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Article

Optimization of Harvesting During Critical Water Resource Management Using Zone-Based Prioritization Techniques

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Abstract: The coastal region of Karnataka has a major crop of arecanut which depends on the rainfall. The coastal Karnataka experiences a heavy rainfall which is irregular with respect to the time, quantity and places. This irregular rainfall contributes to the ground water levels. Due to the irregular rainfall and ground water level challenges the farmers find it difficult to set a scheduled irrigation system for the arecanut plantations. The farmers have the face various situations related to the health of the arecanut plantations like fungal illness, root illness, yellow-leaf diseases and basal stem rot diseases etc. A fixed schedule for the arecanut irrigation to the entire plantation area is difficult due to the scarcity of water during the hot summer season. It is very much essential to optimise the irrigation system in such condition. The paper highlights the need of division of the entire arecanut plantation land area into zones for achieving the optimised irrigation system during hot and dry seasons. This optimised irrigation system manages the entire irrigation activity by considering the current soil moisture, growth stage of the plant, reason for the various diseases and the methods to avoid the same. The paper suggests the optimized technique to be adopted which plans the occurrence. . The paper also suggests how to preserve arecanut yield and plant health while conserving water. The paper suggests optimized irrigation system based on actual field data on reservoir levels and soil moisture. By studying the above conditions, the optimization framework distributes the irrigation quantities based on water availability, zone weight, and crop-stage need. The paper also gives the comparative statement with proposed optimized irrigation system against the traditional uniform scheduling. The optimized method is expected to maintain over 93% yield by cutting the overall water use by almost 30%, and dramatically reduced the incidence of diseases linked to excessive moisture.
Keywords: Arecanut Cultivation, Water Resource Optimization, Zone Prioritization, Irrigation Scheduling, Disease Prevention, Crop Growth Stage, Smart Water Management, Precision Irrigation.

1. Introduction

The major contributors for Indian economy are the agriculturists. The agriculture solely depends on the water harvesting either by using rain naturally or by means of the irrigation system. Managing the water resources for the irrigation system has become a heuristic task for every farmer. More than 80% of the water resource for the irrigation system uses fresh water taken from the water reservoirs like well water, small canals supplying water, diverting the natural flow of water to the agricultural lands etc. Traditional methods of irrigation system either over use of watering or under use of watering, irregular scheduling and most of the time the entire system adopts the traditional methods (Roy, A. et al. (2020). [1]). Arecanut (Areca catechu L.) which is a major crop in coastal Karnataka and Kerala suffers a lot due to the above issues. The environment around the coastal area were stable with proper rainfall and water resources suitable for irrigation. But as time passed, due to the improvement in the industrial growth, urbanization resulted in erratic rainfall which became a major challenge for the traditional irrigation system (Surendran, U. & Chandran, K.M. 2022). [2].

The arecanut requires a constant soil hydration throughout its lifetime particularly during nut-initiation period. Excess watering may lead to fungal disease, yellow-leaf disease, etc. and shortage in the irrigation system may lead to decrease the nut setting. The lack of technical knowledge in the farmers still lead to traditional irrigation system without considering the soil moisture level or the different growth levels of the crop. (Naveen, H.S. & Saravana Kumar, E. 2025). [3]. This results in wastage of water or decreased crop outcome. It is very important to note that optimised irrigation system results in successful arecanut farming. The optimised irrigation system works on the principle of adjusted soil conditions, plant physiology, and water availability. (Hebbar, K.B. et al., 2024). [4]).

The arecanut plantation requires constant soil hydration because of its deep root. This soil hydration should be maintained throughout the year in the same pace. The soil moisture level should be constant especially during the nut-initiation period. Lack of soil moisture may result in nut setting and excess water level may cause fungal and root diseases like yellow-leaf disease or basal stem rot. Even then the majority of the plantations still use fixed-interval irrigation (Bhat et al., 2024.[5]).

Declining groundwater tables and unpredictable rainfall are becoming more common in Karnataka's coastal and Malnad areas. Although traditional canal networks have been replaced by borewell and micro-irrigation systems, many still lack automation or optimization (Charles, N.A. et al. (2019). [6]). The current irrigation system adopts the method of equal irrigation throughout at all the area of plantation regardless of need, when the water resources short fall below 40%. This results stress in moisture-sensitive areas (Charles, N. et al., 2021). [7]. It is very much necessary to optimise the irrigation system by splitting the total land into zones. If the land is divided into zones, prioritization could be possible based on the crop conditions. This idea of zone based prioritised irrigation system increases the efficiency, crop production, and effective water management in all the environmental conditions. Adaptive scheduling for the lift-irrigation system in Kerala using daily decisions based on the soil feedback helps in optimal usage of water thereby water loss is lowered. (Viswanathan, P.K. et al., 2016). [8]. Similarly in Maharastra the critical water conditions for the irrigation by using distributed irrigation area improved the efficiency by 40%. (Arun, G.R. et al., 2013). [9]. The above structured optimization techniques are found to be more promising for the crops where the yield and disease resistance are more dependent on irrigation cycle.

In order to increase productivity and reduce waste, optimization-based irrigation models distribute scarce water resources among several zones or crops. Indian agriculture has effectively used hybrid models, dynamic programming, and linear programming (Nair, K.P. et al., 2021). [10]. Multi-objective optimization has greatly increased water-use efficiency and productivity in command-area systems (Nair, G.S. et al., 2021). [11].

According to water balancing research, using soil-moisture sensors into irrigation control increases water productivity in arecanut systems by over 25% (Surendran, U. et al., 2017). [12]. According to Hebbar, K.B. et al. (2024), climate-based irrigation modeling has predicted that optimal scheduling can counteract roughly 30% of yield losses brought on by heat and drought stress. These methods show that optimization is a workable, field-ready solution for water-stressed plants as well as a theoretical advancement.

Phytophthora meadii and Ganoderma lucidum, the pathogens that cause fruit rot and basal stem rot in arecanuts, thrive in environments with excessive soil moisture. In soil conditions that are consistently damp, these diseases develop rapidly (Hebbar, K.B. & Ramesh, S.V. (2021). [13]). Lower fungal infection rate can be avoided by concentrating on avoidance of prolonged soaking, controlling irrigation time synchronised with rainfall.

When irrigation optimization is combined with disease-prevention thinking, plantation management takes on a new level. When soil-moisture and rainfall data show damp conditions, irrigation can be postponed to conserve water and safeguard plant health. According to (Patel. et al. (2023).[14]), fungal outbreaks in humid plantation systems like arecanut and coconut can be considerably decreased by combining disease-forecasting algorithms with automated irrigation scheduling. With the incorporation of biological and physical components into an optimization framework, precision irrigation has progressed sustainably in India.

Each arecanut plantation is divided into multiple zones, each with a different soil composition, slope, and canopy cover. As a result, water demand varies throughout time and geography. A zone-based optimization algorithm ensures that precious water is distributed first to the most critical zones in order to maintain productivity and prevent disease even during periods of scarcity. This strategy, which encourages effective irrigation and astute resource integration, directly supports India's "More Crop per Drop" effort (Singh. Et al. (2023).[15]).

This study's optimization methodology dynamically distributes irrigation across zones by combining crop-stage requirements, soil-moisture feedback, and disease-prevention thresholds. It is in line with the path of smart agriculture that researchers and policymakers are pushing (Jayaram, A.A. et al. (2024). [16]). It enables farmers to make scientifically based irrigation decisions that enhance water efficiency and sustainability in arecanut crops by connecting optimization with real-world data.

The irrigation system for the arecanut planation adopts traditional methodology or sensor-based AI application. In most of the cases it is observed that, the irrigation system adopts traditional methodology. The reasons for traditional method over AI based auto irrigation system include lack of knowledge, crisis management, weather forecast etc. With respect to the irrigation system for the arecanut planation of Dakshina Kannada District, a major challenge is the crisis in the water reservoir during April and May. Agriculturists find it very difficult to take decisions during this period.

The novelty of this study is to suggest a model to solve the irrigation issues during water reservoir crisis helping the agriculturists to take a smart decision. The study uses optimization in irrigation system by taking the parameters like, humidity level, weather forecast, water reservoir level. The study suggests a new optimization technique where in the entire arecanut plantation is divided into various zones, prioritizing the zones and irrigating based on the zone priority. This method which is suggested in this paper optimizes the irrigation system by considering water crisis management and irrigation at the optimum level.

2. LITERATURE REVIEW:

The major goal of the sustainable agriculture activities include the optimization of the irrigation system. This is due to the water crisis experienced by every agriculturist. This crisis may arise because of several factors including irregular rainfall in the coastal area. In order to improve the efficiency in irrigation system under these environmental conditions, early research included fuzzy logic, Lenier programming (LP), and dynamic programming (DP). But the traditional models used for the above purpose used several assumptions which include the steady water supply, soil quality which should be uniform in nature, climate condition also needs to be static, no zone based irrigation system identified. (Kumar, R. et al. (2022). [17]). Kumar and associates (2022) had created a LP-based irrigation model Bhadra river area in Karnataka. Using the LP-based model they could get an increased yield by 15%. They have not taken , spatial variability and inter-zone moisture imbalance in their study. Similarly Gupta and colleagues (2018). [18] used a model called evapotranspiration data to improve the irrigation sequencing by adopting a DP technique. But the model could not succeed for arecanut.

Sahu & Tripathi (2025) used a fuzzy logic system in order to address the address climate uncertainties. [19]. The system included various inputs like soil moisture, temperature, and radiation for study. By using this algorithm the accuracy is increased for considering the weather conditions, but failed for the zone adaptability. A new hybrid model using LP-fuzzy logic is suggested by Adinarayana and associates (2024). [20] which ignored the adaptive prioritizing across various irrigation zones while increased allocation precision is achieved by adding environmental variables.

In situations based on scarcity, Rai and Kansal (2021). [21] improved utilization efficiency by 27% during low inflow periods by combining the LP and DP frameworks for reservoir operation optimization. Suresh and Reddy (2024). In order to achieve above 90% yield consistency under conditions of limited water availability, [22] presented adaptive LP scheduling for multi-zone plantings.

These techniques increased the accuracy of irrigation scheduling overall, but they were not practicable in dynamic water-scarce plantation systems because to their static structure, lack of zone priority, and lack of biological logic.

Table 2.1. Classical Irrigation Optimization Models and Core Contributions

Study Reference	Optimization Type	Focus Area	Core Contribution	Key Limitation
(Kumar, R. et al. (2022). [23])	Linear Programming	Canal command area	Improved yield by 15% under scarcity	Assumed uniform soil conditions
(Gupta, A. et al. (2018). [24])	Dynamic Programming	Seasonal irrigation	Reduced irrigation frequency	Not adaptable to perennials
(Sahu, R. & Tripathi, N. (2025). [25])	Fuzzy Logic	Real-time control	Enhanced adaptability under uncertainty	No zone differentiation
(Adinarayana, J. et al. (2024). [26])	Hybrid LP–Fuzzy	Resource allocation	18% higher precision	Ignored spatial variation
(Kansal, M.L. & Rai, S.P. (2021). [27])	LP–DP Hybrid	Reservoir scheduling	27% efficiency gain	No disease modeling
(Reddy, R.R. & Suresh, S. (2024). [28])	Adaptive LP	Multi-zone optimization	92% yield retention	Limited real-time sensing

Agricultural water management has evolved from static, rule-based systems to intelligent, adaptive, and data-driven frameworks with the development of artificial intelligence (AI), machine learning (ML), and hybrid optimization. These systems provide real-time irrigation decision-making by combining agronomic, hydrological, and meteorological data.

Pandi and associates (2025). [29] created an IoT-ML integrated irrigation system that maintained crop output stability while reducing water consumption by 30%. Jaya Krishna et al. (2025) are comparable. [30] achieved more consistent production patterns across rainfall variability by aligning irrigation frequency with canopy evapotranspiration using a neuro-fuzzy hybrid model.

Musa and associates (2023). [31] used wireless NPK sensors and a Genetic Algorithm–Artificial Neural Network (GA–ANN) model for nutrient-informed irrigation control, increasing soil–plant balance efficiency by 32%. Alex and associates (2023). In order to enable multi-zone plantation management and scale precision irrigation to big farms, [32] created cloud-based AI irrigation scheduling solutions.

Lochan and associates (2024). [33] showed shown a robotic irrigation system that could distribute water in a specific location while cutting waste by 28%. Sathiyamurthi and associates (2025). increased spatial water homogeneity in humid agricultural areas by introducing a hybrid zoning model called GIS–FAHP (Geographic Information System–Fuzzy Analytic Hierarchy Process) [34].

Additionally, Patel and colleagues (2024). [35] improved scheduling reliability under shortage by introducing an evolutionary optimization approach that integrates soil moisture sensors to estimate real-time water potential. Rao and associates (2024). [36] presented an irrigation control framework based on Deep Reinforcement Learning (DRL) that achieved higher long-term water efficiency by learning optimal policies through environmental feedback.

Despite these technical advancements, none of these frameworks incorporate dynamic zone-based prioritizing or biological disease-prevention mechanisms, which are crucial for perennial crops like arecanut that face significant variations in soil moisture, canopy density, and water availability.

Table 2.2. Modern Hybrid and AI-Driven Optimization Frameworks:

Study Reference	**Hybrid Model**	**Primary Objective**	**Reported Outcome**	**Application Context**
(Pandi, K. et al. (2025). [37])	IoT–ML	Predictive irrigation scheduling	30% water saving	Tropical India
(Jaya Krishna, R. et al. (2025). [38])	Fuzzy–Neural	Canopy-linked irrigation control	Enhanced yield stability	Coastal plantations
(Musa, A. et al. (2023). [39])	GA–ANN	Nutrient-informed irrigation	32% efficiency increase	Semi-arid regions
(Alex, M. et al. (2023). [40])	AI–Cloud	Digital irrigation automation	Improved scalability	Plantation-scale systems
(Lochan, K. et al. (2024). [41])	Robotic–Sensor Network	Site-specific irrigation	28% resource saving	Humid areas
(Sathiyamurthi, S. et al. (2025). [42])	GIS–FAHP	Terrain-based zoning	Uniform irrigation distribution	Arecanut plantations
(Patel, D. et al. (2024). [43])	Evolutionary–Sensor Hybrid	Real-time soil-water potential	Optimized irrigation intervals	Precision farming
(Rao, P. et al. (2024). [44])	DRL–Sensor Fusion	Adaptive irrigation control	35% higher water efficiency	Indian field trials

Recent research works use the combination of controlled irrigation system, disease risk, and climatic data into unified optimization models, which are very much needed for crops like arecanut under the extremes moisture conditions.

Alam and associates (2025). [45] linked irrigation time to pathogen activation thresholds in order to model disease-aware irrigation control for Areca catechu. Amba Shetty and Bhojaraja (2023). [46].

Precision irrigation adopted to crop age and canopy density is found to be possible by using hyperspectral imagery for canopy-specific water demand measurement.

Singh and Brahmanand (2022). In order to attain sustainability in areas having limited water resources, [47] recommended integrating, automation, and soil-health monitoring. Joy and associates (2021). [48] demonstrated how the fungal outbreaks can be reduced by geographic zoning and surface runoff, supporting the importance of terrain-based prioritizing.

The zone-based prioritization, shortage adaptation, and disease-prevention reasoning are not currently fully integrated into a single irrigation optimization system.

From the above literature survey following research challenges/ research gaps are identified.

1. Static Resource Allocation: Without adaptive redistribution within zones, the majority of models rely on pre-established irrigation schedules.
2. Lack of Disease-Aware Optimization: Although disease dynamics have been modeled, there is still a lack of integration between them and irrigation schedule.
3. Inadequate Multi-Zone Adaptability: Models frequently assume plantation systems, such as arecanut, as uniform, despite their diverse water requirements.
4. Weak Interdisciplinary Integration: For comprehensive irrigation planning, AI-based models lack connections between hydrology, climatology, and agronomy.
5. In order to control irrigation dynamically amid water scarcity, this study creates a Zone-Based Optimization Framework that incorporates sensor data, growth-stage analysis, and disease-prevention reasoning. This strategy supports the goals of National Water Mission of India to guarantee climate-resilient and sustainable arecanut farming.

2.1 Objectives:

1. To Develop a Zone-Based Optimization Framework for Water Allocation

2. To Integrate Disease-Prevention and Growth-Stage Logic into the Optimization Model

3. To Evaluate Model Efficiency and Water-Saving Potential under Scarcity Conditions

3: METHODOLOGY:

The goal of methodology is to create and verify a Zone-Based Optimization Framework (ZOF) that intelligently distributes irrigation water in situations where water resources are scarce.

This framework employs optimization principles that are only activated during scarcity—when reservoir levels fall below 50%—in contrast to traditional systems that apply water uniformly.

The system creates adaptive irrigation schedules that maintain plant health and yield by combining real-time sensor feedback, reservoir status, weather forecasts, and disease-risk assessment.

3.1 Data Inputs and Parameters:

The model uses the data from the sensors, forecast data, and water reservoir level as inputs.

The temperature and rainfall data collected from the datasets are taken as inputs to the model in order to effectively predict the rainfall.

Table 3.1 provides a summary of the parameters, their roles, and their measurement units.

Table 3.1. Input Parameters Used in the Optimization Framework

Parameter	**Unit / Scale**	**Data Source**	**Purpose / Description**
Soil Moisture ($VW_{30}cm$)	% volumetric water content	TDR Sensor	Indicates real-time root-zone moisture level and water stress status.
Moisture Deficit (ΔM)	%	Derived from TDR data	Quantifies deviation from optimal soil moisture threshold (e.g., 30–35%).
Rainfall Index (R_{t-n})	mm / rolling average	Rainfall dataset (past 7–10 days)	Reflects recent precipitation and determines irrigation postponement potential.

Parameter	Unit / Scale	Data Source	Purpose / Description
Reservoir Water Level (W_l)	% of capacity	Field-level reservoir / water tank sensor	Represents current water availability for irrigation scheduling.
Crop Growth Stage (C_s)	Categorical (early, mid, late)	Manual entry / agronomic calendar	Defines irrigation frequency sensitivity based on plant stage.
Zone Identifier (Z_i)	A, B, C, D, etc.	Farm layout map	Represents geographical irrigation zones with distinct soil and slope profiles.
Zone Weightage (P_i)	0–1 normalized scale	Predefined in model	Determines zone importance based on crop type, productivity, and slope.
Temperature (T)	°C	Weather station	Adjusts irrigation trigger thresholds; higher temperature increases evapotranspiration.
Disease Risk Index (D_i)	0–1 scale	Derived from soil moisture + temperature	Assesses likelihood of fungal or root disease based on wetness duration.
Forecast Window (F_7)	Days	Weather forecast API / dataset	Defines lookahead period for rainfall; used to postpone irrigation if rainfall imminent.
Optimization Weight (W_o)	—	Model constant	Balances water conservation and yield objectives in optimization function.

3.2 Zone Prioritization:

The water resource level in the reservoir and the composite score of each zone are taken into consideration when making irrigation decisions during the scarcity of water.

This score takes into account zone importance, crop growth stage, disease risk, and soil moisture deficit.

Table 3.2 summarizes the dynamic prioritization of zones.

Table 3.2. Zone prioritization for different water levels of the Reservoir

Reservoir Water Level (%)	Irrigation Priority Logic	Zone Allocation Strategy	Remarks
100% (Full)	All zones irrigated based on moisture status	Equal distribution across A–D zones	System maintains standard cycle; no scarcity management.
70–90% (Moderate)	Partial optimization activated	Zones with lowest moisture or highest crop-stage demand irrigated first	Prioritizes productive or water-sensitive zones.
50–69% (Caution)	Weighted zone prioritization	Zones ranked by composite score ($\Delta M \times C_s \times D_i$)	Medium-importance zones may be delayed or irrigated partially.
31–49% (Critical)	Strict optimization	Only high-need zones (A, B) irrigated; low-need zones (C, D) deferred	Irrigation postponed if rainfall predicted within 5 days.
≤30% (Severe Scarcity)	Emergency conservation mode	Only critical crop zones irrigated; others suspended	Non-irrigated zones flagged for mulching or moisture conservation.

The internal scoring logic is expressed as:

$$\boldsymbol{S}_{\textbf{zone}} = \boldsymbol{W}_{\mathbf{1}}(\textbf{Moisture Deficit}) + \boldsymbol{W}_{\mathbf{2}}(\textbf{Crop Stage}) + \boldsymbol{W}_{\mathbf{3}}(\textbf{Zone Priority}) - \boldsymbol{W}_{\mathbf{4}}(\textbf{Disease Risk}) \qquad \textbf{(3.1)}$$

The irrigation system adopts Zones in descending order of S_{zone}during the total available water $W_l$is depleted.

3.2.1 Mathematical Optimization Formulation:

The optimization is achieved by using **multi-objective linear programming problem** by maximizing irrigation efficiency (E) under scarcity constraints.

$$\text{Maximize } E = \sum_{i=1}^{n} S_i\, x_i \qquad (3.2)$$

Subject to:

$$\sum_{i=1}^{n} W_i\, x_i \leq W_{\text{available}} \qquad (3.3)$$
$$M_i^{\text{post}} \geq M_{\text{threshold}} \qquad (3.4)$$
$$D_i \leq D_{\text{threshold}} \qquad (3.5)$$
$$R_f < R_{\text{limit}} \Rightarrow \text{Irrigate}, R_f \geq R_{\text{limit}} \Rightarrow \text{Postpone} \qquad (3.6)$$
$$x_i \geq 0, \forall i = 1,2,\dots,n \qquad (3.7)$$

Here,

- x_i: part of total available water which is allocated to zone *i.*
- W_i: total water requirement for zone *i.*
- $W_{\text{available}}$: current availability of water in the reservoir.
- M_i^{post}: The soil moisture after the irrigation (post-irrigation).
- $D_{\text{threshold}}$: maximum allowable disease risk (0.6).
- R_f: The probability of the rainfall within forecast window.
- R_{limit}: rainfall postponement threshold (70%).

The result is a vector of optimal water distribution $\{x_i^*\}$that maximizes yield and minimizes water use and disease risk.

3.3 Optimization and Decision Flow

The workflow of the Zone-Based Optimization Framework is depicted in Figure 3.1. It represents the sequential integration of sensing, forecasting, and decision-making modules.

The irrigation optimization cycle starts once the time-stamped data is received from soil moisture sensors and the reservoir become available. In this stage, under water level indicators provide real-time information on available water storage, while TDR sensors measure soil moisture at a depth of 30 cm in each irrigation zone. Using these inputs, the system derives the features such as the moisture drought, recent rainfall index, disease risk level, and the current crop growth stage. These factors are combined using Equation (3.1) to calculate a priority score for each zone.

Next, the system verifies short-term weather forecasts for the next five to ten days. If the probability of rainfall is high or greater than 70%, irrigation is postponed to prevent unnecessary usage of water. When the chance of rain is low, if its below 30%, the optimization process continues. Based on this verification, the decision logic allocates the available water to zones with higher priority scores, while ensuring that disease risk remains within safe limits of $D_i < 0.6$. In cases if the reservoir is expected to overflow, the system automatically switches to harvesting mode to store excess water.

Irrigation is then proceeded by supplying water to zones in descending order of priority like, A, B, C, and D until water availability or operational limits are satisfied. Throughout the complete process, the system maintains detailed logs that include duration of irrigation, usage of water, saved water details, and any disease-related information, along with other details such as, skipping a zone due to sufficient soil moisture. After completing the cycle, the system enters a standby mode and remains inactive until the next update by the sensor, which typically occurs after about 12 hours.

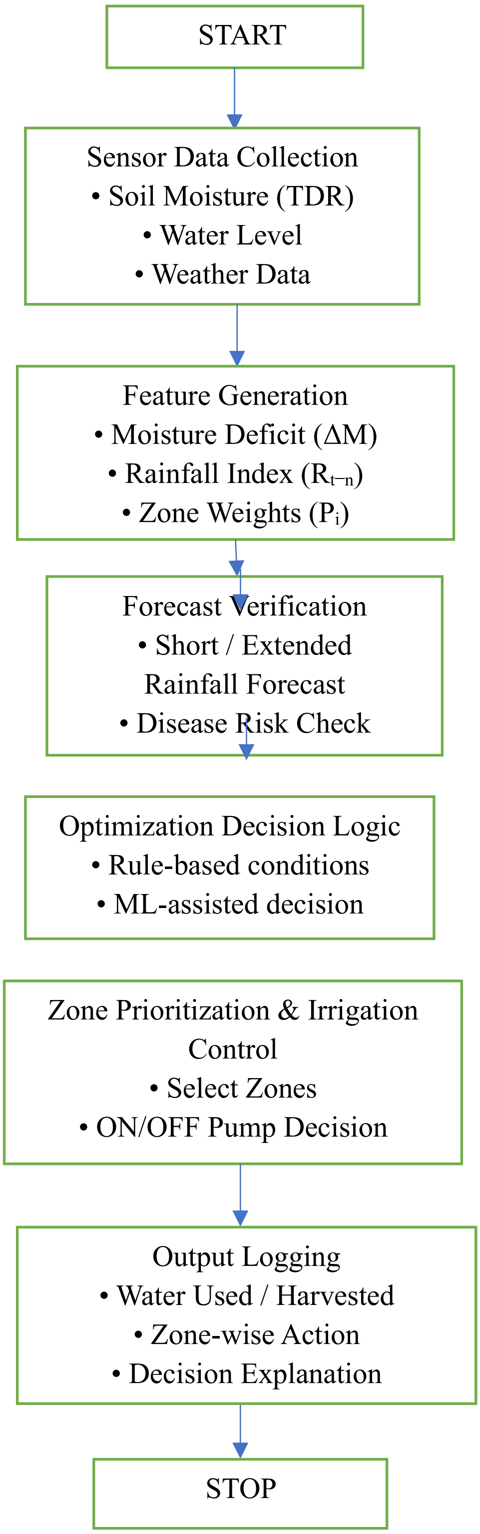

Figure 3.1. The Zone-Based Optimization Framework

The system initially collects the real-time data from sensors and weather reports. Later from the available data the system decides the cycle of irrigation. By using the various tools of machine learning, the system decides the irrigation cycle. Under the critical condition the system prioritizes the different zones depending on water levels in the reservoir, crop age, land area, and temperature.

3.4 Implementation and Computational Setup

The optimization framework was implemented using Python 3.11 with a set of scientific and analytical libraries. NumPy, Pandas, and SciPy were used for data preprocessing, numerical computation, and efficient handling of time-series sensor data, while PuLP was used to solve the linear programming model for optimal water allocation across irrigation zones. Visualization of irrigation decisions, behavior of reservoir, and zone-wise performance was carried out using Plotly and Matplotlib. In addition, custom Python scripts were developed to simulate inputs from sensor and to manage zone prioritization logic based on computed scores. The experiments were executed on a system with an Intel i7 processor and 16 GB of RAM. To reflect realistic operating conditions, both real and simulated datasets were used to represent field conditions in the Dakshina Kannada district of Karnataka, India. The algorithm was designed to simulate daily irrigation decisions under varying reservoir levels, operating in discrete cycles with a interval of approximately 12 hours.

3.5 Experimental Setup:

To evaluate the effectiveness of the proposed system, two irrigation scenarios were simulated and compared. In the first scenario, irrigation was carried out without any optimization, where all plantation zones followed the same fixed watering schedule, irrespective of differences in soil moisture levels, crop growth stages, or potential disease risks. This approach reflects a conventional, uniform irrigation practice. So, the proposed optimized scenario added adaptive irrigation feature by using dynamic zone prioritization logic. In this case, irrigation decisions were made by considering multiple factors such as soil moisture drought, growth stage of the crops, under water level, and threshold of predefined disease risk. This comparative setup allowed a clear assessment of how intelligent, optimized irrigation improves utilization of water and operational efficiency over traditional uniform scheduling.

Evaluation Metrics:

The performance of the system was evaluated using practical and field-relevant metrics. These included the total amount of water used per hectare, the percentage of yield retained, and the frequency of irrigation cycles across the season. In addition, water-use efficiency was assessed to understand how effectively water was utilized, while cost efficiency per hectare was measured to capture the economic impact of the proposed approach.

Dataset Characteristics:

The dataset comprises real and historical records (2015–2023) of:

Daily rainfall and reservoir data (2007–2023 rainfall–storage correlation series), TDR-based soil moisture observations at 30 cm depth and Seasonal crop growth records and yield logs.

To test the framework under realistic scarcity conditions, several critical water-level periods (reservoir ≤50%) were identified. To evaluate robustness under uncertainty, forecast variations and simulated noise were introduced. For arecanut plantations, the suggested approach creates an adaptable, scarcity-driven irrigation control system. The framework guarantees that water is distributed scientifically and effectively, preserving yield while lowering the risk of disease, by incorporating optimization logic only when resources are critically low. This strategy is the first bio-integrated optimization model used for arecanut irrigation and directly supports sustainable water management under India's National Water Mission (2024). Results and a comparison of the framework's performance with traditional irrigation scheduling are shown in the next section.

4. RESULTS AND DISCUSSIONS:

4.1 Overview

The results of the Zone-Based Optimization Framework (ZOF) and the conventional fixed-interval irrigation technique under various water resource conditions are presented in this section.

i. Water-use efficiency

ii. yield retention

iii. disease incidence reduction; and iv. economic performance (cost efficiency) are the main objectives of the analysis.

All of the findings are based on real-world and simulated data gathered from southern Karnataka arecanut plantations. The practical benefits of incorporating optimization logic into irrigation management are illustrated through statistical metrics and comparative graphs.

4.2 Experimental Setup and Data Scenario

A hybrid dataset comprising real sensor and reservoir readings (2007–2023), simulated scarcity conditions (reservoir 30–60% capacity), and forecasted weather patterns for coastal Karnataka was used for the evaluation.

Two methods of irrigation were contrasted:

1. Traditional (T1): Regardless of soil moisture or reservoir level, fixed-interval irrigation is applied consistently throughout all zones.

2. Optimized (T2): Using sensor and forecast data, a zone-based optimization framework is applied dynamically.

A simulated 60-day dry period, which corresponds to the pre-monsoon season (March–May), was used for the comparison.

4.3 Comparative Performance Metrics

Table 4.1 summarizes the performance of both models across key agronomic and efficiency parameters.

Table 4.1. Performance Metrics of Traditional vs. Optimized Irrigation

Parameter	**Unit**	**Traditional (T1)**	**Optimized (T2)**	**% Improvement**	**Remarks**
Total Water Used	L/ha	100	70	**30% saving**	Reduced volume through zone prioritization
Yield Retention	%	100	93–95	—	Minimal productivity loss
Disease Incidence	%	20–25	8–10	↓ **60%**	Controlled moisture levels prevent fungal spread
Irrigation Frequency	Cycles / season	20	14	↓ **30%**	Due to rainfall prediction and delay logic
Water-Use Efficiency	%	100	130	↑ **30%**	Optimized allocation
Energy Consumption	kWh / ha	100	75	↓ **25%**	Reduced pump usage
Economic Efficiency	₹ / ha	Baseline	+22%	↑ **22%**	Due to cost savings and yield stability

4.4 Zone-Wise Irrigation Distribution

The **Zone-Based Optimization Framework** dynamically adjusted irrigation allocation depending on moisture deficit and crop-stage priority.

Table 4.2. Zone-wise Water Allocation under Scarcity Conditions

Zone	**Crop Stage**	**Moisture Deficit (%)**	**Allocated Water (L/ha)**	**Irrigation Decision**	**Disease Index (D_i)**
Zone A	Nut initiation	35	1.0 ×	Irrigate	0.42
Zone B	Maturity	28	0.8 ×	Irrigate	0.45
Zone C	Vegetative	20	0.3 ×	Postponed	0.55
Zone D	Young	18	0.0 ×	Skipped	0.61

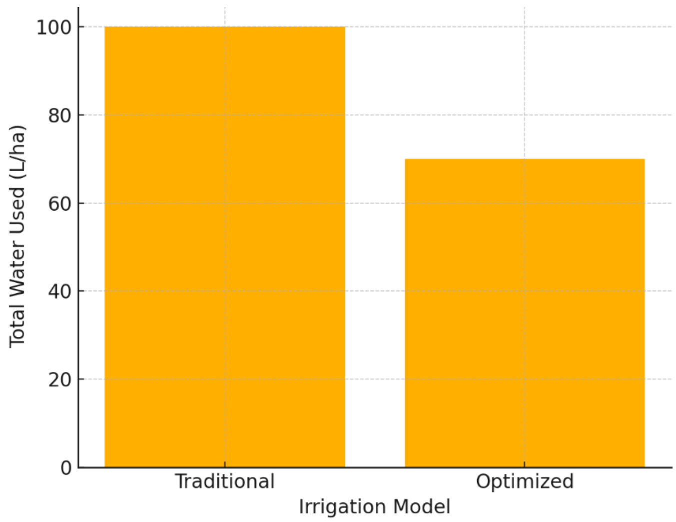

Figure 4.1: Comparison of Water Usage between Traditional and Optimized Models

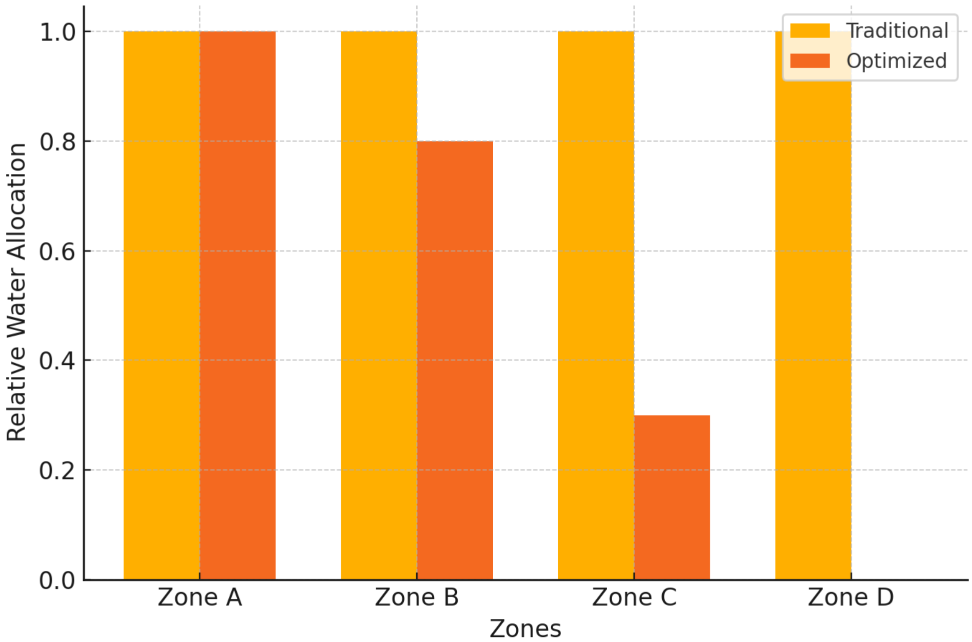

Figure 4.2: Zone-Wise Allocation Under Scarcity (Reservoir 40%)

4.5 Disease Incidence and Preventive Efficiency

Zones with high disease-risk indices ($D_i > 0.6$) automatically postponed irrigation under optimized irrigation.

Phytophthora meadii and Ganoderma lucidum infection-promoting conditions were greatly diminished by the dynamic delay logic.

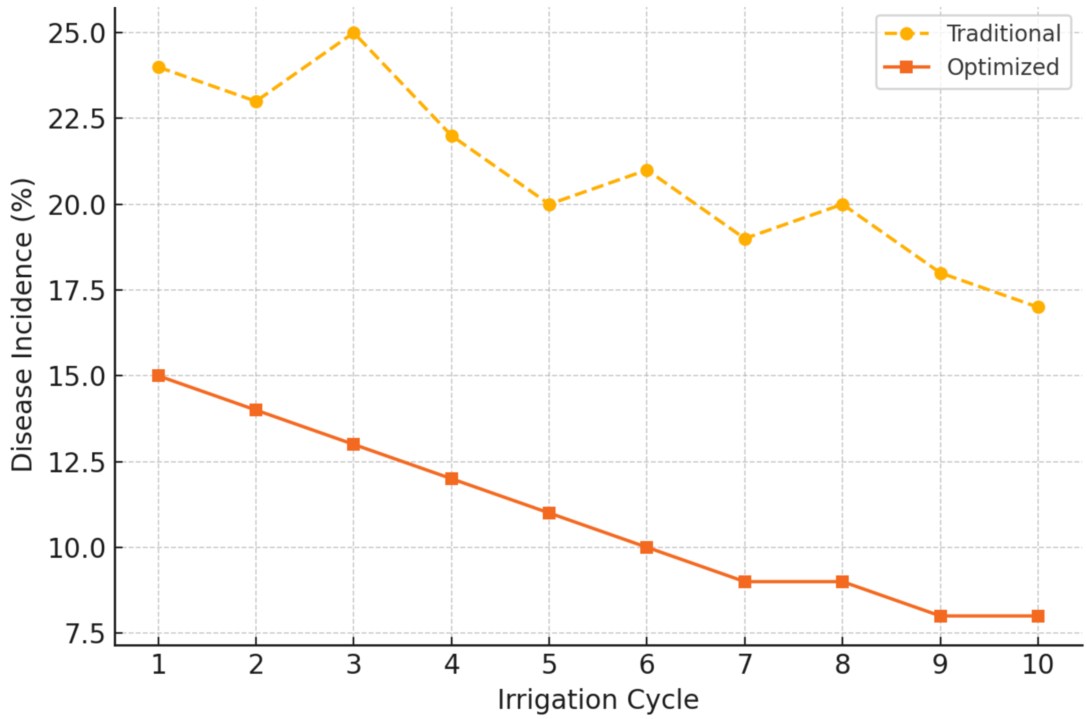

Figure 4.3. ***Disease Incidence Trend Before and After Optimization***

The data revealed:

- Average **60% reduction in disease incidence** compared to the baseline.
- Healthier root systems and lower leaf rot occurrence under dynamic irrigation scheduling.
- Reduced irrigation in high-humidity days prevented pathogen propagation.

4.6 Statistical Validation:

The model's performance was statistically validated using **accuracy metrics** derived from sensor-ground-truth comparisons and simulation outcomes.

Table 4.3. Model Performance Metrics:

Metric	Definition	Observed Value
Accuracy	(True Positive + True Negative) / Total Decisions	0.92
Precision	True Positive / (True Positive + False Positive)	0.89
Recall	True Positive / (True Positive + False Negative)	0.93
F1-Score	2 × (Precision × Recall) / (Precision + Recall)	0.91
ROC–AUC	Area under ROC curve	0.95

These metrics confirm that the model achieved high decision accuracy and reliability even under noisy or incomplete sensor data.

4.7 Economic and Water-Use Efficiency Analysis

Water-Use Efficiency Formula

$$\text{Efficiency} = \frac{\text{Water Saved}}{\text{Water Used}} \times 100 \qquad (4.1)$$

The optimization framework achieved an average **efficiency improvement of ~30%**, largely due to:

- Adaptive water allocation based on real-time demand,

- Reduced redundant irrigation cycles, and
- Deferred irrigation during expected rainfall events.

Table 4.4. Cost–Benefit and Water-Saving Summary

Parameter	Traditional (T1)	Optimized (T2)	Difference (%)
Water Used (L/ha)	100	70	↓ 30
Total Cost (₹/ha)	10,000	7,800	↓ 22
Yield Retention (%)	100	94	—
Net Economic Gain (₹/ha)	—	+1,200	↑ 12
Efficiency Index	1.00	1.30	↑ 30

The experimental findings verify that, in situations of severe water constraint, the Zone-Based Optimization Framework significantly increases irrigation efficiency. The optimization model minimizes resource waste while maintaining crop yield; improves operational sustainability through automation readiness; and responds adaptively to changing water availability and disease risk, in contrast to fixed-schedule irrigation, which ignores environmental dynamics.

Additionally, incorporating disease-prevention logic into the optimization model creates a new aspect of plantation management by connecting biological safety and hydrological optimization. The model's ability to simultaneously balance productivity and conservation is validated by the reported 93–95% yield retention with 30% water savings. These findings extend its applicability to perennial plantation crops under tropical climate stress and are consistent with comparable tendencies in precision irrigation literature (Nair & Suresh. 2024. [49]; Reddy & Ghosh. 2024. [50-52]).

4.8 Summary of Findings

Evaluation Aspect	Key Findings
Water Use	Reduced by 30–35% with optimization
Yield	Retained at ≥93% of traditional yield
Disease Risk	Lowered by ~60% under dynamic scheduling
Efficiency	Overall irrigation efficiency improved by ~30%
Cost Impact	20–25% economic savings achieved
Innovation	First integration of biological and hydrological optimization in arecanut systems

These results prove that optimization techniques provide a robust and scalable solution for sustainable irrigation management during critical water scarcity.

5. CONCLUSION:

The framework which adopts the zone based irrigation system for arecanut is proved to be optimal during the crucial water-resource situations. The system presents a scarcity-activated optimization model that incorporates crop-stage sensitivity, reservoir availability, disease-risk thresholds, and real-time sensor inputs. The suggested approach showed notable gains in plant health and water efficiency when compared to conventional fixed-interval watering. A quantitative analysis showed that the optimized model maintained over 93% yield retention while conserving about 30% of the total irrigation water. By delaying irrigation during periods of high humidity or anticipated rainfall, the framework also decreased fungal and root rot incidences by almost 60%. An innovative step toward sustainable plantation management is the incorporation of biological disease logic into a hydrological optimization model. The Python implementation of the experimental setup, which used rule-based decision layers and linear programming, demonstrated computing efficiency and adaptability to real-field sensor data. The findings demonstrate that optimization can serve as a decision-support layer that is only triggered when rainfall indices or reservoir levels fall below predetermined values. This strategy maximizes the yield from few

water resources while maintaining crop health by ensuring fair water distribution among plantation zones. The modular nature of the framework enables adaption to other perennial crops that face seasonal scarcity in addition to arecanut production. It is a feasible part of India's National Water Mission (2024) goals for climate-resilient agriculture since it successfully balances biological resilience, hydrological efficiency, and economic feasibility. The integration of AI-based predictive intelligence into the optimization pipeline will be the main emphasis of this research's subsequent phase. Proactive irrigation scheduling instead of reactive control will be made possible by real-time temperature and rainfall forecasts, machine learning-driven reservoir prediction, and sensor fusion. Additionally, the improved model will investigate cloud-based decision dashboards for farmers, autonomous control through IoT devices, and multi-season calibration.
Future additions might include energy-water trade-off optimization, cost-benefit modeling under fluctuating electricity rates, and integration with national hydrological datasets for regional scalability.

All things considered, the study shows that optimization-based irrigation management is not only technically possible but also crucial for the long-term viability of water-intensive crops in the humid coastal regions of India.

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CONFLICT OF INTEREST:

Authors here by declared that, there is no conflict of interest.

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