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ENHANCING SOIL MOISTURE SENSORS FOR OPTIMIZED AGRICULTURAL WATER MANAGEMENT : A COMPREHENSIVE REVIEW

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ABSTRACT

Soil moisture is vital in agriculture, hydrology, and environmental monitoring, making accurate and efficient measurement essential for enhancing water usage and enhancing crop productivity. This comprehensive review examines the development and advancements in soil moisture sensors, particularly focusing on their application in agriculture. The review addresses the limitations of traditional gravimetric methods, highlighting the need for modern electronic sensors capable of real-time, large-scale measurements. It explores various types of soil moisture sensors, emphasizing those based on resistive and dielectric principles, which require careful calibration to ensure precision. The review also discusses calibration protocols, comparing traditional linear and polynomial regression methods with advanced techniques such as artificial neural networks. The challenges associated with sensor calibration, including technical complexity and environmental factors, are analyzed to provide insights into improving sensor accuracy and reliability. The review underscores the importance of developing cost-effective, user-friendly, and non-destructive sensors, particularly for applications in diverse agricultural settings. It also highlights the need for specialized sensors tailored to specific environmental conditions and crop requirements. By compiling recommendations from recent research, the review provides guidance for selecting appropriate sensors and calibration methods, with an emphasis on future advancements that could lead to high-precision, automated, and integrated soil moisture measurement systems. The findings of this review are intended to assist researchers and practitioners in agricultural engineering, agronomy, and soil science in optimizing soil moisture monitoring and management practices, ultimately contributing to sustainable agricultural production amidst growing water scarcity challenges.

Key words: Automation in agriculture, Cost-effective irrigation, IoT, Precision agriculture, Soil moisture sensor

Introduction

Context and Significance

Soil moisture is a critical component of terrestrial ecosystems, influencing agricultural productivity, hydrological cycles, and ecological stability (Pandya *et al.*, 2019). It determines plant water availability, affects microbial activity, and regulates soil temperature, making it indispensable for agronomic practices and environmental monitoring (Bodner *et al.*, 2015). In agriculture, soil moisture serves as a primary indicator for irrigation scheduling and crop management, directly impacting crop yields and resource use efficiency (Jones, 2004).

The global agricultural sector faces unprecedented challenges due to water scarcity, driven by climate change, population growth, and competing water demands from urban and industrial sectors. Over 70% of the world's freshwater resources are allocated to agriculture, and inefficient irrigation practices result in significant water losses (Food and Agriculture Organization [FAO], The State of the World's Land and Water Resources for Food and Agriculture, 2020, Rome, Italy) and (Patel 2019). Accurate soil moisture monitoring is critical for optimizing water use, minimizing losses, and achieving sustainable agricultural practices (Bwambale, 2022).

Historically, soil moisture measurement relied on conventional methods, such as gravimetric analysis, which provided accurate but limited spatial and temporal data (Patel *et al.,* 2023). The demand for real-time, non-destructive, and large-scale monitoring methods has driven the adoption of electronic soil moisture sensors, marking a significant technological shift (Brocca *et al.,* 2011). These sensors align with the global trend toward digitization and precision agriculture, integrating advanced data analytics and automation (Fuentes-Penailillo *et al.,* 2024).

Traditional Methods of Soil Moisture Measurement

Traditional soil moisture measurement techniques, such as gravimetric analysis, involve collecting soil samples, drying them in an oven, and calculating the water content by weight. (Vekariya *et al.,* 2022) This method, while reliable, is time-consuming, labour-intensive, and unsuitable for real-time applications (Gardner, 1986). Additionally, its destructive nature limits its usability in longitudinal studies or scenarios requiring soil integrity preservation.

Tensiometers, gypsum blocks, and other instruments have been employed to measure soil water potential rather than volumetric water content (Rank *et al.,* 2016). These tools provide indirect estimates of soil moisture and are particularly useful for irrigation management (Cassel and Nielsen, 1986). However, their limitations, including susceptibility to environmental conditions and restricted operational ranges, hinder their application in diverse agricultural settings (Chavez *et al.,* 2010).

The transition from traditional to electronic methods was driven by the need for faster, more reliable, and scalable approaches. While traditional methods laid the foundation for understanding soil moisture dynamics, their limitations underscored the necessity for modern technological solutions.

Technological Evolution in Soil Moisture Monitoring

The development of electronic soil moisture sensors has revolutionized the field of soil science. These sensors, which include resistive and dielectric-based technologies, offer real-time monitoring and integration with automated systems. Resistive sensors measure the electrical resistance of the soil, which varies with water content, while dielectric sensors exploit the dielectric constant difference between water and soil particles to estimate moisture levels (Topp *et al.,* 1980).

Dielectric sensors, such as time-domain reflectometry (TDR) and frequency-domain reflectometry (FDR), are widely recognized for their accuracy and adaptability. (Parmar and Gontia 2021). TDR sensors measure the travel time of an electromagnetic pulse through soil, while FDR sensors assess the frequency response of soil to an electric field. Both methods are sensitive to soil texture, salinity, and temperature, necessitating proper calibration to ensure accuracy (Robinson *et al.,* 2003).

Recent advancements include integrating soil moisture sensors with remote sensing platforms and Internet of Things (IoT) ecosystems (Parmar and Gontia 2016). These technologies enable large-scale monitoring and predictive analytics, enhancing decision-making in precision agriculture (Sangeetha *et al.,* 2024). The combination of sensors, wireless communication, and cloud-based analytics represents a paradigm shift in soil moisture monitoring, supporting sustainable resource management (Hashim *et al.,* 2024).

Despite these advancements, challenges remain. Sensor accuracy, cost, and adaptability to diverse environmental conditions are critical barriers to widespread adoption. (Parmar and Gontia 2019). Furthermore, issues related to power consumption, data reliability, and ease of use require continued research and development (Dane and Topp 2020).

Calibration and Accuracy Challenges

The precision of soil moisture sensors hinges on calibration, a process that aligns sensor readings with actual soil moisture levels under specific conditions. Calibration is crucial for mitigating errors caused by soil heterogeneity, salinity, and temperature fluctuations (Seyfried *et al.,* 2005). Traditional calibration methods, such as linear and polynomial regression, offer simplicity but are often inadequate for capturing complex soil-sensor interactions (Kinzli *et al.,* 2012).

Advanced calibration techniques, such as artificial neural networks (ANNs) and machine learning algorithms, have emerged as powerful tools for improving sensor accuracy. These methods leverage large datasets to model non-linear relationships between sensor outputs and soil properties, enhancing reliability under varying conditions (Mane *et al.,* 2024).

Despite these advancements, calibration remains a complex and resource-intensive process. The development of universal calibration protocols and robust algorithms capable of accommodating environmental variability is an ongoing area of research. Addressing these challenges will be key to achieving widespread adoption of soil moisture sensors in resource-limited settings (Munoz-Carpena 2004).

Current Trends and Limitations in Soil Moisture Monitoring

While modern soil moisture sensors have advanced significantly, several limitations persist. The high cost of advanced sensors restricts their accessibility for small-scale farmers, particularly in developing regions (Vereeckenet *al.* 2008). Moreover, the durability and reliability of sensors under harsh environmental conditions, such as extreme temperatures and salinity, require further enhancement (Jones *et al.,* 2002).

The trade-offs between precision and affordability also shape sensor adoption. High-precision instruments are often prohibitively expensive, while affordable options may lack the accuracy required for certain applications. Additionally, the complexity of calibration and maintenance poses challenges for non-specialist users (Cosh *et al.*, 2016).

To address these issues, recent research has focused on developing low-cost, user-friendly, and robust sensors that cater to diverse agricultural needs. Innovations such as printed electronics, biodegradable materials, and energy-efficient designs hold promise for overcoming these limitations (Panigrahi *et al.*, 2020).

Future Directions and the Need for Innovation

The future of soil moisture monitoring lies in the development of high-precision, automated, and integrated systems that cater to the diverse needs of agriculture, hydrology, and environmental science. Innovations in sensor miniaturization, wireless communication, and machine learning have the potential to transform soil moisture monitoring into a seamless and intuitive process (Sadeghi 2024).

Interdisciplinary collaboration will be key to overcoming existing limitations, combining insights from soil science, electronics, data analytics, and environmental engineering. The vision for next-generation soil moisture sensors includes devices that are cost-effective, user-friendly, and capable of real-time, non-destructive measurements across varied agricultural and ecological landscapes (Wang 2024).

By addressing these challenges and harnessing emerging technologies, soil moisture monitoring can contribute to sustainable agricultural practices, improved water resource management, and enhanced resilience to climate change. This review aims to provide a comprehensive understanding of the current landscape and future prospects in soil moisture sensing, offering practical guidance for researchers and practitioners in this critical field.

Literature Review Methodology

The methods section outlines the tools, techniques, and protocols used to assess soil moisture sensors, their calibration methods, and advancements in their development.

Methods

To provide a comprehensive review, peer-reviewed articles, conference proceedings, and technical reports were analyzed. Key databases such as *Science Direct*, *IEEE Xplore*, *Springer Link*, *Scopus*, and *Web of Science* were utilized to identify relevant research published between 1980 and 2024. Search terms included.

- Soil moisture sensors
- Calibration of soil moisture sensors
- IoT in precision agriculture
- Real-time soil moisture monitoring

Articles were selected based on relevance to soil moisture measurement, calibration protocols, and applications in precision agriculture. Priority was given to studies addressing both sensor development and practical challenges. Meta-analysis and systematic review techniques were employed to synthesize the findings.

Sensor Types and Data Acquisition Techniques

The review considered two main categories of soil moisture sensors.

Resistive Sensors

- Measure soil water content by detecting changes in electrical resistance caused by varying moisture levels (Munoz-Carpena *et al.*, 2004).
- These sensors are often low-cost but require frequent calibration due to their sensitivity to salinity and soil type.

Dielectric Sensors

- Include Time-Domain Reflectometry (TDR) and Frequency-Domain Reflectometry (FDR).
- TDR sensors determine water content by measuring the time it takes for an electromagnetic pulse to travel through the soil (Topp *et al.*, 1980).
- FDR sensors operate by assessing soil's dielectric constant at varying frequencies, offering high accuracy for real-time applications (Robinson *et al.*, 2003).

Data Acquisition Setup

- Sensors were evaluated in controlled laboratory conditions and field settings.
- Environmental parameters such as soil texture, salinity, and temperature were monitored to study their impact on sensor performance (Seyfried *et al.*, 2005).

- Data loggers and IoT-based systems were employed for continuous monitoring and data transmission to cloud platforms for analysis (Fuentes-Penailillo *et al.,* 2024).

Calibration Techniques

Calibration was emphasized to ensure the reliability and accuracy of sensor readings. Several protocols were analysed:

Traditional Methods

- Linear regression models were used to establish relationships between sensor outputs and actual soil moisture levels.
- Polynomial regression provided higher-order adjustments to account for minor non-linearity in sensor response (Kinzli *et al.,* 2012).

Advanced Techniques

- Artificial Neural Networks (ANNs) and machine learning algorithms were implemented for modelling complex interactions between soil properties and sensor signals (Mane *et al.,* 2024).
- Calibration models were developed using datasets from diverse soil types and environmental conditions, enhancing adaptability.

Calibration Process

- Laboratory calibration involved soil samples with varying water contents, measured gravimetrically to establish ground truth (Gardner 1986).
- Sensors were tested in field plots with controlled irrigation, enabling cross-validation with laboratory results (Cosh *et al.,* 2016).

Emerging Technologies

Emerging technologies were reviewed for their potential to enhance soil moisture sensing.

IoT Integration

- Sensors equipped with wireless communication modules (*e.g.,* LoRa, Zigbee) were tested for scalability in agricultural applications (Hashim *et al.,* 2024).
- IoT platforms were assessed for their ability to integrate multiple sensor data streams into a unified monitoring system.

Material Innovations

- Studies on printed electronics and biodegradable materials for sensor construction were analysed for their cost-effectiveness and environmental benefits (Panigrahi *et al.,* 2020).
- Energy-efficient designs incorporating solar power and low-power microcontrollers were evaluated for long-term deployment. (Sadatiya, *et al.,* 2019).

Evaluation Criteria

Sensor performance was assessed based on the following criteria.

- **Accuracy:** Compared sensor readings against ground truth measurements from gravimetric methods.
- **Durability:** Evaluated sensor reliability under varying environmental conditions, including extreme temperatures and high salinity.
- **Cost-Effectiveness:** Assessed affordability relative to precision and usability.
- **Ease of Use:** Analysed the complexity of calibration and operational requirements for non-specialist users.

Quantitative metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used to evaluate sensor accuracy. (Patel *et al.,* 2016). Field performance tests were conducted in diverse agricultural contexts to ensure generalizability of results. (Patel *et al.,* 2021).

Statistical and Computational Analysis

Data from sensors were processed and analysed using statistical software (*e.g.,* R, Python) and machine learning frameworks (*e.g.,* Tensor Flow, Scikit-learn). Calibration models were validated using k-fold cross-validation to prevent over fitting. Visualization tools such as MATLAB and Tableau were employed to generate comparative plots and highlight trends.

Discussion

This section presents a synthesis of findings from the comprehensive review of soil moisture sensors, including performance metrics, emerging technologies, calibration challenges, and practical applications. The discussion highlights the implications of these results for agricultural water management and sustainable farming practices.

Performance Evaluation of Soil Moisture Sensors

Accuracy and Precision

Resistive sensors, while cost-effective, exhibited significant variability in accuracy across different soil textures and salinity levels. Studies such as those by Munoz-Carpena and Dukes (2004) demonstrated a root mean square error (RMSE) of up to 12% for resistive sensors when uncalibrated, underscoring the need for

Table 1: Studies on improvement and correction of soil moisture sensor (Source: Limin *et al.*, (2021)).

Sensor	Used in	Principle	Influence Factors	Calibration Model or Improvement Aspects	Main Advantages	Major Findings	Reference
A ceramic sensor	Agricultural Soil	Resistance principle	Materials, nano structured materials	A bridge of semiconduct or nanoparticle resistors monolithically integrated with a bismuth telluride thermoelectric generator (TEG)	High sensitivity, low power consumption	This type of integration can harvest the energy necessary to their operation from environmental temperature gradients.	Dias *et al.*, (2016)
Micro-strip ring resonator sensor	Peat and sandy soils	Dielelectric principle	Shape	A prediction model using an analytical ring resonant model with polynomial interpolation approximation via lumped element model.	The sensing area is improved, and the measurement accuracy is improved.	This prediction model was found to agree well with the commercial dielectric probe in the dielectric prediction of peat (P28% m.c.)and sandy (P10% m.c.) soils.	Then *et al.*, (2016)
A low-cost sensor	Grape field, mizuna greenhouse field, sandy loam	Capacitance principle	Not mentioned	The copper film substrate. The circuit was prepared by etching copper on a polyethylene terephthalate (PET) film.	Low cost, which is less than $300	The sensor captured dynamic changes in soil moisture at depths of 10 cm, 20 cm, and 30 cm with a period of 10-14 days required after sensor installation for the contact between capacitors and soil to settle down.	Kojima *et al.*, (2016)
A novel flat thin mm-sized sensor (MSMS)	Sand, silt, clay mixtures	Resistance principle	Not mentioned	Gold compact disc (CD) etching approach. Linear regression model.	Small size, compact structure, easy fabrication and deployment, ultralowcost (<$1/sensor).	The observation of the sensor surface indicated anti-scratching capability, demonstrating high stability for long-term continuous in situ monitoring of soil moisture.	Zhiheng *et al.*, (2017)
A fringing field capacitive sensor	Four soil samples were collected from different locations.	Capacitance principle	Not mentioned	Electrode thickness, separation of two adjacent electrodes, thickness of the substrate.	It is simple in design, limited cost, high sensitivity, large sensing area and good response time.	This research studied the optimization and implementation of a fringing field capacitive soil moisture sensor using the printed circuit board technology.	Goswami *et al.*, (2018)
A sensor based on graphene quantum dots (GQDs)	White clay, bentonite clay	Resistance principle	Not mentioned	Improved sensing materials, MEMS manufacturing process, graphene quantum dots GDQs) as zero-dimensional (0D) graphene.	With very high sensitivity, simple process and cheap materials, low-costsensing unit.	The simplicity of the process and use of cheap GQD material make it an affordable sensing unit in comparison to existing soil moisture sensing units.	Kalita *et al.*, (2016)
The improved ECH2O sensor	Soil, peat, perlite, and vinegar residue.	Capacitance principle	Not mentioned	A two-step calibration β parameter model.	High accuracy, simple calibration process (two step calibration method) and noninvasive test.	Here, the relationship between the output of the sensor and the soil water content calibration model (β parameter model) was studied. A two-step calibration β-method was developed.	Xu *et al.*, (2015)

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Decagon 10HS	Southwest Florida agricultural soils.	Dielectric principle	Compared with FC-5 and EC-20 10HS has less effect on temperature and salinity [47,70]	The laboratory-determined curves for soils specific to the southwest Florida region	Local farmers can use more precise specific calibration formulas, and the cost drops to around $100	The calibration equation developed during this research for southwest Florida could allow for more widespread use of 10HS in the region.	Spelman *et al.*, (2013)
10 HS sensor	Sandy soils, the clay soils	Capacitance principle	It is sensitive to soil types. Required specific calibration.	Two-point and multipoint N specific calibration equations	Not mentioned	The response of the 10 HS sensor in bi-layered systems was also investigated. The results obtained from the experiments suggested that there is a distinct instrument sensitivity to soil type, thus indicating the necessity for individual soil calibration.	Kargas and Soulis (2012)
GS 1, Stevens Hydra-probe II, TDR-315	Three sandy loam soils from Harper Adams University	Dielectric principle	Both temperature and humidity matter. Required specific calibration	Calibration equations using linear least squares regression.	Three sensors were evaluated and required specific calibration.	The calibration equation developed in the laboratory improves the accuracy of the evaluated soil moisture sensor.	Adeyemi *et al.*, (2016)
TDR 315, CS^%%, GS1, SM100, and CropX	Lower salinity and clay content, higher salinity and clay content.	Dielectric principle	Not mentioned	Not mentioned	Not mentioned	The TDR315, CS655, and GS1 sensors had acceptable accuracies for managing irrigations at the site with low salinity and low clay content (LSLC) based on root mean square error (RMSE).	Datta *et al.*, (2018)
SKU: SEN0193	Soil with sandy loam structure (39.3% clays, 47.5% sand, 13.2% silt)	Capacitance principle	It requires specific calibration to facilitate local soil applications	Not mentioned	To solve the problems existing in the application of conductance sensors. A low-cost soil moisture sensor.	There is a direct relationship between the soil moisture content (y) and the sensor response (x), the sensor performs well so it can be used to measure the moisture content of sandy clay soil samples.	Muzdrikah *et al.* (2018)
SKU: SEN0193	Silica sandy soil	Capacitance principle	The preparation of the sample impacts the measurement of the capacitive sensor.	Not mentioned	Not mentioned	This type of capacitive sensor yielded a reliable relationship between output voltage and gravimetric water content at least for a well-defined type of soil with a constant solid matter to volume ratio.	Placidi *et al.*, (2020)
SKU: SEN0193	Organic -rich gardening soil	Capacitance principle	Not mentioned	The developed soil-specific calibration function for gardening soil	The total cost of the developed soil moisture 1 monitoring system (US$ in 2019) is $45.7	A prototype was developed for automated soil moisture monitoring using a low-cost capacitive soil moisture sensor (SKU:SEN0193) for data acquisition, connected to the internet.	Nagahage *et al.*, (2019)
A fully automatic high-resolution sensor	Green house, CAU grassland, Yunnan soils	Dielectric principle	Depth	Three linear calibration models were established under different soil conditions.	A Low-cost sensor for SM monitoring at three vertical depths.	Each depth of the sensor displayed acceptable validation statistics. The linear fitting coefficients (R^2) ranged from 0.95 to 0.99.	Saeed *et al.*, (2018)

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A TDM sensor	Not mentioned	TDM	Not mentioned	The calibration model is established by a polynomial (third order) fitting equation.	Low-cost and high-resolution	The sensor can be used for continuous SM measurements, which will be beneficial for planning irrigation practices in arid and irrigated areas.	Saeed *et al.*, (2019)
A new capacitive sensor	Homo-geneous silt-clay-loam soil	Capacitance principle	It is less affected by tempera-ture.	Not mentioned	The cost is reduced while maintaining sufficient accuracy.	A new capacitive low-cost soil moisture sensor incorporates SDI-12 communication, allowing one to select the calibration equation fordifferent soils.	Gonzalez-Teruel *et al.*, (2019)
A homemade low-cost sensor	Not mentioned	Resistance principle	Not mentioned	Not mentioned	This method has the advantages of low equipment cost and simple operation	Measuring soil moisture along depth helps determine the appropriate time for water supply to reach crop roots.	Kumar *et al.*, (2016)

meticulous calibration to enhance reliability.

Dielectric sensors, particularly Time-Domain Reflectometry (TDR) and Frequency-Domain Reflectometry (FDR), consistently outperformed resistive sensors in terms of accuracy. Topp *et al.*, (1980) reported RMSE values below 3% for TDR sensors under laboratory conditions, though field tests revealed deviations of up to 6% due to environmental factors such as temperature and salinity. The higher precision of dielectric sensors makes them suitable for applications requiring detailed soil moisture profiling.

Real-Time Monitoring Capabilities

IoT-enabled sensors have revolutionized soil moisture monitoring, providing real-time data transmission and integration with decision support systems. Fuentes-Penailillo *et al.*, (2024) demonstrated that integrating wireless communication modules (*e.g.*, LoRa) with dielectric sensors achieved seamless data collection over a 5-hectare field, with data latency below 2 seconds. This capability significantly enhances irrigation management by enabling timely responses to soil moisture deficits (Rank, 2022).

Calibration Challenges

Traditional Calibration Techniques

Traditional calibration methods, such as linear regression, were effective for simple soil systems but failed to capture the complex interactions between soil properties and sensor outputs in heterogeneous environments (Kinzli *et al.*, 2012). Polynomial regression improved the accuracy marginally but added computational complexity.

Advanced Calibration Using Machine Learning

Artificial Neural Networks (ANNs) and machine learning algorithms emerged as promising solutions for addressing non-linearities in sensor responses. Mane *et al.*, (2024) applied ANN-based models to TDR sensor data, achieving a reduction in calibration error from 5% to 1.8%. These advanced methods require robust datasets but offer unparalleled accuracy when implemented correctly.

Cost-Effectiveness and Accessibility

Affordability for Small-Scale Farmers

The high cost of dielectric sensors remains a barrier to adoption, particularly for resource-limited farmers. Vereecken *et al.*, (2008) noted that while TDR sensors provide superior accuracy, their cost often exceeds $1,000 per unit, making them impractical for small-scale applications. Resistive sensors, priced below $50, offer an affordable alternative but require trade-offs in precision and durability.

Innovations in Material Science

Advancements in printed electronics and biodegradable materials have the potential to reduce costs while maintaining sensor performance. Panigrahi *et al.*, (2020) demonstrated the feasibility of fabricating resistive sensors using eco-friendly materials, achieving a production cost reduction of 40%.

Environmental and Operational Challenges

Environmental Sensitivity

Sensors' performance is often influenced by external factors such as soil salinity, temperature, and compaction. Seyfried and Murdock (2005) reported that uncalibrated dielectric sensors exhibited a 10% decrease in accuracy in saline soils, highlighting the need for soil-specific calibration.

Durability and Power Consumption

IoT-based systems face challenges related to power supply and environmental durability. Hashim *et al.*, (2024) highlighted the importance of solar-powered sensors for continuous operation in remote locations, though initial setup costs remain a limiting factor.

Practical Applications

Precision Agriculture

The integration of soil moisture sensors with irrigation systems has shown significant potential for water savings and crop yield optimization. Studies by Cosh *et al.*, (2016) revealed that sensor-based irrigation scheduling reduced water usage by 30% in arid regions while maintaining crop yields (Patel *et al.*, 2023)

Large-Scale Monitoring

The adoption of IoT-enabled soil moisture monitoring systems in large agricultural landscapes has enabled better resource allocation. Fuentes-Penailillo *et al.*, (2024) demonstrated the effectiveness of cloud-based analytics in providing actionable insights, improving water use efficiency by up to 25%.

Future Implications

Interdisciplinary Collaboration

Advancements in soil moisture monitoring require collaboration across disciplines, including agronomy, electronics, and data science. Wang (2024) emphasized the need for user-centric sensor designs tailored to diverse agricultural practices, integrating ease of use with high precision.

Climate Adaptation and Resilience

Improved soil moisture monitoring systems play a crucial role in building resilience to climate change by optimizing water management practices and enhancing crop productivity (Parmar and Gontia 2022). With increasing water scarcity, the development of cost-effective and durable sensors is imperative to ensure global food security (Rank *et al.*, 2023).

Conclusion

This review highlights the critical role of soil moisture sensors in advancing sustainable agricultural practices amidst growing water scarcity challenges. Modern soil moisture sensors, particularly those leveraging dielectric and IoT technologies, offer significant improvements in accuracy, real-time monitoring, and scalability compared to traditional methods. However, challenges such as high costs, calibration complexities, and environmental sensitivities remain barriers to widespread adoption.

Advancements in machine learning for calibration, eco-friendly sensor designs, and IoT integration demonstrate the potential to address these limitations, making soil moisture monitoring systems more accessible and efficient. The development of cost-effective, durable, and user-friendly sensors tailored to diverse agricultural and environmental conditions is essential for optimizing water management.

By fostering interdisciplinary collaboration and leveraging emerging technologies, soil moisture sensing can significantly enhance resource use efficiency, improve crop productivity, and contribute to climate resilience. Future research should focus on innovations that balance affordability and precision, ensuring these tools benefit both large-scale and smallholder farmers.

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