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DIGITAL SOIL MONITORING THROUGH IoT AND DRONES FOR SUSTAINABLE AGRICULTURE

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ABSTRACT
Digital soil monitoring integrates the Internet of Things (IoT), unmanned aerial vehicles (UAVs), remote sensing and machine learning to improve soil assessment and support sustainable agriculture. IoT-enabled sensors facilitate the monitoring of soil moisture, temperature, pH, electrical conductivity and selected nutrient indicators. UAV-based imaging supports spatial mapping of soil organic matter, texture, nitrogen-related patterns and salinity-associated variability. Integrating ground-based measurements with aerial observations and geographic information systems enables more detailed soil characterization and site-specific management. These technologies can assist in irrigation scheduling, nutrient management and the identification of areas requiring further soil sampling. However, sensor calibration, laboratory validation, communication limitations, data quality and model uncertainty remain important challenges. Combining digital technologies with conventional soil analysis can strengthen precision agriculture and promote efficient resource utilization.

KEYWORDS: Digital soil monitoring, Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), Soil sensors, Soil health assessment and Sustainable agriculture.

1. INTRODUCTION
Sustainable agriculture increasingly relies on accurate soil information to improve fertilizer-use efficiency and maintain soil health. Soil properties such as pH, electrical conductivity (EC), soil organic carbon (SOC) and available nitrogen, phosphorus and potassium vary considerably across agricultural landscapes. Conventional laboratory analysis provides dependable measurements but may not capture fine-scale spatial variability when sampling is limited. Digital soil mapping offers an alternative by combining soil observations with environmental data and predictive models to characterize soil variation across fields (McBratney et al., 2003; Zhang et al., 2017). The development of the Internet of Things (IoT) and unmanned aerial vehicles (UAVs) has expanded the possibilities for continuous and spatially distributed soil assessment. IoT sensors enable repeated measurements of selected soil properties, while drone-mounted RGB and multispectral sensors provide high-resolution observations of field conditions. Integrating these datasets through geographic information systems and machine-learning techniques can support the identification of management zones and improve site-specific agricultural decisions. However, aerial imagery generally provides indirect estimates of soil characteristics and requires ground-based validation (Mulla, 2013; Zhang et al., 2017). Recent developments also highlight the need to improve data accuracy, interoperability and the practical application of digital soil information. Zhang et al. (2017) identified challenges in producing reliable digital soil maps, particularly in heterogeneous environments. Accordingly, this review focuses on integrating IoT and drone technologies for monitoring soil physical and chemical properties, evaluating their potential, limitations and future applications in sustainable agriculture.

2. Digital Soil Monitoring: Concept and Significance
2.1 Definition and Operating Principle
Digital soil monitoring involves the collection, transmission, processing and interpretation of soil data using digital sensors, communication networks and analytical tools. It integrates stationary probes, portable instruments, automated platforms and UAV-based imagery to provide information on soil properties. The process generally involves sensing, data transmission, storage, quality control, analysis, visualization and management decisions. These technologies support site-specific soil management by identifying variations in soil pH, salinity and nutrient availability and monitoring changes following irrigation, fertilizer application or rainfall. Integrating sensor

networks with digital agricultural systems can improve the availability of soil information and support precision management (Corwin and Scudiero, 2020; Rahman et al., 2024; Chen et al., 2025).

2.2 Why Digital Soil Monitoring is Needed

Digital soil monitoring is important for improving soil health assessment, understanding spatial variability, optimizing water and nutrient use and supporting climate-smart agriculture. Frequent data collection can reduce manual recording and help farmers identify areas requiring targeted sampling, irrigation or fertilizer application. However, the reliability of monitoring depends on sensor accuracy, calibration, installation, soil contact, sampling design and communication reliability. Rapid data collection alone does not guarantee better decisions; measurements must be validated and interpreted according to the intended management objective. Therefore, digital soil monitoring is most effective when reliable measurements are translated into practical and site-specific agricultural recommendations (Hossen et al., 2021; Chen et al., 2025; Sabharwal, 2026).

2.3 Traditional and Digital Monitoring Compared

Aspect	Traditional soil monitoring	Digital soil monitoring
Data collection	Manual sampling followed by laboratory analysis	Automated probes and digital observations combined with laboratory samples
Frequency	Usually periodic or campaign-based	Can be continuous or scheduled at short intervals
Spatial coverage	Depends on sample number and sampling design	Can combine many sensor locations with high-resolution aerial mapping
Turnaround	Laboratory processing may delay decisions	Data may be available quickly after collection and processing
Labour	Field sampling and manual recording are important	Automation can reduce repeated manual tasks
Cost profile	Lower equipment cost but recurring sampling and laboratory costs	Higher initial investment with maintenance, connectivity and calibration costs
Data handling	Reports and spreadsheets are common	Digital databases, dashboards and spatial layers can be integrated
Role in decisions	Supports recommendations based on sampled locations	Can support targeted management when validated and interpreted appropriately

3. Development of Internet of Things in Soil Monitoring

The Internet of Things (IoT) developed through the convergence of internet connectivity, embedded computing, sensor technology and wireless communication. The term Internet of Things was introduced by Kevin Ashton in 1999 in connection with radio-frequency identification (RFID) and the automatic identification of physical objects. Over time, advances in miniaturized electronic components, low-cost sensors and network technologies enabled physical devices to collect and exchange data with limited human intervention. In agriculture, these developments created opportunities to move beyond occasional manual observations towards connected systems for monitoring soil, crops and environmental conditions (Kour and Arora, 2020; Chamara et al., 2022).

During the early stages of agricultural digitalization, soil and environmental observations were mainly collected manually or recorded using standalone data loggers. The development of wireless sensor networks made it possible to collect measurements from multiple locations and transmit them to a central receiver. Subsequently, affordable microcontrollers, mobile communication networks and cloud-based platforms enabled sensors to transfer measurements to online databases and dashboards. These developments helped transform agricultural monitoring from a largely manual process into a connected data pipeline involving data collection, transmission, storage, visualization and decision-making (Kour and Arora, 2020; Chamara et al., 2022).

The application of IoT in agriculture expanded as sensors became more accessible and communication technologies improved. Agricultural IoT systems can collect measurements of soil moisture, temperature and electrical conductivity at selected locations and transmit them to monitoring platforms. Depending on sensor capability and calibration some systems also provide estimates related to soil pH and nutrient status. These data help users observe changes in field conditions over time and support decisions concerning irrigation, soil sampling and nutrient management. Chamara et al. (2022) reviewed agricultural IoT systems and described their use in crop, soil and microclimate monitoring including sensor hardware, communication protocols and data-processing approaches. More recently, IoT-based soil monitoring has increasingly been combined with machine learning, cloud computing and unmanned aerial vehicles (UAVs). Ground-based sensors provide repeated measurements at specific points, while drones collect aerial imagery that can help identify spatial differences across a field. Integrating these data sources allows researchers to relate temporal changes in soil conditions to spatial patterns

and to identify locations that require additional ground sampling. However, the reliability of this approach depends on sensor calibration, suitable ground-reference measurements, reliable data transmission and independent validation of predictive models (Chamara et al., 2022; Sabharwal, 2026).

3.1 Architecture of an IoT Soil Monitoring System

A practical digital soil monitoring system consists of four interconnected layers: the perception layer, network layer, processing layer and application layer. The perception layer includes soil sensors that measure parameters such as moisture, pH, electrical conductivity and nutrient indicators. The network layer transmits observations through Wi-Fi, LoRa or cellular networks, while the processing layer manages data storage, quality control and analysis. The application layer presents results through dashboards, alerts, spatial maps and decision-support tools. Some systems also incorporate actuators for automated irrigation or fertilizer delivery. Sensor selection and installation must consider the target soil property, measurement depth, soil contact and calibration requirements. Each observation should include its unit, timestamp, sensor identity, location and calibration status to support reliable interpretation. The communication technology should be selected according to field size, data volume, power availability and network coverage. Low-power communication networks can transmit small packets from stationary soil sensors, whereas high-resolution UAV imagery requires greater storage and data-transfer capacity. In practical applications, aerial images are often collected during scheduled flights and transferred to a ground station or cloud platform after landing rather than streamed continuously. This separation of sensor communication and image-data transfer helps improve system efficiency and supports the integration of ground measurements with aerial observations (Corwin and Scudiero, 2020; Rahman et al., 2024).

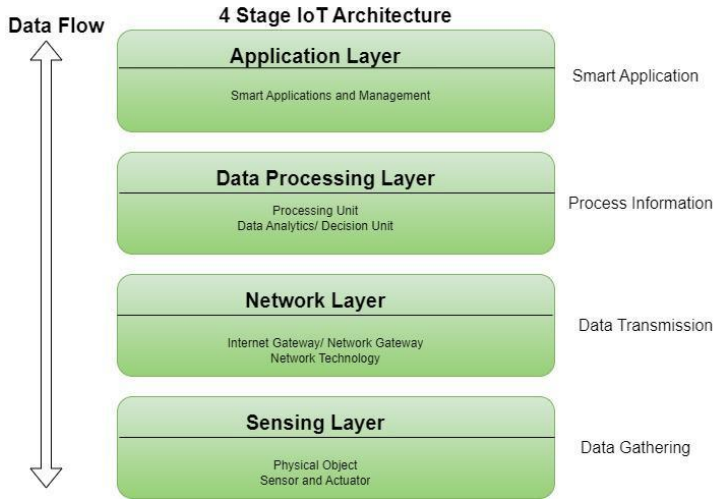


Fig.1 Architecture of an IoT Soil Monitoring System

3.2 Communication technologies

Technology	Typical role in farm monitoring	Main consideration
Wi-Fi	Short-range links in greenhouses, buildings or near a farm gateway	Requires nearby infrastructure and uses more power than many low-power options
LoRa / LoRaWAN	Long-range low-data-rate communication from distributed field nodes	Suitable for sensor readings but not for transmitting large image files
Cellular networks	Remote monitoring through 4G or other available mobile networks	Coverage and service cost vary by location
Bluetooth	Local configuration and short-range data transfer	Limited range for distributed field monitoring
Zigbee	Low-power communication among nearby sensor nodes	Network design and gateway availability are important
NB-IoT	Low-power,wide-area connectivity where supported	Availability depends on the local mobile operator and service

3.3 Microcontrollers, Gateways and Cloud Platforms

Microcontrollers serve as the central processing units of IoT-based soil monitoring systems by acquiring sensor readings, converting signals into usable data and controlling communication with gateways or cloud platforms. Arduino boards are commonly used in low-cost monitoring prototypes because of their simple programming environment and compatibility with different sensor modules. ESP32 microcontrollers offer additional advantages through integrated Wi-Fi and Bluetooth connectivity, making them suitable for systems that require real-time data

transmission and remote monitoring. Abu Sneineh and Shabaneh (2024) demonstrated the use of an ESP32-based system for monitoring pH, temperature and nutrient-solution parameters, while Zuchriadi et al. (2023) explored ESP32-based agricultural monitoring with LoRa communication. Microcontroller selection should consider processing capacity, power consumption, sensor compatibility, communication range and operating conditions to ensure reliable field performance (Abu Sneineh and Shabaneh, 2024; Zuchriadi et al., 2023).

Gateways act as an intermediate communication layer between field-level IoT sensors and cloud platforms. They collect data from multiple sensor nodes through communication technologies such as Wi-Fi, Bluetooth, Zigbee or LoRa and forward the measurements to remote servers using available internet connectivity. Gateways may also perform data aggregation, protocol conversion, temporary storage and preliminary processing, reducing communication overhead and improving system reliability. In agricultural monitoring, Raspberry Pi devices and dedicated LoRa gateways can support data transfer from distributed soil sensors to cloud-based dashboards. The selection of a gateway depends on communication range, power requirements, network availability, processing capacity and deployment cost (Farooq et al., 2019; Ayaz et al., 2019).

Cloud platforms enable the storage, visualization and analysis of time-stamped measurements through dashboards, graphs and alerts. They can integrate multiple sensor streams to identify trends and communicate changes in field conditions. However, unreliable internet connectivity may interrupt data transmission. Local data buffering, automatic synchronization, regular backups and access controls can improve system reliability and protect agricultural records (Chamara et al., 2022; Soussi et al., 2024; Ballestrin et al., 2026).

4. Sensors Used for Digital Soil Monitoring

4.1 Soil pH

Soil pH sensors measure the acidity or alkalinity of soil and provide essential information for assessing soil fertility and nutrient availability. Recent developments include solid-state electrodes, ion-sensitive field-effect transistors (ISFETs), optical sensing approaches and IoT-enabled portable devices for rapid field measurements. Archbold et al. (2023) reviewed the potential of ISFET sensors for in-situ soil pH analysis, highlighting their suitability for proximal soil sensing. Nair et al. (2026) developed an IoT-enabled portable pH meter using solid antimony and silver/silver chloride electrodes, achieving an error below ±0.2 pH units. Vigneshwar et al. (2026) also reported a bio-derived solid-state sensor based on TEMPO-oxidized cellulose nanocrystals for soil pH monitoring.



Fig.2 pH Sensor

4.1.1 All-solid-state soil pH sensor

Nair et al. (2026) developed an IoT-enabled portable pH meter using solid sensing and reference electrodes. The sensor showed a linear response over pH 4.01–9.04, with an error below ±0.2 pH units. This is a recent development aimed at portable soil pH measurement without a conventional liquid-filled reference electrode.



Fig .3 All-solid-state soil pH sensor

4.1.2 Ion-sensitive field-effect transistor (ISFET)

Archbold et al. (2023) reviewed ISFET technology for in-situ soil pH and chemical analysis. ISFETs use a pH-sensitive surface to produce an electrical response and offer potential for compact, rapid measurements. Calibration, temperature effects and long-term stability remain important challenges for agricultural applications.

4.1.3 Wireless IoT soil pH probe

Dragino (2024) describes the SPH01-NB as a wireless soil pH monitoring system that measures soil pH and temperature and transmits the readings to cloud-based platforms through Narrowband Internet of Things (NB-IoT) communication. The device incorporates a solid silver/silver chloride (Ag/AgCl) reference electrode and a

metal pH-sensitive electrode, with temperature compensation and an IP68-rated waterproof probe. Its low-power design supports long-term field deployment and remote monitoring, making it useful for IoT-based agricultural soil assessment.



Fig. 4 Wireless IoT soil pH probe

4.1.4 Colorimetric paper sensor with AI

Ferreira et al. (2025) investigated mobile soil pH classification using colorimetric paper sensors and image-based analysis. The approach combines a chemical colour response with computational interpretation, offering a low-cost alternative for field screening. Its results depend on image conditions, calibration and the soil testing procedure.

4.2 Electrical Conductivity Sensors

Soil electrical conductivity sensors measure the ability of soil to conduct electrical current and are widely used to assess salinity and spatial variability. Recent developments include multi-parameter probes, electromagnetic induction systems, frequency-based sensors and IoT-enabled devices that combine EC measurements with soil moisture and temperature monitoring. Faqir et al. (2024) reviewed advances in agricultural soil and plant sensors, study on selective soil salinity measurement investigated the use of different electrical frequencies to distinguish changes in salt concentration. These technologies support rapid field assessment, although EC readings are influenced by soil moisture, texture, temperature and ionic composition and require calibration against reference measurements.

4.2.1 Multi-parameter EC probe

Multi-parameter soil EC probes measure apparent electrical conductivity and may combine it with soil temperature and volumetric water content measurements. These sensors commonly use electrode-based or electromagnetic measurement principles and can be integrated with microcontrollers, RS485/Modbus interfaces and IoT gateways for automated data acquisition. Faqir et al. (2024) highlighted the growing importance of integrated soil-sensing technologies for precision agriculture. Such probes enable repeated field measurements, support salinity monitoring and help researchers assess changes in soil conditions during crop growth. However, readings require calibration and interpretation according to soil moisture, texture, temperature and ionic composition.



Fig.5 Multi-parameter EC probe

4.2.2 On-the-go EC mapping sensor

On-the-go EC mapping systems use contact electrodes mounted on agricultural equipment to measure apparent soil electrical conductivity while moving across a field. Georeferenced measurements are used to create spatial EC maps and identify management zones with different soil characteristics. Corwin and Scudiero (2020) discussed the value of apparent soil electrical conductivity for characterizing spatial soil variability and guiding site-specific management. These systems can cover large areas more rapidly than conventional point sampling and help target soil sampling and salinity investigations. Nevertheless, EC maps indicate combined soil influences rather than directly measuring individual nutrient concentrations.



Fig. 6 On-the-go EC mapping sensor

4.2.3 Electromagnetic induction sensor

Corwin and Scudiero (2020) explained that mobile EC mapping systems can rapidly characterize field-scale soil variability and guide targeted soil sampling. EMI instruments are particularly useful for identifying salinity patterns and variations associated with soil texture, water content and other soil properties. Their measurements can be georeferenced to generate spatial distribution maps for precision agriculture. However, the readings are influenced by soil moisture, temperature, instrument height and soil profile characteristics, requiring appropriate calibration and field validation.



Fig. 7 Electromagnetic induction sensor

4.3 Soil Moisture and Temperature sensor

Soil moisture and temperature sensors are important components of digital soil monitoring systems because they provide real-time information on soil water availability and thermal conditions affecting root growth and nutrient dynamics. Zhang et al. (2024) reviewed advances in soil moisture monitoring, including time-domain reflectometry (TDR), frequency-domain reflectometry (FDR), electromagnetic sensing and IoT-based wireless sensor networks. Loconsole et al. (2025) further examined invasive and non-invasive sensing technologies and their applications in precision irrigation. These sensors can be integrated with microcontrollers and cloud platforms to support continuous monitoring and irrigation decisions. However, measurement accuracy depends on soil texture, sensor placement, calibration and environmental conditions.



Fig. 8 Temperature Sensor

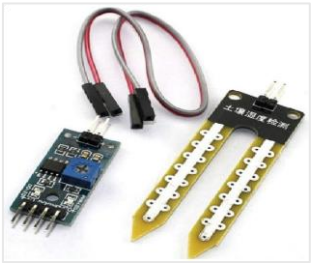


Fig. 9 Soil moisture sensor

4.4 Soil Nutrient Sensors

Soil nutrient sensors are used to estimate the concentration or availability of essential plant nutrients, particularly nitrogen (N), phosphorus (P) and potassium (K), to support site-specific fertilizer management. Pal et al. (2024) reviewed portable sensing technologies, including electrochemical sensors, ion-selective electrodes, optical methods and microfluidic devices, highlighting their potential for rapid soil nutrient assessment. Musa et al. (2024) examined the integration of NPK sensors with wireless sensor networks for precision agriculture and discussed their role in improving nutrient monitoring and fertilizer-use efficiency. More recently, Sobhy and Anandhi (2025) identified IoT-based systems, in-situ sensors, remote sensing and artificial intelligence as complementary approaches to soil nutrient monitoring.



Fig. 10 NPK Sensor

Nitrogen sensors are used to estimate the concentration of plant-available nitrogen, particularly nitrate and ammonium in soil extracts. Hong et al. (2025) developed ion-selective electrodes for detecting nitrate, ammonium and other nitrogen-related ions in agricultural soil extracts. Their sensors demonstrated selective responses and enabled continuous monitoring of nitrogen transformations over 13 days. These sensors can be integrated with microcontrollers and IoT systems for repeated nutrient measurements and improved fertilizer management. However, sensor responses depend on interfering ions, soil extraction procedures and calibration conditions.

Hossain (2024) reviewed electrochemical sensing technologies for phosphorus detection, including potentiometric systems, screen-printed electrodes and electrochemical methods based on phosphate reactions. The review highlighted research on multisensory systems capable of estimating N, P and K from aqueous soil extracts. Such sensors offer potential for rapid, portable soil nutrient analysis and integration with digital monitoring systems. However, phosphate detection remains challenging because phosphorus occurs in different chemical forms and its availability depends strongly on soil pH, mineral interactions and extraction methods.

Hong et al. (2025) developed an ion-selective electrode that showed a near-Nernstian response of 54.00 mV per decade for potassium, demonstrating its potential for quantitative ion detection. Potassium-selective electrodes can be incorporated into portable nutrient analysers and IoT-enabled monitoring systems to support repeated measurements and site-specific fertilizer decisions.

Reza et al. (2025) reviewed recent trends in nutrient sensing for soil and solution-based cultivation, including electrochemical and ion-selective approaches. Nevertheless, potassium measurements require appropriate calibration and consideration of interfering ions, soil moisture and the distinction between soil-solution potassium and laboratory-measured exchangeable potassium.

5. IoT Enabled Soil Health Monitoring Systems

5.1 IoT monitoring for irrigation and farm management

Internet of Things (IoT) technology enables real-time monitoring of soil and environmental conditions to improve irrigation scheduling and farm management. Abdelmoneim et al. (2025) reviewed IoT-based irrigation systems and highlighted the importance of wireless sensor networks, low-power communication technologies and automated data acquisition for efficient water management. These systems collect measurements from soil moisture and temperature sensors and transmit them through microcontrollers and gateways to cloud platforms for visualization and analysis.

Sharma et al. (2025) examined smart irrigation systems integrating IoT, wireless sensor networks and artificial intelligence to support data-driven irrigation decisions. By combining field sensor measurements with weather information and crop water requirements, these systems can help determine irrigation timing and reduce unnecessary water application. Furthermore, integration with drone imagery and GIS can help identify spatial differences in crop growth and field conditions, supporting targeted irrigation and other farm operations. However, reliable implementation requires sensor calibration, stable communication networks and validation under different soil and climatic conditions.

Elsherbiny et al. (2025) developed an IoT-based multimodal framework for optimizing irrigation in wheat by combining soil moisture measurements, weather variables and plant images with deep-learning models. The system evaluated environmental factors such as air temperature, relative humidity and wind speed alongside crop imagery. Integrating these data enabled the researchers to estimate irrigation frequency and crop water requirements. The best-performing model achieved a reported validation accuracy of 97.9% for the evaluated prediction task. Such approaches demonstrate how sensor networks and image analysis can support timely irrigation decisions throughout wheat growth. Continuous monitoring can also help identify water stress earlier than occasional field observations, although performance should be validated across different cultivars and growing environments.

Akshay et al. investigated IoT-based drip irrigation and fertigation management in aerobic rice during the 2022–2023 and 2023–2024 cropping seasons at the ICAR–Indian Institute of Rice Research, Hyderabad. The experiment evaluated different nitrogen management strategies alongside sensor-based irrigation scheduling. Irrigation treatments included scheduling at saturation and at specified levels of soil moisture depletion. The study examined crop growth, grain yield and water-use efficiency under different combinations of irrigation and nutrient management. This research demonstrates the potential of integrating soil water monitoring with fertigation to

improve resource management in aerobic rice. Such systems may be particularly useful where water availability is limited and precise nutrient delivery is required.

Rahman et al. (2024) developed an IoT-based soil characterization system for watermelon cultivation in Bangladesh. The system measured soil moisture, temperature and pH using sensors connected to Arduino and Raspberry Pi hardware. The recorded measurements were uploaded to a cloud platform and made accessible through a mobile application and webpage. To evaluate the system, the researchers compared its measurements with readings from field meters and laboratory analyses. They also investigated the relationship between soil electrical resistivity and salinity and developed an artificial neural network (ANN) model using soil measurements to estimate salinity. This study illustrates how IoT-based monitoring can combine field sensing, laboratory validation and machine learning to characterize soil conditions relevant to watermelon production. However, the relationship between resistivity and salinity can vary with soil moisture, temperature and soil composition, so the model requires validation before being transferred to other fields.

Aarthi et al. (2023) developed a smart soil-property monitoring system and evaluated it in a backyard gardening application involving spinach. The prototype measured soil pH and electrical conductivity and transmitted the observations to a cloud-based platform using an IoT framework. The researchers compared sensor readings with laboratory results to examine the system's performance. The reported pH values were 6.0 from the sensor and 6.7 from laboratory analysis, while the EC values were 0.48 and 0.64 respectively. The differences between these measurements illustrate why field sensors require calibration and comparison with laboratory reference methods. The study provides an example of using IoT for soil fertility monitoring in a leafy vegetable system, although the reported evaluation should not be interpreted as validation across all soil types or commercial spinach production environments.

Brahmanandam et al. (2024) investigated the integration of IoT-based soil monitoring and machine learning for tomato crop disease prediction at a research station in Anakapalle, southern India. Their system collected measurements of soil moisture or humidity, temperature, pH and the major nutrients nitrogen, phosphorus and potassium during the vegetative growth stage. The researchers evaluated several machine-learning algorithms and reported that a hybrid approach combining Bayesian optimization with k-nearest neighbours achieved 95% accuracy, precision and recall for the prediction task. This study demonstrates how sensor-derived soil and environmental information can contribute to crop monitoring and analytical decision support. Nevertheless, the model's reported performance concerns tomato disease prediction in the study setting; it does not by itself demonstrate that IoT sensors can directly measure all soil nutrients with laboratory-level accuracy.

5.2 Soil Salinity Monitoring

Soil salinity sensors are designed to assess soluble salt accumulation and identify salt-affected areas that may restrict crop growth. Horváth et al. (2024) developed an experimental variable-frequency sensing system to improve the discrimination of soil salinity levels. Their study found that measurements between 20 Hz and 250 kHz helped distinguish salt-concentration differences in soils treated with potassium and calcium solutions. El Moatassem et al. (2025) evaluated portable X-ray fluorescence (pXRF) for rapid soil salinity hazard assessment and compared its results with electrical conductivity measurements of soil–water extracts. These approaches offer potential for faster salinity assessment and mapping, although calibration against reference soil analyses remains necessary across different soil types and salt compositions.

6. UAVs and Drones in Digital Soil Monitoring

Unmanned aerial vehicles (UAVs), commonly known as drones, are increasingly used in precision agriculture for collecting high-resolution spatial data and monitoring field variability. Meshram et al. (2024) highlighted the potential of UAV-based remote sensing for soil mapping and agricultural management. UAVs equipped with RGB, multispectral, hyperspectral and thermal sensors can support the assessment of soil properties and the identification of spatial variations across agricultural fields. Wang et al. (2024) further emphasized the role of UAV remote sensing and machine-learning techniques in improving agricultural monitoring and precision management. These technologies can complement ground-based soil sampling and support sustainable soil management

6.1 Role of UAV Platforms

Unmanned aerial vehicles (UAVs), commonly known as drones, are increasingly used in digital soil monitoring because they provide high-resolution spatial information across agricultural fields. UAVs equipped with RGB, multispectral, hyperspectral and thermal sensors can facilitate the assessment of soil surface characteristics, terrain variability and spatial patterns associated with soil properties. Their flexible flight schedules and high spatial resolution make them useful for identifying heterogeneous field zones and selecting locations for targeted soil sampling. However, aerial imagery does not directly measure all soil chemical properties because spectral responses are influenced by soil moisture, surface roughness, crop residues, vegetation cover and illumination conditions. Therefore, reliable soil property mapping requires appropriate flight planning, image processing and calibration using ground-based measurements (Meshram et al., 2024; Wang et al., 2024).

6.2 Types of Drones

UAV type	Strengths	Limitations and suitable applications
Fixed-wing	Long endurance and broad area coverage	Needs suitable launch and recovery space; useful for large-scale surveys
Multi-rotor	Vertical take-off and landing, hovering and flexible flight paths	Usually shorter endurance; useful for small to medium fields and detailed imaging
Single-rotor	Can carry relatively heavy payloads and hover	More complex and potentially expensive; useful for specialized sensor payloads
Hybrid VTOL	Combines vertical take-off with efficient forward flight	Higher system complexity; useful when both coverage and flexible deployment are needed

6.3 Sensors Carried by Drones

Sensor	Primary information	Potential soil-monitoring use
RGB camera	Visible color and surface structure	Surface condition, bare-soil mapping, erosion features and orthomosaics
Multispectral camera	Reflectance in selected spectral bands	Vegetation indices and indirect assessment of crop stress or spatial variability
Hyperspectral sensor	Many narrow spectral bands	Detailed spectral characterization of soil and vegetation where calibrated models are available
Thermal infrared	Surface temperature patterns	Indirect assessment of water stress and spatial thermal variation
LiDAR	Three-dimensional distance measurements	Terrain modelling, drainage patterns and erosion assessment
GNSS/GPS	Geographic position and time	Georeferencing images and linking aerial observations

RGB cameras are relatively inexpensive and are widely used in UAV-based soil monitoring to capture visible surface features and support terrain mapping. Multispectral cameras record reflectance across selected wavelength bands including red, green, blue, red-edge and near-infrared regions. Hyperspectral sensors capture numerous narrow spectral bands that can reveal subtle differences in soil composition. Thermal sensors measure surface temperature patterns while LiDAR provides three-dimensional information useful for topographic mapping and drainage assessment. The suitability of each sensor depends on the target property and field conditions. Vegetation indices derived from multispectral imagery are primarily indicators of crop condition and may indirectly reflect nutrient deficiencies. However, similar spectral responses can result from water stress, disease, pest damage or variations in crop density. Therefore, reliable soil nutrient assessment requires the integration of UAV imagery with ground-based soil sampling and appropriate calibration models (Peña et al., 2025; Wang et al., 2024; Pouladi et al., 2023).

6.4 Flight Planning and Image Processing

UAV-based soil monitoring requires systematic flight planning and image processing to produce accurate and reliable spatial information. The survey begins by defining the mapping objective and selecting suitable flight parameters such as altitude, flight speed, image overlap and flight route. The collected images are processed using photogrammetric techniques to generate orthomosaics and digital surface models. Radiometric calibration and accurate georeferencing are important for ensuring consistency between images and for integrating aerial observations with ground-based soil measurements. Ground-truth data are essential for developing and validating UAV-based soil property prediction models. Soil samples should be collected from representative locations covering the variability of the study area and their geographic coordinates should be accurately recorded. Laboratory measurements are then associated with the corresponding image pixels or spectral information to establish predictive relationships. Separating training and validation datasets by location or field can provide a more realistic assessment of model performance and reduce the risk of overestimating prediction accuracy (Makam et al., 2024; Wang et al., 2024; Ballestrin et al., 2026).

7. UAV-Based Soil Property Mapping

Unmanned aerial vehicles (UAVs) equipped with multispectral, hyperspectral and RGB sensors offer high-resolution observations for mapping soil variability across agricultural fields. These images can be integrated with soil sampling data, geographic information systems (GIS) and machine-learning algorithms to estimate properties

such as soil organic carbon, texture and selected chemical characteristics. Lyu et al. (2025) developed a digital soil mapping framework combining UAV imagery, satellite data and ensemble learning to predict soil organic carbon, total nitrogen, pH, available phosphorus and available potassium. Their findings showed that multi-source data integration can improve prediction accuracy, although performance varied by soil property and data source.
Qi et al. (2025) used UAV multispectral imagery and machine-learning algorithms to predict soil organic carbon in tobacco-growing fields. Their research demonstrated the potential of spectral indices, particularly those involving red-edge and near-infrared bands, for mapping soil carbon variability. Cheng et al. (2025) investigated UAV-supported ground-penetrating radar to estimate soil electrical properties and map spatial variations in soil salinity. These studies illustrate two complementary approaches: spectral modelling for soil property prediction and UAV-supported geophysical sensing for mapping subsurface variability. However, reliable soil property maps require representative ground sampling, laboratory calibration and independent model validation

7.1 Soil organic matter mapping

Soil organic matter (SOM) mapping using unmanned aerial vehicles (UAVs) provides high-resolution information on soil variability and supports precision soil management. Yan et al. (2023) used UAV hyperspectral imagery and machine-learning models to map SOM at 1 m spatial resolution in agricultural fields. Their random forest model achieved an R^2 of 0.53, demonstrating the potential of hyperspectral imagery for field-scale SOM estimation.
Reyes et al. (2024) evaluated UAV multispectral imagery acquired under bare-soil conditions to predict soil organic carbon (SOC) in a long-term experimental field in Germany. Their best-performing model achieved an R^2 of 0.54 and an RMSE of 1.9 g kg^{-1}, and the resulting maps showed spatial patterns associated with organic fertilization.
Xie et al. (2025) investigated SOM prediction during the jointing stage of winter wheat using UAV multispectral imagery and machine-learning models. Their study demonstrated that vegetation spectral information can support SOM prediction when bare-soil imagery is unavailable. These studies highlight the potential of UAV-based mapping for identifying spatial differences in soil organic matter and supporting targeted soil sampling. However, vegetation cover, soil background conditions and model calibration can influence prediction accuracy.

7.2 Soil texture mapping with hyperspectral imaging and AI

Soil texture mapping using UAV-based hyperspectral imaging and artificial intelligence (AI) enables the spatial estimation of sand, silt and clay fractions across agricultural fields. Song et al. (2023) collected 296 soil samples from three agricultural areas in the Huangshui Basin, China, and combined UAV hyperspectral imagery with machine-learning algorithms to estimate soil texture. Their study demonstrated that spectral preprocessing and calibration using laboratory and field measurements improved the reliability of soil texture estimation and mapping.
Flores Peña et al. (2025) investigated UAV-based hyperspectral imaging combined with AI algorithms for soil texture classification and agricultural monitoring. Their framework integrated hyperspectral data with additional sensing information and machine-learning methods to distinguish soil texture classes. The authors reported classification accuracies of up to 96.5% for the evaluated approach, highlighting the potential of AI-assisted mapping. More recently, Song et al. (2026) combined ground-based sensing, UAV hyperspectral imagery and satellite observations using 838 soil samples collected over three years to improve soil texture estimation. These studies demonstrate the potential of integrating hyperspectral data and AI for high-resolution soil texture mapping, although field sampling and independent validation remain necessary.

7.3 Total Soil Nitrogen Mapping

Total soil nitrogen (TN) mapping using unmanned aerial vehicle (UAV) hyperspectral imagery and machine-learning algorithms enables the assessment of spatial variability in soil nitrogen across agricultural fields. Peng et al. (2023) investigated UAV hyperspectral responses and developed regression models for estimating soil total nitrogen using selected spectral bands and random forest algorithms.
Luo et al. (2026) combined UAV hyperspectral imagery, spectral feature selection and machine-learning models to estimate soil total nitrogen in plateau agricultural regions, achieving a test R^2 of approximately 0.77 with their best-performing model. These approaches enable the development of spatial nitrogen distribution maps that can identify areas with contrasting soil fertility and support targeted soil sampling. However, predictions require calibration against laboratory-measured nitrogen concentrations and independent validation under different soil and surface conditions. Total soil nitrogen (TN) mapping using unmanned aerial vehicle (UAV) imagery and artificial intelligence provides a means of assessing the spatial variability of soil nitrogen across agricultural fields. Hyperspectral sensors capture reflectance patterns associated with soil composition, while machine-learning algorithms establish relationships between spectral information and laboratory-measured nitrogen concentrations. Integrating UAV imagery with georeferenced soil samples and geographic information systems (GIS) enables the generation of high-resolution nitrogen distribution maps. These maps can help identify areas with contrasting soil fertility and guide targeted sampling and nutrient management. However, total nitrogen must be distinguished from plant-available nitrogen because the two parameters represent different aspects of soil fertility.

7.4 UAV-based Nutrient Monitoring and Fertilizer Management

Unmanned aerial vehicles (UAVs) equipped with multispectral and hyperspectral sensors enable crop nutrient status to be assessed through canopy reflectance, vegetation indices and machine-learning models. Yu et al. (2025) reviewed UAV hyperspectral approaches for crop nitrogen monitoring and highlighted their potential for

identifying nutrient variability and supporting precision nitrogen management. The authors also emphasized the need for independent validation because model performance can decline when applied to different crops, growth stages or field conditions.

Zhang et al. (2024) developed a rice fertilization decision method by integrating UAV hyperspectral imagery with the WOFOST crop growth model. Their approach estimated rice biomass and supported nitrogen fertilizer recommendations during the tillering stage, demonstrating the potential of combining drone observations with crop growth modelling.

Zhu et al. (2025) conducted a meta-analysis of hyperspectral and multispectral remote sensing methods for estimating crop leaf nitrogen, phosphorus and potassium. Their findings support the use of spectral information for crop nutrient assessment and highlight the importance of selecting suitable spectral bands and algorithms.

In maize, UAV multispectral imagery has also been used to estimate nitrogen demand under different irrigation conditions. The study published in Agricultural Water Management (2024) used the normalized difference red-edge index (NDRE) to guide nitrogen application and fertigation. Sensor-based treatments reduced nitrogen inputs by 50–60%, although yield reductions of up to 12% occurred in some treatments. These findings demonstrate the potential of UAV-based nutrient monitoring to improve nitrogen-use efficiency while emphasizing the need to balance fertilizer savings with crop yield.

8. Integration of IoT and Drones

The integration of the Internet of Things (IoT) and unmanned aerial vehicles (UAVs) represents an important development in digital soil monitoring by combining continuous ground-based sensing with large-scale aerial observations. IoT networks collect soil and environmental data through connected sensors while drones provide spatial information using multispectral, hyperspectral, thermal and other remote-sensing technologies. Integrating these data sources can improve the assessment of soil variability, support targeted sampling and strengthen data-driven agricultural management. Cloud computing, wireless communication networks, geographic information systems (GIS) and machine-learning algorithms can facilitate data transmission, integration and interpretation. This integrated approach provides a foundation for precision agriculture by connecting real-time soil observations with field-scale spatial mapping and management decisions (Peña et al., 2025; Wang et al., 2024; Pouladi et al., 2023).

8.1 Integrated System Workflow

Stage	Input or operation	Output
1. Ground sensing	Measure moisture, temperature, pH, EC and selected nutrient indicators	Timestamped point measurements
2. UAV survey	Collect RGB, multispectral, hyperspectral, thermal or LiDAR data	Georeferenced images and spatial layers
3. Communication	Send sensor data to a gateway and upload imagery after flight	Centralized datasets
4. Quality control	Check missing data, calibration, location accuracy and sensor drift	Validated measurements
5. Data fusion	Align sensor points with image pixels and soil sample results	Combined spatial and temporal dataset
6. Analysis	Apply statistical or machine-learning models and GIS tools	Soil property estimates and uncertainty maps
7. Decision support	Compare mapped conditions with crop needs and validated thresholds	Targeted sampling or management recommendations
8. Evaluation	Compare predicted values with independent field and laboratory data	Accuracy and reliability assessment

8.2 Complementary strengths

Ground-based IoT sensors and UAVs provide complementary types of information for digital soil monitoring. Soil probes measure properties at specific locations and can record changes repeatedly over time, making them suitable for continuous monitoring of soil moisture, temperature and electrical conductivity. In contrast, UAVs collect aerial imagery across larger areas during scheduled flights, enabling the identification of spatial differences in soil and crop conditions. Ground sensors therefore provide temporal detail while UAV imagery provides broader spatial coverage. Combining both sources can reduce the limitations associated with relying on either monitoring approach independently (Corwin and Scudiero, 2020; Rahman et al., 2024).

For example, a ground-based sensor can detect an increase in soil moisture following irrigation but cannot represent the entire field unless a sufficient number of sensors are installed. UAV imagery can identify spatial differences across the field but generally represents conditions at the time of image acquisition. Integrating

repeated sensor measurements with aerial maps allows spatial patterns to be interpreted alongside temporal changes. A similar approach can guide targeted soil sampling for pH, electrical conductivity, soil organic matter and nutrient status. The combined information can support more efficient field assessment and help identify areas requiring further investigation (Pouladi et al., 2023; Zheng et al., 2024).

8.3 Data Fusion and Predictive Models

Data fusion combines observations from different sources to develop a more comprehensive understanding of field conditions. In integrated digital soil monitoring, predictive models may incorporate UAV spectral bands, vegetation indices, topographic characteristics, ground sensor readings, weather data and laboratory soil measurements. Statistical approaches such as linear regression provide interpretable baseline models, whereas random forests, support vector regression and neural networks can capture more complex nonlinear relationships. The choice of model should depend on the target soil property, dataset size and quality of the available observations rather than model complexity alone (Mulla, 2013; Liakos et al., 2018; Sharma et al., 2020).

Reliable prediction requires representative calibration data and independent model validation. A model developed using samples from a single field or sampling date may perform poorly when applied to different soil types, seasons or environmental conditions. Spatial cross-validation and independent field testing can provide more realistic estimates of model performance and transferability. Roberts et al. (2017) explained that validation strategies should account for spatial and other forms of data dependence to avoid overly optimistic performance estimates. Wadoux et al. (2021) also discussed important considerations in machine learning for digital soil mapping. In addition, uncertainty maps can identify areas where predictions are less reliable and help prioritize further soil sampling. Integrating these procedures improves confidence in model outputs and supports more defensible agricultural decisions (Roberts et al., 2017; Wadoux et al., 2021).

9. Applications in Sustainable Agriculture

The integration of IoT sensors, UAV imagery and predictive analytics can support sustainable agriculture through variable-rate fertilization, irrigation scheduling, soil salinity surveillance, soil organic matter mapping and identification of areas requiring additional soil sampling. Repeated measurements can also help assess changes in soil conditions following conservation practices or modifications in fertilizer and irrigation management. By combining real-time observations with spatial information, digital monitoring systems can support more targeted field operations and improve the availability of information for farm-level decision-making (Pouladi et al., 2023; Zheng et al., 2024).

For nutrient management, integrated monitoring can help identify areas with different fertility levels and support fertilizer application according to crop requirements and spatial variability. Ground-based soil tests and plant measurements remain essential for confirming nutrient deficiencies and establishing appropriate fertilizer rates. Fountas et al. highlighted the role of farm management information systems in organizing agricultural data and supporting operational decisions, while Wolfert et al. discussed the potential of data-driven agriculture to improve farm management. Although these technologies may help reduce unnecessary input application and improve nutrient-use efficiency, the actual benefits depend on sensor accuracy, model reliability, suitable recommendations and effective implementation. Field trials are therefore necessary to demonstrate improvements in yield, resource-use efficiency and environmental performance rather than assuming that digital monitoring alone guarantees sustainability (Hossen et al., 2021; Chen et al., 2025; Sabharwal, 2026).

10. Limitations and Challenges

The integration of IoT sensors and UAVs for digital soil monitoring faces several challenges, including high initial investment, maintenance requirements and the need for regular sensor calibration. Soil sensor accuracy can be affected by texture, moisture, temperature and chemical composition, while UAV operations are constrained by battery life, weather conditions, payload capacity and flight regulations. Limited rural connectivity, large data storage requirements and compatibility issues between different devices can further complicate system implementation. In addition, farmers and extension personnel require adequate training to operate equipment and interpret digital outputs, while farm data must be protected through appropriate privacy and access controls. Remote sensing cannot directly measure all soil chemical properties and spectral responses may be influenced by vegetation cover, crop stress and surface conditions. Therefore, reliable digital soil monitoring requires proper calibration, field validation, effective data management and careful interpretation of model predictions (Datta and Taghvaeian, 2023; Duangsuwan et al., 2020).

11. Future Prospects

The future of digital soil monitoring lies in integrating artificial intelligence, machine learning, IoT sensors and UAV remote sensing to improve the accuracy and efficiency of soil property assessment. Advanced predictive models, edge computing and improved communication networks may enable faster data processing and reliable monitoring in areas with limited internet connectivity. The development of low-cost sensors, standardized calibration procedures and regional soil databases could make these technologies more accessible to farmers. Farmer-oriented decision-support systems may help translate soil measurements and spatial maps into practical recommendations for irrigation, nutrient management and targeted soil sampling. Furthermore, repeated digital observations can support climate-smart agriculture by identifying soil moisture stress, salinity risks, nutrient imbalances and changes in soil organic matter. However, long-term field validation is essential to establish the reliability, economic feasibility and environmental benefits of these technologies (Pouladi et al., 2023; Zheng et al., 2024).

12. CONCLUSION

Digital soil monitoring through IoT and UAVs enables frequent and spatially detailed assessment of agricultural soils. IoT sensors monitor soil moisture, temperature, pH, electrical conductivity and selected nutrient indicators, while UAVs map field variability using advanced imaging sensors. Integrating these data with GIS and analytical models supports precision irrigation and nutrient management. However, reliable implementation requires accurate calibration, ground validation, cost-effective technologies and appropriate data management. Combining ground sensors, UAV imagery and laboratory analysis can improve soil assessment and resource-use efficiency. Despite challenges related to cost, connectivity, maintenance and technical skills, integrated IoT–UAV systems offer significant potential for sustainable agriculture when their accuracy and agronomic benefits are validated under field conditions (Corwin and Scudiero, 2020; Rahman et al., 2024).

REFERENCES

1. Aarthi, R., Sivakumar, D., & Mariappan, V. (2023). Smart soil property analysis using IoT: A case study implementation in backyard gardening. Procedia Computer Science, 218, 2842–2851.
2. Abdelmoneim, A. A., Kimaita, H. N., Al Kalaany, C. M., Derardja, B., Dragonetti, G. and Khadra, R. (2025). IoT sensing for advanced irrigation management: A systematic review of trends, challenges, and future prospects. Sensors, 25(7), 2291. https://doi.org/10.3390/s25072291
3. Abu Sneineh, A. and Shabaneh, A. A. (2024). Design of a smart hydroponics monitoring system using an ESP32 microcontroller and the Internet of Things. MethodsX, 11, 102401. https://doi.org/10.1016/j.mex.2023.102401
4. Ahmad, I., et al. (2024). UAV-based precision agriculture: Sensors, image processing and applications. Drones.
5. Ahmed, N., et al. (2022). Remote sensing and machine learning for soil salinity mapping in agricultural landscapes. Remote Sensing.
6. Akshay, D. V. S., Kumar, R. M., Sree, S. P., Sreedevi, B., Prasad Babu, M. B. and Sakhare, A. S. (2024). Optimizing growth and yield in aerobic rice through IoT-based drip irrigation and fertigation. International Journal of Plant & Soil Science. https://doi.org/10.9734/ijpss/2024/v36i74720
7. An Electrical Conductivity Sensor for the Selective Determination of Soil Salinity (2024). Sensors, 24(11), 3296. This study investigated frequency-dependent electrical conductivity measurements for distinguishing soil salt concentrations. https://doi.org/10.3390/s24113296
8. Angelopoulou, T., Tziolas, N., Balafoutis, A., Zalidis, G., & Bochtis, D. (2020). Remote sensing techniques for soil organic carbon estimation: A review. Remote Sensing, 12, 123. https://doi.org/10.3390/rs12010123
9. Archbold, G., Parra, C., Carrillo, H. and Mouazen, A. M. (2023). Towards the implementation of ISFET sensors for in-situ and real-time chemical analyses in soils: A practical review. Computers and Electronics in Agriculture, 209, 107828. https://doi.org/10.1016/j.compag.2023.107828
10. Ayaz, M., Ammad-Uddin, M., Sharif, Z., Mansour, A. and Aggoune, E. H. M. (2019). Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk. IEEE Access, 7, 129551–129583. https://doi.org/10.1109/ACCESS.2019.2932609.
11. Ballestrin, R., Schmith, J., Arnhold, F., Müller, I., & Pereira, C. E. (2026). Drone-based data acquisition for digital agriculture: A survey of wireless network applications. AgriEngineering, 8(2), 41. https://doi.org/10.3390/agriengineering8020041
12. Brahmanandam, P. S., et al. (2024). Integrating IoT for soil monitoring and hybrid machine learning in predicting tomato crop disease in a typical South India station. Sensors, 24(19), 6177. https://doi.org/10.3390/s24196177
13. Chamara, N., Islam, M. D., Bai, G., Danyao, L., & Zhang, Y. (2022). Internet of Things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. Internet of Things, 18, 100187. https://doi.org/10.1016/j.iot.2020.100187
14. Chen, S., Arrouays, D., Mulder, V. L., Poggio, L., Minasny, B., Roudier, P., et al. (2022). Digital mapping of GlobalSoilMap soil properties at a broad scale: A review. Geoderma, 409, 115567. https://doi.org/10.1016/j.geoderma.2021.115567
15. Chen, X., Zhang, H., & Wong, C. U. I. (2025). Dynamic monitoring and precision fertilization decision system for agricultural soil nutrients using UAV remote sensing and GIS. Agriculture, 15(15), 1627. https://doi.org/10.3390/agriculture15151627
16. Cheng, Q. et al. (2025). Combined measurement of soil permittivity and electrical conductivity using UAV-based ground penetrating radar. Water Resources Research, 61(10), e2024WR039519. https://doi.org/10.1029/2024WR039519
17. Corwin, D. L., & Scudiero, E. (2020). Review of soil salinity assessment using proximal and remote sensing methods.
18. Datta, S., & Taghvaeian, S. (2023). Soil water sensors for irrigation scheduling in the United States: A systematic review of literature. Agricultural Water Management, 278, 108148. https://doi.org/10.1016/j.agwat.2023.108148

19. Development of a Low-Cost Measurement System for Soil Electrical Conductivity and Water Content (2025). AgriEngineering, 7(10), 329. This study focused on a more affordable system for measuring soil EC and water content for agricultural monitoring. https://doi.org/10.3390/agriengineering7100329
20. Duangsuwan, S., Teekapakvisit, C., & Maw, M. M. (2020). Development of soil moisture monitoring by using IoT and UAV-SC for smart farming application. Advances in Science, Technology and Engineering Systems Journal, 5(4), 381–387. https://doi.org/10.25046/aj050444
21. El Moatassem, T., Lazaar, A. and Kebede, F. (2025). Soil salinity hazard monitoring with portable X-ray fluorescence spectrometry and electrical conductivity meters. Frontiers in Soil Science, 5, 1661473. https://doi.org/10.3389/fsoil.2025.1661473
22. Elsherbiny, O., Zhou, L., He, Y. and Qiu, Z. (2025). Precision farming: Using an IoT multimodal data-driven deep network to optimize irrigation in wheat crops. Expert Systems with Applications. https://doi.org/10.1016/j.eswa.2025.128583
23. European Commission Joint Research Centre. (2021). Soil monitoring and digital soil mapping: Methods and applications.
24. European Environment Agency. (2022). Soil monitoring in Europe: Indicators and data systems. [Verify report metadata before submission].
25. European Space Agency. (2023). Earth observation for soil monitoring and sustainable agriculture.
26. FAO. (2021). Digital technologies in agriculture and rural areas: Status report.
27. FAO. (2022). The State of Food and Agriculture 2022: Leveraging automation in agriculture for transforming agrifood systems. Rome: Food and Agriculture Organization.
28. FAO. (2024). The State of Food and Agriculture 2024: Value-driven transformation of agrifood systems. Rome: Food and Agriculture Organization.
29. Faqir, Y., Qayoom, A., Erasmus, E., Schutte-Smith, M. and Visser, H. G. (2024). A review on the application of advanced soil and plant sensors in the agriculture sector. Computers and Electronics in Agriculture, 226, 109385. https://doi.org/10.1016/j.compag.2024.109385
30. Farooq, M. S., Riaz, S., Abid, A., Abid, K. and Naeem, M. A. (2019). A survey on the role of IoT in agriculture for the implementation of smart farming. IEEE Access, 7, 156237–156271. https://doi.org/10.1109/ACCESS.2019.2949703
31. Fauziah, et al. (2024). Enhancing soil nutritional status in smart farming: The role of IoT-based management for meeting plant requirements. International Journal of Agronomy, 2024, 8874325. https://doi.org/10.1155/2024/8874325
32. Ferreira da Silva, A., Ohta, R. L., Tirapu Azpiroz, J., Esteves Ferreira, M., Marçal, D. V., Botelho, A. et al. (2025). AI enabled, mobile soil pH classification with colorimetric paper sensors for sustainable agriculture. PLOS ONE, 20(1), e0317739. https://doi.org/10.1371/journal.pone.0317739
33. Flores Peña, P., Ale Isaac, M. S., Gîfu, D., Pechlivani, E. M. and Ragab, A. R. (2025). Unmanned aerial vehicle-based hyperspectral imaging and soil texture mapping with robust AI algorithms. Drones, 9(2), 129. https://doi.org/10.3390/drones9020129
34. Garcia, L., et al. (2021). IoT architectures and wireless sensor networks for smart agriculture: A review. Sensors..
35. Goudos, S., et al. (2022). Internet of Things and agricultural unmanned aerial vehicles in smart farming: A comprehensive review. Internet of Things, 18, 100187. https://doi.org/10.1016/j.iot.2020.100187
36. Gul, D., & Jeelani, N. (2026). Integration of unmanned aerial vehicle and Internet of Things sensor networks in agriculture: An artificial intelligence-driven analytical review for smart farming. IntechOpen. https://doi.org/10.5772/acrt20250106
37. Horváth, J., Kátai, L., Szabó, I. and Korzenszky, P. (2024). An electrical conductivity sensor for the selective determination of soil salinity. Sensors, 24(11), 3296. https://doi.org/10.3390/s24113296
38. Hossen, M. A., Diwakar, P. K., & Ragi, S. (2021). Total nitrogen estimation in agricultural soils via aerial multispectral imaging and LIBS. Scientific Reports, 11, 12693. https://doi.org/10.1038/s41598-021-90624-6
39. Islam, M. R., Oliullah, K., Kabir, M. M., Alom, M., & Mridha, M. F. (2023). Machine learning enabled IoT system for soil nutrients monitoring and crop recommendation. Journal of Agriculture and Food Research, 14, 100880. https://doi.org/10.1016/j.jafr.2023.100880
40. Khosravi, V., et al. (2022). Soil organic carbon prediction using remote sensing and machine learning. Catena.
41. Kim, J., et al. (2023). Edge computing and wireless communication for agricultural IoT systems. Sensors.
42. Kour, V. P., & Arora, S. (2020). Recent developments of the Internet of Things in agriculture: A survey. IEEE Access, 8, 129924–129957. https://doi.org/10.1109/ACCESS.2020.3009298
43. Li, M., et al. (2022). UAV multispectral imagery for soil property mapping under agricultural conditions. Remote Sensing.
44. Li, X., Zhang, Y., Bao, Y., et al. (2020). Hyperspectral remote sensing for soil properties: Recent advances and future directions. Remote Sensing. https://doi.org/10.3390/rs12060999
45. Li, Y., et al. (2023). UAV-based hyperspectral remote sensing for soil property estimation: A review. Remote Sensing.

46. Loconsole, D., Elia, M., Conversa, G., De Lucia, B., Cristiano, G. and Elia, A. (2025). Soil Moisture Sensing Technologies: Principles, Applications, and Challenges in Agriculture. Agronomy, 15(12), 2788. https://doi.org/10.3390/agronomy15122788
47. Luo, Y., Tang, B.-H., Wang, D. and Cai, F. (2026). Estimation of soil total nitrogen in plateau agriculture regions from UAV hyperspectral data. Remote Sensing, 18(10), 1532. https://doi.org/10.3390/rs18101532
48. Lyu, Y. et al. (2025). Optimizing soil properties mapping: A comparative study of UAV and satellite imagery with ensemble learning framework. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. https://doi.org/10.1109/JSTARS.2025.3631151
49. Makam, S., Komatineni, B. K., Meena, S. S., et al. (2024). Unmanned aerial vehicles (UAVs): An adoptable technology for precise and smart farming. Discover Internet of Things, 4, 12. https://doi.org/10.1007/s43926-024-00066-5
50. McBratney, A. B., Mendonça Santos, M. L. and Minasny, B. (2003). On digital soil mapping. Geoderma, 117(1–2), 3–52. https://doi.org/10.1016/S0016-7061(03)00223-4
51. Morales, P., et al. (2025). Digital soil mapping using multi-source remote sensing and environmental covariates. Geoderma.
52. Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems Engineering, 114(4), 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009
53. Musa, P., Sugeru, H. and Wibowo, E. P. (2024). Wireless sensor networks for precision agriculture: A review of NPK sensor implementations. Sensors, 24(1), 51. https://doi.org/10.3390/s24010051
54. Nair, N., Akshaya, A. V., Bosco, M. J., Ranjith, K. R., Ananthasuresh, G. K. and Joseph, J. (2026). An IoT-enabled, all-solid electrode, portable pH meter for soil pH measurement. Measurement, 271, 120966. https://doi.org/10.1016/j.measurement.2026.120966
55. NASA. (2023). Soil moisture active passive and remote sensing applications for agriculture.
56. Pal, A., Dubey, S. K., Goel, S. and Kalita, P. K. (2024). Portable sensors in precision agriculture: Assessing advances and challenges in soil nutrient determination. TrAC Trends in Analytical Chemistry, 180, 117981. https://doi.org/10.1016/j.trac.2024.117981
57. Patel, P., et al. (2021). IoT-based smart agriculture monitoring systems: Recent developments and challenges. Sensors.
58. Patle, G., Ningthoujam, A., Yurembam, G., & Jhajharia, D. (2026). A comprehensive review of sensor technologies and IoT platforms for precision agriculture: Indian context. Current World Environment, 21(1), 18–34. https://doi.org/10.12944/CWE.21.1.3
59. Peña, et al. (2025). Unmanned aerial vehicle-based hyperspectral imaging and soil texture mapping with robust AI algorithms. Drones, 9(2), 129. https://doi.org/10.3390/drones9020129
60. Peng, T., Zhao, L., Zhang, A., Yang, X., Zhou, Z. and Chang, X. (2023). UAV hyperspectral response characteristics and estimation model construction of soil total nitrogen. Transactions of the Chinese Society of Agricultural Engineering, 39(4), 92–101. https://doi.org/10.11975/j.issn.1002-6819.202211021
61. Pouladi, N., Gholizadeh, A., Khosravi, V., & Borůvka, L. (2023). Digital mapping of soil organic carbon using remote sensing data: A systematic review. Catena, 232, 107409. https://doi.org/10.1016/j.catena.2023.107409
62. Qi, G., Lu, H., Zang, Y., Zhang, J., Li, X. and Hu, X. (2025). Predicting soil organic carbon content by combining unmanned aerial vehicle multispectral images and machine learning algorithms. Journal of Soil Science and Plant Nutrition, 25, 5675–5689. https://doi.org/10.1007/s42729-025-02490-0
63. Rahman, M. N., Sozol, S. S., Samsuzzaman, M., Hossin, M. S., Islam, M. T., Islam, S. M. T., & Maniruzzaman, M. (2024). Soil characterization of watermelon field through Internet of Things: A new approach to soil salinity measurement.
64. Ramos, A., et al. (2024). Integrating UAV imagery and in-situ sensor networks for precision agriculture. Computers and Electronics in Agriculture.
65. Rani, M., et al. (2022). Internet of Things-based soil nutrient monitoring for precision agriculture. Sensors.
66. Rao, S., et al. (2023). Low-cost soil sensing and IoT-based decision support for precision agriculture. Computers and Electronics in Agriculture.
67. Reyes, J., Wiedemann, W., Brand, A., Franke, J. and Ließ, M. (2024). Predictive monitoring of soil organic carbon using multispectral UAV imagery: A case study on a long-term experimental field. Spatial Information Research, 32, 683–696. https://doi.org/10.1007/s41324-024-00589-7
68. Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Arroita, G., et al. (2021). Cross-validation strategies for data with temporal, spatial, hierarchical or phylogenetic structure. Ecography, 44, 1–14.
69. Sabharwal, A. (2026). Advancing sustainable agriculture: Integrating AI and IoT for soil nutrient management—A systematic review. Soil Use and Management. https://doi.org/10.1111/sum.70201
70. Shahab, A., et al. (2024). Internet of Things-based agricultural management: A review of technologies and applications.
71. Sharma, V., Kaur, G., Sreethu, S., Chhabra, V. and Kashyap, R. (2025). Smart irrigation systems in agriculture: An overview. Computers and Electronics in Agriculture. https://doi.org/10.1016/j.compag.2025.111008

72. Singh, A., et al. (2023). Proximal soil sensing and digital soil mapping for precision agriculture. Geoderma.
73. Singh, K., et al. (2024). UAV remote sensing for soil and crop monitoring in precision agriculture. Smart Agricultural Technology.
74. Sinha, S. K., et al. (2022). A comprehensive review of FET-based pH sensors: Materials, fabrication technologies, and modeling. Electrochemical Science Advances, 2(5), e2100147. https://doi.org/10.1002/elsa.202100147
75. Sobhy, D. M. and Anandhi, A. (2025). Soil nutrient monitoring technologies for sustainable agriculture: A systematic review. Sustainability, 17(18), 8477. https://doi.org/10.3390/su17188477
76. Song, Q., Gao, X., Song, Y., Li, Q., Chen, Z., Li, R., Zhang, H. et al. (2023). Estimation and mapping of soil texture content based on unmanned aerial vehicle hyperspectral imaging. Scientific Reports, 13, 14097. https://doi.org/10.1038/s41598-023-40384-2
77. Song, Q., Hu, J., Li, L., Li, S. et al. (2026). Estimation and mapping of soil texture content combining ground-based sensing, UAVs, and satellite imagery. Environmental Earth Sciences, 85, 218. https://doi.org/10.1007/s12665-026-12944-y
78. Soussi, A., et al. (2024). Smart sensors and IoT technologies for precision agriculture: A review.
79. Verma, S., et al. (2025). Artificial intelligence and IoT for soil fertility monitoring and fertilizer recommendations. Agriculture.
80. Vigneshwar, J., Lakshmi Priya, G. and Selvamuthukumaran, T. (2026). Bio-derived TEMPO-oxidized cellulose nanocrystal (TOCNC) based green solid-state sensor for soil pH monitoring. BMC Chemistry. https://doi.org/10.1186/s13065-026-01925-8
81. Vishnoi, S., et al. (2026). An evaluation of machine learning for soil analysis in Internet of Things-enabled smart farming.
82. Wadoux, A. M. J. C., & McBratney, A. B. (2021). Digital soil science and beyond. Soil Science Society of America Journal, 85, 1313–1331. https://doi.org/10.1002/saj2.20296
83. Wang, J., Zhang, S., Lizaga, I., Zhang, Y., Ge, X., Zhang, Z., et al. (2024). UAS-based remote sensing for agricultural monitoring: Current status and perspectives. Computers and Electronics in Agriculture, 109501. https://doi.org/10.1016/j.compag.2024.109501
84. Xie, S., Wang, X., Zhu, X. and Li, Y. (2025). Prediction of soil organic matter content in winter wheat jointing stage based on UAV multispectral and machine learning. Measurement, 256, 118508. https://doi.org/10.1016/j.measurement.2025.118508
85. Yadav, R., et al. (2023). Smart soil monitoring systems using IoT sensors and cloud platforms: A review. Journal of Agriculture and Food Research.
86. Yan, Y., Yang, J., Li, B., Qin, C., Ji, W., Xu, Y. and Huang, Y. (2023). High-resolution mapping of soil organic matter at the field scale using UAV hyperspectral images with a small calibration dataset. Remote Sensing, 15(5), 1433. https://doi.org/10.3390/rs15051433
87. Zhang, C., et al. (2020). Digital agriculture and remote sensing for sustainable crop and soil management. Remote Sensing.
88. Zhang, G. L., Liu, F. and Song, X. D. (2017). Recent progress and future prospect of digital soil mapping: A review. Journal of Integrative Agriculture, 16(12), 2871–2885. https://doi.org/10.1016/S2095-3119(17)61762-3
89. Zhang, H., et al. (2024). Soil moisture monitoring using remote sensing and machine learning: Recent developments and applications.
90. Zhang, X., Feng, G. and Sun, X. (2024). Advanced technologies of soil moisture monitoring in precision agriculture: A review. Journal of Agriculture and Food Research, 18, 101473. https://doi.org/10.1016/j.jafr.2024.101473
91. Zhang, Y., et al. (2021). UAV remote sensing and machine learning for agricultural monitoring: A review. Remote Sensing.
92. Zhang, Z., Wang, S., Ma, J., Wang, C., Zhang, Z., Li, X., Zheng, W. and Hu, C. (2025). From retrieval to fate: UAV-based hyperspectral remote sensing of soil nitrogen and its leaching risks in a wheat–maize rotation system. Remote Sensing, 17(24), 3956. https://doi.org/10.3390/rs17243956
93. Zhao, L., et al. (2021). Soil spectroscopy and machine learning for rapid soil property assessment. Soil Use and Management.
94. Zheng, G., Chen, T., Wang, Y., Li, X., Dai, W., Xu, M., Jiao, C., & Zhao, C. (2024). Rapid monitoring of the spatial distribution of soil organic matter using unmanned aerial vehicle imaging spectroscopy. Annals of GIS, 30(3), 367–381. https://doi.org/10.1080/19475683.2024.2360213
95. Zhou, X., et al. (2022). Machine learning for soil property prediction using proximal and remote sensing data. Geoderma.
96. Zuchriadi, A., Rahayu, F., Anggraeni, S., Razi, M. A., Oktaviandri, M. and Irga, I. (2023). Agricultural monitoring system using ESP32 microcontroller with IoT-based LoRa transmission. Jurnal Mantik, 7(2). https://doi.org/10.35335/mantik.v7i2.3823