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IoT-Enabled Precision Irrigation and AI-Based Crop Monitoring for Optimising Water Use and Crop Productivity

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Abstract

Agricultural production is increasingly challenged by water scarcity, climatic variability, rising input costs and the need to improve productivity without increasing pressure on natural resources. Precision irrigation supported by the Internet of Things (IoT) provides an opportunity to replace fixed or experience-based irrigation schedules with decisions informed by real-time field observations. This paper examines an integrated approach in which soil-moisture and environmental sensors continuously collect information, wireless communication transfers the observations to a processing platform, and artificial intelligence (AI) assists in interpreting field conditions and determining irrigation requirements. The proposed framework combines soil moisture, soil temperature, air temperature, relative humidity, rainfall and crop-growth information with irrigation and yield records. A comparative field design involving conventional and smart-irrigation practices can be used to evaluate water consumption, irrigation frequency, crop growth, yield, water-use efficiency and economic performance. Descriptive statistics, correlation analysis, regression modelling and appropriate comparative tests can be used to assess relationships between sensor-derived variables and agricultural outcomes. AI models such as Random Forest, Support Vector Machine and Artificial Neural Networks may be evaluated for irrigation requirement prediction, subject to the availability and quality of sufficient field data. The approach is intended to demonstrate how IoT-generated information can support timely irrigation decisions while reducing unnecessary water application. Rather than assuming that technology automatically produces savings, the study emphasizes field calibration, sensor reliability, farmer usability, affordability and local agro-climatic conditions. The proposed framework is particularly relevant to small and medium-scale farms where water-use efficiency and low-cost decision-support mechanisms are important considerations.

Keywords: Internet of Things, precision irrigation, smart farming, artificial intelligence, soil moisture, crop monitoring, water-use efficiency, precision agriculture.

1. Introduction

Agriculture increasingly requires production systems capable of responding to changing climatic conditions while using water and other inputs more efficiently. Conventional irrigation practices commonly depend on fixed schedules, visual assessment, farmer experience or generalized recommendations. Although such approaches can be effective under relatively stable conditions, they may not adequately reflect temporal changes in soil moisture, rainfall, temperature and crop water requirements. Precision irrigation seeks to address this problem by applying water according to field and crop conditions rather than treating the entire production area as spatially and temporally uniform.

The development of Internet of Things technologies has expanded the possibilities for precision irrigation. IoT systems can connect field sensors, communication networks, data-processing platforms and decision-support applications. Soil-moisture sensors, for example, can provide direct information about water availability in the root zone, while weather sensors can capture environmental variables affecting evapotranspiration and crop water demand. Recent reviews describe IoT-based irrigation as an increasingly important approach for real-time monitoring, automated scheduling and resource optimisation.

The integration of AI adds an analytical dimension to this architecture. Instead of merely displaying sensor readings, an AI model can identify relationships among soil, weather, crop and irrigation variables and potentially estimate irrigation requirements. Thus, the combination can be conceptualised as:

Sensors → Communication → Data Processing → AI Analysis → Irrigation Recommendation → Field Action → Feedback

This integrated structure is consistent with the broader development of Agriculture 4.0, in which connected sensing, data analytics and automated decision-making are used to support agricultural management.

2. Review of Related Literature

2.1 IoT in Precision Irrigation

IoT-based agricultural monitoring generally consists of three functional elements: sensing, communication and application. Sensors collect field observations; communication technologies transmit the information; and software platforms transform the observations into information useful for management.

Soil moisture is particularly important because irrigation should ideally respond to water availability within the crop's effective rooting zone. Additional variables such as soil temperature, air temperature, humidity and rainfall can improve interpretation of moisture conditions. Wireless sensor networks have consequently become an important component of agricultural monitoring systems. Earlier research demonstrated the feasibility of distributed wireless sensing for irrigation scheduling, while subsequent studies have incorporated IoT and remote communication technologies.

The communication layer may employ Wi-Fi, Bluetooth/BLE, cellular networks or low-power wide-area technologies such as LoRaWAN. The appropriate choice depends on farm size, connectivity, energy requirements, terrain and cost. LoRa-based systems are particularly relevant where low-power, long-distance communication is required, although network infrastructure and gateway availability must be considered.

2.2 AI-Assisted Irrigation

IoT produces data, but data alone does not guarantee better irrigation decisions. AI and machine learning can provide a mechanism for identifying patterns within multidimensional agricultural datasets. Regression models can estimate continuous irrigation requirements, whereas classification models can categorize conditions such as **irrigation required** and **irrigation not required**.

Potential input variables include:

- Soil moisture
- Soil temperature
- Air temperature
- Relative humidity
- Rainfall
- Crop growth stage
- Previous irrigation
- Historical yield
- Weather forecasts, where available

3. Research Objectives

1. To evaluate the effectiveness of IoT sensors for real-time monitoring of soil and environmental conditions.
2. To develop an AI-assisted approach for estimating crop irrigation requirements.
3. To compare conventional and sensor-based irrigation with respect to water consumption and irrigation frequency.
4. To assess the influence of irrigation optimisation on crop growth and yield.
5. To evaluate the economic and practical feasibility of IoT-enabled precision irrigation for small and medium-scale farms.

4. Research Methodology

4.1 Research Design

A quantitative field-experimental design is appropriate for assessing the effectiveness of IoT-enabled precision irrigation. Where feasible, farms or comparable field plots can be divided into two groups:

Group	Irrigation approach	Main basis of decision
Control	Conventional irrigation	Existing farmer practice
Intervention	Smart irrigation	Sensor and AI-assisted recommendation

The study should avoid assuming that the intervention will necessarily outperform conventional practice. Instead, the comparison should empirically determine whether measurable differences occur.

4.2 IoT Architecture

The proposed architecture is:

Field Conditions → Sensors → IoT Gateway → Cloud/Edge Platform → Database → AI Model → Irrigation Recommendation → Controller/Farmer → Field → Feedback

The sensing layer can include:

Sensor/Source	Variable	Purpose
Soil-moisture sensor	Volumetric soil moisture	Determine soil-water status
Soil-temperature sensor	Soil temperature	Characterise root-zone conditions
Weather station	Air temperature	Estimate environmental demand
Humidity sensor	Relative humidity	Support atmospheric assessment
Rain gauge	Rainfall	Account for natural water input
GPS/GNSS	Location	Associate observations with field position
Crop observations	Growth stage	Adjust irrigation requirement

4.3 Data Collection

Sensor readings should be collected at a predetermined interval appropriate to the crop, sensor capabilities and research objectives. Each observation should include a timestamp and, where applicable, geographical or plot identification.

The database should contain:

- Sensor observations
- Irrigation events
- Irrigation duration
- Estimated or measured water volume
- Rainfall
- Crop-growth observations
- Fertiliser applications
- Crop-health observations
- Final harvested yield
- Production costs

Sensor calibration and missing-data management are particularly important because erroneous measurements can propagate through the AI model and produce inappropriate recommendations.

5. AI Model Development

The AI component should follow a reproducible pipeline:

Data collection → Data cleaning → Feature engineering → Training/testing split → Model training → Hyperparameter optimisation → Validation → Performance evaluation

Possible models include:

Random Forest

Random Forest can model nonlinear relationships and interactions between soil and weather variables while generally requiring limited assumptions about the functional form of those relationships.

Support Vector Machine

Support Vector Machine can be useful for classification problems, such as determining whether irrigation is required. Its performance, however, depends on appropriate feature scaling and parameter selection.

Artificial Neural Network

ANNs can capture complex nonlinear relationships among environmental variables. Their disadvantage is that they can require substantial training data and may be less interpretable than simpler models.

6. Performance Evaluation

Cross-validation should be used where the available dataset permits it, with careful attention to temporal dependence. Randomly mixing highly related observations from the same time period between training and testing can produce overly optimistic estimates of predictive performance.

7. Field-Level Evaluation

The technical performance of the system should ultimately be connected with agricultural outcomes.

Important indicators include:

Indicator	Measurement
Water consumption	Total irrigation water applied
Irrigation frequency	Number of irrigation events
Water-use efficiency	Yield relative to water used
Crop yield	Harvested yield per unit area
Input cost	Irrigation-related expenditure
Labour requirement	Labour used for irrigation
Net return	Gross return minus production costs

A central comparison can therefore be expressed as:

Conventional irrigation → Water use → Crop growth → Yield → Cost

versus

IoT/AI irrigation → Water use → Crop growth → Yield → Cost

The purpose is not simply to minimize water use. Excessive reduction in irrigation could negatively affect crop development and yield. The desired outcome is therefore optimal water application, not minimum water application.

8. Proposed Smart Irrigation Decision Framework

The proposed decision mechanism can operate as follows:

1. Sensors measure soil and environmental conditions.
2. Data are transmitted to the gateway or processing platform.
3. Data are checked for missing or abnormal observations.
4. Relevant features are extracted.
5. The AI model estimates irrigation requirement or irrigation status.
6. The system compares the prediction with predefined agronomic thresholds.

7. An irrigation recommendation is generated.
8. The farmer or automated controller initiates irrigation.
9. Subsequent sensor measurements assess the effect.
10. New observations are incorporated into the decision process.

9. Expected Contribution

The principal contribution of the proposed research is the integration of three components that are often considered separately: real-time sensing, intelligent analysis and field-level irrigation management.

The technical contribution lies in establishing an IoT architecture capable of collecting continuous agricultural observations. The analytical contribution lies in evaluating AI models for irrigation-related prediction. The agricultural contribution lies in assessing whether these technologies can improve water-use efficiency without compromising crop productivity. Finally, the socio-economic dimension addresses whether such a system is realistic for small and medium-scale farms.

10. Conclusion

IoT-enabled precision irrigation provides a pathway from conventional schedule-based irrigation towards continuous, data-driven water management. Soil-moisture and environmental sensors can provide information about changing field conditions, while communication networks allow these observations to reach farmers or analytical platforms. AI can subsequently assist in transforming multidimensional sensor information into irrigation recommendations.

The most meaningful evaluation, however, must extend beyond technological performance. A successful smart irrigation system should demonstrate an appropriate balance between water conservation, crop productivity, economic feasibility, reliability and farmer usability. The proposed IoT–AI framework therefore provides a suitable basis for field experimentation and for examining whether smart irrigation can contribute to more efficient and sustainable crop production.

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