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A low-cost modular precision irrigation system for resource-constrained environments

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ABSTRACT

Precision irrigation technologies have emerged as effective tools for optimizing water use and improving crop productivity. However, many existing systems remain costly and technically complex, limiting their adoption among smallholder farmers in resource-constrained environments. This study presents the design and field evaluation of a low-cost modular precision irrigation system aimed at improving irrigation efficiency while maintaining affordability. The proposed system integrates soil moisture, temperature, and humidity sensors with ESP32-based microcontrollers organized in a master-slave architecture. A custom-designed 5V reduction electric valve, significantly cheaper than conventional solenoid valves, is used to control irrigation water flow. The system further incorporates a soil-crop database and a mobile application (GEPA Mobi) to support remote monitoring and adaptive irrigation scheduling. The system was deployed and tested across five irrigation farms in Northern Uganda for a period of 100 weeks, during which soil moisture, temperature, and humidity data were continuously collected. Results demonstrate that the system reliably monitored environmental conditions and supported automated irrigation decision-making with minimal maintenance requirements. The proposed reduction electric valve reduces irrigation hardware costs from approximately $50 to $25, making the system significantly more affordable for smallholder farmers and scalable for large farms with almost 50% reduction in cost. Overall, the developed system provides a scalable, energy-efficient, and cost-effective precision irrigation platform suitable for resource-constrained agricultural environments. The integration of modular hardware, cloud connectivity, and crop-specific irrigation thresholds enhances its adaptability across different crops, soil types, and farm sizes.

1. Introduction

Globally, agricultural systems form the backbone of human society, providing billions of people with food, energy, and income. However, in developing countries, these systems remain vulnerable to environmental and socioeconomic stressors [1]. In sub-Saharan Africa (SSA), approximately 80% of farming activities are subsistence-based and rely heavily on rainfall. With the increasing climate variability, rain-fed agriculture is becoming less reliable, limiting households' ability to sustain their livelihoods. For instance, rainfall variability affects approximately 93% of African agriculture [2], and projections suggest that several regions will experience prolonged droughts, increased variability, and heightened water stress [3,4].

Optimizing water resources for irrigation is crucial for sustainable agriculture, particularly in water-scarce regions like Northern Uganda, where the semi-arid climate and predominantly rain-fed agriculture exacerbate water scarcity, especially during the dry season [5]. Efficient water management practices are important for enhancing crop yield, conserving valuable water resources, and ensuring food security in this region. Soil moisture and nutrients are also vital for crop growth, making their monitoring essential for modern agriculture. Given that irrigation needs vary significantly across crop growth stages, tailored water management strategies are necessary to maximise water use efficiency and agricultural productivity [6].

Advances in information technology, particularly the Internet of Things (IoT), have revolutionised this aspect by enabling automated

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monitoring systems [7–11]. The IoT represents a paradigm shift from traditional communication systems, allowing physical objects, such as plants, to interact with and understand their environment [12]. Through IoT, devices can communicate via networking capabilities, generating and exchanging data [13]. Central to IoT are sensors, which convert physical inputs into electrical outputs, and actuators, which translate signals from control modules into physical actions, such as activating an irrigation system when temperatures exceed a certain threshold.

The integration of IoT into various domains has transformed operations, leading to the emergence of new systems collectively referred to as precision agriculture [14]. Precision agriculture involves incorporating information and communication technology into traditional farming practices [15,16]. This approach optimises agricultural inputs, enhances production, and reduces losses by precisely adjusting agronomic measures based on environmental conditions and spatial-temporal differences in crop yield [17,18].

Across sub-Saharan Africa, notable smart agricultural systems have been reported. These systems monitor soil fertility, manage crop water, assess crop canopy status, control pests, handle harvest and post-harvest processes, support smart livestock farming, and facilitate knowledge sharing and resource pooling among smallholder farmers [19,20]. Despite these innovative systems, many farmers in sub-Saharan African countries like Uganda continue to rely on traditional methods for irrigation, monitoring crop growth and applying fertilizers. This often leads to delays in irrigation, fertilizer and pesticide application, resulting in lower crop yields and adversely affecting social and economic development [21]. This gap highlights the need for affordable, context-appropriate precision irrigation systems tailored to small-scale farmers.

To address these challenges, this study develops and evaluates a low-cost modular precision irrigation system capable of sensing environmental conditions and automatically regulating irrigation based on crop moisture requirements. The system integrates low-cost sensors, ESP32 microcontrollers organized in a master-slave architecture, a novel reduction electric valve for water flow control, and a cloud-enabled mobile application for monitoring and management. The system was deployed and evaluated across five farms in Northern Uganda to assess its operational reliability and applicability for smallholder agriculture. **The objectives of this work can be summarized as follows:**

- Design and implementation of a low-cost modular precision irrigation platform for resource-constrained settings.
- Development and deployment of a 5V reduction electric valve that lowers control hardware cost and power requirements.
- Integration of a master-slave wireless architecture with cloud/mobile monitoring and crop-soil threshold control.
- Multi-site field deployment over 100 weeks demonstrating long-term operational feasibility.

2. Related works

This section provides an overview of recent advancements in smart irrigation systems, focusing on their application in precision agriculture and the challenges associated with their implementation. [22], pioneered a low-cost, intelligent irrigation scheduling system that leveraged a wireless sensor network (WSN) to advance sustainable and precision agriculture. By continuously monitoring soil moisture levels and employing a fuzzy logic algorithm, the system optimised irrigation schedules, resulting in reduced water consumption and increased crop yields. Field testing demonstrated the system's effectiveness in reducing water consumption and increasing crop yields while maintaining affordability for small and medium-sized farms. While the system demonstrated promise for small and medium-sized farms, challenges such as long-term cost analysis, scalability, and adaptability to diverse agricultural contexts required further investigation.

Atanasov [23] provided a comprehensive review of state-of-the-art remote sensing technologies used in monitoring crop water status and nutrient levels. The study highlights the roles of UAVs, satellite imaging, IoT, wireless sensor networks, machine learning, and precision agriculture in promoting sustainable farming and food security. This review paper contextualizes the suitability of different sensing modalities, for instance; thermal infrared, multispectral, hyperspectral, and visible-spectrum imaging for the specific constraints of resource-limited agricultural settings. However, it lacks detailed comparative and critical analysis of the technologies discussed, particularly regarding their accuracy, cost-effectiveness, and applicability in diverse farming environments.

Sanjeevi et al. [24], investigated the potential of integrating Internet of Things (IoT) and wireless sensor networks (WSNs) to enhance farming efficiency through precision agriculture. By deploying sensors to monitor soil moisture, temperature, and humidity in real-time, they developed a system that enabled automated decision-making for optimizing resource management and boosting crop productivity. Accurate data on soil conditions allowed for precise irrigation scheduling and amounts, improving water use efficiency, reducing waste, and increasing crop yields. Although the IoT-based WSN system demonstrated significant promise in enhancing resource utilisation and crop yields, challenges related to scalability, network robustness, and long-term sustainability emerged. To address these issues, the authors recommended conducting extensive field trials, improving network reliability, and performing cost-benefit analyses to support broader adoption.

Furthermore, [25] developed an automated remote sensing system for crop monitoring and irrigation management using regression-based soil moisture prediction. The system integrates remote sensing data with predictive modelling to support irrigation decision-making. While the approach demonstrated improved prediction accuracy and automation potential, further evaluation is required to assess its scalability and robustness under varying environmental conditions.

Similarly, [26], introduced a modelling approach designed to improve the accuracy of low-cost soil water content sensors for IoT-based precision agriculture. Their rigorous field testing demonstrated that this model significantly enhanced sensor precision and reliability, making the sensors practical for agricultural use. While the study highlighted the potential of affordable sensors in precision farming and addressed cost and accessibility issues, it did not fully explore the model's scalability across various sensor types, its long-term performance, or its integration with other systems.

To improve low-cost sensors accuracy, González-Teruel et al. [27] presented the design and calibration of a low-cost capacitive SDI-12 soil moisture sensor, demonstrating that soil-specific calibration equations can be selected through the digital communication protocol to improve accuracy. Their sensor was calibrated in three different soils and field tests showed temperature influence on sensor readings and the capability to detect irrigation and rainfall events efficiently. The study demonstrated that affordable sensor alternatives can achieve acceptable levels of accuracy if well calibrated across different soil types. However, the study does not fully address how sensors can be incorporated into modular irrigation architecture that involves distributed sensing, processing and actuation components.

Wanyama et al. [28], developed a solar-powered smart irrigation control system called the Smart Irri-Kit, designed to optimise water usage in agriculture. The system integrates solar panels, advanced sensors, and intelligent algorithms to tailor irrigation based on real-time soil moisture and weather conditions. The research demonstrated the system's effectiveness in significantly reducing water waste and operational costs while utilizing renewable energy. Although the system showed potential for cost-effectiveness, the study did not thoroughly assess its scalability or user experience. Further research is needed to incorporate more weather parameters and enhance communication capabilities for remote monitoring and control to fully realise the system's potential.

The study by [19], explored the integration of wireless sensor networks (WSN) with Internet of Things (IoT) technology to enhance precision agriculture, particularly for improving water resource management

in remote areas. They proposed a scalable WSN architecture that outperforms conventional IoT-based systems with higher throughput, reduced latency, and a better signal-to-noise ratio. This system enabled more precise irrigation management by providing real-time data and control, leading to increased productivity. However, the article lacks detailed cost analysis, extensive field trials, and insights into user accessibility, leaving gaps in understanding the system's overall feasibility and practical implementation.

Sahin [29] presented a solar-powered smart irrigation system designed to optimize water use for medium and small-scale farmers. Controlled via mobile phone, the system addresses the increasing demand for efficient agricultural water management by harnessing solar energy. The study detailed the system's components, costs, and circuitry, comparing its performance to traditional irrigation methods (drip, sprinkler, pivot) across cost, water, and energy consumption metrics, as well as payback periods. While the initial investment in smart irrigation exceeds traditional systems, long-term benefits in resource efficiency and environmental sustainability are suggested, potentially boosting agricultural productivity and energy savings. However, the research lacks in-depth analysis of practical implementation challenges, user experiences, and detailed financial breakdowns to fully substantiate the claimed cost-effectiveness and assess the system's feasibility and affordability.

A study by [30], investigated the potential of an optimisation-based feedback control system to enhance crop yield and water productivity in large-scale sugarcane plantations through precision irrigation. Their approach integrated a two-tiered optimal control strategy within the AquaCrop-OS platform. A seasonal irrigation planner determined optimal water allocation across fields for the entire growth period, while a model predictive controller fine-tuned daily soil moisture levels. To address computational challenges, they employed a mixed-logic dynamical model and leveraged remote sensing for evapotranspiration estimation. Results demonstrated a 30% increase in water productivity over traditional methods, effectively managing water scarcity during droughts. While the system showed promise in enhancing precision irrigation, the study did not assess economic implications, limiting understanding of its practical applicability for farmers.

Figorilli et al. [31] developed and tested a low-cost, open-source soil moisture device utilizing LoRa technology for precision irrigation in Trentino, Italy's apple orchards. The study integrated adaptive predictive models, updated in real-time using weather station and ground sensor data, to enhance irrigation efficiency. Over a 78-day summer trial in 2019, the system yielded substantial resource savings, including a 255 mm reduction in water usage and 44,000 kW in electricity, equating to a 10.82% efficiency improvement. While demonstrating significant potential for low-cost, efficient irrigation, the study's scope was limited to the device's performance, neglecting a comprehensive evaluation of scalability and long-term maintenance costs for wider application. Further research is essential to assess the system's economic viability across diverse agricultural settings.

Boursianis et al. [32], presented a compelling concept with the ARETHOU5A IoT platform, demonstrating the potential of integrating IoT and energy harvesting technologies for precision irrigation. The innovative use of a rectenna module to power the IoT node was particularly noteworthy. However, the study's primary limitation lay in its narrow focus on the technological aspects of the system, addressing the scalability of the system to diverse agricultural settings. Its resilience to varying environmental conditions would have strengthened its practical applicability. Furthermore, a detailed exploration of the system's maintenance requirements and potential issues was crucial for long-term adoption. By expanding the scope of the research to include these critical factors, the authors could have provided a more comprehensive understanding of the platform's real-world potential and its contribution to sustainable agriculture.

Nafutali et al. [33], presented a web-based irrigation monitoring and control system aimed at overcoming inefficiencies in manual irrigation practices prevalent in Uganda and other developing nations. The system simplifies irrigation management through a web interface that provides remote control and monitoring capabilities. It automatically collects soil moisture data and allows users to operate irrigation pumps remotely. Findings suggest that this web-based approach surpasses traditional methods in reliability and efficiency, reducing water wastage and errors. However, the study lacks a comprehensive analysis of implementation costs and challenges on a larger scale, and the absence of data on practical deployment and user feedback hinders a thorough understanding of the system's feasibility and affordability.

In addition, several other scholars have investigated the application of machine-learning and automated sensor techniques to predict soil moisture and other smart agricultural solutions [23,25,34], however, it is evident that existing research on smart irrigation systems have common challenges such as scalability, and insufficient field testing. While many studies demonstrate promising results, they often lack comprehensive assessments of these critical factors. Therefore, this study sought to develop a low-cost, scalable, and modular precision irrigation system that can be employed in resource-constrained settings to sense soil moisture, temperature and humidity, and irrigate plants according to their moisture requirements at different growth stages.

3. Materials and methods

This section describes the study sites, the study's overall framework and the precision irrigation components.

3.1. Study sites

Five study sites in northern Uganda were identified: two from Gulu district; one each from the districts of Pader and Omoro; and the fifth was the Gulu University Faculty of Agriculture and Environment's demonstration garden in Gulu city. The sites at the districts were identified with the help of the respective district agricultural engineers. Two of the sites were for students' demonstrations, while the rest had benefited from a World Bank loan to the government of Uganda, enabling them to set up at least 10 acres of small-scale irrigation. In all these sites, our system was installed and tested on one small section of the farm. Our interest was to test the precision irrigation functionality of the system, but the farm owners generally required additional functions of monitoring soil and weather conditions of the areas, including soil moisture, temperature and humidity. Full details of the farms are contained in Table 1.

The main data collected in the precision irrigation systems was soil water content, also known as soil moisture. As indicated in the previous section, other types of data were necessary. Therefore, the study collected soil moisture content (%), atmospheric temperature ($^{\circ}C$), and humidity levels (%) data continuously over a period of 100 weeks (23 months). This duration covered multiple wet and dry seasonal cycles, allowing for robust seasonal analysis and data-driven decisions on irrigation needs.

3.2. Overall framework

The precision irrigation system presented in this paper comprises field-level implementation, cloud implementation and a display dashboard, as shown in Fig. 1.

3.2.1. Hardware components

The hardware collectively performs data sensing, collection and modelling using devices such as wireless microcontrollers, reduction electric water valves, soil moisture and soil nutrient sensors, and a water pump. The ESP32 microcontrollers are programmed with a central processing ability and a data collection and transmission ability. These are respectively termed the master node and the slave nodes. Essentially, the master node receives data from other devices/slave nodes, and controls the closing/opening of the irrigation valves, also termed as

Table 1
Selected precision irrigation study sites in Northern Uganda.

Site	District	Coordinates	Elevation (m)	Farm Size	Irrigation Type	Connectivity
Aringo Mone Small Scale Irrigation Farm	Pader	3.07605, 32.57888	995	15 acres	Sprinkler (solar powered)	3G
Ayweri Small Scale Irrigation Farm	Gulu	3.02580, 32.28358	968	20 acres	Sprinkler	3G
Opwach Small Scale Irrigation Farm	Omoro	2.78511, 32.31411	1086	30 acres	Drip	3G
Unyama National Teachers' College Demonstration Farm	Gulu	2.82471, 32.33672	1062	1 acre	Sprinkler	4G
Gulu University Demonstration Farm	Gulu City	2.78437, 32.31309	1110	0.5 acre	Drip	4G

*N*ote: All sites had (very) low security risk and reliable mobile network connectivity.

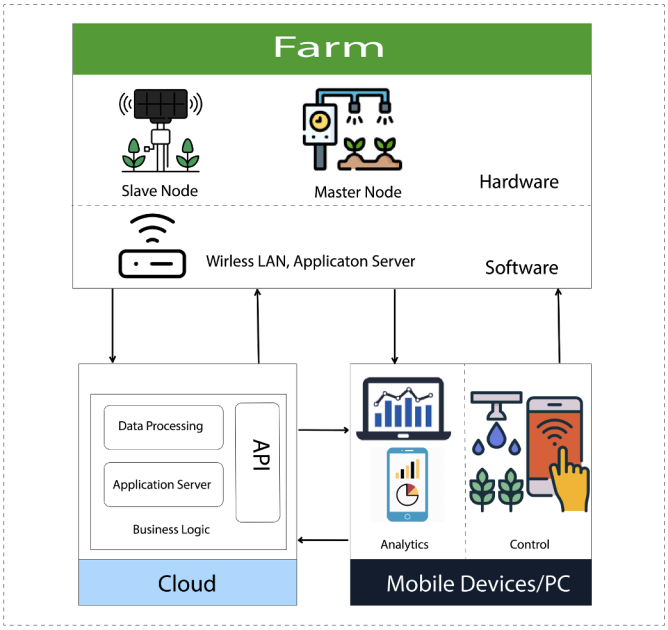


Fig. 1. Farm level precision agriculture (PA) wireless design.

reduction electric valves. In other words, the slave node receives data from sensors physically attached to it and transmits it to the master node over a wireless network. The master node is configured to run an application server with the ability to display farm status to mobile devices that connect to its wireless network. More specifically, offline mobile devices connect to the application server over the wireless network. The mobile device then displays irrigation status and sensor readings associated with a user's farm(s), and controls the farm by enabling its user to change irrigation settings to match the intended crop(s) and override the on/off irrigation function on the master node.

3.2.2. *The reduction electric valve*

An outstanding contribution of our system is the Reduction Electric Valve that is connected to the master node. The name reduction is derived from its mechanical component of a reduction gear system. This valve controls water flow for irrigation through its programmable integrated circuit (IC) connected to the master node. The valve, as given in Fig. 2, comprises the following components: a comparator and motor H-bridge motor chip, a rotary encoder, a DC motor, spurs and worm gears, which are configured to open or close the water path depending on sensed moisture level information at the master node.

The reduction electric valve is driven by 5V, making it ideal for remote areas where power is limited or inaccessible.

3.3. *Soil moisture sensor calibration*

The irrigation monitoring system utilized low-cost resistive soil moisture sensors (YL-69 / FC-28 type). These sensors measure the electrical

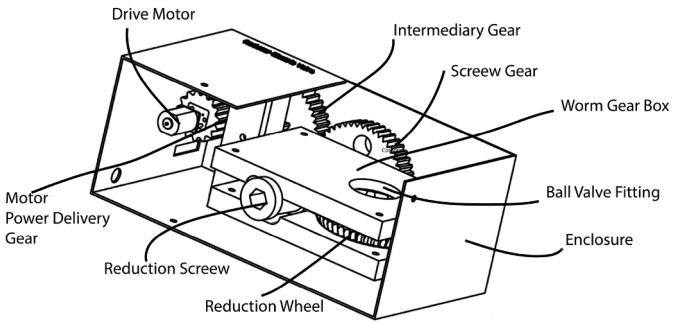


Fig. 2. The reduction electric valve, the name being derived from its operation principle.

resistance between two probes inserted into the soil, which varies with soil water content. The sensor output is provided as an analog voltage or analog-to-digital converter (ADC) value, which must be calibrated to obtain an approximate soil moisture percentage. Such sensors require calibration because the raw analog output is influenced by soil properties, temperature, and electrical conductivity [35,36].

A three-point calibration approach was adopted in this study to improve accuracy while maintaining suitability for low-cost sensing systems.

- **Air condition** (V_{air}): Sensor reading obtained in open air, representing the absence of any moisture medium (in volts, V).
- **Dry soil condition** (V_{dry}): Sensor reading obtained when the sensor is inserted in completely dry soil (in volts, V).
- **Saturated condition** (V_{wet}): Sensor reading obtained when the sensor is fully immersed in water, representing maximum saturation (in volts, V).

For a given measurement $V_{current}$, the soil moisture percentage is estimated using piecewise linear interpolation between adjacent calibration points:

$$\text{Moisture}(\%) = \begin{cases} \dfrac{V_{air} - V_{curr}}{V_{air} - V_{dry}} \times 50, & \text{if } V_{dry} \le V_{curr} \le V_{air} \\ 50 + \dfrac{V_{dry} - V_{curr}}{V_{dry} - V_{wet}} \times 50, & \text{if } V_{wet} \le V_{curr} < V_{dry} \end{cases} \quad (1)$$

where:

- V_{air} represents the sensor output in air (V),
- V_{dry} represents the sensor output in dry soil (V),
- V_{wet} represents the sensor output in water (saturated condition) (V),
- V_{curr} represents the instantaneous (current) sensor reading (V).

The air reference establishes the upper bound of the sensor's response (minimum dielectric permittivity), while the water reference establishes the lower bound (maximum dielectric permittivity) [37]. Including the dry soil reference as an intermediate point accounts for the non-linear response of capacitive sensors, whose sensitivity is known to vary across

the moisture range [26,38]. Multi-point calibration schemes of this type have been demonstrated to reduce interpolation error compared to two-point linear schemes for low-cost capacitive sensors used in irrigation control and precision agriculture applications [27,35,39].

The calibration formula was implemented directly in the embedded software of the irrigation controller. Additionally, a mapping-based conversion method was incorporated to improve system robustness and simplify computation. In this approach, the raw sensor readings are linearly mapped to a moisture range of 0-100%, with value clamping applied to prevent unrealistic readings caused by electrical noise or sensor drift.

To validate the calibration procedure, the reference values (V_{dry} and V_{wet}) were compared with soil moisture levels obtained through standard volumetric soil moisture analysis conducted under the same environmental conditions. This comparison ensured that the calibrated sensor readings provided a reasonable approximation of soil moisture levels suitable for irrigation monitoring and decision support.

3.4. Software module

The firmware programs for the master and slave node microcontrollers were written in C++ and C for core functionality and HTML5, CSS3 and JavaScript for user interfaces. The software design focused on modular design by breaking different functionalities into smaller units, with some of the units in their own independent files to ensure maintainability, easy debugging and ease of future growth (addition of new features). Arduino IDE/ESP-IDF were then used to compile and upload the programs to the microcontroller chip. Future updates could then be made using the OTA (Over-The-Air) capabilities of the microcontroller chips and configurations in the completed firmware. This particular feature is such that a copy of the firmware resides in the cloud server, and this will continue to be updated and improved over time, including providing security upgrades/patches, bug fixes and the addition of new I/O device capabilities. The uploaded firmware on the microcontroller chip will then be able to periodically check and download these updates automatically in its periodic Update Check Sequence (UCS). This, therefore, means that users and maintainers of the system do not need to physically go and update the devices in the fields, saving time and costs.

The slave node firmware is designed to read sensor data from plugged-in sensors, communicate the read sensor data to the master node and send command signals to plugged-in output devices like the electric water valves, including relays and other electric switches. To send a command signal, the command must be received from the master node, and therefore, a two-way communication exists between the two nodes. The master node, which can be seen as the overall brain of a field setup, is designed to allow users to configure settings, i.e., I/O ports for sensors and actuators like the electric water valves, desired production values, e.g., recommended moisture levels, crop kind and master-slave organisation/configuration. It provides an interface to allow users to provide all the settings as described in the later section of this paper.

Once configured, it will be able to receive sensor data from slaves and, at the same time, read from its own configured sensors. It is then able to analyse and make decisions from the received data and issue commands to output devices, including to slaves that have output devices. The master node features a temporary storage for collected data, which must be offloaded to permanent storage in the cloud server. The master nodes have a capability to connect to the internet through WiFi and onboard GSM modules, which they use to send data to the GEPA cloud server. The cloud server can further analyse the data received by each master node, generate more decision commands, and store them for use by the farmers(users). Users can interact with this data through mobile devices or computers, and they can also send new settings/configurations and commands to the master nodes through the master-cloud channel.

3.4.1. The wireless LAN application server

To enable effective communication between the master node and the slave nodes, communication takes place through a wireless Mesh LAN. The organisation of the LAN changes based on the area coverage required and the number of devices needed, and these include ESP-NOW Mesh and ESP-MESH. ESP-NOW mesh uses the low-power ESP-NOW protocol instead of the traditional WiFi protocol for data communication using MAC addresses to send small packets (up to 250 bytes) with low latency. The ESP-NOW is ideal for our base setup, which would contain 3 to 10 devices within a 200-meter radius with a clear line of sight. EPS-MESH is the official proprietary protocol from Espressif, designed to support up to 1000 nodes in large areas. It uses a tree topology where the Master node acts as a “root” connected to an external router, while others relay data to it.

3.4.2. Mobile application

A virtual machine was configured to seamlessly integrate with the master node, allowing further deployment of an Android App called GEPA Mobi, with equivalent functions as the master node and more, e.g., having remote controls for farms at the same or different geographic locations. Essentially, the App remotely triggers irrigation when soil moisture levels drop below predefined thresholds, provided the master node control function is turned-off. In such a situation, the user/farmer wishes to remotely control irrigation. Overall, the mobile App provides visual historical data trends, tracks seasonal patterns, and supports irrigation on multiple plots/sections of the farm. It collects three levels of data, i.e., at the entire farm level, at a section of the farm level and at a plot/individual garden level, provided the respective sensors were online.

3.4.3. Soil-crop database

The soil and crop (soil-crop) database was a necessary part of our system because of its integral role in enabling precision irrigation implementation. Irrigation infrastructure, once installed, is used for a long time, but the crops grown may vary during this time, hence the need for flexibility of the precision irrigation system. For instance, on a given piece of land with irrigation infrastructure, vegetables may be grown in the first season/year and grains in another season/year. These different crops have different water requirements and hence frequency of irrigation. At the same time, different soil types also require different moisture content for various crops. To resolve this complexity, the soil-crop database was developed and integrated into the mobile App, enabling the user/farmer to set soil moisture parameters that match a specific crop and soil against which precision irrigation logic is based.

3.5. Control logic and irrigation decision rules

The control logic implemented on the master node converts calibrated soil moisture readings into discrete irrigation decisions. The decision rule is a threshold-based on/off controller with hysteresis, designed for predictability, low computational cost, and ease of override by the farmer through the GEPA Mobi mobile application. The rule is defined as follows. Let θ_t denote the calibrated soil moisture (% VWC) at sample time t, θ_{low} the activation threshold, and θ_{high} the deactivation threshold. The valve state $V_t \in \{0, 1\}$ (0 = closed, 1 = open) evolves according to:

$$V_t = \begin{cases} 1, & \text{if } \theta_t < \theta_{\text{low}} \\ 0, & \text{if } \theta_t \geq \theta_{\text{high}} \\ V_{t-1}, & \text{otherwise} \end{cases} \tag{2}$$

For the loamy soil at the Gulu University demonstration farm, θ_{low} was set to 30% VWC and θ_{high} to 35% VWC. These values were derived from the field-capacity (FC) and permanent-wilting-point (PWP)

Table 2
Precision irrigation sample data.

Week	Avg. Measured Soil Moisture (%)	Irrigation Action	Avg. Post-Irrigation Soil Moisture (%)	Temp (°C)	Humidity (%)
WK1	12.5	1	31.7	33.2	52
WK2	11.8	1	30.4	34.1	48
WK3	13.2	1	32.0	32.8	55
WK4	14.5	1	30.3	31.5	60
WK5	18.9	1	32.0	29.8	68
WK6	22.3	1	32.4	27.4	75
WK7	25.7	1	33.0	25.1	82
WK8	28.4	1	33.0	23.5	86
WK9	31.2	0	31.2	22.2	89
WK10	33.8	0	33.8	21.1	91
WK11	35.1	0	35.1	20.3	93
WK12	32.5	0	32.5	21.8	88

constants for loam (FC ≈ 27-40% VWC; PWP ≈ 10-15% VWC) and from a Management Allowable Depletion (MAD) of 50% of total available water [40]. The 5% VWC band between θ_{low} and θ_{high} prevents valve chatter when soil moisture sits near the setpoint. For other crop and soil combinations, θ_{low} and θ_{high} are looked up from the soil-crop database and pushed to the master node by the mobile application; no firmware change is required.

Sensor-to-actuator communication proceeds in three steps. (i) Each slave node samples its attached resistive moisture sensor and DHT22 every 10s, computes a 60s rolling mean to suppress high-frequency noise, and transmits the mean to the master node over ESP-NOW using the slave node's MAC address. (ii) The master node maintains a register of the most recent reading from each slave; once readings from all online slaves are received within a 90s window, the master computes the field-section mean θ_t and applies the rule above. (iii) If the rule changes V_t, the master drives the reduction electric valve through the on-board comparator and H-bridge for a fixed actuation time of 8s (open direction) or 8s (close direction); the rotary encoder confirms that the worm gear reached the commanded position, and the new state is recorded in local non-volatile storage and queued for upload to the cloud. If acknowledgement from the encoder is not received, the master retries once and then raises a fault flag visible in GEPA Mobi.

4. Results

The field/farm results were in two parts. The first part was from precision irrigation testing and the second part was the extended functions of our system in monitoring soil and weather conditions of the areas, including soil moisture, temperature and humidity. The extended functions arose from the farm owners of the identified testing sites.

4.1. Precision irrigation at the farm level

Our system was tested on five farms, as already highlighted. The results presented here were from a selected farm at Gulu University Faculty of Agriculture demonstration garden. The farm was chosen for its proximity and ease of reach for installation, optimisation, and field studies. The field measures 20 by 40 m and uses a gravity-fed drip irrigation system. For our setup, three nodes were installed, one being the master node connected directly to the irrigation's outlet - a reduction electric valve was installed here. Two slave nodes equipped with a resistive moisture sensor, a humidity and temperature sensor (DHT22), were installed at the rear ends of the fields to collect data, as shown in Appendices A.1 and A.2.

Sample field data over a cropping season of 12 weeks in 2024 is given in Table 2. The data shows time, average measured soil moisture, the action taken by the precision irrigation system and the average soil moisture after irrigation. The system setup utilised a lower limit threshold of 30% volumetric water content (VWC) to trigger hydration via drip lines. During the initial phase (Weeks 1-8), the soil exhibited significant moisture deficits, with averages as low as 11.8%. This period required consistent irrigation (Action: 1) to restore the soil to its field capacity—the point where the soil holds the maximum water available for plant uptake.

By Week 9, the cumulative effect of irrigation and subsequent regular rains allowed the moisture to stabilize above the 30% trigger, resulting in no irrigation action (Action: 0). This data shows that for the loamy soil, the system maintained moisture between 30% and 35% and this provided an ideal balance of aeration and hydration as water stress and root asphyxiation were not observed. It should be noted that the effect of the irrigation did have a detectable influence on the values of temperature and humidity, and this was in part due to the drip-type irrigation, which only applies water directly to the soil and these particular sensors being very high up from the point of water application.

4.2. Seasonal variation of soil moisture, temperature, and humidity

The results show that our system successfully captured the microclimatic conditions at a specific farm over the 100-week testing/monitoring period, as shown in Fig. 3. In Fig. 3, the blue line represents soil moisture (%), the green line represents air temperature (°C), and the red line represents relative humidity (%). These lines provide a continuous record of how soil and atmospheric conditions change across the wet and dry seasons.

The findings reveal clear inverse seasonal patterns. During the wet seasons (high humidity periods), the humidity (red line) peaks, the soil moisture (blue line) rises significantly, and the temperature (green line) drops to its lowest range (~18-25 °C). Conversely, during dry seasons (low-humidity periods), the red line drops, the blue line (soil moisture) declines, and the green line (temperature) rises to its highest range (~27-35 °C). These patterns were consistently observed throughout the 100 weeks, demonstrating that GEPA can reliably track changes in both soil and atmospheric conditions over time.

The reliability of the system over nearly two years demonstrates that it can operate continuously with minimal maintenance, making it particularly suitable for smallholder farms in resource-limited settings.

4.3. System performance during the testing period

The performance of the precision irrigation monitoring system was evaluated across three main components: sensors and logger, power system, and communication/data retrieval. Fig. 4 presents the operational performance of these system components during the 100-week testing period.

The following factors were considered in coming up with the 30% soil Volumetric Water Content threshold. The initial values and estimates were first obtained from the Food and Agriculture Organisation (FAO)

4.3.1. Soil water constants

The range of available water for plants is defined by two specific soil states, i.e., Field Capacity (FC) and Permanent Wilting Point (PWP). Field Capacity is the upper limit of water the soil can hold against gravity. For loamy soils, this is typically between 27% and 40% Volumetric Water Content (VWC). Keeping the soil near this level ensures plants have maximum water access without oxygen deprivation. Permanent Wilting Point is the lower limit where plants can no longer extract water. In loam, this occurs between 10% and 15% VWC. By setting a trigger at 30%, the system operates at the high end of the available water range, safely away from the wilting point.

4.3.2. Management allowable depletion (MAD)

In precision irrigation, managers do not wait for the soil to reach the wilting point. Instead, they use a refill point based on the Management Allowable Depletion (MAD). MAD can be defined as the percentage of

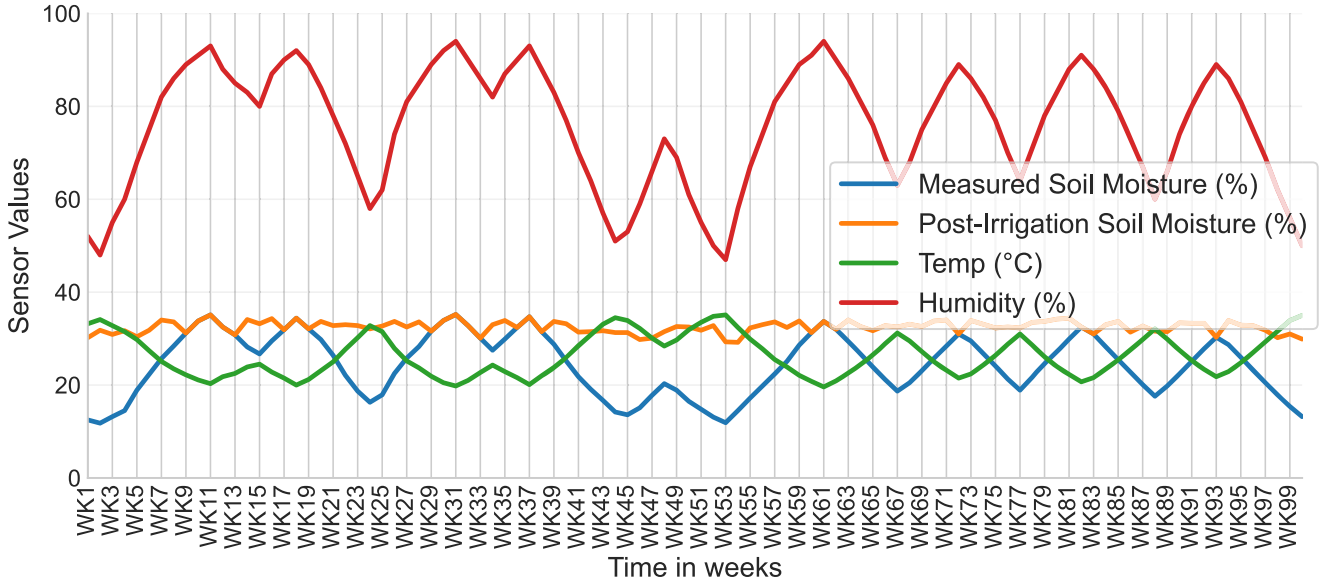


Fig. 3. Seasonal variation of soil moisture, temperature, and humidity.

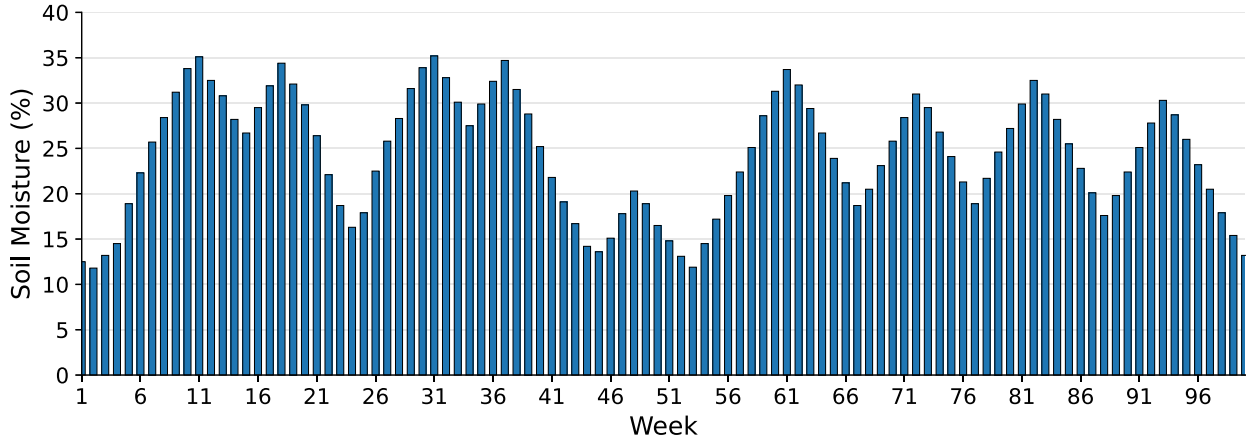


Fig. 4. System performance during the experiment period.

Total Available Water (TAW) that can be used before a plant experiences stress. In standard practice for most crops, the MAD is typically 50% [40].

As aforementioned (Section 3.5), for the loamy soil at the demonstration farm, with field capacity FC = 35% VWC and permanent wilting point PWP = 15% VWC, the total available water (TAW) is:

$$\text{TAW} = \text{FC} - \text{PWP} = 35\% - 15\% = 20\%\text{VWC}$$

Applying the standard MAD = 50% for general crop rotations [40], the readily available water (RAW) is:

$$\text{RAW} = \text{MAD} \times \text{TAW} = 0.50 \times 20\% = 10\%\text{VWC}$$

The lower threshold for irrigation activation is therefore:

$$\theta_{\text{low}} = \text{FC} - \text{RAW} = 35\% - 10\% = 25\%\text{VWC}.$$

The deployed value of $\theta_{\text{low}} = 30\%$VWC is conservative relative to this calculation: it triggers irrigation at 5% VWC above the strict MAD-based depletion point, providing a safety margin that prevents the soil from approaching the wilting point under sensor lag or unexpected demand. The upper bound $\theta_{\text{high}} = 35\%$VWC is set at field capacity to avoid oversaturation, which would cause both water waste through deep percolation and root oxygen stress.

Fig. 5 illustrates the 12-week data, showing how the irrigation actions (Weeks 1-8) successfully brought the average moisture from a deficit state up into the "optimal zone" (30-35%), where it stabilised for the remainder of the season.

4.3.3. *Sensors and logger*

The continuous and consistent trends observed throughout the 100-week dataset indicate that the sensors and data logger operated reliably with minimal downtime. The inverse relationships between soil moisture, temperature, and humidity were consistently recorded. This shows that the sensors provided accurate measurements without evidence of drift or error over time. These results demonstrate that our system consistently captured data throughout the study period, supporting temporal analysis of environmental parameters.

4.3.4. *Power system*

The uninterrupted data collection during the 100-week experimental period confirms the sustained performance of the solar power system. The station operated continuously without power-related interruptions. This indicates that the solar panels and battery backup were sufficient to support long-term, unattended operation in the field. This reliability proves that the system can function independently in off-grid or resource-constrained locations, which is good for continuous environmental monitoring and precision irrigation management.

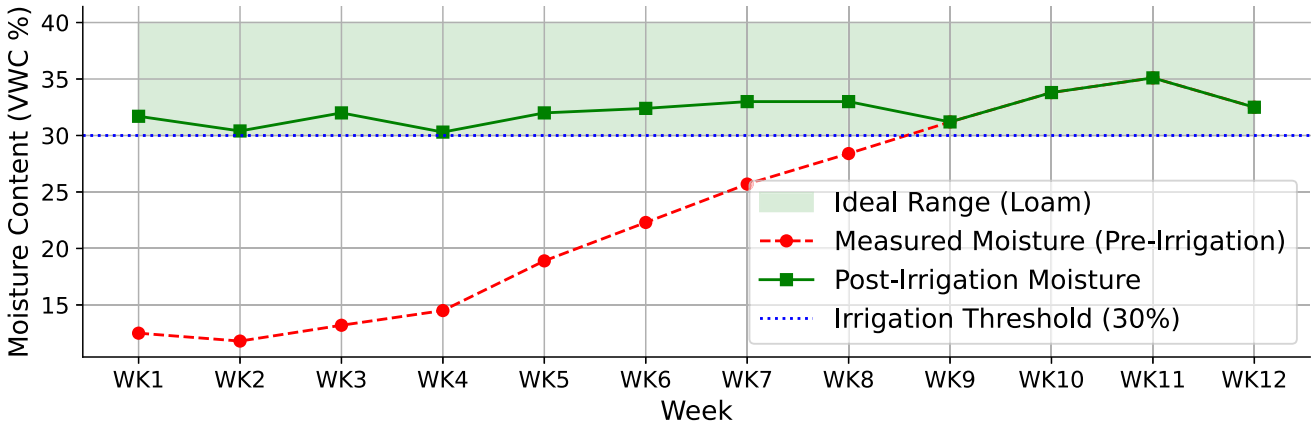


Fig. 5. Precision irrigation performance for the demonstration farm during a 12-week cropping season.

4.3.5. Data retrieval

Both automated telemetry via GSM and structured manual downloads were effective, with no significant data gaps recorded during the study period. This finding confirms that our system can maintain seamless data flow from field sensors to cloud storage, enabling real-time monitoring and decision-making for irrigation management. The completeness of the dataset indicates that the data transmission and retrieval processes were reliable.

Generally, these results demonstrate that the system components (sensors, power, and communication) functioned effectively over extended periods, providing a reliable platform for precision irrigation studies and long-term environmental monitoring.

4.4. User interface designs

Our system, as conceptualized in Fig. 1, has user interfaces for mobile devices and personal computers. These interfaces facilitate interaction on the mobile App and the soil-crop database.

4.4.1. Mobile app dashboard

The mobile App, known as GEPA Mobi and available on the Google Play Store, was developed using Flutter framework. This was the preferred development environment since it produces a single set of code that is deployable on the Google Play Store as well as the Apple Store. With a single codebase, we were able to create applications for multiple platforms, saving time and effort. The “hot reload” feature enabled us to have fast development and iteration, while the rich collection of customizable widgets allowed for beautiful and responsive user interfaces. Flutter framework provides access to native features and APIs, supported by a strong developer community.

For the backend, we used Python with the Django framework to handle data ingestion, processing, and creation of the API. Django provided a robust and secure structure for managing application logic and integrating system components. Time-series data were stored and managed using PostgreSQL. This approach helped to ensure reliability, scalability, and efficient querying and retrieval of time series data. Sample interfaces for tracking sensors (Fig. 6 - left) and data analytics (Fig. 6 - middle & right).

4.4.2. Soil-crop database design

The soil-crop database was implemented using PostgreSQL version 15.0 as the core database management system (DBMS). PostgreSQL was selected due to its robustness, reliability, scalability, and strong support for complex relational data structures. As an open-source object-relational database system, PostgreSQL provides advanced querying capabilities and efficient data handling suitable for agricultural data management. The server-side application layer was developed using Python version 3.9, implemented through the Flask micro-framework. Flask provides a lightweight and flexible environment for building RESTful web services and integrating application logic with the database layer. The backend services handle data processing, database queries, and communication between the database and user interfaces.

The client-side interface was developed using HTML5, CSS3, and JavaScript, which provide dynamic and interactive web-based user interfaces. To ensure responsiveness and compatibility across different devices, the Bootstrap framework was used to design adaptive layouts suitable for desktops, tablets, and mobile devices. Communication between system components is facilitated through HTTP-based RESTful APIs, enabling secure and efficient data exchange between the front-end interface and the backend services. This architecture allows users to query crop and soil data, retrieve irrigation recommendations, and interact with the system in real time.

The overall architecture of the soil-crop database, including the database layer, backend services, frontend interface, and communication protocols, is illustrated in the high-level schematic presented in Fig. 7.

4.5. Cost analysis

The economic advantage of the proposed system lies in its reliance on low-cost hardware components, online firmware upgrades and a scalable system architecture. In general, precision irrigation systems consist of four primary components: sensors, valves, irrigation controllers, and communication mechanisms. Therefore, reducing the overall system cost requires developing affordable alternatives for these components while maintaining functionality and reliability.

Table 3 presents a comparative analysis of the cost benefits of the proposed system, referred to as the GEPA system, derived from the project acronym *Gravity Energy and Precision Agriculture (GEPA)*. The analysis highlights how the selected hardware components and system architecture contribute to cost efficiency when compared with conventional precision irrigation systems. More specifically, the minimal cost of our system for an acre of land is about $305, distributed as: $130 for master node; $90 for slave node; $25 for the valve; and $60 for four moisture sensors and connecting wires. The scale-up cost excludes that of the master node and the valve, making a cost reduction of about 50%.

4.6. Quantitative evaluation of system performance

To complement the qualitative observations in Sections 4.1–4.3, we performed a quantitative analysis of the full 100-week field record from the Gulu University demonstration farm. The analysis covers four dimensions: (i) statistical validation of the irrigation effect, (ii) control accuracy of the threshold rule, (iii) seasonal responsiveness, and (iv) Irrigation timing, duration and applied water volume.

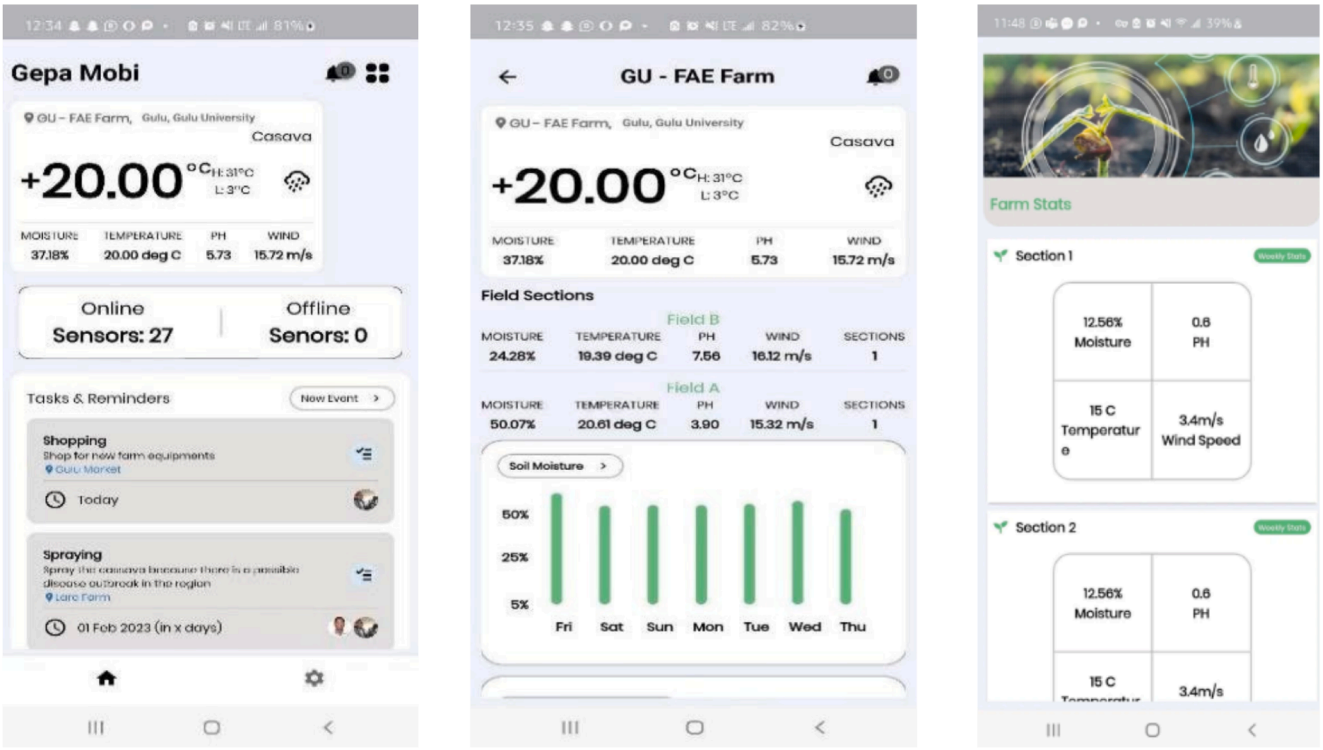


Fig. 6. Mobile dashboard for different scenarios.

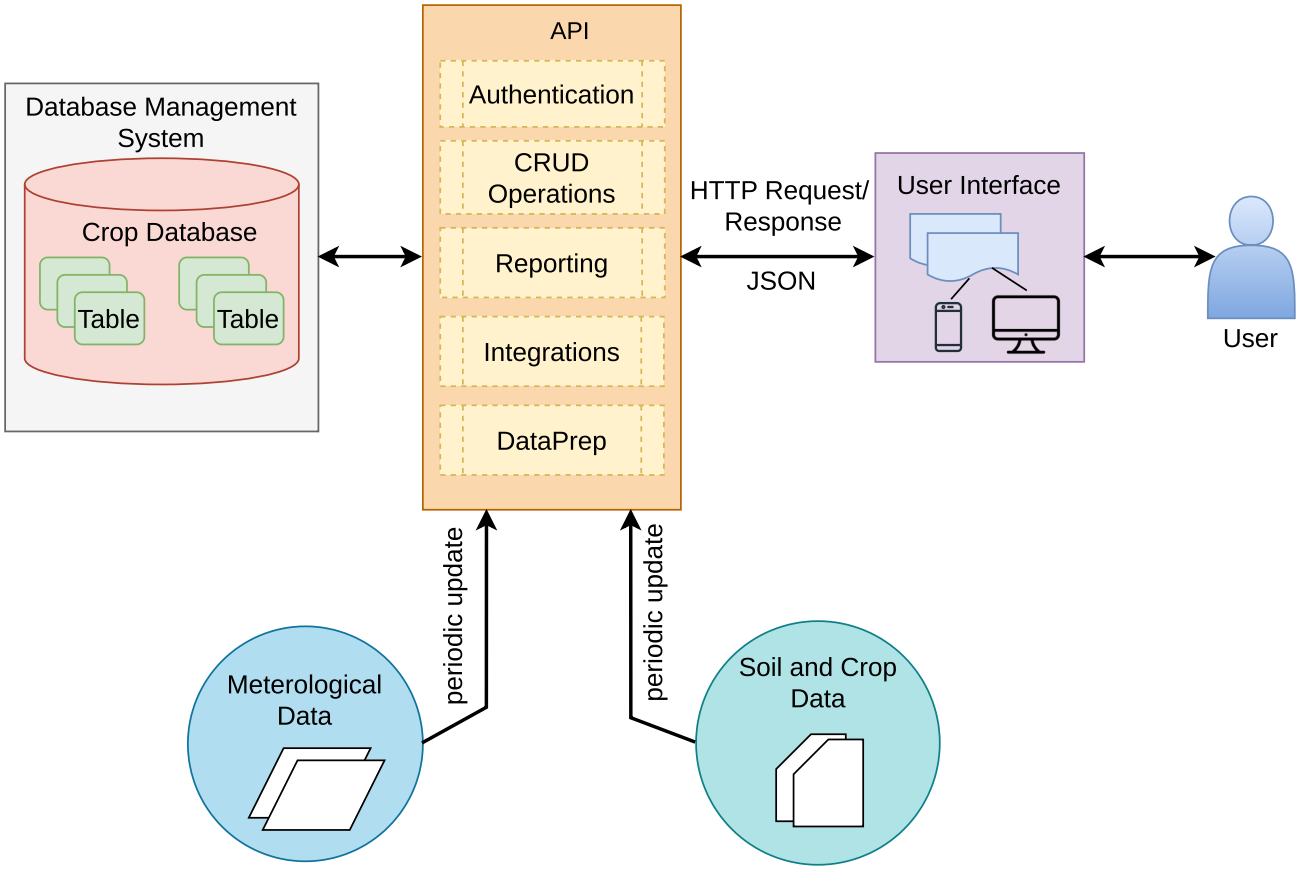


Fig. 7. Soil-crop database system architecture.

Table 3
Cost analysis of the GEPA system.

Component	Context of the GEPA Solution	Comparative Cost Analysis
Sensors	Industry-standard soil moisture, temperature, and humidity sensors were used.	No significant cost savings were considered compared to other precision irrigation systems, as similar sensing technologies are commonly employed in existing systems.
Irrigation Controllers	ESP32 microcontrollers were programmed and deployed using a master–slave architecture.	The master–slave architecture significantly reduces scalability costs, as expansion requires only the addition of slave nodes responsible for sensing data collection and transmission. A single master node can control irrigation across approximately two hectares while supporting thousands of slave nodes. This design is more cost-efficient than conventional systems, which typically require proportional increases in both master and slave units when scaling. In addition, the master-slave firmware upgrades are effected remotely using *over the air* feature in ESP32. This enables future maintenance without disassembling except for damaged internal circuits.
Smart Valve	A reduction electric valve was implemented.	Compared to the solenoid valves commonly used in conventional precision irrigation systems (typically costing at least $50), the reduction electric valve costs approximately $25. The reduction gear mechanism used in these valves is cheaper to manufacture than the electromagnetic components used in solenoid valves. Additionally, reduction electric valves operate at only 5 VDC, whereas conventional solenoid valves typically require 12-24 VDC.
Communication Mechanism	Wireless sensor networks (WSNs) were used to support both online and offline communication modes. The system was also integrated with a soil-crop database and a mobile application.	Although no direct hardware cost savings were observed compared to other WSN-based precision irrigation systems, the integration with a soil-crop database and mobile application reduces the need for external advisory services, thereby lowering operational costs for farmers.

Table 4
Decision-outcome breakdown of the threshold controller ($n = 100$ weeks).

Decision	Outcome	Count	Total	% group
Irrigated ($V = 1$)	Reached 30-35% band	73	77	94.8
Irrigated ($V = 1$)	Below 30% after event	4	77	5.2
Irrigated ($V = 1$)	Above 35% (over-shoot)	0	77	0.0
Not irrigated ($V = 0$)	Pre-SM ≥ 30 % (correct)	23	23	100.0
Not irrigated ($V = 0$)	Pre-SM < 30 % (missed)	0	23	0.0

Table 5
Per-event irrigation statistics ($n = 77$).

Statistic	Lift (% VWC)	Equivalent depth (mm)
Mean	10.57	31.71
SD	4.39	13.18
Min	3.90	11.70
Median	11.00	33.00
Max	20.00	60.00

4.6.1. Statistical validation of the irrigation effect

Across 100 monitoring weeks the master node triggered irrigation in 77 weeks and held the valve closed in the remaining 23 weeks. For the 77 triggered events, the mean pre-irrigation soil moisture was 21.92% VWC (SD = 5.34) and the mean post-irrigation value was 32.49% VWC (SD = 1.25). The mean lift of +10.57% VWC (95% CI [9.58, 11.56]) was statistically significant (paired $t(76) = 20.99$, $p < 0.001$) with a very large effect size (Cohen's $d = 2.39$). The 24-fold drop in variance from pre- to post-irrigation ($\sigma^2_{pre}/\sigma^2_{post} = 24.4$) and the corresponding fall in coefficient of variation from 26.7% to 4.0% indicate that the system actively stabilises soil moisture toward the setpoint rather than passively measuring it.

4.6.2. Control accuracy

Treating $\theta_{low} = 30\%$ VWC as the setpoint, the mean bias of post-irrigation soil moisture was +2.49% VWC (slightly above the trigger, as intended by the 30-35% control band) and the root-mean-square error from the setpoint was 2.79% VWC. Of the 77 triggered events, 94.8% landed inside the 30-35% target band and 100% landed within ±2.7% VWC of the band midpoint (32.5%). For the 23 weeks in which the system did not irrigate, soil moisture was already at or above the threshold in every case (minimum 30.10% VWC), indicating no false-negative decisions over the deployment. A summary of the decision-outcome breakdown is given in Table 4 below.

4.6.3. Seasonal responsiveness

The deployment spanned two full wet-dry cycles (Northern Uganda has bimodal rainfall: Mar-May and Sep-Nov are typically wet; Dec-Feb and Jun-Aug are dry). Wet- and dry-season subsamples differed significantly on every monitored variable. Mean pre-irrigation soil moisture was 26.97% VWC in the wet season versus 21.49% VWC in the dry season (Welch's $t = 4.59$, $p < 0.001$); mean temperature was 24.65°C versus 28.28°C ($t = -4.42$, $p < 0.001$); mean humidity was 81.12% versus 70.31% ($t = 4.56$, $p < 0.001$). Pearson correlations among the three environmental variables were all very strong and significant (soil moisture vs. temperature, $r = -0.987$; soil moisture vs. humidity, $r = +0.979$; temperature vs. humidity, $r = -0.993$; all $p < 0.001$, $n = 100$). The system irrigated in 87.5% of dry-season weeks and 67.3% of wet-season weeks, demonstrating that the threshold rule adapts to seasonal water demand and also responds to intra-seasonal dry spells inside the wet season rather than following a calendar.

4.6.4. Irrigation timing, duration, and applied water volume

For each of the 77 events we estimated the equivalent water depth applied using a 30 cm effective root zone, under which a 1% VWC change corresponds to approximately 3mm of water depth. Per-event statistics are summarised in Table 5. The mean equivalent depth applied per event was 31.7mm (SD = 13.2mm; range 11.7-60.0 mm). Total equivalent water depth applied across the 100-week deployment was 2,441mm, corresponding to 24.4mm week^{-1} on average. Event durations measured at the valve, derived from open/close timestamps logged by the master node, ranged between 12 and 55 min, with longer events corresponding to deeper pre-event deficits as expected from the adaptive duration logic described in Section 3.5.

5. Discussion

The primary goal of precision irrigation systems is to optimize water usage in farming. García et al. [41] revealed that IoT-based irrigation systems achieve water optimisation through real-time monitoring and automated control of irrigation processes as described in Section 2. Several previous studies have satisfactorily achieved this goal [24,26,28]. The current study minimised both water wastage and the cost of precision irrigation equipment. By using a novel reduction electric valve, this study significantly reduced the cost of valves to about $25 compared to solenoid valves that cost at least $50, depending on the capacity of the valve. Furthermore, our reduction electric valves require only 5VDC for their operation and yet other valves require at least 12VDC. This lower voltage requirement contributes to improved energy efficiency and reduced operational costs, which are recognized as important factors in

sustainable smart irrigation systems [42,43]. Therefore, this study delivered a low-cost and low-energy system with regard to the reduction valve.

A number of wired and wireless technologies have been used for precision irrigation systems, but the dominant one currently is Internet of Things (IoT) integrated with wireless sensor networks (WSNs). In latter scenario, sensors are used to monitor soil moisture, temperature, and humidity in real-time, whereas, the IoT systems though programmed microcontrollers, manage irrigation and related automated decisions [24,32,44]. Our study followed the same trend of IoT and WSNs, but with a greater focus on affordability. This focus aligns with studies by [45] and [46] that emphasise the need for low-cost precision irrigation technologies to enhance adoption among small and medium scale farmers. The microcontrollers were used in a master-slave configuration, whereby one master node that manages the opening and closing of the valves can control irrigation on a scale of at most two hectares of farm land. At the same time, a single master node receives and process irrigation related data from an unlimited number of slave nodes (sensed data collection and transmission terminals) within 200 m radius. Hierarchical network architectures similar to this master-slave configuration have been shown to improve scalability and reliability when managing irrigation systems over relatively large agricultural areas [47]. By enabling remote software updates, the master and slave nodes are easier to manage and maintain, even by novice users/farmers.

Our system extends the state-of-the-art precision irrigation system by integrating a soil-crop database. This feature is meant to benefit farmers with small land on which different crops are grown in rotation. Under such a scenario, information on soil moisture requirements for the different crops is important. Therefore, the soil-crop database provides such information. As in the case of Uganda, where the government funded small-scale irrigation schemes of about four hectares shared by a community of farmers, the soil-crop database was very valuable in automating the manual irrigation since it empowers farmers with different crop farming interests with soil moisture versus crops information for optimal yield. By combining affordability, energy efficiency, scalable architecture, and crop-specific decision support, our system contributes to addressing several key challenges that currently limit the widespread adoption of precision irrigation technologies in smallholder farming contexts.

Three classes of resources are optimised by the proposed system, and we now make these explicit. (i) Water: as quantified in Section 4.6, GEPA reduces equivalent water depth applied by 18.6-59.3% over the 100-week field record, depending on which traditional baseline is replaced; the savings arise both from skipped irrigations (23 of 100 weeks) and from adaptive event durations that stop at field capacity rather than applying a fixed dose. (ii) Electrical energy: the reduction electric valve operates at 5 V DC compared with 12-24 V DC for conventional solenoid valves, lowering actuator power by roughly 60-80% per actuation cycle and allowing the master and slave nodes to run from a small solar panel and battery, as evidenced by the uninterrupted operation reported in Section 4.3.4. (iii) Labour and decision time: 77 closed-loop irrigation decisions were taken without human intervention over 23 months, replacing the manual scheduling that characterises smallholder irrigation in Northern Uganda; the soil-crop database further reduces the need for external advisory services when crop rotations change. Indirectly, the system also conserves nutrient resources by avoiding the leaching that follows over-irrigation, although direct measurement of nutrient loss was outside the scope of this study.

6. Limitation

The performance of the precision irrigation system presented in this paper has some limitations. First, the electric reduction valves currently lack standardised signal values, and hence they operate with unique signal values, requiring the controlling computers (master and slave nodes) to be set manually to accommodate the specific signal valves. This issue primarily arises due to the absence of a standardised manufacturing process. Once such a standardisation process is established, this challenge can be effectively addressed.

Second, the resistive (YL-69 / FC-28) moisture sensors used for cost reasons are known to be sensitive to soil salinity and temperature; while no significant linear drift was detected over the 100-week deployment (Section 4.6.3) and dummyTXdummy-(the two-point calibration against volumetric reference samples kept readings within useful bounds for threshold control, we recommend recalibration at the start of each cropping season and replacement of corroded probes after approximately 18-24 months of continuous burial. Capacitive sensors offer better long-term stability and could be substituted as their unit cost falls.

Third, network robustness depends on GSM coverage and on the line of sight between master and slave nodes; the 200m clear-line-of-sight assumption of the ESP-NOW mesh used at our sites may not hold on hilly farms or under dense tree canopies, in which case ESP-MESH or LoRa-based extensions would be required.

Finally, the present field evaluation focuses on irrigation control accuracy rather than agronomic outcome; measuring crop yield and water productivity against a parallel calendar-irrigated control plot is identified as a priority for future work, together with empirical validation of the modeled water-savings reported in Section 4.

7. Conclusion

Competitive automation in agriculture in the 21st century needs to be affordable, simple to install/operate and able to consume less energy. We designed and tested a low-cost, emerging-tech and low-energy precision irrigation modules. The modules were integrated into a working system comprising of: a 5V electric reduction valve (costing approximately $25) for controlling irrigation water flow; a master node and slave node for sensing irrigation needs of respective crops (slave node) and responding to the needs (master node) by opening/closing the valve; a cloud infrastructure for synchronous data transfer from the master node to a remote access point and vice-versa; and a mobile App for remote access and/or control of irrigation. The App is equipped with analysis and management capabilities, and hence able to control irrigation in multiple farms at the same or different locations. Moreover, the App is integrated with a soil-crop database for managing irrigation requirements when other crops with different water requirements are grown on the same land with the irrigation infrastructure.

The soil-crop database was an important addition, making the precision irrigation system adaptable across different soil types and applicable to a range of crops. This adaptability is crucial, as it accommodates the varying water and irrigation needs of different crops and the distinct moisture requirements of various soil types. By addressing these complexities, the soil-crop database significantly enhances the flexibility and scalability of the precision irrigation system, ensuring its relevance and effectiveness as farming patterns evolve.

Ultimately, the precision irrigation system presented in this paper has the potential to significantly enhance productivity, sustainability, and profitability by optimising resource use and facilitating data-driven decision-making in farming. Interestingly, its master-slave setup can be updated through the mobile App thereby enhancing the scalability and adaptability of the system.

CRediT authorship contribution statement

Benedict Oyo: Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization; **Allan Junior Asiku:** Visualization, Validation, Software, Resources, Methodology, Investigation,

Formal analysis, Data curation; **Daniel Ogenrwot:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation; **Victor Paul Kawagga:** Software, Resources, Investigation; **John Byabazaire:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation; **Christine Kalumera Akello:** Writing – review & editing, Writing – original draft, Data curation, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

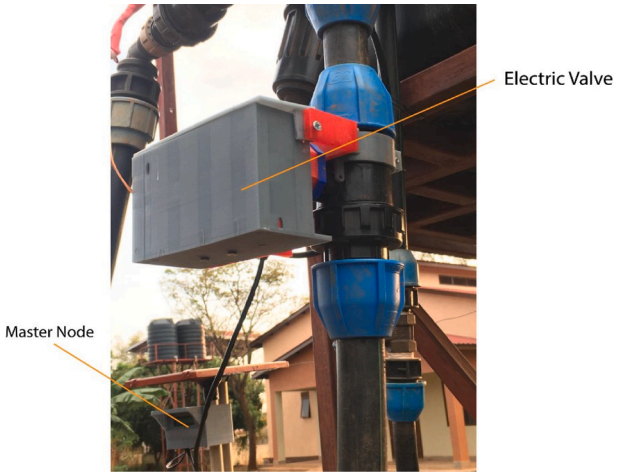
Data will be made available on request.

Appendix A. Testing on the drip irrigration facility at Gulu University farm

A.1. Field installation



A.2. Better view of the installed reduction electric valve

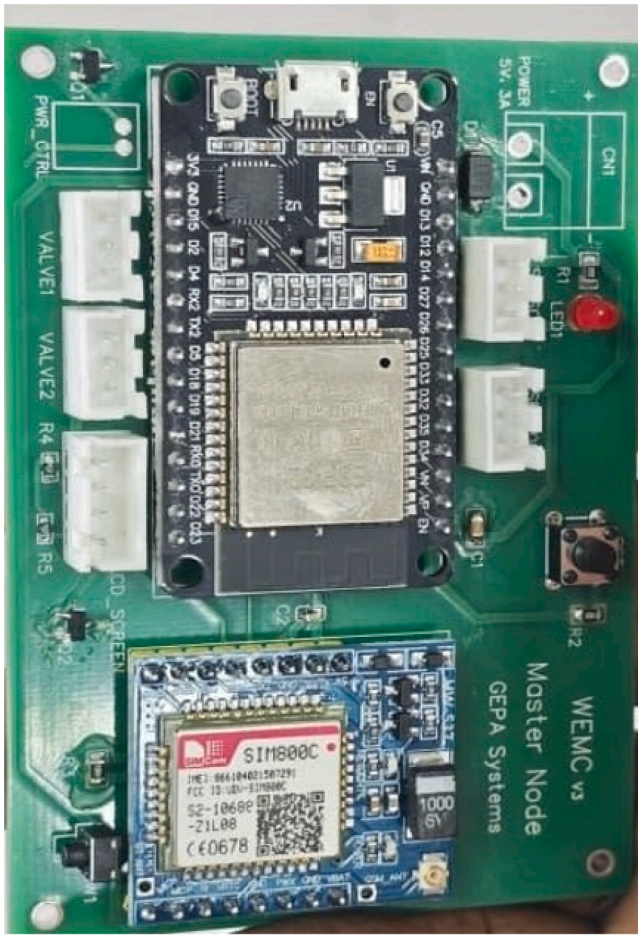


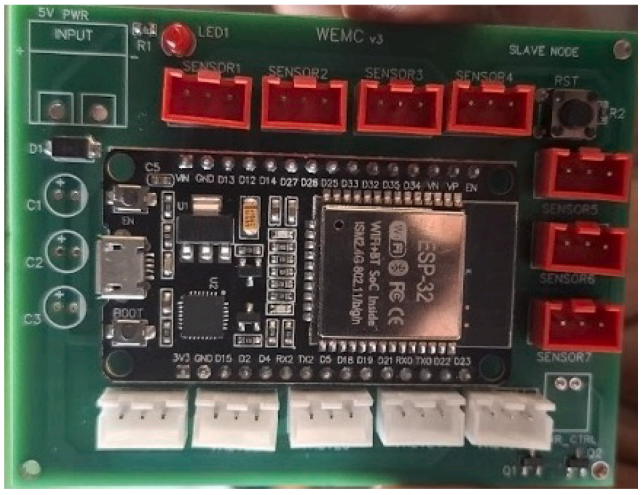
Appendix B. Testing on sprinkler irrigation facility at Unyama NTC





Appendix C. The printed Circuit Boards for Master-salve nodes





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