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Review Paper on Soil Moisture for Precision Agriculture using Machine Learning Technique

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Abstract
Soil moisture plays a pivotal role in crop growth, nutrient uptake, irrigation planning, and climate variability assessment. Accurate and timely estimation of soil moisture is essential for precision agriculture, enabling resource-efficient and sustainable farming practices. Traditional measurement methods, such as gravimetric sampling and sensor-based techniques, offer high accuracy but are often limited by high cost, labor-intensive deployment, and insufficient spatial coverage. Recent advancements in machine learning have introduced alternative data-driven approaches capable of predicting soil moisture using multisource inputs, including weather parameters, remote sensing imagery, soil characteristics, and vegetation indices. This review presents a comprehensive analysis of machine learning techniques employed for soil moisture estimation and prediction, including Support Vector Machines (SVM), Random Forests (RF), Artificial Neural Networks (ANN), Gradient Boosting models, and Deep Learning frameworks such as LSTM and CNN. The study further examines model performance metrics, dataset challenges, feature selection strategies, sensor fusion techniques, and approaches to overcome data sparsity. Additionally, the review highlights the integration of IoT-based monitoring systems and cloud-enabled platforms to support real-time soil moisture analysis for precision farming. The findings indicate that hybrid deep learning models and remote-sensing–enabled prediction approaches achieve superior accuracy compared to conventional models. Future research should focus on scalable frameworks, transfer learning, and adaptive models to improve prediction robustness across diverse agro-climatic regions.
Keywords: - Soil Moisture; Precision Agriculture; Machine Learning; RIoT-based Smart Farming; Crop Water Management; Environmental Monitoring

1. INTRODUCTION

Soil moisture is one of the most critical parameters influencing agricultural productivity, ecosystem stability, and hydrological processes. It directly regulates plant physiological activities such as germination, nutrient solubility, root development, and transpiration. Precise monitoring of soil moisture is therefore essential for optimizing irrigation scheduling, reducing water wastage, improving crop yield, and supporting climate-resilient farming strategies. In the context of increasing global food demand and declining freshwater resources, precision agriculture has emerged as a promising paradigm that leverages technology to enhance decision-making, resource

efficiency, and environmental sustainability. Soil moisture estimation serves as a core component of this paradigm, enabling data-driven irrigation planning and adaptive crop management.
Traditional soil moisture monitoring techniques, including gravimetric sampling, tensiometers, neutron probes, and time-domain reflectometry (TDR) sensors, provide accurate local measurements; however, these methods are labor-intensive, cost-prohibitive, and limited in spatial coverage. Moreover, manual measurements lack temporal continuity and are impractical for large agricultural fields with heterogeneous soil structures. Remote sensing techniques using optical, microwave, and thermal satellite imagery have addressed some of these challenges by offering large-scale observations. However, remote sensing data alone often suffer from resolution limitations, atmospheric disturbances, and temporal gaps between satellite passes. Therefore, integrating field-level data with computational techniques has become essential to generate accurate, continuous, and scalable soil moisture predictions.
Machine learning has become a transformative solution in this domain due to its ability to learn complex, nonlinear relationships among variables such as soil texture, rainfall patterns, vegetation indices, temperature, humidity, and land surface properties. Shallow learning models like Support Vector Machines (SVM), Random Forests (RF), k-Nearest Neighbors (KNN), and Gradient Boosting algorithms have shown strong predictive performance with limited training data. These models effectively handle structured datasets and are suitable for feature-based soil moisture regression. In contrast, deep learning architectures—including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Autoencoders, and hybrid deep models—have demonstrated superior generalization for high-dimensional inputs such as satellite imagery, spatiotemporal sequences, and multisensor data fusion. LSTM, in particular, is widely used for soil moisture time-series forecasting due to its capability to preserve long-term dependencies and handle seasonal variations.

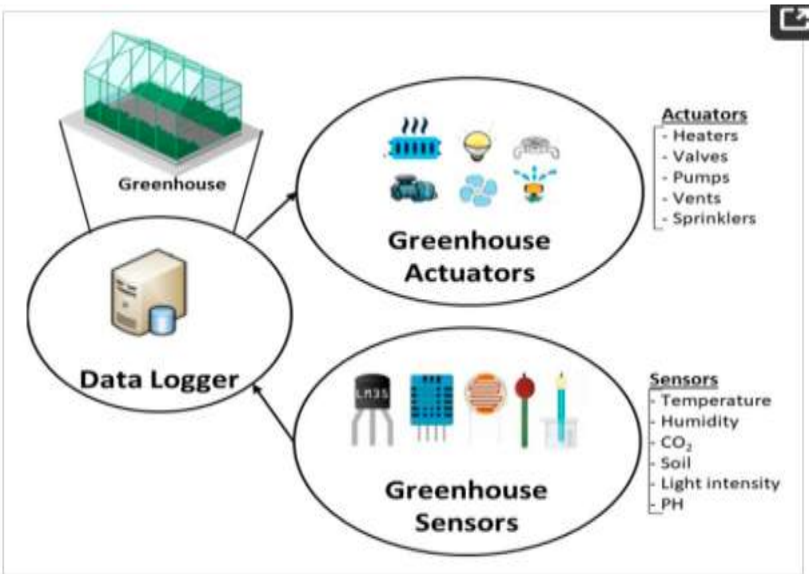

Figure 1: Smart architecture diagram

Recent advancements have also integrated Internet of Things (IoT) devices, wireless sensor networks (WSN), and edge computing for real-time moisture monitoring and automated irrigation systems. By combining sensor data with machine learning models deployed on cloud platforms, farmers can receive actionable insights such as irrigation alerts, crop water stress predictions, and yield forecasts. Despite promising progress, challenges remain in data sparsity, sensor calibration, soil heterogeneity, and model transferability across diverse agroclimatic zones. Addressing these concerns requires hybrid models, adaptive learning methods, and cross-regional datasets to enhance scalability and robustness.

2. SOIL MOISTURE

Soil moisture is a fundamental parameter that influences crop growth, soil health, irrigation planning, and agricultural productivity. It determines the availability of water to plants, regulates nutrient uptake, and affects critical physiological processes such as germination, transpiration, and photosynthesis. In modern agricultural ecosystems, efficient water management has become increasingly important due to global challenges such as climate change, declining freshwater resources, and increasing food demand. Precision agriculture has emerged as a transformative approach to address these challenges, enabling site-specific crop and soil management through data-driven monitoring, analysis, and optimal resource utilization. Within this framework, soil moisture acts as a key variable in designing irrigation schedules, improving water-use efficiency, and ensuring crop resilience under varying environmental conditions.

Traditional soil moisture measurement techniques—such as gravimetric analysis, tensiometers, neutron probes, and time-domain reflectometry (TDR)—offer high accuracy but are limited in scalability and practicality for large farming areas. These methods are often labor-intensive, expensive, and provide point-based measurements that fail to capture spatial variability across heterogeneous fields. In contrast, remote sensing approaches using optical, thermal, and microwave sensors provide large-scale observations, enabling regional moisture mapping. However, environmental factors like cloud cover, atmospheric disturbances, and soil surface roughness can reduce accuracy. To overcome these limitations, sensor-based monitoring systems, including Internet of Things (IoT) networks, wireless sensor nodes, and automated irrigation controllers, have gained traction due to their ability to generate continuous real-time field data with minimal human intervention.

Recent technological developments have led to the integration of multisource data—including in-field sensors, satellite imagery, and radar-based sensing—with advanced computational and analytical tools. Such systems not only provide real-time soil moisture insights but also support decision-making for variable-rate irrigation, fertilizer optimization, drought prediction, and environmental sustainability. These innovations further contribute to precision agriculture by minimizing water wastage, reducing energy consumption in irrigation pumps, and maintaining soil fertility.

Despite significant advancements, challenges remain in ensuring cost-effective deployment, sensor calibration, long-term durability, data synchronization, and scalability across diverse soil types and climatic conditions. Future research must emphasize adaptable sensing technologies, intelligent irrigation systems, cross-regional soil databases, and low-power autonomous field monitoring solutions to fully harness soil moisture intelligence for next-generation farming.

3. LITERATURE REVIEW

Recent research has significantly advanced soil moisture estimation using machine learning techniques, particularly where non-invasive sensing technologies such as Ground Penetrating Radar (GPR), remote sensing, and radar-based soil analysis are involved. Panyavaraporn et al. (2025) conducted a comparative study using tree-based algorithms including Random Forest (RF) and Gradient Boosting methods to enhance soil moisture prediction from GPR data, demonstrating that ensemble models outperform single learner approaches due to their improved ability to capture nonlinear spatial variations. Similarly, Akinsunmade (2025) investigated soil structure alteration using GPR responses and highlighted the importance of soil physical property interpretation in data-driven agricultural management practices. Li et al. (2024) estimated soil moisture in desert steppe environments using radar-based signatures and emphasized the applicability of GPR in heterogeneous and low-vegetation regions, while Alzubaidi et al. (2024) proposed a deep learning framework for GPR-based soil compaction analysis, demonstrating strong performance in identifying horizontal soil stratification using neural networks.

Complementary studies have integrated hybrid computational models and optimization methods for agricultural soil monitoring. Liu et al. (2023) estimated farmland soil moisture using the AEA-based GPR technique and reported that algorithmic enhancements can improve signal interpretation accuracy under field variability. Dabboor et al. (2023) incorporated compact polarimetric radar features combined with machine learning, showcasing the effectiveness of advanced feature extraction in improving soil moisture retrieval accuracy across diverse terrains. Liu et al. (2023) explored the role of visual-spectrum color features along with supervised machine learning models, offering a rapid and cost-effective alternative for soil moisture estimation in agriculture. Uthayakumar et al. (2022) further demonstrated that wideband radar sensors paired with machine learning models, such as SVM and neural networks, enable high-resolution moisture mapping suitable for agricultural deployment.

Remote sensing approaches have also been extensively studied for crop-specific soil moisture monitoring. Chen et al. (2021) estimated soil moisture over winter wheat fields using machine learning models trained on satellite observations, demonstrating their utility in seasonal agricultural water planning. Earlier work by Riese and Keller (2018) fused hyperspectral and GPR datasets to improve soil moisture estimation and highlighted the potential of multimodal sensing in overcoming limitations of single-source data.

Collectively, these studies indicate a strong shift from traditional soil monitoring methods toward hybrid frameworks combining machine learning, radar technologies, and remote sensing. While existing models show promising accuracy, challenges remain regarding data generalization across varying soil textures, sensor calibration, climatic variability, and transferability of models across large-scale agricultural landscapes. The literature suggests future opportunities in deep hybrid models, IoT-integrated sensing, multimodal data fusion, and real-time predictive soil moisture systems for precision agriculture.

4. SOIL MOISTURE USING MACHINE LEARNING

Soil moisture is a critical factor influencing crop development, irrigation management, nutrient transport, and overall agricultural productivity. In precision agriculture, accurate estimation of soil moisture is essential for optimizing water usage, improving crop yield, and enabling climate-resilient farming practices. As global water scarcity intensifies and food demand continues to rise, farming systems must shift from traditional uniform irrigation strategies to data-driven, site-specific water management approaches. Machine learning (ML) has emerged as a powerful tool to support this transition by enabling accurate soil moisture prediction through the analysis of multisource data such as in-field sensors, meteorological information, satellite imagery, hyperspectral data, and soil physical properties.

Conventional soil moisture measurement techniques, including gravimetric sampling, tensiometers, neutron probes, and time-domain reflectometry (TDR), provide point-based, highly accurate readings but lack spatial scalability and are often labor-intensive, costly, and limited in temporal coverage. Remote sensing methods using microwave and optical satellites address spatial limitations but face challenges such as atmospheric interference, coarse resolution, and calibration difficulty. Machine learning bridges this gap by integrating heterogeneous data sources and learning nonlinear relationships between environmental variables to estimate soil moisture with improved accuracy, flexibility, and computational efficiency.

Different machine learning algorithms have been applied for soil moisture modeling depending on data type and complexity. Shallow learning models such as Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting Machines (GBM), and k-Nearest Neighbors (KNN) are effective for regression tasks involving structured tabular datasets and have shown reliable prediction performance across diverse soil textures and climatic conditions. In contrast, deep learning models—including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and hybrid deep frameworks—are suited for high-dimensional inputs such as satellite imagery, radar data, and spatiotemporal sequences. CNN models are widely used for extracting spatial moisture patterns from remote sensing images, while LSTM networks effectively capture time-series dynamics for seasonal moisture trend forecasting.

Emerging approaches also integrate Ground Penetrating Radar (GPR) signals, multispectral imagery, and IoT-based sensor networks to generate real-time soil moisture insights. Data fusion techniques combining field sensors with satellite and radar data further enhance model robustness by compensating for noisy, missing, or unevenly distributed observations. These advancements support automated irrigation systems, precision water scheduling, disease control, and drought monitoring, thereby reducing resource wastage and enabling sustainable agricultural practices.

Despite these advances, key challenges persist, including model transferability across diverse soil types, limited labeled datasets, sensor calibration issues, and the need for explainable machine learning models to support agronomic decision-making. Future research must focus on hybrid ensemble–deep learning architectures, cross-regional training datasets, energy-efficient IoT deployments, and interpretable AI frameworks to enable widespread adoption in field conditions.

5. CONCLUSION

Soil moisture prediction plays a crucial role in precision agriculture by enabling efficient irrigation management, enhancing crop productivity, and conserving water resources. This review highlights that traditional soil moisture measurement techniques, while accurate at localized scales, are limited by labor intensity, high costs, and insufficient spatial coverage. Emerging machine learning approaches, when integrated with sensors, remote sensing platforms, and radar technologies such as Ground Penetrating Radar (GPR), provide scalable, accurate, and real-time solutions for soil moisture estimation. Tree-based models, regression algorithms, and ensemble learning have shown strong performance for structured datasets, while deep learning models, particularly those using radar and multispectral imagery, demonstrate superior capabilities in handling large, nonlinear, and heterogeneous environmental data.

The reviewed studies emphasize significant progress in combining multisource data—ranging from satellite imagery to hyperspectral bands and radar signals—for improving predictive accuracy. However, challenges persist due to soil heterogeneity, variations in terrain, inconsistent sampling density, and lack of generalized models applicable across diverse agroclimatic zones. Limited availability of labeled datasets and sensor calibration issues further restrict model transferability in real-world farming scenarios. Future research should focus on hybrid deep learning architectures, multimodal data fusion, cloud-enabled IoT sensing systems, and adaptive models capable of learning from diverse field conditions. Additionally, developing benchmark datasets, improving interpretability of AI-driven models, and designing low-cost real-time soil monitoring frameworks will significantly enhance practical implementation.

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