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IoT-Based Smart Irrigation System for Precision Soil Moisture Monitoring and Water Optimization

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ABSTRACT: Agriculture remains a vital sector for global food security and economic stability; however, it is increasingly affected by climate variability, soil degradation, and water scarcity, particularly in rain-fed regions. Efficient soil moisture and nutrient management is essential to improve crop productivity and optimize resource utilization. This study presents an IoT-based smart agriculture framework for real-time soil moisture monitoring and automated irrigation control to support efficient water management in rain-fed farming systems. The proposed system integrates a low-cost soil moisture sensor with an Arduino-based microcontroller to continuously monitor soil moisture and trigger irrigation based on a predefined threshold. The sensor data are transmitted to a digital platform for real-time visualization and decision support. Experimental evaluation demonstrated soil moisture measurement performance with errors ranging from approximately −2.1% to +2.4%. The system successfully detected moisture conditions and initiated automated irrigation, reducing manual intervention and supporting responsive irrigation management. Soil fertility assessment further identified deficiencies in key nutrients, supporting nutrient-specific management recommendations. The proposed framework provides a practical basis for precision irrigation and integrated soil management, while further large-scale and long-term validation is required to establish its generalizability and scalability.

1. INTRODUCTION

Agriculture is a key global sector supporting food security, livelihoods, and economic growth. According to recent FAO projections, global agricultural production is expected to grow by about 14% by 2034, driven mainly by productivity gains and technology adoption. However, climate change, soil degradation, and water scarcity continue to challenge sustainable output, especially in rain-fed regions [1],[2]. Soil health, moisture availability, and climate conditions remain critical factors influencing crop productivity. In this context, IoT-based smart farming and real-time soil sensing technologies are increasingly being used to improve irrigation efficiency, resource management, and sustainable agricultural practices [3],[4].

The evolution and enhancement in technology and hardware have brought in drastic applications based on the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML), providing a new approach and opportunities for precision agriculture. IoT-enabled cultivation has brought in drastic change in irrigation systems that help in regular monitoring of the eco-system, tracing various attributes that can influence specific crop cultivation and trigger the supply of water automatically based on the crop cultivation requirements, thereby reducing the wastage of water and providing best practices for farming. [5]-[7]. An advanced soil monitoring system embedded with soil sensors provides data-driven decision-making, helping farmers to maintain the proper soil conditions to grow and produce the best yield [8]. Problems like inefficient irrigation, limited information access, pest infestations, soil degradation, and limited resource usage are the hurdles that bring the productivity down [9]-[11], resulting in huge economic losses and unsustainable use of natural resources. Advancement in technology helps in interconnected devices, sensors, machines, cloud platforms and central control systems, providing solutions to control and monitor agricultural operations remotely [12]-[13].

Farmers can reduce operational costs and environmental impacts with the latest innovative machines and sensors, transforming the digital ecosystem with applications. The recently introduced concept of virtualization has a metaverse in place that is an add-on to build and transform a digital ecosystem with extended support to agriculture knowledge transfer practices [14]-[17]. IoT and the metaverse help farmers to practically visualize and experience simulated cultivation environments and potentially handle and engage to bring in sustainability in cultivation practices. Live streaming of data from soil moisture sensors helps in scheduling water resource supply, resulting in reduced resource wastage [18]-[20]. In collaboration with an AI-based predictive model, the system optimizes and strengthens the framework in optimization of strategies that help cultivation and bring in power to agricultural sustainability [21]-[25].

The research explores a framework that brings in smart agriculture system integrated with an IoT-based soil moisture sensor, AI-driven analytics, and Metaverse technology aiming to enhance water-use, automate irrigation process, and provide actionable insights to farmers through digital platform. The study includes:

- Collection of field data through farmer interactions in a specific location (Patancheru), Hyderabad, INDIA.
- Analysis of soil properties, including pH levels and acidity.
- IoT-based automation for soil moisture detection and efficient irrigation management.
- Generation of digital soil reports and SMS-based notifications for farmers.

2. METHODOLOGY

The proposed study develops an IoT-based smart irrigation framework for real-time soil moisture monitoring and efficient water resource management in rain-fed agricultural systems. The methodology is organized into four structured phases: field data collection, soil nutrient analysis, IoT system design, and automated irrigation control. The various phases of the proposed approach are illustrated in Figure 1 and are described in the following subsections.

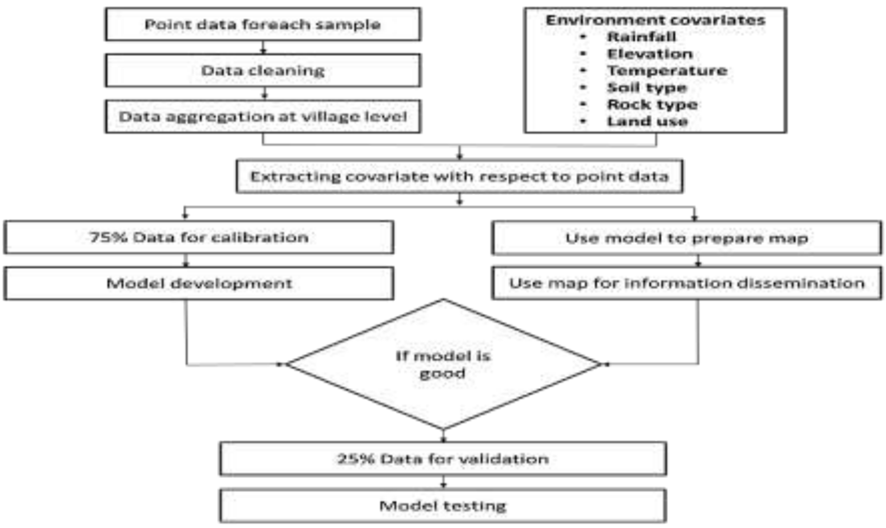

Figure 1. Workflow diagram of the proposed study

Phase 1: Field Survey and Data Collection:- This phase includes extensive field visits, farmer interaction, observation and structured interviews were carried out to collect data focusing on the existing agricultural practices, challenges and collection of soil samples. The collected dataset was the base to build the irrigation framework.

Phase 2: Soil Analysis and Nutrient Assessment:- Soil pH is measured using six major soil attributes to analyze acidic and non-acidic physicochemical characteristics of soil, considering the temperature, rainfall, soil type, and land-use patterns as shown in Table 1.

Table 1. Soil sample with default attributes

Status	Organic Carbon	Phosphorus	Potassium	Sulfur	Boron	Zinc
Sufficient	48	59	77	48	38	45
Deficient	52	41	23	52	62	55

The dataset revealed potassium exhibited a high percentage (75%), and other attributes like boron and zinc showed deficiency levels. To improve the soil assessment and its fertility two additional macronutrients were added: calcium (Ca) and magnesium (Mg) as shown in Table 2. revealing significant deficiency of Ca (90%) and Mg (75%).

Table 2. Soil samples with additional attributes (Calcium and Magnesium)

Status	Organic Carbon	Phosphorus	Potassium	Calcium	Magnesium	Sulfur	Boron	Zinc
Sufficient	43	31	21	10	28	51	80	42
Deficient	57	69	79	90	72	49	29	58

Nutrient status is classified using standard critical limits for nitrogen (N), phosphorus (P), and potassium (K) as shown in Table 3. Soil nutrient concentrations is categorized into low, medium, and high levels. Nitrogen values below 225 kg ha^{-1}, phosphorus below 10 kg ha^{-1}, and potassium below 116 kg ha^{-1} are considered as deficient values. Based on the classification results, variable-rate nutrient management strategies are generated. Nutrient-deficient soils received recommendations for approximately 25% additional NPK fertilizer application, whereas nutrient-sufficient soils are recommended 25% lower fertilizer usage to improve nutrient-use efficiency and minimize environmental impacts.

Table 3. Standard critical limits for low, medium, and high levels of nitrogen (N), phosphorus (P), and potassium (K)

Plant Nutrient	Critical level (Kg/ha)		
	Low	Medium	High
N	<225	225-560	>560
P	<10	10-25	>25
K	<116	116-280	>280

Critical thresholds for secondary and micronutrients are also considered, including Sulphur (10 mg kg^{-1}), zinc (0.6 mg kg^{-1}), boron (0.5 mg kg^{-1}), copper (0.2 mg kg^{-1}), iron (4.5 mg kg^{-1}), and manganese (2.0 mg kg^{-1}). When nutrient concentrations falls below these limits, nutrient-specific recommendations are generated automatically. Recommended application rates includes boron at 1 kg ha^{-1} and Sulphur at 30–45 kg ha^{-1} depending on crop type. Zinc application recommendations varied from 2.0 to 5.0 kg ha^{-1} based on cultivation requirements.

Phase 3: IoT-Based Automated Irrigation System:- This phase develops an IoT-enabled irrigation framework for continuous soil moisture monitoring and automated water management. Data acquisition and processing are implemented using a microcontroller, which continuously receives soil moisture readings and identifies moisture levels below or above the prescribed threshold. The proposed IoT-based architecture integrates the soil moisture sensor, microcontroller, threshold-based irrigation control, and digital data transmission into a unified monitoring system. When the soil moisture level falls below the predefined threshold, the microcontroller automatically initiates irrigation, while irrigation is stopped when the required moisture level is reached. The threshold was selected based on the reference soil moisture conditions representing dry and adequate moisture states. During calibration, moisture conditions of 25%, 50%, 75%, and 100% were considered to distinguish dry, moist, wet, and saturated soil conditions, respectively.The measured data are simultaneously transmitted to a digital platform for real-time visualization and decision support. This integrated system helps prevent unnecessary water application, reduces manual intervention, and supports efficient water management and optimal crop growth. The proposed framework also supports Digital Soil Mapping (DSM) using the collected nutrient data to identify nutrient-deficient zones and recommend appropriate nutrient requirements, thereby supporting precision agriculture practices.

Before field measurements, the soil moisture sensor was calibrated using reference soil moisture conditions. Sensor readings were compared with the corresponding reference moisture values, and the observed deviations were used to assess sensor accuracy. Following calibration, the sensor was interfaced with the Arduino microcontroller for data acquisition. Measurements were recorded under different soil moisture conditions using soil samples representative of the study area, and the sensor response was evaluated over the considered moisture range. The sensor readings are acquired and processed through the Arduino microcontroller and transmitted to the digital platform for real-time visualization. The displayed soil moisture status enables continuous monitoring and supports timely irrigation decisions based on the predefined moisture threshold. The measured soil moisture values were compared with the corresponding reference moisture values to determine the measurement error. The measurement error was calculated as the difference between the sensor-measured value and the corresponding reference value, expressed as given in equation 1:

$\boldsymbol{Error}(\%) =$ Measured Value -Reference Value (1)

The reference values represent the actual soil moisture conditions used for sensor calibration and performance evaluation [12]. The experimental setup comprised the soil moisture sensor, Arduino microcontroller, indicator LED, irrigation control unit, and digital data-transmission interface. The overall system architecture, calibration procedure, comparison of sensor and reference measurements, and field deployment are illustrated in figure 2.

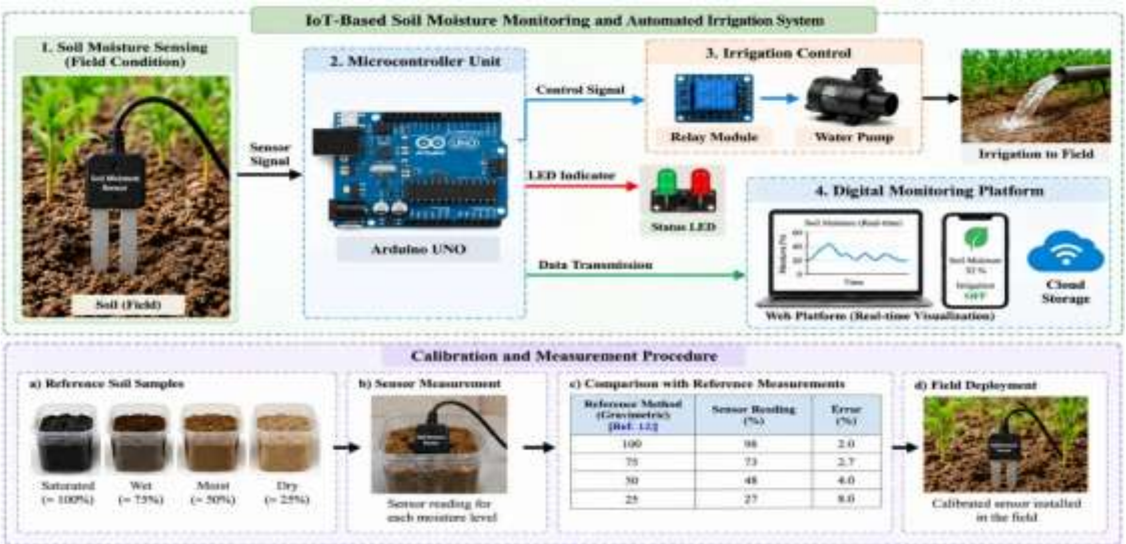

Figure 2. Experimental setup, calibration, and measurement procedure for the IoT-Based soil Moisture monitoring and automated irrigation system

Phase 4: Metaverse-Enabled Smart Farming Platform:- IoT, AI, Metaverse technology, interactive digital agricultural ecosystem collaboration, field data collection and transmitting to cloud-based platform, visualized within a virtual environment is part of this phase. Knowledge sharing, expert consultation, collaborative problem-solving and eliminating geo location constraints are the key considerations provided to farmers to get response on figure tips on their smartphones and other devices.

Phase 5: Digital Recommendation and Reporting System:-During this phase, a computational module is developed for soil classification, nutrient assessment, recommendation generation, and report preparation based on soil moisture and fertility status. The system provides soil amendment recommendations, including poultry manure application at 2.5 t ha^{-1} and seed priming using 1% zinc sulphate heptahydrate ($ZnSO_4 \cdot 7H_2O$) and 1% monopotassium phosphate (KH_2PO_4) to enhance nutrient availability and crop resilience. The recommendations are disseminated through digital platforms and SMS notifications [26]-[30].

3. RESULTS AND DISCUSSION

This section presents the experimental results and analysis of the proposed IoT-based smart irrigation system. The findings include soil moisture sensor performance, nutrient status evaluation, and system response under varying field conditions.Symptoms of growth stress, leaf discoloration, reduced vigor, and poor plant development are illustrated in Figure 3. This is due to inadequate soil fertility, moisture, and nutrient imbalances impacting the yield and degradation of soil health. Figure 4 represents soil fertility status for six key soil nutrients, namely organic carbon, phosphorus, potassium, Sulphur, zinc, and boron. The analysis indicates that potassium exhibited the highest proportion of sufficient samples (77%), whereas boron showed the highest percentage of deficient samples (62%). Organic carbon and Sulphur displayed nearly equal distributions between sufficient and deficient categories; zinc deficiency was observed in 55%. Figure 5 illustrates the nutrient status of soils, highlighting the predominance of organic carbon and phosphorus deficiencies, which may adversely affect overall crop performance. Figure 6 illustrates the soil fertility status of different nutrients, revealing severe deficiencies in calcium, potassium, and magnesium, whereas boron exhibits the highest level of sufficiency. Table 4 shows a comparative analysis of the nutrient status of OC and P with sufficient and deficient, which is plotted as Figure 7 in a violin type representing the distribution, variability, and concentration of observations for each nutrient. which help in deeper understanding of soil fertility across the study area.

Figure 3. Plant with unfertile soil, without water and nutrient deficiencies

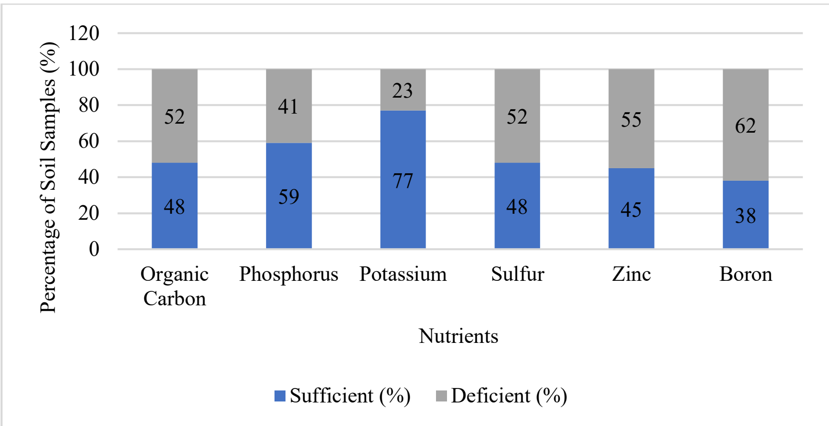

Figure 4. Soil fertility status (in %)

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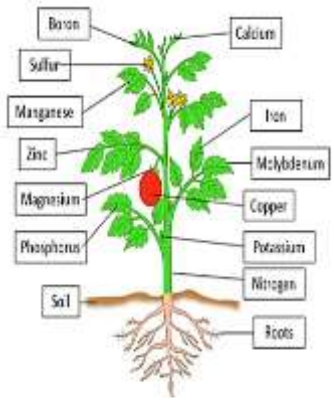

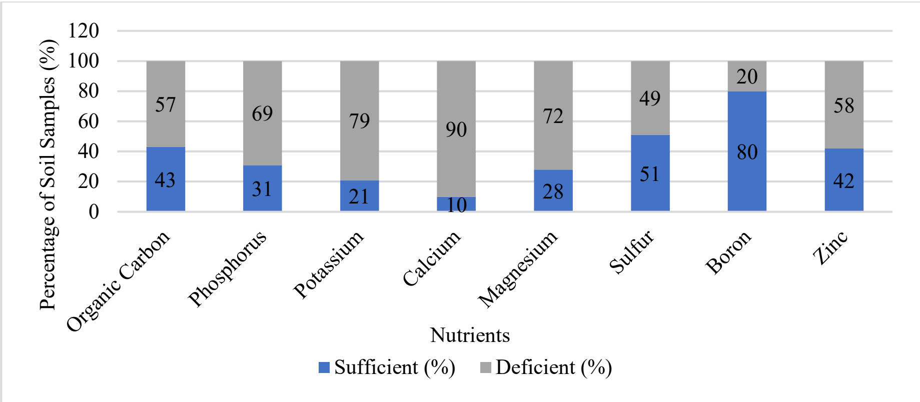

Figure 5, Plant with fertile soil, water, and rich nutrients

Figure 6. Soil fertility status based on organic carbon, phosphorus, calcium, magnesium, sulfur, boron, and zinc

Table 4. Data set based on sufficient and deficient levels of OC and phosphorus

Status	Organic Carbon	Phosphorus
Sufficient	48	59
Sufficient	43	31
Deficient	52	41
Deficient	57	69

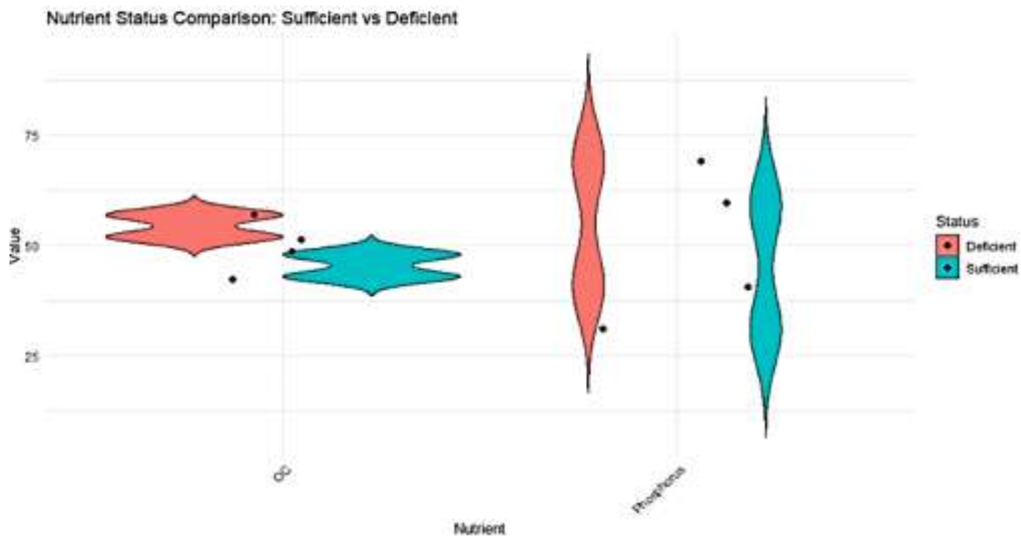

Figure 7. Nutrient status comparison: Sufficient vs deficient with organic carbon and phosphorus attributes

The soil moisture sensor is interfaced with an Arduino microcontroller, where pin 4 is configured as an input for sensor data acquisition, and pin 13 is configured as an output for LED indication. The LED provides a visual signal of soil moisture status by turning ON and OFF at one-second intervals, representing dry and moist soil conditions, respectively. The Arduino program initializes serial communication and continuously reads sensor data in an iterative loop. A logical flag is used to represent moisture status, where TRUE indicates sufficient moisture presence and FALSE indicates dry soil conditions. The irrigation response time was evaluated by observing the interval between detection of soil moisture below the predefined threshold and activation of the irrigation control. The Arduino continuously monitored the sensor output, and the control signal was activated when the measured moisture level crossed the predefined threshold. The one-second sampling interval provided the temporal basis for monitoring the threshold transition and system response. The collected experimental data, presented in Table 5, includes actual soil moisture percentage, measured values, and corresponding error percentages for performance evaluation of the sensor system. Figure 8 represents the data set, which is a bar graph representing the values processed and fetched by the moisture sensor.

Table 5. Data set streamed live by the moisture sensor

Moisture in Soil in %	2.5	5	7.5	10	13	15	18	20	23	25	28	30	33	35	38	40	43	45	48	50
Value Measure in %	1.2	3.8	8.2	11	15	17	19	22	22	23	26	31	32	32	37	39	42	43	48	48
Error %	-1	-1	0.7	1	2.4	1.8	1.2	2.4	-1	-2	-2	1	-0	-1	0.4	-1	-1	-2	0.6	-2

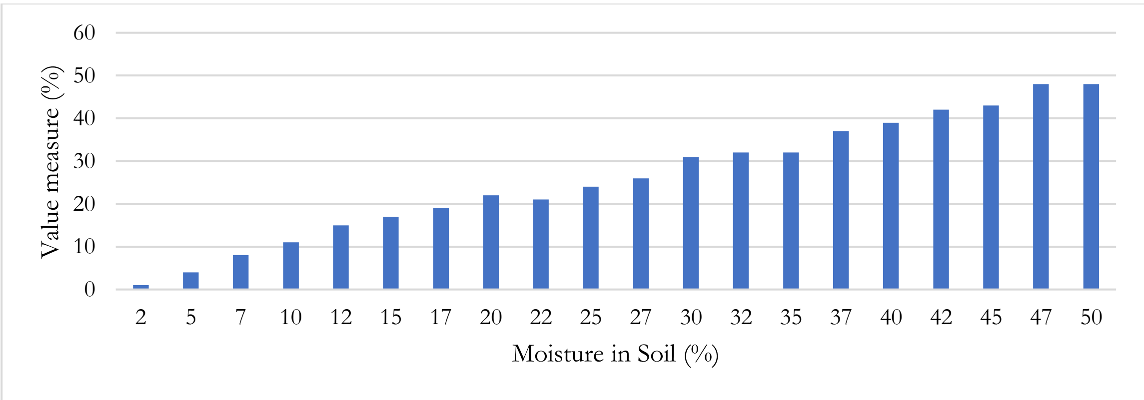

Figure 8. Data set in % based on moisture in soil and value measure

Despite its operational simplicity, threshold-based irrigation has certain limitations. A fixed soil moisture threshold may not adequately represent variations in crop water requirements, soil characteristics, weather conditions, and crop growth stages. Consequently, a threshold suitable under one set of conditions may result in over- or under-irrigation under changing environmental conditions. Therefore, the moisture threshold should be adjusted according to crop stage, soil properties, and prevailing environmental conditions. Future improvements should incorporate dynamic thresholds using real-time environmental and crop-related data.Long-term sensor reliability is also an important consideration for field deployment. Prolonged exposure to soil moisture and environmental conditions may cause sensor drift or degradation, potentially affecting measurement accuracy over time. Periodic recalibration may therefore be required to maintain reliable measurements. The present study demonstrates sensor performance under the tested soil moisture conditions; however, long-term field monitoring was not conducted. Future work should evaluate sustained sensor performance over extended periods and establish appropriate recalibration intervals.

System performance may also vary across different soil types and crops because soil moisture characteristics and crop water requirements are not uniform. Therefore, the threshold established under the present study conditions cannot be directly generalized to other soil types or crops without appropriate calibration and adjustment. The sensing approach can be adapted to different agricultural conditions, provided that the moisture thresholds are determined according to specific soil and crop requirements. Further validation across diverse soil types and crops is required to establish the generalizability of the proposed framework.Reliable network connectivity is an important requirement of the proposed IoT framework because sensor data must be transmitted to the digital platform for real-time monitoring and decision support. Intermittent or weak connectivity may interrupt data transmission and limit remote visualization. However, the local Arduino-based sensing and irrigation control can continue to operate based on the predefined moisture threshold. Future implementations should evaluate the system under different network conditions and incorporate suitable data-buffering or communication mechanisms to improve reliability.

The energy consumption of the proposed system is associated with the soil moisture sensor, Arduino microcontroller, data-transmission unit, and irrigation-control components. Since the present study primarily evaluates soil moisture monitoring and automated control performance, the energy consumption of individual components was not separately quantified. Future work should therefore quantify component-level and overall system energy consumption during long-term field deployment.Finally, larger-scale field validation is required to establish the reliability, scalability, and practical applicability of the proposed framework under diverse agricultural conditions. The present study demonstrates the system under the tested field conditions; however, extended deployment across larger cultivation areas and over longer periods would provide stronger evidence of sustained performance and scalability.

Future work will focus on long-term and larger-scale field validation across different soil types, crops, and climatic conditions. The system can further be enhanced through dynamic moisture thresholds, weather-forecast integration, energy-efficient communication, and machine-learning-based predictive irrigation. Integration with cloud and mobile platforms may also improve remote monitoring and decision support.

4. CONCLUSION

This study developed an IoT-based smart irrigation framework for real-time soil moisture monitoring, automated irrigation control, and soil nutrient assessment in rain-fed agricultural systems. The proposed system continuously monitors soil moisture and supports timely irrigation decisions, thereby reducing manual intervention and supporting efficient water management. Experimental evaluation demonstrated sensor measurement errors ranging from approximately −2.1% to +2.4%. Soil fertility assessment identified substantial deficiencies in calcium, potassium, and magnesium, while boron exhibited the highest level of sufficiency, highlighting the importance of nutrient-specific soil management. The integration of soil moisture sensing, automated irrigation, nutrient assessment, and digital recommendations provides a practical framework for precision agriculture. However, the use of fixed moisture thresholds, potential sensor drift, dependence on network connectivity, unquantified component-level energy consumption, and limited long-term and large-scale validation remain important considerations. Future work will focus on long-term field validation across different soil types and crops, dynamic moisture thresholds, weather-data integration, energy-efficient communication, and machine-learning-based predictive irrigation.

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AUTHOR CONTRIBUTIONS

Phuke Rakesh Rao: Conceptualization, Methodology, Investigation, Data Curation, Writing – Original Draft, and **Visualization.**

Ramandeep Sandhu: Methodology, Formal Analysis, Investigation, Validation, and Writing – Review & Editing.

Harpreet Kaur Channi: Conceptualization, Methodology, Formal Analysis, Validation, Supervision, and Writing – Review & Editing.

Minu Choudhary: Data Curation, Investigation, Formal Analysis, and Writing – Review & Editing.

Babita S. Gawate: Investigation, Validation, Resources, and Writing – Review & Editing.

Sukhada Aloni: Methodology, Investigation, Validation, and Writing – Review & Editing.

Arathi S. Kamble: Investigation, Data Curation, Visualization, and Writing – Review & Editing.

All authors contributed to the interpretation of the results, reviewed the manuscript critically, approved the final version, and agreed to be accountable for all aspects of the work.

CONFLICT OF INTEREST

The authors state no conflict of interest.

ETHICS STATEMENT

The study involved no human or animal participants and used no personally identifiable information. Therefore, ethical approval and informed consent were not applicable.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [FS] on request.

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