INTEGRATED SMART WATER-FOCUSED IRRIGATION SYSTEM USING IOT AND AI/ML

(IoT Smart Water Management & Automated Irrigation Scheduling)

Project ID: 25-26J-520

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Department of Software Engineering

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DECLARATION

I declare that this is my own work, and this Thesis does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Signature of the Supervisor   Date

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Signature of the Co-supervisor   Date

ABSTRACT

Agriculture in Sri Lanka relies heavily on reservoir-fed irrigation systems, with more than 70% of cultivated land dependent on water sourced from reservoirs, tanks, and canal networks. Traditional irrigation scheduling methods guided largely by farmer intuition or fixed timetables frequently result in water wastage through over-irrigation, crop stress through under-irrigation, and an absence of synchronization with upstream reservoir availability. These inefficiencies are exacerbated by the effects of climate change, which introduce unpredictable rainfall variability and recurrent dry spells that challenge even the most experienced agricultural practitioners.

This individual research function, forming part of the group project 'Integrated Smart Water-Focused Irrigation System Using IoT and AI/ML' (Project ID: 25-26J-520), proposes the design, development, and evaluation of an IoT-Enabled Machine Learning-Driven Smart Water Management System for Automated Irrigation Scheduling. The proposed system constitutes the field-level operational core of the broader platform, translating hydrological availability and agronomic need into precise, automated delivery of water to crops in pilot agricultural fields.

The system integrates three tightly coupled technological layers. First, a sensing layer comprising soil moisture probes, DHT11/DHT22 humidity and temperature sensors, and ultrasonic reservoir water-level monitors provide continuous real-time observation of field and reservoir conditions. Second, a machine learning decision engine — built upon online regression, decision tree, and random forest models trained on pilot field data — dynamically computes crop-specific irrigation requirements within a five-second latency budget, replacing rule-based thresholds with adaptive, data-driven scheduling. Third, a microcontroller-based actuation subsystem (Arduino/ESP32) operates solenoid valves and submersible pumps to release precisely the computed water volume to each irrigation line. The entire pipeline is supported by secure low-power wireless communication over LoRaWAN and NB-IoT protocols with MQTT/TLS encryption, Raspberry Pi edge gateways for local aggregation, and cloud hosting on Microsoft Azure IoT Hub or AWS IoT Core.

A bilingual (Sinhala/Tamil/English), mobile-optimized React and Flutter dashboard presents real-time field status, irrigation schedules, and water-usage analytics to farmers, reservoir operators, and agricultural officers. Critical threshold alerts are dispatched via SMS, email, and push notifications. Solar-powered IoT nodes ensure sustainable, low-maintenance operation in remote agricultural settings.

The expected outcomes include a significant reduction in irrigation water usage compared with traditional practices, improved crop yields through timely and crop-specific irrigation, a data-to-actuation loop completing within five seconds and demonstrated scalability from a single pilot farm to a multi-reservoir irrigation network. The solution is positioned for strong commercial viability as a localized, low-cost smart irrigation product suited to Sri Lanka and comparable agrarian economies.

Keywords: *IoT, Smart Irrigation, Machine Learning, Random Forest, MQTT, LoRaWAN, Soil Moisture Sensing, Automated Irrigation, Crop Water Requirements, Edge Computing, Smart Agriculture, Water Conservation*

ACKNOWLEDGEMENT

The successful completion of this research would not have been possible without the invaluable guidance, support, and encouragement of numerous individuals and institutions, to whom I wish to express my sincere gratitude.

I am deeply grateful to my supervisor, Ms. Hansi De Silva, whose expert guidance, constructive feedback, and unwavering support throughout every phase of this research have been indispensable. Her depth of knowledge in IoT systems and machine learning, combined with her commitment to academic rigor, has profoundly shaped both the direction and quality of this work. I also extend my sincere thanks to my co-supervisor, Ms. Karthiga Rajendran, for her thoughtful advice and technical insights that helped refined the methodology and broaden the scope of the research.

I wish to acknowledge the academic staff and faculty of the Department of Software Engineering at the Sri Lanka Institute of Information Technology, Malabe, for the foundational knowledge and research skills they have imparted throughout my undergraduate study. The resources and facilities made available by SLIIT have been essential to the development of this work.

My sincere appreciation also goes to my group members - Dilruksha A.G.C.D. (IT22561770), Trishni W.R.M. (IT22076366), and Abishek S. (IT22186942) for their collaboration, technical discussions, and the spirit of teamwork that has made our collective project a coherent and well-integrated system. The complementary nature of our individual contributions has greatly enriched the overall research outcome.

Finally, I owe a profound debt of gratitude to my family and friends for their patience, encouragement, and moral support throughout this journey. Their belief in my abilities has been a constant source of motivation.

Hesara P.K.A.N.

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April 2026

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LIST OF ABBREVIATIONS

Abbreviation	Description
IoT	Internet of Things
ML	Machine Learning
AI	Artificial Intelligence
WSN	Wireless Sensor Network
API	Application Programming Interface
MQTT	Message Queuing Telemetry Transport
NB-IoT	Narrowband Internet of Things
LoRaWAN	Long Range Wide Area Network
LTE	Long Term Evolution (4G)
ANN	Artificial Neural Network
LSTM	Long Short-Term Memory (Recurrent Neural Network model)
ARIMA	AutoRegressive Integrated Moving Average
GUI	Graphical User Interface
UI/UX	User Interface / User Experience
SQL	Structured Query Language
NoSQL	Non-relational Database Query Language
GIS	Geographic Information System
DoA	Department of Agriculture (Sri Lanka)
MA	Mahaweli Authority (Sri Lanka)
FAO	Food and Agriculture Organization
ADB	Asian Development Bank
IWMI	International Water Management Institute
ESP32	Espressif Systems 32-bit microcontroller
RPi	Raspberry Pi
TLS	Transport Layer Security
SaaS	Software as a Service
CI/CD	Continuous Integration / Continuous Deployment
SLIIT	Sri Lanka Institute of Information Technology

CHAPTER 1 - INTRODUCTION

1.1 Background Study and Literature Review

1.1.1 Background Study

Agriculture constitutes a foundational pillar of Sri Lanka's economy and society, directly supporting the livelihoods of approximately 30% of the population and contributing significantly to national food security and export earnings. The country's agricultural production is deeply intertwined with its irrigation heritage; more than 70% of all cultivated land depends on water sourced from a network of ancient and modern reservoirs, irrigation tanks, and inter-basin canals administered under the oversight of the Mahaweli Authority and the Department of Irrigation [1]. The elaborate reservoir-to-field canal system that characterizes Sri Lankan paddy cultivation - connecting upstream storage bodies to downstream farm plots through weirs, branch canals, and field channels - has sustained agrarian communities for over two thousand years and remains the backbone of domestic rice production today.

Despite this inherited sophistication, the operational management of water delivery from reservoir to crop remains largely traditional and is increasingly inadequate given modern challenges. Irrigation scheduling at the farm level is guided primarily by farmer intuition or by fixed timetable-based water release schedules set at the irrigation scheme level. These approaches have several well-documented shortcomings. Fixed schedules fail to respond to real-time variability in soil moisture conditions, ambient temperature, or crop water demand at different growth stages, producing systematic mismatches between water supply and actual agronomic need [2]. When schedules over-allocate water - as is common during cooler or wetter periods - the excess application saturates root zones, creates anaerobic soil conditions, and contributes to wasteful run-off that depletes reservoir stocks for downstream users. When schedules under-allocate - as occurs during unexpected dry spells - crops experience moisture stress, particularly at sensitive phenological stages such as tillering in paddy or grain filling in maize, resulting in demonstrably reduced yields.

Climate change has compounded these pre-existing inefficiencies. Sri Lanka's rainfall pattern historically characterized by two distinct monsoon seasons - the South-West monsoon from May to September and the North-East monsoon from December to February - has exhibited increasing variability since the early 2000s [2]. Inter-annual variability in monsoon onset and intensity, combined with more frequent and prolonged dry spells in the Dry Zone provinces where irrigated paddy cultivation is most intensive, has assumed of predictable seasonal water availability untenable. The 2023 drought episode that caused the Udawalawa reservoir to reach critically low levels directly threatening the cultivation plans of tens of thousands of farming families in the Uda Walawe basin is emblematic of the vulnerability that fixed-schedule irrigation creates in the face of hydro-climatic uncertainty [14].

Water is also a contested resource within irrigation schemes. When multiple farming blocks draw upon the same distribution canal, the failure of any individual block to follow coordinated discharge schedules degrades supply reliability for all downstream users. The absence of real-time visibility into field-level water consumption means that reservoir operators cannot accurately gauge aggregate demand, cannot respond proactively to over-abstraction, and cannot enforce equitable water distribution. The resultant inefficiency is not merely agronomic; it contributes to social conflict between upstream and downstream water users and imposes financial burdens on irrigation authorities tasked with maintaining infrastructure.

The Internet of Things (IoT) and Machine Learning (ML) represent the most promising technological pair for addressing these interlocking challenges. IoT sensors notably capacitive soil moisture probes, DHT-series humidity and temperature sensors, and ultrasonic or float-based water-level transducers can be deployed at low cost across large agricultural areas to provide continuous, real-time observation of the field conditions that drive irrigation demand. When these heterogeneous sensor streams are aggregated, preprocessed, and fed into ML models trained on historical crop-water dynamics, the resulting decision engine can estimate irrigation requirements far more accurately and adaptively than any rule-based threshold can achieve [3][4]. Automated actuation solenoid valves and submersible pumps controlled by microcontrollers receiving ML outputs then closes the loop between decision and physical water delivery, eliminating the lag and human error inherent in manual valve operation.

Internationally, smart irrigation systems leveraging this IoT-ML combination have demonstrated compelling results. Research from the Middle East and Mediterranean basin has documented water savings compared with conventional scheduling methods [6]. In the South and South-East Asian context, where smallholder farms dominate and water scarcity is a growing concern, the affordability and energy efficiency of the hardware stack particularly with solar-powered sensor nodes and low-power wireless protocols such as LoRaWAN and NB-IoT - are critical to real-world adoption. In Sri Lanka specifically, early field experiments indicate measurable water savings when IoT-driven irrigation replaces farmer-guided scheduling [5][11].

1.1.2 Literature Review

A substantial body of academic and applied research has explored smart irrigation systems over the preceding decade, collectively establishing the conceptual and technical foundations upon which this research builds. The review below examines the most relevant prior works across four themes: IoT-based sensing and data collection, ML-driven irrigation decision models, wireless communication architectures for agricultural IoT, and integrated smart-irrigation platforms.

Mallikarathne et al. (2024) conducted one of the most directly relevant studies in the Sri Lankan context, deploying a Wireless Sensor Network (WSN)-based smart irrigation system for domestic crop varieties [6]. The system employed capacitive soil moisture probes and DHT22 temperature-humidity sensors connected to ESP32 microcontrollers, with data transmitted over Wi-Fi to a centralised server. The authors demonstrated measurable reductions in water consumption compared with farmer-controlled scheduling. However, the study employed simple threshold-based decision logic rather than adaptive ML models, and the Wi-Fi communication architecture limited deployment radius to farmhouses with infrastructure connectivity a significant constraint in Sri Lanka's rural Dry Zone.

Jayathilake (2023) applied Artificial Neural Networks (ANNs) to predict water level dynamics in the Muthurajawela wetland area near Colombo [7]. While the study's focus was hydrological monitoring rather than irrigation control, it demonstrated the efficacy of LSTM-based sequence models for time-series prediction of water-related variables in a Sri Lankan environmental context. The study finding that LSTM architecture outperformed classical statistical models including ARIMA for non-stationary hydrological series is directly applicable to the reservoir-level forecasting component of the present system.

Herath (2023) employed a deep machine learning architecture for water level prediction in Sri Lanka's detention areas [9]. The research used historical gauge records and rainfall data to train convolutional neural network (CNN) and LSTM hybrid models, achieving strong predictive accuracy in multi-step-ahead water level forecasting. The study highlighted the importance of data preprocessing for noisy sensor streams, a finding that directly informs the imputation and normalization pipeline designed in the present function.

The International Water Management Institute (IWMI) has documented the structural characteristics of water use in the Walawe Basin [8], one of Sri Lanka's largest and most productive irrigation schemes. The report identified coordination failures between reservoir operations and farm-level irrigation as a primary cause of inefficient water use and called for digital monitoring solutions that could provide real-time demand signals from fields to reservoir operators. This recommendation directly motivates the integration of field-level IoT sensing with upstream reservoir management a coordination objective that distinguishes the present system from existing pure farm-level solutions.

Nandasena (2024) examined sedimentation dynamics in Sri Lankan reservoirs and their long-term implications for irrigation water storage capacity [5]. The study provides quantitative context for the urgency of optimizing water use efficiency: as effective storage capacity declines due to sedimentation, the imperative to extract maximum agricultural productivity per cubic meter of water stored increases correspondingly. This finding reinforces the economic and environmental case for the water savings the present system targets.

IRJMETS (2022) reported on the design of an IoT-based smart irrigation system specifically calibrated for Sri Lankan agricultural conditions [11]. The system architecture described in that study comprising ESP32 sensor nodes, a Node-RED MQTT broker, and a web dashboard closely resembles the communication and middleware architecture adopted in the present research. However, the IRJMETS study did not incorporate ML-based decision making; irrigation triggers were determined by static soil moisture thresholds set by the researcher, which the present work explicitly addresses as a key limitation.

Kumar et al. (2021) presented a comprehensive comparison of ML algorithms including Support Vector Regression (SVR), Random Forest, and Gradient Boosting for irrigation demand estimation using multi-sensor data from paddy fields in South India [cited as analogous domain]. The study found that ensemble methods, particularly Random Forest, consistently outperformed single-model approaches in generalization accuracy across varying soil types and crop growth stages. The Random Forest architecture adopted in present research is directly motivated by this comparative evidence.

Goap et al. (2018) proposed a smart irrigation system that integrated weather forecast data from online APIs with in-field soil moisture sensing, feeding a Random Forest classifier that recommended irrigation decisions with a documented accuracy of approximately 95% [analogous domain]. The system demonstrated the value of augmenting sensor data with external meteorological inputs — a design choice replicated in the present work through integration of Department of Meteorology weather forecast feeds.

Gondchawar and Kawitkar (2016) provided an early but influential survey of IoT applications in smart agriculture, cataloguing sensor modalities, wireless protocols, and cloud platforms applicable to precision farming [analogous domain]. Their taxonomy of agricultural IoT sensors differentiating resistive from capacitive soil moisture probes, and evaluating the trade-offs between ZigBee, Wi-Fi, LoRa, and cellular communication protocols in terms of range, power consumption, and bandwidth informed the hardware selection decisions documented in Section 2.1.4.

Al-Kababji et al. (2022) examined the performance of LoRaWAN networks under varying agricultural terrain conditions, finding that the protocol supported reliable telemetry at ranges of up to 10 km in open flat terrain well suited to Sri Lanka's Dry Zone paddy landscapes with sensor node lifetimes of two to five years on battery power alone when solar charging was unavailable [analogous domain]. This evidence underpins the selection of LoRaWAN as the primary wireless protocol in the present system.

Collectively, this body of literature establishes that IoT-based sensing, ML-driven decision-making, and automated actuation individually hold strong promise for smart irrigation; that integration of these three components into a unified, field-deployable system with real-time cloud connectivity remains an open engineering challenge; and that the Sri Lankan agronomic context introduces specific requirements affordability, solar power, bilingual interfaces, and reservoir synchronization not comprehensively addressed by any existing published system.

1.2 Research Gap

Despite considerable progress in smart irrigation research globally, several critical gaps remain unaddressed, particularly in the context of Sri Lanka's reservoir-fed agricultural system.

The most pervasive gap in existing systems is their reliance on rule-based, fixed-threshold decision logic. Virtually all commercially deployed and academically described IoT irrigation systems in Sri Lanka trigger irrigation when soil moisture falls below a predetermined value commonly 30% volumetric water content irrespective of crop type, growth stage, ambient temperature, or weather forecast [5][11]. Such static thresholds are calibrated for average conditions and perform poorly at the extremes of the operating envelope: during heat waves, when evapotranspiration rates are elevated, the threshold may be too conservative; during cool periods, it may trigger unnecessary irrigation. ML-driven models that dynamically estimate crop evapotranspiration (ETc) by integrating reference evapotranspiration (ET0), crop coefficient (Kc), and real-time environmental data can adapt to these variations, but no published Sri Lankan field study has deployed and evaluated such models at scale.

A second gap concerns field-to-reservoir integration. Existing farm-level smart irrigation systems operate as isolated units; their actuation decisions are made without reference to the current or projected water availability in the upstream reservoir [8]. This means that a farm-level system might schedule aggressive irrigation during a period when the reservoir is at a critically low level, contributing to premature depletion that harms all downstream users. Conversely, it may withhold irrigation during periods of abundant reservoir supply, missing opportunities for crop-benefit that the reservoir could safely support. The present research addresses this gap by incorporating upstream reservoir water level as an input feature to the ML decision model and as a constraint on the actuation layer.

A third gap relates to energy sustainability. Most existing smart irrigation deployments in Sri Lanka rely on mains electricity or standard alkaline batteries for sensor node power, which limits their deployment radius to electrified farm plots and increases operational maintenance costs for battery replacement [11]. Solar-powered sensor nodes with rechargeable battery backup, designed for the power budget constraints of LoRaWAN communication, have not been systematically implemented and evaluated in the Sri Lankan agricultural environment.

A fourth gap concerns user accessibility. Dashboard interfaces for existing systems are developed in English and target technically literate users, effectively excluding the smallholder farming population which forms most irrigated cultivators in Sri Lanka from meaningful engagement with the system [6]. A bilingual (Sinhala/Tamil/English) interface, optimized for mobile access in areas of limited connectivity, has not been developed and evaluated in conjunction with an IoT-ML irrigation system.

The present research addresses all four of these gaps within a single, integrated system design, representing a substantive advance over the current state of the art in the Sri Lankan smart irrigation domain.

1.3 Research Problem

The central problem this research addresses is the persistent inefficiency and unsustainability of irrigation water management in Sri Lanka's reservoir-fed agricultural ecosystems, arising from the inadequacy of current decision-making practices and the absence of integrated technological solutions that bridge sensing, adaptive intelligence, and automated control.

More specifically, the research problem may be articulated as follows:

"How can an IoT-enabled, machine learning-driven Smart Water Management System be designed, implemented, and evaluated to dynamically optimize irrigation scheduling at the field level replacing static, rule-based practices with adaptive, data-driven decisions while synchronizing field-level water use with upstream reservoir availability, thereby reducing water wastage, improving crop productivity, and supporting sustainable irrigation management in Sri Lanka's reservoir-fed agricultural ecosystems?"

Traditional irrigation management is reactive, labor-intensive, and inherently unable to account for the multifactorial nature of crop water demand. Farmers who irrigate by intuition or fixed schedule lack the real-time field data needed to differentiate between a crop that is genuinely stressed and one that merely appears dry on the surface. Without quantitative, continuous soil moisture measurements, irrigation decisions are necessarily conservative defaulting to over-watering as insurance against yield loss or insufficiently responsive to sudden deterioration in soil moisture during periods of unexpectedly high evapotranspiration.

Existing IoT-based systems provide the data stream that manual scheduling lacks but fail to exploit it adaptively. By replacing the static threshold with ML models that learn the relationship between environmental conditions and crop water requirement from historical field data, and by providing this intelligence with a microcontroller-based actuation backend and a farmer-accessible dashboard interface, this research aims to close the gap between available water resources and actual agronomic need.

1.4 Research Objectives

1.4.1 Main Objective

To design and develop an IoT-enabled, ML-driven Smart Water Management System that optimizes irrigation scheduling by integrating real-time soil, weather, and reservoir data, thereby reducing water wastage and improving crop productivity in Sri Lanka's reservoir-fed agricultural ecosystems.

1.4.2 Specific Objectives

1. To deploy an IoT sensor network comprising soil moisture probes, DHT11/DHT22 humidity and temperature sensors, and ultrasonic reservoir water-level sensors across pilot agricultural fields, calibrated to Sri Lankan agro-climatic conditions.
2. To establish a secure, low-power wireless communication infrastructure using LoRaWAN and NB-IoT protocols with MQTT/TLS encryption, connecting field sensor nodes to Raspberry Pi edge gateways and cloud platforms.
3. To develop and train machine learning models — including online regression, decision trees, and random forest ensembles — on pilot field data to dynamically compute crop-specific irrigation requirements, replacing static threshold-based scheduling.
4. To implement a microcontroller-based actuation system (Arduino/ESP32) that operates solenoid valves and submersible pumps in accordance with ML-generated irrigation instructions, while preserving farmer manual-override capability.
5. To synchronise field-level irrigation decisions with upstream reservoir water availability, incorporating reservoir water level as both an ML input feature and an actuation constraint.
6. To develop a bilingual (Sinhala/Tamil/English) mobile-optimised web and mobile dashboard providing real-time field visualisation, irrigation schedule management, water-usage analytics, and SMS/email/push alert notifications.
7. To evaluate system performance against defined metrics: percentage reduction in irrigation water usage, improvement in crop yield indicators, data-to-actuation latency, farmer usability scores, and system uptime.

1.4.3 Business Objectives

8. To deliver a commercially viable, low-cost smart irrigation product — deployable on smallholder farms of less than 2 hectares — that reduces

agricultural water expenditure and labour costs while increasing crop yield, generating measurable return on investment for adopting farmers.

9. To develop a modular, scalable system architecture that supports deployment expansion from a single pilot farm to a multi-reservoir irrigation network, enabling the system to serve irrigation scheme administrators, the Mahaweli Authority, and the Department of Irrigation as a basin-level water management tool.
10. To establish revenue streams through product sales (IoT irrigation kits comprising sensors, microcontrollers, actuators, and solar power units), a monthly cloud analytics subscription model, and public-private partnership arrangements with the Ministry of Agriculture and the Department of Irrigation.
11. To position the solution for regional market expansion across comparable agrarian economies in South and South-East Asia and Sub-Saharan Africa, where reservoir-fed irrigation systems and water scarcity challenges analogous to Sri Lanka's are widespread.

CHAPTER 2 - METHODOLOGY

2.1 Methodology

The development of the IoT-Enabled Machine Learning-Driven Smart Water Management System follows an Agile-Scrum methodology adapted for embedded systems and IoT research projects. The Agile framework was selected over traditional Waterfall approaches for several compelling reasons. First, the interdependence between hardware deployment, data collection, and model training means that requirements for the ML component cannot be fully specified until sensor data from pilot fields have been collected; iterative development cycles allow requirements to be refined as empirical evidence accumulates. Second, the research team is distributed across four complementary modules, and Scrum-style sprint planning, daily stand-ups, and sprint retrospectives provide the coordination mechanism needed to maintain alignment across modules. Third, the research timeline — spanning approximately twelve months from initial deployment to final evaluation — naturally accommodates a series of two-week sprints, allowing incremental delivery of testable system components.

The research methodology proceeds through six phases, each described in detail in the subsections below: Feasibility Study and Planning; Requirement Gathering and Analysis; System Designing; Implementation; Testing; and Deployment and Maintenance.

2.1.1 Feasibility Study / Planning

Prior to committing to the full system design and implementation, a structured feasibility study was conducted across four dimensions: technical, operational, financial, and legal.

Technical Feasibility: The core hardware components ESP32/Arduino microcontrollers, capacitive soil moisture probes, DHT22 sensors, LoRaWAN gateways, and Raspberry Pi devices are all commercially available, well-documented, and widely used in agricultural IoT deployments globally. The selected ML algorithms (Random Forest, Decision Trees, online regression) are supported by mature Python libraries (scikit-learn, TensorFlow) that have been validated in comparable soil-moisture prediction and irrigation scheduling studies. Cloud platforms (Azure IoT Hub, AWS IoT Core) provide enterprise-grade MQTT broker services and scalable storage at affordable tier pricing. The technical stack is therefore proven and available. The primary technical risk lies in wireless communication reliability across agricultural terrain; this is mitigated by selecting LoRaWAN, which has demonstrated 10 km+ range in flat open landscapes comparable to Sri Lanka's Dry Zone paddy fields.

Operational Feasibility: Farmers in Sri Lanka's pilot target areas (Dry Zone irrigation schemes) have increasingly demonstrated willingness to adopt mobile phone-based agricultural services. The bilingual (Sinhala/Tamil/English) dashboard interface removes the language barrier that has limited adoption of English-only agricultural technology platforms. The manual-override functionality preserves farmer agency over irrigation decisions, reducing resistance to automation. Agricultural officers and irrigation scheme managers, who are accustomed to data-driven reporting requirements, represent a natural early-adopter base for the dashboard's analytics and coordination features.

Financial Feasibility: A prototype system covering one pilot field of approximately one hectare is estimated to require the capital costs detailed in Table 2.1 below.

Table 2.1: Project Cost Breakdown

Component	Unit Cost (LKR)	Notes
Soil Moisture Probe (x4)	6,000	Capacitive type, field-rated IP65
DHT22 Temp/Humidity Sensor (x4)	3,200	Calibrated to tropical range
Ultrasonic Water Level Sensor (x2)	4,400	Reservoir/canal deployment
Arduino/ESP32 Microcontroller (x4)	8,000	With relay shields
Raspberry Pi 4 (Edge Gateway x1)	18,000	4 GB RAM configuration
LoRaWAN Gateway (x1)	35,000	Dragino LG308 or equivalent
Solar Panel + Battery Kit (x4 nodes)	32,000	20W panel + 5Ah LiPo
Solenoid Valves (x4)	12,000	1-inch, 12V DC
Submersible Pump (x2)	14,000	750W agricultural grade
Relay Switches & Wiring	4,500	Per node
Cloud Platform (12 months)	18,000	Azure IoT Hub Basic tier

Dashboard Development (estimate)	45,000	Freelance frontend/backend
Miscellaneous / Contingency (10%)	20,000	Cables, enclosures, tools
TOTAL ESTIMATE	~220,100	Single 1-ha pilot deployment

Legal Feasibility: The system operates entirely within the legal framework of Sri Lanka. Sensor deployment on private agricultural land requires landowner consent, which is obtained through written agreements with pilot farm participants. The LoRaWAN frequency band (AS923 in Sri Lanka) is licensed and managed by the Telecommunications Regulatory Commission of Sri Lanka (TRCSL); commercial LoRaWAN gateway operation requires TRCSL registration. Data protection practices comply with Sri Lanka's Personal Data Protection Act No. 9 of 2022, which governs the collection and processing of personally identifiable information including user location and operational data on the platform.

Project Timeline (Gantt Chart Description)

The project spans twelve months divided into five phases. Phase 1 (Months 1–2): Literature review, requirements gathering, feasibility study, and hardware procurement. Phase 2 (Months 3–4): Field sensor deployment, edge gateway configuration, and LoRaWAN network commissioning. Phase 3 (Months 5–7): Data collection, preprocessing pipeline development, and ML model training and validation. Phase 4 (Months 8–9): Actuation layer implementation, dashboard development, and system integration. Phase 5 (Months 10–12): System testing, evaluation against performance metrics, documentation, and report writing. Milestones include: hardware deployment sign-off (Month 4), ML model validation (Month 7), integrated system demonstration (Month 9), and final evaluation report submission (Month 12).

Table 2.2: Risk Management Plan

Risk	Likelihood	Impact	Mitigation Strategy
LoRaWAN signal attenuation in heavy crop canopy	Medium	Medium	Survey site topology; deploy repeater nodes if range drops below 500 m.
Sensor failure due to moisture ingress or lightning	Low-Medium	High	Use IP65-rated enclosures; install surge protectors on field nodes.
Insufficient pilot field training data for ML models	Medium	High	Augment with public datasets (IWMI, FAO); transfer-learn from similar crops.
Cloud platform cost overrun	Low	Medium	Set budget alerts; migrate to self-hosted broker (Mosquitto) if required.
Farmer resistance to automated irrigation	Low-Medium	Medium	Emphasise manual-override; conduct stakeholder workshops; use bilingual UI.
Power supply failure at remote sensor nodes	Low	High	Solar + battery backup sized for 5 days of cloud cover; alert system if battery < 20%.
Data breach of farmer operational data	Low	High	MQTT/TLS encryption; JWT authentication on dashboard API; quarterly security audit.

Table 2.3: Communication Plan

Stakeholder	Communication Channel	Frequency	Purpose
Project Supervisor	Face-to-face meeting / MS Teams	Bi-weekly	Progress review, guidance, milestone sign-off
Group Members	WhatsApp / GitHub	Daily stand-up	Sprint planning, task coordination, integration testing
Pilot Farmers	Field visits / Phone calls	Monthly	Deployment updates, feedback collection, training
Irrigation Officers	Email / Field visits	Monthly	Reservoir data access, coordination requirements
SLIIT Department	Email / Viva voce	Per milestone	Academic reporting, ethical clearance

2.1.2 Requirement Gathering & Analysis

Requirements were gathered through a combination of literature analysis, consultation with domain experts (agricultural officers and irrigation scheme managers), review of existing IoT irrigation deployments in Sri Lanka, and structured interviews with representative pilot farmer participants. The requirements are categorised into functional, non-functional, and data requirements.

Functional Requirements

Table 2.4: Functional Requirements

ID	Requirement Name	Description
FR-01	Real-Time Data Collection	The system shall gather soil moisture, temperature, humidity, and reservoir water level readings continuously from IoT sensors at intervals of 10–30 minutes.
FR-02	Data Transmission	The system shall transmit collected sensor data securely to edge/cloud servers via LoRaWAN, NB-IoT, or 4G LTE using MQTT/TLS protocols.
FR-03	Data Preprocessing	The system shall handle missing values through imputation, filter outlier readings, and normalise heterogeneous sensor units before model inference.
FR-04	ML-Driven Irrigation Scheduling	The system shall apply trained ML models to dynamically compute crop-specific irrigation requirements, completing the inference within 5 seconds.
FR-05	Automated Actuation	The system shall control irrigation pumps and solenoid valves based on ML outputs, with minimal manual intervention required.
FR-06	Manual Override	The system shall allow farmers to override automated schedules through a web or mobile interface at any time.
FR-07	Dashboard Monitoring	The system shall provide real-time dashboards visualising soil conditions, water usage, and irrigation schedules in Sinhala, Tamil, and English.
FR-08	Alerts & Notifications	The system shall send SMS, email, and push notifications when critical thresholds such as drought stress or reservoir depletion are detected.
FR-09	Data Logging & Reporting	The system shall maintain historical records of water usage, crop irrigation cycles, and system performance events.
FR-10	Reservoir Synchronisation	The system shall incorporate upstream reservoir water level into irrigation decisions to prevent over-abstraction during low-availability periods.

Non-Functional Requirements

Table 2.5: Non-Functional Requirements

Category	Requirement
Performance	Data-to-actuation loop must complete within ≤5 seconds under normal network conditions.
Scalability	Architecture must support scaling from a single farm plot to a multi-reservoir irrigation network without re-engineering the core platform.
Reliability	IoT devices must maintain ≥99% uptime; redundant 4G LTE fallback must activate within 60 seconds of LoRaWAN failure.
Security	All data in transit protected by MQTT/TLS; device authentication via pre-shared keys or X.509 certificates; dashboard access secured by JWT tokens.

Energy Efficiency	IoT sensor nodes must operate indefinitely on solar + battery, with a minimum battery reserve of 72 hours at full cloudy-day power budget.
Maintainability	Modular microservice architecture; each component (sensing, ML, actuation, dashboard) upgradeable independently without full system redeployment.
Usability	Dashboard must achieve ≥80% task completion rate among farmer participants with no prior technical training in structured usability tests.
Affordability	Total hardware cost per pilot hectare must remain below LKR 250,000 to be accessible to smallholder farmers.
Availability	Dashboard application must maintain ≥99.5% uptime excluding scheduled maintenance windows.

Data Requirements

- Time-series soil moisture readings (% volumetric water content, sampled at 15-minute intervals)
- Ambient temperature (°C) and relative humidity (%) from DHT22 sensors, co-located with each soil moisture probe
- Reservoir and canal water level readings (cm, from ultrasonic sensors), sampled at 30-minute intervals
- Weather forecast data (24–72 hour ahead temperature, humidity, and rainfall probability) from Meteorological Department APIs
- Crop type and phenological stage metadata per field zone (paddy, maize, vegetables)
- Historical irrigation events and volumes (from manual farm records and previous automated logs) for ML training
- Irrigation scheme water release schedules (from Irrigation Department records) for reservoir synchronisation

2.1.3 Designing

The system architecture follows a three-tier IoT reference model comprising a Perception Layer (sensors and actuators), a Network Layer (communication protocols and edge gateways), and an Application Layer (cloud services, ML engine, and dashboard). Figure 2.1 depicts the full system architecture.

The Perception Layer comprises soil moisture probes, DHT11/DHT22 sensors, and ultrasonic water-level sensors deployed in pilot fields, alongside solenoid valves and submersible pumps as actuators. Each sensor node is managed by an Arduino or ESP32 microcontroller that samples readings, timestamps them, and transmits them to the Network Layer.

The Network Layer consists of LoRaWAN end-nodes (sensor devices) communicating with a LoRaWAN gateway (Dragino LG308 or equivalent) covering a radius of up to 5 km. The gateway forwards received packets to a Raspberry Pi edge node, which performs local aggregation, temporal interpolation for missing values, and buffering. The edge node communicates with the cloud platform over 4G LTE using MQTT/TLS, with the LoRaWAN gateway providing a backup path. The MQTT broker (hosted on Node-RED) distributes messages to the appropriate cloud services.

The Application Layer is hosted on Microsoft Azure IoT Hub or AWS IoT Core and comprises: a time-series database (Firebase Realtime Database or MySQL time-series extension) for telemetry storage; a Python-based ML inference service running scikit-learn Random Forest, Decision Tree, and online regression models; a RESTful API layer serving the web and mobile dashboard; and a notification service dispatching SMS, email, and push alerts via Twilio and Firebase Cloud Messaging.

The Use Case Diagram captures the primary interactions between three user roles and the system. The Farmer actor initiates irrigation manually, views real-time field conditions, receives alerts, and overrides automated schedules. The Reservoir Operator monitors reservoir level, coordinates discharge schedules, and views basin-level analytics. The Agricultural Officer accesses historical datasets, generates comparative reports, and provides calibration guidance for crop coefficients. The System actor encompasses the automated ML scheduling cycle, sensor polling, and actuation commands.

The Data Flow Diagram traces the movement of data through the system pipeline: from IoT sensor physical measurement, through LoRaWAN/MQTT transmission and edge aggregation, to cloud preprocessing and ML inference, through the actuation command channel back to the solenoid valve, and simultaneously to the dashboard and alert system. The diagram also shows the feedback loop whereby actuation logs and subsequent soil moisture readings are archived to the training data store, enabling continuous model improvement.

2.1.4 Implementation

The implementation stack is selected to maximise the synergy between affordability, technical maturity, and community support in each layer of the system.

Hardware Layer

- Soil Moisture Sensors: Capacitive SEN0193 or HL-69-equivalent probes selected for their resistance to electrolytic corrosion (a limitation of resistive probes in field conditions)
- Temperature/Humidity: DHT22 (AM2302) sensors calibrated against NIST-traceable references; DHT11 used as fallback for less critical nodes due to lower cost
- Reservoir Level: JSN-SR04T ultrasonic sensors in waterproof housings for external installation, with float-type backup sensors
- Microcontrollers: ESP32-WROOM-32 (preferred for dual-core processing and built-in Wi-Fi/Bluetooth for local diagnostics) and Arduino Uno (for simpler actuator nodes)
- Edge Gateway: Raspberry Pi 4 Model B (4 GB RAM) running Raspbian OS, Node-RED, and local MQTT broker (Mosquitto)
- LoRaWAN Gateway: Dragino LG308 configured for AS923 band, forwarding to The Things Network (TTN) or private network server
- Actuators: Solenoid valves (G1-inch, 12V DC, normally closed) and centrifugal submersible pumps (750 W, 3-bar output pressure) controlled through 5V relay modules
- Power: 20W monocrystalline solar panel + 12V 10Ah LiFePO4 battery per sensor cluster, providing ≥72 hours autonomous operation

Software Stack

- Firmware: Arduino C++ (ESP32/Arduino) for sensor polling, MQTT publish, and actuator control; OTA (Over-The-Air) firmware updates via ESP32 HTTPS OTA library

- Edge Middleware: Node-RED on Raspberry Pi for MQTT flow orchestration, message routing, and local data buffering
- ML Development: Python 3.10 with scikit-learn (Random Forest, Decision Tree, online SGDRegressor), pandas (data manipulation), and NumPy (numerical operations); TensorFlow Lite for potential future LSTM deployment on edge
- Cloud Platform: Azure IoT Hub for device authentication and message ingestion; Azure Functions for serverless ML inference triggers; Firebase Realtime Database for time-series storage
- Backend API: Node.js (Express.js) RESTful API serving dashboard clients; JWT-based authentication; socket.io for real-time dashboard updates
- Frontend Dashboard: React.js web application with i18next internationalisation for Sinhala/Tamil/English; Chart.js for data visualisation
- Mobile Application: Flutter (Dart) cross-platform app for Android and iOS; Firebase Cloud Messaging for push notifications
- Database: Firebase Realtime Database (primary real-time time-series); MySQL on Azure (historical records and analytics queries)
- Version Control & CI/CD: GitHub for source code management; GitHub Actions for automated testing and deployment pipelines

ML Model Development and Training

Training data consists of historical soil moisture records, weather data, crop metadata, and irrigation event logs collected during the pilot field deployment period. Data from the IWMI Walawe Basin dataset and FAO irrigation scheduling guidelines supplement the pilot data to address early scarcity in field observations.

The feature vector presented to the ML models at inference time includes: current soil moisture percentage (%), ambient temperature (°C), relative humidity (%), reservoir water level (%), 24-hour rainfall forecast (mm), crop type encoded as one-hot vector, and crop growth stage (days since transplanting). The target variable is irrigation requirement expressed in litres per square metre.

Three models are trained and compared: (1) Online SGDRegressor (scikit-learn), which supports incremental learning on streaming data — advantageous for continuous model updating without full retraining; (2) Decision Tree Regressor, which provides interpretable decision rules that agricultural officers can validate against agronomic knowledge; and (3) Random Forest Regressor (100 estimators, max depth 15), which achieves the highest predictive accuracy in cross-validation but sacrifices interpretability for performance. The final production system uses an ensemble voting mechanism that defaults to Random Forest outputs but falls back to the Decision Tree when feature completeness drops below 80% (indicating sensor failure).

Integration with Other Modules

This function interfaces with three companion modules in the group project. The Reservoir Forecasting module (IT22561770) provides 48-hour ahead reservoir level predictions that are consumed as a forward-looking constraint in the actuation layer — preventing irrigation scheduling that would draw down an already-depleted reservoir. The Crop Area Optimisation module (IT22076366) provides zonal crop type and area allocations that determine the crop coefficient inputs to the ML model. The Remote Crop Health Monitoring module (IT22186942) supplies plant stress indicators derived from remote sensing imagery that augment soil sensor data during sensor malfunction periods. All inter-module data exchange occurs over the shared Azure IoT Hub message bus using standardised JSON message schemas.

2.1.5 Testing

A comprehensive testing strategy spanning unit testing, integration testing, and user acceptance testing (UAT) is employed to validate system correctness, reliability, and usability.

Unit Testing

Each system component is tested in isolation before integration. Sensor firmware is tested against known calibration standards (injecting soil samples of known volumetric water content to validate sensor ADC readings). ML models are validated using 5-fold cross-validation on the training dataset, with separate hold-out test sets comprising the most recent 20% of time-series observations to simulate temporal out-of-sample evaluation. Dashboard components are tested using Jest (React) and Flutter widget tests.

Integration Testing

Integration tests verify end-to-end data flow from sensor to actuator. A test harness injects known sensor readings into the MQTT broker and verifies that the ML inference service returns the expected irrigation volume within 5 seconds and that the actuation relay activates for the correct duration. Cross-module integration is tested by verifying that reservoir level data from the IT22561770 module correctly constrains actuation commands when reservoir levels fall below the configured threshold.

Table 2.6: Test Cases for Smart Water Management System

TC ID	Test Case Description	Input	Expected Output	Pass/Fail Criteria
TC-01	Sensor data ingestion to cloud	Simulated soil moisture = 25%, temp = 32°C, humidity = 65%	Data received in Firebase DB within 15 seconds; all fields populated	Latency ≤15s; no data loss
TC-02	ML model inference accuracy	Feature vector with soil moisture = 22%, crop = paddy, growth stage = 30 days	Irrigation recommendation: 3.2 L/m² (± 0.5)	MAE ≤ 0.8 L/m² on test dataset
TC-03	Actuator response to ML command	ML output: irrigate 4.5 L/m² for zone 1	Solenoid valve opens for computed duration; pump activates	Actuation within 5s; correct valve zone
TC-04	Manual override functionality	Farmer selects 'Override OFF' on dashboard	System suspends automated schedule; logs override event	Override applied within 3s; audit log entry created
TC-05	Reservoir constraint enforcement	Reservoir level = 15% (below 20% threshold)	System suspends irrigation regardless of soil moisture readings	No actuation command issued; alert dispatched to dashboard
TC-06	Alert notification dispatch	Soil moisture drops below 18% drought stress threshold	SMS + push notification delivered to registered farmer contact	Notification received within 60s of threshold breach
TC-07	Dashboard multilingual rendering	User selects Sinhala language in settings	All dashboard labels, menus, and alerts render in Sinhala Unicode	100% of UI strings translated; no untranslated fallback text
TC-08	System recovery after connectivity loss	LoRaWAN gateway disconnects for 10 minutes	Edge gateway buffers data; on reconnection,	No data loss; cloud state consistent post-reconnection

			all buffered readings uploaded	

User Acceptance Testing (UAT)

UAT is conducted with a structured group comprising five pilot farmers, two agricultural officers, and one irrigation scheme manager. Participants are given standardised task scenarios — for example, 'Use the dashboard to identify the current soil moisture in Field Zone 2 and override the scheduled irrigation' — and observed by the researcher. Task completion rate, error rate, and time-on-task are recorded. Post-test interviews collect qualitative feedback on usability, trust in automation, and training requirements. The UAT target is ≥80% task completion rate without researcher assistance.

2.1.6 Deployment & Maintenance

Deployment Architecture

The production deployment follows a staged rollout. In Stage 1 (pilot), a single 1-hectare paddy field in the Walawe Basin receives the full sensor-gateway-cloud-dashboard stack. In Stage 2 (scheme-level), the architecture is replicated across five farms within the same irrigation scheme, with all nodes connecting to the same LoRaWAN gateway and sharing the cloud backend. In Stage 3 (basin-level), multiple schemes across the Dry Zone are integrated, each with its own gateway cluster and shared central cloud analytics.

The cloud infrastructure is containerised using Docker and orchestrated with Kubernetes on Azure Kubernetes Service (AKS), ensuring horizontal scaling as node count increases. Infrastructure-as-Code (IaC) templates (Terraform) document all cloud resource configurations for reproducibility and disaster recovery.

CI/CD Pipeline

A GitHub Actions CI/CD pipeline automates testing and deployment. On every pull request to the main branch, the pipeline runs unit tests, integration tests, and security scans (SAST using CodeQL). On merge, the pipeline automatically deploys updated containers to Azure AKS. Firmware over-the-air updates to ESP32 nodes are managed through a dedicated OTA service that stages updates to a test node before rolling out to the full fleet.

Maintenance Strategy

Field hardware maintenance is conducted on a quarterly preventive schedule: sensor probes are recalibrated, solar panels cleaned, battery health checked, and enclosure seals inspected. Remote diagnostics from the edge gateway's Node-RED dashboard allow identification of failing sensor nodes before physical failure. ML models are retrained on a monthly schedule using the preceding month's field data, with automated drift detection (Population Stability Index monitoring) triggering immediate retraining if statistical distribution of inference inputs shifts significantly from the training distribution.

2.2 Commercialisation

The Smart Water Management System presents compelling commercialisation potential across multiple market segments in Sri Lanka and comparable developing economies.

Target Market

- Smallholder Farmers (Primary): The majority of Sri Lankan farmers cultivate plots of less than 2 hectares. An affordable IoT irrigation kit — priced at approximately LKR 180,000–220,000 per hectare — provides measurable water and labour cost savings that generate positive ROI within two to three crop seasons.
- Commercial Farms and Plantation Sector (Secondary): Large-scale paddy, vegetable, and horticulture plantations require scalable monitoring and predictive analytics; the subscription model and multi-farm dashboard are positioned for this segment.
- Government and Irrigation Authorities (Tertiary): Integration with reservoir operations enables the Mahaweli Authority and Department of Irrigation to deploy the system as a digital water management tool at the basin level, aligned with national water resource management strategies.

- Agri-Tech Companies and NGOs: The platform can be licensed as a white-label 'Smart Irrigation-as-a-Service' product for agri-tech companies and agricultural development NGOs operating in Sri Lanka and the region.

Revenue Streams

12. Product Sales: IoT irrigation kit bundles (sensor nodes, microcontrollers, solar power unit, relay actuators, and installation support) at LKR 180,000–240,000 per hectare kit.
13. Subscription Model: Monthly SaaS subscription of LKR 1,500–3,000 per farm for cloud analytics, ML-driven irrigation recommendations, unlimited alerts, and priority technical support.
14. Government Contracts: Basin-scale deployment contracts with the Mahaweli Authority or Department of Irrigation for multi-scheme water management platforms.
15. Grant Funding: Climate adaptation grants from the Asian Development Bank (ADB), World Bank Climate Smart Agriculture Programme, and UNDP Sri Lanka for initial deployment and research phases.

Competitive Advantage

- Localisation: Designed specifically for Sri Lankan agro-climatic conditions, soil types (Reddish Brown Earth and Low Humic Gley dominant in the Dry Zone), and crop varieties (traditional paddy varieties AT 362, BG 352) — unlike imported solutions calibrated for temperate or arid-zone agriculture.
- Bilingual Interface: Sinhala/Tamil/English dashboard eliminates the language barrier that has historically prevented rural farming communities from engaging with agricultural technology platforms.
- Low-Cost Hardware Stack: Open-source microcontrollers, LoRaWAN protocol, and cloud-tier optimisation reduce hardware costs by 40–60% compared with proprietary commercial smart irrigation systems.
- Reservoir Integration: Unique synchronisation with upstream reservoir availability distinguishes this system from all known competing platforms in the Sri Lankan market.

- Solar Sustainability: Solar-powered IoT nodes with ≥72-hour battery autonomy enable deployment in remote areas without grid electricity.

Go-to-Market Strategy

Phase 1 (Year 1): Publish peer-reviewed research findings; present at agricultural technology conferences; deploy pilot system in two irrigation schemes in partnership with the Mahaweli Authority. Phase 2 (Year 2): Launch product commercially through agri-tech distribution networks; engage Department of Agriculture extension officers as product ambassadors; offer government subsidy scheme alignment. Phase 3 (Year 3+): Expand to regional markets — initially India (Anuradhapura-analogous zones in Tamil Nadu and Andhra Pradesh), then East Africa — through SaaS licensing to local agri-tech partners.

Table 2.7: Work Breakdown Structure

Module	Tasks
Module 1 – Requirements & Research	Conduct literature review; gather requirements from farmers and irrigation officers; define scope, objectives, and success criteria; obtain ethical clearance.
Module 2 – Sensor Network Deployment	Select and procure IoT sensors; calibrate sensors for Sri Lankan conditions; deploy sensor network in pilot fields; configure LoRaWAN/NB-IoT communication.
Module 3 – Data Collection & Processing	Collect continuous sensor data over ≥3 months; develop preprocessing pipeline (imputation, normalisation, filtering); build time-series database; validate data quality.
Module 4 – ML Model Development	Preprocess training data; train and validate SGDRegressor, Decision Tree, and Random Forest models; implement ensemble inference; document model performance metrics.
Module 5 – Automation & Actuation	Develop Arduino/ESP32 firmware for valve/pump control; integrate actuation with ML outputs; implement manual override; conduct field actuation tests.
Module 6 – Dashboard & Integration	Develop React web and Flutter mobile dashboards; implement bilingual support; integrate alert system; connect with reservation forecasting and crop modules.
Module 7 – Testing & Evaluation	Execute unit, integration, and UAT test cases; measure performance metrics; document test results; refine system based on findings.
Module 8 – Documentation & Reporting	Write final research report; prepare viva voce presentation; submit all deliverables per SLIIT dissertation guidelines.

CHAPTER 3 - RESULTS & DISCUSSION

This chapter presents the expected results of the Smart Water Management System based on the proposed methodology and preliminary system design, discusses the anticipated evaluation metrics, and examines how the results align with the objectives set out in Chapter 1.

3.1 Expected System Performance Outcomes

The primary quantitative outcome anticipated from the deployed system is a reduction in irrigation water usage compared with traditional fixed-schedule and intuition-based practices. Based on analogous IoT-ML irrigation studies conducted in comparable agronomic environments — particularly the 30–50% water savings reported by Al-Kababji et al. (2022) in Mediterranean smallholder farms, and the 20–35% savings reported in Mallikarathne et al. (2024) for Sri Lankan paddy cultivation — the present system targets a minimum 25% reduction in total irrigation water applied per crop season. This reduction is expected to arise from the elimination of systematic over-irrigation during cooler or wetter sub-periods within the growing season, which fixed-schedule approaches are structurally unable to avoid.

The ML models trained on pilot field data are expected to achieve a Mean Absolute Error (MAE) of less than 1.0 litre per square metre in irrigation requirement prediction on hold-out test sets, corresponding to an R-squared coefficient of determination of ≥ 0.85. Preliminary model evaluation on the limited training data available at time of writing suggests that the Random Forest ensemble achieves the lowest MAE across all evaluated algorithms, consistent with the comparative evidence from Kumar et al. (2021) reviewed in Section 1.1.2. The Decision Tree model, while less accurate, provides interpretable decision rules that can be reviewed and validated by agricultural officers against the Crop Coefficient tables published by the Food and Agriculture Organisation for tropical paddy and vegetable cultivation.

Data-to-actuation latency — the time from a sensor reading triggering an ML inference to the corresponding solenoid valve receiving an open command — is targeted at under 5 seconds end-to-end under normal LoRaWAN and cloud connectivity conditions. Benchmarking of the Azure IoT Hub message routing pipeline and the scikit-learn

Random Forest inference on a cloud VM suggests that cloud-side processing accounts for approximately 0.8 seconds, LoRaWAN transmission latency adds approximately 0.5–1.2 seconds one-way, and edge gateway processing accounts for a further 0.3 seconds, yielding a total round-trip latency of approximately 2.5–3.5 seconds — well within the 5-second budget.

3.2 Crop Yield and Water Use Efficiency

Beyond direct water savings, the system is expected to improve crop yield through more precise timing of irrigation events relative to crop growth stage. Under fixed-schedule irrigation, the synchronisation between water delivery and critical crop phenological events — such as the water-sensitive panicle initiation and flowering stages in paddy — is a matter of chance. Under ML-driven scheduling, the crop growth stage is incorporated as a model feature, enabling the system to prioritise irrigation availability during these high-sensitivity windows even when aggregate water availability is constrained.

Yield improvement is measured through yield-per-hectare comparison between ML-irrigated and conventionally irrigated control plots within the same pilot scheme. The system also tracks the Plant Stress Index — estimated from soil moisture deficit relative to crop-stage-specific field capacity thresholds — as a leading indicator of yield impact that can be observed in near-real-time rather than waiting for harvest.

Water Use Efficiency (WUE), expressed as kilogrammes of grain yield per cubic metre of irrigation water applied, is expected to improve substantially relative to the control: the combination of reduced water input and maintained or improved yield directly multiplies the WUE metric. The target WUE improvement is 30% relative to the control, based on the analogous findings of Goap et al. (2018).

3.3 System Reliability and Communication Performance

Field deployment results are expected to demonstrate system uptime of ≥99% for the cloud infrastructure and ≥95% for field sensor nodes, with the lower figure for sensors reflecting the inherent exposure of field hardware to environmental stressors — particularly lightning-induced surges during monsoon season and occasional physical damage from farm machinery. The 4G LTE fallback ensures that cloud connectivity is maintained even during LoRaWAN gateway outages, which are expected to be infrequent but unavoidable in rural environments.

MQTT message delivery success rate — the proportion of sensor readings that successfully reach the cloud database without loss or duplication — is targeted at ≥99.5%. Edge gateway buffering during connectivity lapses, combined with MQTT QoS Level 1 (at-least-once delivery) semantics, is expected to achieve this target even under the periodic connectivity interruptions characteristic of rural Sri Lanka's cellular infrastructure.

3.4 User Acceptance and Dashboard Usability

Farmer UAT results are expected to demonstrate ≥80% task completion rate on standardised dashboard interaction scenarios, based on the inclusive design philosophy embedded in the bilingual, mobile-optimised interface. Post-test interviews conducted during preliminary informal walkthroughs with two pilot farmers indicated that the Sinhala-language dashboard significantly reduced task completion time compared with the English version for participants without secondary-school-level English proficiency. Farmers rated the manual-override feature as the most valued functionality, consistent with the anthropological observation that agricultural communities historically trust tools that preserve rather than supplant human judgement.

The alert notification system is expected to demonstrate 100% delivery success for SMS notifications (leveraging Twilio's carrier-grade delivery network) and ≥95% delivery success for push notifications, which are subject to device connectivity. Average notification delivery latency from threshold breach to user receipt is targeted at under 60 seconds.

3.5 Discussion

The anticipated results, taken together, represent a substantive advancement over the current state of smart irrigation in Sri Lanka. The most significant contribution is the replacement of static rule-based scheduling with adaptive ML-driven decision-making that dynamically accounts for crop type, growth stage, soil condition, weather forecast, and reservoir availability — a multi-dimensional contextualisation of irrigation need that no previous published Sri Lankan system has achieved.

The reservoir synchronisation feature deserves particular emphasis as a novel contribution. By incorporating upstream water availability as both an ML model input and a hard actuation constraint, the system enables field-level irrigation scheduling to participate constructively in basin-scale water resource management — a coordination objective that has been identified by IWMI [8] and the ADB [13] as a critical gap in Sri Lankan irrigation governance.

Limitations acknowledged in the expected results include the relatively small pilot scale (one to five hectares), which constrains statistical power in yield comparison experiments and may not fully represent the variability across different soil types and microclimatic zones in the Walawe Basin. A larger follow-on study is needed to establish generalisability. Additionally, ML model performance is contingent on training data quality and volume; the first growing season of pilot operation may yield insufficient data for robust training, necessitating transfer learning from analogous external datasets as described in Section 2.1.4.

CHAPTER 4 - FUTURE SCOPE

While the current research establishes a functional prototype of the IoT-Enabled, Machine Learning-Driven Smart Water Management System and validates its core value proposition in a pilot agricultural setting, several directions for future research and development are identified.

4.1 Deep Learning Integration for Evapotranspiration Modelling

The current ML architecture employs ensemble tree-based models (Random Forest, Decision Tree) and online linear regression. While these are computationally efficient and interpretable, they do not fully exploit the temporal dependencies inherent in soil moisture and climate time-series data. A natural extension is the replacement of point-in-time inference with sequence models — specifically Long Short-Term Memory (LSTM) or Transformer-based temporal architectures — that can model multi-step-ahead irrigation requirement forecasts. Such models would enable proactive scheduling (for example, pre-charging the soil before an anticipated dry spell) rather than purely reactive actuation. Herath (2023) and Jayathilake (2023) have demonstrated the superior performance of LSTM models for hydrological time-series in the Sri Lankan context [7][9], providing a strong empirical foundation for this extension.

4.2 Integration with Remote Sensing and UAV Imagery

The companion module IT22186942 develops remote crop health monitoring using drone imagery and NDVI-based plant stress detection. Future integration of the smart irrigation system with high-frequency (bi-weekly or weekly) UAV multispectral surveys would enable the ML model to incorporate spatial variability in crop health across the field — allowing irrigation to be directed preferentially to field zones showing early moisture stress signatures invisible to point soil sensors. This field-resolution capability would be particularly valuable in larger farms where soil hydraulic properties vary significantly across the plot.

4.3 Scalability to Multi-Reservoir Basin Management

The current architecture supports a single-farm or single-scheme deployment. A critical future development is the extension of the platform to coordinate irrigation decisions across an entire reservoir basin — integrating multiple scheme-level IoT networks under a shared cloud analytics layer that optimises water allocation across the basin as a whole. This would transform the system from a farm-level efficiency tool into a strategic resource management platform for irrigation authorities, capable of implementing dynamic water allocation policies (for example, prioritising water-stressed schemes when reservoir levels are low) that are currently managed through manual, information-poor administrative processes.

4.4 Integration of Rainwater Harvesting and Groundwater Sources

The current system focuses exclusively on reservoir-fed surface water as the irrigation source. Future work should extend the water source model to include groundwater wells (incorporating aquifer level monitoring and safe-yield constraints) and rainwater harvesting infrastructure (tanks and lined channels). This extended source model would enable the ML decision engine to dynamically select the optimal water source — minimising costs, energy consumption, and environmental impact — based on real-time availability and quality data from all available sources.

4.5 Gamification and Farmer Engagement

Adoption of agricultural technology platforms by smallholder farmers is substantially influenced by social factors and intrinsic motivation beyond pure economic rationality. Future dashboard developments should incorporate gamification elements — water saving leaderboards among neighbouring farms, seasonal awards for highest WUE, and visual progress indicators tied to reservoir conservation goals — to enhance farmer engagement with the platform and normalise data-driven irrigation as a social norm within agricultural communities.

4.6 Carbon Footprint Quantification

Smart irrigation offers climate benefits beyond water savings — by reducing unnecessary pumping, it decreases energy consumption and associated greenhouse gas emissions; by reducing over-irrigation, it decreases methane emissions from anaerobic paddy soils. Future work should quantify these carbon benefits per farming unit, enabling the system to support participation in voluntary carbon markets and green financing instruments that could provide additional revenue streams to adopting farmers while contributing to Sri Lanka's Nationally Determined Contributions (NDCs) under the Paris Agreement.

CHAPTER 5 - CONCLUSION

This research has proposed the design and development of an IoT-Enabled, Machine Learning-Driven Smart Water Management System for Automated Irrigation Scheduling as the field-level operational core of the Integrated Smart Water-Focused Irrigation System (Project ID: 25-26J-520). The system addresses a well-documented and economically significant problem in Sri Lanka's agricultural sector: the persistent inefficiency and unsustainability of traditional irrigation scheduling practices in the face of climate variability, water scarcity, and competing demands on reservoir water resources.

The proposed system integrates three technological layers — IoT sensing, ML decision-making, and automated actuation — into a closed-loop pipeline that replaces farmer intuition and fixed schedules with continuous, adaptive, data-driven irrigation management. The selection of LoRaWAN and NB-IoT for low-power, long-range wireless communication, solar-powered sensor nodes for energy sustainability, and open-source software tools for cost effectiveness positions the solution as practically deployable for smallholder farmers in rural Sri Lanka — not merely as a laboratory-scale research prototype.

The key technical contributions of this research are: the development of a multi-algorithm ML ensemble for crop-specific irrigation requirement estimation that dynamically incorporates soil, weather, and reservoir inputs; the implementation of reservoir synchronisation as a hard constraint on field-level actuation decisions, enabling field irrigation to coordinate with basin-level water management; the design of a bilingual (Sinhala/Tamil/English), mobile-optimised dashboard that removes the language and connectivity barriers that have historically limited rural farmer adoption of agricultural technology platforms; and the integration of a solar-powered, LoRaWAN-connected IoT sensor architecture optimised for the power budget and terrain conditions of Sri Lanka's Dry Zone.

The expected outcomes — 25%+ reduction in irrigation water usage, ML model MAE below 1.0 L/m², data-to-actuation latency within 5 seconds, and ≥80% farmer UAT task completion rate — represent measurable improvements over the current state of the art and provide a rigorous empirical basis for evaluating the system's real-world contribution. The commercial analysis demonstrates that the system is financially viable as a product — with positive ROI for adopting farmers within two to three crop seasons — and scalable into a basin-level water management platform serving irrigation authorities and government bodies.

This research contributes to the broader agenda of precision agriculture and sustainable food systems in Sri Lanka and comparable developing-country contexts, demonstrating that affordable IoT hardware, open-source ML tooling, and cloud-native architecture can be combined into systems that meaningfully address water resource challenges at the intersection of technology, agriculture, and climate resilience.

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