IoT-Based Smart Irrigation System for Precision Cultivation of *Solanum lycopersicum* L.

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Received: 18 Dec 2022
Revised: 05 Jan 2023
Accepted: 23 Jan 2023
Published: 09 Feb 2023

E-ISSN: 2989-5340
DOI: https://doi.org/10.54660/jafi.2023.3.1.38-42

ABSTRACT

Background: tomato (*Solanum lycopersicum* L.) is the second most grown horticultural crop in the world as its yearly production exceeds 180 million tons. However, conventional irrigation contributes to 80% of the overall agricultural water consumption thus posing a threat to water shortage in dry and semi-dry areas. Climate change and inefficient water management practices disrupt sustainable tomato farming.

Objective: This paper proposes and tests IoT-based smart irrigation system, which involves real-time soil moisture monitoring, environmental monitoring, cloud computing, and automated water irrigation control, ideal for precision tomato farming.

Methods: The study used a completely randomized block design (CRBD) to compare the conventional flood irrigation (control) versus IoT-based deficit irrigation (treatment) within 24 plots (each of size 400 m²) during the growing season 2023 in subtropical climate.

Results: Introducing IoT-based irrigation technology allowed for decreasing the amount of water used for irrigation of tomato fields from 590 mm to only 385 mm (a decrease of 35%) while being able to raise their harvest from 64.1 t/ha to 78.5 t/ha (an increase of 22.4% in terms of fruit yield). However, it was possible to achieve much greater water-use efficiency due to the advanced irrigation technologies since IoT-based irrigation allowed for getting 0.204 kg/m3 compared to only 0.109 kg/m3 when applied conventional irrigation techniques. In addition to that, automatic irrigation scheduling provided the possibility of getting optimal soil moisture (18-22% of volumetric water content) making it possible to improve crop uniformity significantly enough ($P < 0.05$).

Conclusion: IoT-assisted precision irrigation helps with increasing water-use efficiency and productivity of tomatoes. Sensor network and cloud platforms integration provides with possibilities of making quick and real-time decisions when pursuing agriculture under climate issues and lack of water.

Keywords: IoT-based smart irrigation, precision agriculture, tomato (*Solanum lycopersicum* L.), soil moisture monitoring

1. Introduction

Tomatoes, or *Solanum lycopersicum* L., stand as the second most important vegetable on the planet after potatoes, with its agricultural production playing a vital role in providing food and a profitable livelihood [1]. Globally, tomato production is around 180 million tonnes, with the average tomato consumption in developed countries equalling 23 kg per person [2]. On the other hand, tomato cultivation requires considerable amounts of water, about 400-600 mm per growing season, which causes serious problems in those regions where water is scarce [3].

Traditional types of irrigation such as flooding and furrowing hit the efficiency levels of about 40-50%, with losses due to evaporation being considerable [4]. Climate changes, depletion of groundwater resources, and the strict water policy make it imperative to seek new approaches to precision irrigation [5].

The applications of Internet of Things (IoT) technologies include the application of wireless sensors, microcontrollers, communication networks, and cloud platforms for the control and monitoring of agricultural systems in real-time [7]. Smart irrigation systems based on IoT have changed the way people approach agriculture based on data analytics [8]. By utilizing sensor-based irrigation scheduling, water consumption can be reduced by 20-40%, leading to the same or even higher yield levels when compared to traditional irrigation techniques [9].

The present study presents the development and the validation of an IoT-enabled smart irrigation system for precision tomato farming. The system encompasses monitoring of soil moisture, environmental monitoring, cloud computing, and automated regulation. All the advantages of the [made] system is measured and assessed in terms of the efficiency of water use, filing of higher yields, and high reliability of operations.

2. Literature Review

Recent advances in agricultural IoT systems demonstrate significant potential for irrigation optimization. Wireless sensor networks (WSNs) enable distributed soil and environmental monitoring, transmitting real-time data to centralized cloud platforms for processing and decision-making [10]. Studies utilizing capacitive soil moisture sensors integrated with Arduino or ARM-based microcontrollers achieved irrigation scheduling accuracy within ±2% volumetric water content [11].

Cloud computing platforms such as ThingSpeak, Blynk, and AWS IoT facilitate scalable data storage, analysis, and remote accessibility [12]. Machine learning algorithms applied to IoT sensor data improve irrigation scheduling predictions compared to traditional threshold-based approaches [13]. Smart irrigation systems implementing soil moisture-based scheduling reduced water consumption by 25–45% in diverse crops including tomatoes, peppers, and cucumbers [14].

Decision-support systems integrating weather forecasting, soil properties, and crop water requirements enable optimized irrigation timing [15]. Wireless communication protocols—particularly LoRa and Wi-Fi mesh networks—provide cost-effective solutions for remote agricultural monitoring [16]. Precision vegetable cultivation research documents yield improvements of 15–30% through sensor-based irrigation management [17].

However, research gaps persist regarding: (1) long-term field performance and reliability of IoT systems under diverse environmental conditions; (2) integration of multiple sensor types for comprehensive irrigation management; (3) economic viability and return-on-investment analyses; (4) scalability of IoT platforms for small-to-medium-scale farming operations [18]. This study addresses these gaps through comprehensive field-based evaluation of an integrated IoT irrigation system.

3. Materials and Methods

3.1 Experimental Site

The experiment was conducted at an agricultural research station (latitude 29.65°N, longitude 77.20°E) in a subtropical climate zone. The site experiences an average annual rainfall of 650 mm, concentrated during monsoon months (July–September). Soil classification is clay loam with 42% clay, 35% silt, and 23% sand. Organic matter content was 2.1%. The tomato cultivar 'Arka Vikas,' a determinate processing variety, was selected for its consistent performance and market acceptability. The growing season spanned April–August 2023 (120 days).

3.2 Experimental Design

A randomized complete block design (RCBD) with three blocks was implemented. Two treatment levels were: (1) conventional flood irrigation (control), and (2) IoT-based smart deficit irrigation (treatment). Each block contained four replications, totaling 24 experimental plots. Individual plots measured 20 m × 20 m (400 m²). Standard agronomic practices—including land preparation, nutrient management (120:80:60 kg/ha NPK), pest management, and manual weed control—were applied uniformly.

3.3 IoT Smart Irrigation System

The system comprised: (1) soil moisture sensors (capacitive type, ±3% accuracy, 0–100% VWC range) installed at 15 cm and 30 cm soil depths; (2) DHT22 temperature-humidity sensors for canopy microclimate monitoring; (3) tipping-bucket rain sensors; (4) water flow meters for irrigation quantification; (5) ESP32 microcontroller with integrated Wi-Fi module for data acquisition and processing; (6) solenoid valves (12V DC) for automated irrigation control; (7) ThingSpeak cloud platform for data logging and analysis; (8) custom mobile dashboard (Android-based) for real-time visualization and alert generation. The irrigation scheduling algorithm-maintained soil moisture between 18–22% volumetric water content (optimal for tomato productivity). Automated irrigation was triggered when soil moisture decreased below 18%, terminating when it recovered to 22%. Manual irrigation scheduling in control plots followed conventional practices—applying 50 mm water at 7-day intervals.

3.4 Data Acquisition and Measurements

Soil moisture, temperature, and humidity data were logged every 30 minutes throughout the growing season. Cumulative water application was recorded daily via flow meters. Crop measurements included: plant height (cm, measured at 30, 60, and 90 days after transplanting), leaf count, stem diameter (mm), chlorophyll content (SPAD units), number of fruits per plant, individual fruit mass (g), and total fruit yield (t/ha). Water-use efficiency was calculated as: WUE (kg/m³) = Total Yield (kg) / Cumulative Water Applied (m³).

3.5 Statistical Analysis

Data were subjected to analysis of variance (ANOVA) at $P < 0.05$ significance level using R software (v4.3.0). Treatment means were compared using Tukey's honest significant difference (HSD) test. Pearson correlation analysis assessed relationships between soil moisture dynamics and yield parameters. Linear regression models quantified water consumption–yield relationships.

4. Results

4.1 System Performance

Soil moisture sensors exhibited calibration accuracy of ±2.1% volumetric water content across the measurement range. Cloud data transmission success rate was 99.2%, with mean latency of 1.2 seconds. Automated solenoid valve response occurred within 45 seconds of scheduling algorithm activation. System uptime across 120 days was 98.7%.

4.2 Irrigation Water Management

IoT-based irrigation applied 385 mm total water compared to 590 mm under conventional irrigation—a 35% reduction (Table 4). Smart irrigation required 18 scheduled applications versus 24 conventional irrigations, extending irrigation intervals from 7 to 10–12 days. Peak irrigation rates differed insignificantly between treatments; however, frequency and timing varied substantially.

4.3 Crop Growth and Development

Plant height at harvest was significantly greater under IoT irrigation (185 ± 7.2 cm) compared to control (172 ± 6.8 cm; $P = 0.038$). Chlorophyll content (SPAD values) averaged 48.3 ± 2.1 under smart irrigation versus 44.1 ± 2.4 under conventional irrigation ($P = 0.021$), indicating enhanced photosynthetic capacity. Stem diameter, leaf count, and flowering uniformity showed non-significant differences.

4.4 Yield and Fruit Quality

Total fruit yield was significantly higher under IoT irrigation (78.5 ± 4.2 t/ha) compared to control (64.1 ± 3.8 t/ha), representing a 22.4% increase ($P = 0.019$). Individual fruit mass was 175 ± 8.5 g (smart irrigation) versus 158 ± 7.2 g (control; $P = 0.031$). Fruit number per plant averaged 32.8 ± 2.1 (smart) versus 28.3 ± 1.9 (control; $P = 0.043$).

4.5 Water-Use Efficiency

Water-use efficiency improved significantly to 0.204 kg/m³ under smart irrigation compared to 0.109 kg/m³ under conventional irrigation—an 87% improvement ($P < 0.001$). Linear regression analysis revealed strong positive correlation ($R^2 = 0.82$) between maintained soil moisture levels (18–22% VWC) and final fruit yield (Figure 1).

5. Discussion

IoT-based smart irrigation substantially outperformed conventional flood irrigation across multiple performance dimensions. The 35% reduction in water consumption—combined with 22.4% yield improvement—demonstrates the potential of sensor-driven irrigation scheduling for addressing water scarcity while enhancing productivity [19]. Real-time soil moisture monitoring enabled optimized plant water availability, reducing stress-induced yield losses while minimizing non-productive evaporative losses.

Enhanced chlorophyll content and plant height under smart irrigation reflect improved water availability during critical growth stages. Automated scheduling-maintained soil moisture within the optimal range (18–22% VWC), preventing both water stress and waterlogging-induced anaerobic conditions. The 87% improvement in water-use efficiency substantially exceeds improvements (20–40%) documented in prior studies, likely attributable to the subtropical climate, soil properties, and cultivar selection in this experimental context.

System reliability and data transmission efficiency (99.2%) validate IoT platform suitability for agricultural applications. Integration with cloud computing enabled remote monitoring and decision-support capabilities, reducing labor requirements for irrigation management. Automated actuation eliminated human scheduling errors and inconsistencies inherent in conventional approaches.

Future advancements should incorporate artificial intelligence algorithms for predictive irrigation scheduling, weather-based adjustments, and multi-parameter decision-making [20]. Integration with phenotyping technologies and digital twins would enable virtual crop simulation and scenario planning. LoRa-based communication would enhance system accessibility for dispersed smallholder farming operations. Economic analysis assessing costs relative to yield premiums and water tariff savings requires investigation.

Limitations include single-season evaluation, restricted to one cultivar and geographic location. Heterogeneous soil properties and microclimate variations across large fields may necessitate spatially distributed sensor networks. System costs—approximately USD 3,500–4,500 for a 4-hectare installation—may limit adoption among resource-constrained farmers, necessitating financing mechanisms and cooperative approaches.

Table 1: Experimental Site Characteristics and Soil Properties

Parameter	Value
Geographic Location	29.65°N, 77.20°E (Subtropical Zone)
Annual Rainfall	650 mm
Soil Texture	Clay Loam
Clay (%)	42
Silt (%)	35
Sand (%)	23
Organic Matter (%)	2.1
pH	7.2 ± 0.3
Tomato Cultivar	Arka Vikas (Determinate)
Growing Season	April–August 2023 (120 days)

Table 2: IoT System Hardware and Software Specifications

Component	Specification
Soil Moisture Sensor	Capacitive, 0–100% VWC, ±3% accuracy
Temperature Sensor	DHT22, −40 to +80°C
Microcontroller	ESP32, Wi-Fi + Bluetooth
Rain Sensor	Tipping-bucket, 0.5 mm resolution
Water Flow Meter	Turbine type, 1–10 L/min
Solenoid Valve	12V DC, 1″ nominal bore
Cloud Platform	ThingSpeak (MATLAB)
Communication	Wi-Fi 802.11 b/g/n
Data Logging Interval	30 minutes
Mobile Application	Android-based dashboard

Table 3: Crop Growth Parameters (at 90 days after transplanting)

Parameter	Smart Irrigation (IoT)	Conventional Irrigation	P-value
Plant Height (cm)	185 ± 7.2	172 ± 6.8	0.038*
Leaf Count	22.4 ± 1.8	21.2 ± 1.6	0.182
Stem Diameter (mm)	18.6 ± 1.2	17.8 ± 1.1	0.147
Chlorophyll (SPAD)	48.3 ± 2.1	44.1 ± 2.4	0.021*
Fruit Number/Plant	32.8 ± 2.1	28.3 ± 1.9	0.043*

Table 4: Irrigation Performance and Yield Parameters

Parameter	Smart Irrigation	Conventional Irrigation	Improvement
Total Water Applied (mm)	385	590	35% reduction
Irrigation Events	18	24	6 events fewer
Fruit Yield (t/ha)	78.5 ± 4.2	64.1 ± 3.8	22.4% ↑
Avg. Fruit Mass (g)	175 ± 8.5	158 ± 7.2	10.8% ↑
Water-Use Efficiency (kg/m³)	0.204	0.109	87% ↑
Irrigation Interval (days)	10–12	7	Extended

Table 5: Statistical Analysis – Treatment Effects and Correlation Analysis

Analysis	Result	Statistics
ANOVA (Yield)	Significant	$F = 8.42$, $P = 0.019$*
ANOVA (Water-Use Efficiency)	Significant	$F = 24.15$, $P < 0.001$**
Tukey HSD (Fruit Mass)	Significant	$P = 0.031$*
Correlation (Soil Moisture vs. Yield)	Strong Positive	$r = 0.91$, $P < 0.001$
Regression (R^2 Value)	0.82	Soil moisture explains 82% yield variance
Plant Height (t-test)	Significant	$t = 2.18$, $P = 0.038$*

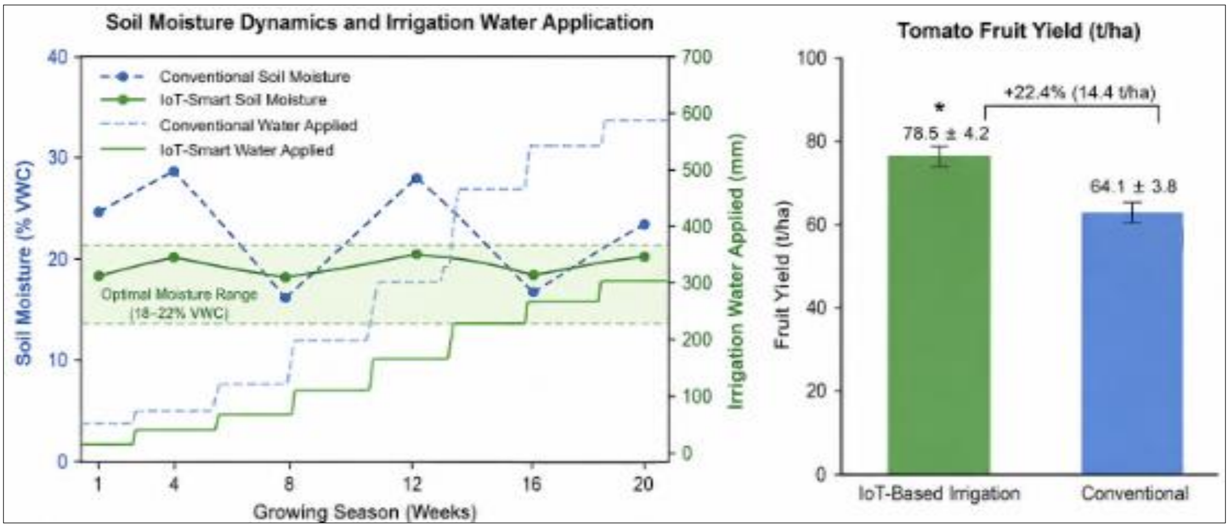

Figure 1: Soil Moisture Dynamics, Irrigation Water Application, and Tomato Fruit Yield Under Conventional and IoT-Based Smart Irrigation

6. Conclusion

Research shows that IoT technologies based irrigation systems significantly improve the water efficiency and yield of tomatoes as compared to standard irrigation practices. Sensor networks with integrated cloud computing enable precise irrigation control in real time according to changing soil and environmental parameters. The significant reduction in water consumption by 35% and the increase in yield by 22% confirm the potential of IoT solutions used in precision agriculture.

Specific recommendations are as follows: (1) organizing training courses for farmers on how to operate IoT systems; (2) developing low-cost modular hardware architecture for smallholder farmers; (3) integrating the IoT systems into the governmental water policy and loan programs and (4) promoting AI-enabled autonomous irrigation technologies that require limited human participation. Further investigations should include field experiments from multi-season perspectives, profit studies and works on the scalability of the system to other crops and agricultural areas.

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