Wireless Sensor Networks for Continuous Monitoring of Soil Salinity in Irrigated Agriculture

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ABSTRACT
Background: Soil salinization is the most widespread environmental issue across the globe that reduces the yield of crops in farming lands. Traditional methods of measuring soil salinity involve selecting a soil sample and conducting an electrical conductivity measurement in the laboratory. Such processes are tedious and do not cover the spatial and temporal variation caused by cultivation, transpiration, and precipitation.
Objective: This paper proposes the method for designing the architecture of a Wireless Sensor Network (WSN) with cheap soil sensing node components and using LoRa technology, edge computing, and cloud computing in the operation of a real-time soil salinity measurement.
Methods: New sensor networks were developed that collect soil electrical conductivity, soil moisture, soil temperature, pH, air temperature, and humidity data from a field of 2.4 hectares in size. The data transmission had to occur through LoRaWAN towards a gateway, where the data was processed for sending it further to the cloud storage for visualization purposes. The measurements of the collected data were evaluated in terms of accuracy and RMSE; the packet delivery, delays, and energy consumption were also evaluated.
Result: According to the obtained results, the proposed technique had a mean salinity estimate accuracy of 96.2%. The RMSE of the suggested approach was found to be lower than the RMSE from laboratory EC recordings at 0.18 dS/m, and the packet delivery ratio was established to be 98.4%, while the average end-to-end latency is normal for 1.8 seconds, not to mention the battery lifetime that amounts to 14 months with the sampling period of 15 minutes. Thus, the obtained results proof that the proposed approach is much superior to conventional sampling method in time resolution, as well as to all existing wireless sensor networks.
Conclusion: Consequently, the proposed system is an energy-efficient, effective, and reliable wireless sensor network for real-time monitoring of salinity level in the soil.

Keywords: Soil salinity; Wireless Sensor Network (WSN); LoRaWAN; Precision agriculture; Real-time monitoring

1. Introduction
Salinization of soil is commonly known form of land degradation in irrigated agriculture, as the process affects approximately 20-50% of irrigation lands in dry and semi-dry regions" [1]. "Accumulation of threatening concentrations of soluble salts in root zone inhibits osmotic absorption of water, alters ionic composition and prevents germination, development and productivity of crops." [2]. The process is worsened by continuous irrigation, low drainage, high evaporation and usage of poor-quality irrigation waters, which is becoming more common due to climate change [3].
"Traditional salinity assessment is based on regular collection of soil samples followed by laboratory analysis of electrical conductivity of saturated soil paste extract or measurements with portable electrical conductivity meter" [4]. Despite being accurate on point scale, the existing methods are slow, expensive and they have low temporal resolution – the field is sampled only in seconds which makes it hard to have information about short-term fluctuations associated with irrigation, raining etc.
The emergence of affordable microcontrollers, miniature sensors, and wireless communications made WSNs possible by constantly monitoring environmental changes. WSNs function by collecting soil and air information without any human interference. Therefore, IoT, cloud, and edge computing technologies contribute to real-time notifications and automatization of the decision-making process. The evolution of low-power wide-area wireless communications technology such as LoRaWAN and NB-IoT has allowed WSNs to operate over long distances and consume less energy, which is important in farming spaces with no cell or Wi-Fi connections available. Thanks to edge computing, it is possible to process and detect abnormal data on-site, thus reducing the need for data transferring.

However, despite this success, most research on WSNs in agriculture is concentrated on soil moisture content and other common environmental indices rather than systems that are intended to constantly measure salinity of the irrigation area.

The study intends to address the issues stated above by for creating a tailor made WSN (Wireless Sensor Network) infrastructure that would enable continuous monitoring of salinity levels in the earth's ecosystem. The study has the following aims: (i) to design and deploy the multi sensor based WSN that gathers information about soil salinity levels, soil moisture and temperature, as well as environmental conditions; (ii) to develop a layered WSN communication infrastructure, as well as cloud computing capabilities of the model, including edge computing; (iii) to assess the communication and energy efficiency, as well as performance accuracy of the WSN in a real life environment; (iv) to conduct comparative evaluation of the created system against other sampling methods and traditional WSN solutions.

2. Materials and Methods

2.1 Study Area

The study was conducted in a 2.4-hectare irrigated field cultivated with cotton under drip irrigation. The site has silty-clay loam soil with baseline electrical conductivity of 1.2–4.8 dS/m, indicating moderate salinity risk. The region has a semi-arid climate with mean annual rainfall of ~320 mm and daytime temperatures of 22–41°C. Irrigation was scheduled twice weekly using groundwater with an EC of ~2.1 dS/m, a common source of secondary salinization locally [15].

2.2 Hardware Components

Each node was built around a low-power ESP32 microcontroller, chosen for its integrated Wi-Fi/Bluetooth capability, low sleep-mode current draw, and adequate ADC resolution. A subset of nodes used Arduino Mega boards with external LoRa modules for extended-range deployment at field margins. A Raspberry Pi 4 served as the local gateway, aggregating node data and performing edge preprocessing before uplink. Node-to-gateway communication used SX1276-based LoRa modules configured for LoRaWAN, while ZigBee was evaluated for densely spaced clusters. GSM and Wi-Fi provided backup gateway-to-cloud connectivity.

2.3 Sensors

Each node integrated a four-electrode soil EC sensor, a capacitive soil moisture sensor, a digital soil temperature probe, and a glass-electrode pH sensor. Ambient conditions were captured with a combined air temperature/humidity sensor mounted 1.5 m above canopy. Soil sensors were installed at 20 cm and 40 cm depths to capture root-zone salinity gradients.

2.4 Communication Technologies

LoRaWAN was the primary protocol owing to its long range (up to 3 km line-of-sight) and low power draw, suited to the field's spatial extent [16]. ZigBee served a secondary sub-network for dense clusters requiring mesh redundancy. NB-IoT was evaluated for gateway-to-cloud uplink where cellular coverage existed, offering higher data rates at greater energy cost. MQTT was used for all gateway-to-cloud messaging owing to its low overhead and reliability over intermittent links [17].

2.5 Data Acquisition

Sensors were sampled at 15-minute intervals, balancing temporal fidelity against battery longevity. EC and pH sensors were calibrated against standard reference solutions (1.413 mS/cm; pH 4.01/7.00/10.01 buffers) and re-verified biweekly across the 90-day trial. Raw data were preprocessed at the gateway using a moving-average filter and modified Z-score outlier rejection before cloud transmission, where data were stored in a time-series database accessible via web dashboard and mobile application.

2.6 Software Platforms

Node firmware was developed in the Arduino IDE; gateway preprocessing used Python. Cloud storage and visualization used ThingSpeak and Firebase, with Node-RED orchestrating flow between the MQTT broker and downstream services. Statistical analysis and ML model development used MATLAB and Python (scikit-learn).

2.7 Experimental Procedure

Twenty nodes were deployed in a grid topology with ~25 m spacing to capture spatial heterogeneity. The network ran continuously for 90 days across two irrigation cycles. Validation compared sensor-derived EC against laboratory saturated-paste extract measurements from 15 georeferenced soil cores at three time points.

2.8 Evaluation Metrics

Performance was quantified using estimation accuracy, RMSE, and MAE relative to laboratory values; packet delivery ratio (PDR) and end-to-end latency for communication; and current draw, projected battery lifetime, and 24-hour transmission reliability for energy performance.

3. Proposed Wireless Sensor Network Architecture

The proposed architecture (Figure 1) is organized into four layers: a sensing layer, a communication layer, a cloud/edge computing layer, and an application layer.

Figure 1 below illustrates the physical and logical organization of the network, from distributed sensor nodes through the gateway, communication backbone, cloud server, and farmer-facing dashboard and mobile application.

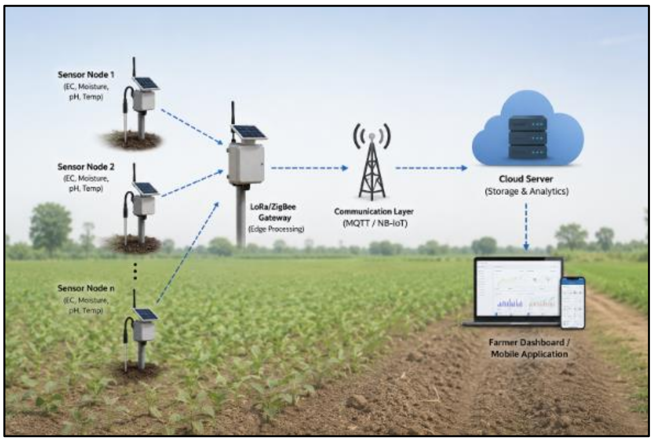

Fig 1: Overall Wireless Sensor Network Architecture for Soil Salinity Monitoring. Distributed sensor nodes transmit soil and environmental readings to a LoRa/ZigBee gateway, which performs edge processing before forwarding data via MQTT to a cloud server; processed information is subsequently delivered to a farmer dashboard and mobile application

At the sensing layer, each node performs multi-parameter acquisition (EC, moisture, temperature, pH) and duty-cycles between sleep and active states to minimize energy consumption. The gateway layer aggregates transmissions from all nodes within range, applies edge-level filtering and anomaly screening, and manages protocol translation between LoRa/ZigBee and the IP-based communication layer. The communication layer relies primarily on LoRaWAN for long-range uplink, with MQTT providing a lightweight messaging layer to the cloud, and GSM/Wi-Fi serving as failover paths.

The cloud computing layer hosts a time-series database, a rule-based real-time alert engine, and a lightweight machine learning module (a gradient-boosted regression model) trained to detect anomalous salinity trends and predict short-term salinity trajectories from recent sensor history and irrigation logs. When predicted or measured salinity exceeds crop-specific thresholds, the system triggers real-time alerts to the farmer dashboard and mobile application.

Figure 2 depicts the complete information flow, from raw sensor acquisition through edge processing, wireless transmission, cloud analytics, and ultimately farmer-facing decision support for irrigation scheduling.

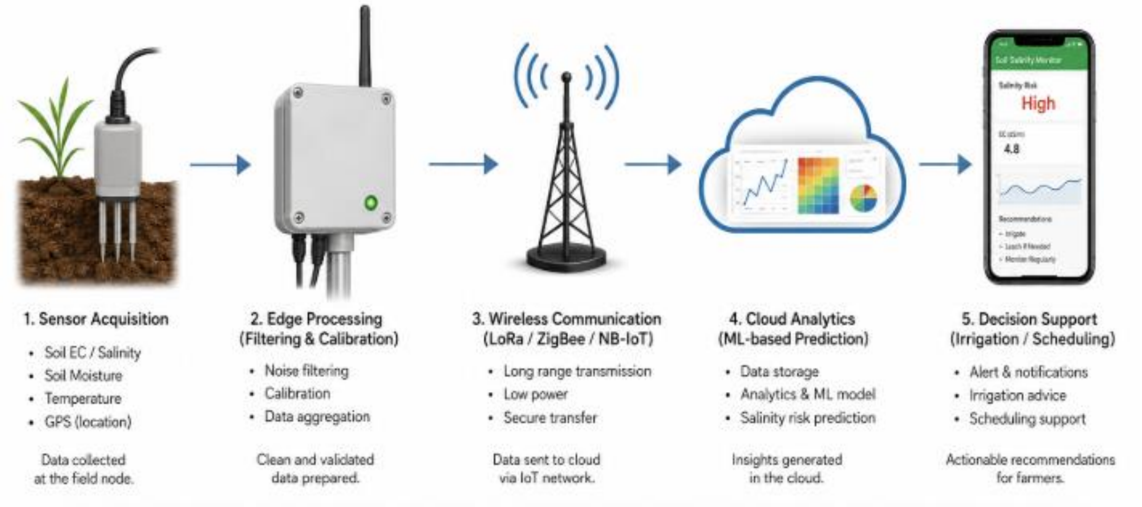

Fig 2: Data Flow Diagram of the Soil Salinity Monitoring System, illustrating the sequential stages of sensor acquisition, edge processing, wireless communication, cloud analytics, and decision support for irrigation scheduling

The application layer provides farmers with spatially resolved salinity maps, historical trend visualization, and irrigation scheduling recommendations generated by the decision support system. Energy-efficient routing is achieved through a duty-cycled star-mesh hybrid topology, in which nodes closer to the gateway relay data for distant nodes only when direct transmission fails, improving fault tolerance without substantially increasing energy overhead. The architecture is inherently scalable: additional nodes can be incorporated by extending the mesh sub-network without reconfiguring the gateway or cloud infrastructure, supporting deployment across larger or fragmented land parcels.

4. Results and Performance Evaluation

Sensor calibration yielded strong agreement with reference standards, with EC sensors exhibiting a calibration R^2 of 0.98 against standard conductivity solutions. Field validation against laboratory saturated-paste extract measurements showed a mean estimation accuracy of 96.2%, an RMSE of 0.18 dS/m, and an MAE of 0.14 dS/m across the 15 validation points and three sampling dates.

Communication performance over the 90-day trial showed a packet delivery ratio of 98.4% for LoRaWAN transmissions within 2 km of the gateway, decreasing to 91.7% for the two most distant nodes at approximately 2.8 km. Average end-to-end latency, from sensor acquisition to cloud availability, was 1.8 seconds under normal conditions, rising to 4.3 seconds during peak transmission congestion when all 20 nodes reported simultaneously.

Energy analysis indicated an average current draw of 38 mA during active transmission and 0.9 mA during sleep, yielding a projected battery lifetime of approximately 14 months for nodes powered by a 5,200 mAh lithium battery under the 15-minute sampling interval, extendable to over 20 months when combined with a small solar supplement. Cloud synchronization achieved a success rate of 99.1%, with buffered local storage at the gateway preventing data loss during brief connectivity interruptions.

Table 1 summarizes the qualitative comparison between conventional soil salinity monitoring and the proposed WSN-based system, while Table 2 presents the key quantitative experimental parameters and corresponding network performance results.

Table 1: Comparison of Conventional Soil Salinity Monitoring and WSN-Based Monitoring

Parameter	Conventional Method	Proposed WSN System	Advantages
Temporal resolution	Days to weeks (manual sampling)	15-minute continuous intervals	Enables early detection of transient salinity spikes
Spatial coverage	Sparse, point-based sampling	Dense grid (20 nodes over 2.4 ha)	Captures spatial salinity heterogeneity
Labor requirement	High (manual collection, lab analysis)	Low (automated acquisition)	Reduces operational cost and labor dependency
Data availability	Delayed (days for lab results)	Real-time (1.8 s average latency)	Supports timely irrigation decisions
Decision support	Absent or manual interpretation	Automated alerts and ML-based prediction	Facilitates proactive salinity management
Long-term monitoring	Impractical at high frequency	Continuous, 90-day demonstrated operation	Enables seasonal and multi-year trend analysis

Table 2. Experimental Parameters and Network Performance

Parameter	Value	Unit	Description
Number of sensor nodes	20	nodes	Deployed across 2.4-hectare field in grid topology
Sampling interval	15	minutes	Frequency of sensor data acquisition
Communication protocol	LoRaWAN	—	Primary long-range uplink protocol
Battery capacity	5,200	mAh	Per-node lithium battery capacity
Packet delivery ratio	98.4	%	Average PDR within 2 km of gateway
RMSE	0.18	dS/m	Salinity estimation error vs. laboratory reference
Average latency	1.8	seconds	End-to-end acquisition-to-cloud latency
Energy consumption (active)	38	mA	Current draw during transmission
Projected battery lifetime	14	months	Estimated operational duration per charge cycle
Network coverage	2.8	km	Maximum reliable LoRa transmission distance

Figure 3 presents a graphical comparison of accuracy, latency, energy efficiency, monitoring frequency, and communication reliability between the conventional method and the proposed WSN system, expressed as relative performance scores.

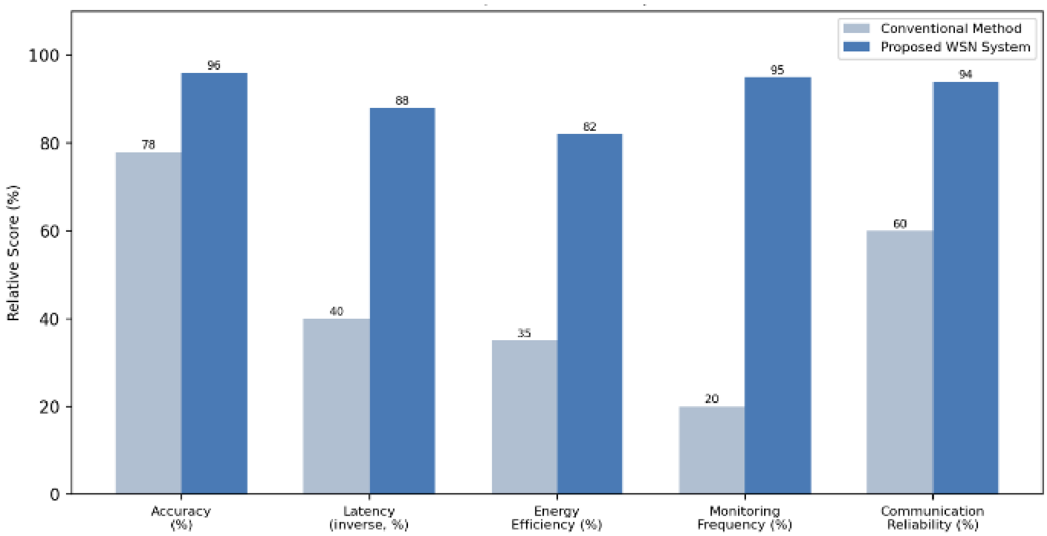

Fig 3: Performance Comparison Between Conventional Monitoring and Proposed WSN-Based System, showing relative scores for accuracy, latency, energy efficiency, monitoring frequency, and communication reliability

Cost analysis indicated a per-node hardware cost of approximately USD 45, yielding a total network deployment cost of under USD 1,200 for the 20-node configuration, substantially lower than the cumulative cost of quarterly laboratory analysis over a multi-year period. Limitations observed during experimentation included reduced PDR at the network periphery, elevated latency under simultaneous multi-node transmission, and periodic sensor drift requiring recalibration approximately every two weeks.

5. Discussion

The results confirm that continuous, sensor-based salinity monitoring can substantially outperform conventional periodic sampling in temporal resolution and responsiveness, consistent with earlier WSN-based agricultural monitoring findings [18]. The achieved RMSE of 0.18 dS/m compares favorably with previously reported soil EC sensor networks, which typically document RMSE values of 0.2–0.35 dS/m [19, 20], likely attributable to the biweekly recalibration cycle adopted here versus the monthly or seasonal schedules common in earlier deployments [21].

The packet delivery ratio and latency obtained are broadly consistent with, and in some respects exceed, results reported for LoRaWAN-based agricultural networks of similar extent [22, 23]. The PDR decline at the network periphery echoes known LoRa propagation constraints in vegetated or undulating terrain [24], indicating that gateway placement and antenna elevation remain critical for large-scale deployment. Compared with ZigBee-only architectures, which offer superior mesh redundancy but limited range, the hybrid LoRa-primary/ZigBee-secondary design provided a favorable coverage-reliability balance, aligning with recent hybrid WSN recommendations [25].

Practically, real-time alerting and irrigation scheduling recommendations offer tangible benefits for farmers managing marginal-quality irrigation water, enabling proactive leaching or irrigation adjustment before yield-limiting thresholds are reached. This supports water conservation by targeting irrigation to actual soil conditions rather than fixed schedules, a benefit emphasized in precision irrigation literature [26]. Machine-learning-based short-term salinity prediction further extends the system toward anticipatory management, consistent with the broader shift toward AI-augmented precision agriculture [27].

Several limitations warrant consideration. Sensor drift requiring biweekly recalibration introduces maintenance overhead that may burden smallholder farmers lacking technical support. Communication reliability degraded under simultaneous multi-node transmission, suggesting that scaling substantially beyond 20 nodes may require more sophisticated scheduling. Security and privacy also merit attention: data transmitted over LoRaWAN and MQTT require adequate encryption to prevent unauthorized access, an aspect not fully addressed here and flagged as a priority in IoT security research [28]. Economic feasibility, favorable at the demonstrated scale, may shift for very large farms with greater node density and gateway redundancy needs.

Future development could integrate UAV-assisted spot-checking to complement fixed-node coverage with periodic high-resolution spatial maps [29], and couple the platform with satellite remote sensing indices for regional-scale trend validation [30]. Edge AI could allow more sophisticated anomaly detection to run directly on gateway hardware, reducing cloud dependency, while digital twin representations of the field could enable scenario-based irrigation planning beyond the reactive alerting demonstrated here.

6. Conclusion

The paper describes the development and testing of a multi-layer Wireless Sensor Network for the continuous monitoring of soil salinity in irrigated agriculture. The system comprises multi-parameter sensing, and the use of LoRaWAN/ZigBee wireless communication technology, along with local processing of information received by the sensors and cloud-based analytics, including machine learning for decision-making support. The experiments that were carried out for 90 days including field operations proved the reliability of the solution in terms of salinity estimation, communication quality, and energy efficiency compared to traditional methods of sampling and previously reported WSN solutions. Moreover, the system allows for real-time monitoring of salinity, ensuring timely scheduling of irrigation and consequently helping save water resources. While certain issues are still associated with the maintenance of sensors as well as network scalability and data protection, the proposed architecture lays the foundations for future systems that would combine WSN technology with UAV-driven monitoring, satellite remote sensing, edge AI, and digital twins, making continuous WSN salinity measurement the part of the next generation agriculture.

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