The Application of the Internet of Things in Soil Monitoring

Yiming Ren

{2065427294@qq.com }

School of Mechanical and Electrical Engineering, Henan Agricultural University, Zhengzhou, 450000, China

Abstract. The global population is expected to approach 10 billion by 2025. According to the United Nations, global agriculture needs to increase by at least 60% to ensure food security. However, for a long time, soil monitoring has lacked high-precision and low-cost real-time field data, which has become a major challenge for increasing agricultural production. In response to this issue, this article reviews and summarizes four applications that solve soil monitoring problems through Internet of Things (IoT) technology. The combination of the lot and 3D printing technology makes multi-point monitoring more economically feasible. The combination of the Internet of Things and drones can solve the problem of difficult power supply for traditional sensors, etc. The Internet of Things, combined with fuzzy logic controllers, transforms sensor data into soil health grades and fertilization suggestions. The Internet of Things combined with machine learning accurately recommends crops. At present, there are still some bottlenecks. For instance, in extreme environments such as cold regions and coastal salt fields, sensors are prone to accuracy drift. In the future, targeted solutions need to be made based on these issues. Meanwhile, efforts should be made to promote the integration of "sensors - satellites - models" to make the technology more accessible to small-scale farmers. This review provides easier, cheaper and more efficient technical solutions for enhancing agricultural efficiency and ensuring food security, and has very significant reference value both in theory and practical application.

Keywords: Internet of Things Technology, Soil monitoring, Smart Agriculture

1 Introduction

The Monitoring Needs of Global Agriculture. By 2050, the global population will approach 10 billion. The United Nations has explicitly demanded that agricultural production increase by 60% to ensure food security. The issue of food security in low - and middle-income countries has drawn global attention, and population growth is one of the core factors driving this problem. The expansion of the total population directly boosts the total demand for grain, while the differentiated growth trend of urban and rural populations further intensifies the pressure on the

ICMEEA 2026, April 24-26, Singapore, Singapore

DOI 10.4108/eai.24-4-2026.2364856

grain system: The growth of the rural population has a positive impact on the incidence of malnutrition in low-income, lower-middle-income and upper-middle-income countries, among which upper-middle-income countries are most significantly affected by this. The impact of urban population growth varies by national income level. It only alleviates malnutrition in middle - and high-income countries, while in low-income countries, it may instead exacerbate the problem [1].Soil moisture, as a key factor determining the efficiency of water and fertilizer utilization, has long been lacking "high-precision, low-cost, and real-time" field monitoring data, which has become the core bottleneck restricting the improvement of agricultural production efficiency. Meanwhile, the United Nations Sustainable Development Goals (SDGs) further emphasize that agriculture needs to break through resource constraints through technological innovation, and the upgrading of soil monitoring technology is an important prerequisite for achieving this goal.

Traditional soil monitoring relies on manual sampling and laboratory analysis, which have significant limitations. The breakthrough paths of Internet of Things (IoT) technology in soil monitoring: In response to the pain points of traditional monitoring, this review proposes four IoT integration technology paths, namely the combination of IoT and 3D printing technology [2], and the combination of IoT and unmanned aerial vehicles [3,4]. The combination of loT and fuzzy logic controller [5], as well as loT and machine learning [6], enables the "real-time, precise and low-cost" monitoring of soil.

Research objective: To address the bottleneck of soil monitoring lacking high-precision, low-cost, and real-time data, increase agricultural production by 60% to ensure food security, and at the same time promote the popularization of related technologies to small-scale farmers and extreme environments such as cold regions and coastal salt fields.

Research content: Review the four major integrated application paths of IoT with 3D printing, unmanned aerial vehicles, fuzzy logic controllers, and machine learning; Analyze issues such as sensor accuracy drift in extreme environments; Propose future research directions such as the integration of "sensors - satellites - models" in a trinity.

2 The Combination of LoT and 3D Printing Technology

Eleftheria Maria Pechlivani et al. achieved the economic feasibility of "multi-point monitoring per hectare" for the first time through the combination of low-power capacitive sensors, NB-loT/LoRaWAN wireless modules and 3D-printed shells, which is adapted to the complex environment of outdoor farmland. Its core technology design is to make a 3D-printed shell with PETG material. The core advantage is that it has waterproof and UV-resistant properties, which can protect IoT devices from damage caused by rain and sun exposure. At the same time, it adopts a modular design. When sensors or electronic components (such as power supplies) fail, they can be quickly replaced to ensure the continuity of monitoring. The main hardware components are divided into three parts. The first is the smart controller, which is equipped with an Adafruit ESP32 V2 controller (for data processing and Bluetooth transmission), a 20,000mah power bank (for power supply), a 2-inch IPS LCD screen (for data display), and an Omron multi-functional sensor board (for monitoring air temperature, humidity, air pressure, and visible light). The shell size matches the hardware specifications to ensure convenient handheld operation. Adjustable rod, two-section 3D printed structure (each section is 50cm), hollow design to protect the cable, height can be adjusted through the hole position to adapt to users of different heights, avoiding cable exposure and damage. The third is the ground sensor kit. The 3D-printed base and protective cap fix the Adafruit STEMMA soil temperature and humidity sensor and the DFRobot SEN0249 soil pH sensor. The base has a built-in threaded and screw structure to ensure stable contact when the sensor is inserted into the soil and protect the probe from external force damage [2].

Furthermore, in the research of Alessandro Comegna et al. in the development of the SHYPROM (Soil HYdraulic PROperties Meter) Internet of Things soil profile moisture monitoring system, 3D printing technology was taken as the core support for hardware adaptation and functional guarantee. It forms a collaborative system of "customized hardware - stable transmission - remote monitoring" with the Internet of Things system, effectively solving the pain points of complex assembly and insufficient protection in the deployment of traditional sensors.From the perspective of the path of technological integration, 3D printing mainly serves the structural fixation and environmental protection of Internet of Things sensors The capacitive soil moisture sensor of the system adopts three pairs of stainless steel tubular electrodes, which need to be fixed layer by layer along the acrylic tensiometer tube (the distance between the electrode center and the tube top is 11.5cm, 18.5cm, and 25.5cm). The research uses 3D-printed PLA (polylactic acid) cylinders (derived from the.STL file designed by Fusion 360) as electrode fixing rings to precisely wrap the gap between the electrode and the acrylic tube. This not only ensures the stability of the electrode position to guarantee the accuracy of moisture measurement, but also protects the electrode solder joints and connecting cables from soil friction or moisture damage. Provide structural support for the long-term field data collection of Internet of Things sensors. Meanwhile, in response to the waterproofing requirements for the field deployment of the Internet of Things system, a 3D printed waterproof external box (SHYPROM_BOX folder.STL file) was researched and designed to accommodate core components such as the ESP32 SIM800L microcontroller and the solar charging module, preventing rainwater and soil moisture from eroding electronic components. Ensure the stability of IoT data transmission (to the ThingSpeak cloud).

The customization and low-cost features of 3D printing further meet the promotion needs of the Internet of Things system: The fixed rings and waterproof boxes printed with PLA material have a low cost (the cost of a single set of printing can be ignored), and the.STL files can be directly shared, supporting rapid replication in other research or application scenarios. The modular design of the printed components (such as the matching size of the electrode fixing ring and the tensiometer tube) simplifies the assembly process of the Internet of Things sensor, enabling deployment without professional processing equipment and facilitating the promotion and application of this Internet of Things monitoring system in various soil profile scenarios [3].

3 The Combination of Lot and Unmanned Aerial Vehicles (RF-UIoT System)

Yu Luo et al. proposed a technology combining IoT and unmanned aerial vehicle (UAV) to solve the power supply bottleneck of underground Internet of Things (UIoT) nodes, overcome the application difficulties of radio frequency energy in underground scenarios, and achieve the automation of large-scale farmland and long-term in-situ soil monitoring.The working principle of the core technology design system is that the unmanned aerial vehicle (UAV) serves as a "mobile radio frequency energy transmitter + data relay carrier", building a closed loop of data and energy links from "underground - air - cloud". Firstly, it provides mobile radio frequency power supply. By carrying the radio frequency transmitter on the UAV, it offers the sole energy source for underground UIoT nodes, replacing traditional solar panels and batteries.Then, data relay is carried out to receive soil data returned by underground nodes via the ZigBee protocol, and then uploaded to the cloud server via the Internet. Finally, by leveraging its flexible flight capabilities, it breaks through terrain limitations, solving the problem that traditional fixed monitoring solutions are difficult to scale up and achieve wide coverage.

Its core hardware equipment and parameters include a UHF radio frequency transmitter (Powercast TX91503 model, with a frequency of 915MHz. Although it has greater attenuation than 433MHz, it can reduce the size of the node antenna and is suitable for large-scale deployment), an 8dBi gain patch antenna (for directional energy propagation), and an RTK positioning system (for precise control of flight attitude and position). Reduce energy reception fluctuations;The transmission power is as low as 2W (EIPR is 36dBm, approximately 3W), which can meet the demand of 15cm deep nodes to receive 2dBm of energy. With a fixed flight altitude of 1.6 meters, the transmitter is suspended 4cm above the ground (the measured optimal charging position), and it can still operate stably at a wind speed of 11mph [4,5].

4 LoT is Combined with the Fuzzy Logic Controller (FLC)

Rajan Prasad et al. developed a "loT+FLC" integrated system in response to the particularity of soil nutrient monitoring in farmland in semi-arid regions, achieving the transformation from "data collection" to "fertilization decision-making" and resolving the predicament of regional monitoring.The core technology design of FLC is divided into A three-stage workflow. The first one is fuzzification. The digital signal of the NPK sensor after A/D conversion (reflecting the concentrations of N, P, and K) is mapped to "Low (Low), Medium (Medium), and High (High)" fuzzy language variables through membership functions, avoiding frequent switching of judgments caused by minor fluctuations in data.The second is fuzzy reasoning. Based on the data set of soil samples from the semi-arid regions of India, an "IF-THEN" rule base is constructed. According to the fuzzy membership degree matching rules of the input nutrients, a fuzzy output is generated. The third is defuzzification, which converts the ambiguous output into a clear "soil health grade (low/medium/high)", providing a clear basis for subsequent decision-making.Connection with the IoT alarm system The soil health grade and nutrient gap analysis output by FLC serve as the core basis for IoT alerts. For instance, when "the soil health grade is low and the nitrogen gap is significant", the system automatically recommends "high-nitrogen fertilizers", sends SMS alerts to farmers via the Arduino WiFi module, and simultaneously stores the data in the Google Cloud database. For trend analysis [6].

The research of Andi Wahyunita Hakis et al. aimed at soil nutrient management in clay pepper cultivation, constructed an automated system deeply integrated with the Internet of Things (IoT) and Mamdani fuzzy algorithm, and formed a closed loop of "real-time data collection - intelligent decision-making - remote control". Effectively address the pain points of poor real-time performance and ambiguous decision-making in traditional soil management.

In the system, IoT undertakes the core functions of data transmission and remote interaction: With the ESP32 microcontroller as the hardware core, it integrates soil pH, humidity, DHT22 temperature and humidity, and NPK multimodal sensors. Field data is automatically collected every 15 minutes. After preprocessing through "calibration - filtering - normalization", it is transmitted in real time to the Blynk platform via loT for remote viewing. Meanwhile, input the clean data into the Mamdani fuzzy algorithm module; In addition, loT is also responsible for converting the results of algorithmic decisions into execution instructions, controlling the actions of irrigation and nutrient solenoid valves, and achieving an automated connection of "perception - decision-making - execution".

The Mamdani fuzzy algorithm focuses on the intelligent processing of uncertain data: it uses trigonometric/trapezoidal membership functions to complete fuzzification, and the soil pH (acidic ≤5.5, neutral ≈6.5, alkaline ≥7.5) and humidity (ADC value: The values such as dry > 3000, normal 2000-3000, moist ≤2000, and temperature (low temperature ≤25℃, suitable temperature 25-30℃, high temperature ≥30℃) are converted into linguistic sets. Complete rule reasoning based on four core rules (such as "pH acidic/alkaline and low temperature → nutrient activation"); The precise execution parameters of irrigation/nutrient supply (such as 100% nutrient duty cycle) are output through the center of gravity method for deblurring.

The 22-day field test verified the effectiveness of the fusion solution: The system classification accuracy rate reaches 84%, and the average F1 score is 88.5%. The Mamdani fuzzy algorithm has a control accuracy rate of up to 99.8% for nutrient transport, with an irrigation control success rate of 75.8%. Moreover, the reasoning time is less than 0.05 seconds, and it can respond to soil dynamic changes in real time.This fusion model not only leverages the real-time and remote advantages of IoT but also utilizes the fuzzy decision-making capability of the Mamdani algorithm to adapt to the uncertainties of the agricultural environment, providing a feasible paradigm for the automated nutrient management of precision agriculture [7].

5 The combination of IoT and machine learning

Shabnom Mustary et al. constructed a closed-loop system of "real-time monitoring - intelligent analysis - crop recommendation", reducing the waste of agricultural resources, enhancing production efficiency, and promoting the adaptation of technology to rural scenarios. Its core technical design is a dual-module collaborative system. The first one is the soil and fertilizer monitoring module (LOT-driven), which realizes the full-chain collection, transmission, and storage of soil data, providing "real-time and multi-dimensional" high-quality training and inference data for machine learning. The second one is the crop recommendation module (machine learning-driven), which builds a recommendation model based on soil data. Through feature analysis, multi-model training (such as random forests, regression models), and model evaluation and selection, it outputs the optimal crop planting suggestions. System workflow: Form an intelligent chain of "monitoring (IoT) → analysis (machine learning) → recommendation (crop adaptation) → feedback (data iteration)" to ensure that decisions are in line with the actual soil conditions and improve resource utilization efficiency [8].

6 Limitations and deficiencies

From the perspective of data accuracy, precision drift directly leads to distortion in the monitoring of the core parameters of the sensor. In temperature-sensitive scenarios, sensors are significantly affected by temperature fluctuations: In the liquid oxygen (-180℃) and liquid hydrogen (-250℃) environments of spacecraft, the sensor oscillator experiences frequency deviation due to low temperatures. Meanwhile, the sensors near the solar array have to endure drastic temperature changes ranging from -70 ℃ to + 83℃, further intensifying the oscillator drift and causing deviations in the readings of parameters such as soil moisture and temperature. For instance, when the ambient temperature reaches 30℃, the reference deviation of the dielectric constant of the sensor will cause the humidity reading to drift by ±4%. If this sensor is used for farmland irrigation decisions, this deviation will misjudge the dry and wet state of the soil. When irrigation is needed, it may be delayed due to a higher reading, or when irrigation is not needed, it may be over-irrigated due to a lower reading, directly affecting the growth of crops. In a high-saline-alkali environment (with electrical conductivity EC>10 dS/m), electrical conductivity coupling interference can disrupt the linear calibration of sensors. For instance, the soil NPK sensor may, due to calibration failure, mistakenly measure the actual nitrogen content of 2.5mg/kg as 4mg/kg, leading to a misjudgment of soil fertility. The accuracy drift of pH sensors can confuse the acidity/alkalinity grades of soil, such as misjudging neutral soil with a pH of 6.5 as acidic soil with a pH of 5.5, which affects the selection of acid-tolerant/alkali-tolerant crops.

From the perspective of time synchronization, accuracy drift undermines the temporal consistency of data in sensor networks. Wireless sensor networks rely on precise time synchronization to achieve multi-node data collaboration. However, accuracy drift can lead to oscillator frequency deviation, which in turn affects the performance of time synchronization algorithms. For instance, the internal sensors of spacecraft need to meet the collaborative requirement of "time deviation not exceeding 10 microseconds", but the accuracy drift caused by temperature will increase the synchronization deviation of the ALCC (Adaptive Local Clock Control) algorithm from the ideal 2.23μs to 478.62μs, far exceeding the threshold. Even for the optimized SW-PID algorithm, when the synchronization interval is extended from 10 seconds to 600 seconds, the average deviation will sharply increase from 5.45μs to 4440.08μs. This timing deviation can lead to "spatio-temporal misalignment" of multi-sensor data - for instance, if the timestamp deviation between the temperature sensor and the pressure sensor in a certain area of a spacecraft exceeds 20 microseconds, it will be impossible to accurately associate the coupling relationship of "high temperature - high pressure", thus losing the value of joint analysis. In soil monitoring, the timing of sensor data at different points is disordered, and it is also impossible to construct an accurate spatial distribution map of soil parameters [9].

From the perspective of decision support, accuracy drift causes sensor data to lose its guiding significance, thereby triggering a chain of decision-making errors. In agricultural scenarios, the accuracy drift of soil sensors can directly affect core decisions such as fertilization and crop recommendation: If the NPK sensor misjudges "low nitrogen" as "medium nitrogen" due to drift, it will lead to insufficient fertilizer application, resulting in reduced crop yields due to nitrogen deficiency. The fuzzy logic Controller (FLC) relies on sensor data to generate "soil health grades". If data drift causes a "low health grade" to be misjudged as "medium", the best time to supplement fertilizers will be missed. In spacecraft scenarios, sensor accuracy drift can affect equipment status monitoring - for instance, micrometeorite detection sensors, due to time synchronization drift, cannot accurately record the impact time and position, thus losing their risk warning function. If the temperature sensor drifts, it may misjudge whether the equipment is "overheated" or "too cold", causing unnecessary heat dissipation/heating operations and wasting energy [6].

From the perspective of hardware and technology promotion, precision drift accelerates the hardware wear and tear of sensors and restricts the application scope of the technology. Accuracy drift is often accompanied by abnormal operation of sensor components: in a high-saline-alkali environment, sensor accuracy drift occurs simultaneously with salt spray corrosion of the probe. For instance, the pH sensor probe may experience response delay due to corrosion, extending the data acquisition cycle from 1 second to over 10 seconds and losing real-time monitoring capability. In low-temperature environments, although the PETG material sensor housing is UV-resistant, temperatures below -100 ℃ will make the housing brittle. At the same time, the internal sensor will be frequently calibrated due to precision drift, accelerating the aging of electronic components. In addition, accuracy drift makes it difficult for sensors to adapt to extreme scenarios - in polar soil monitoring, sensors cannot work stably due to low-temperature drift. In the coastal salt field scenario, the drift caused by salt and alkali shortens the sensor's lifespan from one year to three months, significantly increasing the usage cost and ultimately restricting the promotion of Internet of Things soil monitoring technology to extreme environment farmland scenarios [2].

7 Suggestions for future research

The integration of "sensor-satellite-model" in a trinity will break through the limitations of a single technology in future soil monitoring and form a multi-scale and three-dimensional monitoring system: Ground loT network: Achieve centimeter-level depth soil profile monitoring and obtain microscopic field data; Satellite remote sensing: Covering kilometer-level areas, achieving macroscopic monitoring of large-scale soil conditions; Land surface model: Based on loT and satellite data, it predicts future available soil water volume to support irrigation scheduling. Data assimilation technology: Reducing the scale difference between "micro-macro" data to the hundred-meter level, achieving integrated irrigation dispatching from "single farmland" to "river basin", and adapting to large-scale agricultural production scenarios.

Existing optical satellites (Sentinel-2, Landsat) are vulnerable to cloud coverage limitations, while SAR satellites (Sentinel-1) conduct all-weather observations but have limited accuracy when used alone. In the future, it is necessary to develop a pixel-level fusion algorithm of Sentinel-2 (with a resolution of 10-20m) and Sentinel-1, and use SAR to retrieve soil moisture to supplement the optical vegetation index (NDVI/EVI), to solve the problem of data deficiency in tropical rainy areas (such as the main sugarcane production areas in Brazil). At the same time, it is compatible with medium and high-resolution satellites such as CBERS-4, distinguishes the field infrastructure of small plots, and combines the "sensor-satellite-model" framework to achieve cross-scale connection of "soil micro-parameters - regional macroscopic conditions", reducing the estimation error of low-resolution satellites (such as MODIS).

EnKF assimilation only updates a single variable (such as LAI), resulting in lagging responses of crop models (WOFOST, DSSAT).In the future, particle filtering should be introduced to achieve synchronous updates of multiple variables, such as LAI and soil moisture. The transpiration retrieved by satellites should be integrated into the AquaCrop model to replace traditional meteorological estimation. For small sample areas, a "transfer learning + assimilation" framework was developed to utilize large farm data to reduce the parameterization cost of small-scale farmer models, such as the Sentinel-2 assimilation parameters of transferable southern plantations in northeastern Brazil.

To address the complexity of constellation configuration and the dynamic changes in network topology of inter-satellite links (ISL), it is necessary to develop a multi-layer and multi-domain collaborative routing scheme based on reinforcement learning. By constructing a dynamic interaction model of satellite nodes, real-time perception of constellation position, link connectivity, and task load changes is achieved, enabling rapid response of routing convergence and adapting to the large-scale communication requirements of millions of ground users and thousands of links. Meanwhile, an adaptive topology reconfiguration mechanism is explored to address the issues of long coverage time and frequent switching of low Earth orbit (LEO) satellites, ensuring service continuity and stability [10,11].

8 Conclusion

This review proposes four integration paths of the Internet of Things with 3D printing, unmanned aerial vehicles (UAVs), fuzzy logic controllers, and machine learning to achieve real-time, precise, and low-cost soil monitoring. At the same time, it discovers bottlenecks such as sensor accuracy drift in extreme environments.It provides feasible technical solutions for enhancing agricultural efficiency and increasing global agricultural production by 60% to ensure food security. It holds significant reference value both in theory and practical application. In the future, soil monitoring will develop towards a trinity integration of "sensors - satellites - models", achieving cross-scale data collaboration. At the same time, we will specifically break through the technical bottlenecks in extreme environments, promote the wider popularization of related technologies among small-scale farmers, and further empower the development of smart agriculture.

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