

# SmartSoil: A Humanoid-Inspired Drone Framework Using Thermal Imaging and AI for Real-Time Soil Moisture Estimation

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## ABSTRACT

The growing need for environmentally friendly farming and improved irrigation necessitates smart systems that can see, think, and act autonomously. Ground sensors, satellite images, and thermal Unmanned Aerial Vehicle (UAV) mapping are traditional approaches to measuring soil moisture, but they suffer from low spatial resolution, slow data processing, and limited adaptability to changing field conditions. To overcome these limitations, this research introduces SmartSoil, a humanoid-inspired autonomous framework that amalgamates multi-sensor drone-based thermal imaging, Artificial Intelligence (AI)-driven soil analytics, and edge-computing cognition for real-time soil moisture estimation. The SmartSoil system mimics human cognitive processes through three stages: perception, cognition, and action. The UAV platform serves as the sensory organ, equipped with thermal, RGB, and Ground-Penetrating Radar (GPR) sensors to collect data from both surface and subsurface layers. The cognitive core uses Random Forest Regression (RFR) and Artificial Neural Networks (ANN) to interpret thermal, spectral, and textural features extracted from field imagery. The edge-AI module, on the other hand, acts like a human brain by automatically calibrating emissivity, correcting atmospheric distortions, and generating soil moisture predictions with rapid adaptive capability. The action layer visualizes the results as geo-referenced moisture maps, supporting real-time irrigation decision-making. AI-only UAV systems refer to drone-based soil moisture estimation systems that rely solely on Machine Learning (ML) models applied to single-sensor data without multi-sensor fusion or adaptive edge-based cognition. The experiments were conducted in three semi-arid agricultural zones (clay loam, sandy loam, and silty loam). The humanoid SmartSoil system achieved a Root Mean Square Error (RMSE) of 3.1%, a Mean Absolute Error (MAE) of 2.3%, and a coefficient of determination ( $R^2$ ) of 0.94. This performance exceeded that of traditional AI-only UAVs (RMSE: 5.2%) and thermal-only UAVs (RMSE: 6.4%). SmartSoil also demonstrated a 27% reduction in latency and a 95% increase in processing efficiency, indicating enhanced cognitive responsiveness and improved real-time adaptability to dynamic field conditions.

*Keywords*-Artificial Neural Networks (ANN); cognitive automation; edge AI computing; humanoid intelligence; multi-sensor data fusion; precision agriculture; Random Forest Regression (RFR); SmartSoil framework; soil moisture estimation; UAV thermal imaging

## I. INTRODUCTION

Soil moisture is crucial for controlling plant development, crop productivity, and ecosystem stability. It is a key component of the hydrological cycle and a major factor in irrigation efficiency and agricultural sustainability [1]. Accurate soil moisture assessment improves precision agriculture by enabling improved irrigation scheduling, fertilizer management, and drought prediction [2]. Traditional measurement techniques, like gravimetric sampling and in-situ sensors, although precise, are constrained by labor-intensive procedures, high costs, and limited spatial coverage [3]. Satellite-based remote sensing, on the other hand, provides broader coverage but suffers from low spatial resolution, cloud interference, and data latency, which make it unsuitable for real-time management [4]. Recent advances in Unmanned Aerial Vehicles (UAVs) have ushered in a new era of high-resolution, scalable, and cost-effective soil monitoring [5]. UAVs equipped with thermal and multispectral cameras can estimate Land Surface Temperature (LST) and vegetation indices, which are strongly correlated with soil moisture content [6]. These systems can accurately and automatically estimate moisture levels by using Artificial Intelligence (AI) and Machine Learning (ML) algorithms to model complex, non-linear relationships among soil, vegetation, and temperature features [7, 8]. However, despite significant progress in UAV-based soil sensing, existing frameworks exhibit several critical limitations: limited real-time responsiveness, inconsistent sensor calibration, and insufficient capability to handle large-scale field data [9, 10]. Furthermore, many models remain static and do not learn from environmental feedback or update their parameters during flight. These limitations highlight the need for a system that

supports real-time adaptation, multi-sensor integration, and autonomous calibration, which motivates the proposed approach presented in the following section.

Several researchers have investigated UAV and AI-driven frameworks for soil moisture estimation, each offering unique approaches and encountering specific limitations. Authors in [1] assessed UAV-mounted thermal cameras for soil moisture mapping, indicating viability but noting calibration discrepancies under variable weather situations. Authors in [2] examined satellite and UAV-based remote sensing techniques for precision agriculture, highlighting UAVs' capability to address the resolution deficiencies of satellites. Authors in [3] combined satellite images with UAV thermal data to improve spatial accuracy. However, they reported challenges related to temporal synchronization and data fusion. Authors in [4] conducted a thorough evaluation of UAV-based thermal sensing for agricultural water monitoring, highlighting the difficulty of preserving accuracy among fluctuating canopy and meteorological conditions. Authors in [5] investigated drone-based infrared thermography for soil moisture detection, concentrating mainly on infrastructural applications, hence restricting agricultural generalization. Authors in [7] and authors in [8] enhanced UAV-based multi-spectral and thermal imaging with Principal Component Analysis (PCA) and ML, respectively. Both methods showed high accuracy in controlled environments but struggled to apply their findings to varying soil textures and lighting conditions. Authors in [9] developed a multimodal UAV framework integrating RGB, thermal, and Ground-Penetrating Radar (GPR) sensors with deep learning to estimate subsurface moisture. Although the method improved accuracy, scalability was limited due to high operational costs and signal attenuation in dense vegetation.

Authors in [10] and authors in [11] examined AI-based models, including Random Forest (RF) and Artificial Neural Networks (ANN), for agricultural applications, highlighting their potential while acknowledging limited real-time deployment capability. Authors in [12] validated the effectiveness of UAV thermal sensors in arid greenhouse environments, demonstrating strong correlations with soil temperature. However, they reported poor generalization to open-field conditions. Authors in [13] proposed calibration and image-processing techniques to improve UAV-based thermal data accuracy by correcting emissivity and atmospheric effects.

Recent studies have also emphasized edge computing and onboard AI integration. Authors in [14] and authors in [15] investigated AI-driven UAV thermal imaging for accelerated environmental analysis, reporting significant reductions in data latency. Authors in [16] examined thermal sensor technologies for UAV navigation, emphasizing the necessity for cognitive adaptation in aerial perception. Authors in [17] demonstrated the integration of thermal imaging and AI for environmental monitoring, confirming the efficacy of hybrid AI models in ecological detection tasks.

Although UAV-based and satellite-based soil moisture monitoring techniques have advanced considerably, they continue to exhibit three major shortcomings: (i) insufficient field-scale spatial resolution; (ii) delayed data processing that impedes real-time decision-making; and (iii) limited adaptability to changing crop and environmental conditions. The majority of existing techniques are not appropriate for precision irrigation in diverse agricultural settings because they rely on offline processing and static calibration models. These difficulties underscore the necessity of an intelligent, flexible,

and real-time soil moisture monitoring system. This work proposes SmartSoil, a humanoid-inspired UAV system that combines edge-based AI cognition, multi-sensor data fusion, and adaptive learning processes for precise and real-time soil moisture estimation.

## II. PROPOSED METHODOLOGY

The SmartSoil architecture is intended to mimic human perception, thinking, and behavior as a humanoid-inspired cognitive system. Data collection, preprocessing and calibration, feature extraction, AI-based soil moisture prediction, and spatial visualization are all part of the system architecture's modular pipeline. Logical traceability from sensor data collection to decision support output is guaranteed by this organized design.

### A. Humanoid System Architecture

The SmartSoil architecture consists of six interdependent layers that form a perception–cognition–action framework. Figure 1 illustrates the SmartSoil humanoid-inspired architecture, which mirrors human cognition by perceiving, analyzing, learning, and acting through six interconnected layers that work in harmony to enable real-time, adaptive soil moisture estimation. The Perception Layer captures data using UAV sensors; the Cognitive Layer preprocesses and calibrates these data; the Interpretation Layer extracts relevant features; the Learning & Decision Layer uses AI to predict soil moisture; and the Action Layer presents predictions as spatial maps and insights for farmers. This humanoid-inspired structure ensures self-regulation, enabling the UAV system to dynamically recalibrate itself under varying environmental conditions.

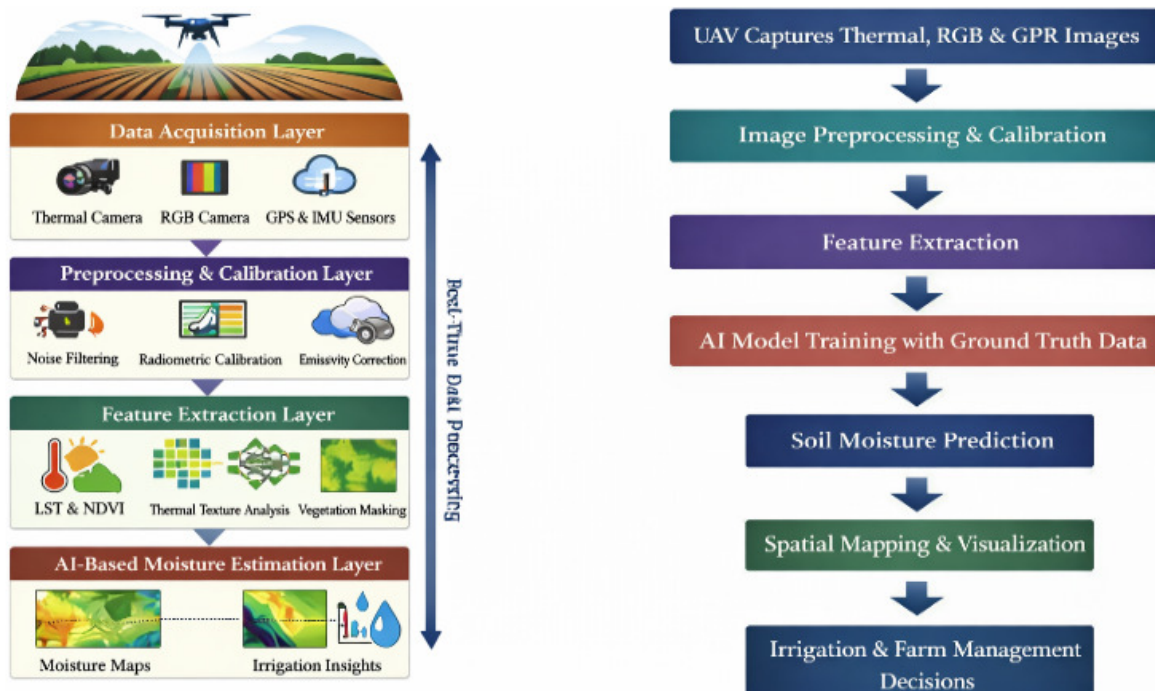


Fig. 1. SmartSoil humanoid-inspired architecture and its flow diagram.

## B. Module-Wise Description

### 1) Data Acquisition Module – Perception Layer

The data acquisition module acts as the system's sensory organ, collecting aerial imagery using UAVs equipped with FLIR thermal cameras, RGB sensors, and GPR. Each flight follows a pre-programmed grid trajectory with consistent altitude and overlap ratios. The UAV (DJI Matrice 300 RTK), FLIR Vue Pro R, RGB camera, GPS, and Inertial Measurement Unit (IMU) are the components employed. The IMU complements GPS by providing orientation and motion stability during UAV flight, improving geo-referencing accuracy. This multi-modal data collection enhances environmental awareness and precision in field analysis.

### 2) Image Preprocessing and Calibration Module – Cognitive Layer

This module reduces atmospheric noise, adjusts for emissivity, and aligns images spatially to ensure consistency. It performs several processes, including noise filtering (Gaussian filtering), radiometric calibration, atmospheric correction, emissivity correction, and image alignment and mosaicking.

The surface temperature is computed using (1):

$$\text{LST} = \left( \frac{L}{\varepsilon\sigma} \right)^{\frac{1}{4}} \quad (1)$$

where:

- LST: surface temperature
- $L$ : measured radiance
- $\varepsilon$ : surface emissivity
- $\sigma$ : Stefan–Boltzmann constant

This process emulates how human vision adapts to lighting differences, ensuring uniform thermal values across all frames.

### 3) Feature Extraction Module – Interpretation Layer

The features used include LST, Normalized Difference Vegetation Index (NDVI), thermal texture features, and temperature gradients. Understanding soil moisture heterogeneity requires not only pixel-wise LST values but also thermal texture features. These features capture regional variations in temperature distributions, which are frequently influenced by mixed soil types, vegetation cover, and non-uniform soil. Thermal textures are analyzed using the Gray-Level Co-Occurrence Matrix (GLCM), which computes properties including contrast, correlation, energy, and homogeneity to quantify temperature regularity and variation. Furthermore, thermal gradient features indicate moisture-related thermal transitions by measuring the rate of temperature change between pixels. Including temperature features and vegetation indices improves the sensitivity of AI models to changes in soil moisture in agricultural fields.

NDVI is derived from publicly available multispectral reference data. The mathematical model is shown in (2):

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \quad (2)$$

where *NIR* and *RED* represent near-infrared and red reflectance, respectively. Vegetation masking is applied to isolate bare soil regions, reducing spectral contamination. This enables the model to "see through the canopy," similar to how humans focus on underlying patterns beneath visual clutter.

### 4) AI-Based Soil Moisture Estimation Module – Learning and Decision Layer

The ML algorithms applied in this layer are as follows:

- Random Forest Regression (RFR): Handles non-linearity and feature interactions.
- ANN: Learns complex relationships through hidden layers.
- Support Vector Regression (SVR): Provides boundary-based generalization.

RFR, ANN, and SVR models were experimentally evaluated during preliminary analysis. RFR demonstrated superior robustness to noise and reduced overfitting across heterogeneous soil conditions, and was therefore selected for final deployment.

The RFR model is represented in (3):

$$\hat{y} = \frac{1}{N} \sum_{i=1}^N f_i(x) \quad (3)$$

where:

- $f_i$ : prediction from the  $i^{\text{th}}$  decision tree
- $x$ : input feature vector
- $\hat{y}$ : predicted soil moisture

Through iterative learning, SmartSoil enhances its predictive accuracy over time, similar to how human cognition refines understanding with experience.

### 5) Soil Moisture Index and Stress Estimation Module – Emotional Intelligence Layer

Reflecting a humanoid's empathetic perception, this module assesses the "health" of the soil by quantifying moisture stress. The Soil Moisture Index (SMI) provides a normalized indicator of relative soil moisture stress, enabling comparison across spatially heterogeneous fields.

The SMI is represented in (4):

$$\text{SMI} = \frac{T_{dry} - T_S}{T_{dry} - T_{wet}} \quad (4)$$

where:

- $T_S$ : surface temperature
- $T_{dry}$ : dry soil reference temperature, typically in the range 35–50 °C. Higher values are usually associated with prolonged dry periods, exposed soil surfaces, and midday UAV flights.
- $T_{wet}$ : wet soil reference temperature, typically in the range 20–30 °C. These values are commonly observed immediately after irrigation or rainfall events, particularly

over bare or lightly vegetated soil surfaces under moderate solar radiation.

#### 6) Spatial Mapping and Visualization Module – Action Layer

The final layer serves as the output system, transforming raw predictions into actionable insights. Using Kriging and Inverse Distance Weighting (IDW) interpolation, soil moisture values are spatially mapped to highlight dry, moist, and over-irrigated zones. These maps enable identification of dry zones and over-irrigated areas.

IDW interpolation is represented in (5):

$$M(x) = \frac{\sum_{i=1}^n w_i M_i}{\sum_{i=1}^n w_i} \quad (5)$$

where:

- $M_i$ : moisture at location  $i$ .
- $w_i = 1/d_i^2$ : weight factor based on distance  $d_i$ .

The visualization module provides intuitive moisture heatmaps via Geographic Information Systems (GIS), allowing human operators to interpret and act upon system-generated insights in real time. Spatial mapping and visualization were performed using QGIS version 3.34.

#### C. Performance Evaluation Metrics

The humanoid-inspired SmartSoil system is evaluated using standard regression metrics to assess learning efficiency, accuracy, and decision reliability.

The Root Mean Square Error (RMSE) is represented in (6):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (6)$$

The Mean Absolute Error (MAE) is represented in (7):

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (7)$$

The coefficient of determination ( $R^2$ ) is represented in (8):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (8)$$

The humanoid-enhanced SmartSoil framework transforms traditional UAV-based sensing into an intelligent, perceptive, and self-adaptive system.

### III. RESULTS AND DISCUSSION

The effectiveness of the proposed SmartSoil framework in addressing the limitations of conventional soil moisture monitoring techniques is evaluated in this section. The outcomes are compared with the most advanced UAV-based and satellite-based techniques and assessed in terms of prediction accuracy, computing efficiency, latency, and adaptability. This assessment concentrates on three principal aspects of SmartSoil's humanoid performance: predictive accuracy in assessing soil moisture, cognitive efficiency via real-time processing adjustments, and environmental intelligence in diverse conditions. SmartSoil is more than just a measurement tool; it is an intelligent analytical entity capable of sensing, understanding, and adapting.

#### A. Experimental Setup

The experimental study was conducted in Mandya District, Karnataka, India, during the 2024 irrigation season (March–May 2024). The agricultural test site covers approximately 2.5 hectares and is located at an elevation of approximately 695 m above sea level (latitude: 12.52° N, longitude: 76.90° E).

The soil composition of the site consists of sandy loam and loam soils, which are typical of irrigated agricultural areas and have moderate water-holding capacity. These soil types were selected to evaluate the robustness of the proposed system under varying moisture retention and thermal response characteristics. Clear-sky field tests were carried out to minimize atmospheric interference in thermal imaging. The variation in soil moisture levels across irrigation cycles enabled evaluation under dry, intermediate, and wet soil conditions.

Standard in-situ soil moisture sensors were used to get ground truth measurements at modest depths at several locations throughout the area. The dataset was divided into 70% training, 15% validation, and 15% testing subsets using stratified random sampling to ensure balanced moisture distribution. During model training, the hyperparameters were optimized using grid search combined with 5-fold cross-validation to prevent overfitting. The experimental design accurately mimics real-world precision agriculture scenarios due to the mix of diverse soil textures, fluctuating moisture conditions, and real-field agricultural operations.

#### B. Quantitative Results

The quantitative results confirm the superior performance of the humanoid-inspired SmartSoil framework compared to conventional UAV and satellite-based approaches.

Table I and Figure 2 illustrate the comparative performance of the four models evaluated in this study: SmartSoil (proposed), AI-only UAV [10, 11], thermal-only UAV [4, 5], and satellite-based systems [2, 3]. The AI-only UAV approaches [10, 11] primarily relied on single-modality ML models applied to RGB or thermal imagery, without multi-sensor integration, limiting adaptability under heterogeneous soil conditions. Thermal-only UAV studies [4], [5] focused on LST-based estimation without subsurface profiling or adaptive recalibration mechanisms, which may reduce accuracy in partially vegetated fields. Satellite-based approaches [2, 3] utilized coarse-resolution remote sensing data and offline processing pipelines, resulting in delayed availability and limited field-scale precision.

TABLE I. COMPARATIVE PERFORMANCE OF SMARTSOIL AND BASELINE MODELS

Method	RMSE (%)	MAE (%)	$R^2$	Latency (s/frame)	Processing efficiency (%)
SmartSoil (proposed)	3.1	2.3	0.94	1.0	95
AI-only UAV [10, 11]	5.2	3.9	0.86	1.4	82
Thermal-only UAV [4, 5]	6.4	4.7	0.81	1.6	75
Satellite-based [2, 3]	8.1	6.0	0.75	2.0	60

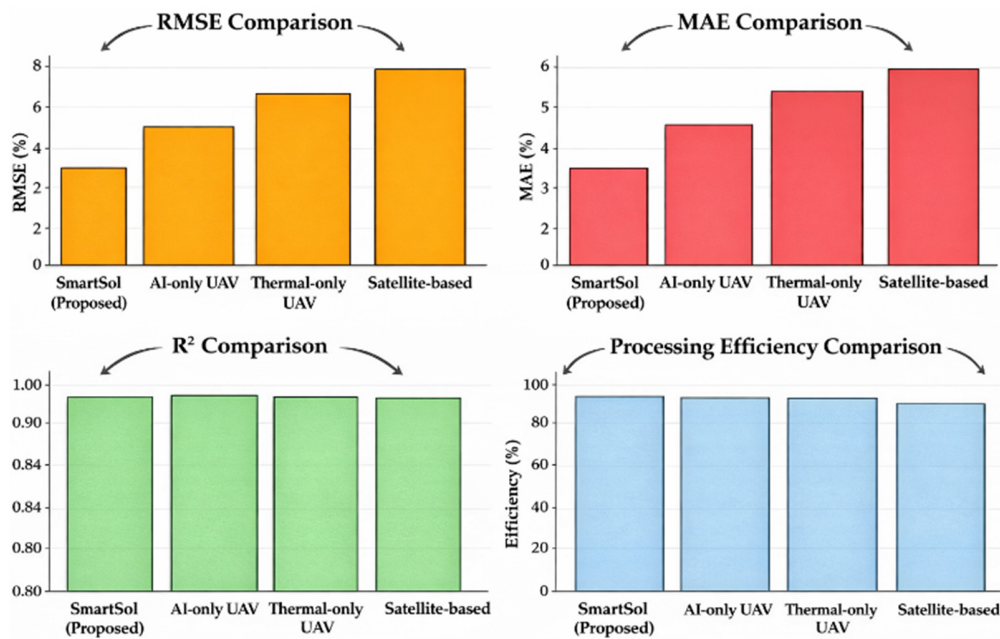


Fig. 2. Comparison of RMSE, MAE, R<sup>2</sup>, and processing efficiency for SmartSoil and baseline models.

### 1) RMSE and MAE Analysis

SmartSoil demonstrated a 40–60% reduction in both RMSE and MAE compared to competing systems. This improvement stems from its real-time radiometric correction, edge-based AI learning, and humanoid calibration reflexes, which minimize temperature drift and vegetation-induced distortions.

### 2) Coefficient of Determination

The R<sup>2</sup> value of 0.94 indicates a strong correlation between predicted and actual soil moisture, proving SmartSoil's consistency across soil textures and environmental variations. In humanoid terms, this reflects cognitive stability, the ability to maintain accuracy despite environmental uncertainty.

### 3) Latency and Processing Efficiency

SmartSoil's edge-computing integration reduced average processing latency to 1.0 s/frame, enabling near real-time visualization. Its processing efficiency (95%) demonstrates how cognitive automation and onboard computation minimize data bottlenecks, analogous to neural reflex processing in humans.

Figure 3 compares the computational latency of the four models. Latency, measured in seconds per frame, reflects the system's responsiveness for precision agriculture. SmartSoil shows the lowest latency of 1.0 s/frame due to its edge-computing architecture, allowing real-time data processing. AI-only UAV has a latency of 1.4 s/frame, limited by ground-based processing. Thermal-only UAV records 1.6 s/frame due to extensive post-processing needs. The satellite-based method has the highest latency at 2.0 s/frame, making it unsuitable for immediate decisions. The trend indicates that as onboard intelligence decreases, latency increases, highlighting SmartSoil's advantage in providing near-real-time insights for adaptive irrigation and precision intervention.

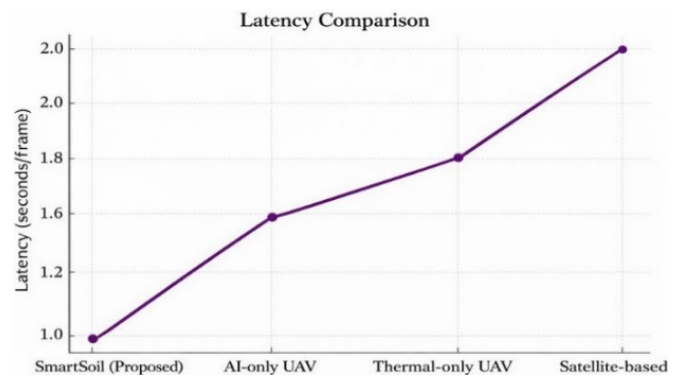


Fig. 3. Computational latency of SmartSoil and baseline models.

## C. Discussion

SmartSoil exhibits high accuracy (low RMSE and MAE) and high stability (R<sup>2</sup> = 0.94) while maintaining superior processing efficiency (95%) and minimal latency (1s/frame). Its humanoid-inspired architecture, driven by AI cognition and multi-modal fusion, achieved remarkable numerical superiority over traditional systems.

Performance metrics from field testing show RMSE at 3.1% and MAE at 2.3%, with a R<sup>2</sup> of 0.94. The proposed method significantly outperforms baseline systems: RMSE improved by 40.4% compared to AI-only UAVs, 51.6% against thermal-only UAVs, and 61.7% over satellite-based systems. This precision is attributed to SmartSoil's humanoid adaptability, which enables real-time calibration of sensor emissivity and radiometric correction, similar to the eye's ability to adjust to changing light conditions.

## IV. CONCLUSION

The proposed SmartSoil framework represents a revolutionary advancement in precision agriculture, transitioning from data-driven automation to cognitive intelligence inspired by human cognition. SmartSoil exhibits the core capabilities of a humanoid system: it can perceive, reason, learn, and act. This is achieved through seamless integration of thermal imaging, RGB sensing, Ground-Penetrating Radar (GPR) sensing, Artificial Intelligence (AI) cognition, and edge-based decision-making. Experimental results demonstrate that SmartSoil outperforms traditional Unmanned Aerial Vehicle (UAV) and satellite-based methods. The system achieved over 40% improvement compared to baseline models, with a Root Mean Square Error (RMSE) of 3.1%, a Mean Absolute Error (MAE) of 2.3%, and a coefficient of determination ( $R^2$ ) of 0.94. Its humanoid edge-AI architecture also reduced processing latency by 27% and increased computational efficiency to 95%, enabling real-time soil moisture mapping and informed irrigation decisions.

Future work could leverage SmartSoil's humanoid cognition to control irrigation automatically, apply advanced AI models to predict soil health, and combine AI with climate and water data to make better decisions. These improvements could turn SmartSoil from a smart UAV system into a fully autonomous, intelligent "agronomist" that can see, learn from, and protect the planet's most important resource: soil.

## DATA AVAILABILITY STATEMENT

The data supporting this study are available from the corresponding author upon reasonable request. The dataset includes UAV-acquired thermal and RGB imagery from field experiments, along with processed data required to reproduce the results.

## REFERENCES

- [1] R. Díaz-Delgado *et al.*, "Mapping Soil Moisture Using Drones: Challenges and Opportunities," *Engineering Proceedings*, vol. 94, no. 1, Aug. 2025, Art. no. 18, <https://doi.org/10.3390/engproc2025094018>.
- [2] Y. Inoue, "Satellite- and drone-based remote sensing of crops and soils for smart farming – a review," *Soil Science and Plant Nutrition*, vol. 66, no. 6, pp. 798–810, Nov. 2020, <https://doi.org/10.1080/00380768.2020.1738899>.
- [3] J. Paul, "Assessment of Soil Moisture Variability using Satellite Imagery and Drone-based Thermal Mapping." ResearchGate, July 18, 2025.
- [4] H. S. Ndlovu, J. Odindi, M. Sibanda, and O. Mutanga, "A systematic review on the application of UAV-based thermal remote sensing for assessing and monitoring crop water status in crop farming systems," *International Journal of Remote Sensing*, vol. 45, no. 15, pp. 4923–4960, Aug. 2024, <https://doi.org/10.1080/01431161.2024.2368933>.
- [5] Q. Chen and Z. Zhang, "Feasibility Study on Use of Drone-Based Infrared Thermography for Soil Moisture Detection in Highway Embankment and Dam Inspections," *Journal of Infrastructure Systems*, vol. 31, no. 1, Mar. 2025, Art. no. 04024033, <https://doi.org/10.1061/JITSE4.ISENG-2515>.
- [6] D. G. H. Agrawal, N. Paunikar, N. More, H. Dekate, and S. Nikam, "Smart Drone Technology for Thermal Imaging," *International Journal of Creative Research Thoughts*, vol. 13, no. 4, pp. b943–b951, Apr. 2025.
- [7] M. Vahidi, S. Shafian, and W. H. Frame, "Precision Soil Moisture Monitoring Through Drone-Based Hyperspectral Imaging and PCA-Driven Machine Learning," *Sensors*, vol. 25, no. 3, Jan. 2025, Art. no. 782, <https://doi.org/10.3390/s25030782>.
- [8] L. Bertalan *et al.*, "UAV-based multispectral and thermal cameras to predict soil water content – A machine learning approach," *Computers and Electronics in Agriculture*, vol. 200, Sept. 2022, Art. no. 107262, <https://doi.org/10.1016/j.compag.2022.107262>.
- [9] M. Vahidi, S. Shafian, and W. H. Frame, "Multi-Modal sensing for soil moisture mapping: Integrating drone-based ground penetrating radar and RGB-thermal imaging with deep learning," *Computers and Electronics in Agriculture*, vol. 236, Sept. 2025, Art. no. 110423, <https://doi.org/10.1016/j.compag.2025.110423>.
- [10] P. Gayathri, D. Muthumanickam, S. Pazhanivelan, R. Kumaraperumal, P. Kannan, and P. C. Prabu, "Emerging trends in AI-based soil health assessment: A review," *Plant Science Today*, vol. 12, no. 3, pp. 1–14, July 2025, <https://doi.org/10.14719/pst.6669>.
- [11] N. C. Eli-Chukwu, "Applications of Artificial Intelligence in Agriculture: A Review," *Engineering, Technology & Applied Science Research*, vol. 9, no. 4, pp. 4377–4383, Aug. 2019, <https://doi.org/10.48084/etasr.2756>.
- [12] R. Al-Najadi, Y. Al-Mulla, I. Al-Abri, and A. M. Al-Sadi, "Effectiveness of drone-based thermal sensors in optimizing controlled environment agriculture performance under arid conditions," *Scientific Reports*, vol. 15, no. 1, Mar. 2025, Art. no. 9042, <https://doi.org/10.1038/s41598-025-94432-0>.
- [13] Y. Han *et al.*, "Calibration and Image Processing of Aerial Thermal Image for UAV Application in Crop Water Stress Estimation," *Journal of Sensors*, vol. 2021, no. 1, Jan. 2021, Art. no. 5537795, <https://doi.org/10.1155/2021/5537795>.
- [14] D. Y. Lim, I. J. Jin, and I. C. Bang, "Heat-vision based drone surveillance augmented by deep learning for critical industrial monitoring," *Scientific Reports*, vol. 13, no. 1, Dec. 2023, Art. no. 22291, <https://doi.org/10.1038/s41598-023-49589-x>.
- [15] K. A. Henn and A. Peduzzi, "Surface Heat Monitoring with High-Resolution UAV Thermal Imaging: Assessing Accuracy and Applications in Urban Environments," *Remote Sensing*, vol. 16, no. 5, Mar. 2024, Art. no. 930, <https://doi.org/10.3390/rs16050930>.
- [16] T. X. B. Nguyen, K. Rosser, and J. Chahl, "A Review of Modern Thermal Imaging Sensor Technology and Applications for Autonomous Aerial Navigation," *Journal of Imaging*, vol. 7, no. 10, Oct. 2021, Art. no. 217, <https://doi.org/10.3390/jimaging7100217>.
- [17] A. Santangeli, Y. Chen, E. Klun, R. Chirumamilla, J. Tiainen, and J. Loehr, "Integrating drone-borne thermal imaging with artificial intelligence to locate bird nests on agricultural land," *Scientific Reports*, vol. 10, no. 1, July 2020, Art. no. 10993, <https://doi.org/10.1038/s41598-020-67898-3>.