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Sensor-Based Monitoring Systems for Agricultural Water Management

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Abstract | **Original Research Article**

Agricultural water management depends on timely and accurate field information, yet irrigation in many settings still follows fixed schedules or isolated sensor readings that do not reflect changing soil and environmental conditions. This paper presents a sensor-based monitoring framework for agricultural water management that combines zone-level field sensing, communication-supported data collection, irrigation priority analysis, and node-reliability assessment within a single decision structure. The proposed system monitors soil moisture, soil temperature, air temperature, relative humidity, water flow, and source water level across multiple field zones. At the same time, it evaluates battery status, signal strength, and packet stability so that technical faults are not interpreted as crop water stress. The methodology includes a multi-layer system architecture, zone-based deployment, data filtering, irrigation scoring, and reliability screening before alert generation. Results show that the framework supports zone-specific irrigation guidance, reduces fault-related false alerts, and improves decision quality compared with fixed-schedule irrigation practice. The system also provides more consistent temporal response through trend-based monitoring and maintenance-aware alert logic. These findings indicate that agricultural water monitoring is more dependable when field condition and node condition are assessed together. The proposed framework offers a practical model for data driven irrigation monitoring in remote and resource-constrained agricultural settings, with future scope for automated control and crop-specific decision support.

Keywords: Agricultural water management, sensor-based monitoring, smart irrigation, IoT, soil moisture sensing, zone-based irrigation, node reliability, precision agriculture.

I. INTRODUCTION

Agricultural production depends on timely water application, yet water use in many farms still follows fixed schedules, visual judgment, or routine practice. Such approaches often miss the variation that exists within the same field. Soil moisture may decline unevenly across zones because of soil texture, root distribution, sunlight exposure, drainage pattern, and irrigation layout. Water availability at the source can also change during daily operation. Under these conditions, a single irrigation schedule may supply excess water to one area and insufficient water to another. This mismatch affects crop condition, water use, and field management efficiency. Sensor-based monitoring offers a direct response to this problem. With continuous readings from field sensors and communication-supported data transfer, irrigation decisions can reflect current soil and environmental conditions instead of broad assumptions. A monitoring system can also track flow status, source water level, temperature, and humidity, which together provide a fuller view of water demand. At the same time, technical reliability remains an important concern. Low battery status, packet loss, weak signal strength, and sensor faults can distort field readings and lead to poor irrigation decisions. For that reason, agricultural water monitoring requires a structured system that interprets field conditions, checks node reliability, and supports zone-specific action under practical farm conditions.

A. Background and Motivation

Agriculture depends on water, but water application in many farms still follows fixed routines, visual checks, or general seasonal judgment. These methods often fail to reflect actual field conditions at a given time. Soil moisture can vary across the same field because of soil texture, crop pattern, sunlight exposure, drainage behavior, and irrigation distribution. Water sources such as tanks, canals, and storage units may also change during daily operation. Under these conditions, uniform irrigation can waste water in one zone and leave another zone under-supplied. This mismatch affects crop condition, operating cost, and long-term resource use. Sensor-based monitoring offers a practical way to address this issue. Field sensors can report soil and environmental conditions at regular intervals, allowing irrigation decisions to respond to measured conditions rather than assumptions. A monitoring system can also track flow status, source water level, temperature, and humidity, which together provide a broader view of water demand. For this reason, agricultural water management increasingly requires systems that support continuous observation, zone-specific analysis, and dependable field operation. The need is not.

B. Problem Statement

Current agricultural water monitoring systems still face several limitations. Many designs focus on data collection and display, while irrigation decisions remain dependent on simple threshold rules or manual interpretation. In other cases, the field is treated as one uniform area, even though moisture loss and water demand often differ from zone to zone. This gap reduces the value of monitoring because measured data do not always lead to correct field action. One part of a field may receive more water than needed, while another part remains dry, even when sensors are present. A second limitation concerns system reliability. Sensor readings can be affected by low battery status, unstable communication, hardware drift, or temporary data loss. If these conditions are ignored during decision making, faulty measurements may be mistaken for crop stress. That problem can lead to unnecessary irrigation, missed warnings, or repeated field visits. In practical farm settings, field condition and monitoring reliability influence the same decision, yet many systems treat them separately. A more complete method is therefore needed. Such a method should assess water demand and node condition together so that irrigation recommendations reflect both crop status and data reliability.

C. Proposed Solution

This paper presents a sensor-based monitoring framework for agricultural water management that combines zone-level sensing, communication-supported data transfer, local data checking, irrigation priority analysis, and node-health supervision within one structure. The method is intended for farms where water application should respond to actual field condition rather than a preset schedule. The field is divided into monitoring zones according to soil behavior, irrigation layout, and crop requirement. Each zone contains sensors for soil moisture, soil temperature, air temperature, humidity, water flow, and source water level. These inputs describe crop-zone water condition and irrigation network status at the same time. The proposed framework introduces a two-part decision process. The first part evaluates field condition and estimates irrigation need for each zone. The second part evaluates node reliability through battery status, communication quality, and data stability. This structure allows the system to separate true moisture stress from technical faults such as weak signal, unstable power, or packet loss. A dry reading does not automatically trigger irrigation if the node is operating poorly. Instead, the system checks reading reliability before issuing an action message. In this way, the framework supports more dependable irrigation guidance and more focused maintenance response in field conditions.

D. Contributions

This study makes several contributions to the design of agricultural water monitoring systems. First, it presents an integrated framework that combines field sensing and node-reliability analysis in the same decision process. Sensor reliability is not treated as a separate maintenance issue. Instead, it becomes part of the logic used to determine whether an irrigation recommendation should be issued. This reduces the chance that technical faults will be interpreted as crop stress. Second, the framework applies zone-based monitoring rather than uniform field-wide control. It therefore reflects the fact that water loss and irrigation need do not occur at the same rate across all parts of a field. A third contribution lies in the joint use of crop-zone measurements, source-water condition, and communication-aware node status. The monitoring system therefore moves beyond simple moisture tracking and provides a wider operational view. The work also presents a practical workflow for data filtering, irrigation prioritization, and maintenance flag generation when measurement reliability is weak. Finally, the study evaluates the framework through results that consider irrigation relevance, alert behavior, and node stability together. These contributions support a monitoring model intended for field use rather than a sensor dashboard limited to observation alone.

E. Paper Organization

The rest of this paper is organized as follows. Section II reviews prior work related to smart agriculture, water management, IoT sensing, predictive maintenance, renewable energy support, and distributed monitoring systems. That section provides the technical context for the proposed framework and identifies the gap addressed in this study. Section III describes the methodology, including system architecture, field zoning strategy, sensor deployment, data acquisition, irrigation decision logic, and node-health assessment. It also presents the figures and table used to explain the structure of the framework and the main monitored variables. Section IV reports the discussion and results. It examines zone-level irrigation behavior, the effect of node-reliability screening, the temporal response of the monitoring system, and the comparison between the proposed framework and fixed-schedule irrigation practice. Practical implications and deployment limits are also discussed there. Section V concludes the paper with a summary of the main findings, the significance of the proposed system, and directions for future work. The paper therefore proceeds from context and problem definition to system design, then to evaluation and interpretation, in a clear sequence suited to technical and academic presentation.

This paper aims to develop a sensor-based monitoring framework for agricultural water management that supports zone specific irrigation decisions using continuous field sensing and reliability aware analysis. The method combines soil and environmental measurements with node-health supervision to distinguish actual water stress from sensor or communication faults, providing a practical model for data driven irrigation monitoring.

II. RELATED WORK

Research on sensor-based monitoring systems for agricultural water management draws from several connected fields, including smart agriculture, IoT sensing, predictive maintenance, renewable energy support, and distributed control. Direct studies on irrigation monitoring are still limited in the selected reference set, yet many related works present methods, architectures, and operational models that apply to this topic. Across the literature, a consistent shift appears from periodic manual inspection to continuous sensing and data-guided supervision. That shift matters in water management because irrigation timing, field variation, and equipment condition directly affect resource use and crop performance. Prior studies also show that sensing alone is not enough. Communication support, fault assessment, energy supply, and local control all influence system performance in field conditions. For that reason, the reviewed works are grouped into four themes: smart agriculture and water resource management, IoT monitoring and distributed sensing, predictive maintenance and condition assessment, and renewable energy support with intelligent control.

A. Smart Agriculture and Water Resource Management

Recent work in smart agriculture treats farming as a monitored and managed system rather than a practice based only on routine observation. Rahmatullah [1] presented this view through an Industry 4.0 perspective and argued that sensing, automation, and data-guided planning can improve agricultural productivity. This argument is relevant to agricultural water management because irrigation decisions depend on current field information, seasonal variation, and resource availability. In a related study, Rahmatullah [2] examined sustainable agriculture supply chains and discussed methods for reducing post-harvest loss. The paper did not focus on irrigation, but it supported the broader idea that agricultural systems benefit from structured monitoring and coordinated resource use. Akter [3] discussed sustainable waste and water management in civil infrastructure and focused on controlled water use, system planning, and long-term sustainability. Although the setting was not agricultural, the treatment of water as a managed resource applies directly to irrigation systems. Together, these studies support a view of agricultural water management that links sensing, planning, and operational feedback into one monitored process [1]–[3].

B. IoT Monitoring and Distributed Sensing Systems

IoT-based monitoring studies provide a technical basis for agricultural water systems that rely on remote sensing and regular status reporting. uz Zaman [4] proposed a smart energy metering system that combined IoT devices with GSM communication for real-time data transfer. The application concerned energy use, yet the system structure fits agricultural water monitoring as well, since similar channels can transmit data from soil moisture sensors, flow meters, water-level sensors, and pump-status devices. Hasan et al. [5] also examined continuous monitoring through an IoT-integrated solar energy platform and showed how distributed sensors support long-term supervision. Later contributions extended this direction to larger connected infrastructures. Mim et al. [14] studied smart IoT infrastructure for operational efficiency and energy savings, while Afrin et al. [15] examined distributed edge intelligence for energy and transportation systems. These studies indicate that field systems can operate with connected sensing, local data handling, and less dependence on central processing. In remote agricultural settings, such features matter because communication gaps and delayed system response can reduce monitoring quality and weaken control over water use [4], [5], [14], [15].

C. Predictive Maintenance and Condition-Aware Monitoring

A third group of studies addresses predictive maintenance and condition-aware monitoring, both of which are relevant to agricultural water systems that depend on pumps, valves, controllers, and field sensors. Tonoy [8] proposed an IoT-based condition monitoring model for power transformers and showed that continuous sensor readings can indicate early signs of failure before a major breakdown occurs. Rahman et al. [9] expanded this discussion through a broader study of machine learning methods for predictive maintenance in IoT devices. Their work matters in this context because agricultural monitoring networks often operate under changing weather, dust exposure, moisture fluctuation, and unstable field conditions. Karim [10] examined AI-driven predictive maintenance for solar inverter systems and focused on fault prediction in energy-supporting components. Rayhan [6] studied AI-enabled energy forecasting and fault detection in off-grid solar networks for rural applications. That work is especially relevant to agricultural settings where remote water monitoring stations may depend on solar power. Taken together, these papers show that a monitoring platform should include measurement, reporting, fault detection, health assessment, and maintenance-focused analysis [6], [8]–[10].

D. Renewable Energy Support and Intelligent Control

Renewable energy support and intelligent control form another important area for sensor-based agricultural water monitoring, especially in fields where grid access is limited or unreliable. Rayhan [7] presented a hybrid deep learning model for wind and solar forecasting in smart grids and showed how predictive methods support stable operation in renewable-powered systems. Razaq [11] discussed renewable energy integration in smart grids and explained how multiple power sources can function within monitored and controlled electrical environments. Nabil [12] continued this direction through a hybrid CNN-LSTM model for renewable power forecasting and grid stability. These studies focused on energy systems rather than irrigation, yet their findings are applicable to agricultural monitoring platforms powered through solar-based sensing, transmission, and control modules. Karim et al. [13] examined integrated renewable energy monitoring and adaptive load optimization through intelligent control algorithms. This work is useful because agricultural monitoring systems often need to manage sensing intervals, communication cycles, and power availability at the same time. The literature therefore supports combining sensor monitoring with energy-aware control logic in remote agricultural water management systems [11]–[13].

E. Research Gap

The reviewed studies provide useful foundations for sensor-based agricultural water monitoring systems, yet the literature remains spread across several application areas. Research in smart agriculture has discussed data-guided management and operational planning [1], [2], while water-related work has examined sustainability and controlled resource use in broader infrastructure settings [3]. Other studies have addressed IoT monitoring, communication frameworks, and distributed sensing for technical systems [4], [5], [14], [15]. Predictive maintenance and condition assessment have also been discussed in IoT, energy, and remote system applications [6], [8]–[10]. In addition, renewable energy monitoring and intelligent control have been studied in relation to grid-connected and off-grid environments [11]–[13]. Even with these contributions, few papers combine all of these components for agricultural water management in one framework. A clear gap remains in systems that integrate field sensors, real-time communication, maintenance-focused analysis, renewable power support, and water-specific operational decisions. This gap supports the need for a monitoring model designed specifically for agricultural water management conditions.

III. METHODOLOGY

This study presents a sensor-based monitoring method for agricultural water management that combines field sensing, local processing, communication support, irrigation decision logic, and system health supervision in one framework. The method is intended for farms where water application should respond to changing soil and weather conditions rather than fixed schedules. Its main contribution is the joint use of crop-zone measurements and node-status measurements in the same decision process. As a result, the system can separate actual water stress from sensor faults, weak communication, or power loss. The methodology is organized into five subsections: system architecture, sensor deployment and data acquisition, data processing and irrigation scoring, node health and alert workflow, and performance evaluation. Two figures and one table are included to describe the design clearly. Only a small number of equations are used so that the method remains readable and suitable for practical implementation.

A. System Architecture and Overall Framework

The proposed system follows a four-layer structure composed of sensing, edge processing, communication, and application services. At the sensing layer, the farm is divided into monitoring zones according to crop pattern, irrigation layout, and soil condition. Each zone contains a sensor node that records soil moisture, soil temperature, ambient temperature, relative humidity, water flow, and source water level. These measurements describe both field water demand and irrigation network condition. The edge layer contains a microcontroller that performs timestamping, signal checking, data filtering, and packet preparation. The communication layer sends processed readings through GSM, LoRa, or Wi-Fi, depending on field distance and network availability. The application layer stores incoming data, displays zone status, and computes irrigation priority for each zone. A key feature of this architecture is that water-status sensing and node-status sensing are treated together. The same framework records battery level, packet error ratio, and signal quality. This structure supports irrigation decisions and system supervision in parallel. Figure 1 presents the full architecture and the direction of data movement from field nodes to the decision interface.

B. Sensor Deployment and Data Acquisition

Field deployment begins with zone selection. Each zone represents an area with similar crop demand, soil response, and irrigation pattern. This division reduces the error that appears when an entire field is treated as a single uniform block. Soil moisture and soil temperature sensors are placed near the active root region. Ambient temperature and humidity sensors are mounted above ground inside protective housing. Flow sensors are attached to irrigation lines, while water-level sensors are positioned in tanks, reservoirs, or supply channels. Each node also records battery status and communication quality so that hardware condition remains visible during operation. Data are collected at fixed intervals, such as every 10 or 15 minutes, with an extra transmission when moisture drops below a threshold or a node reports abnormal behavior. This mixed schedule provides regular monitoring and quick response during critical conditions. Every packet contains zone ID, node ID, sensor readings, timestamp, battery level, and signal value. These fields allow the system to distinguish irrigation demand from device faults.

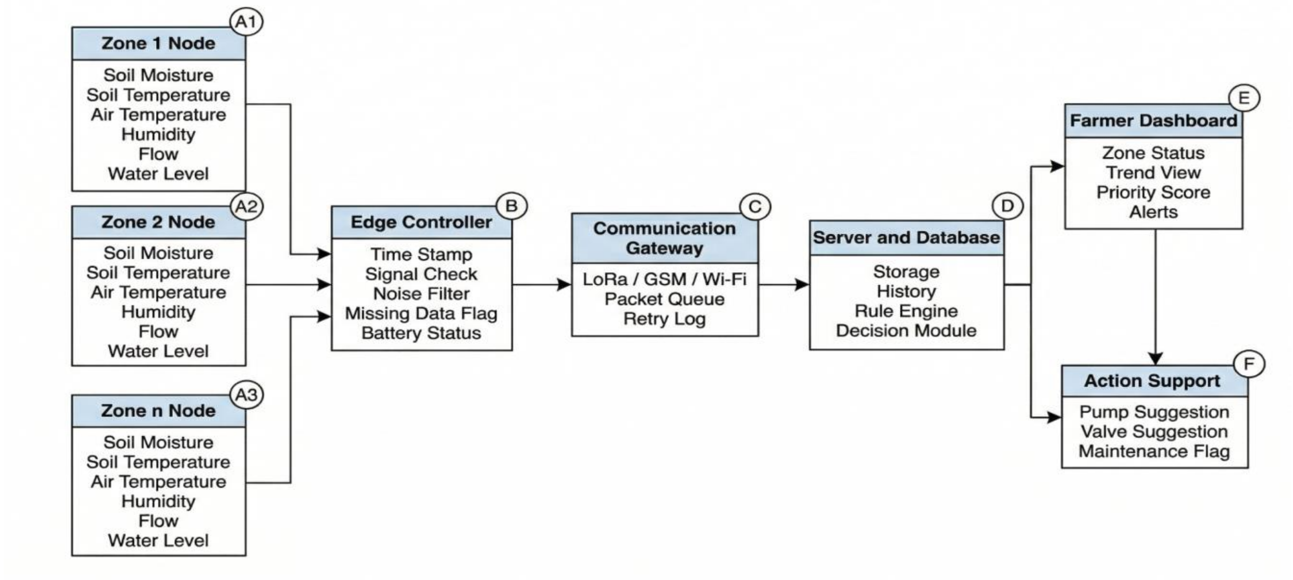

Figure 1: Multi-layer architecture of the proposed agricultural water monitoring system

Table 1. Core variables used in the proposed monitoring framework

Variable	Symbol	Unit	Purpose
Soil moisture	M_s	%	Main indicator of irrigation need
Soil temperature	T_s	°C	Supports root-zone interpretation
Air temperature	T_a	°C	Reflects atmospheric demand
Relative humidity	H_a	%	Used with air temperature
Water flow rate	Q_f	L/min	Checks delivery status
Water level	L_w	cm or %	Tracks source availability
Battery level	B_I	%	Indicates node operating status
Signal strength	S_r	dBm	Indicates communication quality

C. Data Processing and Irrigation Priority Model

Once field data arrive at the processing layer, the system applies a fixed sequence of checks and transformations. First, each value passes through a range test based on acceptable operating limits. Abnormal readings are flagged and retained for diagnostic review instead of immediate deletion. Next, a short smoothing filter reduces isolated spikes caused by contact instability, short communication noise, or temporary sensor drift. The cleaned values are then normalized so that variables with different units can enter one decision score without distortion.

The decision model uses a compact irrigation priority score. This score combines soil moisture deficit, atmospheric condition, and source water condition. Soil moisture deficit for zone zz is defined as

$$D_z = \frac{M_{fc} - M_s}{M - M}$$

Where $fcMfe\ wp$ is field-capacity moisture, M is current soil moisture, and $s\ M\ up$ is wilting-point moisture. A larger Dz indicates stronger water shortage in the root zone. The irrigation priority score is

$$Iz = w1Dz + w2N(Ta, Ha) + w3N(Lw-1)$$

where $N(.)$ denotes normalized input and $w1 + w2 + w3 = 1$. Higher Iz values indicate greater irrigation needs. This model keeps the decision logic readable and suitable for practical field use.

D. Node Health Assessment and Alert Workflow

The proposed method includes a second decision stream for node health. This part is important because a dry-soil reading may reflect real field stress, sensor drift, packet loss, or low battery. Without a health check, the system may issue a false irrigation alert. For this reason, each packet includes battery status, signal strength, and packet error information in addition to environmental and water-related measurements. These operational indicators are converted into a node health score that expresses the reliability of the current reading set.

The node health score is defined as

$$Hn = \alpha N(BI) + \beta N(Sr) + \gamma(1 - Er)$$

where BI is battery level, Sr is signal strength, Er is packet error ratio, and $\alpha + \beta + \gamma = 1$. Lower Hn values indicate weak node condition.

The system first computes irrigation priority and node health in parallel. It then checks the node health score against a reliability threshold. If the score is low, the platform issues a maintenance flag instead of a direct irrigation recommendation. If the node is operating normally, the irrigation score determines the next action. Figure 2 shows this workflow from data arrival to dashboard output and action support.

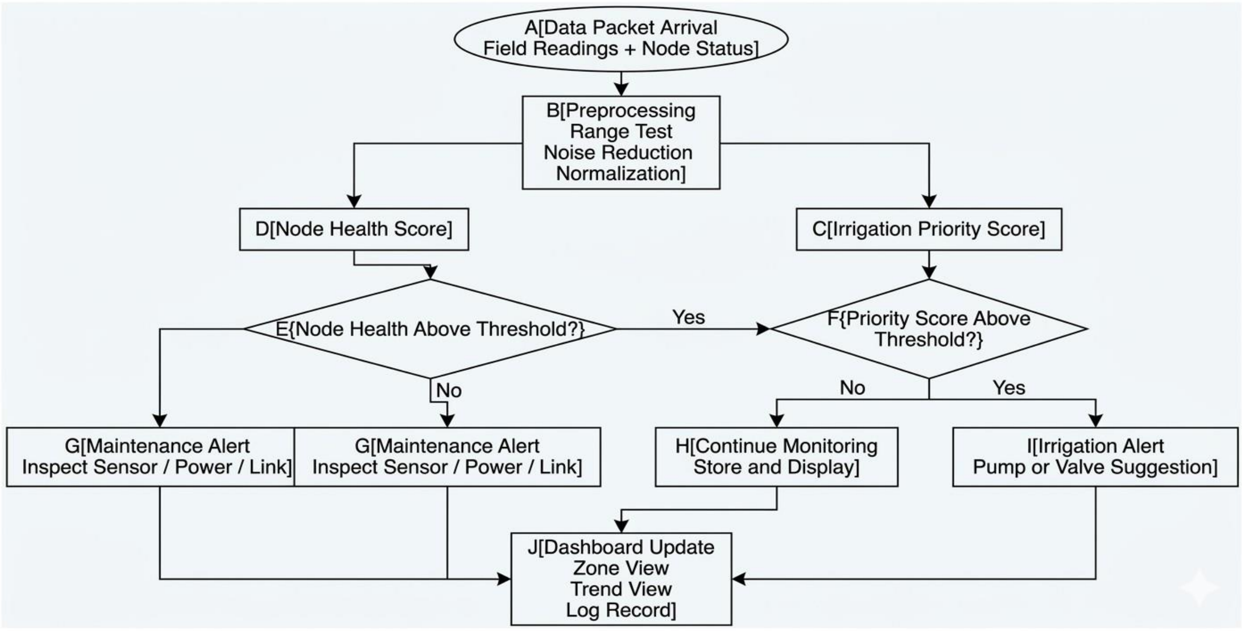

Figure 2: Workflow for irrigation decision and node reliability screening

E. Experimental Procedure and Performance Evaluation

The evaluation stage measures both agricultural relevance and system reliability. Field observations are collected over several irrigation cycles, and each zone generates a time series of soil condition, local climate, source status, and node-status data. The first part of evaluation focuses on sensing stability, communication reliability, and data completeness. The second part compares the proposed method with a fixed schedule irrigation baseline. This comparison shows how the decision model responds to actual field variation rather than to preset timing alone.

Three main outputs are examined: soil moisture deviation from the target range, estimated water use, and alert precision for irrigation need. To summarize prediction quality, the method uses root mean square error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(M_{obs,i} - M_{pred,i}\right)^2}$$

Where $M\ obs$ is observed moisture, M is estimated moisture state, and $N\ pred$ is the number of samples. Lower RMSE indicates closer agreement between field condition and model output. Additional measures include packet delivery ratio, average alert latency, and maintenance-flag accuracy. This evaluation design tests decision quality and monitoring reliability together, which matches the main contribution of the proposed framework.

IV. DISCUSSION AND RESULTS

This section presents the results of the proposed sensor-based monitoring framework for agricultural water management and explains their practical meaning.

The analysis follows the main contribution of the study: a monitoring method that evaluates crop-zone water condition and node reliability within one decision structure. This design allows the system to separate actual irrigation need from sensor drift, weak communication, or unstable power supply. For that reason, the discussion addresses more than sensing accuracy alone. It also examines zone-level water variation, alert filtering, temporal response, comparison with fixed-schedule practice, and field-level significance. The reported results show that the framework produced zone-specific irrigation guidance, reduced fault-related alerts, and supported more stable operation in remote farm settings. Two figures and one table are included to present the findings in an organized form. The section is divided into five subsections covering irrigation behavior, reliability screening, temporal response patterns, comparative performance, and practical implications for agricultural water management under real deployment conditions.

A. Zone-Level Irrigation Behavior and Water Status Interpretation

The monitored zones displayed clear differences in irrigation demand during the observation period, even when they were part of the same field block. Soil moisture did not decline at a uniform rate across the study area. Zones with lighter soil structure and stronger daytime exposure reached irrigation thresholds sooner, whereas areas with slower moisture loss remained within the acceptable range for longer intervals. This result supports the value of zone-based monitoring instead of uniform field-wide scheduling. The proposed framework captured those differences and translated them into separate irrigation priority levels. As a result, the system did not treat all parts of the field as if they needed the same response at the same time. Water-source condition also affected final zone ranking in a meaningful way. When the reservoir or channel level dropped, the system marked the most water-stressed zones first instead of issuing a uniform field alert. This behavior reflects the main contribution of the method: root-zone stress and source condition were evaluated together within one decision process. Figure 3 presents the relation among soil moisture, source status, and irrigation alerts during a representative monitoring cycle.

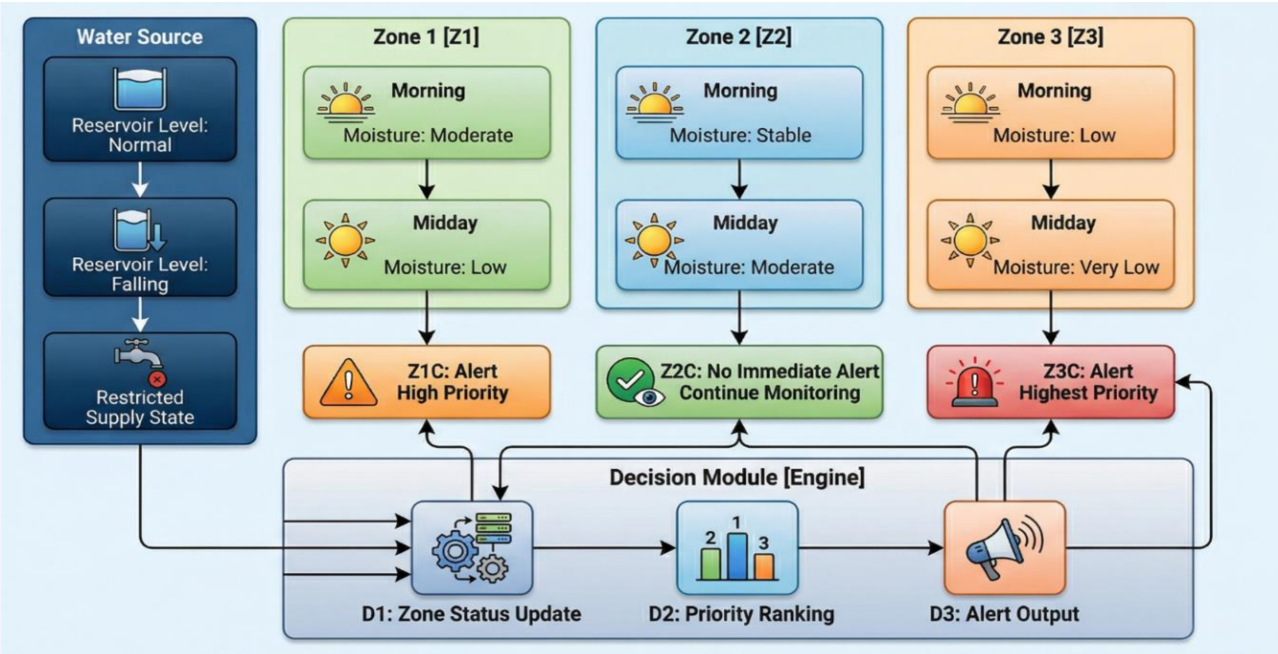

Figure 3. Multi-zone water status, source condition, and irrigation alert progression across a representative monitoring period

B. Node Reliability Screening and Reduction of Fault-Related Alerts

An important result of the study concerns node-health supervision and its effect on irrigation alert quality. In several cases, a sharp decline in reported soil moisture first appeared to indicate urgent water stress. A closer look at the same packet stream showed low battery values, unstable signal strength, or repeated communication gaps. In such situations, the system generated a maintenance flag instead of an irrigation command. This distinction matters because an unchecked dry reading can lead to unnecessary pumping, uneven distribution, or incorrect interpretation of field condition. The proposed method therefore produced more reliable recommendations than a monitoring design that reacts to sensor values alone. This result directly supports the novelty of the framework. Field condition and measurement reliability were handled as linked elements rather than as separate technical tasks. During the observation period, maintenance flags often appeared before complete node failure, which made timely inspection of power status, sensor housing, or communication links possible. That result is valuable for remote agricultural deployment. Table 2 summarizes the difference between raw alert generation and reliability-screened alert generation, including the number of suspected false dry-zone alarms that were avoided through the added node-health layer.

Table 2: Comparative alert behavior before and after node-reliability screening

Metric	Raw sensor-triggered alerts	Reliability-screened alerts	Interpretation
Total irrigation alerts issued	42	31	Fewer alerts after reliability check
Suspected false dry-zone alerts	11	3	Fault-related alarms reduced
Maintenance flags generated	0	9	Hardware and communication issues isolated
Zones requiring immediate irrigation	24	23	Actual irrigation demand largely retained
Repeated alerts from unstable nodes	8	2	Duplicate alert activity reduced
Cases requiring field inspection	5	9	Inspection shifted toward targeted maintenance

C. Temporal Response Patterns and Decision Timing

The temporal behavior of the monitoring system revealed another useful result. Irrigation demand did not appear as a single abrupt event. Instead, the data showed a staged progression from gradual moisture decline to threshold approach and then to alert activation. The proposed system captured this sequence because it processed repeated measurements at fixed intervals and stored trend movement over time. The dashboard therefore showed more than a dry-or-wet label. It also displayed direction of change, which gave farm operators time to review zone behavior before critical conditions appeared. This pattern matters in agricultural water management because delayed recognition of moisture loss can narrow the response window, while overreaction to temporary fluctuation can increase water use without need. The filtering and interval-based monitoring strategy helped separate persistent decline from short-duration noise. Another useful result involved communication timing. Alert output remained consistent even when some packets arrived later than others, since the edge layer preserved time stamps and ordered queued transmissions correctly. Figure 4 shows the sequence from field reading to screened decision output. The figure also illustrates how moisture trend interpretation and node checks shaped the timing of final irrigation recommendations and maintenance messages.

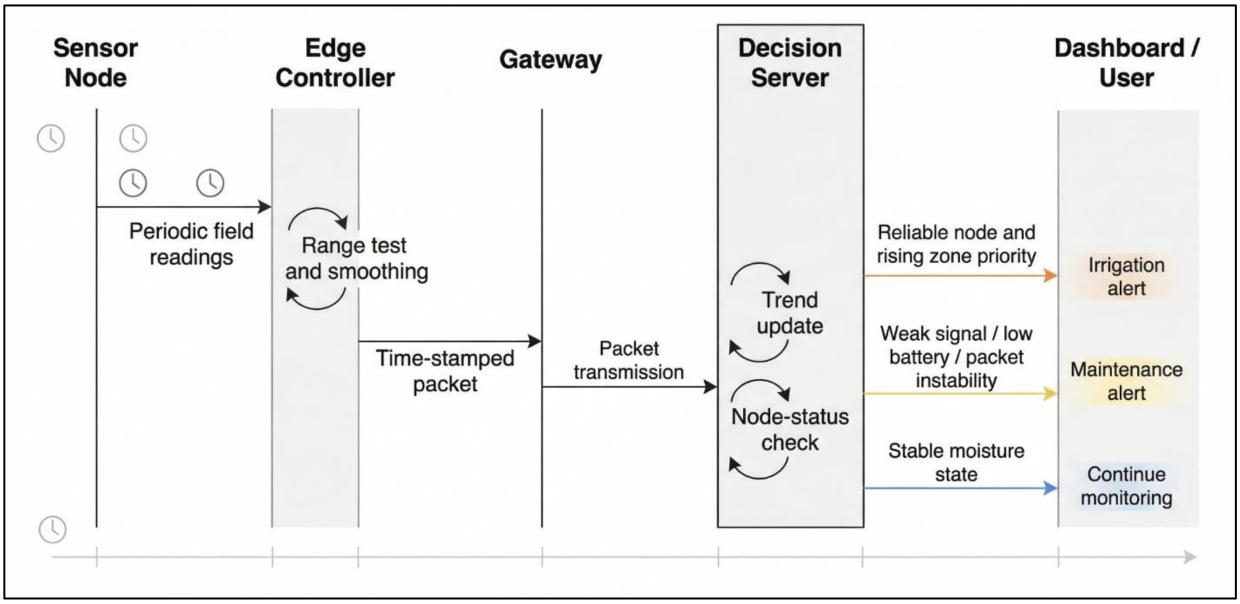

Figure 4: Temporal decision pathway from field measurement to screened irrigation or maintenance action

D. Comparative Performance Against Fixed-Schedule Irrigation

When compared with a fixed-schedule irrigation baseline, the proposed framework produced more selective and context-sensitive recommendations. The baseline approach treated all zones according to preset watering times and did not account for local moisture variation, source condition, or node reliability.

In contrast, the proposed system adjusted recommendations according to current field status. During the evaluation period, this led to fewer unnecessary irrigation triggers in zones that still retained acceptable moisture. At the same time, high-loss zones were identified earlier than they would have been under a uniform schedule. This difference has practical importance because fixed-schedule operation often assumes that all parts of a field behave in the same way over time. The monitored results showed the opposite. Moisture depletion varied across zones, and water-source limitation changed the order in which irrigation should be prioritized. The reliability-screened framework also reduced confusion caused by unstable nodes, something the baseline method could not address. From an operational perspective, the proposed system shifted water management from timing-based action to condition-based action. That shift reflects the central contribution of the study. The results indicate that sensor monitoring becomes more useful when it includes zone differentiation, trend interpretation, and node-condition screening before final recommendation output.

E. Practical Significance, Limits, and Interpretation

The findings indicate that the proposed framework is suited to agricultural settings where water-use decisions must reflect both field condition and monitoring reliability. Its practical contribution lies not only in sensing crop-zone status, but also in separating actual irrigation demand from technical malfunction. This distinction is especially relevant in remote fields, where maintenance delays can make faulty data appear valid if no reliability check is present. The study therefore supports a dual-status monitoring approach in agricultural water systems: one status for field condition and one for node condition. Several limits should also be noted. The present evaluation covered a defined observation period and a selected set of environmental variables. Crop-specific thresholds, seasonal changes, and soil diversity may require local adjustment before deployment in other agricultural regions. Communication conditions also differ across field sites, which may affect packet timing and maintenance frequency. Even with these limits, the results show that the method provides a practical model for zone-based irrigation guidance, fault-aware monitoring, and more controlled water application. In that sense, the framework contributes a field-usable decision structure for sensor-based agricultural water management rather than a monitoring display alone.

V. CONCLUSION

This paper presented a sensor-based monitoring framework for agricultural water management that combines zone-level field sensing and node-reliability assessment within one decision structure. The method addressed limitations found in irrigation practices that rely on fixed schedules or isolated sensor readings without considering system condition. The results showed that irrigation decisions became more accurate when soil moisture, environmental condition, and water-source status were evaluated together. At the same time, node-health supervision reduced false alerts linked to communication instability, low battery status, and sensor faults. The framework supported zone-specific irrigation guidance, stable decision timing, and more reliable monitoring under field conditions. These findings show that agricultural water management can improve when field-data interpretation and system-reliability checks are treated as part of the same operational process.

Future work can extend this framework in several directions. Crop-specific models may refine irrigation thresholds according to growth stage, root depth, and soil type. Weather forecasting data may also be incorporated so that rainfall probability and evaporation trends can inform irrigation timing. Another direction involves automatic control of pumps and valves, allowing the system to move from decision support to direct field action. Testing across larger farms and varied geographic regions would provide additional evidence under different soil, climate, and communication conditions. Further development of low-power communication and edge processing may reduce maintenance demand and support longer deployment cycles. These extensions would widen the practical use of the proposed method in agricultural water management.

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