Installation of Rainwater Harvesting (RWH) System for Combating the Problem of Water Scarcity Using Machine Learning and GIS

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Abstract — Global water scarcity has emerged as one of the most critical environmental challenges of the 21st century, affecting over 2.3 billion people worldwide. Rainwater Harvesting (RWH) represents a sustainable, cost-effective strategy for alleviating freshwater stress, particularly in semi-arid and drought-prone regions. This study presents an integrated framework that combines Machine Learning (ML) algorithms with Geographic Information System (GIS) spatial analysis to optimize the siting, design, and operational parameters of RWH systems in the Bangalore Urban and Rural Districts of Karnataka, India. Annual average rainfall in the study area ranges from 800 mm (Doddaballapura Taluka) to 1009 mm (Bangalore North Taluka), providing substantial harvestable potential. Using multi-criteria decision analysis (MCDA) integrated with Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) models, we evaluated 14 spatial parameters including slope, soil texture, land use/land cover (LULC), drainage density, lineament density, and rainfall distribution across 5,824 km² of study area. The ML ensemble achieved an overall accuracy of 91.3% (AUC = 0.94) in delineating RWH suitability zones. GIS-based analysis identified 38.6% of the study region as highly suitable for RWH installation. Economic analysis using Benefit-Cost Ratio (BCR = 2.67), Net Present Worth (NPW = Rs. 8,240 per household), and Payback Period (PBP = 4.2 years) confirmed strong financial viability. The integrated ML-GIS model reduced site selection time by 73% compared to conventional methods and demonstrated that strategic RWH deployment could supplement 42% of annual household water demand in the region. This framework provides a scalable, replicable methodology applicable to data-scarce regions globally.

Keywords: Rainwater Harvesting; Machine Learning; Geographic Information System; Water Scarcity; Suitability Analysis; Karnataka; Random Forest; Multi-Criteria Decision Analysis

I. INTRODUCTION

Water is among the most critical natural resources sustaining human civilization. Of the approximately 1.39 billion km³ of total water on Earth, only 36 million km³ constitutes fresh water, and a mere 3% of this is accessible for human consumption (UNDP, 2006). The global population has tripled in 70 years while water use has grown six-fold, and projections indicate that within 25 years, fully one-third of the world's population will experience severe water scarcity (UNFPA, 2001). In developing nations like India, water scarcity is compounded by inequitable distribution, infrastructure deficits, and climate variability.

India, with one of the highest population densities and rapidly expanding urban centers, faces an acute freshwater crisis. The Karnataka State Water Policy mandates minimum per capita water supply standards of 40 liters per person per day (LPCD) in rural areas and 135 LPCD in city corporation areas standards frequently unmet in water-stressed zones (Karnataka State Water Policy, 2002). The Bangalore Urban District records an annual average rainfall of 936 mm, while the Bangalore Rural District averages 879 mm, with 54% of annual rainfall concentrated in the June-September South-West Monsoon season. This temporal concentration creates significant opportunities for rainwater harvesting but also challenges related to storage and distribution.

Rainwater Harvesting (RWH) the systematic collection, storage, and utilization of precipitation represents one of the most viable strategies for augmenting freshwater supplies, particularly in regions characterized by seasonal rainfall patterns. RWH approaches include rooftop catchment systems, surface runoff harvesting, check dams, percolation pits, and watershed-scale interventions (Mays, 2019). Domestic Rooftop Rainwater Harvesting (DRWH) systems, in particular, have demonstrated effectiveness in supplementing household water supplies, reducing groundwater depletion, and delivering measurable socioeconomic benefits to rural communities (Ahmed et al., 2020).

However, the effectiveness of RWH interventions is highly site-dependent, requiring nuanced understanding of local topography, hydrology, soil characteristics, land use patterns, and socioeconomic conditions. Traditional approaches to RWH site selection have relied on expert judgment and field surveys methods that are time-intensive, subjective, and difficult to scale. The integration of Machine Learning (ML) with Geographic Information Systems (GIS) offers transformative potential for addressing these limitations by enabling data-driven, spatially explicit suitability analyses at regional scale.

Machine learning algorithms, including Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), have demonstrated strong performance in hydrological applications including groundwater potential mapping, flood risk assessment, and watershed characterization (Chen et al., 2021; Arabameri et al., 2022). GIS provides the spatial analytical framework necessary to integrate heterogeneous environmental datasets and translate model outputs into actionable site selection maps. The combination of ML predictive power with GIS spatial intelligence creates a robust platform for RWH planning.

Despite the growing body of literature on individual ML or GIS applications in water resource management, limited studies have systematically integrated both approaches for RWH system planning, particularly in the Indian subcontinent context. Furthermore, most existing studies lack comprehensive economic validation of ML-GIS derived RWH recommendations. This study addresses these gaps by developing and validating an integrated ML-GIS framework for RWH suitability mapping and economic analysis in the Bangalore Urban and Rural Districts of Karnataka a region experiencing significant water stress despite moderate rainfall endowment.

A. Objectives

The specific objectives of this study are: (1) to assess the spatial distribution of RWH suitability across the study districts using ML-integrated GIS analysis; (2) to evaluate the performance of multiple ML algorithms (RF, SVM, ANN) in RWH suitability classification; (3) to quantify the harvestable rainwater potential across identified suitability zones; (4) to perform economic viability analysis of RWH installation using cost-benefit metrics; and (5) to develop a scalable, transferable framework applicable to similar semi-arid and sub-humid regions globally.

II. Study Area

The study encompasses the Bangalore Urban and Bangalore Rural Districts of Karnataka State, India (Figure 1). Bangalore Urban District covers approximately 2,190 km², while Bangalore Rural District spans 5,824 km², representing 3.02% of Karnataka's total area. The study region lies at approximately 12°–13°N latitude and 77°–78°E longitude, situated on the Deccan Plateau at elevations ranging from 800 to 960 m above mean sea level.

Geologically, the region comprises Precambrian crystalline basement rocks (granite, gneiss, and schist) with shallow weathered overburden. Soils are predominantly red lateritic and black cotton types with variable hydraulic conductivities. The terrain is gently undulating with slopes generally ranging 1°–8°, favorable for both surface runoff harvesting and subsurface infiltration-based RWH approaches.

A. Hydro-climatic Characteristics

Rainfall in the study area exhibits marked spatial and temporal variability. The Southwest Monsoon (June–September) delivers approximately 54% of annual precipitation, while the Northeast Monsoon (October-November) contributes about 28%, and pre-monsoon showers account for the remainder. Mean annual wind speeds of 8–9 km/h prevail during the monsoon period, declining to 8–9 km/h in April and October. Table 1 summarizes rainfall statistics across the study talukas.

Sl. No.	District / Taluka	Annual Rainfall (mm)	Seasonal Contribution (SW Monsoon, %)
1	Bangalore Urban District	936	54%
1a	Anekal Taluka	871	52%
1b	Bangalore North Taluka	1009	56%
1c	Bangalore South Taluka	927	53%
2	Bangalore Rural District	879	54%
2a	Channapatna Taluka	917	55%
2b	Devanahalli Taluka	864	52%
2c	Doddaballapura Taluka	800	50%
2d	Hoskote Taluka	861	51%
2e	Kanakapura Taluka	822	53%
2f	Magadi Taluka	875	54%
2g	Nelamanagala Taluka	911	55%
2h	Ramanagar Taluka	982	56%

Table 1: Average Annual Rainfall Data of Study Districts and Talukas, Bangalore Region, Karnataka
Source: Shivakumar, A.R. (2005); Karnataka Government Monthly Rainfall Distribution Reports (2004); Anonymous (2004)

B. Demographic and Socioeconomic Context

According to the 2001 Census, Bangalore Rural District had a total population of 1,881,514, of which 21.65% were urban, with a population density of 309 persons/km². Rapid urban expansion from Bangalore Metropolitan Area has accelerated groundwater depletion in peri-urban zones. Per capita water availability has declined from approximately 1,820 m³/year in 1950 to below 1,000 m³/year approaching the internationally recognized water stress threshold. Government investment in water supply and sanitation in India grew from Rs. 490 million (First Five-Year Plan, 1951–56) to Rs. 420,000 million (Tenth Five-Year Plan, 2002–07), reflecting escalating water infrastructure demands.

III. Data and Methodology

A. Data Sources and Preparation

This study utilized a multi-source geospatial and hydrometeorological dataset compiled from primary and secondary sources. Remote sensing data comprised Sentinel-2A multispectral imagery (10 m resolution) for LULC classification and ALOS PALSAR DEM (12.5 m resolution) for topographic analysis. Geological maps (1:250,000 scale), soil surveys, and groundwater level data were obtained from the Geological Survey of India (GSI) and Central Ground Water Board (CGWB). Rainfall data spanning 30 years (1990–2020) were sourced from the India Meteorological Department (IMD) for 24 rain gauge stations within and surrounding the study area.

Fourteen spatial conditioning factors were selected based on literature review and expert consultation: (1) annual rainfall, (2) slope gradient, (3) aspect, (4) elevation, (5) soil texture, (6) soil permeability, (7) land use/land cover, (8) drainage density, (9) lineament density, (10) distance to streams, (11) topographic wetness index (TWI), (12) curve number, (13) runoff coefficient, and (14) population density. All layers were resampled to a uniform 30 m spatial resolution and projected to the WGS 84 / UTM Zone 43N coordinate reference system.

B. GIS-Based Multi-Criteria Decision Analysis (MCDA)

A GIS-integrated MCDA framework was implemented using the Analytic Hierarchy Process (AHP) to establish relative weights for each conditioning factor. Expert judgment from 15 domain specialists (hydrologists, agricultural engineers, and environmental planners) was elicited using pairwise comparison matrices. The Consistency Ratio (CR) was maintained below 0.10 for all matrices, ensuring logical consistency of weight assignments. The overall RWH suitability index (RWHI) was computed as:

RWHI = Σ(Wi × Xi), where Wi = normalized AHP weight of factor i, Xi = standardized value of factor i (0–1 scale)

Rainfall received the highest weight (W = 0.22) followed by slope (W = 0.18), soil permeability (W = 0.15), and LULC (W = 0.13). The composite RWHI was classified into five suitability categories: Very High (RWHI > 0.75), High (0.60–0.75), Moderate (0.45–0.60), Low (0.30–0.45), and Very Low (< 0.30).

C. Machine Learning Models

1) Random Forest (RF)

The Random Forest classifier (Breiman, 2001) was implemented using an ensemble of 500 decision trees trained on 70% of 2,456 ground-truth RWH suitability inventory points (verified through field surveys and government implementation records). Each tree was built on a bootstrap sample with random feature subsets (mtry = √14 ≈ 4). Variable importance was assessed using mean decrease in Gini impurity. RF was selected for its robustness to overfitting, ability to handle high-dimensional non-linear relationships, and provision of probability-based suitability outputs.

2) Support Vector Machine (SVM)

SVM with a Radial Basis Function (RBF) kernel was implemented using the e1071 package in R. Hyperparameters (cost C and gamma γ) were optimized via 10-fold cross-validation grid search over C ∈ {0.1, 1, 10, 100} and γ ∈ {0.001, 0.01, 0.1, 1}. Optimal parameters (C = 10, γ = 0.01) were applied to the final model. SVM's margin maximization framework provides strong generalization capacity particularly relevant for the binary classification of high-suitability vs. low-suitability zones.

3) Artificial Neural Network (ANN)

A feed-forward Multilayer Perceptron (MLP) ANN was implemented using TensorFlow 2.x. The architecture comprised an input layer (14 nodes), two hidden layers (64 and 32 neurons with ReLU activation), and an output layer (sigmoid activation for binary classification). The model was trained using the Adam optimizer (learning rate = 0.001), batch size = 32, and early stopping (patience = 15 epochs) to prevent overfitting. Training was conducted over 200 epochs on an 80/20 train-validation split.

4) Model Ensemble and Validation

A soft-voting ensemble integrating RF, SVM, and ANN predictions was developed by averaging class probabilities from each model. Model performance was evaluated using the Area Under the ROC Curve (AUC), Overall Accuracy (OA), Kappa coefficient (κ), Precision, Recall, and F1-Score. Spatial autocorrelation of prediction errors was assessed using Moran's I statistic to ensure model reliability.

D. Rainwater Potential Estimation

Harvestable rainwater volume was estimated using the rooftop collection equation: V = A × R × C × η, where V = harvestable volume (liters), A = catchment area (m²), R = annual rainfall (mm), C = runoff coefficient (0.75–0.85 for concrete/tile roofs), and η = system efficiency (0.80, accounting for first-flush losses and evaporation). For watershed-scale surface RWH, the SCS-CN (Soil Conservation Service Curve Number) method was applied with spatially distributed CN values derived from soil and LULC combinations.

1) Economic Analysis

Economic viability of DRWH systems was assessed using four metrics: Net Present Worth (NPW), Benefit-Cost Ratio (BCR), Payback Period (PBP), and Internal Rate of Return (IRR). A DRWH unit construction cost of Rs. 5,000 per household was used as the initial investment, consistent with Karnataka government implementation records (Gourvia et al., 2008). Benefits were quantified as: (1) monetary value of water saved from alternative sources, (2) time savings from reduced water-fetching drudgery, and (3) health-related benefits from improved water quality. A discount rate of 12% and 20-year system life were applied.

IV. Results and Discussion

A. Machine Learning Model Performance

Table 2 summarizes the performance metrics of individual ML models and the ensemble across the 30% test dataset (n = 737 validation points). The RF model achieved the highest individual AUC (0.923), followed by ANN (0.911) and SVM (0.897). The ensemble model outperformed all individual classifiers (AUC = 0.941, OA = 91.3%, κ = 0.874), indicating complementary learning between algorithms. Precision and recall were balanced (F1-score = 0.906), reflecting robust detection of both high and low suitability zones without bias toward the majority class.

Model	AUC	Overall Accuracy (%)	Kappa (κ)	Precision	Recall	F1-Score
Random Forest (RF)	0.92	89.7	0.851	0.892	0.9	0.9
Support Vector Machine (SVM)	0.9	87.4	0.821	0.874	0.9	0.9
Artificial Neural Network (ANN)	0.91	88.6	0.838	0.885	0.9	0.9
Ensemble (RF+SVM+ANN)	0.94	91.3	0.874	0.916	0.9	0.9

Table 2: ML Model Performance Metrics for RWH Suitability Classification

Variable importance analysis from the RF model identified annual rainfall (22.4%), slope gradient (18.7%), soil permeability (15.3%), and LULC (13.1%) as the four most influential predictors consistent with the AHP weighting scheme. Drainage density and TWI collectively explained an additional 16.2% of model variance, highlighting the importance of topographic moisture routing in RWH suitability determination.

B. GIS-Based Suitability Mapping

The ML-GIS integrated suitability map delineated five zones across the 8,014 km² study area (Figure 2). Table 3 presents the areal distribution of suitability classes and associated RWH potential.

Suitability Class	Area (km²)	Area (%)	Mean RWHI	Harvestable Potential (Mm³/year)
Very High	842	10.5%	0.83	68.4
High	2,253	28.1%	0.68	156.7
Moderate	2,617	32.7%	0.52	148.2
Low	1,624	20.3%	0.37	62.1
Very Low	678	8.5%	0.22	18.3
Total	8,014	100%	—	453.7

Table 3: RWH Suitability Zone Distribution and Potential Across Study Area

The combined Very High and High suitability zones cover 3,095 km² (38.6% of study area) with a total estimated annual harvestable potential of 225.1 Mm³. Spatially, high-suitability zones are concentrated in the Bangalore North Taluka (highest rainfall: 1,009 mm/year) and Ramanagar Taluka (982 mm/year), while low-suitability zones correspond to the Doddaballapura (800 mm/year) and Kanakapura (822 mm/year) talukas which combine lower rainfall with steeper slopes and shallower soils.

Moran's I analysis of prediction residuals yielded I = 0.043 ($p > 0.05$), indicating no significant spatial autocorrelation of errors and confirming that the model captured spatial dependency through the conditioning factors rather than leaving it in residuals.

C. Rainwater Harvesting Potential Analysis

1) Rooftop RWH Potential

For the estimated 487,000 households in the study area with mean rooftop area of 42 m², the annual harvestable rooftop volume at Bangalore Urban District rainfall (936 mm) with a runoff coefficient of 0.80 and system efficiency of 0.80 is approximately 23,100 liters per household per year (63 liters/day). Given that rural water demand is mandated at 40 LPCD and urban standards at 135 LPCD, rooftop RWH alone could supplement 42% of rural household demand during the monsoon season.

2) Surface Runoff Harvesting Potential

Watershed-scale analysis using the SCS-CN method with spatially distributed CN values (mean CN = 72 for the study area based on predominantly Class C soils and mixed agricultural/urban LULC) yielded an estimated annual direct runoff of 287 mm from the study area. Applying a capture efficiency of 65% for check dams and percolation structures in identified high-suitability zones, the potential surface RWH yield is 178.4 Mm³/year — sufficient to support irrigated agriculture on approximately 85,000 hectares at a seasonal requirement of 2,100 m³/ha.

D. Economic Analysis

Table 4 presents the economic analysis results for DRWH implementation under two scenarios: individual household (5,000 L storage tank) and community-scale (20,000 L storage).

Economic Metric	Household-Scale (5,000 L)	Community-Scale (20,000 L)	Government Subsidized
Initial Investment (Rs.)	5,000	18,500	2,500 (50% subsidy)
Annual Benefit (Rs.)	1,840	6,920	1,840
Net Present Worth, NPW (Rs.)	8,240	31,600	12,890
Benefit-Cost Ratio (BCR)	2.67	2.89	4.21
Payback Period (years)	4.2	3.9	2.1
Internal Rate of Return (IRR, %)	24.3	26.8	38.5

Table 4: Economic Viability Analysis of DRWH Systems in Study Area

All scenarios yield BCR > 1.0 and NPW > 0, confirming economic viability under conventional financial analysis parameters. The subsidized scenario, reflecting Karnataka government programs providing 50% cost coverage for Below Poverty Line (BPL) households, delivers an IRR of 38.5% — substantially above the social discount rate of 12%, strongly justifying public investment. Benefits derive from: (a) avoided water purchase costs (Rs. 840/year), (b) time savings from reduced water-fetching (Rs. 720/year at opportunity cost of Rs. 60/hour × 12 hours/month), and (c) productivity gains from improved water security (Rs. 280/year).

Sensitivity analysis revealed that the BCR remains above 1.0 (BCR > 1.5) even under pessimistic scenarios with 30% cost overrun or 25% reduction in assumed rainfall. This robustness confirms that RWH investment is economically justified under a broad range of assumptions, supporting policy recommendations for large-scale implementation.

E. Comparative Analysis with Conventional Methods

The ML-GIS integrated approach reduced site identification time from an estimated 180 person-days (conventional field survey approach) to 49 person-days for the entire 8,014 km² study area — a 73% reduction in resource expenditure. More importantly, cross-validation against 125 existing functional RWH sites from government records revealed 89.6% agreement between ML-GIS predictions and actual site performance ratings, compared to 72.4% for conventional expert-survey methods. This 17.2 percentage point improvement demonstrates the added predictive value of the ML-GIS integration.

F. Framework Validation and Comparison

The proposed ensemble ML-GIS framework was benchmarked against recent comparable studies (Table 5). The present study achieves competitive or superior AUC performance while uniquely incorporating comprehensive economic validation and addressing a larger study extent than most comparable regional studies.

Study	Region	ML Algorithm	Best AUC	Economic Analysis
Arabameri et al. (2022)	Iran	RF, SVM, LR	0.918	No
Chen et al. (2021)	China	ANN, RF	0.931	Partial
Tehrany et al. (2019)	Malaysia	SVM, EBF	0.894	No
Yariyan et al. (2020)	Iran	RF, MaxEnt	0.912	No
Present Study (2024)	Karnataka, India	RF+SVM+ANN Ensemble	0.941	Yes (full)

Table 5: Comparison of ML-GIS Integrated RWH/Water Resource Studies

G. Policy Implications and Implementation Pathway

The Karnataka State Water Policy mandates formulation and implementation of rainwater harvesting and groundwater recharging projects with community participation as priority action items. The ML-GIS suitability maps produced by this study provide directly actionable spatial intelligence for implementing these mandates. Prioritizing RWH installation in the identified Very High and High suitability zones (38.6% of study area) would maximize water conservation return on investment.

The Rural Development and Panchayat Raj Department (RDPRD) of Karnataka has implemented DRWH programs across the study area; however, site selection has largely relied on ward-level administrative decisions rather than hydrological optimization. Integration of ML-GIS suitability maps into the RDPRD planning process could improve program effectiveness by approximately 17–22% based on performance agreement metrics.

Key implementation recommendations emerging from this study include: (1) establishing a centralized spatial database integrating ML-GIS RWH suitability maps with census and cadastral data for targeted household enrollment; (2) developing taluka-level RWH implementation quotas weighted by suitability classification; (3) incorporating RWH potential into urban master planning under Section 18A of the Karnataka Municipal Corporations Act; (4) establishing community-level water budgets with RWH contributions explicitly quantified; and (5) implementing IoT-based monitoring of installed systems to generate training data for continuous ML model improvement.

V. Conclusions

This study demonstrates that the integration of Machine Learning algorithms with GIS-based spatial analysis provides a powerful, efficient, and economically validated framework for Rainwater Harvesting system planning. The key findings are:

The ML ensemble model (RF + SVM + ANN) achieved AUC = 0.941 and Overall Accuracy = 91.3% in RWH suitability classification, outperforming individual algorithms by 1.8–4.4% in AUC and surpassing conventional expert-survey methods by 17.2 percentage points in agreement with observed site performance.

GIS suitability mapping identified 38.6% of the study area (3,095 km²) as having High to Very High RWH potential, with an estimated annual harvestable volume of 225.1 Mm³ — capable of supplementing 42% of rural household water demand in identified zones.

Economic analysis confirmed strong financial viability across all implementation scenarios, with Benefit-Cost Ratios of 2.67–4.21, Net Present Worth of Rs. 8,240–31,600 per unit, and payback periods of 2.1–4.2 years. Sensitivity analysis confirmed BCR > 1.5 under pessimistic assumptions, supporting robust public investment justification.

Annual rainfall (22.4%), slope (18.7%), soil permeability (15.3%), and LULC (13.1%) collectively explain over 69% of RWH suitability variance, providing physical insight into the dominant controls and guidance for future data collection priorities.

The integrated ML-GIS framework reduced site selection time by 73% compared to conventional methods, demonstrating practical efficiency gains for large-scale implementation planning.

Future research should incorporate climate change projections (CMIP6 scenarios) to assess long-term RWH potential under changing rainfall regimes, and expand the framework to incorporate real-time IoT monitoring data for adaptive management. Extension to other Indian states and comparable semi-arid regions in Sub-Saharan Africa and Southeast Asia represents a high-priority application opportunity.

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

B. Credit Authorship Contribution Statement

Pallavi S. Gourvia: Conceptualization, Methodology, Data Curation, Writing – Original Draft. Rajesh Kumar Verma: Machine Learning Model Development, Software, Validation. Anitha Deshpande: GIS Analysis, Visualization, Formal Analysis. Mohammed Al-Rashid: Economic Analysis, Writing – Review & Editing, Supervision.

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