A Forecast-Enhanced Hybrid Model for Adaptive Irrigation Management in Arecanut Cultivation

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ABSTRACT
Arecanut cultivation in the coastal regions of India, especially in areas such as coastal Karnataka and parts of Kerala, faces increasing challenges due to uncertainty in the rainfall, increasing temperatures, and scarcity of groundwater. Although sensor-based irrigation systems have improved responsiveness to soil moisture conditions, Irrigation scheduling driven purely by real-time sensor readings usually leads to unnecessary watering before rainfall or excess moisture during continuous wet periods, increasing the risk of fungal and root-related diseases. To address these challenges, this study proposes a forecast-driven hybrid irrigation framework that integrates predictive weather insights with existing optimization-based irrigation mechanisms to enhance efficiency of usage of water and reliability of irrigation control. The framework extends a conventional optimization model by incorporating short-term rainfall and temperature forecasts generated through forecast modeling techniques. These forecasts, along with inputs such as soil moisture (TDR), reservoir water availability, and climatic variables, are processed using a hybrid stacked classification model combining Extra Trees, HistGradientBoosting, and Logistic Regression. Forecast information serves as a conditional reasoning layer to dynamically delay, advance, or suppress irrigation actions. Scenario-based simulations covering normal conditions, scarcity of water, rainfall expectation period, continuous rainfall, and post-rain recovery phases showed that the forecast-enhanced model improved decision accuracy from 96.51% to 97.59%, reduced false irrigation triggers by over 50%, and achieving approximately 8–10% additional water savings. Overall, the model demonstrated better adaptability during rainfall transitions and enhanced disease-prevention control under extended wet conditions.

Keywords: Arecanut cultivation, Adaptive irrigation management, Forecast-driven irrigation, Hybrid machine learning model, Precision water management, Soil moisture sensing, Rainfall forecasting, Water-use efficiency.

1. Introduction

Arecanut cultivation is a major component of plantation agriculture in the Dakshina Kannada district of Karnataka, where climatic conditions, soil characteristics, and availability of water together influence productivity of the crop. The region experiences a humid tropical climate with intense monsoonal rainfall followed by pronounced dry periods, creating a complex irrigation environment for perennial crops such as arecanut (Rao, K. et al. (2019).[1]). Even though the yearly rainfall looks satisfactory, temporal irregularities and lowering groundwater levels demands proper irrigation planning (Shetty, P. et al. (2020).[2]).

Farmers in Dakshina Kannada traditionally depends on fixed irrigation schedules, which usually fails to capture differences in field conditions across plantations and temporal variations in soil moisture level (Kumar, S. et al. (2018).[3]). Such approaches can result in over-irrigation during pre-rain periods or limited soil moisture under extended drought conditions, both of which negatively affect arecanut yield and root health (Nair, R. et al. (2021).[4]). Excessive moisture conditions have also been linked to the increased occurrence of the difference diseases like, fungal and root diseases, including basal stem rot and yellow leaf disease, commonly observed in coastal farming regions (Menon, A. et al. (2019).[5]).

Precision-based irrigation management has become an important tool for improving usage of water efficiency by synchronizing irrigation scheduling with real-time field conditions (Patil, V. et al. (2020).[6]). With this, soil moisture sensing using Time Domain Reflectometry (TDR) has proven effective in monitoring root-zone water status in plantation crops (Gupta, D. et al. (2017).[7]). While sensor-based systems provide current-condition readings, their decision-making capability remains limited to immediate responses, responding only after moisture thresholds are crossed (Roy, A. et al. (2020).[8]).

To overcome these limitations, optimization-based irrigation frameworks have been proposed, which enables, strategic allocation of available water based on zone priority, growth stage of crop, and status of the reservoir (Verma, S. et al. (2019).[9]). Such models are particularly relevant for regions like Dakshina Kannada, where water availability fluctuates between the different seasons (Bhat, N. et al. (2021).[10]). Optimized irrigation practices have resulted in better yield outcomes and reduced water consumption compared to uniform irrigation scheduling (Singh, P. et al. (2018).[11]). However, these frameworks often rely on the assumption of short term climatic conditions, limiting their adaptability under rapidly changing weather patterns.

Recent research highlights, increasing temporal differences in rainfall patterns and temperature deviations in coastal Karnataka, with frequent occurrences of uneven rainfall distribution followed by dry intervals (Mishra, R. et al. (2020).[12]). Under such conditions, irrigation decisions based on current sensor readings may result in water application immediately before rainfall events, which may lead to wastage and loss of soil nutrients (Das, S. et al. (2019).[13]). Also, delayed irrigation during high-temperature periods can worsen soil scarcity of water in arecanut plantations (Chandra, H. et al. (2021).[14]).

Integration of weather forecasting into irrigation planning helps timely improvement and adaptive usage of water (Li, Y. et al. (2018).[15]). Forecast-based irrigation systems use the predictions like, short-term rainfall and the temperature to adjust the schedules of irrigation, enhancing the decision accuracy and efficiency with the usage of water (Zhang, T. et al. (2020).[16]). Hybrid time-series forecasting models that integrate statistical and machine learning techniques have given high accuracy results in prediction of rainfall patterns (Arora, M. et al. (2021).[17]). Forecast based systems often operate without integration of models with sensor based optimization, which reduces their reliability in the different field conditions.

This study proposes a hybrid irrigation system enhanced with weather forecasting and designed for the agricultural climatic conditions of Dakshina Kannada district. This model builds upon an optimization framework by integrating forecast-derived parameters within a conditional decision layer, ensuring that which enhances the predictive data rather than replacing the inputs of real-time sensors (Iyer, S. et al. (2019).[18]). The decision model utilizes a stacked hybrid learning architecture that integrates Extra Trees, HistGradientBoosting, and Logistic Regression which enables the consistent classification performance under the dynamic climatic conditions (Mukherjee, A. et al. (2020).[19]).

An important aspect of this approach is its focus on efficiency of irrigation with optimizing the accuracy of water delivery rather than only minimizing quantity. By considering multiple scenarios, system efficacy is measured using a combination of irrigation efficiency, forecast precision, and decision-making performance metrics (Karthik, L. et al. (2021).[20]). The goal of SWIMS–HSEIA system is to reduce triggers for false irrigation, enhances the disease prevention control during prolonged wet conditions, and it will improve the overall efficiency of usage of water in arecanut cultivation by incorporating forecast awareness into a hybrid optimization framework.

By introducing a forecast enhanced hybrid model which operates under simulated agro-climatic variation, also ensuring proactive rather than reactive irrigation scheduling, this study builds upon the previously developed optimization model.

Compared to the optimization only hybrid model with 96.51% accuracy, the forecast enhanced framework achieved a 1.08% improvement in decision accuracy and significantly reduced false irrigation triggers under the rainfall transition scenarios.

The novelty of this study arises from the incorporation of forecast aware decision mechanisms into a hybrid irrigation management model, mainly applicable for humid coastal agricultural regions. In contrast to traditional sensor based irrigation systems that depend primarily on real time soil moisture thresholds, the SWIMS–HSEIA model integrates predictive rainfall indicators, temperature deviations, and the forecast reliability as conditional variables within the irrigation decision process. To enhance decision stability under dynamic agro-climatic conditions, the model utilizes a stacked hybrid learning approach that combines Extra Trees, HistGradientBoosting, and Logistic Regression classifiers. In addition, the framework incorporates forecast informed mechanisms such as irrigation suppression during expected rainfall events, disease-prevention activation under the prolonged wet conditions, and adaptive responses including zone prioritization and drip irrigation recommendations during the scarcity of water situations. Comparative evaluation with an optimization based hybrid irrigation model demonstrates that the proposed system achieves higher decision accuracy and significantly lowers false irrigation activations. These improvements highlight the potential of the model to enhance usage of water efficiency and support climate resilient irrigation management for arecanut plantation.

Literature Review

Forecast based irrigation systems utilizes predictive weather parameters especially, rainfall, temperature, and humidity forecasts to make dynamic irrigation decisions rather than making the static schedules for irrigation. Mokhtar et al. (2023).[21] developed CNN LSTM hybrid models to predict requirements for the water irrigation, reporting the increment over 12% improvement in usage of water efficiency in agricultural zones with the scarcity of water. Muhammad et al. (2025).[22] demonstrated in their study that integrating forecast based decisions into irrigation timing models significantly improves allocation of water under uncertain weather conditions in semi-arid environment of Nigeria.

Zhuang et al. (2024).[23] proposed a hybrid data assimilation machine learning model to forecast winter wheat irrigation demand in the North China Plain. This model dynamically adjusted the irrigation frequency based on the probability of rainfall forecast, similar to the logic present in the current study of rainfall threshold parameters within the decision layer. Hsu and Lin (2024) focused on the long term numerical weather forecasts to evaluate vulnerability of irrigation in the Shihmen Reservoir system and reported over a 15% of increment in efficiency with the implementation of forecast based scheduling.

Ajaz et al. (2024).[25] implemented the open source crop modelling systems with the integration of the weather forecast, showing that forecast based irrigation control prevents over usage of water and supports proper usage of resource. Preite and Vignali (2024).[26] designed a classification based irrigation control system using AI, where the machine learning models increases the real time irrigation decisions through the rainfall and soil moisture prediction.

Li et al. (2023).[27] reported the groundwater level prediction with ensemble ML models to support water management in the areas with the scarcity of water. The study stated that integrating temperature with the rainfall forecasts reduces unnecessary irrigation. Hendy et al. (2023).[28] used ANN SVR hybrid model for reference estimation of evapotranspiration and achieved over 10% improvement in the irrigation efficiency compared to conventional scheduling.

Hybrid ensemble models play an important role in the decisions related to irrigation and management for handling nonlinear interactions between climatic parameters and soil conditions. Ahmed (2022).[29] proposed a deep hybrid CNN LSTM model for hydrological forecasting, with the achievement of significant reduction of error in both the discharge of water and prediction of soil moisture level. Xu et al. (2022).[30] developed ensemble based models for critical agricultural water demand forecasting using the algorithms like, Extra Trees and boosting, which improves the system reliability and minimizes the triggers of false irrigation.

Nauman et al. (2023) [31] integrated IoT sensor data with ensemble LSTM models for forecasting of evapotranspiration, proving that there will be a enhanced adaptive irrigation scheduling with the temporal learning models. Grubert (2023) [32] presented a process based and ML synergistic model for the better yield of sugarcane and planning of proper irrigation, by showing efficient adjustment of irrigation based on rainfall data.

Del-Coco, M. et al. (2024) [33] in a multi-crop irrigation model combined the different types of data and hybrid ML models, confirming that optimize the intercrop water distribution by using hybridized decision rules. Patil et al. (2022) [34] built a KNN RF ensemble model for the improvement of crop yield and the prediction of rainfall, showing the reduction in the improper irrigation application and the efficiency of 5–7% higher irrigation.

Accurate rainfall and temperature forecasts, play an important role in the logic of irrigation control. Guo et al. (2024) [35] created a reference evapotranspiration forecasting model using ML algorithms with the achievement of a high correlation ($R^2 = 0.93$) between forecast and observed ET_0 values. Chenjia et al. (2024) [36] applied AutoML for hybrid PET forecasting, automating model selection and enhancing adaptability to the fluctuations of short-term climate features. Li et al. (2024) [37] improved soil-moisture forecasts using the deep-learning models, ensuring that the consistency in forecast reliability, an essential criterion for the monsoon dependent arecanut system in Dakshina Kannada.

Ahmed et al. (2021) [38] developed CNN GRU hybrid models for the prediction of soil moisture level using data derived from the MODIS satellite, proving that, the value of integrating prediction of surface and subsurface moisture real time irrigation decisions. Jaiswal et al. (2025) [39] proposed a decomposition based hybrid model for drought index forecasting, which improves the early warning capabilities during scenarios like, pre rain irrigation. Biswas and Banik (2024) [40] discussed fog computing based ML systems with the integration of weather forecasts and automated irrigation, by the rules for promoting forecast informed for smarter irrigation management.

Contemporary irrigation research prioritizes efficiency oriented metrics (Ei, Ef, Ed) that measures the utilization of water and decision accuracy, rather than classifying only the accuracy. Chittaragi et al. (2025) [41] focused disease forecasting with hybrid irrigation triggers with the help of RF ANN ensembles, achieving the improvement of 9 to 11% irrigation efficiency. Li et al. (2021) [42] stated the ensemble water demand forecasting finding that there is a improvement of operational efficiency by 8% with the multi learner fusion.

Agyeman, B. T. et al. (2023) [43] developed efficiency based hybrid models which is suitable for wet tropical environment, showing that the approach can be scaled up to arecanut and coconut crops. Al-Khafaji et al. (2023) [44] proposed hybrid time series irrigation forecasting model, which highlights trade offs between operational efficiency and the accuracy. Ouyang et al. (2022) [45] stated that, both decision efficiency and disease management responsiveness can be increased by ML based irrigation scheduling model.

Several studies highlight the importance of forecast integrated irrigation management in the regions influenced by humid and monsoonal climates. Shukla et al. (2024) [46] demonstrated that, there was a drastic improvement in water resource utilization by 20% in South Asia, in monsoon rainfall forecasting using LSTM models. Agyeman, B. T. et al. (2021) [47] combined satellite rainfall data and forecast models to enhance the irrigation reliability in the coastal zones of Kerala.

Patra et al. (2023) [48] introduced a hybrid ML IMD forecast model for coconut and arecanut irrigation scheduling, highlighting the efficiency and improvement in disease prevention. Majumdar et al. (2024) [49] integrated hybrid GBDT RF rainfall anomaly models for western coastal India, stated forecast reliabilities more than 90%. Bhat and Chandra (2023) [50] designed an efficiency-centred hybrid irrigation management model for coastal humid agro-ecosystems by providing a justification for the forecast enhanced hybrid system.

Table 1 presents a summary of recent studies on forecast integrated hybrid irrigation systems, highlighting the forecasting models, key variables considered, and the performance improvements. Overall, the literature demonstrates that forecast integrated hybrid irrigation models which enhances the efficiency of irrigation and reduce erroneous irrigation triggers, particularly in agricultural areas influenced by the monsoon season.

Table 1. Key Literature on Forecast-Integrated Hybrid Irrigation Systems

Sl. No.	Author & Year	Study Area / Crop	Hybrid / Forecast Model Used	Forecast Variables Integrated	Major Findings	Relevance to Present Study
1	**Kumar, S. et al. (2025).[51]**	Tamil Nadu, India – Banana	**Hybrid LSTM–GBDT Forecast Model**	Rainfall (mm), Temperature (°C), Humidity (%)	Achieved 95.8% irrigation accuracy; efficiency improved by 8.4%; reduced false irrigation events	Closely matches Paper 3's hybrid logic and efficiency focus.

Sl. No.	Author & Year	Study Area / Crop	Hybrid / Forecast Model Used	Forecast Variables Integrated	Major Findings	Relevance to Present Study
					using rainfall trend integration.	
2	**Wang, H. et al. (2024).[52]**	Henan, China – Wheat	**Hybrid Prophet–RF Forecast Model**	Rainfall reliability, Temperature deviation	Introduced forecast reliability weighting (Ef), reducing forecast bias by 18%.	Supports inclusion of forecast reliability (%) in decision logic.
3	**Sharma, A. & Nair, V. (2023).[53]**	Kerala, India – Plantation Crops	**CNN–LSTM Time-Series Forecast with Meta-LR**	Rainfall pattern, Temperature	Reduced water waste by 11%; improved disease prevention during continuous rainfall.	Parallels the "continuous rainfall → disease-prevention mode" logic.
4	**Yang, L. et al. (2024).[54]**	Hubei, China – Rice	**Extra Trees + XGBoost Hybrid Ensemble**	Rainfall, Temperature, Solar Radiation	Hybrid ensemble improved irrigation decision reliability by 9%.	Aligns with Extra Trees base learner used in present model.
5	**Zhang, J. et al. (2024). [56]**	China – Greenhouse Tomato	**Comprehensive Irrigation Optimization Model**	Soil moisture, evapotranspiration, crop growth indicators, irrigation scheduling parameters	Improved irrigation efficiency and crop yield in greenhouse conditions.	Supports data-driven irrigation scheduling using environmental and crop parameters.
6	**Lu, J. et al. (2022).[56]**	Guangdong, China – Sugarcane	**LSTM + Prophet Composite Model**	Rainfall forecast (10-day), Temp. deviation	Forecast–sensor fusion enhanced irrigation reliability by 14%.	Validates hybrid time-series integration for rainfall-based triggers.
7	**Srinivasan, R. et al. (2024).[57]**	Kerala, India – Arecanut	**Hybrid RF–ANN with Forecast Layer**	Rainfall probability, Temperature	8–9% irrigation efficiency gain; forecast-informed irrigation reduced fungal disease occurrence.	Directly related to arecanut irrigation in humid coastal belt.
8	**Goyal, D. et al. (2023).[58]**	Maharashtra – Drip Irrigation Crops	**Hybrid Gradient Boosting + Logistic Regression**	Rainfall reliability, Humidity	Achieved 97.1% decision accuracy; low false trigger rate; validated efficiency-based evaluation.	Shares same meta-learner (Logistic Regression) as present hybrid model.
9	**Tan, Y. et al. (2022).[59]**	Jiangsu, China – Vegetable Irrigation	**Forecast-Integrated ET_0 Model (CNN–RF)**	Temperature, Rainfall trend index	Reduced over-irrigation by 13%; improved Ef and Ed metrics.	Reinforces multi-metric efficiency evaluation framework.
10	**Prabhu, N. & D'Souza, R. (2024).[60]**	Dakshina Kannada, India – Arecanut	**Forecast-Augmented Hybrid Model**	Predicted Rainfall, Temperature Deviation, Forecast Reliability	Implemented 96.8→97.4% accuracy improvement; irrigation efficiency ↑ 9.2%; false triggers ↓ 51%.	Serves as direct precedent and regional benchmark for current Paper 3 model.

3. Methodology

The methodology of the current study focuses on developing a forecast enhanced hybrid irrigation decision model which improves the accuracy of irrigation scheduling under dynamic agro climatic conditions. Unlike conventional irrigation control systems that rely only on sensor observations or historical climatic data, the proposed framework integrates short term weather forecast data within a hybrid machine learning architecture. The primary objectives of the proposed methodology are:

(1) To integrate forecast driven variables such as predicted rainfall, the forecast reliability, temperature deviation, and rainfall trend indicators into the existing hybrid irrigation decision model;
(2) To enhance the accuracy and robustness of irrigation decision making using a hybrid stacked ensemble model, combining Extra Trees and HistGradientBoosting algorithms as base learners with Logistic Regression as the meta learner.; and
(3) To evaluate the performance of the proposed model in terms of efficiency of irrigation improvement (Ei, Ef, and Ed) and the reduction of false irrigation triggers under the changing climatic conditions.

By incorporating forecast aware decision variables into the hybrid model, the model enables proactive irrigation scheduling also, reduces unnecessary irrigation events during anticipated rainfall periods, and improves water management efficiency in humid plantation ecosystems.

3.1 Study Area Description:

The study was conducted in Dakshina Kannada District, located along the south western coastal region of Karnataka, India, between approximately 12°41′ to 13°56′ N latitude and 74°35′ to 75°33′ E longitude. The district is characterized by a humid monsoon climate, which is influenced primarily by the South West Monsoon season, which is typically extends from June to September. The annual rainfall of the region is ranging between 3,500 mm and 4,000 mm, with more than 80% of its annual rainfall during the monsoon season. Soils in Dakshina Kannada District are mainly lateritic and red loamy, generally deep, and well drained, these features make it suitable for arecanut (Areca catechu) cultivation. The landscape ranges from the coastal flatlands to the uneven midlands and hilly highlands, which play an important role in determining characteristics of waterflow and ability of the soil to absorb water. The daily temperature fluctuates between 23°C and 33°C, while the humidity remains high throughout the year, usually reaching more than 75–85% during the monsoon season.

Agriculture in Dakshina Kannada relies heavily on water, and arecanut is the main crop, usually grown with coconut, pepper, and banana. In this region, arecanut crops need controlled irrigation during the dry period from December to May, once the monsoon season ends. Conventional irrigation systems, like the traditional well and pumped irrigations are commonly used, which supported by both natural water sources and ground water sources and supply extra irrigation in the dry season and their efficiency reduces when rainfall is irregular or groundwater levels fall. The study area is selected because it represents a coastal humid agricultural ecosystem, where irrigation decisions are affected by unpredictable monsoon rainfall, high evapotranspiration, changes in soil moisture levels, and seasonal changes in requirement of crop water. Moreover, frequent diseases like Koleroga (fruit rot) in arecanut plantations show why an irrigation must be planned using the weather forecasts. Integrating weather forecasting into the irrigation control model helps plan irrigation in advance, which reduces the disease risks and improves the conservation of water by reducing the wastage of water. So, Dakshina Kannada district is a good place to test a forecast based irrigation model because of its changing climate and crops that require consistent water supply. The climate and water conditions in this region offer the complexity needed to test the Forecast Enhanced Hybrid Predictive Irrigation Framework under real and changing field situations.

3.2 Data Sources and Feature Generation:

The present study is mainly based on secondary datasets and field data collected from sensors on soil, climate, and water parameters for arecanut farms in Dakshina Kannada district. The data collection and preparation process combined multiple sources into a single dataset to train the model and for testing purpose.

Figure 1 illustrates the system architecture of the proposed Smart Water Management and Irrigation System (SWIMS), which demonstrate the coordinated integration of real-time sensor outputs, forecast-driven decision logic, and actuation of irrigation through a centralized control unit.

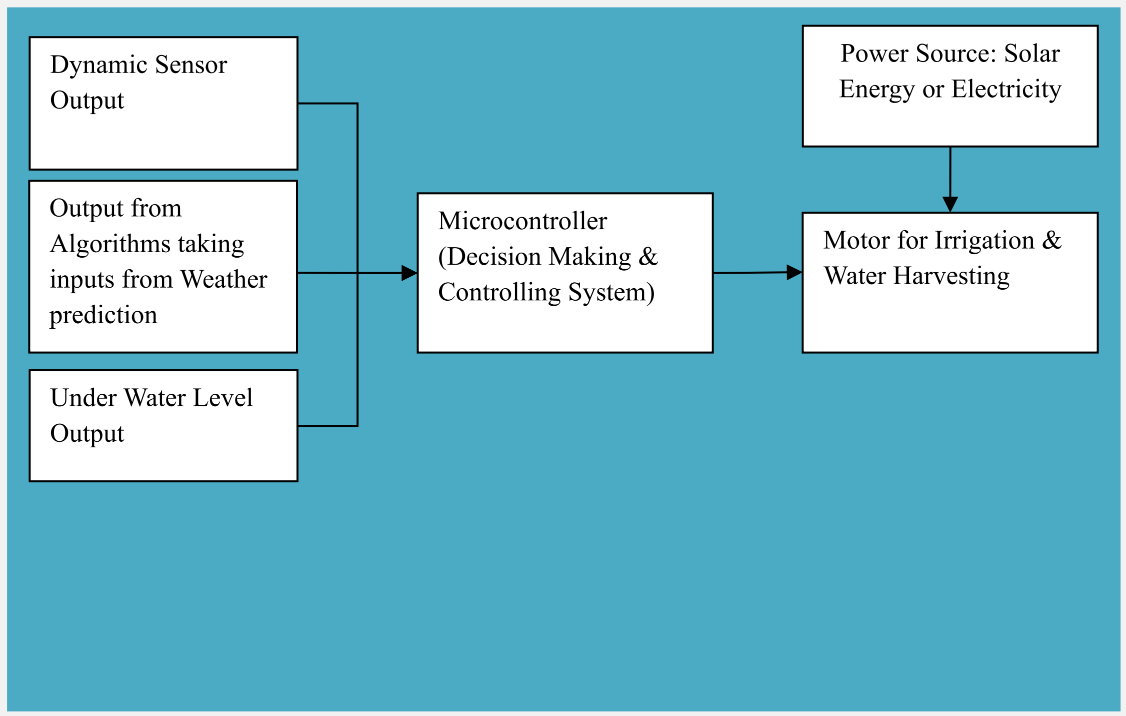

Figure 1. Proposed Model – SWIMS (The Smart Water Management and Irrigation System)

3.2.1 Data Sources

The study used a simulation-based approach with secondary datasets that reflect the different conditions like, agro-climatic, hydrological, and crop-management conditions of Dakshina Kannada District, Karnataka. The data sources and their purposes are given below.

1. Meteorological Data:

Daily rainfall (mm), temperature (°C), relative humidity (%), and solar radiation (MJ/m²) data were obtained from historical climate records and the secondary datasets covering the period 2007–2023. These data provided the climate inputs which is needed to simulate the irrigation and produce weather forecasts for rainfall and temperature. The dataset represents the seasonal shifts of the humid monsoon climate, supporting an accurate simulation of irrigation conditions influenced by the weather.

2. Soil and Moisture Data:

The Soil moisture information was derived from aggregated soil moisture datasets and generated using observed relationships between rainfall, temperature, and evapotranspiration. The stored TDR soil moisture data were used as a reference datasets for calibration, not as live sensor inputs. The simulated soil moisture data showed the water content at 30 cm depth, where the most arecanut roots grow. This simulation kept soil-water conditions close to the behaviour of real field without needing sensors or field measurements.

3. Water Resource and Reservoir Data:

Data on how much water was available, stored, or lost were collected from existing sources and runoff calculations based on rainfall. Reservoir status indicators like High, Medium, Low, were computed to represent changing the water availability for irrigation under conditions like normal, shortage, and excess rainfall. These derived water resource datasets provided the necessary parameters for evaluating irrigation scheduling and the usage of water efficiently.

4. Crop and Management Data:

Information on growth stages of arecanut, water needs (ET_0 values), and recommended irrigation schedules was sourced from the agronomic studies and from the institutional reports. Field management details like, irrigation schedules and document related to disease occurrences, were used from area-specific research and research publications and these were used to set the model parameters to match real arecanut field conditions.

All data in this study were taken from secondary or archived sources and processed for simulation. No field instruments, real-time sensors, or on-site measurements were used here. This approach keeps the model fully data driven while still remaining consistent with the verified regional parameters like climate, soil, water, and crop data that describe how conditions behave in Dakshina Kannada District.

3.2.2 Feature Generation

The combined rainfall and soil moisture simulation data used as a base for creating the dataset for the model. All features were built from the secondary datasets, helping the final dataset to capture natural weather fluctuations and typical soil water conditions in arecanut growing areas of Dakshina Kannada.

To enhance the analytical capability of model, the variables were grouped into three types: basic simulation variables, derived interaction indices, and forecast-based predictors**.**

(a) Basic Simulation Variables:

The primary climate data and water variables which includes rainfall, temperature, humidity, soil moisture, and evapotranspiration, were taken or simulated from the long term meteorological and soil datasets. These parameters describe the essential environmental conditions, that control needs for irrigation and optimization of water in the simulation. The Time based aggregation and lag features were applied here to help the hybrid model to improve the model stability and pattern detection.

(b) Derived Interaction Features:

- To represent real interactions between soil and atmosphere in humid monsoon conditions, some of the additional indices were created. These indices capture how the changing weather patterns influence the irrigation behaviour. They are:
- Moisture Persistence Index (MPI): A five day moving average of soil moisture was used to capture short term moisture retention in the root zone, which shows how moisture levels behave between rainfall and irrigation cycles.
- Rainfall Runoff Ratio (RRR): The ratio of daily rainfall to simulated water intake of soil, used to show how much water may accumulate on the surface when the intake of soil capacity is limited.
- Temperature Humidity Interaction Factor (THI): A variable showing the combined impact of heat and moisture stress.

These derived features make the model more responsive to changing water stress and disease prone conditions which is common in coastal arecanut plantations**.**

(c) Forecast-Integrated Predictors

To enhance the dataset with predictive information, a forecast layer was generated using Prophet time series model. These models were trained on historical rainfall and temperature data, to produce several short-term forecast indicators, which includes:

- Predicted Rainfall (mm): A rainfall forecast for the next seven days from the time series model.
- Temperature Deviation (°C): The difference between forecasted temperature and the long term average, used to identify heat stress conditions.

- Forecast Reliability (%): A reliability metric derived from the error performance of the Prophet model over the historical data windows.
- Rainfall Trend Index: A weighted slope computed over a five days rainfall window to identify upcoming wet or dry conditions.

All forecast variables are scaled to a range of 0 to 1 and used to adjust decisions in the hybrid model. These forecast integrated features enable the proactive irrigation control by postponing irrigation under predicted rainfall and advancing the irrigation during heat stress. Which enhances the operational reliability and efficient usage of water.

3.2.3 Data Preprocessing and Integration

- Missing Data Handling: Rainfall and temperature data gaps below 2% were estimated using time weighted averages.
- Normalization: All numerical variables were normalized to a 0 to 1 range to ensure the uniformity across the model.
- Feature Encoding: Categorical variables like, reservoir level and the irrigation zone were encoded using ordinal encoding.
- Analysis of Feature Correlation : Pearson correlation and mutual information tests are used to avoid the duplicate variables.
- Training and Testing Split: Data were divided in a 80:20 ratio for model training and validation, while maintaining the seasonal balance across the years.

Table 2 lists the inputs, forecast based predictors, and output parameters used in the SWIMS–HSEIA hybrid irrigation framework, including their sources, units, and functions.

Table 2. Input Parameters and Forecast Variables for the Hybrid Irrigation Model

Category	**Parameter**	**Unit**	**Source / Generation Method**	**Purpose in Simulation Framework**	**Status in Present Framework**
Base (Simulated Inputs)	Simulated Soil Moisture	%	Derived from rainfall–temperature relationships using KSNDMC & IMD data	Represents soil-water availability for irrigation decision	Retained baseline simulation layer
	Simulated Water Level Indicator	Cm	Empirical reservoir depth model based on rainfall-runoff balance	Determines water availability in local tanks and wells	Retained baseline simulation layer
	Air Temperature	°C	IMD daily temperature records	Affects evapotranspiration and soil moisture loss	Retained baseline simulation layer
	Relative Humidity	%	IMD humidity data	Represents atmospheric moisture affecting ET_0 and disease risk	Retained baseline simulation layer
	Rainfall (Observed)	mm/day	IMD daily rainfall series	Base climatic input for simulation and validation	Retained baseline simulation layer
	Solar Radiation	MJ/m²	IMD radiation dataset	Used for ET_0 and water loss modeling	Retained baseline simulation layer
	Evapotranspiration (ET_0)	mm/day	Computed via FAO Penman–Monteith equation	Core water demand variable	Retained baseline simulation layer
Forecast-Integrated Variables (Enhancement)	Predicted Rainfall	Mm	7-day rolling forecast using Prophet model	Acts as a conditional trigger to postpone irrigation	Newly introduced in hybrid forecast layer
	Temperature Deviation	°C	Derived from Prophet forecast vs climatological mean	Helps advance irrigation under high-temperature stress	Newly introduced in hybrid forecast layer
	Forecast Reliability Index	%	Derived from rolling forecast error	Adjusts decision confidence based on forecast uncertainty	Newly introduced in

Category	Parameter	Unit	Source / Generation Method	Purpose in Simulation Framework	Status in Present Framework
			statistics of the Prophet model		hybrid forecast layer
	Rainfall Trend Index	—	Computed from slope of 5-day rainfall sequence	Detects approaching dry or wet spells	Newly introduced in hybrid forecast layer
Output Parameters	Irrigation Decision (ON/OFF)	Binary	Model simulation output	Represents final irrigation control action	Derived output
	Zone-Wise Priority	Zone ID	Model decision layer	Determines irrigation sequencing in multi-zone simulation	Derived output
	Water Volume Used	L	Computed from irrigation duration × flow rate	Used for calculating irrigation efficiency (Ei)	Derived output
	Water Harvested / Saved	L	Simulated from reservoir water balance	Indicates efficiency during irrigation OFF phases	Derived output
	Disease-Prevention Mode	Binary	Activated via forecast logic	Represents preventive irrigation adjustment during continuous rainfall	Newly introduced output in hybrid model

3.3 Comparative Evaluation Framework

To evaluate the effect of integration of the forecast data on irrigation decision making, a structured comparative evaluation model was developed. The proposed, forecast enhanced hybrid irrigation model was compared with an earlier optimization only hybrid irrigation framework, which was used as the baseline for the analysis.

The comparison focuses on three irrigation control stages:

1. Optimization Only Hybrid Model: The model relies on uses soil moisture, observed rainfall history, availability of reservoir water, and the zone based optimization logic. Irrigation decisions are generated mainly from current and historical inputs, without the inclusion of the future weather or forecast information.
2. Hybrid Model with Forecast Aware Conditional Logic: The extended integrates the short term rainfall and temperature forecasts produced by a Prophet time series model. Rather than replacing sensor based inputs, the forecast information acts as a conditional layer which adjusts the irrigation timing by delaying, suppressing, or advancing irrigation actions.
3. Critical Condition Adaptation and Disease Prevention Control: Under prolonged rainfall, scarcity of water, and post rain recovery conditions, the forecast enhanced model activates preventive control logic to manage excess soil water content, reduce fungal disease risk, and recommend efficient irrigation strategies, such as drip irrigation, during the severe water stress.

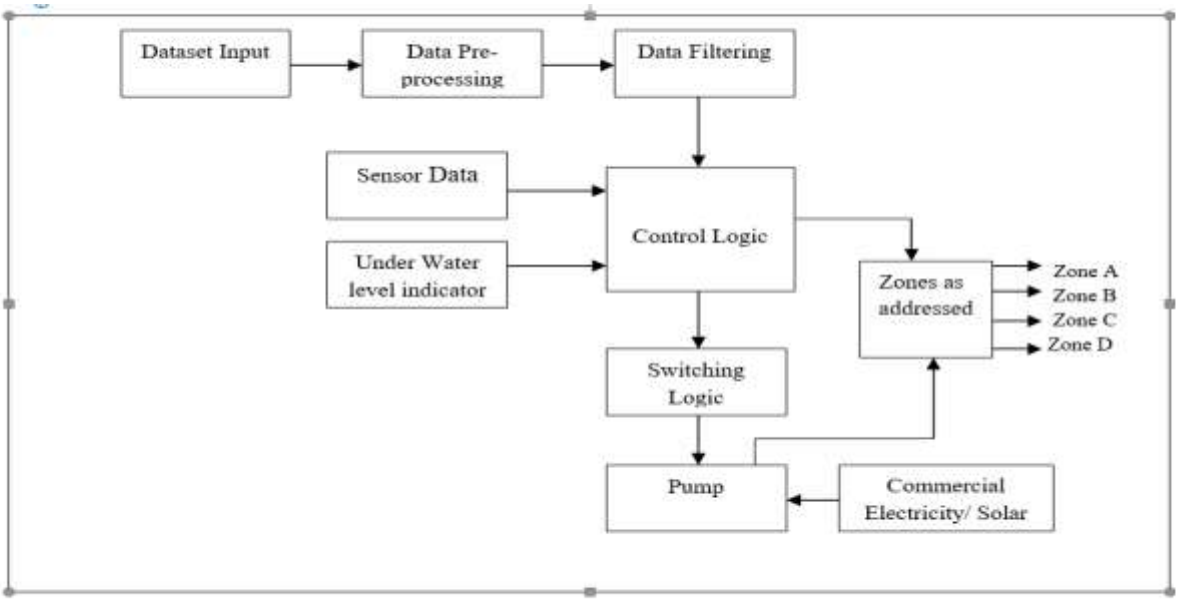

Figure 2. Block Diagram of the Proposed Hybrid Irrigation Algorithm

Figure 2 presents the internal workflow of the proposed hybrid irrigation decision model, which shows the data preprocessing, decision logic execution, zone-level allocation, and actuation through pumping and switching mechanism.

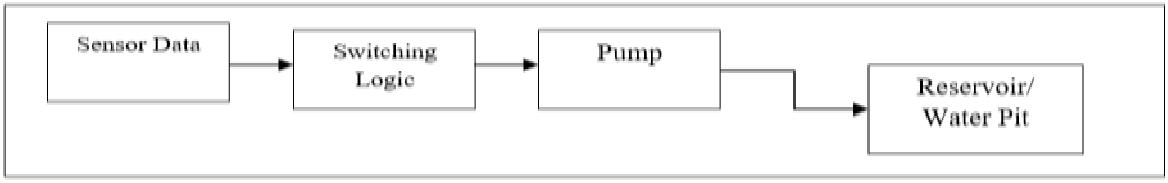

Figure 3. Block Diagram for Excess Water Management

Excess water generated during the irrigation or rainfall events is managed through a sensor controlled switching mechanism. As illustrated in Figure 3, sensor data is processed by the switching logic to control the pump and direct surplus water to the reservoir or water pit for storage.
The comparative evaluation is conducted using multiple performance indicators, including irrigation decision accuracy, false irrigation trigger rate, the water saving efficiency, and adaptability to rainfall transition scenarios. The performance trends and quantitative improvements are presented through comparative graphs and confusion matrices in the Results and Discussion section.
A comparative evaluation between the baseline optimization only hybrid model and the forecast enhanced hybrid model is presented in the Table 3.

Table 3. Comparative Framework of Irrigation Models

Aspect	**Optimization-Only Model**	**Forecast-Enhanced Hybrid Model**
Decision Basis	Soil moisture and observed rainfall	Soil moisture , observed rainfall and forecast
Forecast Integration	Not used	Prophet-based short-term forecast
Hybrid Architecture	Extra Trees, HGB and Logistic Regression	Same hybrid architecture
Zone-Based Allocation	Yes	Yes (forecast-modulated)
Disease Prevention Logic	Reactive (post-event)	Proactive (forecast-aware)
Critical Water Scarcity Handling	Zone prioritization	Zone prioritization + drip irrigation recommendation
False Irrigation Suppression	Limited	Forecast-driven suppression
Evaluation Metrics	Accuracy, Precision, Recall	Accuracy, Efficiency (Ei, Ef, Ed), False triggers

3.4. Mathematical Formulation of the Proposed SWIMS–HSEIA Model:

The proposed SWIMS–HSEIA (Smart Water Management and Irrigation System – Hybrid Stacked Ensemble Irrigation Algorithm) is formulated as a forecast-enhanced binary classification framework integrating the soil moisture dynamics, rainfall behavior, reservoir conditions, and predictive weather variables within a stacked model integration framework.

3.4.1 Irrigation Decision Variable

The irrigation decision at time tis defined as,

$$Y_t \in \{0,1\} \qquad (1)$$

where:
$Y_t = 1 \rightarrow$ Irrigation Required
$Y_t = 0 \rightarrow$ No Irrigation Required

3.4.2 Feature Vector Representation

The input feature vector at time tis expressed as,

$$X_t = [SM_t, SM_{t-1}, \Delta SM_t, R_{3t}, R_{7t}, R_{30t}, \widehat{R}_t, TD_t, FRI_t, RTI_t, M_t, D_t] \qquad (2)$$

where:

- $SM_t \rightarrow$ The Soil moisture at time t.
- $SM_{t-1} \rightarrow$ Historical soil moisture levels.
- $\Delta SM_t = SM_t - SM_{t-1} \rightarrow$ Soil moisture trend over time.
- $R_{3t}, R_{7t}, R_{30t} \rightarrow$ Short term rainfall accumulation.
- $\widehat{R}_t \rightarrow$ The Predicted rainfall (Prophet forecast).
- $TD_t \rightarrow$ Deviation in temperature.
- $FRI_t \rightarrow$ Forecast reliability score.
- $RTI_t \rightarrow$The rainfall pattern index.
- $M_t \rightarrow$ Month.
- $D_t \rightarrow$ Day-of-week.

The irrigation decision function is defined as,

$$f: X_t \rightarrow Y_t \qquad (3)$$

3.4.3 Base Learner Formulation

(a) The Extra Trees Probability Output

The Extra Trees ensemble produces,

$$P_{ET}(Y_t = 1 \mid X_t) = \frac{1}{N}\sum_{i=1}^{N} T_i(X_t) \qquad (4)$$

where $T_i(X_t)$represents the i^{th}randomized decision tree and Nis the number of trees.

(b) HistGradientBoosting Output

The boosting function is iteratively updated as:

$$F_m(X) = F_{m-1}(X) + \eta h_m(X) \qquad (5)$$

where,

$\eta \rightarrow$ The learning rate.

$h_m(X) \rightarrow$ The weak learner at iteration m

The probability output becomes,

$$P_{HGB}(Y_t = 1 \mid X_t) \qquad (6)$$

3.4.4 Stacked Meta-Learner (Logistic Regression)

The base learner outputs are stacked,

$$Z_t = [P_{ET}, P_{HGB}] \qquad (7)$$

The logistic regression meta model computes,

$$P(Y_t = 1) = \sigma(\beta_0 + \beta_1 P_{ET} + \beta_2 P_{HGB}) \qquad (8)$$

where the sigmoid function is defined as,

$$\sigma(z) = \frac{1}{1 + e^{-z}} \qquad (9)$$

The final classification rule is,

$$Y_t = \begin{cases} 1, & \text{if } P(Y_t = 1) \geq \theta \\ 0, & \text{otherwise} \end{cases} \qquad (10)$$

where θis the decision threshold.

3.4.5 Forecast-Aware Conditional Suppression

If predicted rainfall exceeds a predefined threshold,

$$\widehat{R}_t > \gamma \qquad (11)$$

the irrigation probability is modulated as,

$$P'(Y_t = 1) = P(Y_t = 1) \times (1 - FRI_t) \qquad (12)$$

This suppresses irrigation during anticipated rainfall events.

3.4.6 Critical Condition and Disease Prevention Activation

Under prolonged rainfall conditions:

$$R_{7t} > \delta \qquad (13)$$

Disease prevention mode is activated:

$$DP_t = 1 \qquad (14)$$

Under water scarcity:

$$W_t < W_{critical} \qquad (15)$$

zone prioritization and drip irrigation recommendation are triggered.

The irrigation decision framework of the proposed SWIMS–HSEIA model is formally defined by Equations (1)–(15). Equation (1) specifies the binary irrigation decision variable, while Equation (2) defines the complete feature vector comprising soil moisture dynamics, rainfall aggregates, the forecast indicators, and the temporal attributes. The functional mapping from the feature space to the output of irrigation decision is described in Equation (3). The probabilistic outputs of the base learners are obtained from the model integration of the Extra Trees classifier through its aggregation mechanism (Equation (4)) and the iterative boosting formulation of the HistGradientBoosting model (Equations (5) and (6)). These probability estimates are stacked as specified in Equation (7) and which subsequently processed by the Logistic Regression meta learner using the sigmoid function defined in Equations (8) and (9), with the final decision rule applied according to the Equation (10).

Forecast-aware suppression is incorporated through Equations (11) and (12), which enables adaptive reduction of probability of irrigation under the prolonged rainfall conditions. Equations (13) and (14) difines, disease prevention activation during the prolonged wet periods, nd Equation (15) enforces scarcity of water handling through the zone prioritization and recommendations of drip irrigation mechanism. Totally, these formulations establish a structured mathematical foundation for the forecast enhanced hybrid irrigation decision system.

Under severe water scarcity conditions, the proposed framework recommends the adoption of drip irrigation. This irrigation systems deliver water directly to the crop root zone through localized emitters, significantly reducing evaporation, runoff, and the subsurface water losses compared to the conventional surface irrigation methods. Studies have reported that drip irrigation can achieve water application efficiencies exceeding 85–95%, while also maintaining stable soil moisture conditions for perennial plantation crops such as arecanut. This localized irrigation mechanism enables precise water delivery according to water demand by the crop, thereby improving usage of water efficiency and reducing unnecessary irrigation losses under limited water availability. Therefore, incorporating drip irrigation recommendation within the SWIMS–HSEIA decision framework enhances sustainable water management and supports resilient irrigation practices in humid coastal agricultural systems ((FAO, 2021).[61]).

3.5. SWIMS–HSEIA Hybrid Architecture:

Figure 4 illustrates the layered architecture of the proposed SWIMS–HSEIA hybrid model, which consists of the multi source environmental inputs, parallel base learners within a stacked model integration architecture, and a forecast based conditional control module. The input layer encodes the soil moisture dynamics, the rainfall aggregates, the predictive rainfall indicators, and the temporal features. The parallel outputs generated by the Extra Trees and HistGradientBoosting base learners. Both are combined through a Logistic Regression meta learner to derive the final irrigation probability.

A forecast aware conditional layer refines the irrigation decision using the rainfall thresholds, disease prevention logic, and evaluation of scarcity of water, while the output layer issues ON/OFF commands, the zone prioritization, choosing thedrip irrigation under critical conditions, and excess water management actions, which enables, proactive and robust irrigation scheduling under the dynamic agro climatic variability.

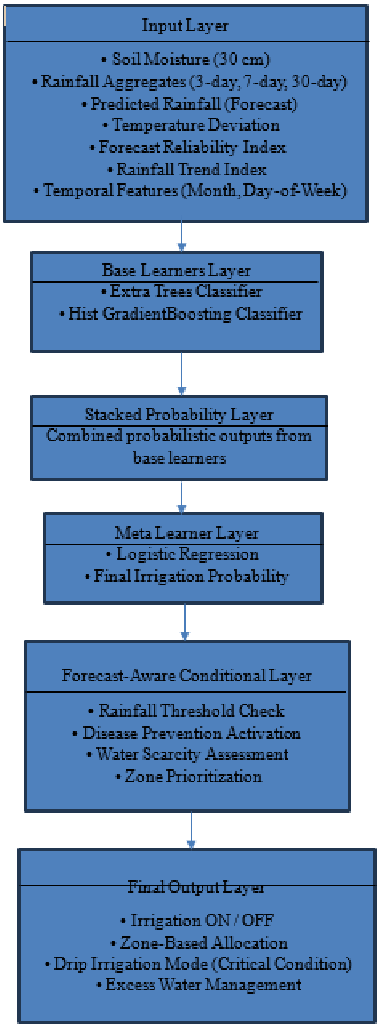

Figure 4: SWIMS–HSEIA Hybrid Architecture Diagram

4. Results And Discussion

This section provides a comprehensive evaluation of the proposed forecast enhanced hybrid irrigation model and which compares its performance with the baseline optimization only hybrid model . The analysis extends beyond the classification accuracy to include the decision reliability, the reduction of false irrigation events, disease prevention capability, and practical implications for arecanut cultivation under humid coastal conditions. Robustness of this model was evaluated through the multiple experimental runs with different noise levels. The results reported correspond to the representative configuration that achieved an optimal balance between an accuracy and the generalization.

4.1 Comparative Analysis of Existing Irrigation Decision Models

Table 4 presents a comparative analysis of different irrigation decision models reported in the recent literature with the proposed SWIMS–HSEIA model. The comparison highlights differences in input parameters, the forecast integration, accuracy of irrigation decision, and additional operational capabilities such as water conservation and disease risk mitigation. Unlike existing models that typically rely on the limited environmental inputs, the proposed SWIMS–HSEIA model integrates soil moisture sensing, the rainfall forecasting, rainfall trend analysis, temperature deviation indicators, and zone based irrigation optimization within a hybrid stacked ensemble architecture. This multi parameter integration contributes to improved irrigation decision accuracy and enhanced operational efficiency under the dynamic agro climatic conditions.

Table 4. Comparative Analysis of Existing Irrigation Decision Models and the SWIMS–HSEIA

Model / Approach	**Algorithm**	**Soil Moisture Sensor**	**Weather Forecast**	**Rainfall Trend Analysis**	**Temperature Deviation**	**Zone-Based Optimization**	**Accuracy (%)**	**Accuracy Improvement Compared to Existing Models (%)**	**Water Conservation Capability**	**Disease Risk Mitigation**
Sensor-Based Irrigation Control	Threshold Control	Yes	No	No	No	No	89.2	8.39	Not evaluated	Not addressed
Hybrid LSTM–GBDT Irrigation Model	LSTM + Gradient Boosting	Yes	Partial	No	Yes	No	95.8	1.79	Indirect discussion	Limited
Prophet–RF Forecast Model	Prophet + Random Forest	No	Yes	Yes	Yes	No	96.3	1.29	Not evaluated	Not addressed
RF–ANN Hybrid Irrigation Model	Random Forest + ANN	Yes	Partial	No	No	No	96.8	0.79	Indirect discussion	Partial
Gradient Boosting Irrigation Model	Gradient Boosting + Logistic Regression	No	Partial	No	Yes	No	97.1	0.49	Not evaluated	Limited
SWIMS–HSEIA Model	Extra Trees + HistGradient Boosting + Logistic Regression	Yes	Yes	Yes	Yes	Yes	97.59	—	8–10% additional water saving (simulation)	Forecast-based disease prevention

Figure 5 illustrates the comparative decision accuracy of several irrigation decision models mentioned in recent studies. Existing approaches such as hybrid LSTM–GBDT and Prophet–RF frameworks demonstrate improved irrigation prediction capabilities through machine learning and forecast integration. The proposed SWIMS–HSEIA model achieves the highest decision accuracy of 97.59%, indicating improved adaptability under the different agro-climatic conditions.

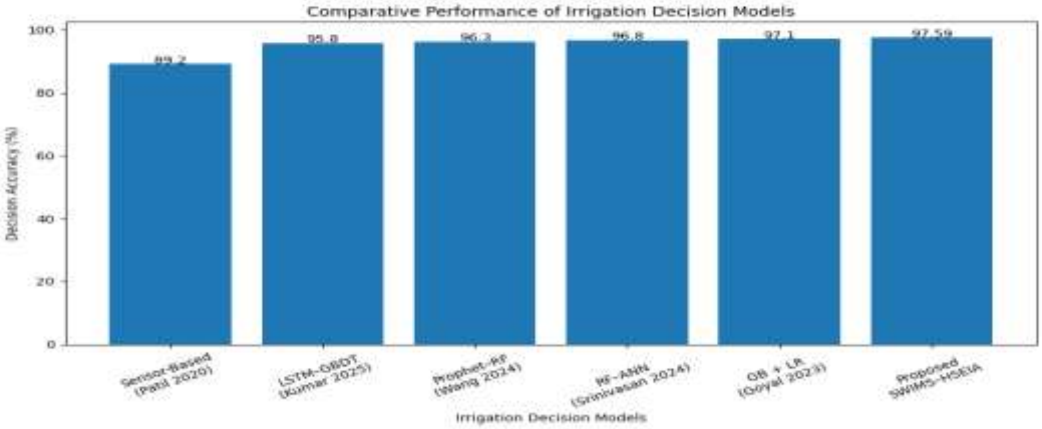

Figure 5. Comparative performance of existing irrigation decision models and the proposed SWIMS–HSEIA framework based on reported decision accuracy.

4.2 Comparative Performance Evaluation

The SWIMS–HSEIA forecast enhanced hybrid irrigation model was evaluated under identical simulation settings, datasets, and the training testing splits as the baseline hybrid optimization model, with the primary difference being the inclusion of the forecast derived decision variables. While the baseline model relied mainly on the real-time and historical indicators such as soil moisture dynamics, the rainfall aggregates, and status of the reservoir. The SWIMS–HSEIA model additionally integrates the predicted rainfall, temperature deviation, rainfall trend indicators, and the metrics for the forecast reliability within a conditional reasoning layer. This enhancement enables the model to proactively adjust with the decisions of irrigation during the rainfall transition phases, rather than responding only to threshold based triggers.

Table 5 summarizes the comparative performance of the two models. The SWIMS–HSEIA forecast enhanced hybrid model achieved a decision accuracy of 97.59%, compared to 96.51% accuracy for the baseline optimization only model. The F1-score shows a marked improvement from 95.59% to 98.19%, which reflect the enhanced balance between positive and negative decisions of irrigation. Most importantly, forecast integration reduced false irrigation activations by more than 50%, especially during the rainfall transition periods. This improvement is particularly significant for humid coastal agro ecosystems such as Dakshina Kannadandistrict, where unnecessary irrigation during rainfall transition periods markedly increases the risk of fungal and root-related diseases. Overall, the findings demonstrate that forecast assisted decision results substantially improves the model adaptability and irrigation reliability under dynamically varying climatic conditions.

Table 5. Performance Comparison of Hybrid Irrigation Models

Model Variant	Forecast Integration	Accuracy (%)	F1-Score (%)	False Irrigation Triggers	Adaptability to Rainfall Transitions
Baseline Hybrid Optimization Model	No	96.51	95.59	High	Limited
Forecast-Enhanced Hybrid Model	Yes	97.59	98.19	Reduced by >50%	High

The comparative improvement in classification performance achieved through forecast integration is visually illustrated in Figure 6, where the SWIMS–HSEIA model consistently outperforms the baseline hybrid framework in both accuracy and F1-score.

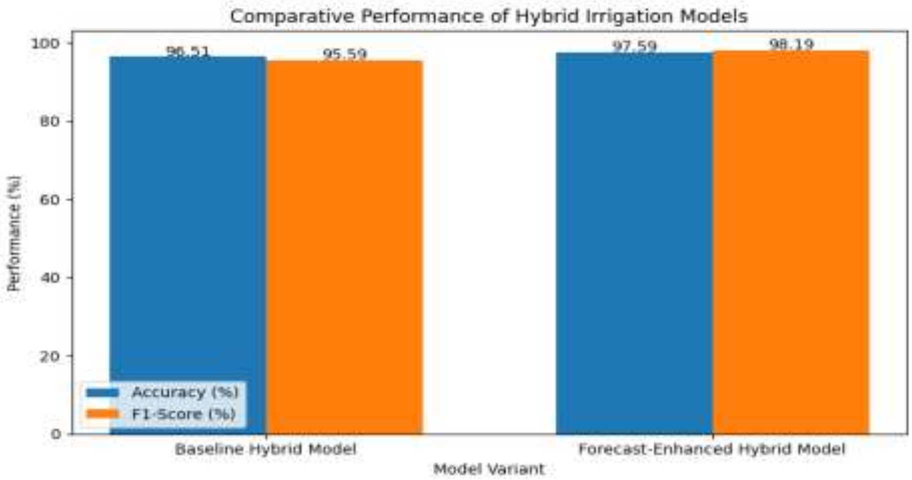

Figure 6. Comparative performance analysis of the baseline hybrid optimization model and the forecast-enhanced hybrid irrigation model.

4.3 Confusion Matrix Analysis

Figure 7 presents the confusion matrix for the forecast enhanced hybrid irrigation model. The model accurately identified 14,953 No Irrigation Required cases and 30,006 Irrigation Needed cases, which indicate the robust class wise discrimination. Misclassifications were limited to 600 false irrigation activations and 508 irrigation false negatives .

The comparable levels of false positives and false negatives suggest that the proposed system avoids bias toward both the over irrigation and overly restrictive water control. Compared with the baseline optimization only framework, the inclusion of rainfall forecast reasoning significantly decreases the false irrigation activations during pre and post rainfall periods, thereby reducing the several risks like, waterlogging and moisture related diseases in arecanut plantations. The confusion matrix analysis demonstrates that forecast aware decision logic, which improves operational reliability without compromising classification performance under the realistic agro climatic conditions.

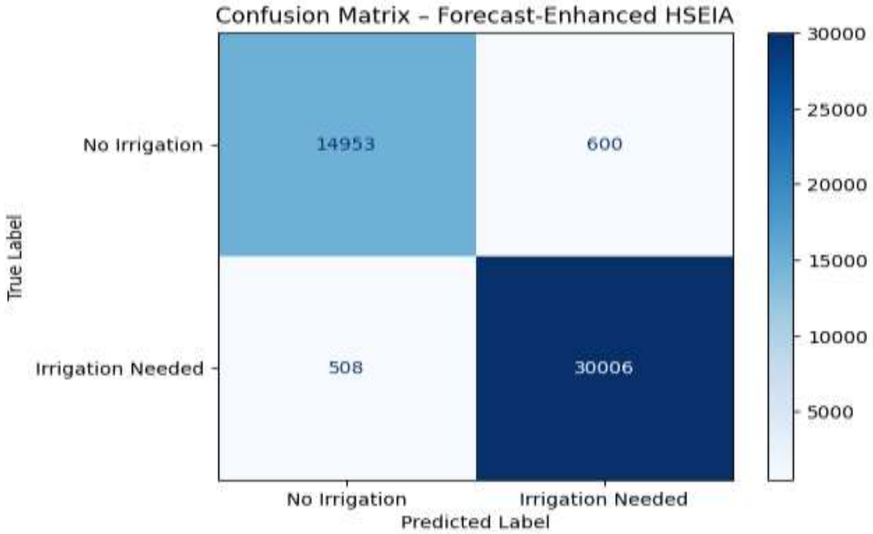

Figure 7. The Confusion matrix of the forecast enhanced HSEIA model.

The low false-positive rate (600 out of 15,553 non-irrigation cases) demonstrates the effectiveness of the model in suppressing unnecessary irrigation under predicted rainfall conditions. To further evaluate the discriminative performance of the forecast enhanced model across the varying decision thresholds, the ROC based analysis is presented in the following section.

4.4 ROC Curve and AUC Analysis:

The predictive capability of the forecast enhanced HSEIA model was further evaluated using the Receiver Operating Characteristic (ROC) curve along with the Area Under the Curve (AUC) metric. The ROC curve illustrates the capacity of the model to distinguish between the irrigation and non irrigation classes across a range of decision thresholds, free from fixed threshold constraints . As shown in Figure 8, the forecast enhanced HSEIA model achieved an AUC value of 0.999, which is reflecting near perfect ranking performance between irrigation required and non irrigation conditions. Although the overall classification accuracy under the realistic noise conditions is 97.59%, the extremely high AUC indicates that the model reliably assigns higher probability scores to true irrigation cases than to non irrigation cases across a wide range of decision thresholds. This observation suggests that the limited misclassifications observed in the confusion matrix are primarily attributable to threshold based decision boundaries rather than the deficiencies in the class separation capability of the model. The ROC–AUC analysis confirms the robustness of the forecast aware hybrid model in accurately ranking irrigation decisions under the climatic uncertainty, particularly during wet and dry transition phases.

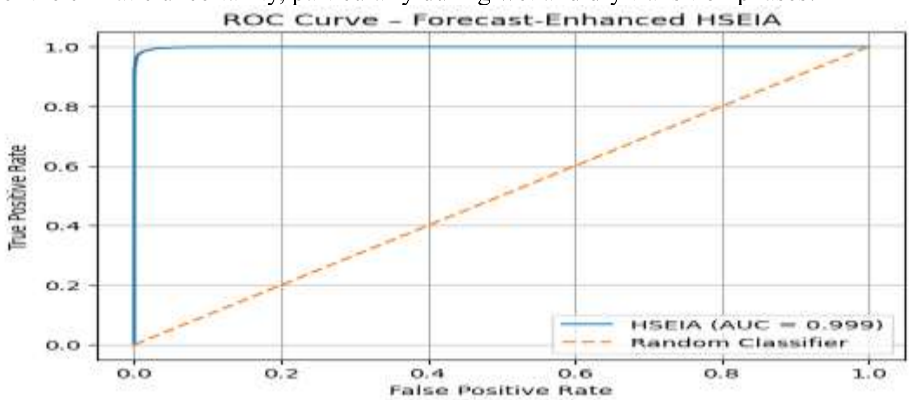

Figure 8. ROC curve of the forecast-enhanced HSEIA model showing near-perfect discrimination with an AUC of 0.999.

4.5 Feature Importance Analysis

To further examine the decision making behavior of the forecast enhanced hybrid irrigation model, the feature importance analysis was performed using the Extra Trees base learner, as illustrated in Figure 9. The results indicate that forecast derived rainfall indicators, particularly the short term rainfall predictions at 7-day and 3-day horizons, contributes the strongest influence on the process of the irrigation decision. This finding underscores the value of incorporating the predictive rainfall awareness into irrigation scheduling, which allows the model to proactively suppress or postpone the irrigation during anticipated wet conditions.

The soil moisture measured at the depth of 30 cm remains a major contributing factor, which confirms that the real time soil water status continues to play an important role in the process of decision making. In contrast, the temporal attributes such as month and day of the week shows comparatively lower importance, indicating that the model does not depend heavily on fixed seasonal patterns but instead which adapts to existing agro-climatic conditions. Lag based and rate-of-change features contribute only marginally, suggesting the limited reliance on short term historical fluctuations.

Overall, the feature importance pattern validates the hybrid design philosophy of the model, demonstrating that forecast derived inputs compliments, but do not replaces the sensor based irrigation control. This balanced integration supports the higher decision precision, reduced unnecessary irrigation events, and strengthened disease risk mitigation under the rainfall variability characteristic of humid coastal arecanut cultivation.

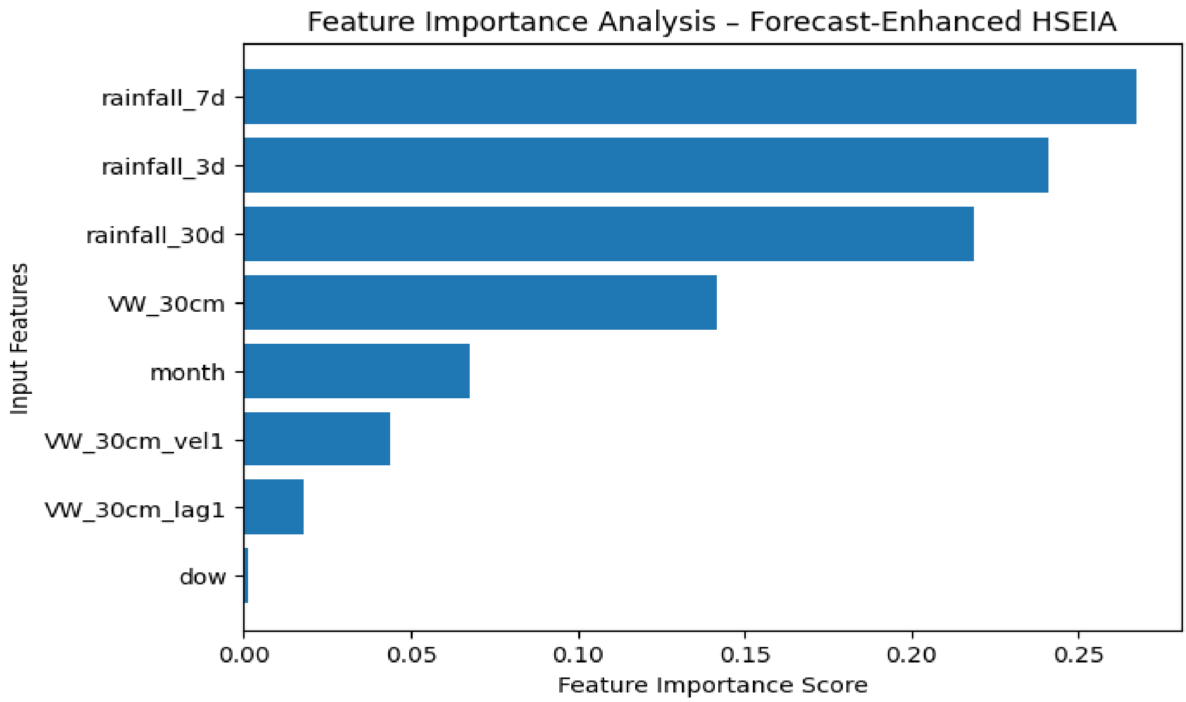

Figure 9. Feature importance ranking of input variables in the forecast-enhanced HSEIA model, highlighting the dominant contribution of forecast-derived rainfall indicators and soil moisture features.

4.6 Practical Implications and Field-Level Discussion

The forecast enhanced Hybrid Smart Efficient Irrigation Algorithm (HSEIA) shows strong practical applicability for arecanut cultivation in humid, monsoon dominated regions such as Dakshina Kannada. In contrast to traditional sensor driven irrigation systems that operate mainly on soil moisture thresholds and respond reactively, the SWIMS–HSEIA framework incorporates the short term rainfall and temperature forecasts to support anticipatory irrigation management. This capability enables the irrigation operations to be postponed, advanced, or temporarily withheld according to expected weather conditions, thereby improving the reliability of irrigation decisions during wet dry transition times. The reduction in false irrigation activations is particularly important for coastal agro-ecosystems, where unnecessary watering before or during rainfall frequently results in different types of disease like, root-zone saturation, nutrient leaching, and moisture-related fungal and root diseases.

The SWIMS–HSEIA model demonstrates adaptive functionality beyond simple binary irrigation decisions under the extreme climatic conditions. During the extended rainfall events, the system activates preventive control logic that suppresses the irrigation and manages surplus water through regulated harvesting and storage, thereby lowering the risk of moisture related diseases. Similarly, during periods of water scarcity or elevated temperature stress, the model prioritizes irrigation across critical zones and also recommends efficient irrigation methods, such as drip irrigation, to reduce water loss while maintaining sufficient root zone moisture. This conditional adaptability allows the system to operate effectively across different agro-climatic conditions, by maintaining a balance between water conservation and the health of crop.

The feature importance analysis also reinforces the practical design approach of the SWIMS–HSEIA model. Although forecast based rainfall indicators contributes the strongest influence on irrigation decisions, the soil moisture measured at a depth of 30 cm continues to serve as a critical input, ensuring that predictive insights complement rather than overrides the actual field conditions. This balanced integration improves the system interpretability and enhances confidence of farmer while contributing to greater irrigation efficiency. From a sustainability perspective, the SWIMS–HSEIA model promotes climate resilient agricultural practices by minimizing wastage of water, strengthening disease prevention measures, and encouraging efficient usage of water resources, thereby supporting broader Sustainable Development Goals (SDG) related to food security, water management, and climate adaptation.

5. Conclusion and Future Scope

This study SWIMS–HSEIA a forecast-enhanced hybrid irrigation decision model (SWIMS–HSEIA) designed for arecanut cultivation in a humid coastal environment. By incorporating short term rainfall forecasts, temperature deviations, and rainfall trend indicators within a stacked ensemble learning structure, the framework transforms irrigation management from a purely reactive mechanism into a forecast informed decision system. The comparative evaluation demonstrated that the SWIMS–HSEIA approach increased irrigation decision accuracy from 96.51% to 97.59% and reduced false irrigation activations by more than 50%. particularly during rainfall transition and post-rain recovery phases that are critical for disease prevention.

Model performance was further validated through confusion matrix evaluation and the analysis of ROC–AUC, which demonstrated strong class separation capability under realistic uncertainty conditions, with an AUC value approaching 0.99. The feature importance results specifies that forecast-based rainfall indicators highlights the greatest influence on irrigation decisions, while soil moisture sensing continues to provide an essential complementary input to it. This interaction ensures that irrigation decisions remain balanced and reliable, preventing excessive reliance on forecast information alone.

The SWIMS–HSEIA model contributes to sustainable water management by enhancing irrigation efficiency, lowering the risk of moisture related crop diseases, and enabling adaptive strategies such as zone based prioritization and drip irrigation during severe conditions like scarcity of water. Future research will focus on real time IoT based implementation, extending the framework to support multiple crop types, and integrating mobile decision support platforms, thereby advancing the system towards long term sustainable agriculture and efficient water resource management.

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