Research Article

Practical Integration of IoT, Intercropping, and Gravity-Fed Drip Systems for Water-Efficient Smallholder Farming

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Abstract: Water scarcity presents a growing challenge to agricultural productivity in developing regions. This paper presents an integrated approach combining IoT precision irrigation, intercropping techniques, and gravity-fed drip systems for smallholder farmers. Laboratory experimentation utilized an ATmega2560 microcontroller with environmental sensors across three upland crop systems. A scalable field deployment architecture was designed using STM32 microcontrollers with CC1101 RF modules. Mathematical modeling revealed significant water savings: IoT precision irrigation alone (8.6%), intercropping with IoT (19.0%), gravity-fed drip irrigation (22% baseline), and 28.7% when IoT integrates with gravity-fed systems, with complete integration achieving 36.9%. Assessment of implementation feasibility showed intercropping ranked highest due to low implementation barriers, while IoT systems ranked lowest despite their technological benefits. The study proposes a phased implementation roadmap that prioritizes accessible techniques before technological investments, effectively bridging advanced irrigation technology with practical smallholder agriculture deployment. Future research should explore climate-specific adaptations and economic optimization models for broader implementation.

Keywords: Intercropping Systems, Gravity-Fed Drip Irrigation, IoT, Precision Irrigation, Water Conservation, Smallholder Agriculture

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1. Introduction

Agriculture plays a fundamental role in developing regions, where smallholder farmers are particularly important for food security. Research shows that farms under 2 hectares produce 30-34% of the global food supply while maintaining higher crop diversity than larger agricultural operations (Ricciardi et al., 2018). However, smallholder farmers in these regions face significant challenges, including limited water resources, climate change impacts, and inefficient irrigation practices (Opare, 2018; Tzanakakis et al., 2020).

Precision agriculture, especially IoT-based irrigation systems, has emerged as a prominent solution to address these challenges (Obaideen et al., 2022). These systems have been widely promoted for their potential to optimize water use, improve crop yields, and enhance overall farm management (Morchid et al., 2025). The growing affordability and accessibility of IoT technologies have led to increasing emphasis on these technological approaches, with numerous studies focusing primarily on IoT implementations for smallholder agriculture (Lamsal et al., 2023; Monchusi et al., 2024; Nigussie et al., 2020). However, the successful implementation of IoT and wireless sensor networks in smallholder agriculture faces significant challenges related to digital transformation practices and sustainability concerns (Bayih et al., 2022; Yuan & Sun, 2024).

For smallholder farmers, as shown in Figure 1, a common strategy to maximize land use and diversify crop production is intercropping. In such systems, precision irrigation becomes even more critical due to the differing water requirements of various crops (Andrews & Kassam, 1976; Morris & Garrity, 1993). While much of the technological focus has been on IoT-based solutions, it is valuable to explore how these modern systems can be integrated with traditional agricultural practices.

The integration of Internet of Things (IoT) technology into irrigation systems has garnered significant attention, resulting in numerous implementations worldwide, including in Sub-Saharan Africa and East Africa (Antony et al., 2020; Nigussie et al., 2020). This automation, coupled with IoT technology, is widely promoted as a means to enhance water management, save time, optimize human labor utilization, and ultimately improve productivity (Gnanavel et al., 2022; Yasin et al., 2019).

Despite the growing technological focus, our research suggests that an integrated approach, combining modern IoT precision irrigation systems with traditional practices like intercropping and gravity-fed irrigation, may offer superior water conservation results compared to technological interventions alone. As smallholder farmers increasingly gain access to affordable IoT devices, it becomes important to evaluate whether these technologies deliver optimal outcomes independently or if they perform best when integrated with established farming methods.

2. **Research Objectives**

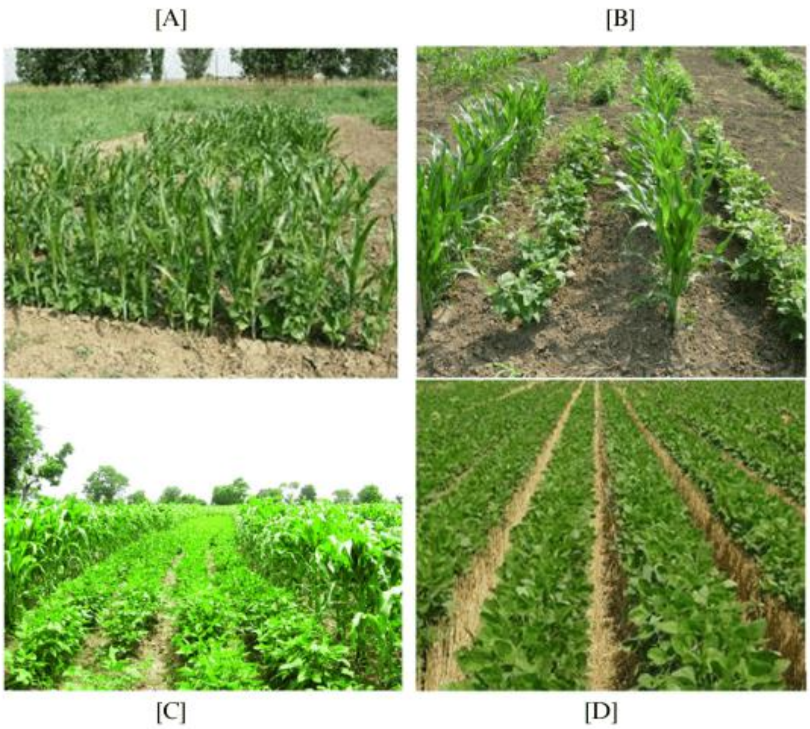

Figure 1. Common East African Community (EAC) cropping systems in smallholder agriculture showing [A] Mixed intercropping, [B] Row intercropping, [C] Strip intercropping, and [D] Relay intercropping.

This study addresses the critical knowledge gap regarding optimal water conservation strategies for smallholder agriculture through a comprehensive comparative analysis of IoT precision irrigation systems and traditional conservation methods. The research objectives include:

- Develop and evaluate an IoT-based precision irrigation architecture for laboratory testing.
- Quantify water conservation performance across IoT precision irrigation, intercropping systems, and gravity-fed drip irrigation through controlled experiments and mathematical modeling.
- Assess implementation feasibility by comparing technical requirements and accessibility factors.
- Propose phased implementation approaches for water-efficient agriculture in smallholder contexts.

3. Materials and Methods

Our research approach consisted of laboratory experimentation and field deployment architecture development. This dual-phase methodology allowed us to test the system's core functionality under controlled conditions while addressing practical implementation challenges. This study uses specific terminology: IoT Precision Irrigation refers to automated sensor-based irrigation control systems (compatible with any delivery method), while Traditional Irrigation represents manual scheduling without sensor feedback using the FAO-56 theoretical baseline. Intercropping reduces total water demand through biological interactions (compatible with any irrigation system), and Gravity-fed drip irrigation improves water delivery efficiency (compatible with any control system). All three technologies can be combined independently or in any combination with cumulative efficiency gains. Water Savings indicates a reduction in consumption compared to the Traditional Irrigation baseline, and Implementation Priority ranks systems based on water savings per unit implementation effort.

3.1 System Architecture and Experimental Design

The system architecture, illustrated in Figure 2, consists of a centralized control unit managing an irrigation network that integrates a water source, pump system, and electronically controlled valves (V1-V4) for multiple crop strips. Each valve, equipped with flow sensors, enables precise water distribution to different crops (beans, maize, onions, and rice) based on crop-specific threshold values. The control logic implements an automated decision-making process based on sensor readings of moisture (Ms), temperature (Ts), and humidity (Hs), with data transmitted to an IoT server for storage, analysis, and remote monitoring.

Moreover, the experimental investigation was conducted in a controlled laboratory environment at Dedan Kimathi University of Technology, Kenya, with ambient conditions (80% relative humidity, 17°C temperature). The control system used an ATmega2560 microcontroller for its ample I/O pins, memory, and communication interfaces, supporting the system's sensor and actuator network, as shown in the electrical schematic (Figure 3).

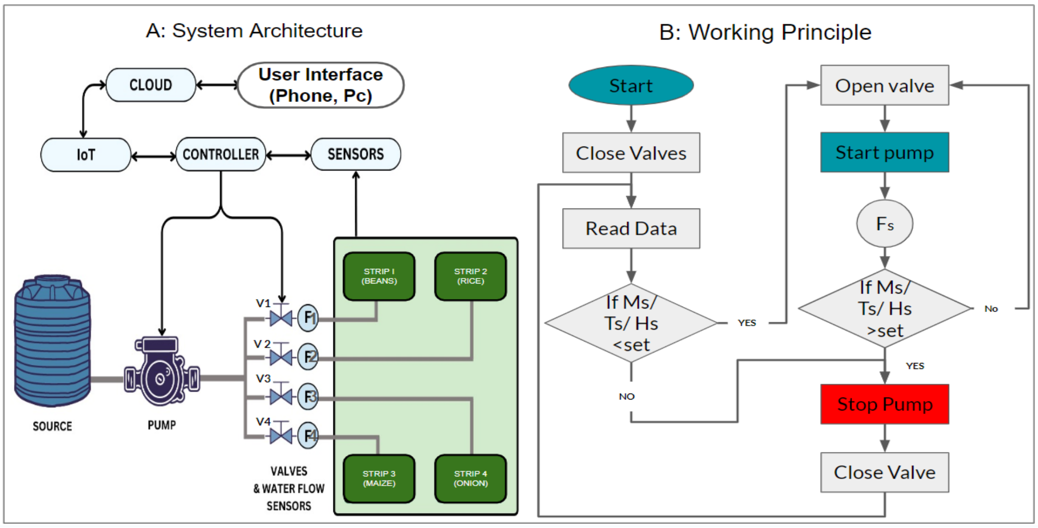

Figure 2. System architecture and working principle of IoT-based precision irrigation for intercropping: [A] System architecture integrating water distribution, sensors, and IoT connectivity for four crop strips. [B] Flowchart of automated irrigation control based on moisture, temperature, and humidity thresholds.

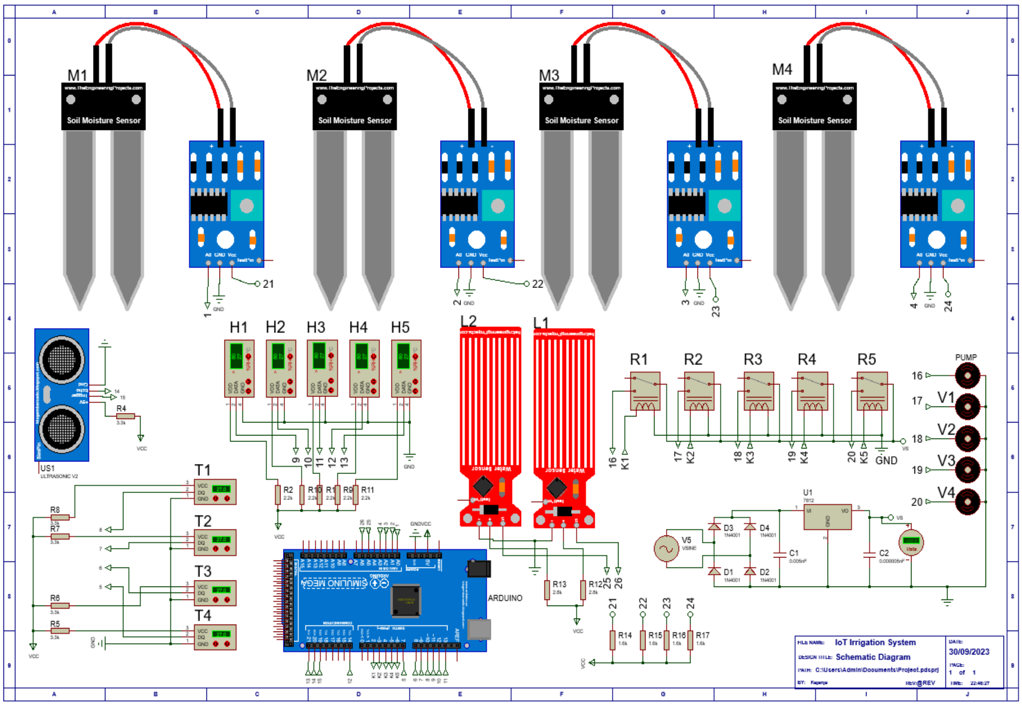

Figure 3. Electrical schematic diagram of the IoT-based irrigation system, showing interconnections between sensors, actuators, and control components.

3.2 Sensor Network and Physical Setup

A comprehensive sensor network was deployed using calibrated soil hygrometer sensors for moisture measurement, DS18B20 waterproof temperature sensors, and SHT10 humidity sensors, with specifications detailed in Table 1. The experimental apparatus consisted of four identical test blocks (60 × 60 × 30 cm), filled with loam soil to 25 cm, providing representative agricultural conditions. The experimental design incorporated four distinct crops: Phaseolus vulgaris (common beans), Zea mays (maize), Allium cepa (onions), and Oryza sativa (rice).

Table 1. Sensor Specifications and Deployment Parameters

Parameter	Sensor Type	Range	Accuracy	Sampling Rate
Soil Moisture	Hygrometer	0-100%	±2%	10 s
Temperature	DS18B20	-55 to +125°C	±0.5°C	10 s
Humidity	SHT10	0-100% RH	±4.5%	10 s
Water Level	MH-Series	0-100 mm	±1 mm	Continuous
Flow Rate	YF-S201	1-30 L/min	±2%	Real-time

Sensor placement depths were carefully determined based on the root zones of each crop type. For beans and onions, sensors were positioned at 15 cm depth, while maize sensors were placed at 20 cm depth to accommodate their deeper root systems. Rice cultivation, requiring precise water level control, utilized sensors at 10 cm depth along with dual water level sensors for enhanced monitoring accuracy. Crops were arranged using standard agricultural spacing with rows spaced at 45 cm for beans, 60 cm for maize, 30 cm for onions, and 20 cm for rice, while individual plants within each row were spaced at 20 cm, 30 cm, 12 cm, and 20 cm, respectively.

3.3 Mathematical Modeling Framework

IoT precision irrigation system control algorithms incorporated the modified FAO-56 methodology for crop water requirements calculation (Allen et al., 1998), as the Equation 1.

$$ET_{crop} = ET_o \times K_c \times d \tag{1}$$

where ET_{crop} represents the total crop water requirement for the growth stage period (mm), ET_o is reference evapotranspiration (mm/day), K_c is the crop coefficient, and d is the duration of the growth stage (days). For resource-constrained deployment scenarios, simplified Hargreaves-Samani calculations were implemented.

$$ET_o = 0.0023 \times (T + 17.8) \times (\Delta T)^{0.5} \times R_a \times f_h \times f_{lab} \tag{2}$$

where T is mean daily temperature (17°C, RH = 80%), ΔT is estimated temperature range (max(8.0, 12.0 × (1 - 80/100)) = 8.0°C), R_a is extraterrestrial radiation (0.082 × 24 × 60 × 0.4 × 0.408 = 19.27 mm/day), f_h is humidity adjustment factor (max(0.88, min(1.0 - 0.12 × 80/100, 1.0)) = 0.904), and f_{lab} combined correction factor accounting for elevation and controlled laboratory environment (0.44).

Water efficiency was calculated as Equation 2.

$$E_{system} = \left(1 - \frac{W_{measured}}{W_{reference}}\right) \times 100\% \tag{3}$$

where E_{system} represents water efficiency percentage, $W_{measured}$ is actual water consumption, and $W_{reference}$ is baseline consumption. From experimental observations, we derived interaction factors for intercropping systems shown Table 2. The interaction factors were then applied to predict water requirements for intercropping systems using Equation 3.

$$W_{intercrop,s} = \sum(r_i \times W_{i,s} \times F_{i,s}) \tag{4}$$

Where $W_{intercrop,s}$ = Water requirement for the intercropping system at stage s, r_i = Crop ratio in intercropping (0.5 for 50:50 systems), $W_{i,s}$ = Monoculture water requirement for crop i at stage s, $F_{i,s}$ = Interaction factor for crop i at stage s (dimensionless).
The traditional irrigation baseline was calculated as Equation 4.

$$W_{baseline} = \frac{(W_{beans} + W_{maize} + W_{onions})}{3} \tag{5}$$

where $W_{baseline}$ = Traditional irrigation baseline (mm), W_{beans} = FAO-56 theoretical water requirement for beans, W_{maize} = FAO-56 theoretical water requirement for maize, W_{onions} = FAO-56 theoretical water requirement for onions, calculated using Equation 1. Interaction factors (used in Equation 4) were derived from experimental observations using Equation 5.

$$F = \frac{2 \cdot W_{intercrop}}{W_{1,mono} + W_{2,mono}} \tag{6}$$

Where: F = Interaction factor, $W_{intercrop}$ = Observed intercropping water consumption, $W_{1,mono}$ = Monoculture water consumption for crop 1, $W_{2,mono}$ = Monoculture water consumption for crop 2, as the Equation 6.

$$W_{IoT} = \frac{(W_{beans,IoT} + W_{maize,IoT} + W_{onions,IoT})}{3} \tag{7}$$

W_{IoT} = IoT system average water requirement (mm), $W_{beans,IoT}$ = IoT measured water requirement for beans, $W_{maize,IoT}$ = IoT measured water requirement for maize, $W_{onions,IoT}$ = IoT measured water requirement for onions, determined through laboratory measurements, as shown in the Equation 7.

$$W_{intercrop} = \frac{(W_{MB} + W_{OB} + W_{MO})}{3} \tag{8}$$

$W_{intercrop}$ = Intercropping system average water requirement (mm), W_{MB} = Maize+Beans intercropping water requirement, W_{OB} = Onions+Beans intercropping water requirement, W_{MO} = Maize+Onions intercropping water requirement, calculated using Equation 8.

$$W_{gravity} = W_{input} \times E_{drip} \times E_{elevation} \tag{9}$$

$W_{gravity}$ = Water requirement with gravity-fed drip irrigation (mm), W_{input} = Input system water requirement (mm), E_{drip} = Drip irrigation efficiency factor, $E_{elevation}$ = Elevation pressure efficiency factor. E_{drip} is estimated at 0.85, informed by field studies reporting 85% application efficiency in drip irrigation systems (Borena & Borena, 2021). $E_{elevation}$ is estimated at 0.92 for gravity-fed systems at 2.5 m operating head used, based on emission uniformity of 91.03% at 3.0 m head (Patle, 2022) and excellent uniformity performance (97.5-98.5%) at 2.5 m head (Martinez et al., 2022). $W_{gravity}$ shown in Equation 9.

$$C_{percent} = \left(\frac{S_{technique}}{S_{total}}\right) \times 100\% \quad (10)$$

$C_{percent}$ = Percentage contribution of technique to total savings (%), $S_{technique}$ = Water savings from individual technique (mm), S_{total} = Total water savings from all techniques (mm), as the Equation 10.

$$P_{score} = \frac{W_{savings} \times S_{scalability}}{C_{implementation} + T_{skill} + C_{complexity}} \quad (11)$$

P_{score} = Implementation priority score (normalized to 0-10 scale), $W_{savings}$ = Water savings percentage (%), $C_{implementation}$ = Implementation cost factor, $S_{scalability}$ = Scalability rating, T_{skill} = Technical skill requirement, $C_{complexity}$ = Maintenance complexity rating, 1-3 scale: 1=low, 2=moderate, 3=high. This formula balances potential impact (water conservation × adoption potential) against cumulative barriers, offering a realistic feasibility assessment for resource-limited smallholder farmers. The P_{score} formula is shown in Equation 11.

Table 2. Derived Interaction Factors for Intercropping Systems

Crop Combination	Crop	Initial Stage	Development Stage
Maize + Beans	Maize	0.9612	0.8563
	Beans	0.9612	0.8563
Onions + Beans	Onions	0.9598	0.8512
	Beans	0.9598	0.8512
Maize + Onions	Maize	0.9570	0.8476
	Onions	0.9570	0.8476

Individual crop interaction factors (Table 4) were derived assuming equal response within each intercropping pair. The single interaction factor calculated from Equation 6 was applied to both crops in each combination, reflecting the assumption that both crops experience similar water use efficiency changes when intercropped together.

3.4 Laboratory Implementation and Proposed Field Deployment Architecture

The laboratory implementation utilized an ATmega2560 microcontroller. As shown in the controlled experimental setup (Figure 4). the physical system consisted of four test blocks with integrated sensor networks that continuously collected data, aggregated readings at regular intervals, and processed them through Node-RED for storage in a database. Real-time analysis of this stored data generated visualization outputs that automatically adjusted irrigation valves based on plant-soil conditions, creating a closed-loop feedback system.

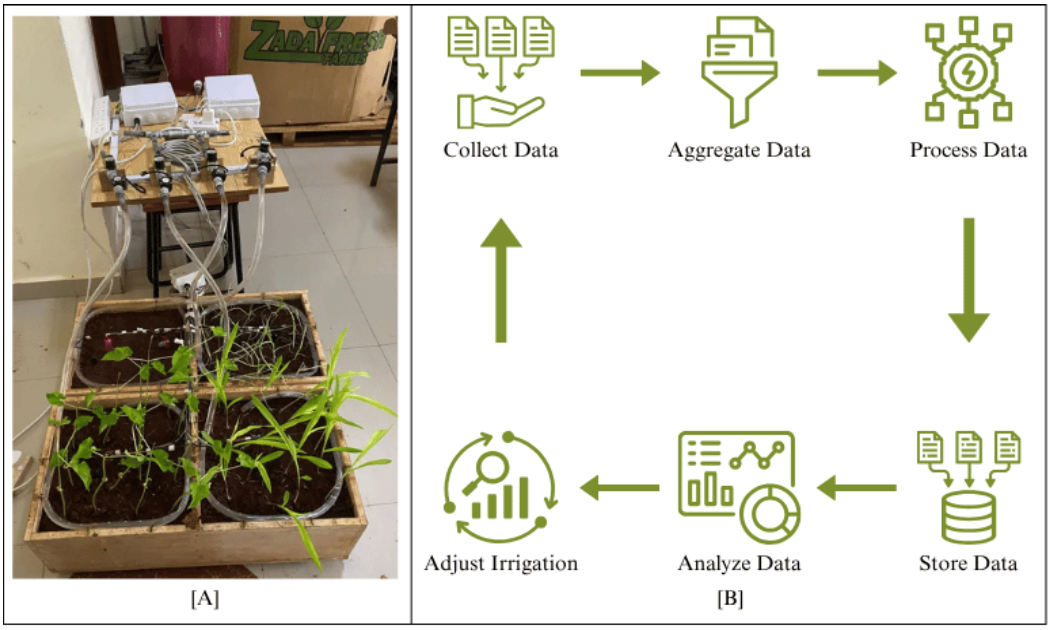

Figure 4. Laboratory implementation of IoT precision irrigation system showing [A] physical setup with four test containers and control board, and [B] closed-loop data workflow from sensor collection through aggregation, processing, storage, analysis, and automated irrigation adjustment.

Building on laboratory insights, a scalable field deployment architecture was designed (but not implemented in the field) utilizing low-power STM32F-series microcontrollers interfaced with environmental sensors (AHT20+BMP280) and CC1101 RF transceivers to form distributed slave sensor nodes (Figure 5A) that could be strategically deployed across agricultural fields to capture agronomic parameters. The proposed master gateway node (Figure 5B), also powered by an STM32F microcontroller, incorporates both a CC1101 transceiver for local sensor data reception and an A9G GSM/GPRS module for long-range communication, enabling dual-radio connectivity through MQTT for cloud integration and SMS for critical data transmission to ensure reliability in regions with intermittent internet infrastructure. This modular and scalable architecture, conceptualized for field implementation (Figure 5C), allows field expansion while integrating gravity-fed irrigation with IoT sensor networks for intercropping strategies.

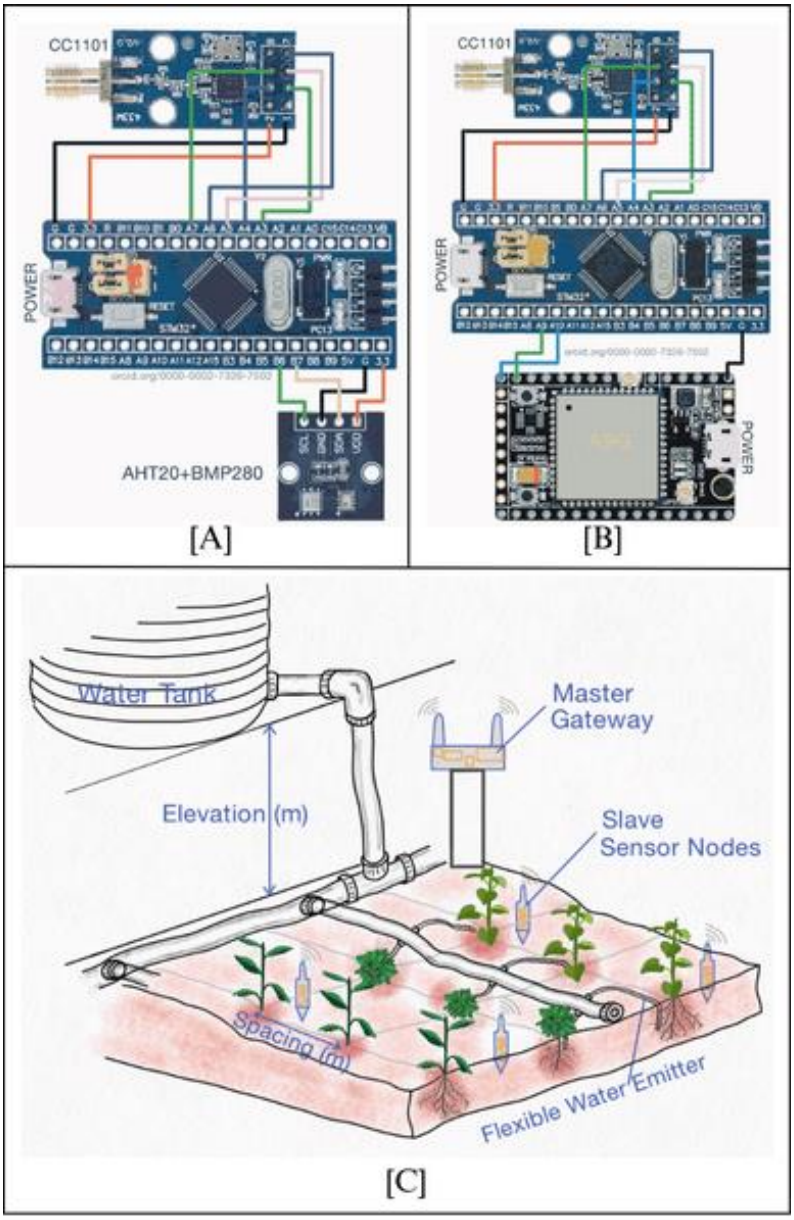

Figure 5. Proposed field deployment architecture showing [A] slave sensor node with STM32F microcontroller, CC1101 transceiver, and AHT20+BMP280 sensors, [B] master gateway with STM32F, CC1101, and A9G GSM/GPRS module for dual connectivity, and [C] conceptual field implementation with gravity-fed irrigation system, distributed sensor nodes, and centralized master gateway for precision irrigation control.

4. Results and Discussion

4.1 Water Savings Analysis

Laboratory experiments on three crop combinations provided baseline interaction factors (Table 2), which were applied through mathematical modeling (Equations (1) to (11)) to predict water savings, as illustrated in Figure 6. The traditional irrigation baseline was established using FAO-56 methodology with laboratory-adjusted ETo = 1.73 mm/day (Equation (2)). For the 37-day total experimental period, crop water requirements were calculated using Equation (1): Beans = 1.73 × (0.35 × 15 + 0.70 × 22) = 35.732 mm; Maize = 1.73 × (0.40 × 20 + 0.80 × 17) = 37.376 mm; Onions = 1.73 × (0.50 × 15 + 0.70 × 22) = 39.625 mm. Traditional irrigation baseline calculated using Equation (5): Wbaseline = 37.578 mm.

Laboratory measurements yielded IoT system values of 32.670 mm (beans), 34.030 mm (maize), and 36.290 mm (onions), with average calculated using Equation (7): WIoT = 34.330 mm, representing 8.6% water savings (Equation (3)). Intercropping systems achieved 11.2% standalone savings through biological interactions calculated using Equations (4) and (8) with interaction factors from Table 2, resulting in 33.359 mm average water requirement. When IoT precision irrigation was combined with intercropping, total savings reached 19.0% versus traditional irrigation baseline, aligning with crop interaction results of Cong et al. (2015) and Nassary et al. (2020).

Gravity-fed drip irrigation demonstrated substantial efficiency when integrated with other techniques, calculated using Equation (9), resulting in 28.7% water savings when paired with IoT systems. The highest efficiency (36.9%) was achieved by combining all three approaches using the complete mathematical framework, representing the theoretical potential achievable under optimal implementation of all technologies, validated through controlled laboratory conditions and mathematical extrapolation. Rice was excluded due to vastly different water requirements (378+ mm vs ~37 mm), with all system-specific calculations detailed in Table 3.

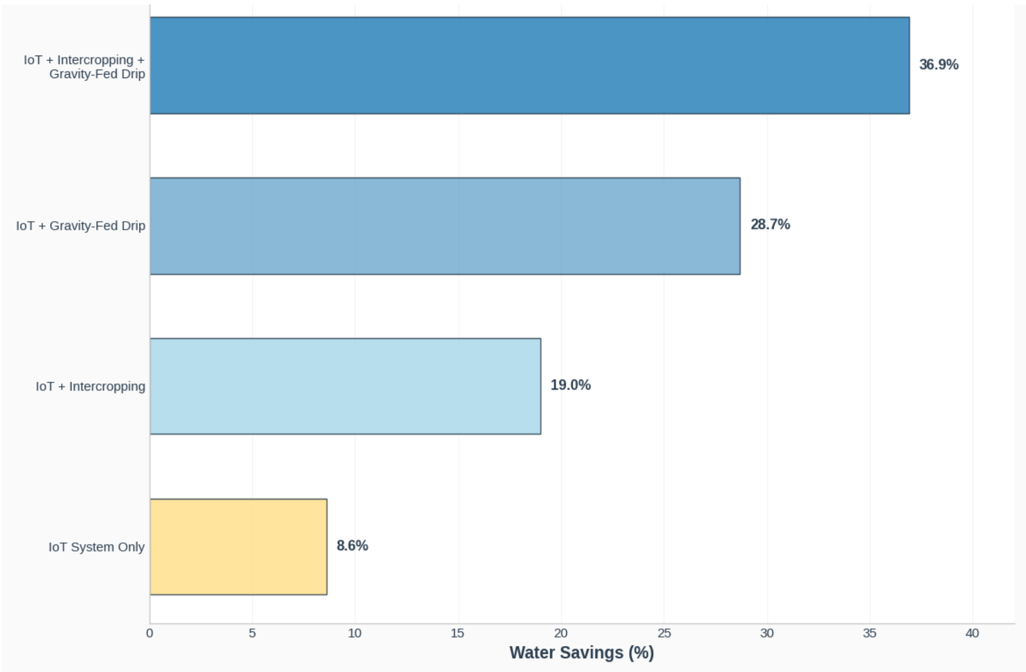

Figure 6. Comparison of water savings across different irrigation system configurations showing IoT System Only (8.6%), IoT and Intercropping combined (19.0%), IoT and Gravity-Fed Drip combined (28.7%), and IoT and Intercropping and Gravity-Fed Drip combined (36.9%).

Table 3. Water Savings Analysis Summary

System Configuration	Water Requirement (mm)	Absolute Savings (mm)	Percentage Savings (%)
Traditional Irrigation	37.578	-	-
IoT System Only	34.330	3.248	8.6
IoT + Intercropping	30.421	7.157	19
IoT + Gravity-Fed Drip	26.777	10.801	28.7
Complete Integrated System	23.728	13.850	36.9

Water requirements (Table 3) were calculated using Equations (1), (5), (7), (8), and (9). Percentage savings were calculated relative to Traditional Irrigation Baseline, unless specifically noted as 'vs monoculture' comparisons.

4.2 Laboratory Implementation and Practical Applications

The IoT system was successfully implemented and tested in laboratory conditions using actual hardware and crop cultivation (Figure 4). The laboratory-scale system achieved 8.6% water savings through automated precision control over four distinct crop test blocks. The implemented system utilized ATmega2560 microcontrollers with integrated sensor networks providing ±2% soil moisture accuracy, ±0.5°C temperature precision, and real-time irrigation control through electronically controlled valves. The laboratory implementation validated the automated decision-making process based on moisture, temperature, and humidity thresholds, demonstrating consistent irrigation management compared to traditional FAO-56 theoretical baseline approaches. The experimental data demonstrates that intercropping systems provide immediate water conservation benefits through biological interactions between crops. The maize-beans combination shows the most significant water reduction, with the 50:50 intercropping system consuming 29.670 mm compared to the expected monoculture average of 33.350 mm (Table 4), representing 11.0% water savings. These results validate the practical feasibility of intercropping as an accessible water conservation strategy requiring minimal technological investment. The scalable field deployment architecture (Figure 5) represents a proposed extension of the laboratory-validated system for broader agricultural implementation. While not yet deployed in actual field conditions, this architecture design provides a roadmap for transitioning from laboratory validation to practical field applications, incorporating lessons learned from the controlled laboratory environment.

4.3 Intercropping System Performance

Intercropping systems demonstrated consistent water savings compared to monoculture systems. The analysis revealed that intercropping contributes 28.2% to the overall water savings, making it a significant factor in the integrated approach and aligning with the results of Maitra et al. (2021) and Morris and Garrity (1993). Table 4 shows the water consumption data comparing IoT precision irrigation systems with intercropping versus monoculture applications.

Table 4. IoT System Performance: Intercropping vs. Monoculture

System	Initial (mm)	Development (mm)	Total (mm)
IoT Beans (Monoculture)	8.460	24.210	32.670
IoT Maize (Monoculture)	12.750	21.280	34.030
IoT Onions (Monoculture)	11.780	24.510	36.290
IoT Maize + Beans (50:50)	10.194	19.476	29.670
IoT Onions + Beans (50:50)	9.713	20.736	30.449
IoT Maize + Onions (50:50)	11.738	19.405	31.143

In Table 4, rice data (346.180 mm initial, 0.000 mm development) was excluded from integrated water savings calculations due to unique paddy cultivation requirements differing substantially from upland crops. The enhanced water use efficiency in intercropping systems can be attributed to complementary resource utilization and reduced competition for water resources (Gao et al., 2009; Yong et al., 2015). The interaction factors developed in our mathematical model using Equations (4) and (6) successfully predicted these savings with high accuracy across different crop combinations.

4.4 *Contribution Analysis and Implementation Assessment*

To understand the relative importance of each water conservation approach, we present two complementary analyses. Total water savings show cumulative benefits compared to the traditional irrigation baseline (37.578 mm): IoT alone achieves 8.6% savings, IoT + intercropping reaches 19.0%, IoT + gravity-fed drip attains 28.7%, and the complete integrated system delivers 36.9% savings. Technology contribution analysis reveals each technique's incremental impact on the total 13.850 mm savings through sequential implementation: IoT contributes 3.248 mm (23.5%), intercropping adds 3.909 mm (28.2%), and gravity-fed drip provides 6.693 mm (48.3%). While intercropping achieves 11.0-11.7% standalone savings versus monoculture, its integration with IoT systems represents 19.0% total savings versus the traditional irrigation baseline.

Implementation assessment revealed unexpected findings regarding IoT viability for smallholder farmers. Our evaluation of implementation factors yielded counterintuitive results: intercropping showed the highest implementation feasibility due to minimal costs and complexity, gravity-fed drip irrigation showed moderate feasibility, while IoT precision irrigation systems showed the lowest feasibility due to high implementation costs and technical complexity. Despite IoT precision irrigation systems providing measurable water savings and operational benefits, high implementation costs and technical complexity significantly impact their practical viability for resource-constrained farmers.

Table 5. Implementation Factors for Different Irrigation Technologies

Factor	**IoT Systems**	**Intercropping**	**Gravity-Fed Drip**
Water Savings (%)	8.60%	11.00%	22.00%
Scalability	Moderate (s=2)	High (s=3)	Moderate (s=2)
Implementation Cost	High (s=3)	Low (s=1)	Moderate (s=2)
Technical Skill Required	High (s=3)	Low (s=1)	Moderate (s=2)
Maintenance Complexity	High (s=3)	Low (s=1)	Moderate (s=2)
Raw Priority Score	1.91	11	7.33
Normalized Score (0-10)	1.7	10	6.7

The factors used in Table 5 represent key determinants of successful smallholder implementation: water conservation benefit, potential for widespread adoption, financial barriers, knowledge requirements, and operational difficulty. Research consistently identifies cost, technical knowledge, and complexity as primary barriers to agricultural technology adoption among smallholder farmers (Fadeyi et al., 2022; Mhlanga, 2023). IoT: 8.6% vs traditional; Intercropping: 11.0% vs monoculture; Gravity-fed drip: 22.0% vs conventional non-IoT irrigation delivery methods were used in the table. Priority ranking based on water savings per implementation effort: intercropping offers immediate 11.0-11.7% savings with minimal cost and complexity, making it the highest priority for smallholder farmers.

4.5 Implementation Priorities and Strategic Framework

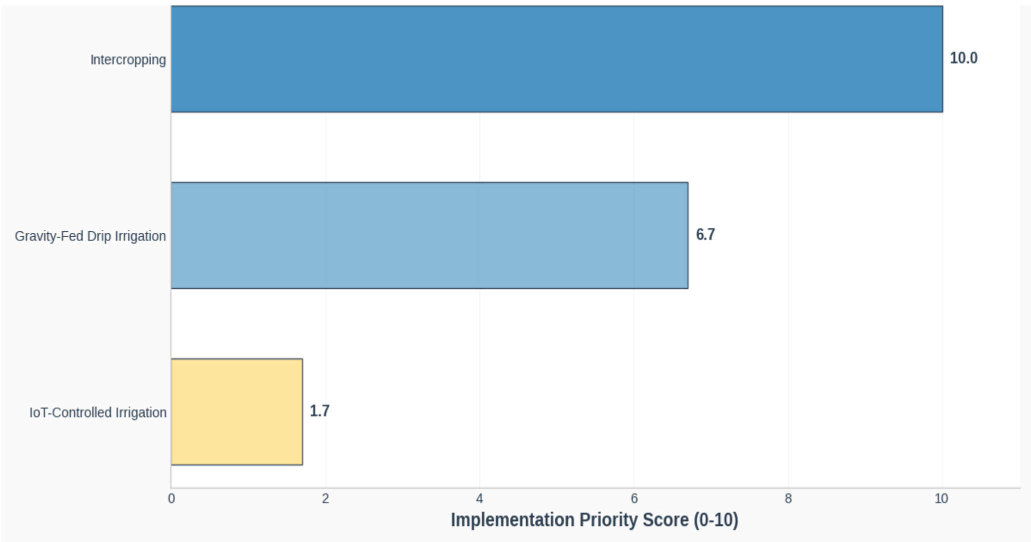

Figure 7. Implementation priority ranking based on water savings efficiency per implementation effort. Intercropping ranks highest (10.0) due to optimal savings-to-cost ratio, followed by Gravity-Fed Drip (6.7) and IoT (1.7).

Based on water savings analysis and qualitative assessment of implementation factors (Table 5) we developed a prioritized ranking of irrigation techniques using Equation **11** and plotted the results as shown in Figure 7. Intercropping emerges as the highest priority technique, followed by gravity-fed drip irrigation and IoT precision irrigation. This ranking informed our phased implementation roadmap for smallholder farmers: beginning with intercropping for immediate 11.0-11.7% savings and minimal costs, followed by gravity-fed drip integration providing 22% baseline improvement with moderate complexity, and concluding with IoT optimization offering 8.6% additional precision control once infrastructure is established.

4.6 Practical Implications for Implementation

The mathematical analysis demonstrates that the complete implementation of all three techniques achieves 36.9% total savings compared to traditional irrigation methods. This represents an absolute water saving of 13.850 mm from the traditional baseline of 37.578 mm. The phased approach allows farmers to achieve progressive water efficiency improvements: starting with 11.0% savings from intercropping, advancing to combined 28.7% savings with gravity-fed drip integration, and ultimately reaching 36.9% efficiency through IoT precision control.

4.7 Discussion of Key Findings

Several important insights emerge from this comprehensive analysis. Despite gravity-fed drip irrigation contributing the largest percentage to total water savings, intercropping emerges as the recommended first step for implementation due to its exceptional feasibility and low implementation barriers, consistent with other research (Andrews & Kassam, 1976). For resource-constrained smallholder farmers, intercropping represents the most accessible entry point to water-efficient agriculture (Maitra et al., 2021; Nassary et al., 2020).

The data demonstrates that combining multiple irrigation techniques produces complementary effects. The water savings from individual techniques, when integrated through our mathematical framework using Equations (1) through (11), show that the complete implementation achieves 36.9% total savings, demonstrating complementary mechanisms of water conservation across different techniques.

While IoT-based precision irrigation demonstrated consistent water savings through automated control and real-time optimization, economic analysis reveals implementation challenges for smallholder applications (Bayih et al., 2022; Fadeyi et al., 2022; Mhlanga, 2023; Obaideen et al., 2022; Yuan & Sun, 2024). The technology excels in precision monitoring and control but faces barriers in cost-effectiveness and technical complexity. The IoT precision irrigation system's strength lies in its optimization capabilities rather than primary water conservation, with the lowest feasibility due to high implementation costs and technical complexity, indicating that IoT technology serves best as an enhancement layer rather than a primary intervention.

5. Conclusions

This study provides a comprehensive evaluation of IoT-based precision irrigation systems through laboratory implementation and theoretical modeling for smallholder agriculture water management. The laboratory-implemented IoT architecture successfully integrated environmental sensor networks and automated control systems to achieve 8.6% water savings through precision control, with sensor accuracy within ±2% for soil moisture and ±0.5°C for temperature measurements under controlled conditions.

The most significant finding is the implementation hierarchy revealed through the implementation feasibility analysis. Traditional water conservation methods (intercropping and gravity-fed drip irrigation) substantially outperform IoT precision irrigation systems in terms of suitability for smallholder farmers. This challenges the predominant technological focus in agricultural water management literature and suggests that traditional approaches may offer more economically viable pathways to water conservation.

The recommended phased implementation sequence achieves progressive water efficiency improvements while managing costs and complexity. The complete integration of all three techniques theoretically achieves 36.9% water savings compared to traditional irrigation methods, validating our integrated approach hypothesis through mathematical modeling. The research demonstrates that successful IoT deployment in smallholder agriculture requires understanding broader technological ecosystems and resource constraints. The proposed scalable field deployment architecture provides a pathway for transitioning from laboratory validation to practical field implementation, though field testing remains as future work.

This perspective advances IoT agricultural research beyond technology-centric approaches toward integrated solutions that address real-world farmer needs and resource limitations. IoT-based agricultural systems should prioritize accessibility, cost-effectiveness, and integration compatibility to achieve widespread adoption and meaningful impact in smallholder farming communities.

6. Future Research Directions

Future research should focus on field-scale implementation and testing of the proposed deployment architecture to validate laboratory findings under real agricultural conditions. Investigation of climate-specific adaptations across different environmental zones, particularly in arid and semi-arid regions, would enhance system applicability. Development of economic optimization models incorporating financing mechanisms and cooperative frameworks could improve accessibility for resource-constrained farmers. Additionally, research into simplified IoT architectures and low-cost sensor alternatives may reduce implementation barriers while maintaining system effectiveness.

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References

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration: Guidelines for computing crop water requirements. FAO Irrigation and Drainage Paper, 56, 1-15. https://www.fao.org/3/x0490e/x0490e00.htm

Andrews, D., & Kassam, A. (1976). The importance of multiple cropping in increasing world food supplies. Multiple Cropping, 27, 1-10. https://doi.org/10.2134/asaspecpub27.c1

Antony, A. P., Leith, K., Jolley, C., Lu, J., & Sweeney, D. J. (2020). A review of practice and implementation of the internet of things (IoT) for smallholder agriculture. Sustainability, 12(9), 3750. https://doi.org/10.3390/su12093750

Bayih, A. Z., Morales, J., Assabie, Y., & de By, R. A. (2022). Utilization of Internet of Things and Wireless Sensor Networks for Sustainable Smallholder Agriculture. Sensors, 22(9), 3273. https://doi.org/10.3390/s22093273

Borena, F. R., & Borena, R. (2021). Performance of drip irrigation at Werer, Middle Awash, Ethiopia. Engineering Science, 6(4), 49-54. https://doi.org/10.11648/j.es.20210604.11

Cong, W. F., Hoffland, E., Li, L., Six, J., Sun, J. H., Bao, X. G., Zhang, F. S., & Van Der Werf, W. (2015). Intercropping enhances soil carbon and nitrogen. Global Change Biology, 21(4), 1715-1726. https://doi.org/10.1111/gcb.12738

Fadeyi, O. A., Ariyawardana, A., & Aziz, A. A. (2022). Factors influencing technology adoption among smallholder farmers: A systematic review in Africa. Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS), 123(1), 13-30. https://doi.org/10.17170/kobra-202201195569

Gao, Y., Duan, A., Sun, J., Li, F., Liu, Z., Liu, H., & Liu, Z. (2009). Crop coefficient and water-use efficiency of winter wheat/spring maize strip intercropping. Field Crops Research, 111(1-2), 65-73. https://doi.org/10.1016/j.fcr.2008.10.007

Gnanavel, S., Sreekrishna, M., DuraiMurugan, N., Saranraj, M., Vijayakumar, P., & Anuradha, D. G. (2022). The smart IoT based automated irrigation system using arduino uno and soil moisture sensor. In 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT) (pp. 188-191). IEEE. https://doi.org/10.1109/ICSSIT53264.2022.9716368

Lamsal, R. R., Karthikeyan, P., Otero, P., Kabir, H., Patel, P., Cho, Y. H., Joung, Y. K., & Shambhu, K. C. (2023). Design and implementation of internet of things (IoT) platform targeted for smallholder farmers: From nepal perspective. Agriculture, 13(10), 1900. https://doi.org/10.3390/agriculture13101900

Maitra, S., Hossain, A., Brestic, M., Skalicky, M., Ondrisik, P., Gitari, H., Brahmachari, K., Shankar, T., Bhadra, P., Palai, J. B., & others. (2021). Intercropping—a low input agricultural strategy for food and environmental security. Agronomy, 11(2), 343. https://doi.org/10.3390/agronomy11020343

Martinez, C. G., Wu, C. L. R., Fajardo, A. L., & Ella, V. B. (2022). Hydraulic performance evaluation of low-cost gravity-fed drip irrigation systems under constant head conditions. IOP Conference Series: Earth and Environmental Science, 1038(1), 012005. https://doi.org/10.1088/1755-1315/1038/1/012005

Mhlanga, D. (2023). Digital technology adoption in the agriculture sector: Challenges and complexities in Africa. Human Behavior and Emerging Technologies, 2023, Article 6951879. https://doi.org/10.1155/2023/6951879

Monchusi, B. B., Kgopa, A. T., & Mokwana, T. I. (2024). Integrating IoT and AI for precision agriculture: Enhancing water management and crop monitoring in small-scale farms. ICONIC 2024 Proceedings. https://doi.org/10.59200/ICONIC.2024.017

Morchid, A., Et-taibi, B., Oughannou, Z., El Alami, R., Qjidaa, H., Ouazzani Jamil, M., Boufounas, E. M., & Abid, M. R. (2025). IoT-enabled smart agriculture for improving water management: A smart irrigation control using embedded systems and Server-Sent Events. Scientific African, 27, e02527. https://doi.org/10.1016/j.sciaf.2024.e02527

Morris, R. A., & Garrity, D. P. (1993). Resource capture and utilization in intercropping: water. Field Crops Research, 34(3-4), 303-317. https://doi.org/10.1016/0378-4290(93)90119-8

Nassary, E. K., Baijukya, F., & Ndakidemi, P. A. (2020). Intensification of common bean and maize production through rotations to improve food security for smallholder farmers. Journal of Agriculture and Food Research, 2, 100040. https://doi.org/10.1016/j.jafr.2020.100040

Nigussie, E., Olwal, T., Musumba, G., Tegegne, T., Lemma, A., & Mekuria, F. (2020). IoT-based irrigation management for smallholder farmers in rural Sub-Saharan Africa. Procedia Computer Science, 177, 86-93. https://doi.org/10.1016/j.procs.2020.10.015

Obaideen, K., Yousef, B. A., AlMallahi, M. N., Tan, Y. C., Mahmoud, M., Jaber, H., & Ramadan, M. (2022). An overview of smart irrigation systems using IoT. Energy Nexus, 7, 100124. https://doi.org/10.1016/j.nexus.2022.100124

Opare, S. (2018). Adaptation to climate change impacts: coping strategies of an indigenous community in Ghana to declining water supply. Climate and Development, 10(1), 73-83. https://doi.org/10.1080/17565529.2016.1184610

Patle, G. T. (2022). Evaluation of a gravity-fed drip irrigation system under varying hydraulic head and land slope for hilly terrain. Agricultural Engineering International: CIGR Journal, 24(2), 147-156. https://cigrjournal.org/index.php/Ejounral/article/view/9117

Ricciardi, V., Ramankutty, N., Mehrabi, Z., Jarvis, L., & Chookolingo, B. (2018). How much of the world's food do smallholders produce? Global Food Security, 17, 64-72. https://doi.org/10.1016/j.gfs.2018.05.002

Tzanakakis, V., Angelakis, A., Paranychianakis, N., Dialynas, M., & Tchobanoglous, G. (2020). Challenges and opportunities for sustainable management of water resources in the island of Crete, Greece. Water, 12(6), 1538. https://doi.org/10.3390/w12061538

Yasin, H. M., Zeebaree, S. R., & Zebari, I. M. (2019). Arduino based automatic irrigation system: Monitoring and SMS controlling. In 2019 4th Scientific International Conference Najaf (SICN) (pp. 109-114). IEEE. https://doi.org/10.1109/SICN47020.2019.9019370

Yong, T., Liu, X., Yang, F., Song, C., Wang, X., Liu, W., Su, B., Zhou, L., & Yang, W. (2015). Characteristics of nitrogen uptake, use and transfer in a wheat-maize-soybean relay intercropping system. Plant Production Science, 18(3), 388-397. https://doi.org/10.1626/pps.18.388

Yuan, Y., & Sun, Y. (2024). Practices, challenges, and future of digital transformation in smallholder agriculture: Insights from a literature review. Agriculture, 14(12), 2193. https://doi.org/10.3390/agriculture14122193