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A Review of Energy-Aware Wireless Sensor Networks for Soil Monitoring, Data Analytics, and Agricultural Forecasting Applications

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Abstract: *The rapid development of precision agriculture, Internet of Things (IoT), wireless communication, and artificial intelligence has created new opportunities for continuous and data-driven monitoring of agricultural environments. Wireless Sensor Networks (WSNs) provide an important technological foundation for smart agriculture by enabling distributed measurement of soil moisture, soil temperature, electrical conductivity, pH, air temperature, humidity, rainfall, and other environmental parameters. However, agricultural WSNs are frequently deployed over large and geographically dispersed fields where sensor nodes have limited battery capacity and may be difficult to access for maintenance.*

Consequently, energy efficiency, communication reliability, data quality, and long-term network operation have become central research concerns. This review examines the development of energy-aware WSNs for soil monitoring and their integration with data analytics and agricultural forecasting. Particular attention is given to sensing architectures, communication technologies, energy-saving mechanisms, routing protocols, edge/cloud processing, machine learning, deep learning, and soil-moisture forecasting.

Keywords: Wireless Sensor Networks, Energy Efficiency, Soil Monitoring, Precision Agriculture, IoT, LoRaWAN, Soil Moisture, Machine Learning, Agricultural Forecasting, Smart Agriculture

I. INTRODUCTION

Agriculture is increasingly being transformed from conventional experience-based management toward data-driven precision farming. Climate variability, water scarcity, declining soil quality, increasing production costs, and the need to improve food productivity have encouraged the development of technologies capable of continuously observing agricultural conditions. Among these technologies, Wireless Sensor Networks (WSNs) have become an important component of precision agriculture because they allow physical parameters to be measured at multiple locations and transmitted wirelessly to gateways or analytical platforms. WSN-based agricultural systems can support irrigation management, crop monitoring, environmental assessment, disease management, fertilization, and yield-related decision-making. Earlier reviews have demonstrated that agricultural WSNs can collect information from distributed sensors while reducing wiring requirements and improving spatial monitoring capabilities.

Soil monitoring represents one of the most important applications of agricultural WSNs. Soil moisture directly influences plant water availability, germination, nutrient uptake, crop growth, and irrigation requirements. Other soil variables, including temperature, pH, electrical conductivity, salinity, and nutrient-related indicators, provide complementary information about soil health and crop productivity. The development of smart soil-monitoring systems therefore enables farmers to move from fixed irrigation schedules toward site-specific and condition-based management.

Despite these benefits, WSN deployment in agricultural environments presents a major energy challenge. Sensor nodes typically operate with small batteries, while agricultural fields may extend over several hectares or even hundreds of hectares. Replacing batteries frequently can be expensive, labor-intensive, and environmentally undesirable. Energy-efficient communication, routing, sensing, processing, and duty-cycle management are therefore essential for extending network lifetime. A comprehensive review of agricultural WSNs identifies sleep/wake mechanisms, MAC optimization, topology control, radio optimization, and energy harvesting among the major strategies for reducing energy consumption.

The emergence of IoT and artificial intelligence has further expanded the role of WSNs. Instead of merely transmitting measurements, modern systems can preprocess data at edge devices, aggregate observations, identify abnormal values, predict future soil conditions, and support automated irrigation. Recent research has demonstrated the integration of WSN data with satellite and climate information for improved soil-moisture estimation, with LSTM models showing strong performance in several comparative experiments. Thus, the contemporary agricultural WSN can be viewed not simply as a communication network but as an intelligent sensing and forecasting infrastructure.

II. ENERGY-EFFICIENT COMMUNICATION TECHNOLOGIES

Communication technology determines the range, energy consumption, bandwidth, and scalability of an agricultural WSN. The choice depends on field size, sensor density, required data rate, infrastructure availability, and energy constraints.

ZigBee and IEEE 802.15.4 have historically been widely used for agricultural sensor networks because of their low-power characteristics and support for mesh networking. However, their relatively limited communication range may require multiple relay nodes or gateways. LoRa and LoRaWAN have gained substantial interest because they support long-range communication with relatively low power consumption. LoRa-based systems can connect distributed field nodes to a gateway, which can then transmit information to cloud services using cellular or Internet connectivity.

Cellular technologies such as 4G, 5G, and NB-IoT can provide broad-area connectivity but may increase energy consumption and operational costs depending on deployment conditions. Wi-Fi is suitable when reliable local power and high data rates are available but is generally less attractive for deeply battery-constrained field nodes.

Table 1. Comparison of Wireless Communication Technologies

Technology	Range	Energy Efficiency	Data Rate	Agricultural Suitability
Wi-Fi	Short–medium	Low–moderate	High	Powered installations
Bluetooth/BLE	Short	High	Moderate	Local sensing
ZigBee	Short–medium	High	Moderate	Greenhouses and local fields
IEEE 802.15.4	Short–medium	High	Moderate	Sensor networks
LoRa/LoRaWAN	Long	High	Low	Large agricultural fields
Sigfox	Long	High	Very low	Small telemetry packets
NB-IoT	Long	Moderate–high	Moderate	Cellular IoT deployments
4G/5G	Long	Lower for battery nodes	High	Gateways and high-data applications

The literature indicates that there is no universally optimal protocol. Instead, protocol selection must consider field dimensions, node density, communication distance, packet frequency, power availability, and the desired application. Recent reviews similarly emphasize the comparative importance of ZigBee, Wi-Fi, LoRa, Sigfox, cellular technologies, and energy-efficient routing in smart agriculture.

III. ENERGY CONSERVATION STRATEGIES

Energy management is central to long-term agricultural WSN operation. One of the simplest approaches is duty cycling, in which a sensor node alternates between active and sleep states. During sleep periods, radio and other components consume substantially less energy. Nodes can wake periodically to measure and transmit data.

Data aggregation is another important technique. Instead of transmitting every individual measurement, intermediate nodes can combine observations and transmit summarized information. This reduces redundant communication. Routing protocols can also select paths according to residual energy, distance, link quality, and traffic load.

Topology control reduces unnecessary communication links and can decrease the number of active nodes. Adaptive sampling further improves energy efficiency by increasing the sampling frequency when environmental conditions change rapidly and reducing it during stable periods.

Energy harvesting provides another promising approach. Agricultural sensor nodes can potentially use solar energy to supplement or replace batteries. However, harvested energy varies with weather, shading, season, and sensor placement, requiring intelligent energy management.

Table 2. Energy-Saving Strategies in Agricultural WSNs

Strategy	Principle	Major Benefit	Limitation
Duty cycling	Alternates active/sleep states	Reduces radio energy	May introduce latency
Adaptive sampling	Changes sensing frequency	Avoids unnecessary measurements	Requires decision logic
Data aggregation	Combines redundant data	Reduces transmissions	Aggregation complexity
Energy-aware routing	Selects efficient paths	Balances energy consumption	Routing overhead
Clustering	Uses cluster heads	Reduces long-distance communication	Cluster-head energy burden
Topology control	Limits active links/nodes	Reduces network traffic	Can affect connectivity
Transmission-power control	Adjusts radio power	Saves transmission energy	May reduce reliability
Solar harvesting	Uses renewable energy	Extends operational lifetime	Weather dependent
Edge analytics	Processes data locally	Reduces cloud transmission	Requires local computation

Experimental and review literature confirms that sleep/wake schemes and other radio and network optimizations can substantially extend the operational lifetime of agricultural sensor systems.

IV. DATA ANALYTICS IN AGRICULTURAL WSNS

The value of a WSN depends not only on data collection but also on the ability to transform measurements into actionable knowledge. Raw sensor data can contain missing values, noise, outliers, communication errors, and sensor drift. Consequently, preprocessing is an essential stage of agricultural data analytics.

A typical analytical pipeline consists of data acquisition, synchronization, cleaning, normalization, feature extraction, aggregation, visualization, prediction, and decision support. Statistical techniques can identify trends and correlations, while machine-learning models can identify nonlinear relationships between soil, weather, and crop variables.

Machine learning has become particularly important in agricultural WSNs. A survey of WSNs combined with machine learning identifies applications involving agricultural prediction, classification, anomaly detection, and network optimization. Models such as Linear Regression, Decision Trees, Random Forest, Support Vector Machines, Artificial Neural Networks, and LSTM networks can be selected according to the data structure and prediction problem.

Random Forest is attractive because it can handle nonlinear relationships and heterogeneous variables while providing useful feature-importance information. Support Vector Machines can perform well with relatively limited datasets. Neural networks can model complex nonlinear relationships, whereas LSTM networks are particularly suitable for time-series forecasting because they can learn temporal dependencies.

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V. SOIL-MOISTURE ESTIMATION AND AGRICULTURAL FORECASTING

Soil-moisture forecasting is an important application of sensor-based agricultural analytics. Instead of reacting only to current moisture values, forecasting models estimate future soil conditions and allow irrigation decisions to be made proactively.

Forecasting systems can incorporate historical soil moisture, soil temperature, rainfall, air temperature, humidity, solar radiation, evapotranspiration, crop stage, and remote-sensing observations. Combining these heterogeneous variables can improve prediction performance, although it also increases computational and data-management complexity.

Recent research has demonstrated that WSN data can be combined with satellite and climate data for soil-moisture estimation. Comparative studies involving Linear Regression, Support Vector Machines, Decision Trees, Random Forest, and LSTM models have reported strong performance from LSTM for temporal soil-moisture estimation. A broader 2025 review of remote-sensing-based soil-moisture prediction found extensive use of Random Forest, Support Vector Regression, and Artificial Neural Networks, reflecting the importance of nonlinear machine-learning methods in this field.

Table 3. Data Analytics and Forecasting Models

Model	Primary Application	Strength	Limitation
Linear Regression	Baseline prediction	Simple and interpretable	Limited nonlinear modeling
Decision Tree	Classification/regression	Easy to interpret	Can overfit
Random Forest	Soil-moisture prediction	Robust nonlinear modeling	Larger computational requirement
SVM/SVR	Regression/classification	Effective with smaller datasets	Parameter selection required
ANN	Complex prediction	Captures nonlinear relationships	Requires training data
CNN	Spatial/feature analysis	Strong feature extraction	Computationally intensive
LSTM	Time-series forecasting	Learns temporal dependencies	Requires substantial training data
GRU	Time-series forecasting	Lower complexity than LSTM	May lose some temporal capacity
XGBoost	Structured prediction	High predictive performance	Requires tuning
Hybrid models	Multi-source forecasting	Combines complementary strengths	Higher complexity

VI. INTEGRATION OF EDGE COMPUTING AND CLOUD PLATFORMS

Cloud computing provides scalable storage and computational resources for agricultural WSNs. However, transmitting every sensor measurement to the cloud can consume considerable communication energy and introduce latency. Edge computing addresses this problem by moving selected processing functions closer to the sensor network.

An edge device can remove erroneous observations, calculate summary statistics, detect anomalies, compress information, and perform lightweight prediction before transmitting information to the cloud. This approach reduces communication volume and can improve response time.

TinyML is a particularly promising development because it enables machine-learning inference on resource-constrained microcontrollers. In agricultural applications, TinyML models may be used for anomaly detection, adaptive sampling, soil-moisture prediction, and local irrigation decisions. Recent reviews of soil-moisture monitoring identify edge computing and TinyML as emerging approaches for scalable and low-latency agricultural systems.

VII. APPLICATIONS OF ENERGY-AWARE WSNS IN AGRICULTURE

Energy-aware WSNs can support a broad range of agricultural applications. In irrigation management, soil-moisture measurements can trigger irrigation only when moisture falls below a defined threshold or when a forecasting model predicts future water stress. In greenhouse agriculture, temperature and humidity monitoring can support automated

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climate control. In open-field farming, distributed sensor networks can monitor microclimatic variability and identify areas requiring different management practices.

Other applications include fertilizer management, salinity monitoring, crop disease prediction, frost alerts, drought assessment, evapotranspiration estimation, yield forecasting, and water-resource optimization. Integration with UAVs and satellite remote sensing further extends spatial coverage. Recent reviews emphasize that WSNs, IoT, and UAV technologies increasingly operate as complementary components of precision agriculture rather than isolated systems.

Table 4. Agricultural Applications of WSN-Based Monitoring

Application	Sensor/Data Sources	Analytical Output	Management Decision
Smart irrigation	Soil moisture, rainfall, weather	Water requirement	Irrigation timing
Soil-health monitoring	pH, EC, moisture, temperature	Soil-condition index	Soil treatment
Fertilization	EC, moisture, nutrient indicators	Nutrient status	Fertilizer application
Crop disease warning	Humidity, temperature, leaf wetness	Disease risk	Preventive treatment
Drought monitoring	Soil moisture, rainfall, temperature	Water-stress index	Water conservation
Yield forecasting	Soil, weather, crop data	Expected yield	Production planning
Greenhouse management	Temperature, humidity, light	Microclimate status	Ventilation/heating
Salinity monitoring	EC, moisture	Salinity risk	Irrigation/soil amendment
Frost warning	Temperature, humidity	Frost probability	Protective action

Table 5. Major Challenges and Potential Solutions

Challenge	Impact	Potential Solution
Limited battery life	Short network lifetime	Energy harvesting and duty cycling
Large field size	Connectivity problems	LoRaWAN and optimized gateways
Sensor drift	Incorrect measurements	Calibration and sensor fusion
Packet loss	Missing data	Reliable routing and retransmission
Data redundancy	Excess energy consumption	Aggregation and compression
Heterogeneous data	Difficult analytics	Data standardization
Model overfitting	Poor field generalization	Cross-field validation
Cybersecurity	Data manipulation	Encryption and authentication
Harsh environment	Hardware degradation	Ruggedized sensors
High deployment cost	Limited adoption	Low-cost modular platforms
Limited computing resources	Complex analytics difficult	Edge computing/TinyML
Connectivity gaps	Interrupted monitoring	Hybrid communication architecture

VIII. FUTURE RESEARCH DIRECTIONS

Future research should move from static sensor networks toward adaptive, self-organizing, and predictive agricultural sensing systems. Energy-aware routing can be combined with machine-learning algorithms that dynamically predict node energy consumption and communication quality. Such approaches could select routing paths based not only on distance but also on residual energy, link reliability, traffic, and expected environmental conditions.

Energy harvesting is another promising research direction. Solar-powered sensor nodes could reduce dependence on batteries, particularly for long-term field monitoring. However, energy-harvesting systems should incorporate energy prediction so that sensing and communication schedules adapt to expected solar availability.

Multimodal sensing will also become increasingly important. Soil sensors can be combined with UAV imagery, satellite observations, weather stations, and crop-growth information. Such data fusion can improve spatial and temporal resolution. Recent literature demonstrates a clear trend toward combining ground sensors with remote sensing and machine learning for more accurate soil-moisture estimation.

Explainable AI represents another important direction. Farmers and agricultural decision-makers may be reluctant to rely on predictions without understanding why a system recommends irrigation or identifies a risk. Explainable models can identify influential variables such as recent rainfall, soil moisture, temperature, and evapotranspiration.

Finally, future systems should consider sustainability throughout the technology lifecycle. Low-power hardware, recyclable sensor components, renewable energy, efficient communication, and long device lifetimes can reduce the environmental footprint of agricultural IoT infrastructure.

Table 6. Proposed End-to-End Architecture

Layer	Technologies	Function	Energy Objective
Sensing	Soil/IoT sensors	Data acquisition	Adaptive sampling
Energy	Battery + solar	Power supply	Energy balancing
Network	LoRaWAN/ZigBee	Data transmission	Low-power communication
Edge	MCU/Raspberry Pi/TinyML	Local processing	Reduce transmission
Cloud	IoT platform/database	Storage	Scalable processing
AI	RF, SVM, LSTM, XGBoost	Prediction	Proactive management
Decision	Dashboard/actuator	Recommendations/control	Optimize resource use

IX. CONCLUSION

Energy-aware Wireless Sensor Networks have become an important technological foundation for precision agriculture because they enable distributed, continuous, and location-specific monitoring of soil and environmental conditions. The literature demonstrates that the effectiveness of agricultural WSNs depends on the combined optimization of sensing, communication, routing, energy management, data processing, and analytics. Duty cycling, adaptive sampling, data aggregation, topology optimization, energy-aware routing, and energy harvesting can extend network lifetime, while low-power long-range technologies such as LoRa/LoRaWAN provide attractive connectivity options for large agricultural areas.

The integration of WSNs with machine learning has substantially expanded their capabilities. Instead of simply reporting current soil conditions, intelligent systems can estimate missing measurements, detect anomalies, forecast soil moisture, identify water stress, and support proactive agricultural decisions. Current research increasingly combines WSN observations with weather and satellite data, while models such as Random Forest, SVM, ANN, and LSTM are being used for soil-moisture prediction and agricultural forecasting.

Nevertheless, practical deployment continues to face challenges involving energy limitations, sensor calibration, connectivity, scalability, cybersecurity, data quality, cost, and model generalization. The next generation of agricultural WSNs should therefore adopt an integrated architecture combining energy harvesting, adaptive sensing, low-power communication, edge intelligence, cloud analytics, multimodal data fusion, and explainable forecasting. Such systems can contribute to more efficient water use, improved soil management, reduced input waste, enhanced crop productivity, and greater resilience to climate variability. The long-term objective should be a self-adaptive agricultural sensing infrastructure capable of learning from field conditions while minimizing its own energy and maintenance requirements.

REFERENCES

1. Chamaraa, N., Islam, M. D., Bai, G. F., & Shi, Y. (2022). Ag-IoT for crop and environment monitoring: Past, present, and future. *Agricultural Systems, 203*, 103497.
2. Nandal, V., & Dahiya, S. (2023). A comprehensive review of energy efficient wireless communication and routing protocols in smart agriculture. *International Journal of Sensor Networks, 43*(2), 99–115.

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3. Ojha, T., Misra, S., & Raghuwanshi, N. S. (2015). Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges. *Computers and Electronics in Agriculture, 118*, 66–84.
4. Rahaman, M. M., & Azharuddin, M. (2022). Wireless sensor networks in agriculture through machine learning: A survey. *Computers and Electronics in Agriculture, 197*, 106928.
5. Sidharta, H. A., Abadi, I. T. N., Risqiwati, D., & Regata, D. (2026). Energy-efficient APTEEN LoRa wireless sensor network for soil moisture monitoring in precision agriculture. *Jurnal Nasional Pendidikan Teknik Informatika, 15*(2).
6. "Energy-Efficient Wireless Sensor Networks for Precision Agriculture: A Review." (2017). *Sensors, 17*(8), 1781.
7. "WSN-Driven Advances in Soil Moisture Estimation: A Machine Learning Approach." (2024). *Electronics, 13*(8), 1590.
8. "Soil Moisture Prediction Using Remote Sensing and Machine Learning Algorithms: A Review on Progress, Challenges, and Opportunities." (2025). *Remote Sensing, 17*(14), 2397.
9. "Soil moisture monitoring technologies in smart agriculture: A comprehensive review." (2026). *Farming System, 4*(2), 100189.
10. "Internet of Things and Wireless Sensor Networks for Smart Agriculture Applications: A Survey." (2023). *IEEE Access, 11*, 145813–145852.