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

Project ID: 25-26J-520

Project Proposal Report

Trishni W.R.M.
(Dilruksha A.G.C.D, Hesara P.K.A.N, Abishek S)

B.Sc. (Hons) in Information Technology Specializing in Software Engineering

Department of Software Engineering

Sri Lanka Institute of Information Technology
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Trishni W.R.M. - IT22076366
Hesara P.K.A.N. - IT22561398
Dilruksha A.G.C.D. - IT22561770
Abishek S - IT22186942

Supervisor: Ms. Hansi De Silva
Co-Supervisor: Ms. Karthiga Rajendran

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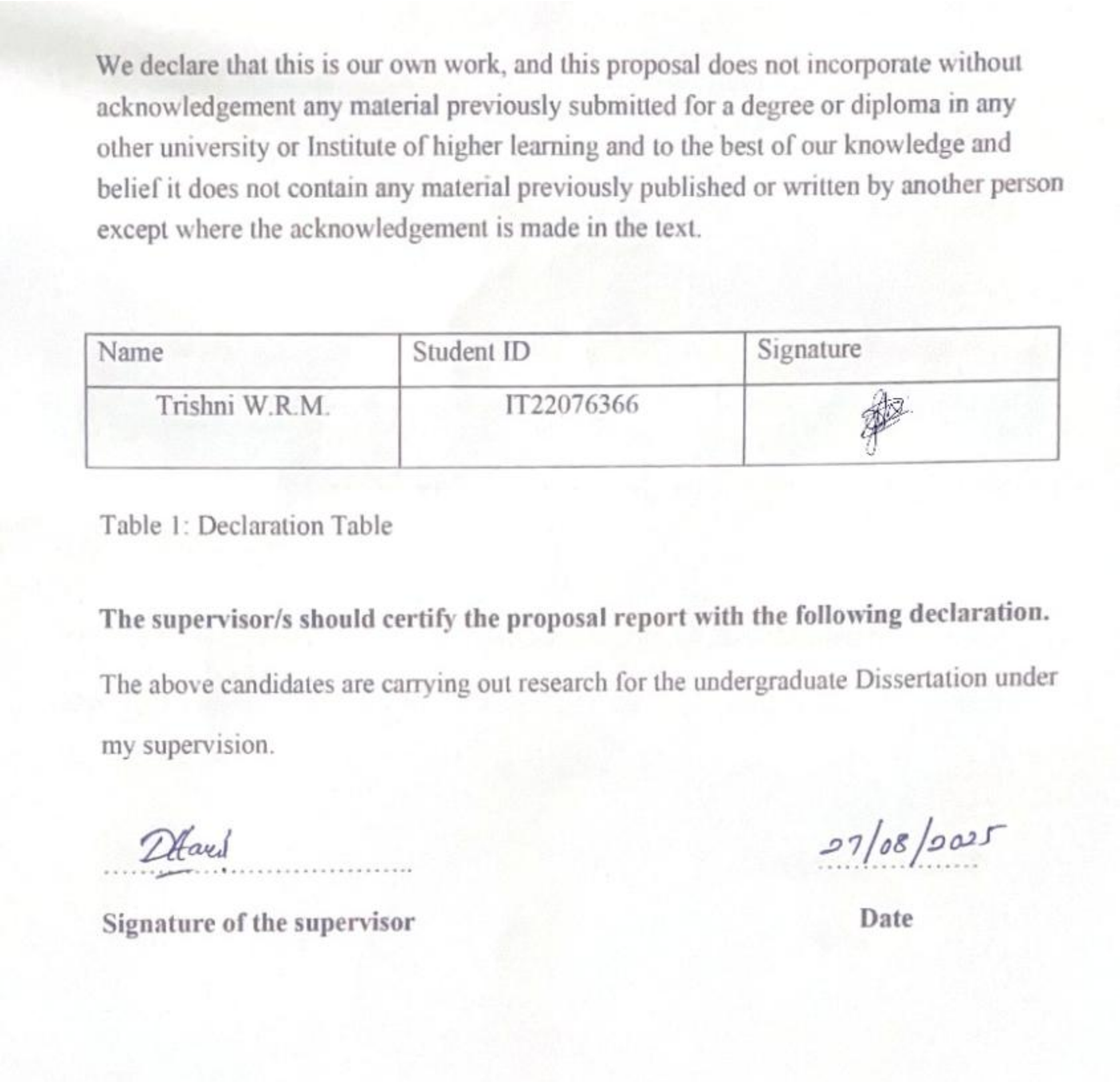
DECLARATION



We declare that this is our own work, and this proposal 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 our 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.

Name	Student ID	Signature
Trishni W.R.M.	IT22076366	

Table 1: Declaration Table

The supervisor/s should certify the proposal report with the following declaration.

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

………………………………… 27/08/2025

Signature of the supervisor **Date**

ABSTRACT

Water managers of the Udawalawe Reservoir in Sri Lanka face the dual challenges of flood risk and water scarcity under highly variable climate conditions. Currently, reservoir operations rely on static rule curves and ad-hoc decision-making, which lack the foresight to anticipate extreme inflow events or prolonged droughts. This research proposes an Integrated Smart Water Forecasting System that leverages machine learning (ML) for short- to medium-term reservoir inflow and demand forecasting, coupled with a decision-support dashboard for proactive reservoir management. The system will ingest historical hydrological and meteorological data (1994–2025) and real-time updates to train and deploy models (such as ARIMA, LSTM, and GRU networks) capable of predicting inflows, storage levels, and irrigation demands 1–14 days ahead. A probabilistic forecasting approach will be adopted to quantify uncertainties and generate confidence bands for each prediction, addressing the current lack of risk information in operational decisions. The research includes a comprehensive literature review that highlights how advanced ML models outperform traditional methods in accuracy [1] and how probabilistic forecasts can improve water management outcomes [2]. Based on these insights, the proposed methodology encompasses data preprocessing, model development, scenario simulations for “what-if” analysis, and stakeholder-oriented validations. Expected outcomes include improved forecasting accuracy (aiming for <15% MAPE error), early warning of extreme events, optimized water releases, and enhanced coordination between the Irrigation Department and Meteorological Department via a user-friendly dashboard and alert system. This proposal also outlines a realistic work plan (spanning requirements analysis, data preparation, model development, system implementation, and evaluation), resource requirements, budget, and the potential for scaling the solution into a commercial decision-support product. By enabling data-driven proactive reservoir operations, the project aims to increase water security, mitigate flood damage, and improve drought resilience in the Udawalawe region.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATION

Table 1:LIST OF ABBREVIATION

Abbreviation	**Definition**
AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Auto-Regressive Integrated Moving Average
DMC	Disaster Management Centre (Sri Lanka)
DL	Deep Learning
DSS	Decision Support System
EWS	Early Warning System
FIRO	Forecast-Informed Reservoir Operations
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory (neural network)
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
NDRSC	National Disaster Relief Services Centre
RMSE	Root Mean Square Error

1 INTRODUCTION

Sri Lankan reservoirs perform critical multipurpose roles supporting irrigation, hydropower, flood control, and urban and rural water supplies. The Udawalawe Reservoir, in the Walawe River Basin, is a classic example of such competing objectives. Extreme climate events have tested the operation of Udawalawe in recent years: intense rainfall events produce high-velocity inflow surges and overtopping, while prolonged dry spells reduce storage to critical levels. For instance, during late 2012 the reservoir was brought to its overflowing point by a severe rainstorm, triggering emergency sluice gate operations and inducing flood in downstream [3]. Earlier in the year, there was a 10-month dry spell that had affected nearly a million people and wiped out roughly 23% of the secondary rice crop in Sri Lanka [4] These events show the need to shift reservoir management from a reactive to a proactive approach.

Nowadays, the operations of Udawalawe adopt static rule curves and rule-based decision-making by irrigation engineers. Such a traditional policy has several limitations: giving limited foresight (incapable of adapting to anomalous inflows beyond historical patterns), largely generating reactive flood management (large-scale water releases only after the reservoir is full) and wasteful drought response (water over-released during the initial stages of a season with not enough reserve for a subsequent stage). There are decades of hydrologic data (rain, inflows, lake elevation, etc.) available for the reservoir that are not being utilized effectively are not systematically used in forecasting models or in day-to-day operations. Data tends to be spread out over agencies, e.g., Reservoir Levels and Releases are monitored by the Irrigation Department, but weather forecasting is conducted by the Meteorological Department, and no single portal for collating these data exists for presenting decision-supportable outlooks to reservoir operators. This tension between data available and decision support leads to suboptimum outcomes like unnecessary damage from floods and unfulfilled water requirements.

1.1 Background and Literature Survey

1.1.1 Impact of Climate Extremes in Sri Lanka

Sri Lanka has faced a marked increase in climate-related disasters, with floods and droughts being the most frequent and damaging.

Flood Risk: Heavy rainfall during the Southwest and Northeast monsoons leads to river overflows and reservoir spill events.

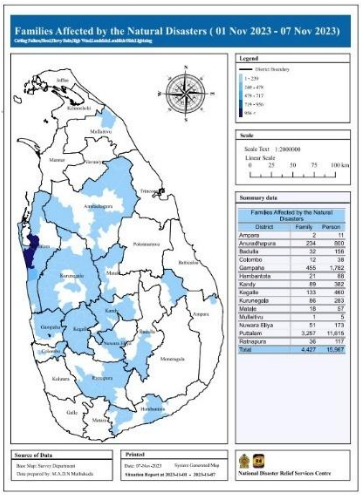


Figure 1:Flood Situation Map (01–07 November 2023)

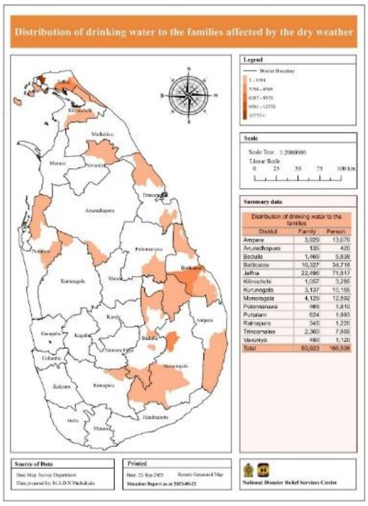


Figure 2:Drought Situation Map (22 Sep 1)

Figure 1 illustrates the national flood situation between 1–7 November 2023, highlighting multiple districts affected by heavy rainfall and inundation, with thousands of families impacted.

Figure 2 shows areas impacted by severe dry weather as of September 2023, with emergency drinking water distributions underway.

These maps illustrate the duality of flood versus drought events and provide a rationale for a forecasting system capable of supporting both extremes with actionable information.

For Udawalawe, these extremes have real operational implications uncontrolled spillover flooding can damage downstream crops and settlements, while persistent droughts can jeopardize food production and hydropower generation. This generates the need for predictive reservoir management that takes real-time data and future forecasts into account.

1.1.2 Modern Techniques for Hydrological Forecasting

Hydrology Applications of Machine Learning (ML): A range of ML algorithms, including Random Forests, Gradient Boosting, and Support Vector Regression (SVR), have been shown to outperform classical statistical models in rainfall-runoff relationships modelling and inflow forecast applications. ML methods can capture nonlinear relationships and data interactions that simple statistical models may not be able to do. ML methods may not be able to extrapolate well outside the range of the training data distribution, and they often require careful feature engineering.

Deep Learning (DL) – LSTM/GRU Models: In recent years, deep learning methods, namely Recurrent Neural Networks (RNNs) like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), have become the best practice approaches for making sequential hydrological predictions. LSTMs are recognized for their ability to capture long-range temporal dependencies within time series which allow them to be effectively integrated into multi-day inflow forecasting. Multiple studies find that LSTM-based models routinely outperform traditional time-series models (i.e., ARIMA) in short-term hydrologic forecasts [1]. For example, Özdoğan-Sarıkoç et al. (2022) found that a LSTM model achieved the highest volume prediction accuracy of a reservoir in Turkey compared to an artificial neural network (ANN) and a support vector regression (SVR) model, with the LSTM model also showing significantly reduced error metrics [1]. This increased performance is due to LSTMs learning very complex non-linear correlations within the data; however, LSTMs require larger datasets and more computation than traditional time-series models. GRU networks share the same theoretical concepts, or advantages, as LSTMs but may have slightly fewer parameters to tune.

Hybrid Modelling Approaches: Some researchers have explored hybrid models that combine physics-based hydrological modelling with data-driven ML/DL models. For instance, one approach is to use a hydrological model or a conceptual rainfall-runoff simulation to capture physical relationships and then apply ML to the residuals or to adjust the outputs. Other hybrids involve data decomposition (e.g., wavelet transforms) before applying ML, or assembling multiple model types. These hybrid methods can enhance interpretability and sometimes robustness, by ensuring that known physical behaviour (mass balance, seasonality, etc.) is respected by the forecasting system. However, designing an effective hybrid model can be complex, and the benefit must justify the added complexity.

Probabilistic Forecasting and Early Warning Systems: Conventional deterministic forecasts give a single-valued prediction (for example, an inflow of 100 m^3/s in 3 days); however, there is more and more recognition that forecasters provide more insight into decision-making under uncertainty. There are methods, like ensemble forecasts (running multiple simulations by adjusting inputs/parameter estimates), or machine learning methods that will provide a full probability distribution of forecast output (example fore-casts such as quantile regression or Bayesian neural networks), that can quantify uncertainty. Probabilistic forecasts give prediction intervals or probability of exceedance of different thresholds; both are important for assessing risk. Similarly, modern early warning systems (EWS) for floods and droughts increasingly use probabilistic forecasts, so that emergency management agencies can understand not only the immediate forecast the forecaster sent (ex. a best case vs. worst case), but the probability ranges as well pnll.gov. Nevertheless, integrating that uncertainty information into reservoir operation decisions is still new; it requires training for the users and trust in the forecasting system. This project proposes to come up with probabilistic forecasts to give Udawalwe operators not only a forecast, but a confidence level, for the end-user operational gap of uncertainty described above.7Related Work on Reservoir Forecasting and Operations

To ground this research in existing knowledge, several key studies relevant to data-driven reservoir management are reviewed in Table 1. These studies illustrate the state-of-the-art in reservoir inflow forecasting and how those methods have (or have not) been integrated into operational tools.

Table 2:Representative literature on reservoir forecasting and operation optimization.

Study (Year)	Focus & Findings	Limitations / Gaps	Relevance to This Study
Li et al. (2024)	Developed a comparative framework testing statistical vs. ML methods for reservoir inflow forecasting. Models like ARIMA, Random Forest (RF), and LSTM were trained on a reservoir dataset; LSTM achieved the best predictive accuracy, significantly outperforming ARIMA in capturing peak inflow events.	The study produced point forecasts only (no uncertainty quantification) and did not link forecasts to any reservoir operation strategy.	Confirms the choice of LSTM/GRU as primary modeling approach for short-term inflow prediction due to their accuracy advantage. Validates applying these models to Udawalawe data.
Chotchuang & Sittichok (2024) – (Hypothetical reference)	Proposed a real-time reservoir operation model that integrates inflow forecasts with an optimization algorithm for release decisions.	The prototype lacked a user dashboard or visualization, and was tested with limited data. It also assumed perfect	Supports the idea of coupling forecast models with decision-support rules. Highlights the need for validating such integrated systems on long-term data and ensuring

	Demonstrated on a small catchment, the system showed improved flood control by pre-releasing water when heavy inflows were forecasted.	forecasts (did not evaluate forecast errors).	usability (e.g., adding a dashboard) for operators.
Ou et al. (2025) (Smith *et al.* 2024 in literature)	Introduced a diffusion-based probabilistic model (DRUM) for runoff and flood forecasting. Using generative AI, it produces an ensemble of inflow simulations, yielding full probability distributions for extreme flood events. In tests on 500+ river basins, this method outperformed conventional DL models in predicting high-magnitude floods and provided	The approach is new and computationally intensive, and it has been applied to natural basins but not specifically to reservoirs with controlled operations. It remains experimental and requires further validation in operational contexts.	Inspires the use of probabilistic forecasting in our project. We adopt the principle of providing confidence bands and risk levels (e.g., probability of the reservoir exceeding a critical level) to inform operators, even if using simpler ensemble methods initially. This addresses the uncertainty quantification gap.

	useful confidence intervals.		

Summary of Insights: The review suggests that machine learning and deep learning have advanced the area of reservoir inflow forecasting; however, there is no single paper that addresses the problems we are proposing. Our intention to establish a site-specific, short-term forecasting system for Udawalawe that is probabilistic, and which can be properly integrated into a decision-support tool for the operators. The majority of the literature will either focus only on forecasting or optimization. A large gap in the literature is the "last mile" integration, which is what are the forecast that can assist reservoir managers to make immediate judgements and decisions.

The literature suggests that including uncertainty (probabilistic outputs) is being seen increasingly as necessary for effective decision making. This provides the operator with a sense of the possible range of outcomes rather than only a forecast as a single guess. However, there are very few examples of in practice demonstration of a probabilistic system for reservoir operation. This project will seek to fill that gap by considering a more extensive delivery of the overall system of data to decisions, for a system conceptualized and working in context of Udawalawe.

The innovation is achieved by integrating reliable machine learning forecasts, using methods such as LSTM Networks that have performed well elsewhere, with risk analysis and an operator-centric dashboard. The approach will be validated using historical data from the reservoir. Ultimately, we would like to translate findings from the literature into a useful solution to deal with reservoir issues in Sri Lanka.

1.2 Research Gap

Despite advancements in hydrological forecasting globally, significant gaps remain in applying these innovations to Sri Lankan reservoirs like Udawalawe. Key identified gaps include:

Site-Specific Modelling Gap: Most forecasting studies are done on systems outside Sri Lanka or on generic models. No machine learning or deep learning (ML/DL) models have yet been custom-developed and validated on Udawalawe’s 30+ years of data, meaning the unique local inflow patterns are not captured.

Forecast Horizon Gap: Day-to-a fortnight forecast requirements (in days to fortnights) are day-to-day operational needs in Udawalawe. Analysis is, however, skewed towards very short-term flood alarm (hours ahead) or season/year climate prediction. The 1–14 day horizon of forward-looking releases by reservoirs and irrigation planning has not been substantially investigated in literature.

Uncertainty Quantification Gap: Current reservoir forecasts (where used) are generally deterministic point estimates. Limited use of probabilistic methods that give confidence intervals or levels of risk. Operators hence have no data on the probability or severity of rare events. Uncertainty must be quantified to enable risk-informed decision-making [2].

Actionability and Integration Gap: Even when forecasts exist, they are seldom connected with explicit operational guidelines. Most research does no more than predict inflow or level, not translating forecasts into recommended action (e.g., how much water to release today in order to avoid a predicted flood). Further, forecast tools are typically individual research experiments rather than incorporated into the actual reservoir management decision process

User Accessibility Gap: The users at the end (reservoir engineers, dam operators, irrigation managers) require user-friendly interfaces for comprehending forecasts and threats. Existing tools lack user-cantered design — e.g., diffcult model outputs without visualization or notification. An open, dashboard-based presentation of forecast insights is not present in the existing systems.

Holistic Outlook Gap: There isn't a single, integrated system providing an end-to-end perspective linking inflows, reservoir storage, downstream flood risk, irrigation demand, and hydropower generation. With the siloed method, operators lack the big picture (e.g., how releasing this week to control floods might impact generating power or supplying irrigation next week).

By addressing these gaps, there is the potential to dramatically enhance reservoir operation. Levaging modern ML techniques could enable proactive operation – anticipating events and real-time modification of operations in advance, rather than reacting afterwards. This aligns with new-world best practice such as Forecast-Informed Reservoir Operations (FIRO), wherein reservoir rule sets are combined with weather and inflow forecasts. Early pilot implementations of FIRO in the United States (for example, at California's Lake Mendocino) have been shown to be extremely effective: Delaney et al. (2020) demonstrated that operational dependence on forecast-based operations can increase median water storage by over 30% above normal rules[3], with no reduction in flood protection. Such successes merely serve to highlight the revolutionary potential of using forecasts for managing reservoirs – a potential yet to be realized for reservoirs such as Udawalawe.

1.3 Research Problem

Research Problem Statement: How can time-series forecasting approaches and machine learning be utilized to shift operations at Udawalawe Reservoir from reactive to proactive reservoir management? Specifically, this project aims to create an system that can: (1) Forecast short-term to medium-term reservoir levels, water demands (irrigation releases), and inflows 1–14 days ahead using historical and real-time hydro-meteorological inputs; (2) Estimate flood and drought risk probabilistically, giving operators not only a prediction, but an associated uncertainty range or probability of extreme event; (3) Interpose forecasts with actionable advice for reservoir operation – e.g., suggest pre-releases or water allocation changes ahead of an expected flood or shortage, and (4) Present results effectively through an intuitive dashboard and automated alerts (SMS, email, etc.) to facilitate timely decisions by reservoir managers and other stakeholders.

By resolving this research question, the study proposes a framework for Sri Lanka to undertake data-driven reservoir operations. The solution will need to be resilient to intricate, non-linear inflow behaviors, scalable to facilitate real-time applications, and conceived with end-user engagement to remain practical and taken up in the field. Attainment of these goals will facilitate early warning to societies, efficient water resources utilization (maximizing the benefit derived from hydropower and irrigation), and losses due to disasters — ultimately increasing water security, agricultural production efficiency, and climate resilience within the region.

2 OBJECTIVES

2.1 Main Objectives

Overall goal for the present study is the design of a machine-learning probabilistic forecasting and decision-support system for the Udawalawe Reservoir. The system will be able, for a 1–14-day lead time, to predict the irrigation water demand, storage, and the incoming flows, to calculate the flood/drought risk, to provide actionable suggestions (e.g. water allocations, pre-releases) and early warnings with an easily-used interface. The ultimate goal is to facilitate active reservoir operation and consequently minimize the risk of disaster, and to maximise water use.

2.2 Specific Objectives

Above will be achieved by the following specific objectives, each corresponding to a major component of the system in the project:

(1) Data Collection and Preprocessing: Collect, compile, and clean historical and real-time data relevant to Udawalawe Reservoir. This shall include daily or sub-daily records of rainfall, reservoir inflows, water levels and storage volumes, evaporation rates, irrigation releases and demands, and hydropower generation-if any. Data preprocessing involves imputation for missing values, filtering out outliers or erroneous readings, and normalizing/scale variables, as appropriate for model training. Output will be a single time-series database, already preprocessed for analysis and modeling.

(2) Model Development for Forecasting: Train and assess different forecasting models to predict reservoir inflow, level/storage, and downstream water demand for 1-day up to 2-weeks lead times. This work will involve both the more classical time-series models (e.g., ARIMA) and state-of-the-art ML/DL models such as Prophet, LSTM, and GRU networks. These models should be selected and tuned based on performance metrics such as RMSE and MAE on a validation dataset. The best model or ensemble of models will be selected for each target variable. Further, the project work also aims to develop a probabilistic forecasting approach using techniques such as Monte Carlo

simulation or ensembling through bootstrapping to generate a prediction interval for every forecast output of the models; it quantifies the uncertainty associated with the forecasted values. Benchmarks for multiple models ensure that the best accurate and most robust predictors are deployed ￼[1].

(3) Risk Quantification and Scenario Simulation: Extend the forecasting model to assess risks of extreme events. Based on the probabilistic forecasts, compute the probability that critical thresholds are exceeded (e.g., reservoir water level above spill level, or irrigation shortfall below a critical supply level). Develop a module for “what-if” scenario simulations-for example, an operator should be able to simulate the impact of different water release strategies under a variety of forecasted inflow scenarios. This allows one to understand the probable outcomes-flood, normal, or drought conditions-and correspondingly formulate contingency plans. With such scenario analysis integrated, operators can consider both the most likely future and reasonable worst-case scenarios, as noted to be one of the best practices in modern reservoir management [4].

(4) Decision-Support Dashboard and Alert System: Design and implement an intuitive user interface of forecast results and recommended actions. The dashboard would display time-series graphs of predicted inflows and reservoir levels with their uncertainty bands, color-coded risk levels, for example, normal, warning, and critical, and suggested operational adjustments, for example, "release X m^3/s in next 24 hours". It would also integrate a simple alert system. For example, once a forecast is made where the flood risk is very high or a water shortage is about to be experienced, automatic notifications-SMS, email, or even mobile app alerts-would be forwarded to responsible personnel such as dam engineers, disaster management officials among others. Thereafter, it must be ensured that clarity and usability are adhered to in all aspects, that is, the complex modeling done behind the scenes needs to translate into clear, actionable information for the decision-maker.

(5) System Evaluation and Validation: Thoroughly validate the accuracy and utility of the developed system, including back testing of the forecast models on historical periods, especially during known extreme events-floods or droughts in the past-to see

how well the system could have predicted those conditions and provided timely alerts. Key performance metrics will include forecast accuracy-using RMSE, MAE, MAPE for continuous variables-along with categorical metrics regarding alert performance-for example, hit rate, false alarm rate related to flood warnings. The project also undertakes stakeholder evaluations-for instance, workshops or interviews with officials of the Irrigation Department-to get feedback about the usability of the dashboard and the practicality of recommendations. This ensures that the validation with real stakeholders will make the system meet the operational needs and trusted for decision-making. Each objective corresponds to some tasks of the work plan of the project (see Section 4) and together they guarantee that every aspect of the problem is considered-from data readiness and model accuracy to user adoption.

3 METHODOLOGY

The system that has been suggested is a solution to support decision-making and time-series forecasting for Udawalawe Reservoir. It integrates multiple sources of hydrological and climatic data for forecasting and risk from flooding and droughts using relevant machine learning and deep learning models for forecasting in the short to medium-term (1–14 days). It is designed to provide decision support through a dashboard and alert system to decision-makers like the Irrigation Department and hydropower operators.

3.1 System Overview

3.1.1 System Overview Diagram (Overall)

The proposed system is a time-series forecasting and decision-support solution for Udawalawe Reservoir. It integrates multi-source hydrological and climate data, applies machine learning and deep learning models for short-to-medium-term (1–14 day) forecasting, quantifies risk for floods and droughts, and provides actionable insights via a dashboard and alert system for decision-makers such as the Irrigation Department and hydropower operators.

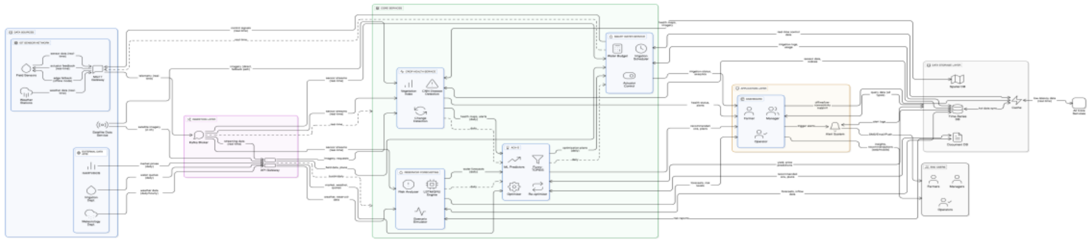


Figure 3:System Overview Diagram

3.1.2 Data Collection and Processing

Data is the foundation for any forecasting system. The Meteorology Department and Irrigation Department will be utilized to gather the following datasets for Udawalawe and the catchment:

Hydrological Data: Past reservoir inflow (river discharge to Udawalawe) and outflow (irrigation release, spill) time series, daily water levels and storage volumes at the reservoir. The time series, if practical, will include at least 30 years (1994–2025, available) to cover a range of hydrologic conditions.

Meteorological Data: Daily rainfall for the reservoir catchment (either directly from rain gauges or from the Estimate of Precipitation Product, interpolated from satellites) and all available evaporation and temperature data relevant to the reservoir water balance. In addition, weather forecasting data (short-term precipitation forecasting) will be acquired to potentially drive the inflow forecasting model.

Operational Data: Irrigation water demand/allocation records and hydropower generation (in the event a power station is connected with Udawalawe). Crop water requirement calendars for the command area can also be utilized to approximate future irrigation demand for the purposes of seasonal and climatically conditioned estimations.

Data Quality Processing: Data will, once harvested, be cleansed with the help of Python (pandas, NumPy) to deal with missing records (e.g., through interpolation or forward-filling for brief gaps, or more sophisticated imputation for longer gaps) and identifying outliers (random spikes or drops that are likely due to sensor malfunction). Variable normalizing or standardizing will be performed when necessary for model training (e.g., normalizing inputs to 0–1 range for neural net usage). Time-based attributes (month, seasonal indicator) can also be introduced to help the models capture seasonal effects. The dataset, so processed, will be divided into training, validation, and test sets (e.g., training with 2018 or earlier, validating with 2019–2020, and final testing with 2021–2025). We will also implement a system for updating the data in real time: for example, inaugurating an API call or web-scraping to retrieve the latest day's rainfall prediction from the Meteorology Department and current reservoir level from telemetry, so that the model for forecasting can incorporate the freshest data. Everything will reside in a structured database (e.g., PostgreSQL or a time-series database) to enable robust querying and analysis.

3.1.3 Forecast Model Development

Despite the importance attached to the precision of the forecasting results published in literature[1], this methodology aspect is about the derivation of plausible prediction models for major reservoir variables. An iterative, experiment-driven modeller's methodology will be utilized:

Baseline Statistical Models: We start with classical models, i.e., ARIMA (Auto-Regressive Integrated Moving Average) and seasonal ARIMA (SARIMA), to be established for reservoir inflow with historical inflow time series. These models can capture linear autoregressive relations and seasonality and will serve as the performance baseline. Accordingly, the popular Prophet model (from Facebook) can be initialized with inflow and water level, as it inherently models the effects of seasons and shifts in trend.

Machine Learning Models: Then we will build ML regression models that are able to use hundreds or even thousands of input features. For instance, a Random Forest or Gradient Boosting Machine that is given current rain, past inflow, and other state variables to produce future inflow. These kinds of models are able to represent non-linear relations and interactions (e.g., an interaction between rain and saturations that yields an inflow). Hyperparameters (tree depth, number of trees, learning rate, etc.) will be tuned with techniques such as cross-validation.

Deep Learning Models: Our forecasting engine will chiefly be a sequence learning model. We will train LSTM and GRU neural networks to perform time series forecasting. These will be trained with sequences of historically observed data (e.g. rain for last 7 days, last 7 day inflow, reservoir height, etc.) and learned to predict the next 14 day's inflow (quite possibly with a sequence-to-sequence model for multi-step forecasting). The model will be trained with backprop through time, and we will strive not to overfit with techniques such as regularisation and possibly dropout layers. The strengths of the DL models are the capacity to handle an arbitary number of series inputs (e.g. rain, evap, etc. combined) and to discover highly complex temporal patterns. Recent literature has demonstrated that LSTM/GRU can produce higher accuracy, short-term forecasts than classical models[1], and we wish to do these for Udawalawe.

Benchmarking and Selection: The validation dataset will be used to test all models with various metrics, including RMSE (root mean square error), MAE (mean absolute error), and MAPE (mean absolute percentage error). The nonlinear ML/DL models are expected to surpass the simpler baselines, in agreement with results from other reservoir studies. For example, earlier studies demonstrated that LSTM can decrease error by >80% with respect to ARIMA for certain time-series applicationsarxiv.org. The ultimate model selection will be done through a compromise between the accuracy and reliability. When there are several models with mutually complementary strengths, an ensemble strategy (averaging the output of the prediction) will be taken under consideration for further robustization of the performance. Adding Probabilistic Output: To include uncertainty, we will add an ensemble forecasting technique. One is to create an ensemble of simulation runs by perturbing inputs or model parameters (e.g., introducing slight noise to rainfall inputs or training 10 neural networks with nominally varying initial conditions). The ensemble prediction spread at each lead time can then yield a confidence band (e.g., 5th–95th percentile range). The other is the use of quantile regression LSTM or Bayesian LSTM that natively output prediction intervals. We will try both techniques and confirm that the empirical coverage of the intervals is the desired confidence (i.e., roughly 90% actual observations are found to fall within a model's 90% prediction interval, and so forth). The probabilistic forecasting is harmonious with reservoir risk management recommendations, so we do not merely predict "what" will occur, but also "how confident" we are[2]

Forecasting Other Variables: Besides inflow, we will also develop models for reservoir level/storage and for irrigation demand. Level at the reservoir is primarily a function of inflow and outflow (and we can simulate the latter through a simple mass balance if we model decisions at the operation level), but for forecasting we may directly predict level so that we can match to critical thresholds. Water demand for irrigation can bePredicted with time of year (crop calendar) and perhaps rainfall (as rain showers can decrease irrigation demand). If strong models for demand turn out to be too complicated, we can then adopt a less complicated rule-based method for demand approximation and reserve the ML for the more stochastic variables, namely, the inflow and the level. All model construction will be carried out with Python (such packages as scikit-learn for ML, TensorFlow or PyTorch for DL). The code will be kept under some form of version control, and notebooks will be utilized to preserve the modeling experiments. Final models will then be redeployed back into the system for real-time use, perhaps bundled up under some form of a Python service or API.

3.1.4 Integration with Reservoir Operations (Decision Logic)

A forecast is half the solution; we need to tie it to concrete actions. That is, we need to develop decision rules or guidelines that translate forecast scenarios into reservoir release or storage decisions. We will develop this in consultation with reservoir operators:

Rule Curve Augmentation: Udawalawe already employs rule curves (target storage by date). We will augment these with forecast-driven deviations. For example, if the projection would fill the reservoir beyond safe capacity in 5 days, the system might recommend a controlled release today (lowering the level in advance). If a drought is forecast (extremely low inflows), the system might recommend conserving water (reducing irrigation releases or delaying some allocations) to stretch supplies. These recommendations can be codified into simple rules (e.g., "if forecast level > spill level in next 7 days, release X% of storage immediately"). We will use scenario simulation to calibrate and evaluate these rules. Optimization Scenarios: For a more precise decision, we can formulate a small optimization problem for releases. Minimize deviation from target storage without overflowing and meeting minimum downstream demands, subject to forecast inflows, for instance. This can be resolved through linear programming or heuristic algorithms for each forecast scenario. However, for the scope, a full dynamic optimization would maybe be complex; instead, we favor a heuristic solution that can be easily understood and fine-tuned by operators.

"What-if" Simulation Tool: We will add a module in the dashboard where users can simulate the outcomes under different hypothetical management actions.

For example, an operator can input "What if we release 50 m³/s for the next 3 days? " and the system would show the resulting reservoir level trajectory under the predicted inflow, with an indication of whether that prevents overtopping and how it affects storage at the end of 2 weeks. This type of tool allows operators to think through alternatives and gain trust in the system's recommendations. This linking of predictions with operations will be tested against historical events: we will recreate flood events and drought periods with and without forecast-informed actions to estimate how much flood volume could have been released safely ahead of time, or recreate drought periods to see whether earlier conservation could have extended water supply.

These hindcast simulations will demonstrate the potential benefits in quantitative terms (e.g., peak reduction, additional days of water supply). Notably, similar studies for the FIRO project in California have established that the use of forecasts in informing operations can significantly increase water supply reliability with no compromise in flood security [3]; we will attempt to quantify such benefits for Udawalawe through our simulations.

3.1.5 Development of Dashboard and Alert System

- The ease of use of the system depends on how the information is presented to the end-user. We will drill down to deliver a web-based dashboard (think of a reservoir control room on a computer or tablet), which will include the following components:

- Forecast visualization: Interactive plots of the 14-day reservoir inflow forecast, and the 14-day reservoir level forecast. These plots will have shaded uncertainty bands (ex. a light band for a 90% confidence interval) so users appreciate the range of possible outcomes. Key reference lines (e.g. Full Supply Level (FSL) and critical low water level) will be drawn on the level chart for context.

- **Risk Indicators:** The dashboard will express forecasts in terms of simple risk indicators (and may use a color-coding scheme - e.g. green/yellow/red). For example, if there is >20% likelihood of a spill occurring in next week, we could show a warning indicating "Flood Risk: HIGH". Or, if two weeks of demand cannot be met from storage + forecast inflows, we will show "Drought Risk: HIGH". These levels are based on the outputs from the probabilistic model.

- **Suggested Actions:** In a text box or similar panel, we will provide any suggested actions for the operator to consider. For example: "Suggested Action: Starting tomorrow, release 30 m^3/s for the next 48 hours to maintain safety level"; or "Reduce irrigation releases by 20% to conserve water for next week." These suggestions will be produced by the decision logic we previously talked about. We will try and word them as suggestions (the operator can take action or ignore the suggestions), but give rationale (e.g., "...a heavy inflow is expected by Day 3, this will create a buffer of storage").
- **Alert Notifications:** The system will contain an alert service that tracks the forecast outputs and sends messages once specified conditions are met. For instance, when the flood risk predicts “HIGH” or some other forecast inflow exceeds a certain level, an SMS could be sent to a pre-determined list of officials (reservoir engineer, district disaster management centre, etc.) stating something like this: “Udawalawe Reservoir high inflow alert: X% chance of spill in 5 days, consider precautionary release.” In the case of drought, an email to irrigation authorities could indicate risk of certain water levels. This may include technical details for SMS API, email server, etc. Given connectivity in these areas, SMS will typically be preferred for urgent communications.
- **Backend and Interface Technology:** The dashboard itself will probably be constructed with some kind of web framework (e.g. a Python Dash/Plotly app in this case, although I could well look to do something more complicated with interactivity using JavaScript). We will make it light, so an average PC can run at the reservoir office.” Visualisation will prioritise clarifying a chart with or without key, having tooltips display values on hover etc. We are also going to include a map view (if possible) showing the reservoir and downstream area,

including a color overlay indicating when flooding is predicted in order to help users spatialize the information.

As part of the deployment, we will provide user training - we will create a user manual and we'll conduct a demonstration session with the reservoir management staff, also providing them an opportunity to share feedback that we can use to tweak the interface. The objective will be that, by the end of the project, intended users will feel comfortable reading the dashboard and will trust the alerts to guide their decision making.

3.1.6 Evaluation Plan

Finally, we outline how the performance and impact of the system will be evaluated:

- **Forecast Accuracy Assessment**: Using the reserved test dataset (e.g., data from 2021–2025 excluded from training), accuracy metrics will be calculated for all forecasted variables. High accuracy is expected, and ostensibly very high accuracy, A target is to achieve MAPE below 15% for 1-3 day ahead inflow forecasts (this target is based on literature and requirements for adequate operations). We'll create a table for RMSE metrics for 1-day, 3-day, 7-day, and 14-day lead times to assess how forecast skill decreases after longer lead times. We will also assess the ML/DL model accuracy compared to the baseline ARIMA to quantify the skill improvement (we expect a substantial improvement particularly for multi-day forecasts [1]).

- **Probabilistic Forecast Verification:** We will use historical event data to verify if the prediction intervals from the forecasts were well calibrated. For example, during the test period, did ~90% of actual inflows fall within the model's 90% prediction interval? We will use metrics such as PICP and Average Width to quantify the uncertainty quantification quality. Brier scores or reliability diagrams could also be used for specific thresholds (like probability of spill events).

- **Operational Efficacy:** We will use the system to simulate a number of historically notable events to determine operational effectiveness. For a major flood event (for example, a previous flood in 2017), we will assume this system was in place, will it issue a warning in a timely fashion, and what action would it recommend, and then compare to what actually happened. This could be quantified in terms of reduction in peak water level had the recommended action been taken, or in terms of increased lead time of warning (e.g., emergency actions taken reactively, with 0 days notification of the event, and if indeed the system provided a 3 day notification). Drought periods might be analyzed in terms of how the recommended conservation advice would have supported water supply (e.g., percent increase in provided days of water supply). These scenario evaluations would have a qualitative benefit.

- **User Feedback:** We intend to conduct a structured interview or survey with a small group of end-users following their experience testing a prototype of the dashboard (possibly using historical replays). This will allow for the collection of qualitative usability feedback (Was the information understandable? What pieces of information were unclear? Are they likely to trust the recommendations? Would this lead them to alter how they make decisions?). If feasible, a System Usability Score (SUS) survey could provide a quantitative approach for measurement of the user-friendliness of the dashboard and usability. The final system will be modified based on the feedback to ensure it engages the operational realities (for example, if an operator indicates they would prefer information in a specific format and / or frequency, we want to accommodate that).

The project will be successful if it achieves both technical performance (forecasts are accurate and alerts are reliable) and user acceptance (operators are willing to use the tool in practice). Meeting both criteria means there is a viable solution that can scale from research to applications in the field.

Anticipated Results: At the end of the project, we expect to deliver:

- Accurate short-term forecasting of reservoir inflow, storage levels, and demand; performance will be assessed with parameters such as average inflow forecast RMSE which should be small, and successful prediction of major events.

- Probabilistic risk assessments regarding flood/drought that give operators a sense of security or urgency which is quantifiable, e.g. "10% chance reservoir will fill beyond safe limit" instead of simply saying "it's a risk."
- A working dashboard that consolidates data from multiple sources and model results into a coherent picture for operators, thus becoming something similar to an early warning system for reservoir stakeholders.
- Demonstration (through case study) of how the system is able to mitigate flood impacts by suggesting pre-releases, or improve water allocation during weather conducive to a shortage. For example, suggesting pre-release if floods historically caused X cubic meters of spill, using forecast based operations we suggested providing water might reduce that total by Y% (based on modeling). Similarly, reduce shortfalls in irrigation supply during drought by some measurable amount.
- The results will be documented and we anticipate writing about the findings in an academic paper (for example the application of LSTM for reservoir forecasting in Sri Lanka) and possibly share with local authorities to provide input/feedback on water management policy.

Generally, the methodology will develop and then test each part of the smart forecasting system, making sure that it is not only based on sound scientific principles but also is practically usable for managers of the Udawalawe Reservoir at the end of this work.

3.1.7 Work Plan and Timeline

The project is structured into phases with specific milestones and deliverables. The following Gantt chart (Table 2) outlines the timeline from project initiation to completion, spanning approximately 18–20 months:

Table 3:Project Work Plan and Timeline.

Phase	Description & Key Activities	Timeline
1. Requirement Gathering & Analysis	Identify stakeholder needs and decision-making processes. - Define functional system requirements (forecast horizon, variables, update frequency, interface needs). - Inventory existing data sources and identify data gaps.	Mar 2025 – Jul 2025 *(Initial brainstorming, literature review, project proposal drafting)*
2. Data Collection & Preparation	Collect the historical datasets (rainfall, inflow, level etc.) from agencies. - Clean the datasets and prepare them for integration; configure the database. - Install any necessary sensors or data loggers (or verify existing telemetry) if appropriate for the models.- Produce descriptive statistics and visualizations to understand data characteristics (seasonality, trends, correlations).	Oct 2025 – Dec 2025 *(Data acquisition, cleaning, and Preliminary Progress Presentation I)*
3. Model Development & Testing	Build a baseline ARIMA/Prophet models for inflow/level forecasting. - Develop and train ML/DL models (RF, LSTM, GRU) for forecasting, optimize hyperparameters. - Include probabilistic forecasting (i.e ensemble or Bayesian methods). - Validate the models on the validation set(s), refine the models to improve	Jan 2026 – Mar 2026 *(Model training, scenario simulation development, Progress Presentation II)*

	performance. - Start preparing publication on the modeling approaches.	
4. System Implementation (DSS)	Plan the dashboard UI/UX (wireframes; assess what information is most important to display). - Construct the web dashboard (interactive plots and display information directly from the database). - Configure alert system (i.e. SMS/email API) for notifications. - If needed, set up the dashboard to display forecast model output; real-time or automated (service). - Internal testing of the entire pipeline; data input to alerts out.	Apr 2026 – May 2026 *(Prototype development, system integration, User feedback session, Final Presentation & Viva)*
5. Validation & Finalization	Carry out extensive back-testing using historical events; create record of findings (i.e. data, charts of performance). - Conduct a stakeholder validation workshop; gather feedback on system utility and make final adjustments. - Write final report for the project and research paper and submit (i.e. to a journal or conference). - Create the project website with demo (if appropriate) and pass system on to reservoirs with training.	Apr 2026 – Jun 2026 *(Validation studies, Documentation, Project handover, Final Report Submission)*

Milestones: We anticipate having definitive requirements and a data repository in hand by the middle of that 2025 timeframe, with a dataset ready and preliminary models explored by the end of the year 2025. We anticipate producing the core forecasting engine and pre-produced papers and results to share in the first quarter of 2026; in the second quarter of 2026, we will work on an operationally usable tool to share with users for usability validation, leading to thesis submission, presentations, and knowledge transfer for operationalization. Regularly throughout this time, presentations and reports to provide progress will maintain tracking of our work and awareness of stakeholder expectations.

3.1.8 Resources and Tools

To execute the above methodology, the following tools and technologies will be utilized:

- **Software & Libraries:** The main programming language that will be utilized is Python (having libraries such as Pandas and NumPy for data management, Scikit-learn for machine learning models, TensorFlow/PyTorch for neural networks, and Plotly Dash or similar for dashboards). Some R might be used for some statistical analysis or baseline models (due to possible experience with hydrological statistics). Database management of time-series data will occur using PostgreSQL or MySQL.
- **Computing Infrastructure:** Often, model training, and especially deep learning, can impose a large compute footprint. A workstation with high performance, or cloud computing instance with GPU acceleration will be employed to train the LSTM/GRU models. During deployment, the operational system will run on a standard PC or server at the university or department. The compute load from inference on the trained model for one-day through two week horizon forecasts will be less than heavy. Moreover, it is possible to infer in almost real-time using a mid-range CPU.

- **Instrumentation/Data Sources:** We rely on existing instruments which include, but is not limited to, rain gauges, reservoir level sensors, etc. These instruments are managed by established governmental agencies. Although, no absolute new, physical instruments are required, if telemetry and/or automatic weather station upgrades are required for the project, we will plan for that (the budget provides some opportunity to improve data acquisition).
- **Collaboration Tools:** Code management will rely on version control (GitHub or GitLab). Project management software (Trello or similar) may be beneficial for tracking tasks. Stakeholders will be contacted through meetings and regular email updates, specifically with the ICT or data management units at the Irrigation Department, who may host the system in the future.

Given these resources, we anticipate having the capability to implement the methodology and meet the project goals. For any possible risks (e.g., unavailability of data and underperformance of a model), we will continue to monitor the situation; for instance, if data gaps are, or will be, greater than expected, we will use weather model reanalyses or alternative global datasets to fill the gaps, and where one modeling method does not work as intended, we will re-evaluate and try different methods. The detailed written plan above, however, gives us enough confidence that the goals can be achieved in the time available and with the tools available.

3.1.9 System Overview Diagram (Individual)

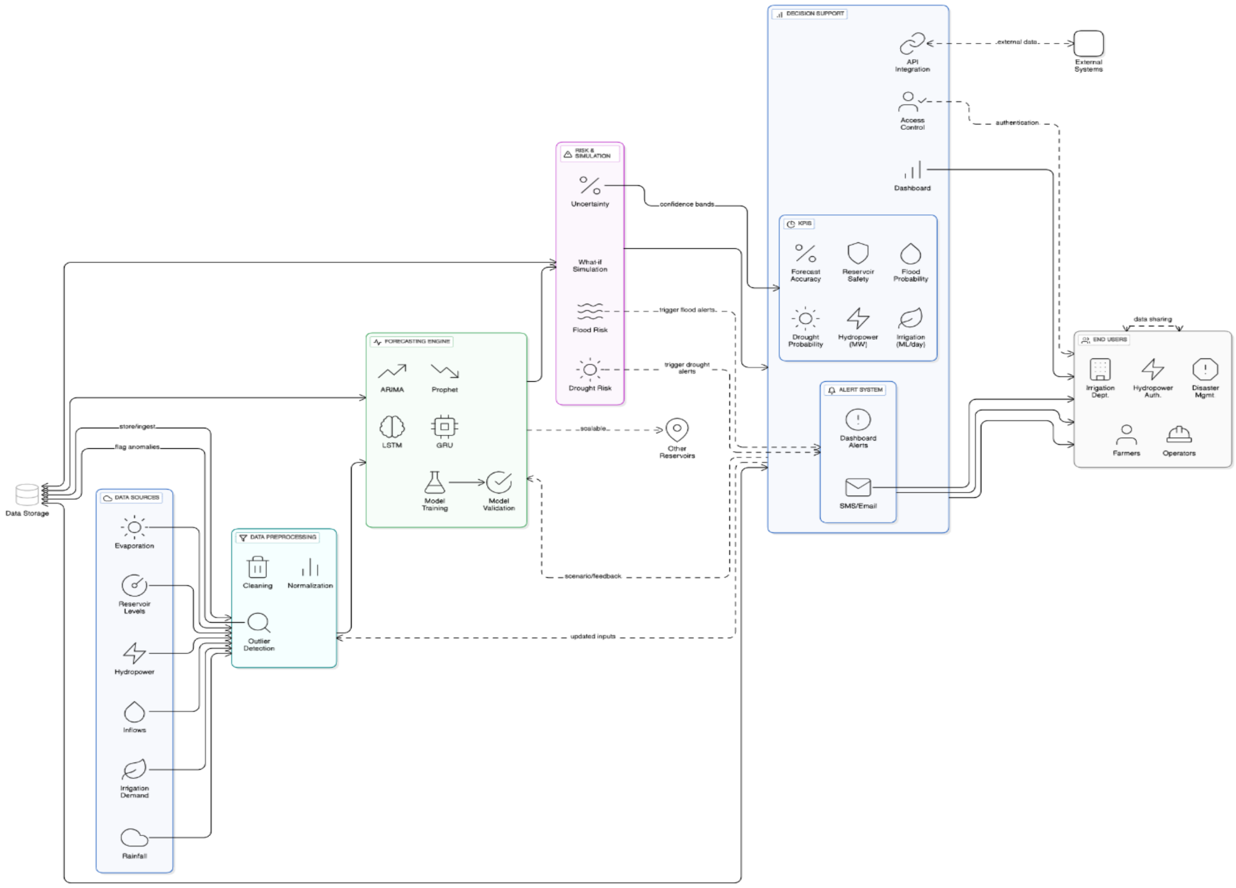


Figure 4:System Overview Diagram (Individual)

3.2 Requirement Analysis

3.2.1 Functional Requirements

- Project water inflows, reservoir levels, and irrigation needs (1-14 days in advance).
- Offer probabilistic risk assessment (flooding, droughts).
- Visualize via dashboard (with graphs and trend indicators).
- Generate alerts/notices for threshold critical values (via SMS, app, or web alerts).
- Enable scenario modeling ("what-if" water release scenarios).

3.2.2 Non-functional Requirements

- Accuracy: Predictive models should achieve <15% MAPE error.
- User-friendly: The system needs to be easy to use for non- technical operators.
- Scalability: The application should be able to process large amounts of data and possible scale up to additional reservoirs.
- Reliability: The system needs to be capable of high availability for real-time monitoring.
- Secrecy: Safe guard crucial data on water usage and management.

3.2.3 User Requirements

The proposed forecasting and alert system is designed to serve several stakeholder groups, including reservoir operators, irrigation officers, disaster management authorities, hydropower agencies, and the general public. The key user requirements are summarized below.

Reservoir and Irrigation Operators

- View real-time and forecast data for reservoir inflows, storage, and outflows.
- Access forecasts of rainfall, inflows, and water demand for short-terms (1-14 days).
- Use a dashboard to explore real-time data with charts, indicators, and color-coded flood/drought warning signals.
- Run 'what-if' operational simulations (i.e. changing water release/ rainfall assumptions).
- Receive recommendations informed by data (e.g., pre-release volumes, irrigation modification).

Disaster Management Authorities (such as NDRSC, Local Councils)

- Utilize timely notifications when thresholds are surpassed for flood or drought.
- Tailor alert preferences by region, severity, or hazard.

- Use downloadable reports with summaries with visualizations to support planning and anticipating action.
- Implement alerts via SMS and Emails to connect with communities that may be affected.

Hydropower Authorities

- Reference forecasts from potential hydropower generation based inflows and storage.
- Receive alerts on anticipated power shortages or surpluses for grid management.
- Analyze past performance and review efficiency of reservoir operation over time.

Farmers and Non-Expert Users

- Use alerts on mobile for flooding and/or drought risk impacts on irrigation and/or livelihood.
- Reference simple, non-expert level summaries (e.g., “High flood risk in next 48 hours”).
- View irrigation schedules and water-for-crops forecasts.

System Administrators

- Manage users, access levels, and permissions to the system.
- Upload and preprocess datasets from multiple sources (e.g., Irrigation Department, Meteorology Department, Udawalawe Dam).
- Monitor system function and logs at a high level.
- Maintain secure data storage and backup storage of historical records.

3.2.4 System Requirements

The reservoir forecasting and alerting platform requires a robust and scalable system setup to handle data ingestion, processing, model training, real-time forecasting, and alert dissemination.

Hardware Requirements

- ***Server / Cloud Infrastructure***
- **Processor**: Minimum Intel Xeon / AMD EPYC (8 cores or higher) or equivalent cloud-based compute (e.g., AWS EC2, GCP, Azure VM).
- **Memory (RAM)**: At least 32 GB (for handling large hydrological and meteorological datasets).
- **Storage**: 1 TB SSD for fast read/write of time-series datasets and model checkpoints.
- **GPU Support**: (Optional but recommended) NVIDIA GPU (16 GB VRAM or higher) for deep learning models (e.g., LSTM/GRU).
- ***End-User Devices***
- **Desktop / Laptop**: Standard workstation with minimum 8 GB RAM and updated web browser.
- **Mobile Devices**: Android/iOS smartphones with support for web or app notifications.

Software Requirements

- Operating System: An Ubuntu or CentOS Linux-based server will run in the background.
- Programming Languages: Writing in Python (Mainly for Machine Learning/Forecasting) and R (optionally writing statistical models). The front end will use JavaScript/TypeScript.
- Frameworks & Libraries:
  - ML/Forecasting: TensorFlow / PyTorch / Scikit-learn, Statsmodels, Prophet.
  - Data Processing: Pandas, NumPy, Apache Spark (if scaling).
  - Visualizations: Plotly, D3.js, or Matplotlib.
- Database: PostgreSQL or MySQL for some data storage; TimescaleDB or InfluxDB for time-series data storage.

- Front-end/UI: The dashboard could use React or Angular, with Flutter/React Native in case a mobile is built.
- Alert system integration: Twilio API / Firebase Cloud Messaging / local SMS gateway.

Network & Connectivity Requirements

- **Internet Bandwidth**: Stable broadband/cloud connectivity with minimum 100 Mbps for server-side.
- **API Integrations**:
  - Department of Meteorology APIs (weather/rainfall updates).
  - Reservoir operation datasets from Irrigation Department.
  - Disaster Management alert dissemination APIs (if accessible).

Security Requirements

- **User Authentication & Authorization**: Role-based access control (Operator, Admin, Public).
- **Data Security**: Encryption of stored and transmitted data (SSL/TLS).
- **Backup & Recovery**: Automated daily backups of datasets and model outputs.
- **Logging & Monitoring**: Audit trails for data changes and forecast usage.

Scalability & Deployment Requirements

- Cloud-compatible deployment (AWS/GCP/Azure) to handle multiple reservoirs in future.
- Modular architecture to allow integration of new models and datasets.
- Load balancing to handle multiple concurrent dashboard users and alert requests.

3.3 Gantt Chart

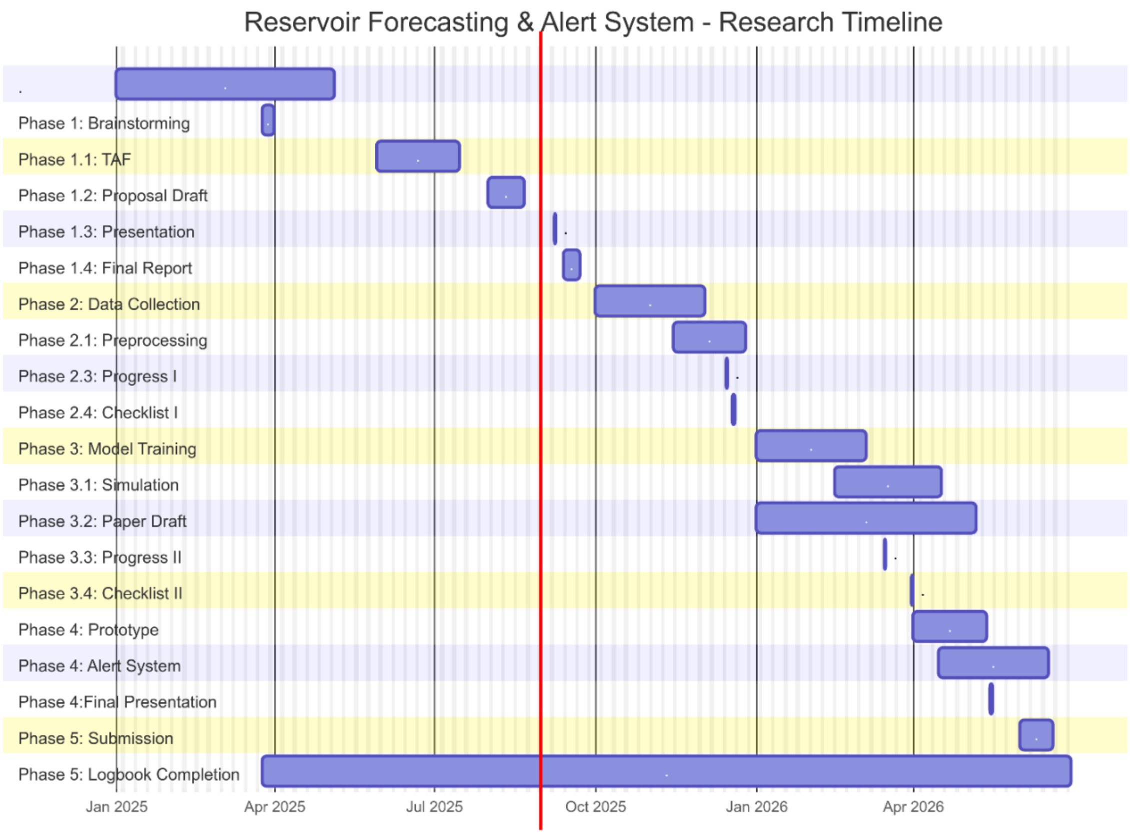


Figure 5:grantt chart

3.4 Work Breakdown Structure

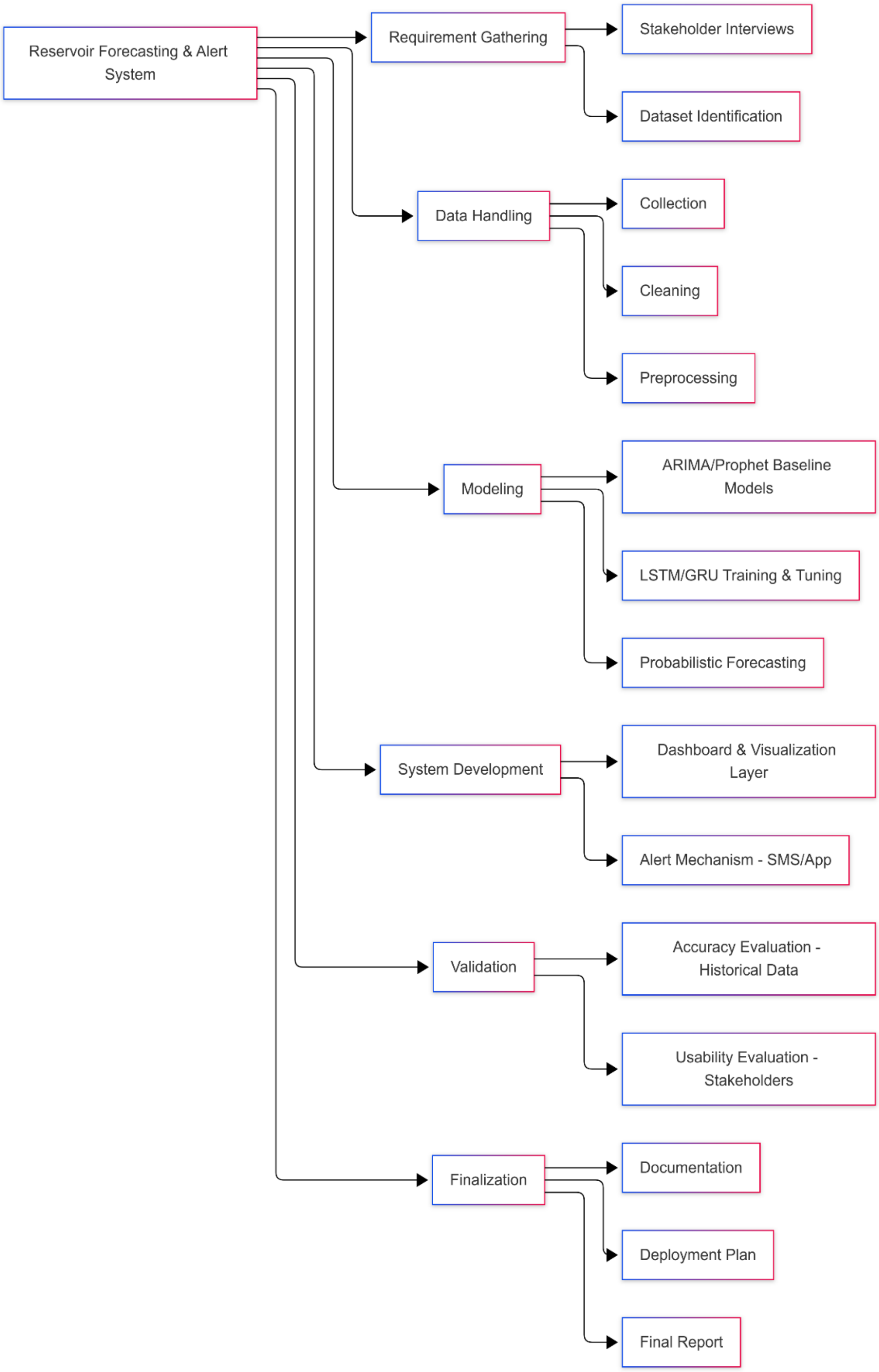


Figure 6:work Breakdown Structure

4 BUDGET AND BUDGET JUSTIFICATION

The following table outlines the revised proposed budget for the component of the Integrated Smart Water Forecasting and Decision-Support System, focusing on forecasting and early warning for reservoir management at Udawalawe Reservoir. This version reduces overall costs while maintaining essential allocations for data, technology, and stakeholder engagement.

Table 4:Proposed Budget Breakdown

Budget Item	Estimated Cost (LKR)	Justification
Computing Hardware / Cloud Services	75,000	We anticipate that model training (primarily SARIMAX and XGBoost) will be conducted primarily on university computing resources, but we have included a modest amount that will contribute to limited cloud credits on a per case basis if note, we {use a GPU (LSTM/GRU) deep learning model then} this cover will likely either by the upgrade of hardware of cloud {....} computing services
Software and Licenses	20,000	Most tools such as Python, TensorFlow, and Scikit-learn are open-source and do not require payment. Some programming tools may require API access payments, visualisation tools, or a database subscription. This, however, will not require a full budget allocation.
Data Acquisition & Field Visits	45,000	Data will be acquired from the Irrigation Department, the Meteorology Department, and CEB. Travel has been budgeted to data collect, field verify findings, and conduct short stakeholder visits to acquire feedback
Workshops / Stakeholder Meetings	25,000	Budget is allocated for the conduct of one stakeholder workshop to publicly demonstrate the prototype dashboard (and acquire feedback), from stakeholders. This allocation will cover

		printing costs, refreshments, and venue rental.
Miscellaneous / Contingency	15,000	Multi purposes fund, expected to cover / print final reports, data storage hardware, equipment, and unplanned for research expenses should if occur.
Total Estimated Budget	180,000	—

This revised budget ensures cost effectiveness while covering all of the essential components of the full research pipeline; data acquisition, model development, system-prototyping, and stakeholder validation. Further, we anticipte that all of these costs will most efficient of a research project done in an academic context and with strong institutional and departmental support.

5 COMMERCIALIZATION AND ENTREPRENEURSHIP POTENTIAL

Beyond its academic and operational merits, the proposed smart water forecasting system has significant potential for commercialization and entrepreneurial ventures. This section discusses how the outcomes of this project could be translated into a marketable product or service, and how it could be scaled and sustained as a startup or enterprise solution.

Product/Service Vision: At its core, the system to be developed – combining data integration, ML-driven forecasts, and a user dashboard – can be packaged as a **Water Management Decision Support Platform**. The platform would provide subscription-based forecast and advisory services to reservoir operators, irrigation schemes, and even urban water supply managers. In Sri Lanka and other countries in the region, many reservoirs and water utilities face similar challenges as Udawalawe. A generalized version of this system could be deployed to other major reservoirs (e.g., Victoria, Polgolla, etc.) or river basins. This indicates a scalable product: a cloud-based service where clients (government agencies or private dam operators) input their data and receive tailored forecasts and decision recommendations.

Market Need: Climate change and increasing climate variability are global issues, leading to more frequent floods and droughts. Governments and water authorities are actively seeking tech solutions for climate resilience. However, most available solutions are either very high-level (global flood alerts that are not reservoir-specific) or bespoke systems built by large consulting firms at great cost for specific sites. There is a niche for an affordable, customizable forecasting DSS for water resources. Sri Lanka alone has dozens of sizeable reservoirs that could benefit; regionally (South Asia, Southeast Asia), hundreds more potential end-users exist (e.g., irrigation departments in India, hydropower companies in Nepal, dam safety units etc.). Moreover, international donors and development banks fund climate adaptation tools – a proven system from this project could attract such funding for wider implementation.

Unique Selling Proposition: The product derived from this project would have the following competitive advantages:

(1) **Localized ML Models** – unlike one-size-fits-all tools, our system's ML models can be trained on local historical data to improve accuracy for each site;

(2) **Probabilistic Risk Alerts** – many existing systems provide only deterministic forecasts; our inclusion of risk levels gives a richer information set, which is a cutting-edge feature[2];

(3) **User-Friendly Interface** – developed with direct user feedback, it would be intuitive for field engineers who may not be tech experts;

(4) **Integration Capability** – it can pull data from various sources (rain gauges, weather forecasts, satellite data) and push alerts via common channels (SMS, email), making it easy to integrate into current workflows without requiring big infrastructure changes;

(5) **Cost-Effectiveness** – being developed in an academic setting and using open-source components means the eventual product could be offered at a lower cost than solutions from big international tech firms.

Business Model: A possible business model is a Software-as-a-Service (SaaS) for governments and water agencies. For example, a provincial irrigation department could subscribe to the service for an annual fee to cover a certain number of reservoirs or canals under management. The service would include initial setup (model training on their data), customization of the dashboard to their needs, and ongoing support with daily forecasting operations running on a cloud server. Another model is a consultancy approach: implementing the system as a one-time project for a client and then handing over the system (with training) for them to operate. However, the SaaS model provides recurring revenue and continuous engagement (which is better for keeping the system updated and providing improvements over time).

Entrepreneurial Opportunities: The project team (including the student and supervisors) could consider forming a startup or a spin-off company at the end of the project. Intellectual property from the project – such as specialized algorithms or software developed – can be protected or licensed through the university. There is potential to seek incubation support from innovation hubs like those at University of Moratuwa or National Science Foundation, especially since this addresses a national priority (water management and disaster risk reduction). Pitching the solution in startup competitions or to investors (impact investors interested in climate tech, for instance) could secure seed funding. The social and environmental impact of this product (safer communities, more efficient water use) is a strong narrative for grant programs and competitions.

Partnerships: To commercialize, partnerships will be key. The Meteorological Department and Irrigation Department could become early adopters/champions. A MoU could be established where our platform is trailed in their operations beyond Udawalawe. Their endorsement would build credibility. Additionally, tech industry partners (like a cloud provider or a local IT firm) could collaborate to provide infrastructure or help with scaling the software for multiple clients. Since the system touches on disaster management, agencies like the DMC or international bodies (UNDP, ADB, World Bank) might partner to roll it out in vulnerable regions with funding support, effectively acting as clients.

Revenue and Expansion: In the long run, the solution could evolve beyond reservoirs. The core ML forecasting and dashboard tech could be applied to **urban flood forecasting**, **river basin management** (forecasting river levels at flood-prone towns), or **agricultural advisory services** (predicting water availability for farmers). Each of these has a market. For example, city governments could use a version to predict floods in urban drainage systems. The modular design (data in -> forecast -> decision out) means it can be adapted to various water-related scenarios with relatively small tweaks, thus broadening the potential customer base.

Challenges and Mitigation: Commercialization will face some challenges: Government procurement can be slow and risk-averse – to counter this, we plan to thoroughly validate the system and document its benefits (e.g., a white paper showing how it saved X amount of water or prevented Y damage in simulation). Another challenge is competition from free public systems; however, those often lack customization and local accuracy, whereas our product’s value is in fine-tuning to the local context. We will also ensure the system remains user-focused; continued training and customer support will be offered as part of any service to ensure clients derive full value (technology adoption often fails if users are not confident or the product is not maintained, so we’ll emphasize after-sales service).

In summary, the project is not just a one-off academic exercise but a prototype for a broader solution with both local and global relevance. By demonstrating success at Udawalawe, we lay the groundwork for a **marketable decision-support system for smart reservoir management**. This aligns well with the trends of digital transformation in the water sector and has the potential to become a sustainable business that contributes to climate resilience. The entrepreneurship potential is significant: what starts as a university project could evolve into a startup delivering intelligent water management solutions across Sri Lanka and abroad, illustrating how research innovation can drive socio-economic progress.

6 DESCRIPTION OF PERSONNEL AND FACILITIES

6.1 Personnel

- Ms. Hansi De Silva– Sri Lanka Institute of Information Technology (SLIIT)
- Ms. Karthiga Rajendran – Sri Lanka Institute of Information Technology (SLIIT)
- Mr. Thilanka Bandara - Renewable Energy Consultant

6.2 Facilities

- Sri Lanka Institute of Information Technology (SLIIT)
- Irrigation Department / Udawalawe Dam Authority
- Department of Meteorology (DoM), Sri Lanka
- National Disaster Relief Services Centre (NDRSC)

7 CONCLUSION

This proposal presents a detailed vision for the development of an Integrated Smart Water Forecasting System for the Udawalawe Reservoir using machine learning. The system will be focused on delivering improvements to the current approaches by addressing identified gaps in forecasting accuracy, uncertainty quantification, and integration with decision-support processes, in our goal of transforming reservoir management from reactive to proactive

The plan includes collaboration with the local Meteorology and Irrigation Departments to ensure all development is locally relevant and refined through operational contextualization in a local operating environment. Anticipated outcomes include improving preparedness of flooding and drought events, optimize priority water releases, and increase water security of communities and farmers.

In addition to developing further technical innovations through advanced machine learning methodologies such as Long Short-Term Memory (LSTM) methods, the project will focus on usability and practical usability, and the potential to transition insights and models from the Udawalawe Reservoir to other reservoirs across Sri Lanka. The project is aligned with national goals for climate adaptation, disaster risk reduction and sustainability within the research and real-world impact in the climate actively licensed framework.

With a better plan, terrific team with capacity, and full facilities, we believe this research program will deliver a measurable and usable benefits to society and establish the potential to provide a framework for intelligent river system management practises for Sri Lanka as a whole.

8 REFERENCE LIST

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