Calibration of an Arduino-based low-cost capacitive soil moisture sensor for smart agriculture

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Abstract: Agriculture faces several challenges to use the available resources in a more environmentally sustainable manner. One of the most significant is to develop sustainable water management. The modern Internet of Things (IoT) techniques with real-time data collection and visualisation can play an important role in monitoring the readily available moisture in the soil. An automated Arduino-based low-cost capacitive soil moisture sensor has been calibrated and developed for data acquisition. A sensor- and soil-specific calibration was performed for the soil moisture sensors (SKU: SEN0193 - DFROBOT, Shanghai, China). A Repeatability and Reproducibility study was conducted by range of mean methods on clay loam, sandy loam and silt loam soil textures. The calibration process was based on the data provided by the capacitive sensors and the continuously and parallelly measured soil moisture content by the thermo-gravimetric method. It can be stated that the response of the sensors to changes in soil moisture differs from each other, which was also greatly influenced by different soil textures. Therefore, the calibration according to soil texture was required to ensure adequate measurement accuracy. After the calibration, it was found that a polynomial calibration function ($R^2 \geq 0.89$) was the most appropriate way for modelling the behaviour of the sensors at different soil textures.

Keywords: IoT; Precision Agriculture; Low-cost capacitive soil moisture sensor; Thermo-gravimetric method; Repeatability and Reproducibility study; Non-linear regression.

INTRODUCTION

The development of the Internet of Things (IoT) techniques in agriculture could contribute to the solution for the three crucial new challenges being faced in the areas of climate change, bioenergy and water management (Hamidov and Helming, 2020). The IoT frameworks can improve the data management, real-time data collection, processing and visualisation in various areas of agriculture. Sensors for measuring air and soil temperature, air pressure, light intensity, soil moisture content and different gases concentration have already been developed within an intelligent wireless sensor network (Gaikwad et al., 2021; González-Buesa and Salvador, 2019; Nyéki et al., 2021; Ruiz-Garcia et al., 2009; Rusu et al., 2019).

Environmental variables have a great influence on crop growth, therefore control and knowledge of these allows better crop production management, as the term ‘Precision Agriculture’ points out (Zhang et al., 2002). The most fundamental of these is considered to be the soil for any crops (Gao et al., 2019; Lichner et al., 2012). Its ability to retain and drain water as well as its nutrient supply capacity are essential properties (Xue et al., 2017). Water is one of the most critical resources for sustainable development, as water will increasingly be used in agriculture in the coming decades. Therefore, real-time monitoring of the changes in soil moisture content is important in order to develop an effective irrigation strategy (Chartzoulakis and Bertaki, 2015; Fereres and Soriano, 2007).

Several techniques and devices have been used to determine the soil water content. There are two approaches. The first is direct and indirect methods (Bitelli, 2011; Su et al. 2014), while the second is remote sensing techniques which focus mainly on the spatial distribution and temporal variation of soil water content (Altese et al., 1996).

The direct techniques include the feel and appearance method (Klocke and Fischbach, 1984), the calcium carbide gas pressure method (Arsoy et al., 2013) and the thermo-gravimetric method (ASTM D2216-98, 1998) which can be used to calibrate other indirect approaches. The indirect methods include a variety of methods such as the gamma ray attenuation method (Wilson, 1971), the neutron scattering method (Elder and Rasmussen, 1994), the Wenner method (Wenner, 1915), the tensiometer method (Schmugge et al., 1980), the soil electrical conductivity method (Zegelin, 1996), the hygrometric method (Schmugge et al., 1980) and the soil dielectric method (Zegelin, 1996).

Despite the many methodologies developed, the dielectric techniques including time domain reflectometry (TDR), frequency domain reflectometry (FDR), and capacitance sensor
stand out from these methods due to their automation capability, on-site measurements, high accuracy and easy installation (Rao and Singh, 2011; Selig and Manusukhni, 1975; Topp and Davis, 1984). Capacitance sensors are often preferred over dielectric techniques because they provide real-time soil water content at a lower cost and consume less energy compared to TDR sensors (Pelletier et al., 2012; Visconti et al., 2014; Zhang et al., 2011). These techniques are widely used and their accuracy depends largely on the experience of the user, careful calibration and different soil properties. The thermo-gravimetric method can be a good tool to calibrate these devices, although due to the time and oven requirements, the calibration process is slow but extremely accurate (Ma et al., 2016; Placidi et al., 2020).

To calibrate capacitive sensors, the sensor-to-sensor variability must always be considered, as this can greatly affect the measurement accuracy (Rosenbaum et al., 2011). To avoid this effect, the sensors can be calibrated individually with the soil samples, but this is time-consuming and difficult to implement for many sensors (Vaz et al., 2013). In addition, two-step calibration procedures or empirical and semi-empirical soil moisture (SM) models can be used to accurately determine the soil moisture content (Domínguez-Nino et al., 2019; Jones et al., 2005). The most frequently-used SM models are the following: i) Kirchhoff Approximation Model (KAM) (Pinel et al., 2020); ii) Integral Equation Model (IEM) (Zhang et al., 2020); iii) Small Perturbation Model (SPM) (Burkholder et al., 2017); iv) Small Slope Approximation Method (SSAM) (Zhang et al., 2018), as well as the semi-empirical models such as the v) Dubois model (Zhu et al., 2019) and the iv) Oh model (Sekertekin et al., 2020).

In this study, we focused on a low-cost capacitance sensor, identified as SKU:SEN0193 (DFROBOT, Shanghai, China). The main goal was to develop a standardized methodology to rapidly and effectively calibrate a capacitance sensor. To the best of the authors' knowledge, the sensor presented in this article has been calibrated twice under laboratory conditions (Nagahage et al., 2019; Placidi et al., 2020). The current paper complements the results already achieved so far by examining the operation of the sensor on three new soil textures (clay loam, sandy loam and silt loam) and introducing a new calibration methodology to facilitate more efficient use.

MATERIALS AND METHODS

Location and sampling methods

Soil samples were collected from the experimental field of the Department of Biosystems and Food Engineering of the Faculty of Agricultural and Food Sciences of Széchenyi István University [N47°54'20.00"; E17°15'10.00"]. The experimental field is an alluvial plain of the Leitha River - on which precision agriculture has been applied since 2001. The three sampling points were appointed according to different physical properties of soil, which were measured by Nyéki (2016), Kulmány and Milics (2017).

Description of low-cost capacitive soil moisture monitoring system

The data-collection system used in this study consisted of four main components: (i) three analog SKU:SEN0193 capacitive soil moisture sensors; (ii) an Arduino Nano v3.0 microcontroller; (iii) a micro SD card adapter and (iv) DS1302 Real-Time Clock module (Table 1). The electrical power required for proper operation was taken from a 20,000 mAh capacity accumulator. The Arduino Nano microcontroller was operated at a speed of 20 MHz. The developed soil moisture monitoring system costs a total of 16.23 Euro (Table 1), making it a possible option to replace a commercial soil moisture sensor (Appendix A).

Specification of analog capacitive soil moisture sensor

Three analog SKU:SEN0193 capacitive soil moisture sensors (DFROBOT, Shanghai, China) v1.2 with dimensions of 99 mm - 16 mm (L x W) were used for this research. The sensor measures soil moisture levels by capacitive sensing rather than resistive sensing. The sensors are made of corrosion-resistant material contributing to increasing their durability. They have an onboard voltage regulator providing an operating voltage range of 3.3 ~ 5.5 V. It has 2 pins for powering the device (5 V and Ground), and an analog output pin. Thus, it is perfect for interfacing with low-voltage microcontrollers. The output of the sensor is given as frequency variables, ranging from 260 Hz (high moisture) to 680 Hz (low moisture). It varies on this pin according to the moisture level (lower moisture level equals higher frequency).

Thermo-gravimetric method for soil moisture estimation

The thermo-gravimetric method was used to calibrate the analog SKU:SEN0193 capacitive soil moisture sensors. Soil moisture content (GWC) was measured by gravimetric method (Black, 1965) in parallel with sensor measurements for each soil texture. It was expressed by weight as the ratio of the mass difference between wet and dry soil samples. To establish this ratio, the water mass is determined by drying the soil sample at a temperature of 100–110 °C in the oven until the mass becomes constant and by measuring the soil sample weight before and after drying. The gravimetric water content level (GWC level) is expressed as a percentage. It is calculated according to the following equation:

\[
GWC(\%) = \frac{w_2 - w_3}{w_3 - w_1} \times 100, \tag{1}
\]

where \( w_1 \) is the empty tare, \( w_2 \) is the weight of wet soil sample and tare, \( w_3 \) is the weight of dry soil sample and tare.

Table 1. The total cost of the developed low-cost capacitive soil moisture monitoring system.

<table>
<thead>
<tr>
<th>Component</th>
<th>Units</th>
<th>Units Cost (€)</th>
<th>Subtotal (€)</th>
<th>Total (€)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SKU:SEN0193</td>
<td>3</td>
<td>1.6</td>
<td>4.8</td>
<td></td>
</tr>
<tr>
<td>Micro SD Card Adapter</td>
<td>1</td>
<td>1.08</td>
<td>1.08</td>
<td></td>
</tr>
<tr>
<td>Arduino Nano v3.0</td>
<td>1</td>
<td>2.40</td>
<td>2.40</td>
<td></td>
</tr>
<tr>
<td>DS1302 Real-Time Clock module</td>
<td>1</td>
<td>3.03</td>
<td>3.03</td>
<td></td>
</tr>
<tr>
<td>Micro SD Card (4GB)</td>
<td>1</td>
<td>4.3</td>
<td>4.3</td>
<td></td>
</tr>
<tr>
<td>Other components</td>
<td>1</td>
<td>0.62</td>
<td>0.62</td>
<td>16.23</td>
</tr>
</tbody>
</table>

The three soil samplings cover clay loam (S1), sandy loam (S2), and silt loam (S3) soil texture according to USDA Soil Taxonomy (Soil Survey Staff, 2003) (Figure 1).
To measure the soil moisture content properly with the capacitive soil moisture sensor, samples from three soil textures were weighed out into four 1725 cm³ plastic pots and they were compacted. Depending on the soil texture and moisture content, the soil samples were ground and homogenized by hand, pestle and mortar or soil grinder before weighing. The dry bulk density of the compacted soils ranged from between 1.20–1.56 g cm⁻³, which fits in well with the range of the typical values of soil dry bulk density (Chaudhari et al., 2013; Zeri et al., 2018). The measurements of soil moisture content were carried out continuously by three capacitive soil moisture sensors at the rate of soil drying in atmospheric conditions 13 times between 25 November 2020 and the end of January 2021. The gravimetric soil moisture content was also measured at the 13 measurement times. All experiments were performed at room temperature (21 °C).

The soil sample plots were allowed to reach equilibrium for 15 minutes, before starting the measurements. Thereafter, the sensors were inserted into the soil in a row at a depth of 6.5 cm from the upper soil surface. Five repetitions of the measurements were carried out for each soil texture to properly describe the soil moisture content by capacitive sensors at each GWC level. One repetition lasted for two minutes with two seconds measurement frequency and an additional eight minutes was required to save the data in appropriate file format for subsequent analysis (Figure 2). The exact volume of soil being measured by sensors is not known, but based on the result of two-sample t-tests performed, the used experimental design has no significant effect on the measured values \((p = 0.122)\).

**Data processing procedure**

The dataset collected from sensor measurements was cleaned first. The values recorded in the first 10 seconds of each repetition per sensor were not considered in calibration. This was necessary because until it reaches the optimal operating time of capacitive sensors the variation is considerable in the dataset thus increasing the uncertainty in the analysis. Therefore, a mean value was generated from the raw data for each repetition at each GWC level separately. Finally, an aggregated value was created from the mean of five repetitions at each GWC level, which was used later for analysing the behaviour of sensors at different soil textures (Figure 3).

**Calibration methods**

The variability observed in the data was caused by the heterogeneity of soil (1), sensor (2), moisture level (3) as well as the repetition of the measurements (4). Therefore, the calibration procedure was carried out considering the soil textures and sensors separately since their variability was considerable. To enable information collection on the behaviour of sensors at different soil textures, the calibration points were registered continuously at different GWC levels. Accordingly, the Repeatability and Reproducibility study was conducted by the range and mean method (Rosenbaum et al., 2010; Tsai, 1988). The value of the Repeatability and Reproducibility was expressed as a percentage using the following formulas:

\[
\%\text{Repeatability} = \frac{\sigma_{\text{repeatability}}}{\sigma_{\text{gauge}}} \tag{2}
\]

\[
\%\text{Reproducibility} = \frac{\sigma_{\text{reproducibility}}}{\sigma_{\text{gauge}}} \tag{3}
\]

The estimate of \(\sigma_{\text{repeatability}} \cdot \sigma_{\text{reproducibility}}\) and \(\sigma_{\text{gauge}}\) was calculated using the classical Gauge Repeatability and
Reproducibility method according to Montgomery and Runger (1993).

To fit and evaluate linear and non-linear regression models R statistical software (R Core Team, 2020) using its package 'rcompanion' (Mangiafico, 2021) was applied. The first model was linear, the quadratic and cubic models were considered as polynomial in the second case, and the third was exponential. Their equations are given below:
Linear $GWC(\%) = a + b \cdot \text{freq}$  

Polynomial $GWC(\%) = a + b \cdot \text{freq} + c \cdot \text{freq}^2 + d \cdot \text{freq}^3$  

Exponential $GWC(\%) = e^{a+b \cdot \text{freq}}$

The selection criteria for the best-fitted model were high coefficients of determination ($R^2$) and low root mean square errors (RMSE). The model parameters were obtained by solving a least square problem with QR factorization using lm function in R statistical software. The uncertainty was determined as the maximum of the absolute value of the residuals.

RESULTS

Sensor variability study

Descriptive statistics

Table 2 shows the descriptive statistics of the frequencies (Hz) measured by sensors. In general, the range of the frequency measured by the three sensors was different for each soil texture at the 13 different measurement times. Sensor 2 measured the lowest, Sensor 3 the highest, while Sensor 1 measured the frequency between the previous two sensors at each soil moisture level. Moreover, it can be found that the sensors show higher dispersion for higher GWC levels (Figure 3).

Reproducibility and Repeatability

One can observe that only 24 percent of the variation in clay loam (1) and sandy loam (2) was caused by Repeatability, while 42 percent of the variability was caused by repetition in silt loam (3). On average the frequency range was the highest for the first sensor 33.54 Hz in clay loam and 30.69 Hz in sandy loam as well as in silt loam. It is concluded that the Repeatability is not substantial. 76 percent of the variability was caused by Reproducibility in clay loam and sandy loam and 58 percent in silt loam meaning the measurements differed between sensors. The results showed that there is a significant amount of variability between the sensors.

Table 2. Descriptive statistics of the frequencies (Hz) measured by sensors. The soil textures are the following S1 = clay loam, S2 = sandy loam, S3 = silt loam.

<table>
<thead>
<tr>
<th>Soil</th>
<th>Sensors</th>
<th>n</th>
<th>Min</th>
<th>Q1</th>
<th>Mean</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Sensor 1</td>
<td>13</td>
<td>278.51</td>
<td>357.39</td>
<td>450.70</td>
<td>525.17</td>
<td>603.41</td>
</tr>
<tr>
<td></td>
<td>Sensor 2</td>
<td>13</td>
<td>260.21</td>
<td>308.07</td>
<td>402.82</td>
<td>470.27</td>
<td>558.41</td>
</tr>
<tr>
<td></td>
<td>Sensor 3</td>
<td>13</td>
<td>324.63</td>
<td>395.70</td>
<td>472.43</td>
<td>536.50</td>
<td>610.47</td>
</tr>
<tr>
<td></td>
<td>GWC level (%)</td>
<td>1</td>
<td>28.37</td>
<td>23.89</td>
<td>13.31</td>
<td>4.50</td>
<td>1.80</td>
</tr>
<tr>
<td>S2</td>
<td>Sensor 1</td>
<td>13</td>
<td>291.28</td>
<td>395.44</td>
<td>478.55</td>
<td>584.32</td>
<td>643.26</td>
</tr>
<tr>
<td></td>
<td>Sensor 2</td>
<td>13</td>
<td>275.38</td>
<td>358.71</td>
<td>439.04</td>
<td>538.60</td>
<td>599.60</td>
</tr>
<tr>
<td></td>
<td>Sensor 3</td>
<td>13</td>
<td>334.63</td>
<td>425.07</td>
<td>498.76</td>
<td>588.91</td>
<td>646.40</td>
</tr>
<tr>
<td></td>
<td>GWC level (%)</td>
<td>1</td>
<td>33.54</td>
<td>27.38</td>
<td>13.31</td>
<td>4.50</td>
<td>1.80</td>
</tr>
<tr>
<td>S3</td>
<td>Sensor 1</td>
<td>13</td>
<td>337.29</td>
<td>410.94</td>
<td>495.74</td>
<td>602.25</td>
<td>622.26</td>
</tr>
<tr>
<td></td>
<td>Sensor 2</td>
<td>13</td>
<td>310.72</td>
<td>366.46</td>
<td>456.17</td>
<td>555.03</td>
<td>580.77</td>
</tr>
<tr>
<td></td>
<td>Sensor 3</td>
<td>13</td>
<td>371.21</td>
<td>434.17</td>
<td>514.73</td>
<td>608.93</td>
<td>626.72</td>
</tr>
<tr>
<td></td>
<td>GWC level (%)</td>
<td>1</td>
<td>21.13</td>
<td>14.31</td>
<td>7.08</td>
<td>1.21</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Table 3. Reproducibility and Repeatability of sensors. The soil textures are the following S1 = clay loam, S2 = sandy loam, S3 = silt loam.

<table>
<thead>
<tr>
<th>Soil</th>
<th>Sensor</th>
<th>Mean</th>
<th>Mean range</th>
<th>$\sigma_{\text{range}}$</th>
<th>%Repeatability</th>
<th>%Reproducibility</th>
<th>$p^*$</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>1</td>
<td>450.70</td>
<td>33.54</td>
<td>41.08</td>
<td>24</td>
<td>76</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>402.82</td>
<td>27.38</td>
<td>35.27</td>
<td>24</td>
<td>76</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>472.43</td>
<td>28.94</td>
<td>21.13</td>
<td>58</td>
<td>11.90</td>
<td>0.001</td>
</tr>
<tr>
<td>S2</td>
<td>1</td>
<td>478.55</td>
<td>30.69</td>
<td>25.00</td>
<td>35.27</td>
<td>24</td>
<td>76</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>439.04</td>
<td>21.50</td>
<td>21.13</td>
<td>58</td>
<td>11.90</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>498.76</td>
<td>21.50</td>
<td>25.00</td>
<td>35.27</td>
<td>24</td>
<td>76</td>
</tr>
</tbody>
</table>

*One-way ANOVA was used to obtain the $p$-value of mean frequency among three soil textures.
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Table 4. Parameters of calibration functions for all sensors at different soil textures, determination coefficient ($R^2$), root mean square error (RMSE) and uncertainty. The soil textures are the following S1 = clay loam, S2 = sandy loam, S3 = silt loam.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Soil Function</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>$R^2$</th>
<th>RMSE</th>
<th>Uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Linear</td>
<td>50.29</td>
<td>-0.0836</td>
<td>–</td>
<td>–</td>
<td>0.87</td>
<td>3.38</td>
<td>10.74</td>
</tr>
<tr>
<td></td>
<td>Polynomial</td>
<td>-45.89</td>
<td>0.6351</td>
<td>-0.0017</td>
<td>1.32E–06</td>
<td>0.89</td>
<td>3.11</td>
<td>11.07</td>
</tr>
<tr>
<td></td>
<td>Exponential</td>
<td>137.48</td>
<td>-0.0056</td>
<td>–</td>
<td>–</td>
<td>0.82</td>
<td>4.05</td>
<td>12.51</td>
</tr>
<tr>
<td>1,2,3</td>
<td>Linear</td>
<td>40.41</td>
<td>-0.0672</td>
<td>–</td>
<td>–</td>
<td>0.77</td>
<td>3.84</td>
<td>10.93</td>
</tr>
<tr>
<td>S2</td>
<td>Polynomial</td>
<td>26.40</td>
<td>0.1154</td>
<td>-0.0006</td>
<td>5.41E–07</td>
<td>0.81</td>
<td>3.46</td>
<td>11.60</td>
</tr>
<tr>
<td></td>
<td>Exponential</td>
<td>231.36</td>
<td>-0.0075</td>
<td>–</td>
<td>–</td>
<td>0.78</td>
<td>3.74</td>
<td>12.88</td>
</tr>
<tr>
<td>S3</td>
<td>Polynomial</td>
<td>59.23</td>
<td>-0.0823</td>
<td>-0.0002</td>
<td>3.2E–07</td>
<td>0.85</td>
<td>2.73</td>
<td>8.74</td>
</tr>
<tr>
<td></td>
<td>Exponential</td>
<td>409.07</td>
<td>-0.0090</td>
<td>–</td>
<td>–</td>
<td>0.83</td>
<td>2.87</td>
<td>9.65</td>
</tr>
</tbody>
</table>

Table 5. Parameters of calibration functions for each sensor at different soil textures, determination coefficient ($R^2$), root mean square error (RMSE) and uncertainty. The soil textures are the following S1 = clay loam, S2 = sandy loam, S3 = silt loam.

<table>
<thead>
<tr>
<th>Soil</th>
<th>Sensor</th>
<th>Function</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>$R^2$</th>
<th>RMSE</th>
<th>Uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>1</td>
<td>Linear</td>
<td>51.27</td>
<td>-0.08</td>
<td>–</td>
<td>–</td>
<td>0.95</td>
<td>2.13</td>
<td>7.97</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Polynomial</td>
<td>-27.93</td>
<td>0.49</td>
<td>-0.00136</td>
<td>1.03E–06</td>
<td>0.96</td>
<td>1.90</td>
<td>7.53</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Exponential</td>
<td>149.75</td>
<td>-0.01</td>
<td>–</td>
<td>–</td>
<td>0.89</td>
<td>3.08</td>
<td>10.45</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Linear</td>
<td>50.15</td>
<td>-0.09</td>
<td>–</td>
<td>–</td>
<td>0.95</td>
<td>2.18</td>
<td>5.91</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Polynomial</td>
<td>-11.10</td>
<td>0.44</td>
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</table>

Calibration for each sensor at different soil textures

The results of soil texture specific sensor calibration are shown in Table 5. Based on the results of the calibration, it can be concluded that the strength of the calibration functions increased with the improvement of RMSE and decrease of uncertainty for each soil texture.

For clay loam, the best results were obtained with the polynomial function in case of all sensors. The determination coefficient of the developed models ranged between 0.96 and 0.97, with an RMSE between 1.68 and 1.96. The smallest uncertainty was detected for the second sensor (±4.78 GWC%), while the measurement uncertainty of the first and third sensors is nearly the same (±7.53 and ±7.47 GWC%).

For sandy loam, the best results were also obtained with the polynomial function in case of all sensors, but the uncertainty of the models is higher compared to the models developed on clay loam. The determination coefficient of the developed models was 0.89 in each case. The RMSE showed a slightly variability between the sensors; it varied between 2.59 and 2.67. The smallest uncertainty was found for the third sensor with ±8.10 GWC (%), while the uncertainty of the first and second sensors was ±11.33 and ±10.97 GWC (%).

For silt loam, the best results were given by the polynomial and exponential function. The coefficient of determination of the developed models ranged from 0.92 to 0.96 between the sensors, but the $R^2$ value of the models was equal in each model. In case of polynomial function, the RMSE values ranged between 1.38 and 1.92, while the RMSE of exponential function was almost similar. The smallest uncertainty was achieved for the first (±5.90 GWC%) and third sensors (±5.44 GWC%) for the polynomial function. In the case of sensor 2, the uncertainty was ±5.44 GWC (%) for exponential function and ±5.56 GWC (%) for polynomial function.

DISCUSSION

The soil capacitive sensors are widely used to predict the soil moisture content in agriculture but their efficiency particularly depends on the calibration procedure. The importance of
calibration was also emphasized by González-Teruel et al. (2018) regarding the use of capacitive sensors (PCB, Technical University of Cartagena, Spain). It was found that calibration of the sensors by soil type was required, but the uncertainty between the sensors was negligible in their study. The importance of sensor (10HS, METER Group Inc., USA) and soil-specific calibration was also emphasized by Domínguez-Nino et al. (2019). Their results showed that using sensor and soil specific calibration, RMSE can be improved by 70 percent while accuracy can be increased by 5 percent. Our results are in line with the findings of Nagahage et al. (2019) and Placidi et al. (2020) who conducted their studies also with the SKU:SEN0193 (DFROBOT, Shanghai, China) sensor. Nagahage et al. (2019) emphasized the role of the mineral content of soil in determining the soil moisture content with capacitive sensors. They found that the determination of soil moisture content in high organic-rich soil mixing with mineral media is challenging because the capacitive soil moisture sensors operate at low frequencies and are sensitive to the soil texture and salinity level. By contrast, they also highlighted that the SKU:SEN0193 sensor is able to work accurately to predict the soil moisture content in loam texture soil when applying a soil-specific calibration procedure. Placidi et al. (2020) indicated that the sample preparation strongly influences the quality of sensor measurements. However, they stated that the SKU:SEN0193 sensor works properly in soils closer to natural conditions, while it is sometimes difficult to apply to determine the soil moisture content in disturbed soils (e.g. mixing) due to low bulk density with high pore space. It can be stated that to achieve the highest measuring accuracy, SKU:SEN0193 sensors must be calibrated for different soil textures in the widest possible measuring ranges under typical soil dry bulk density.

CONCLUSION

A new low-cost measurement system was designed, developed and calibrated for monitoring the soil moisture content. To facilitate widespread use of the sensor, the applicability of the sensors was investigated on clay loam, sandy loam, and silt loam soil textures according to the USDA soil classification. The sensor response with GWC level was examined at the rate of soil drying in the atmosphere conditions using constant sample volume. Based on the obtained results, it can be stated that the response of the sensors to changes in soil moisture differs from each other (Table 2, 3), which was also greatly influenced by different soil textures (Table 4). Calibration according to soil texture was required to ensure adequate measurement accuracy. After calibrating each sensor according to different soil textures, it was found that a polynomial calibration function is the most appropriate for modelling the behaviour of the sensors (Table 5). This result suggests that the soil mixture constituents influence the accuracy of the sensor. Although the experimental investigations are still in progress, the results appear to be promising in order to demonstrate that the sensors can be used to determine moisture content under field conditions.

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Calibration of an Arduino-based low-cost capacitive soil moisture sensor for smart agriculture

[Site-specific management zone delimitation based on soil electrical conductivity]. Agroinform Kft., Budapest, Hungary. (In Hungarian.)


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APPENDIX

Appendix A Wiring of the devices
Appendix B Codes and software design for low-cost soil moisture monitoring system

```cpp
/* INCULED */
#include <SD.h>
#include <SPI.h>
#include <DS1302.h>

/*RTC*/
DS1302 rtc(3, 4, 5);

/*CONST*/
long seconds = 00;
long minutes = 00;
long hours = 00;
long previousMillis = 0;
long interval = 2000;

int CS_pin = 10;
int val1 = 0;
int val2 = 0;
int val3 = 0;

File sd_file;

/*SETUP*/
void setup() {
    /*RTC SETUP*/
    rtc.halt(false);
    rtc.writeProtect(false);
    rtc.setDOW(TUESDAY);  // Set Day-of-Week to TUESDAY
    rtc.setTime(15, 38, 0);  // Set the time to 15:38:00 (24hr format)
    rtc.setDate(27, 8, 2019);  // Set the date to August 27th, 2019 */

    /*SERIAL PORT*/
    Serial.begin(9600);

    /*SD SETUP*/
    pinMode(CS_pin, OUTPUT);
    // SD Card Initialization
    if (SD.begin()) {
        Serial.println("SD card is initialized. Ready to go");
    }
    else {
        Serial.println("Failed");
        return;
    }

    sd_file = SD.open("data.txt", FILE_WRITE);

    if (sd_file) {
        Serial.print("Mos1");
        Serial.print("");
        Serial.print("Mos2");
        Serial.print("");
        Serial.print("Mos3");
        Serial.println("", "");

        sd_file.print("Mos1");
        sd_file.print("","");
        sd_file.print("Mos2");
        sd_file.print("","");
        sd_file.print("Mos3");
        sd_file.println("","");
    }
    sd_file.close();  //closing the file
}
```
The Arduino Code is divided into three parts. The first part is for initializing the code. The different libraries for the devices are taken place here and the global variables are declared. The second part is the setup part. In the setup part, the devices and the serial port for communicating between the PC are initialized by the microcontroller. The third part is the loop. After the setup part, the code is repeated in this method as long as it is powered. Every two seconds, the “data.txt” file in the SD card opens then reads the sensors’ data and requests the current time from the RTC. The data measured is written into the opened text file and it is sent to the computer through the serial port within the senddata method.