

Development and Performance Evaluation of an IoT-Based Smart Irrigation System with Real-Time Data Monitoring for Beetroot (*Beta vulgaris* L.)

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Research Article

Keywords: smart irrigation, Internet of Things, ESP32, beetroot, water-use efficiency, real-time monitoring, Rwanda

Posted Date: October 16th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11385500/v1>

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Additional Declarations: No competing interests reported.

Abstract

Inefficient irrigation wastes water in regions where water is already scarce, and low-cost sensor-driven systems can help to reduce this waste. This study aimed to develop and evaluate an Internet-of-Things (IoT) based smart irrigation system with real-time data monitoring for beetroot (*Beta vulgaris* L.) at the RP-Gishari Demo farm in Rwamagana, Rwanda. The layout of the system was designed in SolidWorks and its circuit was simulated in Proteus. The prototype combines an ESP32 microcontroller with a capacitive soil-moisture sensor, a DHT11 temperature and humidity sensor, a rain sensor, a relay-driven water pump and an LCD. The controller starts irrigation at a volumetric water content (VWC) of 35.0% and stops it at 75.0%, and blocks irrigation when rain is detected. Sensor calibration separated dry ($12.4 \pm 1.2\%$), moderately moist ($48.6 \pm 2.1\%$) and saturated soil ($78.3 \pm 1.5\%$). Over ten irrigation cycles, soil moisture rose from 33.2% before to 74.5% after irrigation, a mean soil moisture regulation of 41.3% (SD of post-irrigation readings 1.8%). The pump responded in 2.45 s on average (range 1.80–3.10 s), and the rain override acted within 45.0 ms. Each cycle used 35.7 L (8.5 L min^{-1} for 4.2 min), compared with 65.0 L in nearby manually irrigated plots, a reduction of 45.1%, and mean plant height increased by 19.6 cm in 30 days (5.2 to 24.8 cm). Because the evaluation was a single 30-day test without replicated treatments, statistical testing, yield measurement or metered energy, the results demonstrate functional performance and indicative water saving rather than a proven agronomic benefit. Replicated, multi-season trials with a controlled comparison are the necessary next step.

1. Introduction

Irrigated agriculture has raised global crop production, but it has also put widespread pressure on freshwater resources: more than half (52%) of the expansion of irrigated area between 2000 and 2015 took place in regions that were already water-stressed in 2000 (Mehta et al., 2024). Using available water more efficiently is therefore a central requirement for sustainable crop production, and smart monitoring and control strategies are regarded as a way to improve irrigation water-use efficiency (Bwambale et al., 2022).

In Rwanda, agriculture is central to the economy and to rural livelihoods, and the rainfall of the Eastern Province is seasonally variable, which makes irrigation important for continuous vegetable production. Irrigation is, however, often scheduled by a fixed timetable or by the farmer's judgement rather than by the measured water status of the soil. Even simple scheduling tools can change water use: in a drip-irrigated beetroot trial with smallholders in Nicaragua, farmers who followed a water chart or tensiometer readings used about 20% less irrigation water than under their usual practice, and the authors noted that irrigation durations estimated by the farmers were often inaccurate, which can lead to over- or under-irrigation (Studer & Spoehel, 2019).

Internet-of-Things (IoT) technologies allow soil moisture, temperature and humidity to be measured continuously by low-cost sensors and used by a microcontroller to start and stop pumps without human intervention (Ayaz et al., 2019; García et al., 2020). Reviews of the field describe the sensing,

communication, decision and actuation layers of such systems and also note the challenges that slow their wider adoption (Abdelmoneim et al., 2025; García et al., 2020). Precision irrigation control is commonly framed as a feedback problem in which the timing and quantity of water are adjusted to keep the water status of the soil or crop within set limits (Owino & Söffker, 2022), and artificial-intelligence approaches are being explored to extend simple threshold logic (Jaiswal et al., 2025; Wei et al., 2024).

The reported benefits are encouraging. In a comparative trial, an IoT-based smart irrigation system increased crop productivity by about 35% and reduced water use by up to 47.8% relative to conventional irrigation (Pratama & Mandela, 2024), and a review of IoT-based drip irrigation cites case studies with yield increases of about 30% and water savings of up to 70% (Jaiswal et al., 2025). Low-cost designs have been built around capacitive soil-moisture sensors, Arduino-type controllers and simple pumps (Abba et al., 2019), and a cloud-connected system that used weather prediction to improve irrigation control during intermittent rain reported tangible water conservation (Et-Taibi et al., 2024).

Most of this work, however, concerns general-purpose prototypes or other crops. In the literature reviewed for this study we found few field evaluations of low-cost, sensor-driven automatic irrigation for a root vegetable such as beetroot that report regulation accuracy, response time, water use and crop growth together; the beetroot trial cited above evaluated scheduling tools rather than automatic control (Studer & Spoehel, 2019). Without such crop-specific information, smallholders and training institutions in Rwanda cannot judge what a simple automatic system can deliver for beetroot. Generating it has practical value: it provides a documented, reproducible design that can be used for water-saving demonstrations and as a teaching platform for sensor calibration and microcontroller programming.

The aim of this study was to develop a smart irrigation system with real-time data monitoring for beetroot. The specific objectives were (i) to design an IoT system for real-time soil monitoring; (ii) to automate irrigation using a soil-moisture sensor and weather data (temperature and humidity); and (iii) to evaluate the performance of the system for beetroot in terms of soil moisture regulation, water consumption, response time and plant growth. The study was exploratory and was framed by three research questions corresponding to these objectives rather than by a statistical hypothesis.

2. Materials and Methods

2.1 Study area and system design

The study was conducted at the Demo-Farm of RP-Gishari College (Rwanda Polytechnic) in Rwamagana District, Eastern Province, Rwanda, at approximately 1.901434° S and 30.411864° E (Fig. 1a). The farm is used for crop-production experiments, irrigation-system testing and technology demonstrations, and the region has the seasonal rainfall variability typical of eastern Rwanda. The study area was mapped in ArcMap (GIS), and a 5 m² plot divided into three zones was planned for the installation.

The physical layout was developed as a three-dimensional model in SolidWorks (Fig. 1b). The design followed seven steps: definition of the required components; a conceptual sketch of the complete

structure; 3D models of the enclosure and supporting structure; arrangement of the sensors, microcontroller and power components; design of the wiring and pipe-routing paths; evaluation of the model for stability, accessibility and component compatibility; and modification to improve functionality and compactness. The electronic circuit was simulated in Proteus before assembly.

The system is built around an ESP32 development module that reads a capacitive soil-moisture sensor placed near the root zone of the beetroot, a DHT11 temperature and humidity sensor and a rain sensor with a binary output (0 = dry, 1 = rainfall). The controller drives a water pump through a relay module, water is delivered from a storage tank through pipes to the crop, readings are shown on a 16 × 2 LCD, and a fan limits heating of the electronics. The integrated Wi-Fi of the ESP32 allows the readings to be transmitted for remote monitoring. The components, materials and software are listed in Table 1.

Table 1
Components, materials and software of the smart irrigation system.

Component	Specification	Function
Microcontroller	ESP32 development module; dual-core, integrated Wi-Fi	Processing of sensor data, control logic and wireless communication
Soil-moisture sensor	Capacitive type (corrosion-resistant)	Measures volumetric water content (VWC) in the root zone to trigger irrigation
Temperature and humidity sensor	DHT11	Measures ambient temperature and relative humidity
Rain sensor	Binary output (0 = dry, 1 = rainfall)	Detects rainfall and blocks irrigation
Relay module and pump	Calibrated micro-pump; flow rate 8.5 L min ⁻¹	Delivers water from the tank to the crop when switched by the ESP32
Display	16 × 2 LCD	Local real-time readout of sensor values and status
Cooling	Fan	Limits heating of the electronics during continuous operation
Water supply	Plastic water tank; pipes	Water storage and distribution to the crop
Enclosure and mounting	Waterproof box; timber assembling board	Protects and organises the electronic components
Wiring and power	Jump wires; electric conductor and switch; USB cable	Signal and power connections, manual switching, power supply and code upload
Software	Arduino IDE; SolidWorks; ArcMap (GIS); Proteus	Code development and upload; 3D layout; mapping of the study area; circuit simulation

2.2 Fabrication and assembly

Assembly followed the 3D layout and comprised six operations: (i) mounting of the ESP32, sensors, relay and display on a timber assembling board; (ii) wiring of the components with jump wires according to the circuit design (Fig. 2b) and housing of the electronics in a waterproof box; (iii) connection of the pump, water tank and delivery pipes (Fig. 2a); (iv) programming of the ESP32 with the irrigation control algorithm in the Arduino IDE and upload of the code through the USB cable; (v) installation of the soil-moisture sensor close to the root zone at the required depth and of the temperature, humidity and rain sensors; and (vi) testing of the system with dry soil to confirm automatic pump activation and automatic shut-down after adequate irrigation (Fig. 2c).

2.3 Experimental design and evaluation procedure

The performance test was a descriptive evaluation of one automatic irrigation system under beetroot cultivation at the Demo-Farm over 30 days. The beetroot was planted under monitored irrigation, the sensors recorded soil and weather conditions continuously, and the system was evaluated under different soil-moisture conditions. Sensor calibration was carried out in dry, moderately moist and saturated soil. Ten irrigation cycles were evaluated. For each cycle the soil moisture before and after irrigation was recorded, and the volume of water supplied was calculated from the pump flow rate and the irrigation time. The response time of the system was recorded during the field tests. Water consumption was compared with that of nearby manually irrigated plots, which received on average 65.0 L per irrigation cycle. Plant height was recorded at the start of the trial (mean 5.2 cm) and after 30 days of cultivation.

2.4 Evaluation parameters

Four simple parameters were used to evaluate the system (Eqs. 1–4). Soil moisture regulation (SMR, percentage points) is the rise in soil moisture produced by an irrigation cycle (Eq. 1):

$$\text{SMR} = M_a - M_b$$

1

where M_a and M_b are the soil moisture (VWC, %) after and before irrigation. Water consumption (WC, L) per irrigation cycle was calculated from the flow rate and the irrigation time (Eq. 2):

$$\text{WC} = Q \times T$$

2

where Q is the water flow rate (L min^{-1}) and T is the irrigation time (min). The response time (RT, s) of the system was defined as the interval between the detection of moisture below the threshold and the activation of the pump (Eq. 3):

$$\text{RT} = T_2 - T_1$$

where T_1 is the time of moisture detection and T_2 is the time of pump activation. Growth performance (GP, cm) of the beetroot was calculated as the gain in plant height (Eq. 4):

$$GP = H_f - H_i$$

where H_f and H_i are the final and initial plant heights (cm).

2.5 Control logic and weather override

The ESP32 compared the soil-moisture reading with two VWC thresholds: a lower threshold of 35.0% for starting irrigation and an upper threshold of 75.0% for stopping it. When the reading fell below 35.0% and the rain sensor indicated no rainfall (value 0), the controller switched the pump on through the relay. When rainfall was detected (value 1), pumping was blocked even if the soil moisture was below the lower threshold, and once the soil moisture reached 75.0% the controller switched the pump off to avoid over-watering. The design also provided for irrigation to be suspended at high ambient humidity, but the humidity limit used is not documented in the project records, so only the rainfall override was evaluated quantitatively.

2.6 Data analysis

Results are presented as means, with standard deviations where they were recorded (sensor calibration and post-irrigation soil moisture). The mean soil moisture regulation was calculated from the mean soil moisture before and after irrigation, and the water saving was calculated as $(WC_{\text{manual}} - WC_{\text{smart}}) / WC_{\text{manual}} \times 100$. The project records give the means of the ten irrigation cycles rather than the individual cycle values, and a single automatic system was compared with nearby manual plots, so no inferential statistical tests were applied and all comparisons are descriptive.

3. Results and Discussions

3.1 Fabricated system and sensor calibration

The design stage produced a three-dimensional model of a raised timber bed with the electronics enclosure, the water tank and a pipe loop around the plant bed (Fig. 1b). The assembled prototype followed this layout, with the enclosure, tank, delivery tubing and sensors installed at the soil container (Fig. 2a), and it was used for the evaluation described below. The controller was programmed with a lower threshold of 35.0% VWC for starting irrigation and an upper threshold of 75.0% VWC for stopping it (Table 2).

The calibration tests gave clearly different readings for the three soil conditions: the mean VWC was $12.4 \pm 1.2\%$ in dry soil, $48.6 \pm 2.1\%$ in moderately moist soil and $78.3 \pm 1.5\%$ in saturated soil (Fig. 3a,

Table 2). The ranges (mean $\pm$ SD) do not overlap, which shows that the sensor can distinguish between the soil conditions on which the irrigation decisions are based. The two thresholds lie between the dry and saturated readings; the upper threshold of 75.0% is 3.3 percentage points below the saturated reading.

Table 2
Control thresholds, sensor calibration results and ambient conditions during field testing.

Item	Value	Unit
Lower threshold (irrigation start)	35.0	% VWC
Upper threshold (irrigation stop)	75.0	% VWC
Calibration, dry soil	12.4 $\pm$ 1.2	% VWC
Calibration, moderately moist soil	48.6 $\pm$ 2.1	% VWC
Calibration, saturated soil	78.3 $\pm$ 1.5	% VWC
Ambient temperature, mean (range)	25.6 (21.4–29.8)	°C
Relative humidity, mean (range)	71.8 (55.2–88.4)	%
Humidity measurement variance	< $\pm$ 2.5	%
Rain sensor output	0 = dry; 1 = rainfall	binary

3.2 Ambient temperature, humidity and rainfall detection

During field testing the mean ambient temperature was 25.6°C, with a range of 21.4 to 29.8°C (Fig. 3b). Relative humidity ranged from 55.2 to 88.4% with a mean of 71.8% and a measurement variance below $\pm$ 2.5%. The rain sensor provided real-time precipitation detection through a binary output, with 0 indicating dry conditions and 1 indicating rainfall, so that the controller could adjust the irrigation decision to the prevailing weather.

3.3 Soil moisture regulation, water consumption, response time and growth

Table 3 summarises the performance parameters and Table 4 compares the water consumption of the smart system with that of the manual plots. Over the ten irrigation cycles the mean soil moisture was 33.2% before irrigation and 74.5% after irrigation, so the mean soil moisture regulation was $SMR = 74.5 - 33.2 = 41.3\%$ (Eq. 1; Fig. 4b). The post-irrigation readings had a standard deviation of 1.8%, i.e. the end point of the cycles was consistent.

Water was delivered by the calibrated micro-pump at a steady 8.5 L min^{-1} , and on average 4.2 min of irrigation were needed to raise the soil moisture from the lower to the upper threshold. The mean water

consumption per irrigation cycle was therefore $WC = 8.5 \times 4.2 = 35.7$ L (Eq. 2). The nearby manually irrigated plots used on average 65.0 L per cycle, so the smart system used 29.3 L (45.1%) less water per cycle (Table 4, Fig. 4a).

The response time ranged from 1.80 to 3.10 s during the field tests, with a mean of 2.45 s (Eq. 3). The mean plant height was 5.2 cm at the start of the trial and 24.8 cm after 30 days of cultivation under automatic irrigation, a growth performance of $GP = 24.8 - 5.2 = 19.6$ cm (Eq. 4).

Table 3
Summary of the performance parameters of the smart irrigation system (ten irrigation cycles; 30-day trial).

Parameter	Calculation	Result
Soil moisture before irrigation, M_b	Mean of ten cycles	33.2%
Soil moisture after irrigation, M_a	Mean of ten cycles	74.5% (SD 1.8%)
Soil moisture regulation, SMR	$M_a - M_b$	41.3%
Response time, RT	$T_2 - T_1$	2.45 s (1.80–3.10 s)
Plant height, start and after 30 days	H_i, H_f	5.2 cm; 24.8 cm
Growth performance, GP	$H_f - H_i$	19.6 cm

SD: standard deviation of the post-irrigation readings. VWC: volumetric water content.

Table 4
Water consumption per irrigation cycle of the smart system and of nearby manually irrigated plots.

System	Q (L min ⁻¹)	T (min)	WC per cycle (L)	Reduction (%)
Smart (automatic)	8.5	4.2	35.7	45.1
Manual	–	–	65.0 (mean)	–

Reduction = $(65.0 - 35.7) / 65.0 \times 100$. – : not reported.

3.4 Automation response and rain override

When the soil moisture fell below the 35.0% threshold and no rainfall was detected, the controller switched the pump on through the relay with a mean activation time of 124.0 ms. When the soil moisture was below the threshold but rainfall was detected, the controller suppressed pump activation; this override took 45.0 ms on average and prevented unnecessary irrigation during rainfall. These latencies describe the relay and override actions and are different from the response time of Eq. 3 (mean 2.45 s),

which spans the interval from moisture detection to pump activation; the project records do not state what accounts for the difference between the two.

4. Discussion

4.1 Functional performance of the system

The prototype performed the three functions it was designed for: it sensed soil moisture and weather, it started and stopped the pump automatically at the programmed thresholds, and it blocked irrigation during rainfall (Sections 3.3 and 3.4). The mean soil moisture was 33.2% before and 74.5% after irrigation, close to the programmed 35.0% and 75.0% thresholds, and the small standard deviation of the post-irrigation readings (1.8%) indicates that the cycles ended at a consistent moisture level. The pre-irrigation mean lies slightly below the 35.0% start threshold, which is consistent with a controller that checks the moisture at intervals and needs a short time to start the pump; the sampling interval is not documented, however, so this explanation remains a hypothesis.

Two points need care when the regulation result is interpreted. First, SMR as defined here is the rise in moisture produced by one cycle, not a measure of how constant the moisture was between cycles; the band between the two thresholds is 40 percentage points wide, so the result shows that each cycle refilled the root zone to the upper threshold rather than that moisture was held in a narrow range. Second, the upper threshold of 75.0% is close to the saturated calibration reading ($78.3 \pm 1.5\%$), which leaves little margin below saturation. Whether these thresholds are optimal for beetroot was not tested, and crop-specific optimisation of the thresholds is a necessary step before the values are recommended to farmers.

4.2 Water saving

The smart system used 35.7 L per cycle against 65.0 L in the manual plots, a saving of 45.1% per cycle. This is of the same order as the savings reported for IoT-based irrigation in other settings, such as up to 47.8% in a comparative trial (Pratama & Mandela, 2024) and up to 70% in the case studies cited in a review (Jaiswal et al., 2025), and it is larger than the roughly 20% obtained with simple scheduling tools in a beetroot trial in Nicaragua (Studer & Spoehel, 2019). The comparison is only indicative, because the baselines, crops, climates and irrigation methods differ among these studies.

The present comparison has further limits. The manual plots were described only as nearby, and their size, soil, schedule and the number of irrigations are not recorded, so it is not known whether they were irrigated to the same target. The saving is expressed per irrigation cycle; the seasonal water use depends also on how often irrigation is applied, which was not compared. The saving can be attributed to stopping irrigation at the upper threshold and to avoiding irrigation during rain, as suggested by the design of the controller, but the project was not designed to separate these contributions.

4.3 Crop response

The mean plant height rose from 5.2 to 24.8 cm in 30 days under automatic irrigation. This shows that the soil conditions maintained by the system were compatible with growth, but it cannot be attributed to the irrigation method: no non-automated control was measured for plant height, yield and root quality were not recorded, and growth also depends on cultivar, season and fertility, none of which was varied or documented here. The growth result is therefore best read as a check that the automatic system did not impair crop development, not as evidence of an agronomic benefit.

4.4 Response time, monitoring and practical aspects

The mean response time of 2.45 s is about 1% of the 4.2 min (252 s) irrigation period, so the delay between detection and pumping is negligible for irrigation of this kind. The relay activation (124.0 ms) and rain-override (45.0 ms) times are shorter still, and the difference between these latencies and the response time of Eq. 3 should be clarified in future tests by logging each step of the control loop. The system includes a local LCD and Wi-Fi capability for remote monitoring (Table 1), but the reliability and latency of data transmission were not quantified. The cost of the prototype and its energy use were also not recorded, so the practical advantage of the system for smallholders cannot yet be expressed as a cost per cubic metre of water saved. Reviews of IoT irrigation identify cost, scalability and long-term performance as the main open questions (Abdelmoneim et al., 2025; García et al., 2020), and these apply here as well.

4.5 Limitations and implications

The main limitations of the study are the following. The evaluation was done at one site, with one system, over 30 days and ten irrigation cycles, without replicated plots or treatments, so no statistical test could be applied and the generality of the results is unknown. The number of plants measured for height and the number and layout of the manual plots are not recorded. Sensor calibration used three soil conditions and no reference method such as gravimetric moisture, and the long-term durability of the capacitive sensor and its behaviour in other soil textures were not tested. The humidity limit of the weather override and the sampling interval of the control loop are not documented. Yield, product quality, energy use and cost were not assessed.

Within these limits, the results suggest that a low-cost ESP32-based closed-loop system can regulate soil moisture between set thresholds, react to rain and use less water per irrigation cycle than manual irrigation in beetroot. Further development should (i) compare automatic and manual irrigation in replicated plots over several seasons, with measured yield and seasonal water use; (ii) optimise the VWC thresholds for beetroot and validate the sensors against a reference method; (iii) meter energy use and cost, and test the combination of the system with solar power; and (iv) extend the control logic with weather forecasts and machine-learning prediction, as explored in recent work (Et-Taibi et al., 2024; Jaiswal et al., 2025; Wei et al., 2024), and test it on other root crops. Because the design uses inexpensive, widely available components, it is also suitable for the practical curriculum of agricultural-engineering programmes.

5. Conclusion and Recommendations

An IoT-based smart irrigation system with real-time monitoring was designed, modelled in 3D and simulated, fabricated, and evaluated for beetroot at the RP-Gishari Demo farm. The system, built around an ESP32 microcontroller with capacitive soil-moisture, temperature, humidity and rain sensors, started irrigation at 35.0% VWC and stopped it at 75.0% VWC. Over ten irrigation cycles it raised the soil moisture from 33.2% to 74.5% (mean SMR 41.3%), responded in 2.45 s on average, and suppressed irrigation within 45.0 ms when rain was detected. Each cycle used 35.7 L, which is 45.1% less than the 65.0 L used in nearby manually irrigated plots, and the mean plant height increased by 19.6 cm in 30 days.

These findings show that a low-cost automatic system can replace manual judgement of irrigation timing and amount in a small beetroot plot and can reduce the water applied per cycle. Because the evaluation was short, unreplicated and without a controlled growth comparison, statistical testing, yield data, energy metering or cost data, the results reflect initial functional performance and indicative water saving, not optimised thresholds or a proven yield benefit.

To build on these baseline results, we recommend that (i) agricultural bodies such as the Rwanda Agriculture and Animal Resources Development Board (RAB) support pilot trials of low-cost sensor-based irrigation kits, particularly in the Eastern Province, once replicated field evidence is available; (ii) training institutions include the prototype in the practical curriculum, using the college demo farm as a learning site for microcontroller programming, sensor calibration and maintenance; (iii) farmers move from fixed-schedule watering towards sensor-based irrigation, starting with small demonstration plots; and (iv) future research test the system over several seasons and on other root crops, validate sensors and thresholds, assess sensor durability in different soil textures, evaluate solar power, and add predictive control based on historical data and weather forecasts.

Declarations

Acknowledgements

The authors express their sincere gratitude to Rwanda Polytechnic–Gishari College (Department of Agricultural Engineering and the Agricultural Mechanization Technology programme), the University of Rwanda (College of Science and Technology), and the University of Lay Adventist of Kigali (UNILAK) for providing the academic support and facilities required to design, build and test the smart irrigation prototype. The authors also thank the college and industry supervisors and their colleagues in the Agricultural Mechanization Technology programme for their guidance and cooperation.

Regarding author contributions, Soulaïman Mwamini led the conceptualization, research tool development, experimental execution, and primary drafting of the manuscript. Triphonie Uwamariya, Jean Nepo Nsengiyumva, Venant Kubwimana, and Marie Jeanne Umuhoza, provided academic supervision, methodological guidance, drafting support, and critical manuscript revisions. Experimental

data collection and statistical analysis were performed by Soulaïman Mwamini, Triphonie Uwamariya, and Venant Kubwimana. All authors read, edited, and approved the final manuscript for publication.

Author Contributions

Ideation and conceptualization: S.M. Supervision and guidance: T.U, J.N.N, V.K. and M.J.U. Development of research and tools: J.N.N., S.M. Data collection and analysis: S.M., T.U. Study design and methodological rigour: S.M., J.N.N., M.J.U. Drafting and revising the manuscript: S.M., T.U., J.N.N., V.K. Review, editing and proofreading: T.U., J.N.N., V.K. and M.J.U.

Funding

This research did not receive any specific grant from public, commercial or not-for-profit funding agencies.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request at *soulaimanmwamini0@gmail.com*.

Ethics Approval and Consent to Participate: This study did not involve human participants, human biological tissue, or animal subjects; therefore, formal ethical approval and informed consent were not required.

Competing Interests: The authors declare that they have no financial, personal, or professional competing interests that could inappropriately influence or bias the research presented in this paper.

Funding: This research received no specific grant, financial subsidy, or dedicated funding from public, commercial, or non-profit funding agencies.

Data and Code Availability: The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

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Figures

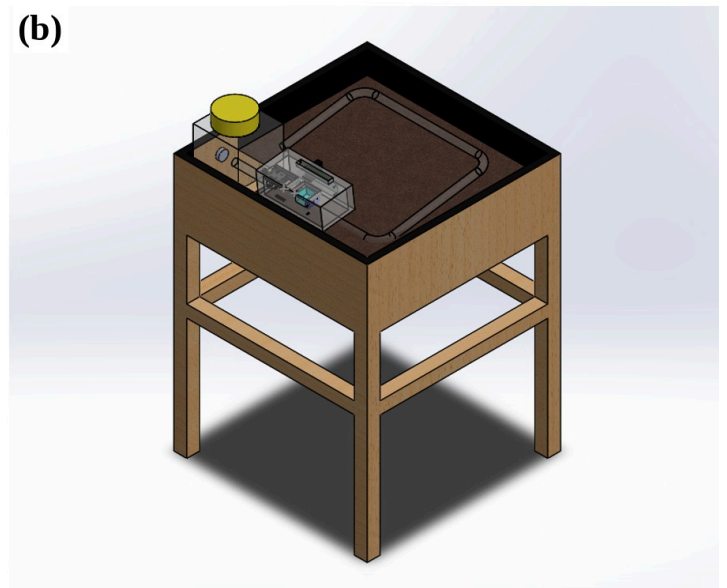
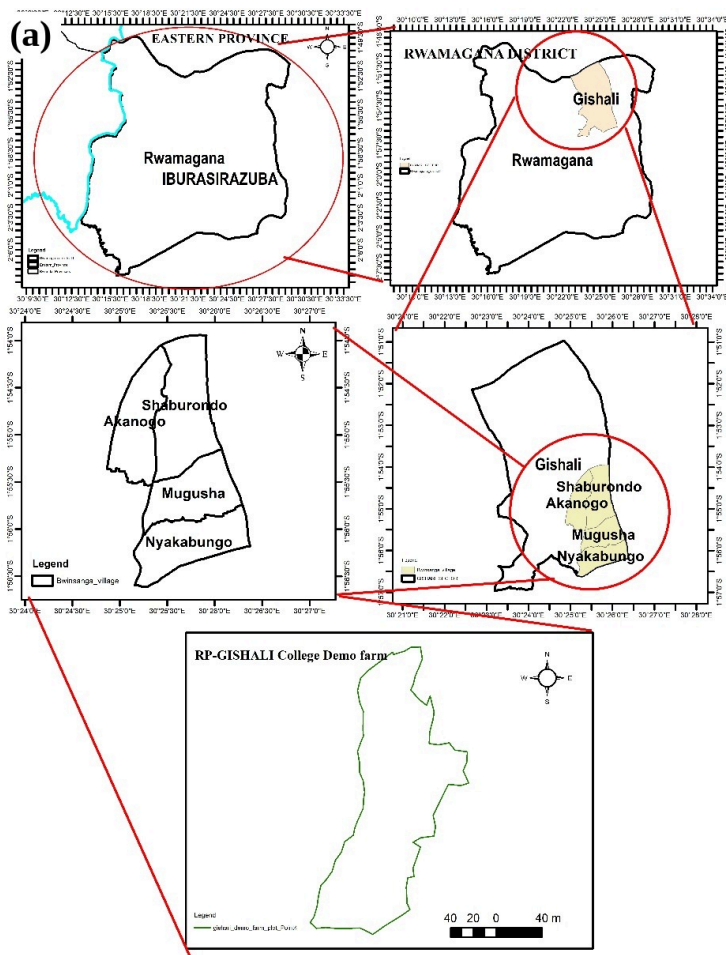


Figure 1

a) Location of the RP-Gishari College Demo farm in Gishali sector, Rwamagana District, Eastern Province (adapted from the project maps); (b) three-dimensional model of the smart irrigation system produced in SolidWorks, showing the raised timber bed, the electronics enclosure, the water tank and the pipe loop around the plant bed.

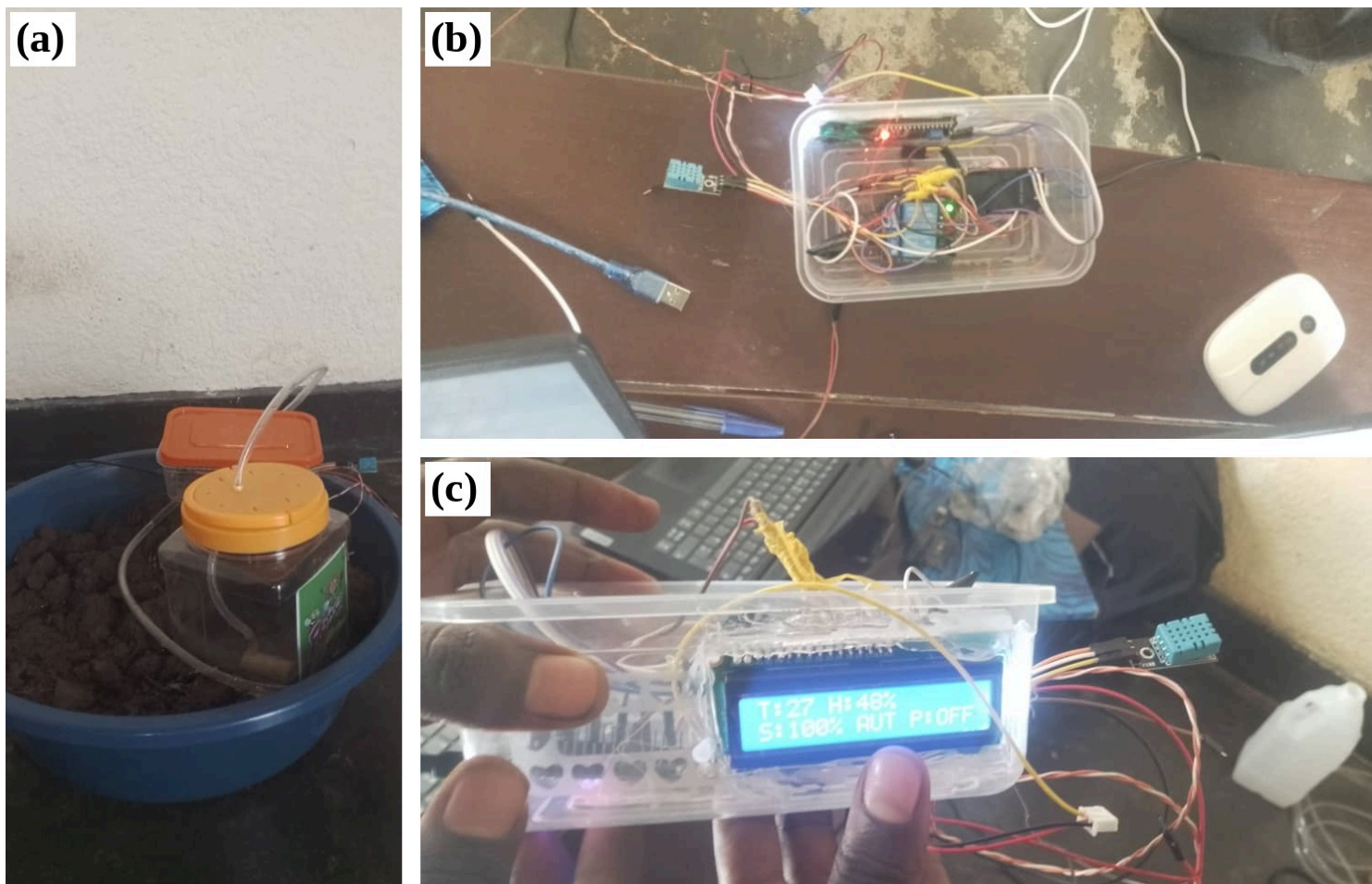


Figure 2

Fabrication and testing: (a) the prototype with the water tank, electronics enclosure and sensors in the soil container; (b) wiring of the ESP32 controller inside its enclosure; (c) the system in operation, with the LCD showing the temperature, humidity, soil-moisture reading, operating mode and pump status.

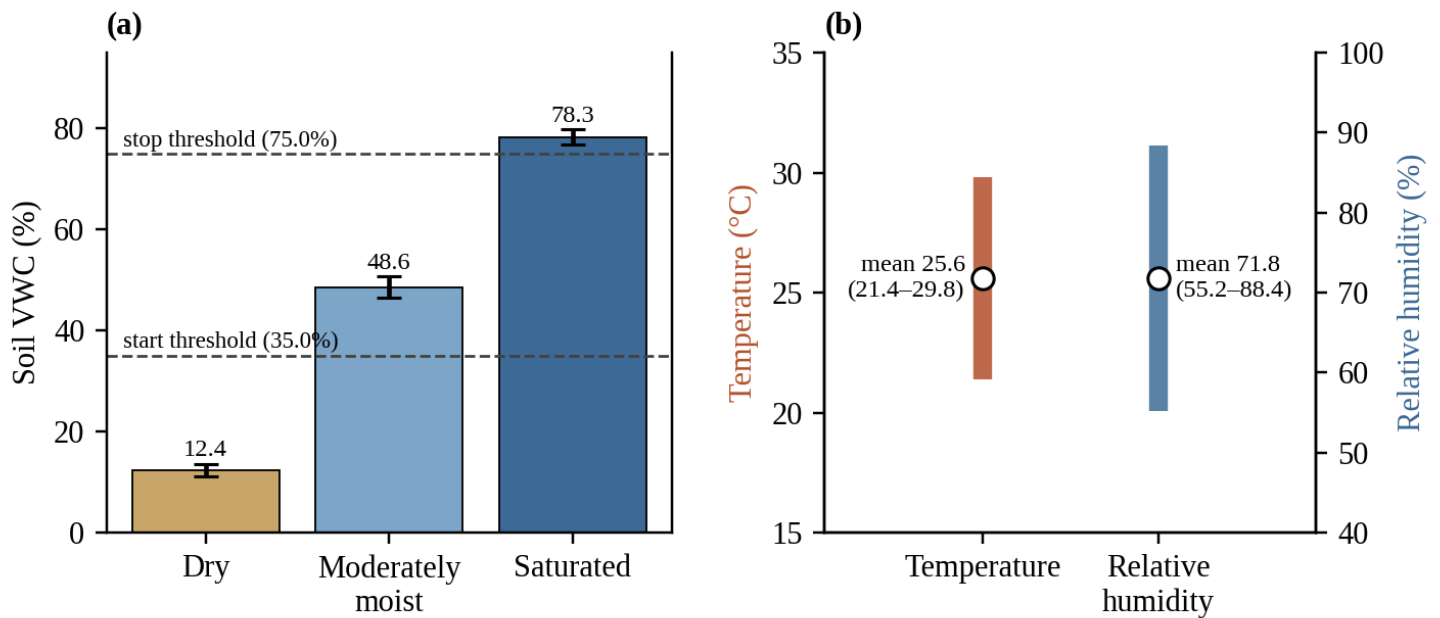


Figure 3

Sensor calibration and ambient conditions: (a) mean soil VWC ($\pm$ SD) measured by the capacitive sensor in dry, moderately moist and saturated soil, with the irrigation start and stop thresholds; (b) mean (circle) and range (bar) of ambient temperature and relative humidity during field testing.

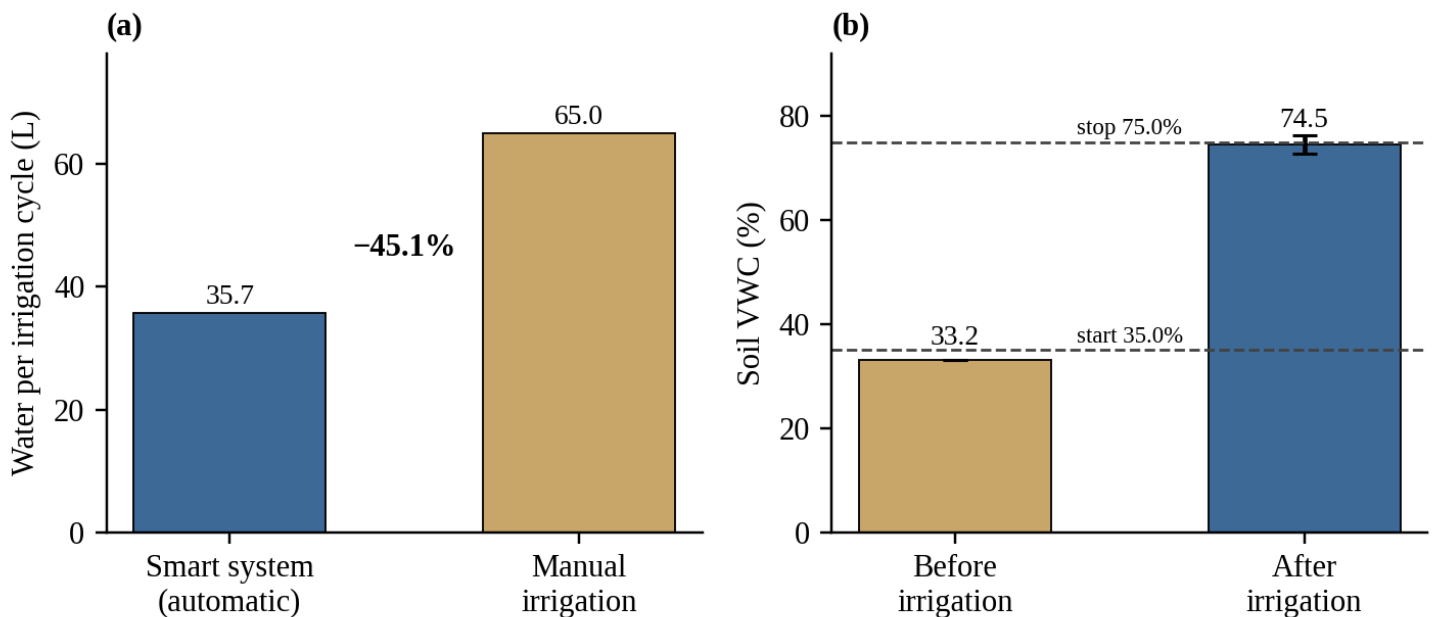


Figure 4

Performance of the smart irrigation system: (a) water consumption per irrigation cycle of the automatic system and of nearby manually irrigated plots; (b) mean soil VWC before and after irrigation (error bar: $\pm$ 1 SD of the post-irrigation readings), with the irrigation start and stop thresholds.

