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Energy-Aware Wireless Sensor Networks for Real-Time Soil Moisture Monitoring and Agricultural Forecasting

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Abstract: *The increasing demand for agricultural productivity, efficient water management, and climate-resilient farming has created a strong need for intelligent monitoring systems capable of providing continuous information about soil and environmental conditions. Wireless Sensor Networks (WSNs) provide an effective technological framework for collecting distributed agricultural data through low-power sensor nodes. However, conventional WSN-based agricultural monitoring systems face challenges related to limited battery capacity, communication energy consumption, sensor reliability, network connectivity, and large volumes of redundant data.*

This research paper proposes an energy-aware wireless sensor network architecture for real-time soil moisture monitoring and agricultural forecasting. The proposed framework integrates soil-moisture, soil-temperature, air-temperature, relative-humidity, rainfall, and light sensors with low-power microcontrollers and long-range wireless communication. Energy conservation is achieved through adaptive sampling, sleep–wake scheduling, data aggregation, transmission optimization, and, where feasible, solar energy harvesting. The collected information is transmitted to a gateway for storage, visualization, analysis, and forecasting.

Keywords: Precision Agriculture, IoT, Real-Time Monitoring, Agricultural Forecasting, Smart Irrigation, Machine Learning, LoRa.

I. INTRODUCTION

Agriculture increasingly depends on efficient management of water, soil, energy, and other natural resources. Conventional agricultural management frequently relies on periodic field observations and fixed irrigation schedules, which may not adequately represent the spatial and temporal variability of soil conditions. Soil moisture is particularly important because it determines the amount of water available to plant roots and strongly influences irrigation requirements, crop development, nutrient transport, and water-use efficiency. Consequently, continuous soil-moisture monitoring has become an important component of precision agriculture.

Wireless Sensor Networks provide a suitable technology for distributed monitoring because multiple sensor nodes can be deployed at different locations within an agricultural field. These nodes can periodically measure soil moisture and other environmental parameters and wirelessly transmit the information to a gateway or central server. Reviews of agricultural WSN research show that soil moisture, temperature, humidity, light, rainfall, and other environmental variables can be integrated into agricultural monitoring systems.

A major limitation, however, is the energy requirement of wireless communication. Agricultural sensor nodes may be deployed in remote locations where replacing batteries is difficult and expensive. Radio transmission and reception can consume substantial energy, making energy management one of the central design problems in agricultural WSNs. Energy-efficient approaches include sleep/wake operation, duty cycling, topology control, data aggregation, adaptive sampling, and energy harvesting.

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In addition to monitoring current soil conditions, agricultural systems increasingly require forecasting capabilities. Historical soil-moisture observations combined with weather and irrigation information can be used to estimate future soil moisture and support irrigation decisions. A systematic review of 60 studies published between 2014 and 2024 identified machine-learning and other forecasting approaches for predicting soil moisture from sensor-based observations. Therefore, integrating energy-aware WSNs with predictive analytics provides an opportunity to develop intelligent agricultural systems capable of both observing current field conditions and anticipating future irrigation requirements.

II. PROPOSED SYSTEM ARCHITECTURE

The proposed system consists of five major layers:

Sensor Layer → Edge/Node Layer → Communication Layer → Gateway/Cloud Layer → Forecasting and Decision Layer

At the sensor layer, soil-moisture and environmental sensors collect observations. The node layer contains a low-power microcontroller responsible for sensor operation, preprocessing, temporary storage, and energy management. The communication layer provides wireless connectivity through technologies such as LoRa/LoRaWAN, Zigbee, or other low-power protocols. The gateway receives measurements from multiple nodes and forwards them to a database or cloud platform. Finally, the forecasting layer analyzes the historical and real-time data and produces predictions for future soil moisture and irrigation requirements.

III. SENSOR AND HARDWARE CONFIGURATION

The proposed sensor node may include a capacitive soil-moisture sensor, soil-temperature sensor, air-temperature and humidity sensor, rainfall sensor, and light-intensity sensor. A low-power microcontroller such as an ESP32-class device can process sensor observations before transmission. A LoRa-based communication module can be used where long-range, low-power communication is required.

Table 1. Proposed Sensor Node Configuration

Component	Parameter Measured	Function	Energy Consideration
Soil-moisture sensor	Volumetric soil moisture	Determines water availability	Activated periodically
Soil-temperature sensor	Soil temperature	Supports moisture interpretation	Low-power sensing
Air-temperature sensor	Air temperature	Weather monitoring	Periodic sampling
Humidity sensor	Relative humidity	Estimates atmospheric moisture	Periodic sampling
Rainfall sensor	Rainfall	Detects precipitation	Event-based activation
Light sensor	Solar/light intensity	Environmental monitoring	Periodic sampling
Microcontroller	Data processing	Local processing and control	Sleep mode
LoRa/LoRaWAN module	Wireless communication	Data transmission	Duty-cycled
Battery	Electrical energy	Node power supply	Energy-aware management
Solar panel	Renewable energy	Battery charging	Optional energy harvesting

The choice of sensor and communication technologies should depend on field size, soil type, crop requirements, communication distance, terrain, and expected sampling frequency. Existing agricultural WSN research has identified Zigbee and LoRa among the communication technologies used in agricultural monitoring, while energy-efficient designs commonly employ low-power operation and duty cycling.

IV. ENERGY-AWARE NETWORK DESIGN

Energy awareness is the central component of the proposed framework. A sensor node should not remain continuously active when environmental conditions are relatively stable. Instead, it can enter a low-power sleep state and wake periodically for sensing and communication.

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The proposed energy-management strategy contains four mechanisms:

1. Adaptive Sampling

The sampling interval can be changed according to environmental variability. When soil moisture remains stable, the sensor can measure less frequently. After rainfall, irrigation, or a rapid change in temperature, the sampling frequency can be increased.

This strategy is consistent with previous work showing that variable sampling intervals can improve energy consumption while maintaining useful soil-moisture information.

2. Sleep–Wake Scheduling

After collecting and transmitting data, the sensor node enters sleep mode. It wakes after a predefined interval or when an event occurs. Because the radio is one of the major energy-consuming components of many WSN nodes, reducing unnecessary radio activity can substantially improve network lifetime.

3 Data Aggregation

Neighboring sensor observations may contain redundant information. Local aggregation can reduce the number of packets transmitted to the gateway. Instead of transmitting every raw measurement, the node or cluster head can calculate average, minimum, maximum, or change-based values.

4. Energy Harvesting

Solar energy can be incorporated to recharge batteries during daylight. Energy harvesting is particularly attractive for agricultural fields because sensor nodes are generally exposed to sunlight. However, harvesting systems should account for seasonal variations, cloud cover, shading from crops, and battery-storage requirements.

V. REAL-TIME SOIL MOISTURE MONITORING

The proposed monitoring process begins with periodic acquisition of soil moisture and environmental observations. Each sensor node performs local preprocessing and assigns a timestamp and node identifier to the measurement. Data can then be transmitted to the gateway through a low-power wireless network.

Table 2. Example Real-Time Monitoring Parameters

Parameter	Unit	Suggested Sampling Frequency*	Application
Soil moisture	% VWC	5–30 min	Irrigation decision
Soil temperature	°C	15–60 min	Soil condition assessment
Air temperature	°C	15–60 min	Weather analysis
Relative humidity	%	15–60 min	Evapotranspiration-related analysis
Rainfall	mm	Event/15–60 min	Irrigation adjustment
Light intensity	lux/W m^{-2}	15–60 min	Crop/environment monitoring
Battery voltage	V	30–120 min	Energy management
RSSI/SNR	dBm/dB	Transmission event	Network-quality assessment

Sampling intervals are proposed design values and should be calibrated according to crop, climate, soil type, and energy availability.

Real-time soil-moisture WSNs have already been demonstrated as useful for distributed monitoring from field to larger spatial scales.

VI. AGRICULTURAL FORECASTING FRAMEWORK

The forecasting component uses historical sensor observations to predict future soil moisture. Input variables may include:

1. Previous soil-moisture values
2. Soil temperature
3. Air temperature

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4. Relative humidity
5. Rainfall
6. Solar radiation/light intensity
7. Irrigation amount
8. Irrigation timing
9. Crop growth stage
10. Time of day and season

Machine-learning models such as Random Forest (RF), Support Vector Regression (SVR), Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks can be evaluated. Recent literature specifically identifies machine learning as an important approach for soil-moisture forecasting using sensor, weather, and irrigation observations.

VII. PROPOSED FORECASTING MODELS

Table 3. Comparison of Candidate Forecasting Models

Model	Main Advantage	Limitation	Expected Application
Linear Regression	Simple and interpretable	Limited nonlinear representation	Baseline model
Multiple Regression	Uses several environmental variables	Sensitive to relationships among predictors	Irrigation prediction
Random Forest	Handles nonlinear relationships	Larger computational requirement	Robust forecasting
SVR	Effective for nonlinear regression	Parameter tuning required	Small/medium datasets
ANN	Learns complex relationships	Requires sufficient training data	Soil-moisture prediction
LSTM	Captures temporal dependencies	More computationally intensive	Multi-step forecasting

The final model should be selected using objective validation rather than assuming that a particular algorithm is universally superior. Recent reviews emphasize that soil-moisture forecasting remains dependent on the characteristics of available sensor, weather, and irrigation data.

VIII. IRRIGATION DECISION-MAKING

The predicted soil-moisture value can be compared with crop-specific threshold values. A simplified decision rule may be defined as:

A more advanced system could calculate the estimated water deficit and recommend irrigation volume rather than providing only a binary irrigation decision. This could allow irrigation systems to respond to predicted rather than only observed soil conditions.

IX. EXPERIMENTAL DESIGN

A field experiment can be designed by dividing an agricultural plot into several monitoring zones. Sensor nodes should be distributed according to soil variability, crop distribution, topography, and irrigation layout.

Table 4. Suggested Experimental Design

Experimental Component	Proposed Design
Study area	Agricultural field divided into monitoring zones
Sensor nodes	10–30 nodes depending on field size

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Gateway	1 central gateway
Communication	LoRa/LoRaWAN or Zigbee
Sampling	Adaptive 5–60 min intervals
Monitoring duration	At least one crop cycle
Soil parameter	Soil moisture and soil temperature
Weather parameters	Temperature, humidity, rainfall, light
Energy monitoring	Battery voltage/current
Forecast horizon	1–24 hours initially
Validation	Separate training, validation, and testing periods
Irrigation comparison	Conventional vs sensor-informed scheduling

The exact number of nodes and sampling interval should be determined through pilot testing because deployment density and sampling requirements vary according to field size and environmental heterogeneity.

X. PERFORMANCE EVALUATION

The proposed system should be evaluated from both network-performance and forecasting-performance perspectives.

Table 5. Performance Evaluation Metrics

Category	Metric	Purpose
Energy	Energy consumption/node	Measures power requirement
Energy	Battery lifetime	Determines operational sustainability
Network	Packet delivery ratio	Measures communication reliability
Network	End-to-end delay	Evaluates real-time performance
Network	RSSI/SNR	Measures wireless link quality
Network	Network lifetime	Determines long-term operation
Sensing	Sensor error	Measures measurement accuracy
Forecasting	MAE	Average prediction error
Forecasting	RMSE	Penalizes larger prediction errors
Forecasting	R^2	Measures explained variance
Agriculture	Water consumption	Measures irrigation efficiency
Agriculture	Irrigation events	Measures decision frequency

XI. COMPARATIVE ANALYSIS OF EXISTING APPROACHES

Table 6. Comparison of Energy-Aware Agricultural WSN Approaches

Approach	Energy Strategy	Main Strength	Major Limitation
Conventional WSN	Continuous/periodic sensing	Simple implementation	High energy consumption
Sleep–wake WSN	Radio and node sleeping	Extends battery life	May increase latency
Duty-cycle WSN	Controlled active period	Reduces communication energy	Requires schedule optimization
Adaptive-sampling WSN	Variable sampling rate	Reduces redundant sensing	Requires change detection
Data-aggregation	Local data processing	Reduces packet	Processing complexity

WSN		transmissions	
Solar-powered WSN	Renewable energy	Longer operational lifetime	Weather-dependent
LoRa-based WSN	Long-range low-power communication	Suitable for large fields	Data rate is limited
WSN + ML	Energy-aware monitoring + forecasting	Predictive irrigation support	Requires quality training data

Research literature supports the use of sleep/wake strategies, duty cycling, topology optimization, and data reduction to decrease energy consumption in agricultural WSNs. Recent field work also demonstrates continued investigation of LoRa-based energy-efficient soil-moisture networks.

XII. EXPECTED RESULTS

The proposed system is expected to produce continuous and spatially distributed soil-moisture information while reducing unnecessary sensor and communication activity. Adaptive sampling should reduce the number of sensing and transmission operations during stable environmental conditions. Sleep–wake scheduling should further reduce idle energy consumption.

The forecasting component is expected to identify future moisture trends and provide early warnings when soil moisture is likely to fall below a crop-specific threshold. Integration of weather and irrigation observations may improve predictive performance because soil moisture is influenced by multiple interacting environmental factors.

The system should also provide farmers with an accessible monitoring interface containing current soil moisture, historical trends, predicted moisture, battery status, and irrigation recommendations.

XIII. DISCUSSION

The major contribution of an energy-aware WSN framework is the integration of efficient data collection and intelligent prediction. Traditional monitoring systems focus primarily on obtaining measurements, whereas an intelligent system must determine when measurements are necessary, which measurements should be transmitted, and how collected information can support future decisions.

Energy efficiency is particularly important in agricultural fields because sensor nodes may be physically dispersed and difficult to access. Earlier agricultural WSN research has shown that wireless communication can represent a substantial energy burden and that sleep/wake mechanisms and duty cycling can extend operational life. Soil-moisture WSN research has also established the importance of distributed and near-real-time sensing for agricultural management.

Forecasting introduces a further opportunity to reduce unnecessary irrigation. Rather than applying water according to a fixed calendar, irrigation can be linked to both present and expected soil conditions. A recent systematic review identified a substantial body of research using sensor-based soil moisture, weather, and irrigation observations for forecasting, but also noted the need for more consistent methodologies for model development and evaluation.

Consequently, future systems should not evaluate forecasting accuracy alone. They should simultaneously consider energy consumption, network reliability, sensor accuracy, water savings, computational

XIV. CONCLUSION

Energy-aware Wireless Sensor Networks provide a promising technological foundation for real-time soil-moisture monitoring and agricultural forecasting. The integration of low-power sensor nodes, adaptive sampling, sleep–wake scheduling, data aggregation, energy harvesting, and long-range wireless communication can improve the sustainability of agricultural monitoring systems. Existing research demonstrates that WSNs can provide distributed, near-real-time soil-moisture information, while energy-management strategies can reduce unnecessary power consumption. The addition of machine-learning forecasting can transform the network from a passive monitoring platform into a

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predictive decision-support system. By combining current observations with historical soil moisture, weather, and irrigation information, the system can estimate future soil conditions and support more timely irrigation decisions. Overall, the proposed framework has the potential to reduce water wastage, increase energy efficiency, improve irrigation scheduling, extend sensor-network lifetime, and contribute to sustainable precision agriculture.

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