	-3.437 + 0.4889 ln x	0.952	0.071
Factory Calibration	1.7E-08x² + 1.2E04x - 0.10		0.069

5.3 Standard Deviation of Gravimetric and TMS-4 Measurements

Gravimetric measurements were compared between all five samples collected in each tank to obtain a Standard Deviation (SD) value for each TWC test in CON and CAS for each locality. These values were used to determine the variability within each test and to observe any differences between the variability found in gravimetric testing and the TMS-4 values. An average SD was also calculated for CON and CAS in each locality. The SD and corresponding locality, soil test, and TWC test are visible for TMS-4 WC in Table 11 and AWC in Table 12. The values for Table 11 were calculated by applying the Logarithmic derived equation corresponding to each locality to convert the TMS-4 value to VWC in cm^3/cm^3, and then calculating SD from these VWC values. These calculations were performed to evaluate sensor-to-sensor variation, rather than the performance of a calibration equation. The empty cells in Table 12 correspond with data that was removed as outlying results from AWC results.

Table 11 SD performed on TMS-4 Measured WC (cm^3/cm^3) related to the Targeted Water Contents (TWC).

	Standard Deviation of TMS-4 Measured SWC					
	Locality B		Locality C		Locality U	
TWC	CON	CAS	CON	CAS	CON	CAS
0%	0.009	0.026	0.009	0.021	0.014	0.004
5%	0.015	0.017	0.005	0.016	0.016	0.007
10%	0.034	0.017	0.017	0.013	0.015	0.015
15%	0.006	0.021	0.017	0.005	0.017	0.008
20%	0.010	0.017	0.025	0.020	0.016	0.010
25%	0.019	0.022	0.030	0.012	0.012	0.005
30%	0.027	0.010	0.011	0.006	0.014	0.026
35%	0.013	0.015	0.005	0.009	0.020	0.021
Av.	0.017	0.018	0.015	0.013	0.015	0.012

Table 12 SD performed on Gravimetric WC (cm^3/cm^3) related to the Targeted Water Contents (TWC).

	Standard Deviation of Sampled SWC					
	Locality B		Locality C		Locality U	
TWC	CON	CAS	CON	CAS	CON	CAS
0%	0.002	0.002	0.011	0.001	0.010	
5%	0.004	0.003	0.013	0.007	0.010	0.020
10%	0.014	0.005	0.012	0.004	0.000	0.010
15%	0.017	0.006	0.018	0.010	0.000	0.040
20%	0.017	0.007	0.027	0.013	0.010	0.030
25%	0.014	0.019	0.043	0.017	0.010	0.010
30%	0.026	0.006		0.031	0.010	0.030
35%	0.017	0.002	0.060	0.007	0.020	0.020
Av.	0.014	0.006	0.026	0.011	0.009	0.023

5.4 Field Data

During the vegetation season in the year 2022, four TMS-4 sensors were placed in each locality with a semi-field trial, two sensors in CON, and two sensors in CAS. Six sensors were placed in Uhrineves, two sensors in CON, and four sensors in CAS. The TMS-4 collected data in Basic Mode for several months, and the SWC was combined into an average for each measured day. These days are depicted as Day of Year (DOY) in Figures 46–62, along with the TMS-4 measurement on the y-axis. Each set of TMS-4 measurements was converted into VWC in cm^3/cm^3 with the derived calibration equations from their corresponding localities.

5.4.1 **Locality B**

Figures 46–49 display the field data for Locality B, with Figure 46 depicting the averaged TMS-4 measurements, Figure 47 depicting the measurements converted to cm^3/cm^3 using the derived Linear equation for Locality B, with the derived CON equation applied to the CON and the derived CAS equation applied to the CAS field data. Figure 48 depicts the converted field data applied to a Polynomial equation, and Figure 49 depicts the converted field data applied to a Logarithmic equation.

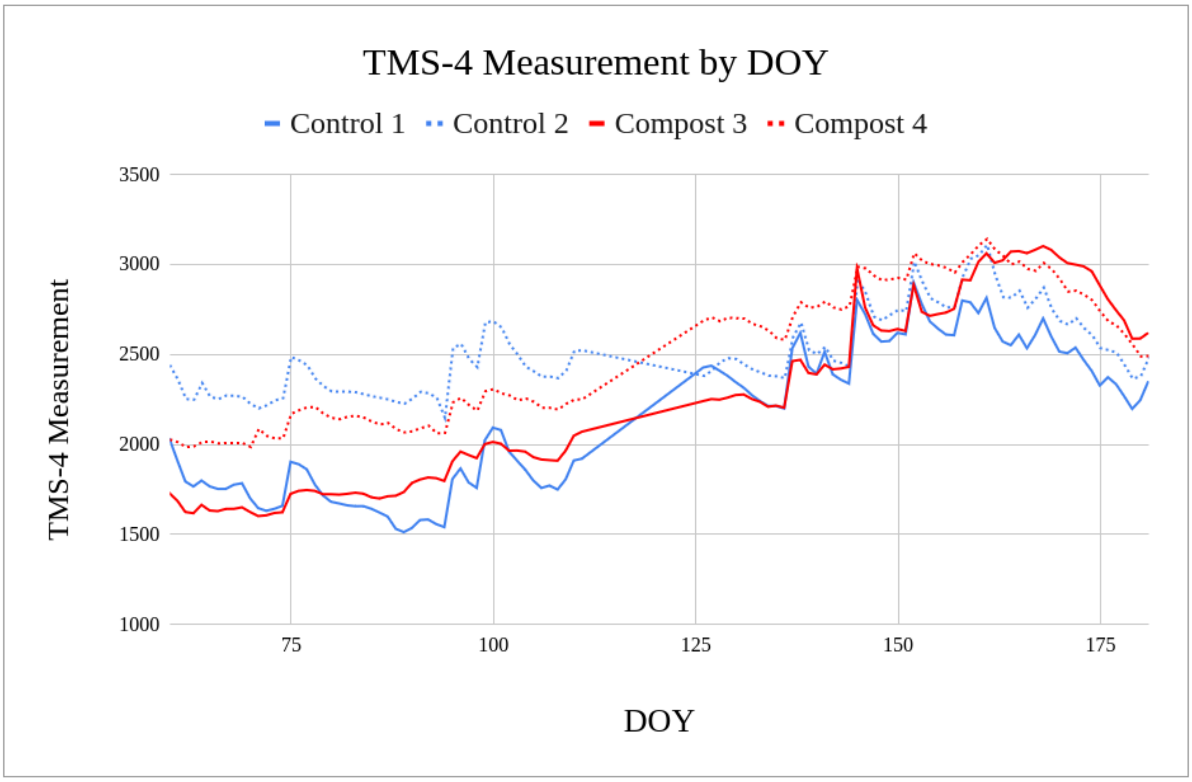


Figure 46 TMS-4 Measurements from Field Experiments by Day of Year, with sensors numbered from 1–4.

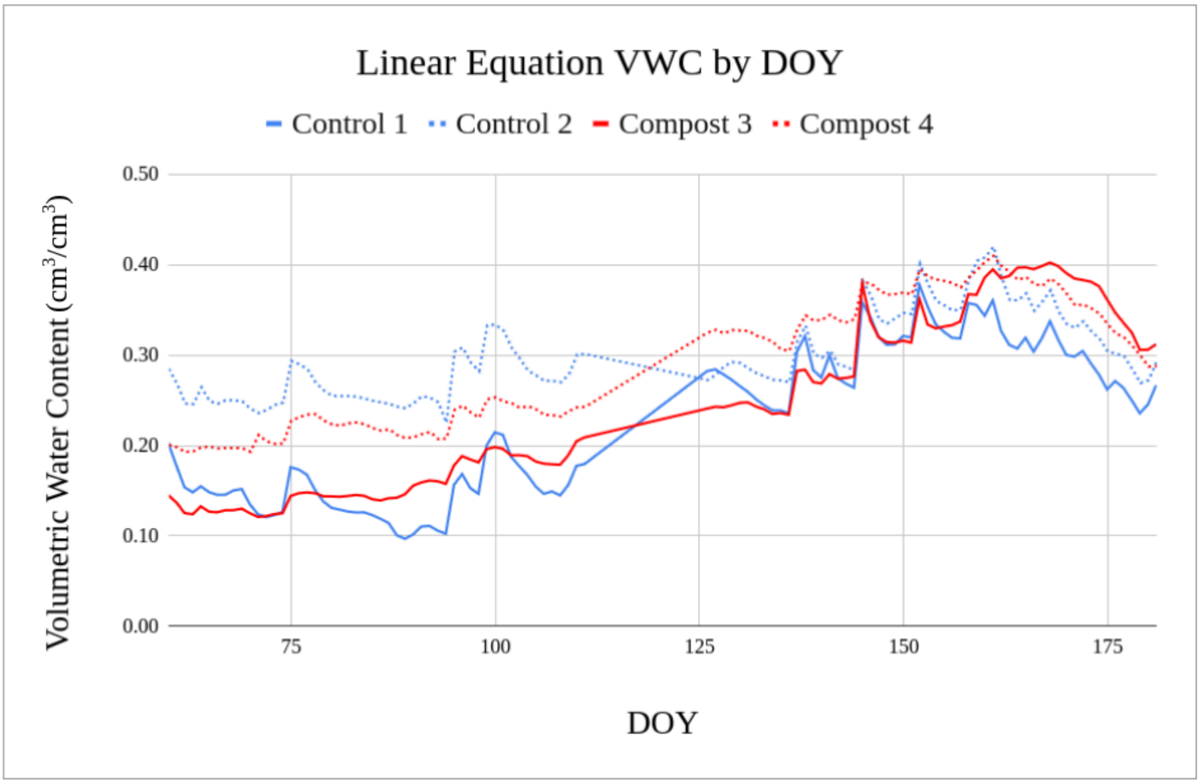


Figure 47 TMS-4 Field Measurements from Locality B Experimental Field Converted to cm^3/cm^3 with Derived Linear Calibration Equation by Day of Year, with sensors numbered from 1–4.

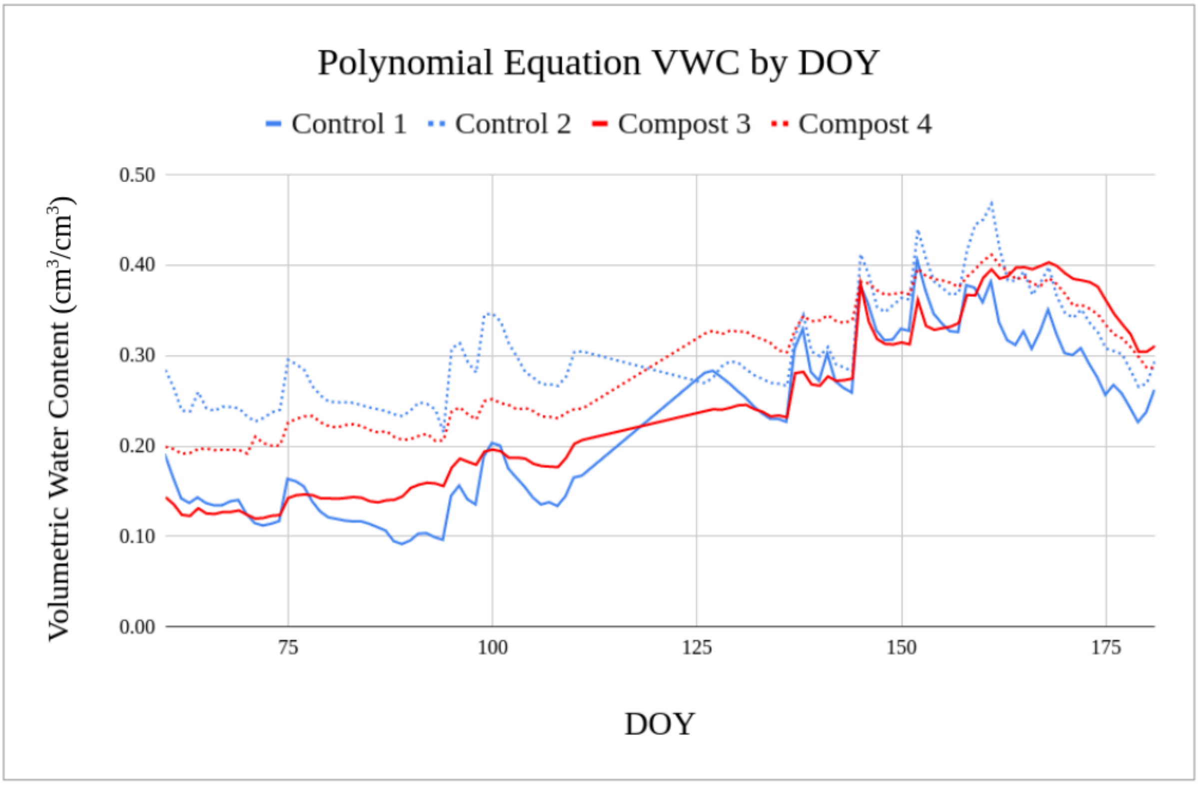


Figure 48 TMS-4 Field Measurements from Locality B Experimental Field Converted to cm^3/cm^3 with Derived Polynomial Calibration Equation by Day of Year, with sensors numbered from 1–4.

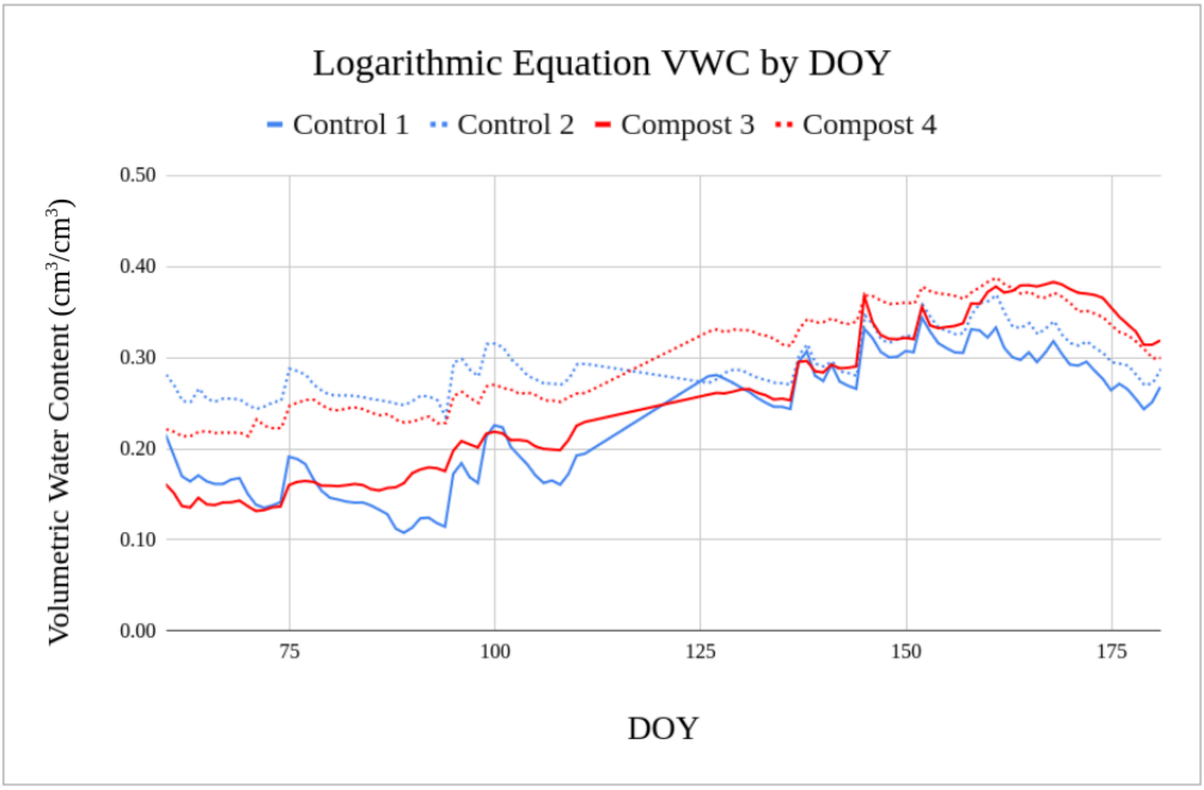


Figure 49 TMS-4 Field Measurements from Locality U Experimental Field Converted to cm^3/cm^3 with Derived Logarithmic Calibration Equation by Day of Year with sensors numbered from 1–4.

5.4.2 **Locality C**

Figures 50–53 display the field data for Locality C, with Figure 50 depicting the averaged TMS-4 measurements, Figure 51 depicting the measurements converted to cm^3/cm^3 using the derived Linear equation for Locality C, with the derived CON equation applied to the CON and the derived CAS equation applied to the CAS field data. Figure 52 depicts the converted field data applied to a Polynomial equation, and Figure 53 depicts the converted field data applied to a Logarithmic equation.

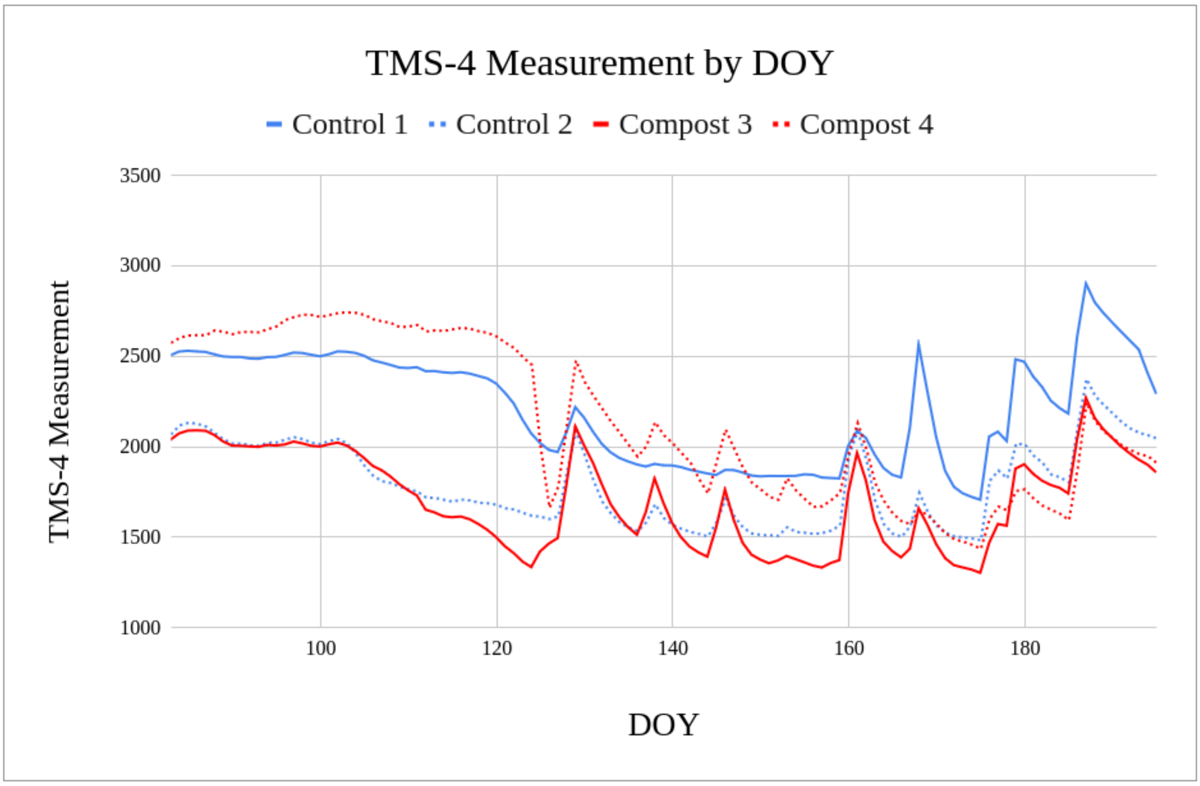


Figure 50 TMS-4 Field Measurements from Locality C Experimental Field by Day of Year, with sensors numbered from 1–4.

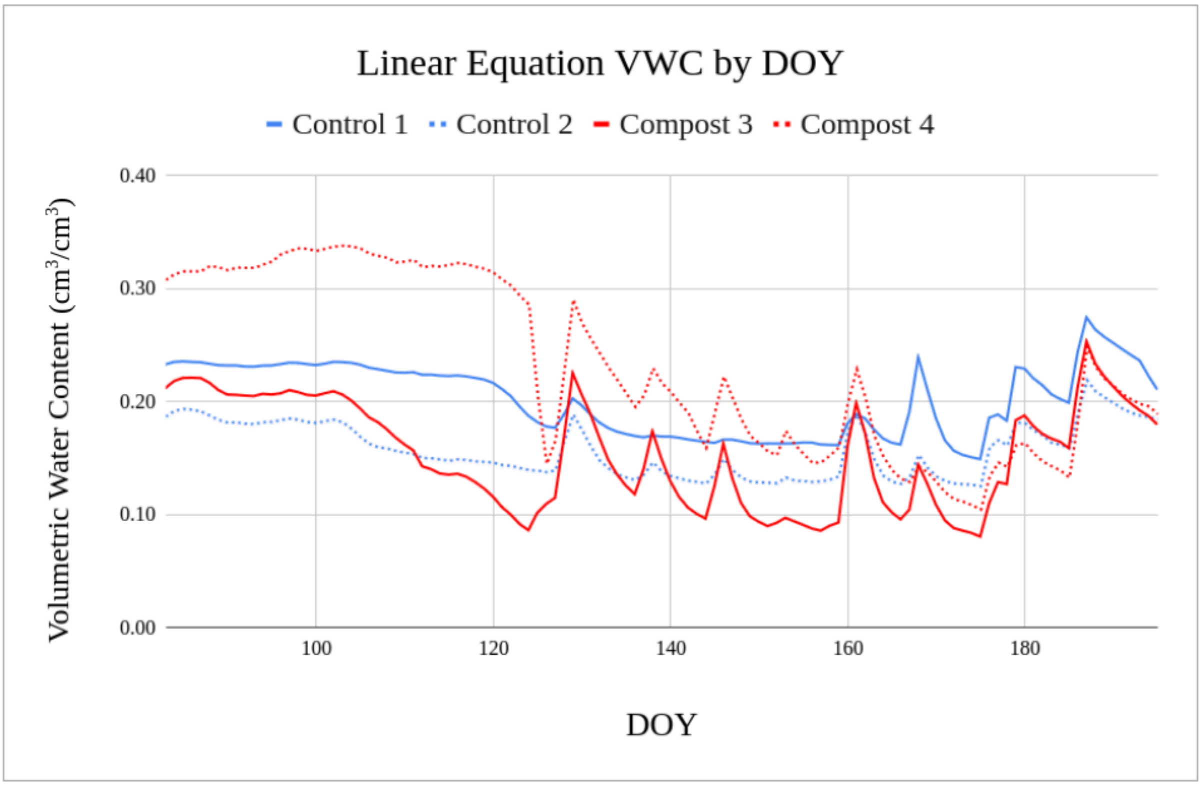


Figure 51 TMS-4 Field Measurements from Locality C Experimental Field Converted to cm^3/cm^3 *with Derived Linear Calibration Equation by Day of Year, with sensors numbered from 1–4.*

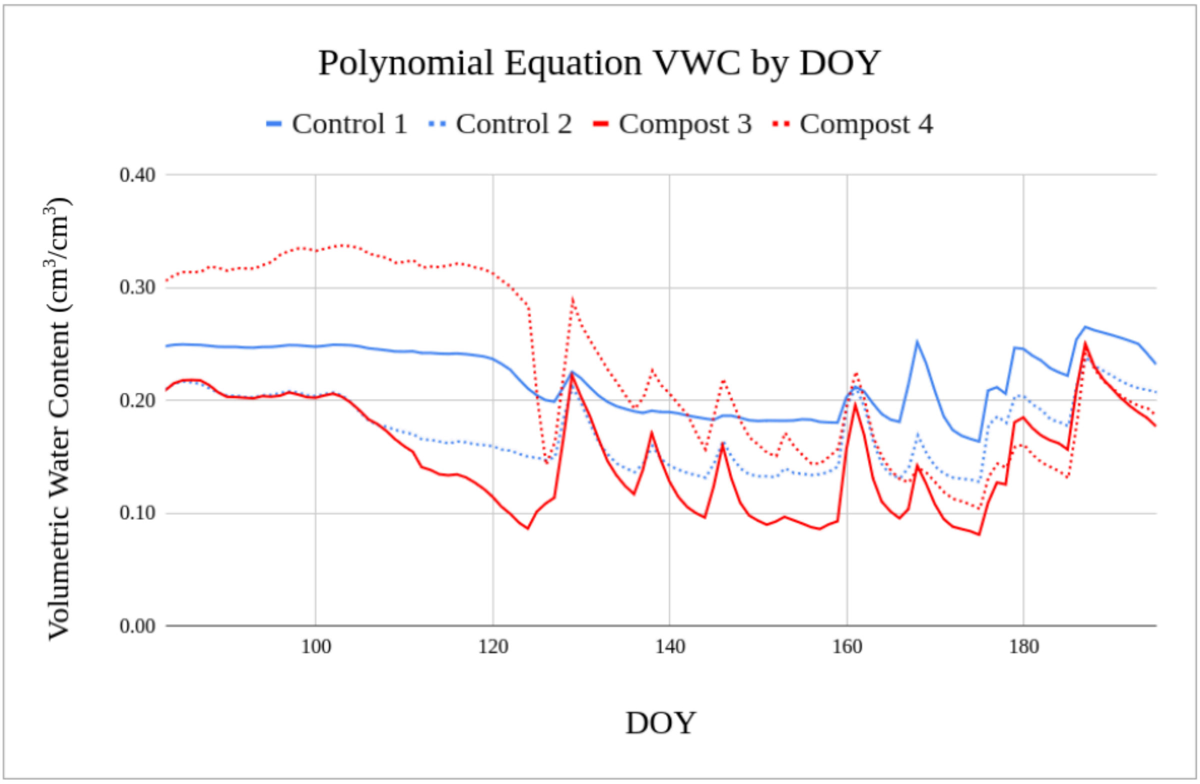


Figure 52 TMS-4 Field Measurements from Locality C Experimental Field Converted to cm³/cm³ with Derived Polynomial Calibration Equation by Day of Year, with sensors numbered from 1–4.

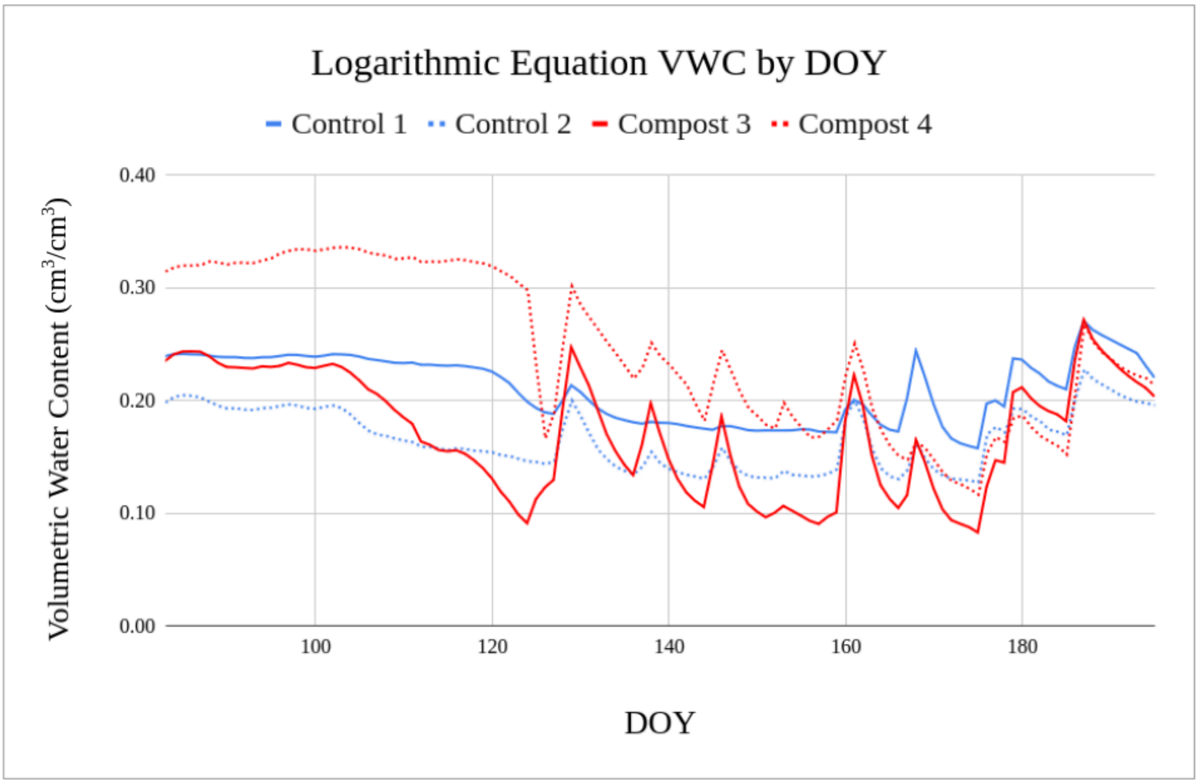


Figure 53 TMS-4 Field Measurements from Locality C Experimental Field Converted to cm³/cm³ with Derived Logarithmic Calibration Equation by Day of Year, with sensors numbered from 1–4.

5.4.3 **Locality U**

Figures 54–57 display the field data for Locality U during the growing season of 2022, with Figure 54 depicting the averaged TMS-4 measurements, Figure 55 depicting the measurements converted to cm^3/cm^3 using the derived Linear equation for Locality U, with the derived CON equation applied to the CON and the derived CAS equation applied to the CAS field data. Figure 56 depicts the converted field data applied to a Polynomial equation, and Figure 57 depicts the converted field data applied to a Logarithmic equation.

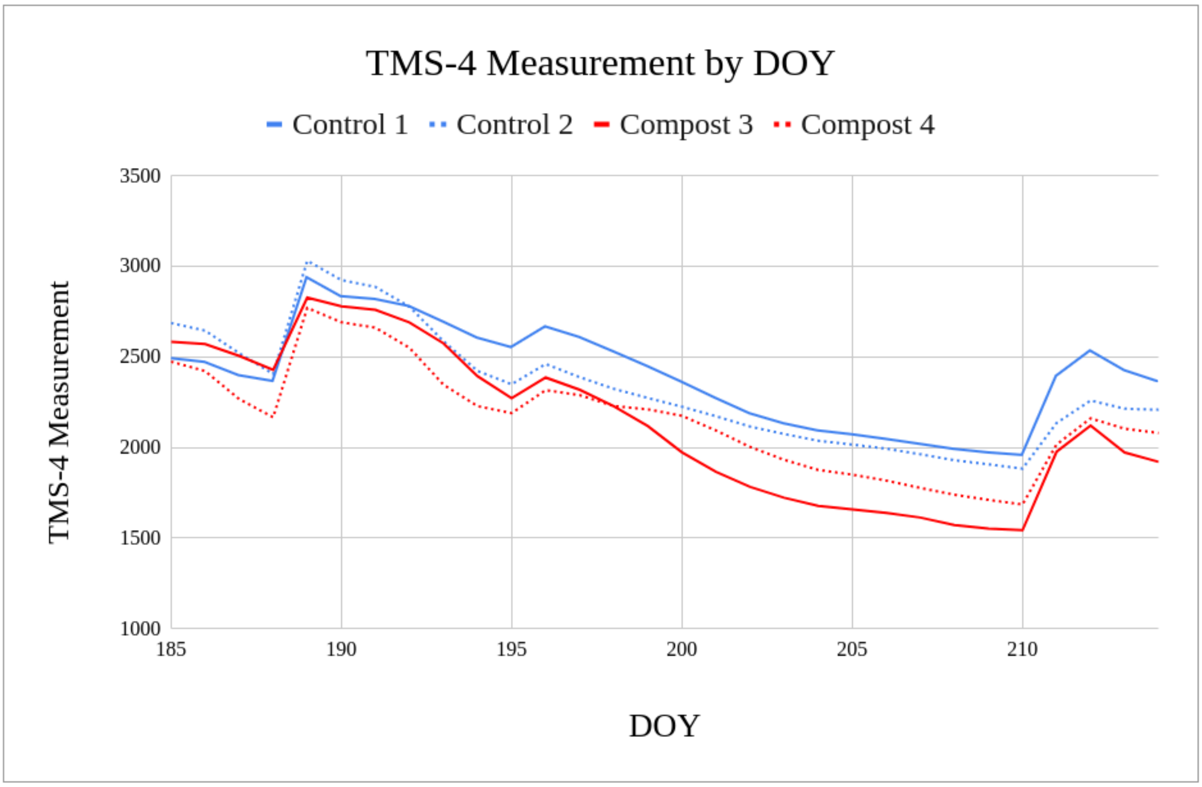


Figure 54 TMS-4 Measurements from Field Experiments by Day of Year, with sensors numbered from 1–4.

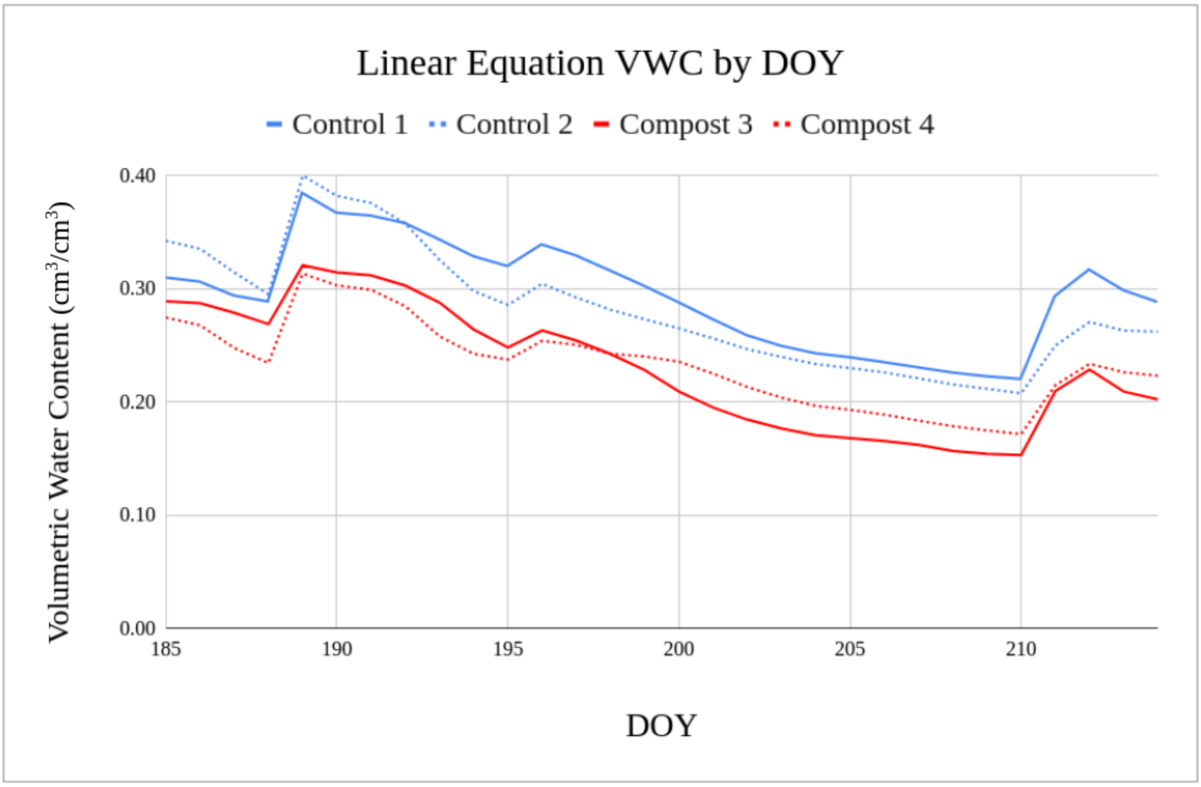


Figure 55 TMS-4 Field Measurements from Locality U Experimental Field Converted to cm^3/cm^3 with Derived Linear Calibration Equation by Day of Year, with sensors numbered from 1–4.

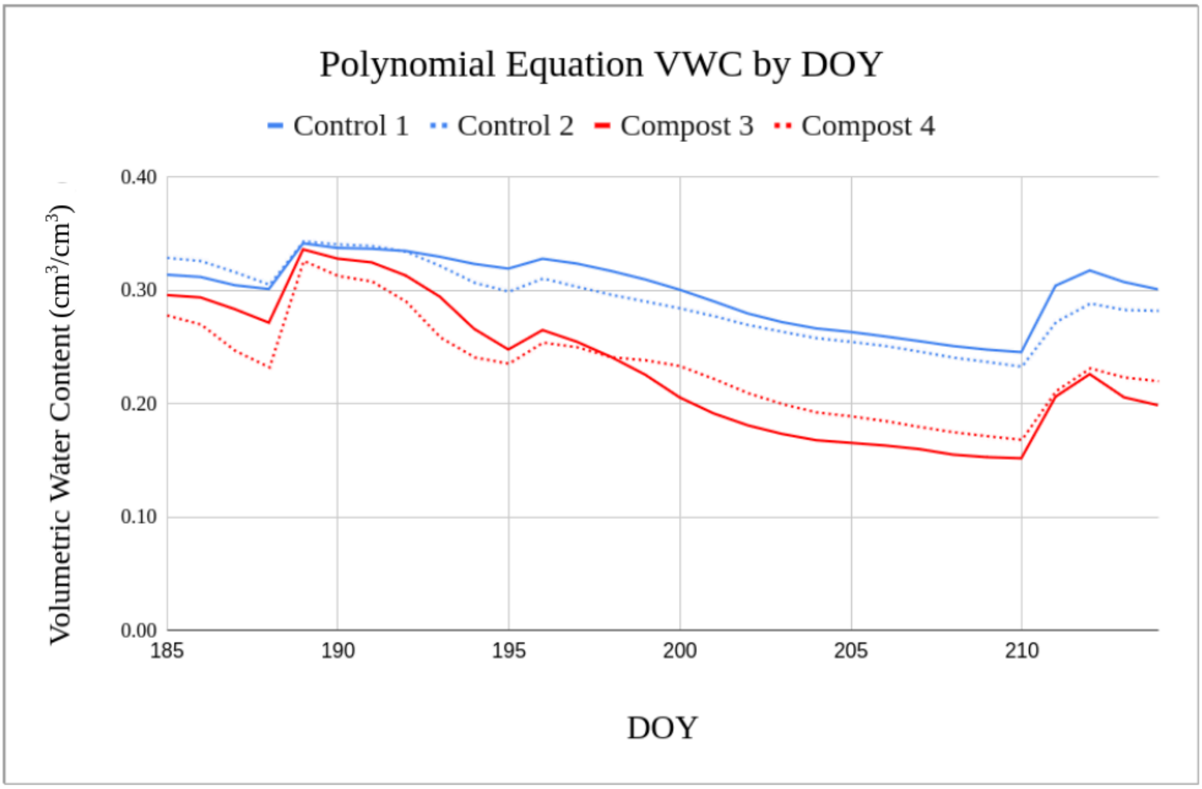


Figure 56 TMS-4 Field Measurements from Locality U Experimental Field Converted to cm^3/cm^3 with Derived Polynomial Calibration Equation by Day of Year, with sensors numbered from 1–4.

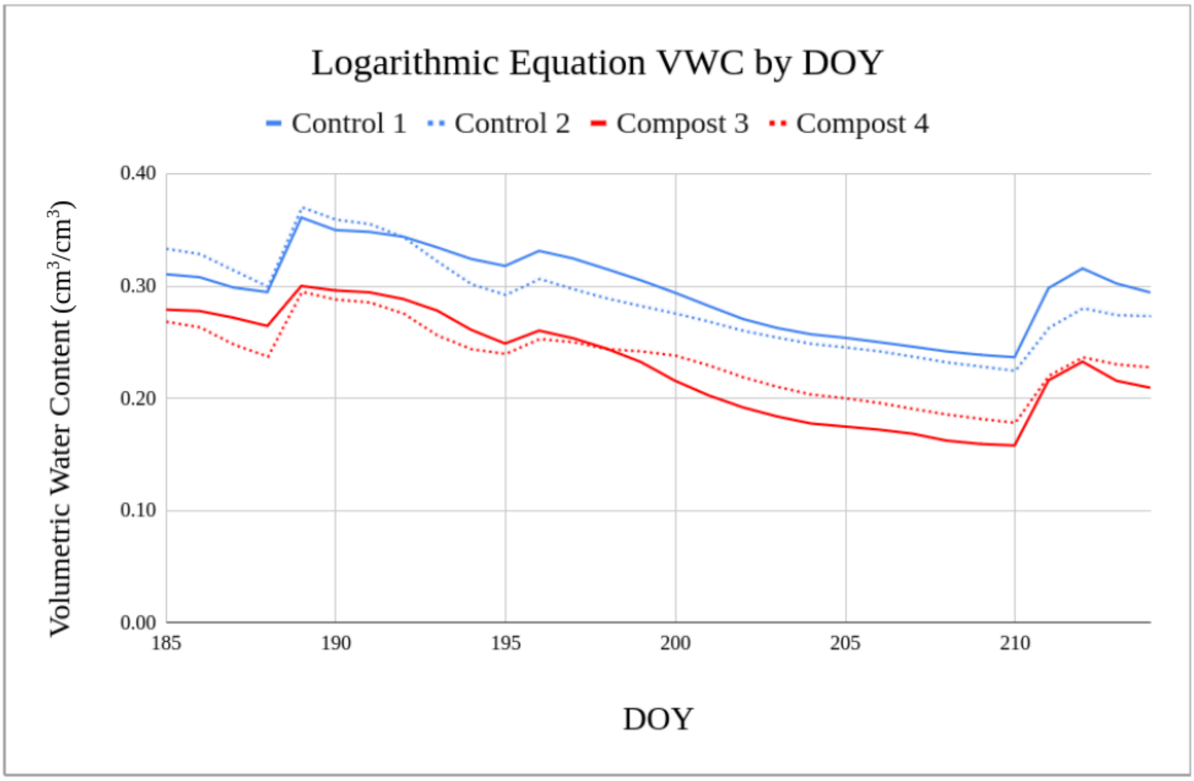


Figure 57 TMS-4 Field Measurements from Locality U Experimental Field Converted to cm³/cm³ with Derived Logarithmic Calibration Equation by Day of Year, with sensors numbered from 1–4.

Figures 58–62 display the field data for Locality U in the growing season of 2023, with Figure 58 depicting the averaged TMS-4 measurements, Figure 59 depicting the measurements converted to cm^3/cm^3 using the derived Linear equation for Locality U, with the derived CON equation applied to the CON and the derived CAS equation applied to the CAS field data. Figure 60 depicts the converted field data applied to a Polynomial equation, and Figure 61 depicts the converted field data applied to a Logarithmic equation. Figure 62 depicts the converted field data applied to the Factory Calibration equation, specifically for the soil texture of Silt Loam, corresponding to the texture obtained from the Particle Size Distribution (PSD) analysis. One notable difference in the following Figures is the increased number of TMS-4 series measurements, due to field monitoring being conducted with six TMS-4 sensors. This experimental field had two plots for CON, and four plots for CAS, with two plots containing the compost used in Locality A, and two plots containing the compost used in Locality C. This configuration is visible in Figure 26.

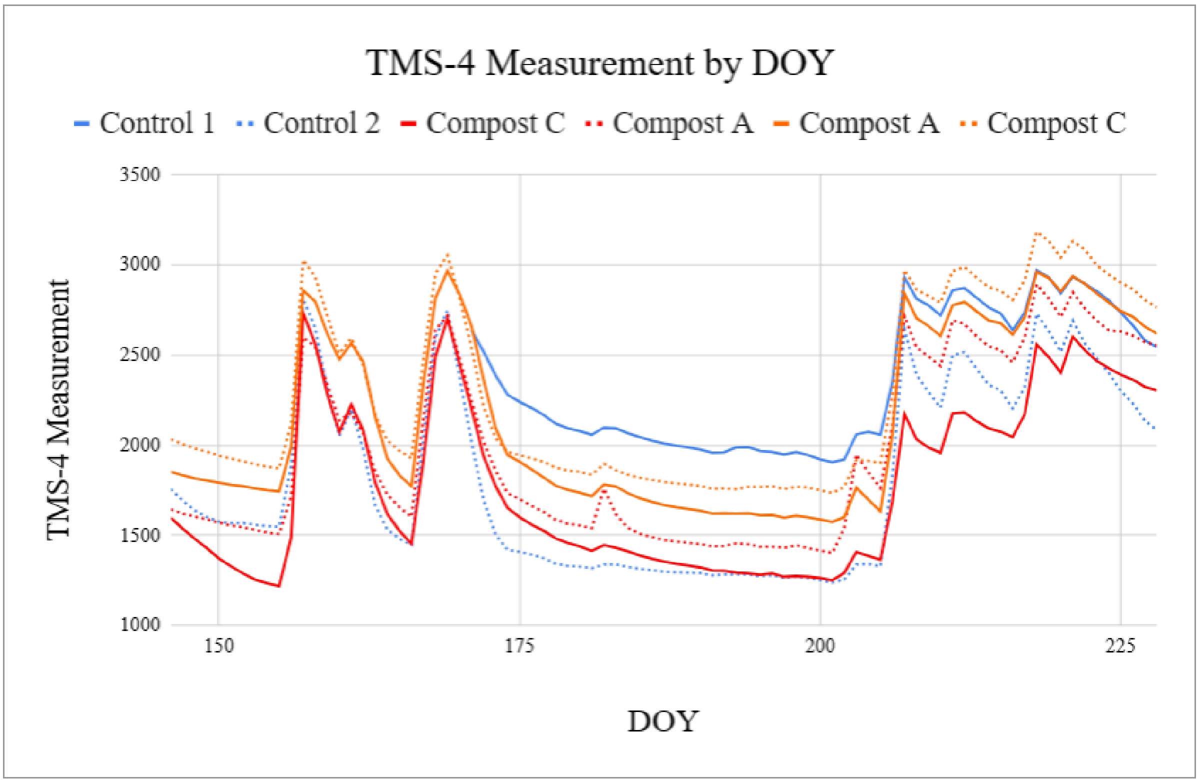


Figure 58 TMS-4 Measurements from Field Experiments by Day of Year, with Two Control Plots, Two CAS Plots with Compost A, and Two CAS Plots with Compost C.

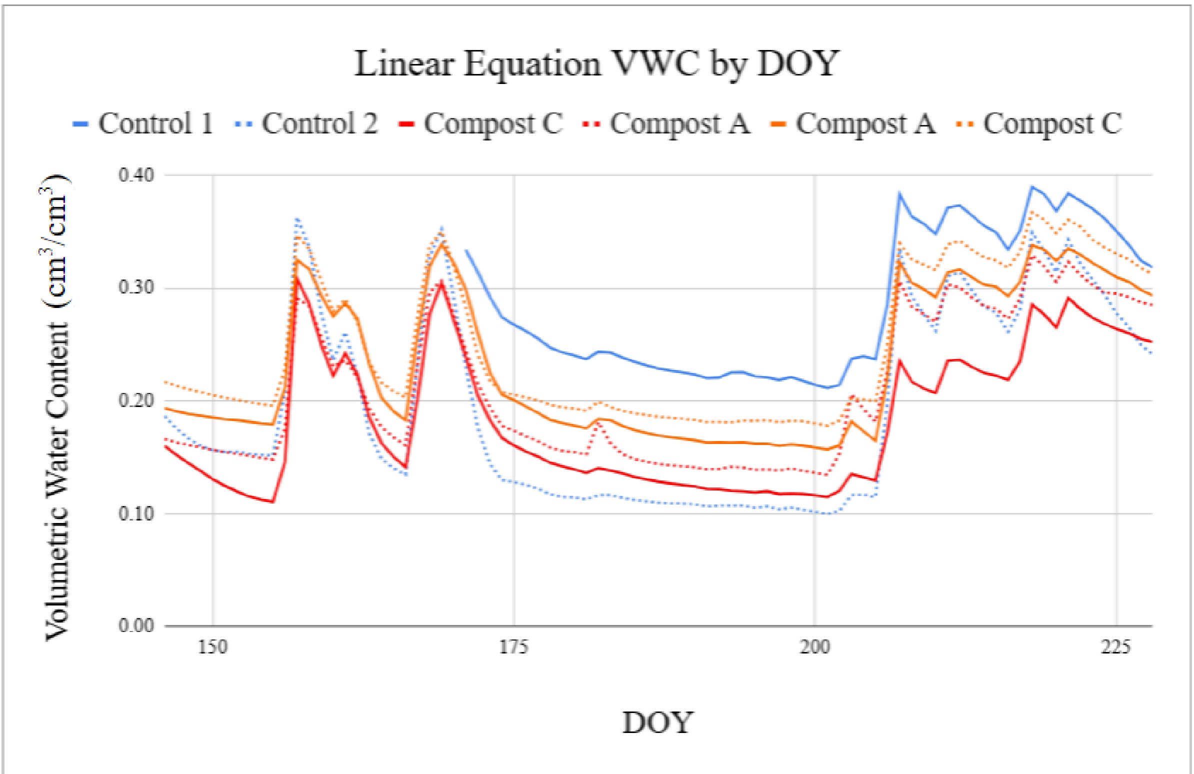


Figure 59 TMS-4 Field Measurements from Locality U Experimental Field Converted to cm^3/cm^3 with Derived Linear Calibration Equation by Day of Year, with Two Control Plots, Two CAS Plots with Compost A, and Two CAS Plots with Compost C.

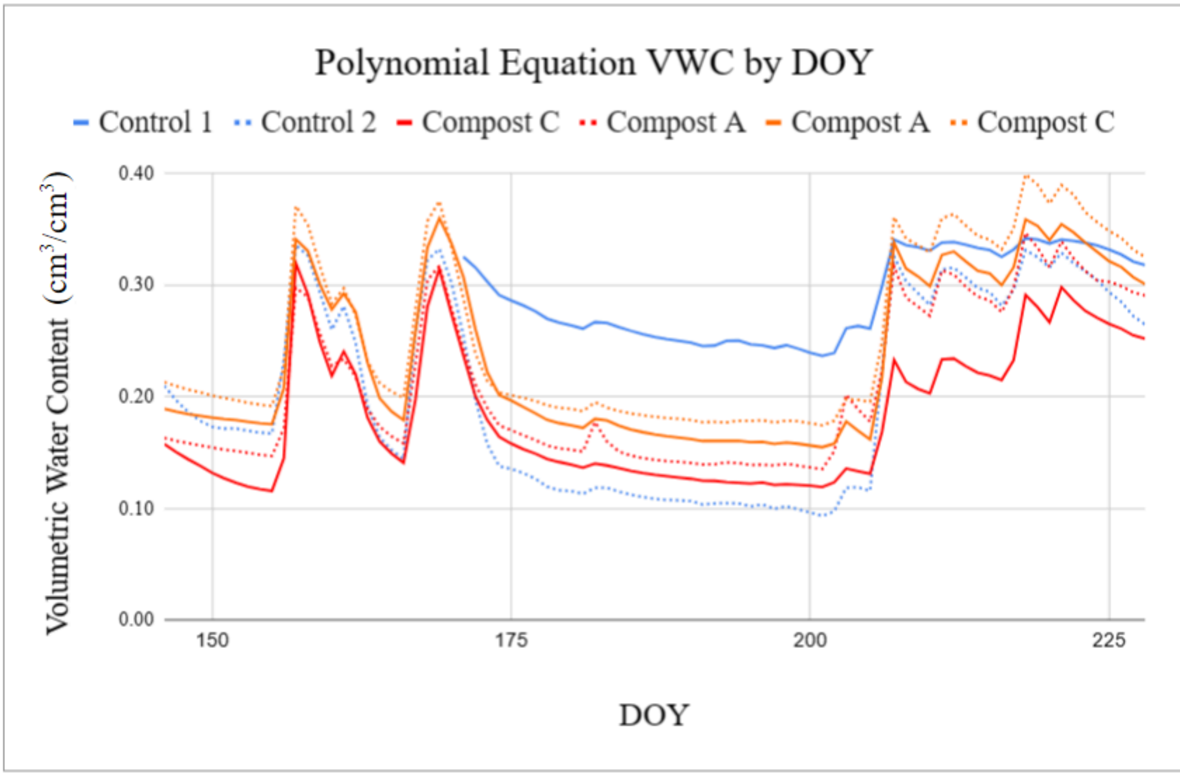


Figure 60 TMS-4 Field Measurements from Locality U Experimental Field Converted to cm^3/cm^3 with Derived Polynomial Calibration Equation by Day of Year, with Two Control Plots, Two CAS Plots with Compost A, and Two CAS Plots with Compost C.

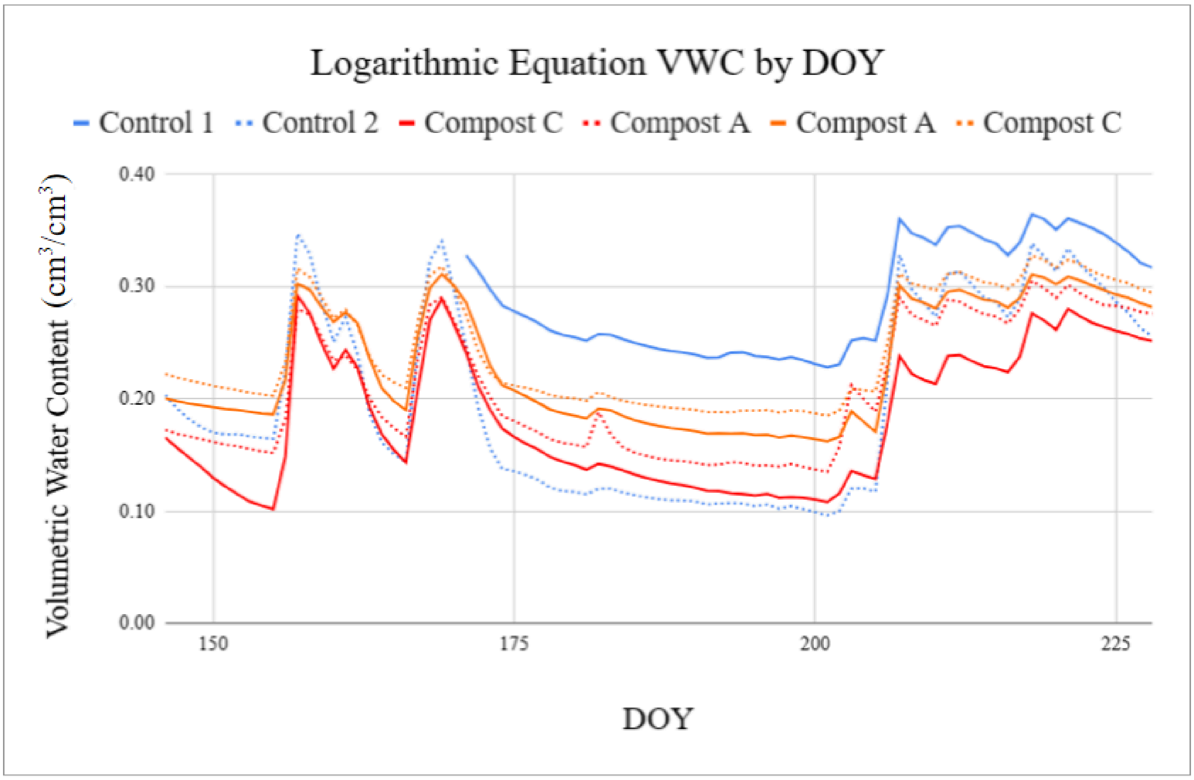


Figure 61 TMS-4 Field Measurements from Locality U Experimental Field Converted to cm^3/cm^3 with Derived Logarithmic Calibration Equation by Day of Year, with Two Control Plots, Two CAS Plots with Compost A, and Two CAS Plots with Compost C.

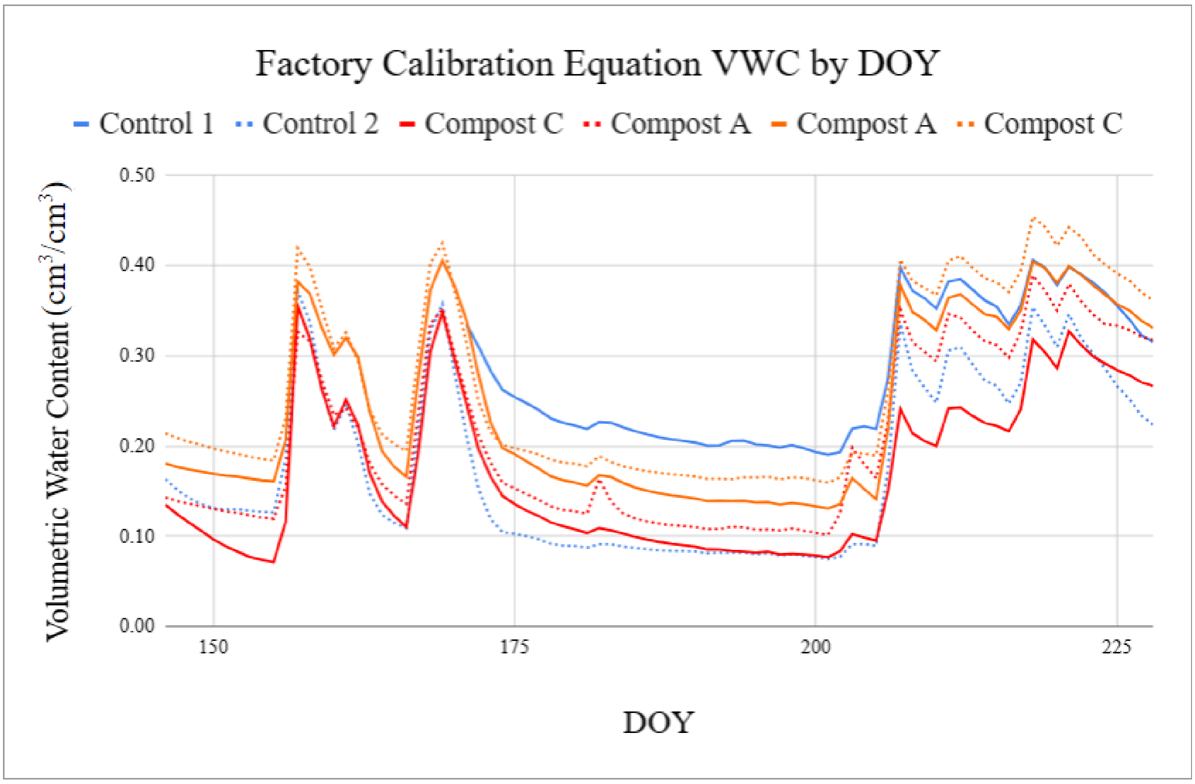


Figure 62 TMS-4 Field Measurements from Locality U Experimental Field Converted to cm^3/cm^3 with the Silt Loam Factory Calibration Equation by Day of Year, with Two Control Plots, Two CAS Plots with Compost A, and Two CAS Plots with Compost C.

Extensive evaluation of the field data was not the aim of the thesis, however, an application of the calibration equations in Locality U for the season 2023 was performed, as the small-plot experiment had a lower risk of error from site variability. The Analysis of Variance (ANOVA), specifically One-Way ANOVA, or Factorial ANOVA, was carried out with SW Statistica (TIBCO Software Inc.) in order to compare the performance of the Linear, Polynomial, and Logarithmic and FC calibration equations derived for Locality U.

In Figure 63, the overall evaluation of Fitted SWC can be seen with the type of equation as the influencing factor. There is no statistical difference between them, which indicates that any of the equations could be used with satisfactory performance. Figures 64 and 65 give a more detailed analysis of the type of equation as an influencing factor, showing the combined effect with the individual sensor performance (Figure 64) or the experimental treatment conducted as CON and both CAS-A and CAS-C (Figure 65). Although neither graph suggests statistical significance (the p-value is higher than 0.05), they both indicate a bigger difference when using the Factory Calibration.

On the other hand, Figure 66 depicts the sensor-to-sensor variability. TMS-4 sensor No. 535 was unfortunately installed later then the other, so actually it justifies its different value, as the ANOVA compares the average. But, the other sensors were installed at the same time according to the schedule given in Figure 26. CAS were expected to give similar results, but it was not confirmed.

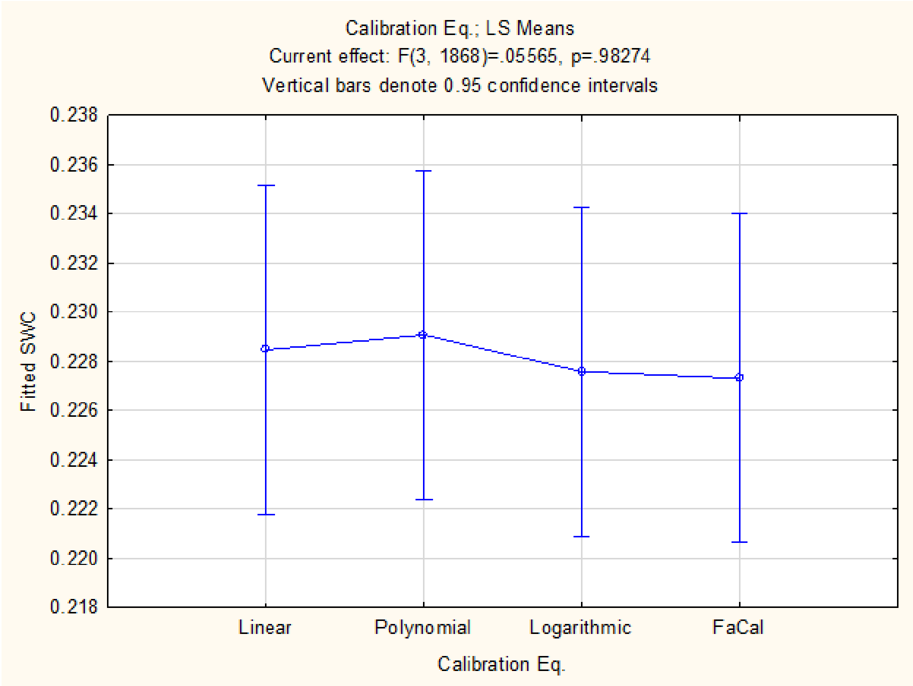


Figure 63 Statistically Non-significant Difference between the Calibration Equation's Overall Performance in Locality U (2023) Conducted by One-Way ANOVA (Source: Author).

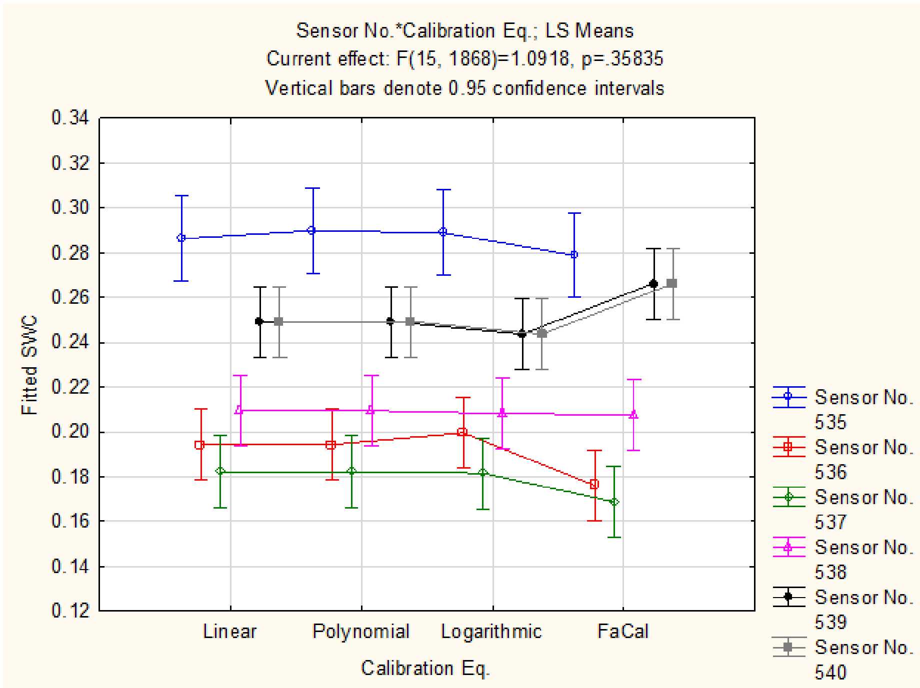


Figure 64 Factorial ANOVA summarizing the influence of calibration equation and sensor on the Fitted SWC (Source: Author).

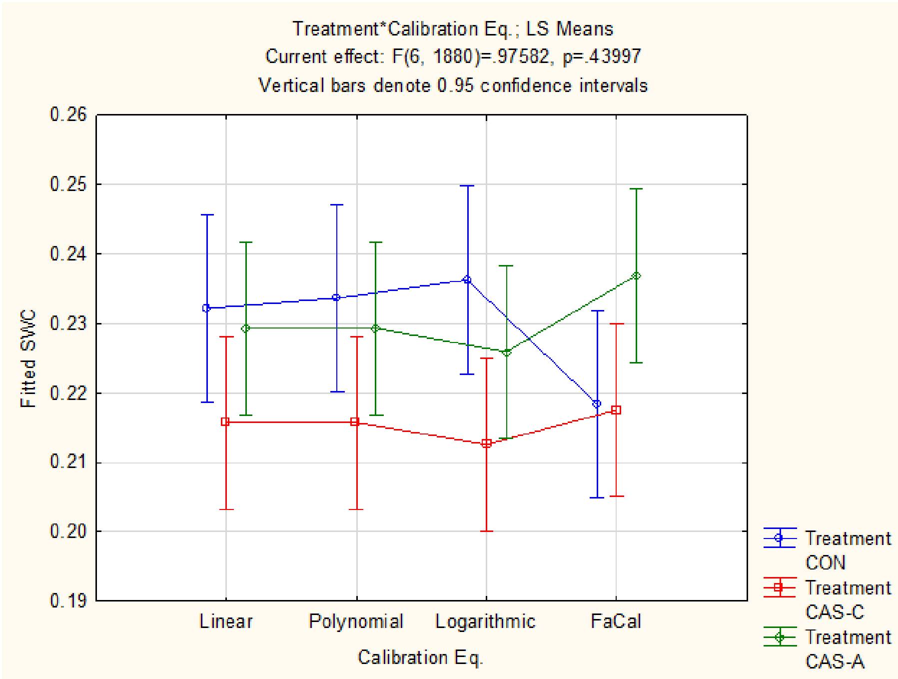


Figure 65 Factorial ANOVA summarizing the influence of calibration equation and experimental treatment on the Fitted SWC (Source: Author).

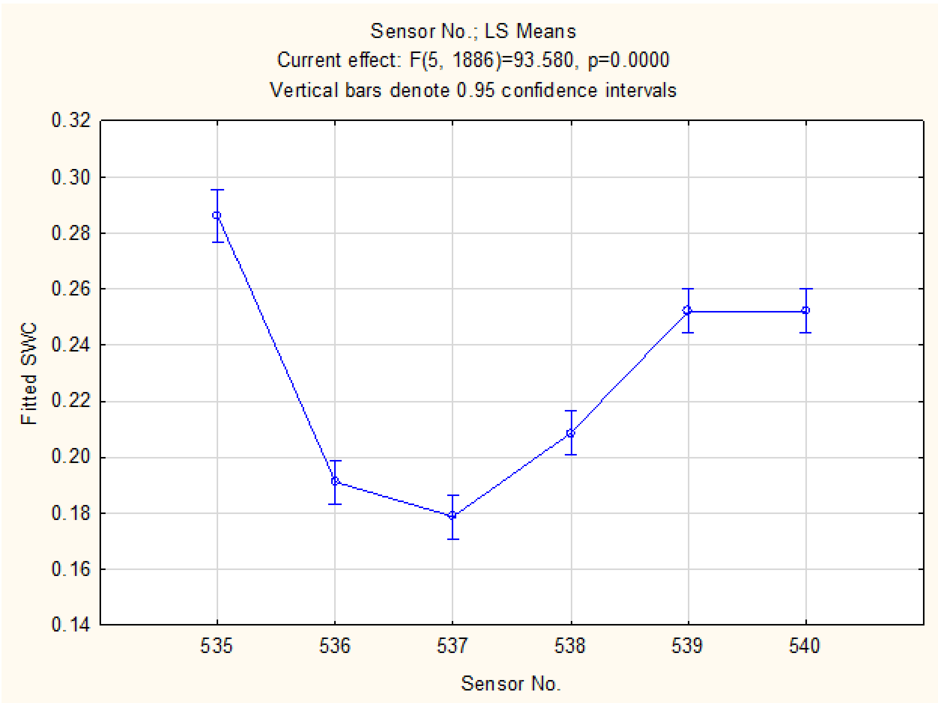


Figure 66 Statistically Significant Sensor-to-Sensor Difference in Locality U (2023) Conducted by One-Way ANOVA (Source: Author).

5.5 Other Soil Properties

The other soil properties recorded in the project included Particle Size Distribution (PSD), Average SOM, pH, Electrical Conductivity (EC), and Water Content (WC). The PSD test was used to define the soil texture in each locality, which is visible in Figure 67. This Figure is generated from project data provided by the Thesis Supervisor.

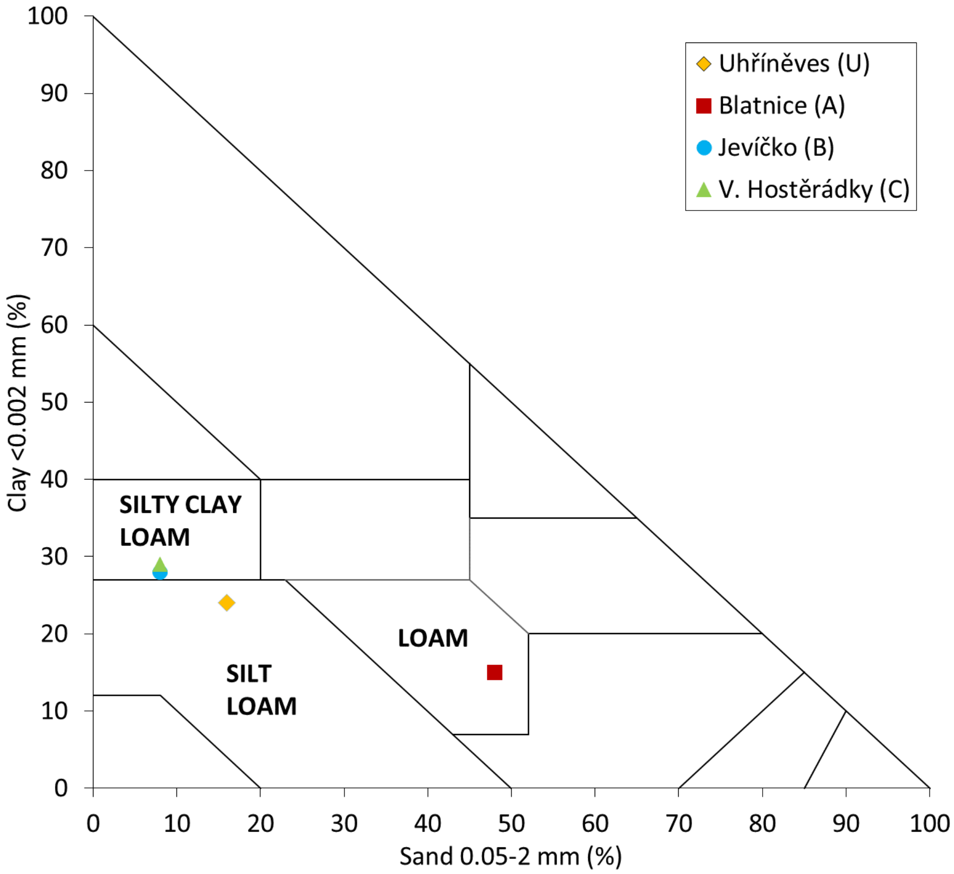


Figure 67 Texture of Soil Localities A, B, C, and U from PSD Analysis.

6 Discussion

6.1 Literature Findings and Experimental Results

6.1.1 Soil Water Content Measuring Methods and the TMS-4 Datalogger

The TMS-4 Datalogger (TMS-4) was used to monitor the temperature and soil moisture patterns of multiple agricultural fields throughout the vegetation season of 2022 and 2023. When choosing a Soil Water Content (SWC) sensor, factors were considered within available monitoring technology, such as the price, size of devices, accuracy of measurements, vulnerability in field settings, and availability of continuous monitoring. Sensors using the dielectric method were reviewed as they are considered to be the most accurate indirect SWC sensors, as gravimetric is the most accurate but is not practical to perform for long-term field experiments (Sharma et al. 2018; Pérez et al. 2023; Mane et al. 2024). Some issues among the available technology were the price and size of the devices, as Dielectric Permittivity (DP) measuring machinery could be costly, and thus beyond the reach of the average farmer (Lekshmi et al. 2014), while bulky machinery made it impractical for field applications (Pérez et al. 2023). The TMS-4 recorded the frequent fluctuations of soil moisture which can occur in minutes and with high variability in a single field (Mane et al. 2024). The sensor can measure temperature and SWC every 15 minutes for up to 10 years without charging the battery (Wild et al. 2019), which makes it ideal for monitoring the changing conditions in the fields. Other methods which measure DP were considered such as Frequency Domain Reflectometry (FDR) and Time Domain Reflectometry (TDR). FDR is known to be affected by ambient temperature, which would have been more stable in a laboratory environment, but was sure to fluctuate in extremes in outside fields throughout the year (Walker et al. 2004; Sharma et al. 2018). TDR was not used due to the potential for soil texture and salinity to affect measurements (Sharma et al. 2018) and the price of the devices. Many indirect SWC measuring methods were available, but the TMS-4 offered advantages unavailable in other methods. One of them is cable-less operation and independence in measuring between sensors, each recording its own measurements into its datalogger. Sensors left in the field unattended are subjected to different disturbances from animals, humans, or machinery. When one TMS-4 is lost, the others continue working independently. Cable-less technology also makes the sensor more resistant to weather and mechanical damage and enables researchers to place individual dataloggers far from each other.

6.1.2 Linearity in Experimental Procedures

SWC is a soil property that varies through time and space in field conditions, due to factors such as temperature, texture, terrain, and vegetation (Mane et al. 2024). Soil Organic Matter (SOM) can influence the variation of SWC over time, as it increases SWR, and can slow water loss from evaporation in soil (Ankenbauer & Loheide 2017). The experimental setup was designed to isolate SOM as the dependent property which determined any changes in the performance of the TMS-4, and to successfully measure controlled intervals of increasing SWC. When measuring SWC with the TMS-4 and gravimetric sampling, multiple replications were used, such as four TMS-4 sensors and five gravimetric samples for each

Targeted Water Content (TWC) test. Linearity of data is a known validation measure to evaluate experimental procedures when testing direct relationships in calibration (Rosenbaum et al. 2010). The average values of our replications were graphed along TWC to evaluate the Linear response of the measured SWC to the TWC, where the R^2 value indicated the Linear fitness of the data. Analysis of the TMS-4 data reflects a successful operation of the device across replications and soil localities, showing a Linear increase of measured SWC with TWC, as evident in Figures 28(a), 29(a), and 30(a), where the R^2 for a Linear trendline ranged between 0.955–0.997. For Locality B, the data for Control Soil (CON) had a higher R^2 value with the Linear equation than Compost-Amended Soil (CAS), however for the other two localities, Linearity was higher for CAS. The gravimetric analysis of the localities had less Linearity than the TMS-4 tests, but was still in a higher range, from 0.995–0.927, however, some outlying values were removed at the recommendation of the supervisor, and the variation in the data is more evident in Figures 28(b), 29(b), and 30(b), where each individual sample is a data series. Analysis of the gravimetric data shows high Linear fitness, suggesting that the measurements are reliable in the Jevicko soil test, but the other localities suffered experimental error reflected in the variability of the measurements. Velke Hosteradky gravimetric data had results consistent with the more reliable Jevicko data in the CAS test, but the CON test had imprecise results that invited doubt in the measurements. The Uhrineves soil gravimetric data had results consistent with Jevicko in the CON test, but the CAS values did not reflect a direct increase of Actual Water Content (AWC) with increasing TWC and yielded a consistent pattern of a decreased AWC in higher TWC tests across all five repetitions.

6.1.3 Calibration of TMS-4 and Gravimetric Measurements

The calibration of SWC was conducted for the TMS-4 measurements using the results obtained by the gravimetric method as a reference. The trends in this data had varying results between localities, however there was a visible difference between values from the CON and the CAS. The relationship between the CON and CAS series was used to identify when the TMS-4 overestimated or underestimated SWC, with SWC given in the actual values yielded from gravimetric testing.

For all three localities, the comparison of CON and CAS data follows a common trend: The measurements are relatively close or even overlapping in rather dry soils, ranging from air-dried soil to between roughly 15–25% AWC, and then above this range of WC the pathways of the datasets diverge, resulting in overestimation or underestimation of the CAS AWC. Although the TMS-4 yielded different trends in results at higher WC, the point of change in data trends was similar between calibration experiments.

For Locality B, the trends are visible in Figure 34, where the CON and CAS series are close together from dry tests to an AWC of 20%, with the measurement around 18% being underestimated for the CAS, as the CON and CAS series values are very close as TMS-4 values, but noticeably different for AWC, with CAS yielding a higher AWC than the CON for a similar TMS-4 value. Above 20%, an inversion occurs where the CAS becomes overestimated compared to the CON, and lower values for AWC in the CAS series correspond with a higher TMS-4 value than for a CON series measurement with a higher AWC. This trend becomes more prominent in the higher AWC range, where the gap between the data series becomes larger along the TMS-4 Value axis while the AWC measurements are close in value. The behaviour of the data in lower AWC measurements is consistent with calibration experiments which determined that SOM affects soil properties which causes an underestimation of SWC in Dielectric Permittivity (DP) based sensors (Bircher et al. 2016). The behavioural inversion of the data, and the WC value where it occurred, is consistent with studies related to a Transition Water Content occurring around 20% where indirect measurements behave differently upon achieving the Transition Water Content (Walker et al. 2004; Bircher et al. 2016; Pérez et al. 2023).

For Locality C, values along the calibration graph depicted in Figure 37, values follow a similar path along both axes and then diverge in higher AWC measurements. The CON and CAS values follow a nearly overlapping pathway with a slight overestimation of WC by the TMS-4 for CAS, up to around 20% AWC. Above 20%, the CAS is greatly underestimated, with measurements for the CON and CAS having close TMS-4 values with the AWC being much higher for CAS. This result is inconsistent with calibration experiments which determined that SOM affects soil properties which causes an underestimation of SWC in DP sensors (Bircher et al. 2016), but the significant change in the trends of the data at higher AWC is consistent with studies evaluating data behaviour upon reaching Transition Water Content (Walker et al. 2004; Bircher et al. 2016; Pérez et al. 2023).

For Locality U, both the values along the calibration graph depicted in Figure 40, values follow a similar path along both axes and then diverge in higher AWC measurements. The CON and CAS values follow a nearly overlapping pathway with a slight overestimation of WC by the TMS-4 for CAS until their paths diverge above 20% AWC. Above 20% AWC, TMS-4 measurements overestimate WC of CAS, and then the datasets become close again at the highest measured AWC for CAS of 35%. The behaviour of the data in higher AWC measurements is consistent with calibration experiments which determined that SOM affects soil properties which causes an underestimation of SWC in DP sensors (Bircher et al. 2016). The behavioural inversion of the data, and the WC value where it occurred, is consistent with studies related to a Transition Water Content occurring around 20% where indirect measurements behave differently upon achieving the Transition Water Content (Walker et al. 2004; Bircher et al. 2016; Pérez et al. 2023). However, the closeness of the datasets shows that the compost amendment of 20 t/ha did not affect the soil in this locality.

6.1.4 **Calibration Equations**

Due to the scarcity of literature and experiments performing calibration equations on measurements made with the Time Domain Transmissometry (TDT) method, experiments using the dielectric method were reviewed, which included experiments with FDR and TDR, much more widely used methods. In the majority of soil-specific calibration experiments, Polynomial equations were selected as the best-fit equation for experimental data (Fares et al. 2016; Karim et al. 2018; Bobrov et al. 2019; Sangara & Patel 2022). The study by Bircher et al. (2016) was one of the few that noted a different equation as their best fit, concluding that the Logarithmic function suited their data, due to the reduced increase at higher SWC.

Calibration equations were derived from trendlines in scatter plots comparing the

TMS-4 WC with the actual sampled SWC. The results differed between each locality, and between CON and CAS experiments. Statistical analyses were used to evaluate the data, but other considerations included the trends in extrapolated values and the closeness of the data trends to trends in experimental results.

The derived Polynomial equations were best fit for the experimental data, and are recommended in FC, which is supported by the many statistical analyses in related experiments which favoured Polynomial equations. However, when higher TMS-4 values are applied to the equation, the output value for predicted WC curves downward in two of our localities, visible in Figure 39(b), and Figure 42(b). These values compromise predictions for WC as low as 35%, which is problematic for our soils which have a Porosity of up to 48%. This downturn occurred in two out of the three localities when extrapolating values. The suitability of the statistical analyses to the experimental data agrees with the consensus in studies that selected Polynomial equations as the best fit derived equation (Fares et al. 2016; Karim et al. 2018; Bobrov et al. 2019; Sangara & Patel 2022). However, the experiment only pushed the TWC up to 35% Volumetric Water Content (VWC), which does not bring the soil in natural field conditions to full saturation. This means that it is possible for a potentially higher TMS-4 reading to be measured in field experiments, where climate and precipitation events may cause the soil to achieve a SWC higher than 35% saturation, and this is true for our field experiments TMS-4 values achieved a SWC measurement of up to 40% in multiple localities. Using the Polynomial equations derived from our calibration experiments on extrapolated values higher than the experimental maximum, or actual values taken from the field in extremely wet conditions, the Polynomial equation can calculate results that directly contradict the reality of soil conditions.

Linear trendlines were often suitable for the lower AWC data but did not maintain fitness with the change in pathway for data that occurs in TMS-4 output for higher AWC. In datasets depicted in Figures 38(a) and 41(a), Linear trendlines had a reduced fitness due to the lowered increase in AWC along with increasing TMS-4 values, especially in CONs. The visible difference in R^2 can be seen in Tables 8 and 9, where the Linear trendline has the lowest fitness between the calibration equations. Linear values are not typically used for soil-specific calibration but can be useful for sensor-specific calibration to evaluate sensor performance in detecting WC of materials with known DP (Rosenbaum et al. 2010). One study conducted by the Czech University of Life Sciences produced a methodology for an earlier model, the TMS-3 Datalogger, and successfully applied a Linear calibration equation, however, this application was unique among the reviewed soil studies (Kodešová et al. 2015).

Logarithmic equations had poorer fit to experimental data compared to the other derived calibration equations in most soil experiments, but still maintained a high R^2, with a minimum of 0.900 and a maximum of 0.989. Only one of the reviewed studies, conducted by Bircher et al. (2016), supported a Logarithmic calibration equation. Bircher et al. (2016) conducted a study of calibrating soils with varying levels of SOM and featured Polynomial and Logarithmic equations as suitable calibration equations for different sensors. The OM content of the experimental soil was 30% and above, intending to isolate SOM as an influence in calibration. Logarithmic equations were fit to one of the studied sensors, as the shape of a Logarithmic calibration equation suits the behaviour of data with a higher amount of SOM, where the drier measurements, up to 20% VWC, have a steep upward progression, which becomes less pronounced and flatter in the higher moisture measurements (Bircher et al. 2016). One notable difference between Logarithmic calibration and other derived equations is visible in the calibration for Locality B, depicted in Figure 34 and Figure 35, where the Logarithmic calibration is the only equation that results in the CAS having a higher SWC for a given TMS-4 value, and with CAS having a higher overall SWC, a trend which agrees with the real values for AWC.

6.1.5 **Soil-Specific, Factory, and Sensor-Specific Calibration**

Soil-specific calibration was discussed with conflicting views in literature, as sources viewed it as a disadvantage for many SWC monitoring methods, describing it as a disadvantage for a given device because it was necessary to improve accuracy before application in soil (Sharma et al. 2018). At the same time, many experiments involving SWC sensors noted that this step is a highly recommended, if not necessary component to accurate SWC measuring. This characterization of soil-specific calibration came from experiments involving many different soil types and experimental set-ups since experiments found the available Factory Calibration (FC) limited for their soil conditions and produced high error, with soil-specific calibration drastically improving their experimental results across all SWC measuring methods (Sharma et al. 2018; Bartosz et al. 2023; Mane et al. 2024). As the author of this study, I can confirm that soil-specific calibration is a time-intensive but ultimately necessary measure in ensuring the improved accuracy of SWC measurements with indirect methods. In the case of this study, it involved up to 16 repetitions of the preparation and packing of soil in a calibration tank for a single soil including Control Soil (CON) and Compost-Amended Soil (CAS) testing. The experiment involved a calibration container with roughly 35 kg of soil and two weeks of laboratory work for each soil.

In the experiment, soil-specific calibration was performed from laboratory calibration with soil samples from the field, and multiple calibration equations were derived and applied to experimental data. In all of our soil localities, the FC was applied, and in each case, the RMSE for the FC was the highest or 2nd highest out of all the equations, in some cases being double or triple that of the other equations, a trend visible in Table 8, and Table 9.

Another point of discussion found during research was the potential for improving experimental results with a sensor-specific calibration, which could be performed on each sensor before field application and then applied to the field results after measuring. This consideration was described as especially important for field experiments with large numbers of cheaper sensors, which produce results with significant variation (Rosenbaum et al. 2010). This measure was found to be beneficial, especially with the lower reliability of FC (Dominguez-Niño et al. 2019).

In the experiment, sensor-to-sensor variation between each TMS-4 was assumed to be negligible, however, this hypothesis was not supported by the experimental findings. Four sensors were used for each soil test, and there were visible trends in their measurements. Sensor #94242533, noted as Sensor 3, had consistently higher measurements for each soil locality, visible in CON and CAS. When calibration equations were applied, the difference between sensor measurements in a single TWC test was found to be up to 7% between the minimum and maximum values. While the minimum value came from different sensors, the maximum value for 38 out of the 48 values for SWC came from Sensor 3. This agrees with the findings from Rosenbaum et al. (2010), whose experimental findings showed in groups of different sensors, one out of five of each type were found to have significantly different measurements

The experimental hypothesis only stated that the sensors would have ‘acceptable’ sensor-to-sensor variation, but the range of 7% difference between several of the TWC tests is large in the context of the steps between tests having a target of 5% difference. For this reason, sensor-specific calibration is recommended for future experiments involving the TMS-4.

6.1.6 **Field Data Application**

When the Calibration Equations were applied to field data, in several experimental fields, the CAS yielded lower values for SWC compared to the CON. This contradicts the laboratory calibration measurements, where CAS yielded higher SWC values. However, the environmental conditions of the soil are quite different, and these different experimental findings can be attributed to the difference in field conditions and distribution of compost. The experimental field, for example, had compost applied to the soil surface, making the soil surface much darker for CAS, which might result in overheating when the soil was not covered yet by the vegetation and thus inducing more rapid evaporation (Yamamoto et al. 2022). For multiple localities Polynomial calibration yielded more extreme minimum and maximum SWC values throughout the season, while Linear and Logarithmic equations yielded less deviation and smoother progression, however in some cases, this trend is reversed, and the Polynomial data clusters together while the Linear and Logarithmic results are farther apart between experiments.

The field data needs to be investigated further, as a basic overview was presented in the thesis namely for the purpose of the evaluation of the derived calibration equations and the overview of their performance when applied to the real field data.

6.2 Complications and Limitations

Unforeseen complications included limitations with the grinder, soil loss from pounding with the mallet, potential for water loss in different seasons, difficulties in executing procedures as the soil was mixed with more water, and operation of the TMS-4.

6.2.1 **Human Error: TMS-4 Operations**

The operation of the TMS-4 was simplified with the Manual and available communication with the manufacturer. One feature of the TMS-4 is multiple setting options for the rate of measurement, as the devices were switched to Experimental Mode for each soil test. A surprise feature was that after switching one sensor from Basic to Experimental Mode, the other three sensors would automatically switch to Experimental Mode without being connected to the control panel on the computer. This occurred nearly every time one of the sensors was switched from Basic Mode to Experimental Mode. Twice in the experiment, one of the sensors did not change automatically along with the others and recorded only one measurement for a soil test. Thankfully, this mistake was discovered immediately after viewing the data, and the device setting was switched and the test was repeated.

In the opposite case, a sensor was left in Experimental Mode overnight and was discovered to have diligently taken over 700 measurements of SWC of the lab desk drawer. These mistakes were discovered immediately or within a day because the sensors were checked before and after each TWC test.

A repeated failure to check the sensors each time or for a long-term experiment could result in lost measurements and data, or exhaustion of the sensor's memory. It is for this reason that caution and routine checks are recommended for experiments using the sensor in multiple settings.

6.2.2 **Human Error: Soil Preparation**

Difficulties with the steps necessary to prepare experimental soil were especially evident in the training experiment. Difficulty with the soil grinder limited the ability to manipulate the aggregate size of the dry soil, soil for locality A was not used for final results, but initial tests were carried out, and the aggregate size was extremely fine due to the soil grinder being stuck at a fine earth particle size setting (2 mm). The grinder was fixed for later experiments, and a larger aggregate size was achieved for experiments with the other localities. Although the difference in particle size of the soil on the two different grinding settings may not be as drastic as a difference in particle size due to soil type, this possibility should be considered when preparing soil for testing.

Pounding the soil with the mallet is a necessary step to achieve a uniform volume of soil throughout the experiment stages, as the amount of water applied and the mass of soil in each stage depends on a uniform volume of soil. Pounding the soil during the drier experiments, such as the air-dried, 5%, and 10% TWC runs, resulted in clouds of dust that delayed progress in each run and resulted in potential loss of soil mass in the upper layers of the tank. Pounding the upper soil layers with a plastic bag around the tank prevented the dust clouds and alleviated some of the soil loss.

Experimenting during different seasons was unavoidable, and because a single test could take 1–2 days, testing in the summer months risked water loss in the soil due to evaporation. This was avoided by covering the calibration tank, packing weighed-out soil layers in plastic bags, and taking samples from underneath the soil surface.

As soil gains a higher SWC, it can behave less as a solid state, and more as a plastic, and eventually liquid state. Although the experiment could aim for 40% WC in further experiments, the soil becomes increasingly difficult to work with, moving towards a plastic state, and is more difficult to mix uniformly with water.

Another source of error could be the adsorbed water returning to samples after drying in the oven. Tins were open when placed in the oven, and there were usually between 20–40 samples in the oven for each drying cycle. Because a large number of samples were exposed to the air after drying and before weighing, samples may have had the chance to accumulate some adsorbed water when removed from the oven. In the final drying cycles, the sample lids were closed with tweezers while the tins were in the oven, to minimise the amount of water adsorbing to the samples.

Dry bulk density had a direct effect on the calculated results, as the gravimetric samples were multiplied by dry bulk density to calculate VWC, which was analysed against the TMS-4 data readings. The calculation resulted in an expected increase in the SWC when calculating from mass to VWC. An alarming trend however is that in some cases the SWC given would approach or even exceed the porosity of the soil.

6.2.3 Complications: Field Experiments

For field monitoring of SWC in the experimental localities, several incidents brought about by agricultural use of the field and exposure of the sensors compromised our data collection. In one experimental field, the sensors had been completely pulled out, which was found on one of the trips to collect TMS-4 data.. Wild pigs or other animals likely played with the sensors. Another sensor area had been completely avoided by the farmers when depositing compost, meaning that although the sensor was in a composted field, there was no compost around the sensor. In another case, soil erosion in the field caused the upper part of the sensor to be exposed, which could influence the accuracy of measurements. Some issues arose from the natural degradation of the experimental field over time, as with the sensor depicted in Figure 68, which became partially uncovered from soil erosion.

Figure 68 TMS-4 in Experimental Field Partially Uncovered from Erosion (Source: Author).

6.2.4 Suggestions for Future Experiments

Throughout the experiment, limitations in experimental procedures were discovered that could be avoided or explored further in future experiments. At the same time, further perspective gained from literature research reveals a larger scope of experimentation that could be applied to calibration and further understanding of TMS-4 application.

During the TMS-4 measuring of SWC in the calibration experiment, there is a visible trend of sensors having a delayed response to increases in SWC. Figure 23 depicts the gradual increase in SWC after insertion in wet soil, evident in the upward curve occurring between the initial and final DP measurements. Measurements tended to stabilise after 10–15 minutes, however, the experiment did not attempt to quantify this temporal change or explore longer periods for the measurements to stabilise. Further experimentation could include quantifying a minimum amount of time to allow the sensors to stabilise.

During literature research, several studies were reviewed to understand the influence of SOM on DP sensor readings. The amounts of SOM used in each experiment varied from unamended control soil to above 30% (Bircher et al. 2016; Mane et al. 2024). For the experiment, the CON and CAS differed in SOM by 1.5%. Although this amount of SOM is equal to the amount used in the experimental fields, the difference is very small compared to the researched experiments. In experiments evaluating organic soils, soil up to 10% SOM was described as mineral soil, and was still much higher than the experimental agricultural soil (Vaz et al. 2013; Mane et al. 2024). The experiment is designed to evaluate the effect of the amount of SOM typical for the tested agricultural fields on sensor performance, so our application of compost for calibration tests is suitable for the experiment, however, a higher amount of SOM and tests with different levels of SOM could be beneficial to explore the influence of SOM on the TMS-4.

Gravimetry was used for the calibration experiment, as a reference of actual SWC in the 'wet up' calibration method. A suggestion for future experiments is to use the sensors and the gravimetric sampling to perform measurements in 'wet up' and 'dry down' methods in laboratory calibration, as 'dry down' methods were discussed as being more accurate for soils of certain textures (Mane et al. 2024). This could be useful, especially with the known influences of SOM on water retention, indicating the potential for different rates of drying to be recorded in lab experiments and applied to field data for evaporation after precipitation events.

For field applications, it can be suggested to reduce all possible spatial variations to obtain representative data, and also, to employ more sensors for data collection to reduce the sensor-to-sensor variation. Within this preliminary study, 2 sensors were applied to each CON and CAS plot in each locality, and from the results the spatial or sensor-to-sensor variability became obvious, and was sometimes more pronounced in the data than CON and CAS differences.

6.2.5 **Ethical Considerations**

There were two instances during our project when I compromised my ethics for the sake of the experiments.

The first was in the Locality Uhříněves, while we were performing hydraulic conductivity measurements in the soil. I laid down in front of the infiltrometer to record measurements. My movement disturbed a mouse who spent the day constantly checking if I was still sitting near her home, and I couldn't move from the chosen spot for several hours while recording the hydraulic conductivity of the soil.

The second was while we were taking field samples from the localities in Moravia. In the field, we met some farmers who asked about our project. We withheld information about coming from Prague, we told them that we were from Brno, since they mentioned some concerns about people from Prague, and we wanted them to like us.

Figure 69 The Mouse in Question, May She Forgive Us (Source: Author).

7 Conclusion

The hypothesis that the TMS-4 Datalogger (TMS-4) will measure Soil Water Content (SWC) with acceptable sensor-to-sensor variation was refuted. Unfortunately, without sensor-specific calibration, the conversion of the TMS-4 values yielded a deviation between sensors of up to 7% Volumetric Water Content (VWC). The experimental results were in agreement with several other reviewed experiments which demonstrated the importance of sensor-specific calibration, especially with low-cost sensors. The variability of measurements in the experiment may be reduced in future experiments if sensor-specific calibration is performed before field application.

The hypothesis that the addition of compost to the soil would affect SWC measurements was supported by the experimental data and research findings. Soil Organic Matter (SOM) is known to affect other Dielectric Permittivity (DP) sensing methods, although the effect can be different depending on the frequency range of the sensor. The resulting changes in sensor performance were different between localities, however for each locality, there was a notable difference between the results for the Control (CON) and Compost-Amended Soil (CAS). The findings of the present study suggest that SOM does affect the performance of the TMS-4, so soil-specific calibration is a necessary measure to ensure the accuracy of TMS-4 measurements. Although the SOM of the CON and CAS only differed by 1.5%, there was a considerable difference noted in TMS-4 measurements.

The aim was to determine a calibration equation for the experimental localities. Many of the reviewed calibration experiments used a derived Polynomial equation, however, despite their statistical fitness to the data, several of our derived Polynomial equations had unsustainable patterns that contradict real conditions. Our derived Logarithmic equations had the opposite result, as they had poorer statistical results than the derived equations, however, the pattern of the equation was a better fit for real conditions. The performance of the Factory Calibration (FC) was not suitable for our data and is consistent with related studies that found the FC to be very limited for real soil application and prone to high error.

The derived calibration equations were applied in the field experiments with different compost treatments. The analysis of the results in the small-plot experiment in Locality Uhříněves with a set of plots with control and two types of compost allowed a more discerning example of the applicability of the calibration equations and showed a slightly better performance of site-specific calibrations over the factory calibration.

The objectives of the thesis were fulfilled. In conclusion, the TMS-4 is recommended but should be used with an adequate number of repetitions and tested before field application.

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9 Symbols and Abbreviations

Av. - Average
AWC - Actual Water Content
C - Carbon
CAS - Compost-Amended Soil
C:N - Carbon/Nitrogen Ratio
CDP - Complex Dielectric Permittivity
CON - Control Soil (Not Amended by Compost)
DM - Dry Matter
DMM - Dielectric Mixing Model
DP - Dielectric Permittivity
EC - Electrical Conductivity
EM - Electromagnetic
FC - Factory Calibration
FDR - Frequency Domain Reflectometry
N - Nitrogen
NH_4^+ - Ammonium
NO_3^- - Nitrate
Ntot - Total Nitrogen
Precip. - Precipitation
PSD - Particle Size Distribution
RMSE - Root Means Squared Error
SD - Standard Deviation
SOM - Soil Organic Matter
SWC - Soil Water Content
TDR - Time Domain Reflectometry
TDT - Time Domain Transmissometry
Temp. - Temperature
TMS-4 - TMS-4 Datalogger
TWC - Targeted Water Content
VWC - Volumetric Water Content
WC - Water Content