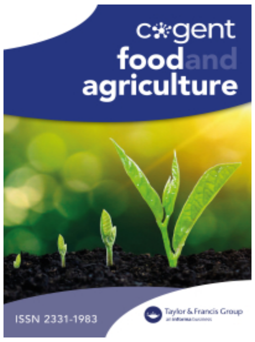


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# Improving the spatial deployment of the soil moisture sensors in smart irrigation systems using GIS

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**ABSTRACT**

Incorporating the Internet of Things (IoT) and smart irrigation systems into developing regions encounters significant financial constraints. To address this gap, this study aimed to identify the most effective locations for the sensor deployment using the Geographic Information System (GIS) techniques, maximizing the spatial coverage of soil moisture states while minimizing the number of required wireless sensor nodes. Ensuring the accuracy of YL-69 soil moisture sensors is pivotal for system efficiency therefore, a volumetric water content (VWC) calibration was conducted. Soil samples from the surface and subsurface layers were subjected to a comprehensive laboratory analysis to assess their physical and chemical attributes. Employing the Soil-Plant-Atmosphere-Water model (SPAW), the available water-holding capacity (AWHC) for these soil samples was estimated. A sensor placement strategy was formulated, aligning with AWHC maps to detect the spatial variations at varying depths. Further soil samples were collected to fine-tune the sensor calibration. Our findings revealed that third-order polynomial regression equations yielded the best correspondence between the sensor readings and the reference VWC measurements, with $R^2$ values ranged from 0.94 to 0.99 for surface layers and 0.95 to 0.98 for subsurface layers. This innovative approach facilitated the deployment of IoT and smart irrigation applications by determining the optimal sensor placement and enhancing the efficiency and cost-effectiveness of the water management systems.

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## 1. Introduction

A significant factor in irrigation systems is the requirement for well-planned water management to avoid water waste. So, building optimal irrigation management depends on having the data for monitoring the field (Campos et al., 2019). The IoT is a promising technology that provides reliable and efficient solutions for the optimization of several domains. IoT solutions are being developed to maintain and monitor agriculture automatically and depress human involvement (Farooq et al., 2019). IoT is currently playing a significant role in agriculture, particularly in irrigation, fertilizer systems, meteorological monitoring, soil monitoring, disease control, and pest control. Its influence is anticipated to expand into additional domains in the future (Vallejo-Gómez et al., 2023), which may contribute to growing agricultural efficiency in using soil, water, and energy (Martinho & Guiné, 2021).

According to Farooq et al. (Farooq et al., 2019), creating IoT systems comes at a significant cost due to devices, sensors, and other infrastructure. The high implementation cost of the WSNs is considered an obstruction. To overcome the cost of WSNs, they may be deployed in limited numbers (Gupta et al., 2020). Thus, effective sensor placement is desired to maximize

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meaningful data (Di Nardo et al., 2018). The optimal configuration of sensors in an agricultural field is attained by employing the minimum number of sensors necessary (Goodrich et al., 2023; Shahra & Wu, 2023). This study used virtual water pollution scenarios in several locations to identify the placement of sensors (Orouskhani et al., 2023). This research examined how optimal sensor placement affects the estimation of pressure heads in a real-world field, revealing that optimally positioned sensors lead to an approximately 30% reduction in the average root mean square error compared to situations where sensor positions are randomly selected.

Nowadays, there is a huge shortage of water, so to get around this problem, smart irrigation plays a significant role. The smart irrigation system (SIS) is important to collect and analyze the data that is gathered based on various sensor devices (Bhavsar et al., 2023; Adenugba et al., 2019; Thakur et al., 2020).

Deep knowledge of soil properties is important for optimizing agriculture practices and management. Meanwhile, the spatial distribution of soil's physical and chemical properties is a fundamental input to any sustainable agricultural practices (AbdelRahman et al., 2020). Spatial variability of chemical properties, such as nutrients, organic matter, and pH, affects field variation in available water content and crop productivity (Steiner et al., 2018; Abdelraouf et al., 2020). In addtition, the spatial patterns of soil physical properties influence soil water availability and the rooting of a plant (Neupane & Guo, 2019; Youssef et al., 2024).

The soil moisture affects the amount of irrigation water that is given to the crop. The level of water retention in the soil is an essential parameter for irrigation management. Therefore, smart irrigation can reduce water consumption by considering the groundwater available to the crop (Campos et al., 2019). Soil water holding capacity (the total amount of water that a soil can hold after draining the excess water) is a major factor in crop production that contributes to the mitigation of the climate change effects by buffering yields against weather variability (Abdallah et al., 2021). Available water holding capacity (AWHC) is the quantity of water stored in soil that is available to plants through their root systems. It is commonly defined as the amount of water held between the field capacity and the wilting point (Libohova et al., 2018).

Efficient irrigation management is a fundamental to minimizing water consumption. For this reason, real-time monitoring of soil water content (SWC) is essential to optimizing the amount and timing of water irrigation (Soulis & Elmaloglou, 2018). To have a measure that indicates exactly the value of moisture, new tests and calibration of the sensor are important to perform (García et al., 2020). The accuracy of reading the sensor is influential in the achievement of smart irrigation targets. The calibration method used in this research was the Volumetric Water Content (VWC) method. This study aimed to determine the optimal spatial sensor network locations by considering the available water holding capacity (AWHC) and the effective root zone based on geographic information system techniques.

## 2. Materials and methods

### 2.1. Characteristics of the study area and soil sampling

The study was conducted in a farm in the recently reclaimed region of Behera Governorate in Egypt. It is located between the latitudinal coordinates of 30°38′26.36" and 30°38′29.54" and the longitudinal coordinates of 30°0′34.95" and 30°0′38.11". The farm covered an area of 1.9 hectares and was cultivated with three-year-old Valencia orange trees. The trees were arranged with a spacing of 5 x 4 meters, and a drip irrigation system consisting of two laterals running along the rows of trees was used for their irrigation. The distance between the drippers was 50 cm, with a discharge rate of 4 L $h^{-1}$. The study area offered an opportunity to evaluate the feasibility and effectiveness of the proposed sensor placement strategy on an operational farm.

Eighteen soil samples were collected from two soil profile depths (0–30 cm surface layer and 30–60 cm subsurface layer) using a regular grid sampling design with approximately 35 x 40 m spacing between points. A handheld GPS device was used to geo-reference sample locations to enable subsequent spatial analysis. The samples were subjected to determination of physical and chemical soil properties, including particle size distribution (sand, silt, clay), saturation percentage (SP), organic matter content (OM), calcium carbonate (CaCO3), electrical conductivity (EC ds/m), total dissolved solids (TDS), pH, as well as the concentrations of cations and anions. SPSS v.20 classical statistical analysis computed descriptive statistics, including minimum, maximum, mean, and standard deviation.

### 2.2. Hardware and software

#### 2.2.1. Soil moisture sensor

The YL-69 soil moisture sensor was commonly used in smart irrigation and Internet of Things (IoT) systems to measure volumetric water content in soils (Kamelia et al., 2018; Fajrin et al., 2018; Vineela et al., 2018). This low-cost sensor was specifically designed to interface with microcontrollers such as the Arduino and NodeMCU. The YL-69 uses two probes operating at variable resistances corresponding to soil moisture levels. Soil conductivity was the measure of how well soil conducts electricity (Abdurahman et al., 2023). Several factors affected the electrical conductivity of soil, including moisture content, soil texture, and dissolved salts. A high moisture content in soil can increase its electrical conductivity (Aravind et al., 2015; Saleh et al., 2016). The YL-69 performed well in sandy soils and responded as expected to variations in salinity and temperature (Adla et al., 2020).

#### 2.2.2. NodeMCU esp8266

NodeMCU esp8266 served as an economical and open-source IoT platform for various applications (Tumpa et al., 2023). The core component of the NodeMCU development board was the ESP8266 chip, which provided wireless connectivity capabilities. Both Arduino and NodeMCU can be programmed using the Arduino Integrated Development Environment (IDE) with C++ code (Malhotra et al., 2017). This study employed the NodeMCU ESP-12 module. Compared to Arduino, NodeMCU was smaller and enabled Wi-Fi connectivity, making it more suitable for IoT applications (Boonchieng et al., 2018).

#### 2.2.3. Soil, plant, atmosphere, and water (SPAW) model

The Soil, Plant, Atmosphere, and Water (SPAW) model was a numerical hydrological model based on the Richards equation that was used with varying degrees of success to evaluate components of the field water cycle (Saxton & Rawls, 2006). The primary input parameters are particle size distribution, specifically clay and soil content. It was applied and validated under different conditions and locations (Aslam et al., 2021; Setyowati et al., 2020). SPAW is an effective tool for estimating agricultural field hydrology based on soil texture and organic matter data (Ouyang et al., 2018). In this study, soil physical properties, such as bulk density, hydraulic conductivity, wilting point, field capacity, saturation, and available water holding capacity were estimated using SPAW.

#### 2.2.4. Arduino IDE

The Arduino IDE was an open-source programming platform used to write code for uploading to Arduino and NodeMCU microcontroller boards. As open-source software, the Arduino IDE was compatible with Windows, macOS, and Linux operating systems, allowing for easy installation on various computer systems. The IDE provided a simple environment for writing and editing code in C++, the primary programming language of Arduino. All the sensors used in this study relyed on code developed in the Arduino IDE to function properly (Zlatanov, 2016).

#### 2.2.5. Soil moisture sensor calibration

Sensor calibration is a fundamental step in SIS design (Setyowati et al., 2020). In this research, the YL-69 soil moisture sensor was calibrated using the volumetric water content method to obtain moisture readings across different saturation levels. The drying of the samples was done by placing them in an oven set at 105 °C for 24 hours. Plastic containers that were sufficiently large to prevent the sensor from contacting the sides were used to store the dried samples. Based on the SPAW results of wilting point, field capacity, and saturation point, water was added to create a range of moisture levels, from dry to saturated. The soil in each container was thoroughly mixed to ensure homogenous moisture distribution. Sensor data was recorded on an Arduino IDE Serial Monitor as analog values and compiled into an Excel sheet once readings stabilized. Figure 1 summarizes the data gathering, analysis, and sensor calibration of this study.

### 2.3. Geographic information system (GIS)

GIS is a system that aids in collecting, storing, analyzing, and presenting geographic information, such as soil features, crop yields, and weather patterns (Bwambale et al., 2022; Obi Reddy et al., 2023). GIS enables the effective determination of crop positioning, land utilization, and the optimization of fertilization and irrigation needs. This was achieved through the integration of data from diverse sources and the consideration of various parameters, including soil pH, temperature, and humidity (Bilotta et al., 2023; Zhao et al., 2023). According to (Zhao et al., 2023), GIS enables farmers in agriculture to increase productivity and reduce expenses by improving land resource management.

The study used Esri ArcGIS 10.4.1 software to map the physical and chemical properties of soil and identify the best placement for sensors. The regional distribution patterns of soil attributes throughout the study area were determined by (Farooq et al., 2019) using ordinary Kriging interpolation techniques in a

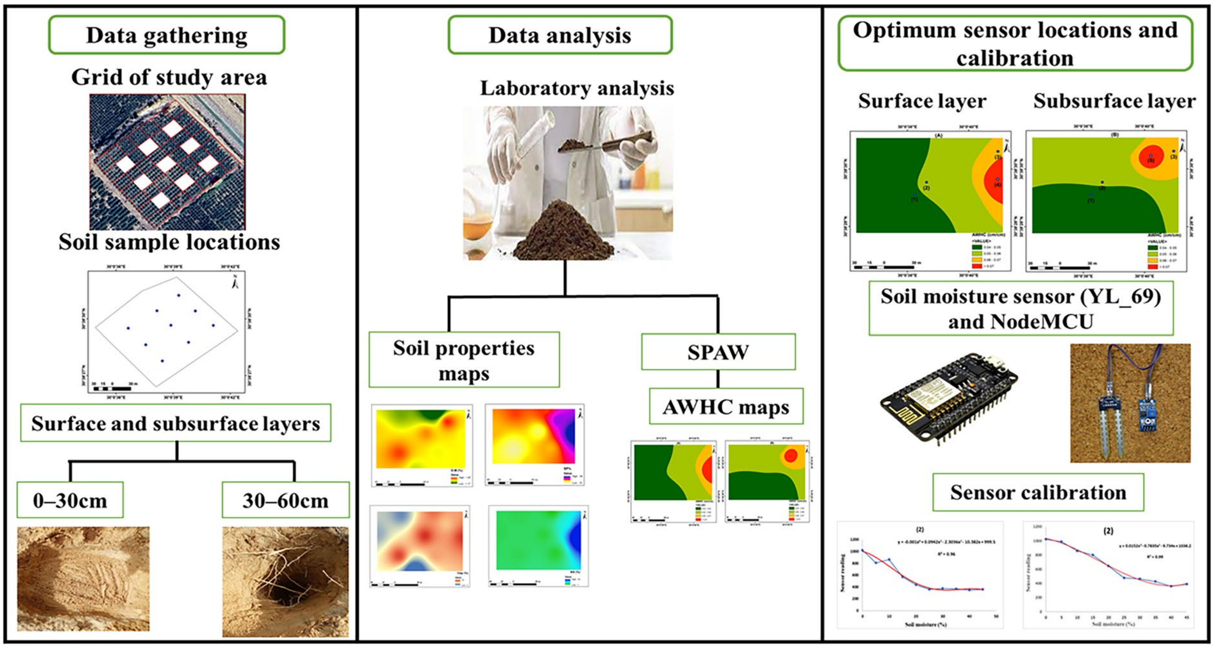


Figure 1. Methodology of the study.

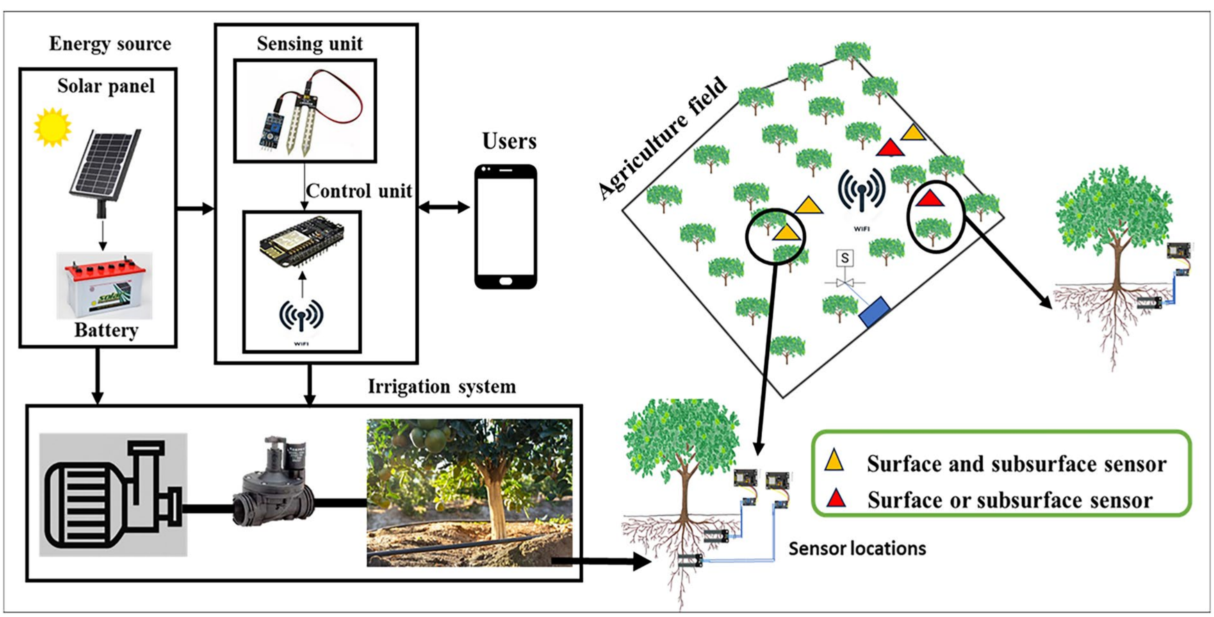


Figure 2. Proposed smart irrigation system.

GIS environment to create spatial variability maps. By using a multi-scale sampling and analysis approach, crucial soil data were obtained to help make decisions about sensor placement and irrigation management in varying conditions.

### 2.4. Proposed smart irrigation system

The proposed smart irrigation system consisted of several components, as shown in Figure 2. An energy source from a solar panel was used to provide electricity to both the nodeMCU (microcontroller unit) and the motor pump. The nodeMCU received the readings from the soil moisture sensor. When the soil moisture reading reached 50% of the Available Water Holding Capacity (AWHC), the nodeMCU sended a signal to turn on the pump. Conversely, when the moisture content reaches 100% of the AWHC, another signal was sent to turn off the pump, as presented in Figure 3. Selection of the sensor locations within the field and soil profile was based on careful consideration of the soil's physical and chemical properties, as well as the effective root zone. This ensured accurate monitoring and control of irrigation based on the specific characteristics and needs of the soil and crop.

## 3. Results and discussion

### 3.1. Descriptive statistics of soil properties

The descriptive statistics presented in Table 1 summarize the soil property characteristics for the surface (0– 30 cm) and subsurface layers, respectively. The sand content of the surface soils ranged from 67.78 to 93% with a mean of 87.25%, while the silt and clay contents ranged from 1.26 to 22.79% (mean of 5.29%) and 2.77 to 9.53% (mean of 7.46%), respectively. Surface soil pH values spanned 8.1 to 8.6, organic matter 1.17 to 1.97%, and electrical conductivity (EC) 0.15 to 0.39 dS/m. Based on the laboratory texture analysis, the surface soils were classified as sand in seven locations and sandy loam or loamy sand in one location each. Notably, TDS, sand, silt, and SP exhibited high standard deviations, reflecting a broad distribution range across the study area.

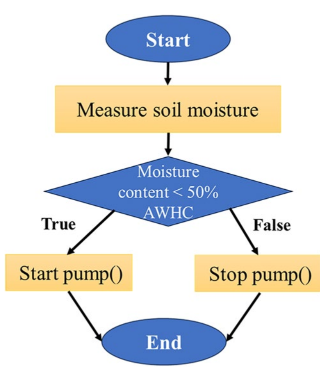


Figure 3. Flow chart diagram of microcontroller.

With a mean sand content of 87.25%, the surface soils were considered coarse-textured, as sand contents greater than 70% are associated with low water and nutrient-holding capacities (Omrani et al., 2021). Sandy soils tend to have low nutrient and water-holding capacities, as the large sand particles promote rapid drainage and the leaching of nutrients like nitrogen. The low silt and clay fractions also indicated that these soils had a minimal capacity to retain cations and anions. Frequent fertilizer applications in small doses were applied to maintain fertility in these soils, and irrigation was required to maintain adequate moisture for plants. The near-neutral mean pH of 8.29 suggests most crops can be supported in these soils without the need for pH modification. However, the variability in pH across samples indicated that a careful monitoring of pH was prudent before planting each season or crop rotation. The soils were non-saline overall based on the low mean EC, but the high standard deviation indicated salinity issues may existed in localized areas. Identifying and monitoring saline patches could help guide salt-tolerant crop selections or remediation efforts like leaching.

While these soils appeared suitable for a range of crops in terms of pH and salinity, nutrient management was a key focus given the coarse texture. Practices like adding organic matter, using slow-release fertilizers, and employing irrigation management to reduce leaching losses was considered to maintain fertility. Analyzing relationships between the measured cations, anions, and soil physical properties could provide further insights into appropriate management strategies.

Table 1. Descriptive statistics for soil properties of the surface layer at (0–30 cm) and subsurface layer (30–60 cm).

| | Minimum | | Maximum | | Mean | | Standard Deviation | |
|---|---|---|---|---|---|---|---|---|
| Statistics | Surface | Sub-surface | Surface | Sub-surface | Surface | Sub-surface | Surface | Sub-surface |
| Sand (%) | 67.78 | 74.42 | 93.00 | 93.13 | 87.25 | 87.38 | 7.65 | 5.64 |
| Silt (%) | 1.26 | 1.88 | 22.79 | 18.43 | 5.29 | 4.85 | 6.74 | 5.22 |
| Clay (%) | 2.77 | 4.54 | 9.53 | 12.37 | 7.46 | 7.77 | 2.32 | 2.49 |
| PH | 8.10 | 8.00 | 8.60 | 8.70 | 8.29 | 8.36 | 0.17 | 0.24 |
| OM (%) | 1.17 | 1.39 | 1.97 | 1.96 | 1.73 | 1.70 | 0.24 | 0.17 |
| EC (ds/m) | 0.15 | 0.11 | 0.39 | 0.16 | 0.20 | 0.14 | 0.07 | 0.02 |
| TDS (ppm) | 97.00 | 72.00 | 250.00 | 101.00 | 126.44 | 87.44 | 47.84 | 9.68 |
| SP % | 15.00 | 19.00 | 35.00 | 33.00 | 21.94 | 23.11 | 5.94 | 5.57 |
| $HCO3^-$ (meq/l) | 0.32 | 0.24 | 0.82 | 0.33 | 0.41 | 0.29 | 0.16 | 0.03 |
| $Cl^-$ (meq/l) | 0.97 | 0.72 | 2.50 | 1.01 | 1.26 | 0.87 | 0.48 | 0.10 |
| $SO4^-$ (meq/l) | 0.23 | 0.17 | 0.59 | 0.24 | 0.30 | 0.20 | 0.11 | 0.02 |
| $Ca^{++}$ (meq/l) | 0.28 | 0.21 | 0.72 | 0.29 | 0.37 | 0.25 | 0.14 | 0.03 |
| $Mg^{++}$ (meq/l) | 0.25 | 0.19 | 0.64 | 0.26 | 0.33 | 0.23 | 0.12 | 0.02 |
| $Na^+$ (meq/l) | 0.89 | 0.66 | 2.30 | 0.93 | 1.17 | 0.81 | 0.44 | 0.09 |
| $K^+$ (meq/l) | 0.09 | 0.07 | 0.23 | 0.10 | 0.12 | 0.08 | 0.04 | 0.01 |
| CaCO3 (%) | 6.46 | 5.80 | 9.79 | 9.33 | 7.68 | 7.65 | 1.18 | 1.08 |

Based on the subsurface layer (30– 60 cm), the sand content varied between 74.42% and 93.13%, with a mean of 87.38%. The silt content ranged from 1.88% to 18.43%, averaging 4.85%, while the clay content ranged from 4.54% to 12.37%, with a mean value of 7.77%. The pH values of the soil ranged from 8.0 to 8.7, with organic matter content ranging from 1.39% to 1.96%. The electrical conductivity (EC) ranged from 0.11 ds/m to 0.16 ds/m. Laboratory analyses indicated that the soil texture in the respective locations was classified as sand, sandy loam, and loamy sand. Notably, TDS, sand, SP, and silt exhibited high standard deviations among all soil properties.

The high mean sand content (87.38%) and coarse textures indicated that the subsurface soils were also sandy. Like the surface soils, this suggested that the subsurface had low nutrient and water retention capacities. Subsurface nutrient leaching was a concern in these freely draining soils. The pH remained near neutral in the subsurface layer, with alkalinity increasing slightly to the mean pH of 8.36. Salinity appeared lower in the subsurface compared to the surface soils based on the lower mean EC.

The consistently high sand contents and coarse textures throughout the soil profile indicated sandy soils predominate across the study area. Nutrient leaching through the profile required deeper soil sampling and analysis to detect subsurface accumulation or depletion patterns. Irrigation and nutrient management plans accounted for the low nutrient and water retention capacities. Practices like organic matter addition, reduced tillage, and fertilizer applications timed with plant demand improved subsurface nutrient retention and availability. Overall, the subsurface layers appeared broadly like the surface soils in key properties like texture, pH, and salinity.

### *3.2. Spatial distribution analysis of soil properties using GIS*

The spatial distribution of sand, silt, clay, SP, EC, and OM in the study area was analyzed for the (0– 30 cm) and (30– 60 cm) layers, as depicted in Figures 4 and 5, respectively. Figure 4(a) illustrates the sand content distribution, revealing higher values in the western region and lower values in the eastern region. In Figure 4(b), the silt fraction demonstrated its highest concentration in the eastern direction, while lower values were observed in the northern and central areas. Similarly, Figure 4(c) displays the distribution of clay, highlighting its highest concentration in the northeast direction, gradually decreasing towards the west. The highest SP value in the study area was depicted in the eastern direction in Figure 4(d).

Figure 4(e) indicates that the highest EC values was observed in the northeast region. Figure 4(e) and (f) demonstrate that both OM and EC exhibited a non-uniform distribution across the study area. Overall, these results highlighted the importance of spatial distribution when studying soil properties. The observed patterns provided valuable information for land management and irrigation.

Figure 5 presents the maps for the 30–60 cm layer, depicting distinct spatial patterns in the distribution of sand, silt, clay, SP, OM., and EC within the study area. The sand and silt maps displayed a contrary association, where regions with the highest sand content matched with those with the lowest silt content, and vice versa. This observation suggestd a clear segregation of these sediment fractions across the study area.

The distribution of clay, as illustrated in Figure 5, revealed its highest concentration in the northeastern part of the study area. The central-southern area showed the lowest clay content. Figure 5 also depicts the distribution of SP, revealing its maximum values on the eastern side of the study area.

The OM. map highlighted a spatial pattern wherein the highest organic matter content was observed in the central part of the study area. This pattern may be attributed to several factors, such as distinct vegetation cover, specific land use practices, or variations in organic matter inputs across the region. In contrast, the eastern part displayed the lowest OM content. In terms of EC, Figure 5 indicated that the middle portion of the study area exhibited higher values compared to the surrounding regions. The observation implied that the EC was comparatively elevated in the specified region, a phenomenon that could be influenced by factors such as the mineral composition of the soil, the characteristics of groundwater, or the methods employed for irrigation.

### *3.3. Comparison of physical parameters in surface and subsurface soil layers*

The laboratory analysis of soil properties, including sand, clay, organic matter (OM), and electrical conductivity (EC) values, facilitated the calculation of various physical parameters in the SPAW (Soil Plant Atmosphere Water) model for the (0– 30 cm) and (30– 60 cm) soil layers. These parameters include the wilting point, field capacity, saturation, hydraulic conductivity coefficient (sat. hydraulic), bulk density, and

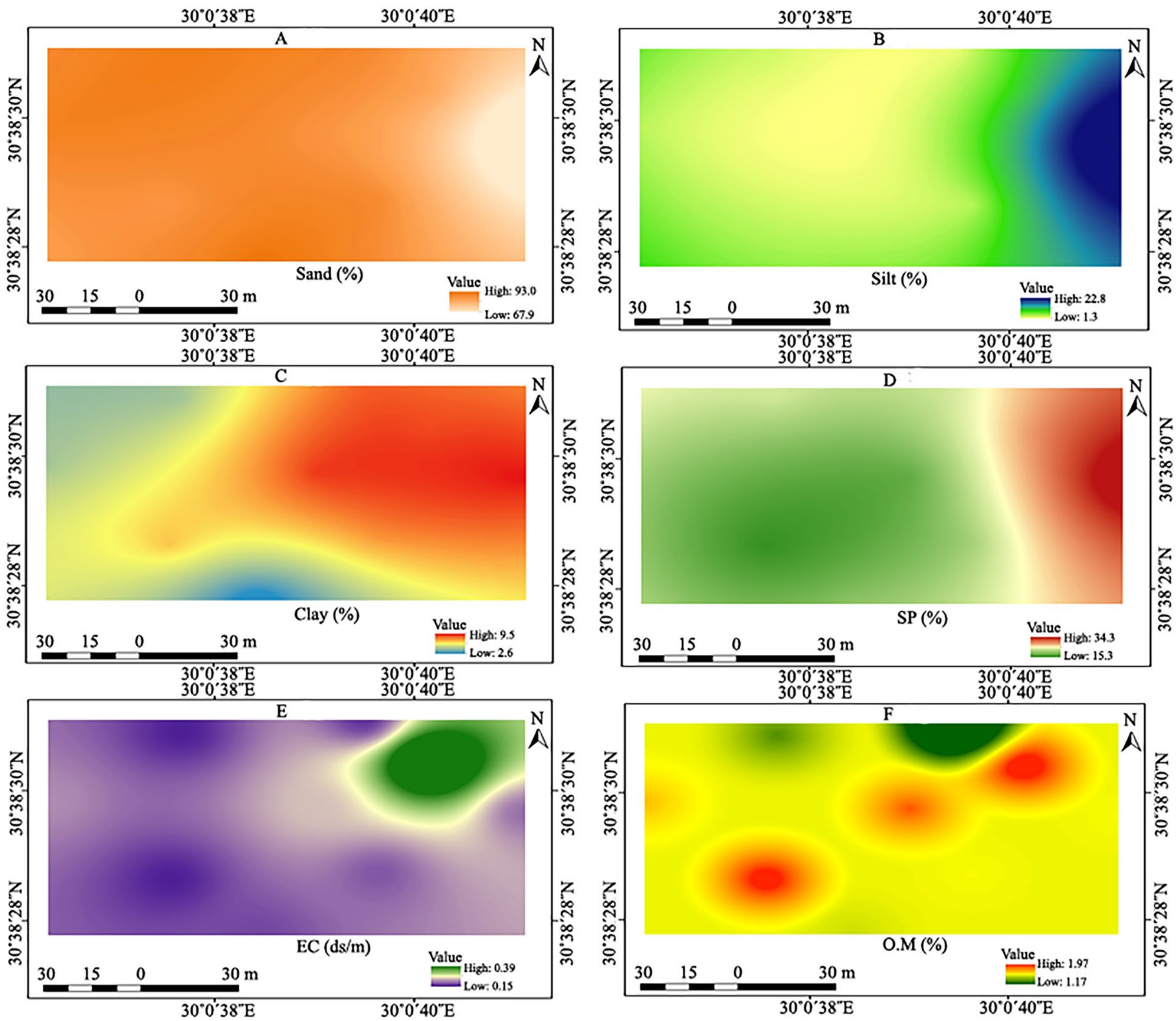


**Figure 4.** Surface Soil Properties Mapping: Sand, Silt, Clay, SP, EC, OM, and CaCO3 (0–30 cm).

available water holding capacity (AWHC), as presented in Table 2.

The mean values of the physical parameters for the (0– 30 cm) layer. The mean wilting point, field capacity, saturation, hydraulic conductivity coefficient, bulk density, and AWHC were reported as 6.41% vol., 11.69% vol., 45.42% vol., 89.95 mm/hr., 1.45 g/cm$^3$., and 0.05 cm/cm, respectively. These values represented the average characteristics of the soil in the specified layer. Similarly, the mean values of the physical parameters for the 30–60 cm layer. Within this layer, the reported values for key soil parameters included a mean wilting point of 6.73% vol., field capacity of 12.00% vol., saturation level of 45.19% vol., hydraulic conductivity coefficient of 85.10 mm/hr., bulk density of 1.45 g/cm3, and available water holding capacity (AWHC) of 0.05 cm/cm. These values indicated the average properties of the soil in the deeper layer.

### *3.4. Optimal sensor placement for water monitoring based on GIS and AWHC analysis*

Figures 6(a) and 7(b) illustrate the maps of available water holding capacity (AWHC) for the (0– 30 cm) and (30– 60 cm) soil layers, respectively. The AWHC maps were divided into four classes based on the soil's capacity to hold water. To determine the optimal sensor locations in the study area while minimizing the number of sensor nodes, we focused on areas with similar water-holding characteristics. Classes 1, 2, and 3 represented regions with similar AWHC values in both the surface and subsurface layers. Therefore, it was recommended to place two sensors in these areas, with one sensor positioned at a depth of 0–30 cm and another sensor at a depth of 30–60 cm. This configuration allowed for monitoring the water content at different soil depths in these locations.

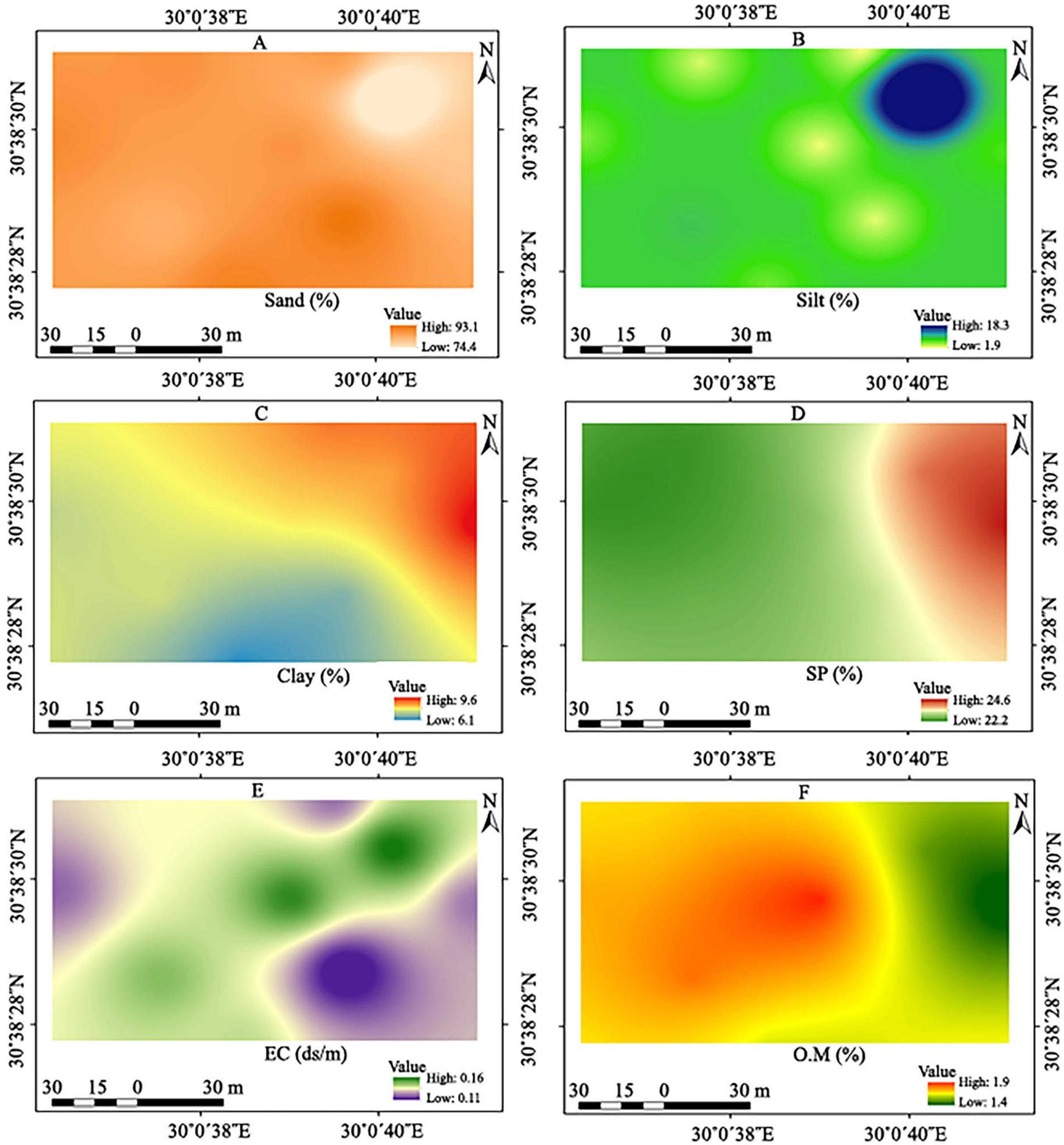


**Figure 5.** Subsurface Soil Properties Mapping: Sand, Silt, Clay, SP, EC, OM, and CaCO3 (30–60 cm).

**Table 2.** Descriptive statistics for the soil physical properties of the surface layer at (0–30 cm) and the subsurface layer (30–60 cm).

| | Minimum | | Maximum | | Mean | | Standard Deviation | |
|---|---|---|---|---|---|---|---|---|
| Statistics | Surface | Sub-surface | Surface | Sub-surface | Surface | Sub-surface | Surface | Sub-surface |
| Wilting Point % vol. | 3.80 | 5.00 | 8.00 | 9.10 | 6.41 | 6.73 | 1.35 | 1.40 |
| Field Capacity % vol. | 8.20 | 9.20 | 16.70 | 15.10 | 11.69 | 12.00 | 2.43 | 2.08 |
| Saturation % vol. | 44.40 | 43.90 | 47.10 | 46.30 | 45.42 | 45.19 | 0.85 | 0.83 |
| Sat. hydraulic Cond. mm/hr. | 57.36 | 54.21 | 138.04 | 115.52 | 89.95 | 85.10 | 24.67 | 21.04 |
| Matric Bulk Density g/cm$^3$ | 1.40 | 1.42 | 1.47 | 1.49 | 1.45 | 1.45 | 0.02 | 0.02 |
| available water cm/cm | 0.04 | 0.04 | 0.09 | 0.08 | 0.05 | 0.05 | 0.02 | 0.01 |

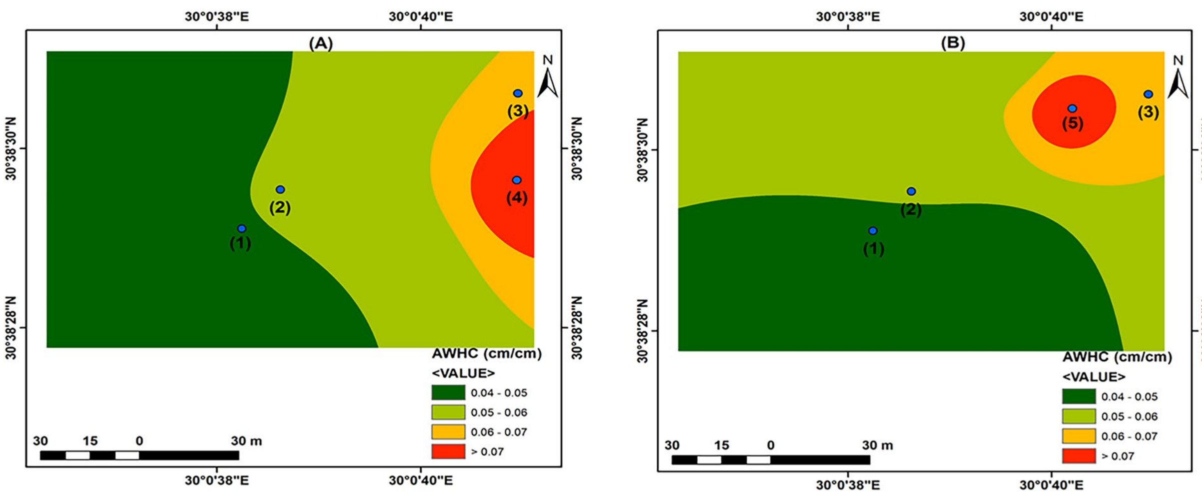


**Figure 6.** Optimal Sensor Placement Based on AWHC Maps: Surface 0–30 cm (a), Subsurface 30–60 cm (b), sensor's location: 1, 2, 3, 4, and 5.

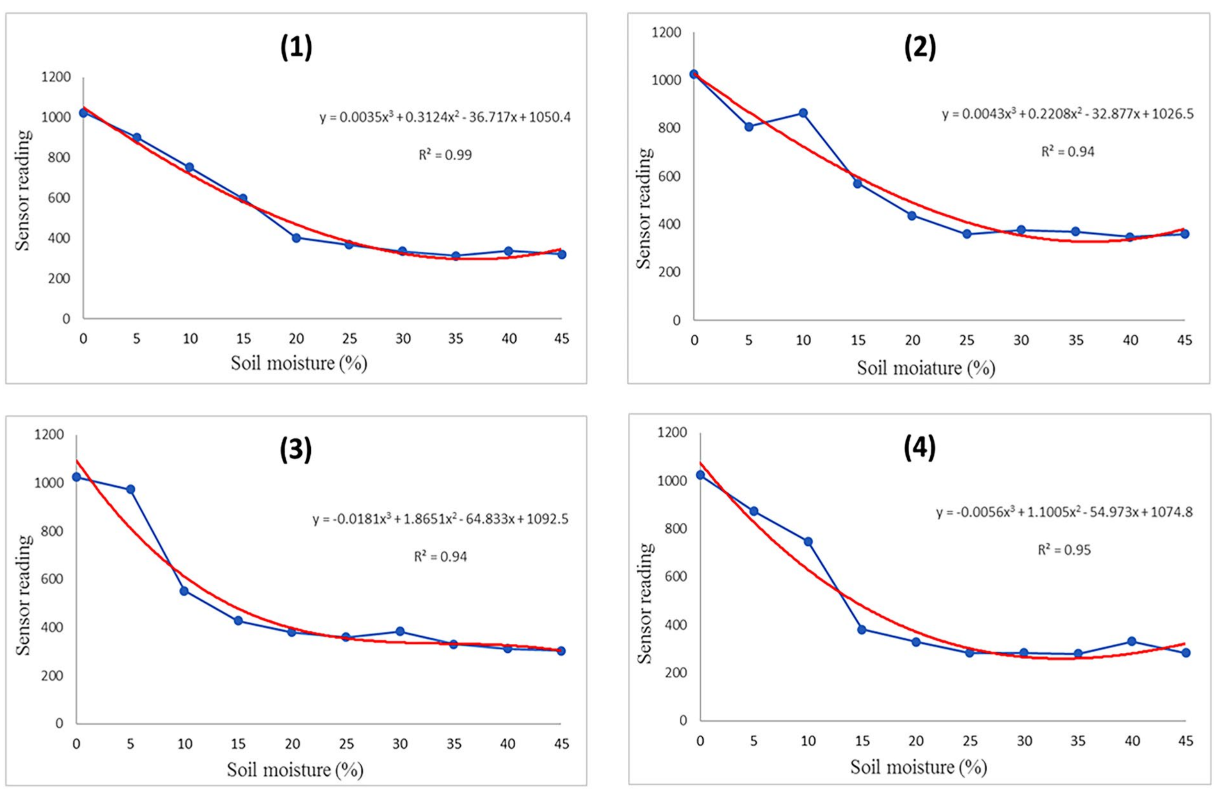


**Figure 7.** Third-order polynomial equations trend lines for the surface layer (0–30 cm) at points 1, 2, 3, and 4.

Class 4 in the surface layer exhibited different water-holding characteristics compared to class 5 in the subsurface layer. In such cases, it was recommended to deploy one independent sensor in each of these areas to accurately capture the soil moisture dynamics at their respective depths. Considering the specific needs of Valencia orange trees, it was significant that the optimal depth of sensor placement is 30– 60 cm. This depth provided valuable information about soil moisture conditions concerning the water uptake capacity of the tree's root system, aiding in efficient irrigation management and overall tree health. This method allowed for efficient soil moisture monitoring while reducing the number of necessary sensor nodes by placing sensors according to observed AWHC patterns (Sahoo et al., 2019). This study addressed the challenge of optimal sensor placement for state estimation in agro-hydrological

**Table 3.** Comparison of sensor placement strategies.

| Method | Description | Advantages | Disadvantages |
|---|---|---|---|
| GIS (Geographic Information System) | Uses spatial data (soil properties, crop types, etc.) to identify optimal sensor locations. | • Considers spatial variability of soil properties.<br>• Identifies areas with similar water needs, reducing sensor count.<br>• Creates visual maps for better decision-making. | • Requires access to spatial data and GIS software.<br>• Data analysis can be complex. |
| Statistical methods | Uses statistical analysis of sensor data to identify areas with high variability. | • Can be used with existing sensor data.<br>• Relatively simple to implement. | • Doesn't account for spatial factors like soil properties.<br>• Require a dense sensor network for accurate results. |
| Manual placement | Sensors are placed based on farmer experience or intuition. | Simple and low-cost | • Ignores spatial variability.<br>• May not be optimal for large fields. |
| Grid-based placement | Sensors are placed in a regular grid pattern across the field. | Ensures even coverage of the field. | • Doesn't account for spatial variability.<br>• require more sensors than necessary. |
| Machine learning | Uses machine learning algorithms to identify optimal sensor locations based on various data sources. | Can learn complex relationships between data points. | Requires large datasets for training. |

systems. A systematic methodology was introduced to determine the minimal number of sensors required to ensure the observability of the entire system. Subsequently, the optimal sensor locations were identified based on the degree of observability. The results demonstrated the efficacy of the proposed procedures and methodologies.

In this study, a methodology was introduced to identify the optimal sensor locations in the presence of heterogeneous. The essential stages involved dynamic order model reduction, minimal sensor selection, optimal sensor placement, and state estimation. The application of the proposed method to a three-dimensional field through simulations yielded satisfying outcomes (Sahoo et al., 2020). In the context of cultivating Valencia orange trees, this optimized placement strategy can help make informed decisions and improve water management practices (Morgan et al., 2007; Mossad et al., 2020).

### 3.5. Optimizing sensor placement in irrigation systems: a comparative analysis

Table 3 compares five methods for placing sensors in smart irrigation systems. It analyze how Geographic Information Systems (GIS) leverage spatial data like soil properties to pinpoint optimal sensor locations. This is contrasted with statistical methods that rely on existing sensor data for analysis, and simpler approaches like manual placement based on experience or placing sensors in a grid pattern. The table also highlights machine learning's potential for complex data analysis and potentially more accurate sensor placement. Finally, it acknowledges that the best method depends on factors like field size, crop type, and budget (Di Nardo et al., 2018; Orouskhani et al., 2023; Soulis & Elmaloglou, 2018; Bwambale et al., 2022).

### 3.6. Sensor calibration analysis

Based on the AWHC maps for the surface and subsurface layers, soil samples were collected from specific locations labeled as 1, 2, and 3 in the (0– 30 cm) depth and points 4 and 5 in the (30– 60 cm) depth. These samples were utilized for sensor calibration purposes. Figure 7 shows the correlation between sensor readings and soil moisture percentage, with dry soil at 0% and saturation at 45%. The sensor readings were measured on an analog scale ranging from 0 to 1023.

The third-order polynomial equations produced the highest coefficient of determination ($R^2$) value for sensor calibration in this study. These findings are in agreement with the related results reported by Series (2020). The $R^2$ values for sensor calibration at points 1, 2, 3, and 4 in the (0–30 cm) layer were approximately 0.99, 0.94, 0.94, and 0.95, respectively. Similarly, in the 30–60 cm layer, the $R^2$ values for sensor calibration at points 1, 2, 3, and 5 were approximately 0.97, 0.98, 0.98, and 0.95, respectively, as illustrated in Figure 8.

The results of the sensor calibration analysis provided important insights into the relationship between the soil moisture percentage and sensor readings. The high $R^2$ values obtained for most of the calibration points indicated a strong correlation between the sensor measurements and the actual soil moisture content. This suggested that the

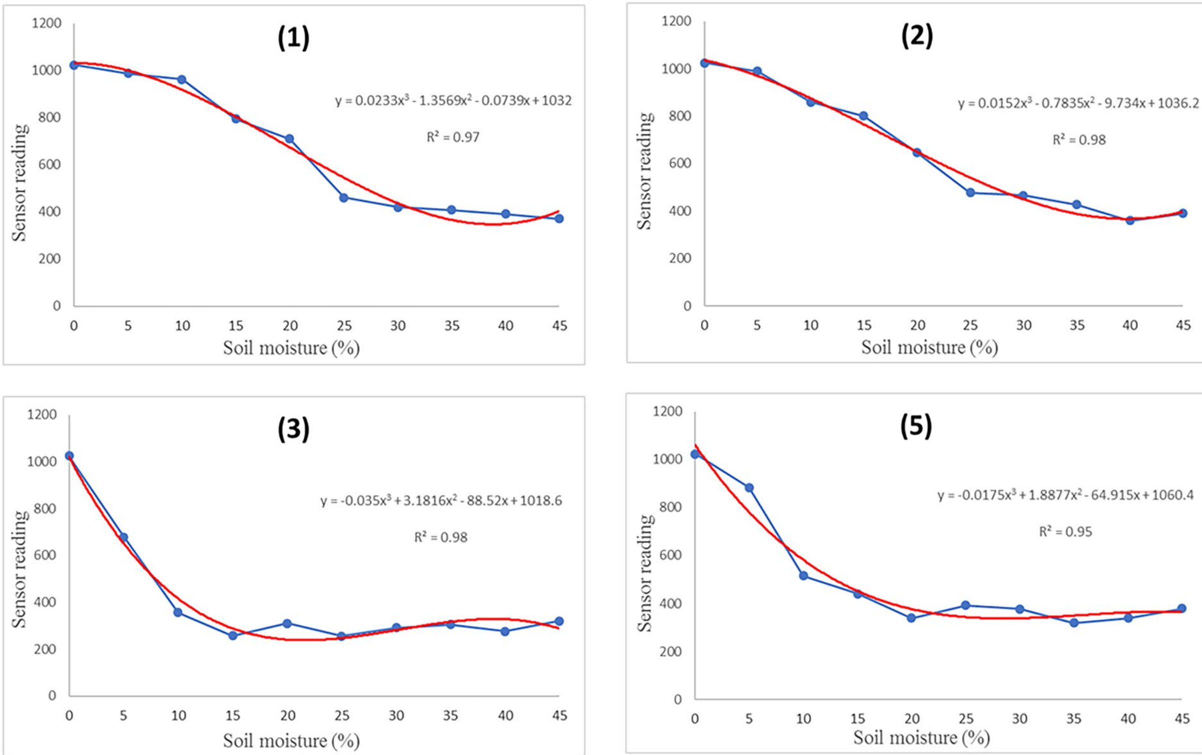


**Figure 8.** Third-order polynomial equations trend lines for the surface layer (30–60 cm) at points 1, 2, 3, and 5.

sensors were reliable in capturing variations in soil moisture levels. Point one sticks out because it had the greatest $R^2$ value in the surface layer, 0.99. This suggested that the sensor values at this location closely related to the real soil moisture percentage. This means that the sensor accurately captured the moisture in that area, making it an excellent position for monitoring soil moisture in the surface layer.

On the other hand, points 2 and 3 in the surface layer exhibited slightly lower $R^2$ values of 0.94. While these values were still relatively high, they indicated a slightly weaker correlation between the sensor readings and soil moisture percentage compared to point one. This suggestd that there might be some factors or variations in soil properties at these locations that are influencing the accuracy of the sensor measurements. In the subsurface layer, the $R^2$ values for points 1, 2, 3, and 5 ranged from 0.95 to 0.98, indicating a strong correlation between sensor readings and soil moisture percentage in this depth range. These values suggested that the sensors were also reliable at capturing soil moisture in the subsurface layer. This study summarized that the YL69 sensor demonstrated a consistent accuracy and precision on average. Moreover, it exhibited the capability to operate reliably while responding appropriately to variations in temperature and salinity, comparable even to capacitive sensors. This positioned the YL69 sensor as a robust and cost-effective soil moisture sensor (Adla et al., 2020). The calibration technique employed in this study was the gravimetric water content method, utilizing a calibration medium comprising a blend of soil and sand, with the sand constituting up to 5% of the total mixture. The experimental outcomes revealed a third-order polynomial curve (Setyowati et al., 2020).

## 4. Conclusions

This study characterized soil properties and assessed soil moisture levels in an Egyptian orange orchard. Soil samples from surface and subsurface layers underwent thorough analysis, revealed sandy composition, low organic matter, and a neutral pH. Advanced GIS techniques unveiled intricate spatial patterns, while the SPAW model calculated vital parameters. AWHC maps categorized the orchard, guiding strategic sensor placement. The calibration of YL-69 sensors demonstrated a high reliability, with $R^2$ ranging from 0.94 to 0.99 for surface layers and 0.95 to 0.98 for subsurface layers, indicating optimal monitoring precision. This multifaceted approach, encompassing soil characterization, GIS mapping, AWHC analysis, and sensor calibration, provided invaluable insights.

Overall, the study's combined results offered crucial guidance for optimizing soil moisture sensor placement and enhancing precision in orange orchard monitoring. Despite the limitations of the current study, it is acknowledge the need for a more comprehensive investigation. Future studies should delve into the robustness of the proposed approach and its application in real-world smart irrigation systems based on these results. This can provide a more holistic understanding of the system's performance and practical implications.

## Authors contribution

Yasser Arafa and Abdel-Ghany El-Gindy contributed to the conceptualization, Mohamed A.Youssef, Abdel-Ghany M. El-Gindy, Mohamed Hafez, and Younes Rashad contributed to the analysis, Mohamed A. Youssef and Mohamed Bourouah contributed in the interpretation of the data, Ahmed Abd-ElGawad and Younes Rashad contributed in writing-original draft preparation, Mohamed A.Youssef and Mohammed A. El-Shirbeny contributed in revising the paper for the final form, Ahmed Abd-ElGawad contributed in funding the work. All authors have read and agreed to the published version of the manuscript.

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## Data availability statement

Data that support the findings of this study are available from the corresponding author upon reasonable request.

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