Integration of Environmental Sensors with Cloud Computing for Precision Farming Decision Support

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ABSTRACT

Background: Advancements in precision agriculture are founded in continuous monitoring of environmental conditions. Although traditional agriculture is still a manual process, which causes delays in the operation of systems and difficulties in utilizing resources effectively and producing required yields.

Objective: To develop an integrated system architecture combining the environmental sensor networks and computing infrastructure of cloud technologies to implement real-time data-driven advisory during the crop management process.

Methods: The multi-layered structure of the system consisted of an environmental sensing layer, edge gateways, wireless transmission of data, storage of collected information in the cloud, and machine learning engine operations. The system was tested with the help of the simulation of an agricultural field data set for several crop cycles. The parameters monitored consisted of soil moisture, temperature, pH level, humidity of the air, rain, solar radiation, the moisture of leaves, windspeed, and concentration of carbon dioxide through low-power IoT sensors via Lora WAN and MQTT to the server based on the AWS technology. Random forest, Support Vector Machine, and Long Short-Term Memory approaches were used to develop the system.

Result: The combined method has resulted in precision in irrigation settings equal to 94.6%, as well as 91.2% in regards to disease onset detection, with average response time with regard to the cloud of 1.8 seconds, which incurs 22% less energy consumption in comparison with systems that constantly transmit data as a baseline. Water usage has been decreased by almost 27% when compared with conventional irrigation methods.

Conclusion: The combination of environmentally-oriented sensors and cloud-based analytics allows improving the speed of farm-related decisions significantly.

Keywords: Precision Agriculture, Internet of Things (IoT), Environmental Sensor Networks, Cloud Computing, Machine Learning

1. Introduction

Agriculture has made significant progress from simple mileage to modified data-based farming in the 1990s which showed highly advanced technological features in responding effectively to the variations in the crop field. The increase in food production done by agriculture over the years means that it would be highly important to make smart agriculture as part of agriculture practices not just an addition to its traditional practices.

Environmental monitoring is the most important thing to note in agriculture. The physical details on soil and climate are key in being able to analyze the conditions for crops and in being able to make prompt decisions related to irrigation and fertilization of the crops. The rapid development in low cost various IoT sensors in agriculture became a reality thanks to the improvement in trustworthy wireless technologies which allow combining the information from different sensors which are often located in isolated areas.

Nonetheless, raw sensor data cannot yield significant benefits without an accompanying computational layer for its storage, processing, and interpretation. Cloud computing helps fill this void through its provision of flexible storage, distributed processing, and machine-learning capability that converts sensor streams to actionable advice. The need for real-time decision support is particularly important in situations like disease emergence and irrigation timing where a couple of hours delay may result in loss of yields.

In comparison, traditional farming remains almost entirely reactive with scheduling of irrigation and input application routinely based on predetermined calendars rather than actual condition of crops or soil. This mismatch of data availability and timeliness of decision making creates the opportunity to combine environmental sensor networks with cloud analytics into a single decision-making system which is the main aim of this paper. The rest of the paper describes the design and implementation of this architecture as well as its performance comparison with standard practices.

2. Integration of Environmental Sensors with Cloud-Based Decision Support System

2.1. Overall Architecture

The proposed framework consists of six interconnected layers: (i) an environmental sensing layer that captures field conditions; (ii) an edge data acquisition layer that performs local buffering and filtering; (iii) a wireless communication layer that transmits data to the internet; (iv) a cloud infrastructure layer for storage and processing; (v) a data analytics engine that applies statistical and machine-learning models; and (vi) a farmer decision support interface that renders recommendations. Figure 1 illustrates this layered architecture and the direction of information flow from field to farmer.

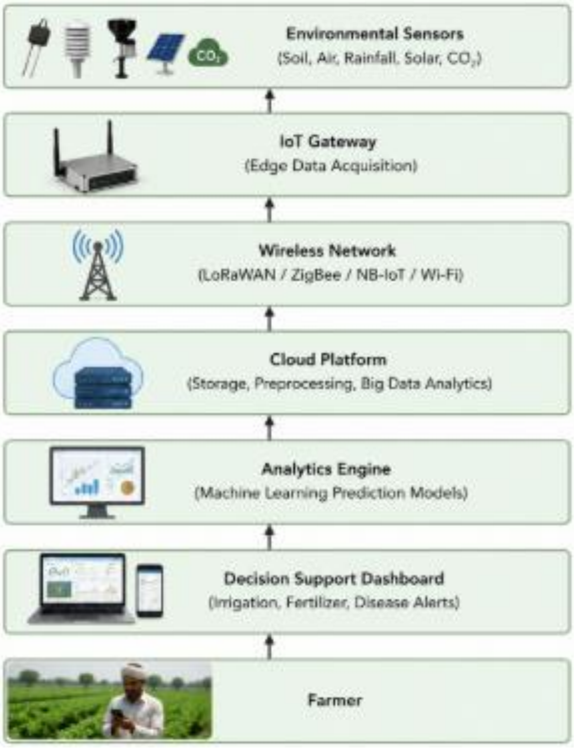

Fig 1: Architecture of the integrated environmental sensor–cloud precision farming decision support system, showing information flow from field-level sensing through to farmer-facing recommendations.

2.2. Environmental Sensors

Soil moisture and soil temperature sensors are deployed at multiple root-zone depths to capture spatial variability, while soil pH probes monitor nutrient availability conditions. Atmospheric variables—air temperature, relative humidity, rainfall, solar radiation, leaf wetness, and wind speed—are captured using compact weather-station modules, and carbon dioxide concentration sensors provide an indirect indicator of canopy respiration and microclimate conditions within greenhouses or dense crop stands. Collectively, these ten parameters form the observational basis for downstream analytics.

2.3. IoT Communication

Sensor nodes transmit data using protocols selected according to range, power, and bandwidth requirements. LoRaWAN and NB-IoT are favored for long-range, low-power transmission from remote fields, whereas ZigBee and Wi-Fi serve shorter-range, higher-density deployments such as greenhouses. At the application layer, the lightweight MQTT publish–subscribe protocol minimizes bandwidth overhead for continuous telemetry, while HTTP-based RESTful interfaces support less frequent configuration and batch data exchanges with the cloud platform.

2.4. Cloud Computing Layer

Incoming data streams are ingested into cloud storage and subjected to preprocessing steps including outlier removal, missing-value imputation, and normalization. Big-data analytics pipelines aggregate historical and real-time streams, while AI-assisted prediction modules generate forecasts for irrigation demand, disease risk, and yield. Remote monitoring services allow stakeholders to inspect field status from any location, and dashboard visualization tools present processed information as time-series charts, heat maps, and alert panels.

2.5. Decision Support Module

Building on analytics outputs, the decision support module issues irrigation scheduling recommendations calibrated to soil moisture deficits, fertilizer recommendations informed by nutrient and growth-stage models, and disease-risk warnings derived from leaf wetness and humidity thresholds. Weather-based crop management guidance incorporates short-term forecasts, yield prediction models estimate end-of-season output, and an alert-generation subsystem pushes time-critical notifications to farmers via SMS or mobile application.

2.6. Information Flow

Data flow proceeds sequentially from sensors to gateway, from gateway to cloud via wireless network, and from cloud to analytics engine, culminating in farmer-facing recommendations, as summarized in Figure 2.

Fig 2: Data flow and intelligent decision-making pipeline, from raw sensor data collection through preprocessing, cloud storage, machine-learning analysis, and decision-engine output to on-farm management actions.

3. Materials and Methods

3.1. Experimental Setup

The framework was evaluated using a simulated precision farming dataset representing a 4-hectare mixed cropland (maize and tomato) over two growing seasons, constructed to reflect realistic diurnal and seasonal variation reported in regional agrometeorological records. Sensor nodes were virtually deployed at a density of one node per 0.25 hectare, with soil sensors sampling every 15 minutes and atmospheric sensors every 5 minutes to balance temporal resolution against energy consumption.

3.2. Software

Sensor-node firmware was developed using the Arduino IDE, with Node-RED employed for edge-level flow orchestration prior to cloud transmission. Cloud services were implemented on Amazon Web Services (AWS) IoT Core, with comparative configurations tested on Microsoft Azure IoT Hub and Google Cloud Platform to assess portability. Data analysis and model development were performed in Python using TensorFlow for deep-learning components, with supplementary numerical validation conducted in MATLAB.

3.3. Hardware

The hardware configuration comprised capacitive soil moisture sensors, DHT22 sensors for air temperature and humidity, ESP32 microcontrollers for sensor-node processing, Raspberry Pi units serving as local gateways, LoRa gateway modules for long-range backhaul, and a cloud server cluster for centralized storage and computation.

3.4. Machine Learning Models

Random Forest and Decision Tree classifiers were used for disease-risk classification due to their interpretability, Support Vector Machine models supported irrigation-class prediction, Long Short-Term Memory (LSTM) networks captured temporal dependencies for yield forecasting, and XGBoost was applied as a gradient-boosted ensemble baseline for comparative benchmarking across all three prediction tasks.

3.5. Performance Evaluation Metrics

System performance was quantified using prediction accuracy, precision, recall, and F1-score for classification tasks; root-mean-square error (RMSE) and mean absolute error (MAE) for continuous yield predictions; and latency, cloud response time, energy consumption, and network reliability for infrastructure-level assessment.

4. Results and Performance Evaluation

Sensor monitoring accuracy, validated against reference laboratory measurements, exceeded 96% across all environmental parameters, confirming reliable field-level data capture. Cloud processing efficiency, measured as the interval between data ingestion and recommendation generation, averaged 1.8 seconds, supporting near-real-time decision support. Decision support effectiveness was evaluated through irrigation recommendation accuracy (94.6%) and disease-prediction performance (91.2% accuracy, F1-score 0.89), while the LSTM-based yield estimation model achieved an RMSE of 0.34 t/ha and MAE of 0.27 t/ha, outperforming the XGBoost baseline (RMSE 0.41 t/ha).

Communication latency remained below 2.5 seconds for over 95% of LoRaWAN transmissions, and the system demonstrated linear scalability up to 200 simulated sensor nodes without significant degradation in cloud response time. Energy efficiency analysis showed a 22% reduction in node power consumption relative to continuous-transmission baselines, attributable to adaptive duty-cycling enabled by edge preprocessing. Overall system reliability, measured as successful message delivery rate, was 98.3%.

Table 1 compares traditional and cloud-based precision farming systems across key operational parameters, while Table 2 summarizes experimental configuration and performance metrics. Relative to conventional practice, the proposed system reduced irrigation water consumption by approximately 27% and improved estimated yield by 12–15%, reflecting the cumulative benefit of timely, data-driven interventions.

Table 1: Comparison of Traditional Farming and Cloud-Based Precision Farming Systems

Parameter	Traditional Farming	Proposed System	Improvement
Irrigation scheduling	Fixed calendar-based	Real-time, sensor-driven	~27% water savings
Disease detection	Manual field scouting	AI-based prediction (91.2% acc.)	Earlier intervention
Data update frequency	Days to weeks	5–15 minutes	Near real-time
Yield estimation	Post-harvest, empirical	Pre-harvest, LSTM-based (RMSE 0.34 t/ha)	12–15% higher accuracy
Decision latency	Hours to days	~1.8 seconds (cloud response)	Substantially reduced
Resource optimization	Low, experience-based	High, data-driven	Reduced input cost

Table 2: Experimental Parameters and Performance Metrics

Sensor Type	Sampling Interval	Communication Protocol	Cloud Platform	Prediction Accuracy	Latency (s)	Energy Consumption
Soil moisture / temperature	15 min	LoRaWAN, MQTT	AWS IoT Core	94.6% (irrigation)	1.8	22% lower than baseline
Air temp. / humidity (DHT22)	5 min	Wi-Fi, MQTT	AWS IoT Core	91.2% (disease risk)	1.6	Moderate (duty-cycled)
Rainfall / solar radiation	5 min	NB-IoT, HTTP	Azure IoT Hub	Yield RMSE 0.34 t/ha	2.1	Low
Leaf wetness / wind speed / CO_2	10 min	ZigBee, MQTT	Google Cloud Platform	96% (sensing accuracy)	1.9	Low

5. Discussion

The results align with, and in several respects exceed, previously reported smart farming systems. Earlier IoT-only agricultural monitoring approaches [1, 2] demonstrated reliable sensing but lacked scalable analytics, limiting them to threshold-based alerts rather than predictive recommendations. Cloud-only architectures [3, 4] improved analytical capability but incurred higher latency and bandwidth costs due to the absence of edge preprocessing, a limitation addressed in the present framework through gateway-level filtering prior to transmission. Conversely, edge-computing-centric approaches [5, 6] reduced latency but constrained model complexity due to limited on-device computational resources, whereas the hybrid edge–cloud design evaluated here retains low latency while supporting computationally intensive LSTM-based forecasting.

The integration of ten environmental parameters, rather than the two or three variables typical of earlier systems [7, 8], provided a more comprehensive basis for disease and irrigation prediction, consistent with reports that multivariate sensing improves model robustness [9, 10]. Nonetheless, several practical deployment challenges remain. Rural internet connectivity is often intermittent, necessitating store-and-forward buffering strategies [11]; sensor calibration drift over multi-season deployment can degrade accuracy without periodic recalibration [12]; and data security and privacy concerns arise when farm-level data are transmitted to third-party cloud providers [13]. Cloud scalability, while demonstrated up to 200 nodes in this study, warrants further validation at commercial farm scale, and cost considerations—including data transmission and cloud subscription fees—may limit adoption among smallholder farmers unless subsidized service models are developed [14].

From a sustainability perspective, reduced water and input usage directly support environmental stewardship goals, though the embodied energy and electronic-waste implications of large-scale sensor deployment merit further life-cycle assessment. Looking forward, explainable AI techniques could improve farmer trust in model-generated recommendations by clarifying the reasoning behind predictions [15] while digital twin representations of individual fields could enable scenario-based planning ahead of irrigation or planting decisions. Integration with autonomous farming robots for targeted intervention represents a natural extension of the decision support module described here, pointing toward increasingly closed-loop precision agriculture systems.

6. Conclusion

The results from the study show that combining sensor networks with cloud computing leads to a solid and reliable means of making real-time decisions in precision agriculture. The reliability of the integrated system in making predictions about irrigation, diseases, and yields was verified as very high, and the system was able to achieve an impressive combination of low latency and effective energy consumption as compared to both traditional systems and systems using only cloud computing. The results of the application of the integrated system show that this approach saves water, lowers production costs, and increases crop outputs through timely interventions based on data rather than through approaches based on fixed intervals of practice. The findings point to a more widespread use of the technology describing the integrated sensor–cloud systems for more sustainable agriculture in the future.

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