International Journal of Artificial Intelligence, Data Science, and Machine Learning
Grace Horizon Publication | Volume 7, Issue 2, 87-90, 2026
ISSN: 3050-9262 | https://doi.org/10.63282/3050-9262.IJAIDSML-V7I2P113

Original Article

Artificial Intelligence for Rainwater Harvesting: A Comprehensive Review

Seema Bardhipur
Civil Engineering, USA.

Received On: 08/03/2026 Revised On: 02/04/2026 Accepted On: 09/04/2026 Published On: 20/04/2026

Abstract *- Rainwater harvesting (RWH) is a decentralized water-supply strategy that supports water security, stormwater management, and climate resilience. Recent literature indicates that artificial intelligence (AI), machine learning (ML), and Internet of Things (IoT)-enabled sensing can strengthen RWH by improving rainfall forecasting, optimizing storage and release, identifying suitable harvesting zones, and monitoring system performance in near real time. Smart cistern studies have shown that forecast-informed control can improve retained and detained stormwater volumes, while geospatial ML models have demonstrated strong performance in delineating rainwater harvesting suitability zones. At the same time, smart RWH architectures increasingly integrate sensors, wireless communication, and data-processing layers to detect leaks, monitor levels, and support automated decisions. This review synthesizes the current state of AI in RWH across planning, operation, monitoring, and optimization and concludes that the field is promising but still limited by data scarcity, modest field validation, and the need for more generalizable, low-cost, and explainable models.*

Keywords - *Artificial Intelligence, Rainwater Harvesting, Machine Learning, Deep Learning, Iot, Smart Cistern, Rainfall Forecasting, Storm Water Management.*

1. Introduction

Rainwater harvesting captures rainfall from rooftops or other catchments for later use and is widely recognized as a practical strategy for reducing pressure on conventional water supplies. Recent reviews describe RWH as a field that spans design, performance, water quality, economics, and environmental assessment, while broader smart-water reviews emphasize that AI, deep learning, and IoT can improve water harvesting, conservation, recycling, and decision-making across the water cycle [1,2].

AI is particularly relevant to RWH because rainfall supply, storage availability, water demand, and water quality are dynamic and uncertain. Conventional rule-based systems may not adapt quickly to changing weather or usage patterns, whereas ML methods can learn nonlinear relationships from historical and real-time data. In hydrology more broadly, ML has been shown to perform strongly in runoff modeling and related forecasting problems, indicating clear transferability to RWH applications [3].

The overall AI-enabled rainwater harvesting workflow is illustrated in Figure 1, which presents the sequence from rainfall/climate inputs through IoT sensing, data processing, operational decisions, and expected outcomes.

The purpose of this review is to examine how AI is being applied in RWH, with emphasis on planning, forecasting, operation, and monitoring. The review also identifies current limitations and priorities for future research.

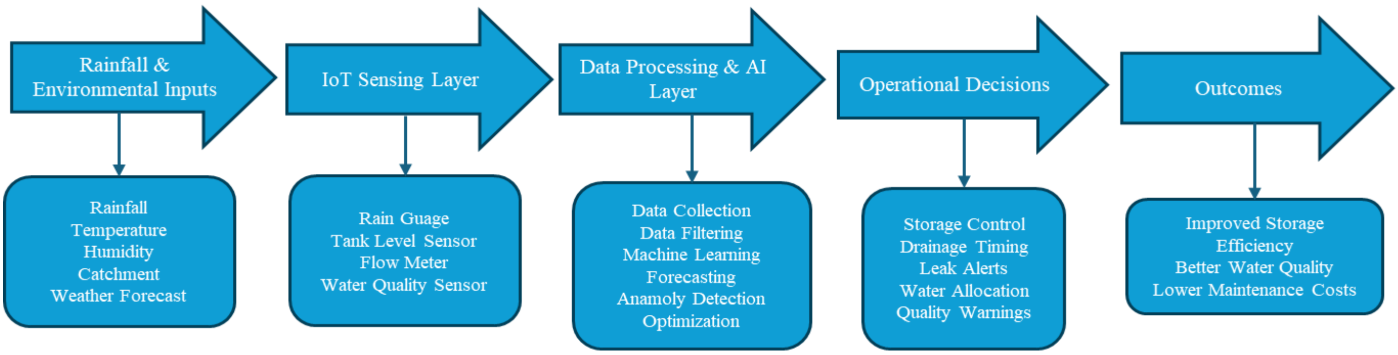

Fig 1: Conceptual Framework Illustrating how AI and IoT Technologies Interact within a Rainwater Harvesting System.

2. Methodological Scope

This review focuses specifically on AI applications within RWH rather than the broader field of water management. The discussion is organized into four domains: (a) harvesting-site identification and planning, (b) rainfall and storage forecasting, (c) intelligent operation and control, and (d) monitoring of water quantity and quality. Because the RWH-specific AI literature remains relatively limited and fragmented, adjacent studies in smart stormwater management and hydrological ML are also considered where they directly inform RWH practice [1,2].

Table 1 summarizes the principal AI applications in rainwater harvesting and shows how the reviewed literature maps across planning, forecasting, control, and monitoring functions.

2.1. AI for Rainwater Harvesting Planning and Site Selection

A major use of AI in RWH is identifying locations where harvesting systems are most suitable. Geospatial ML studies show that rainfall, slope, elevation, drainage density, land use/land cover, and other biophysical factors can be combined to generate suitability maps. In a study from hilly Bangladesh, four ML algorithms and an analytical hierarchy process (AHP) benchmark were compared. Boosted regression trees and random forest achieved AUC values of 0.93, outperforming AHP at 0.82, and drainage density and elevation emerged as the most influential predictors [4].

A more recent study in Ethiopia extended this direction by applying a GIS–ML framework to identify optimal RWH zones in the Choke Watershed. The study integrated twelve biophysical and hydrological factors and reported high-resolution suitability maps, reinforcing the view that AI is moving from conceptual support toward operational planning tools for RWH infrastructure placement [5].

These studies suggest that AI can support not only engineering design but also regional planning, particularly in areas where water scarcity, topographic variability, and land-use complexity make site selection difficult.

Table 1: Major Applications of AI in Rainwater Harvesting

AI Application Area	Main Input Data	Typical AI Methods	Main Outputs / Benefits	Example Use in RWH
Site selection and planning	Rainfall, slope, elevation, drainage density, land use, geology	Random forest, boosted regression trees, XGBoost, GIS–ML models	Suitability maps, optimal harvesting zones	Identifying locations for rooftop or watershed-scale harvesting
Rainfall forecasting	Historical rainfall, temperature, humidity, pressure, weather forecasts	ANN, SVM, ANFIS, LSTM, deep learning	Short-term rainfall prediction	Anticipating tank refill or overflow conditions
Storage prediction	Rainfall, tank level, inflow, outflow, demand	Regression models, neural networks, time-series models	Predicted tank volume and availability	Preventing shortage or overflow
Adaptive control	Forecasts, sensor data, usage patterns	Rule-based AI, reinforcement learning, predictive control	Automated drainage or release decisions	Smart cistern operation
Water quality monitoring	Turbidity, pH, conductivity, contamination indicators	Classification models, anomaly detection, ML	Early detection of poor water quality	Identifying non-potable water conditions
Leak detection and fault monitoring	Flow, pressure, tank level, system anomalies	Anomaly detection, sensor analytics	Leak alerts, fault detection	Detecting pipe or tank leakage
Demand prediction	Consumption history, seasonality, occupancy, irrigation needs	Regression, ANN, LSTM, ensemble methods	Water-use forecasts	Matching supply with demand

2.2. AI for Rainfall Forecasting and Storage Prediction

Forecasting is one of the most important AI functions in RWH because harvesting performance depends on when rain falls, how much falls, and whether storage is available. ML methods are well established in hydrologic forecasting, and review literature on runoff modeling identifies artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), and support vector machines (SVM) among the most widely used data-driven approaches in water applications [3]. These methods are attractive for RWH because they can learn nonlinear relationships between rainfall, catchment response, and downstream storage behavior.

In practice, forecast-informed storage management is increasingly used in smart cisterns. A study on a green-roof-connected smart rainwater harvesting cistern reported that weather forecasting data were used to regulate drainage behavior before predicted rainfall events. Over five years of monitoring, the system increased total retained/detained rainfall from 65.2% to 75.6%, representing a 10% improvement in performance [6]. This provides strong evidence that predictive control can improve RWH effectiveness when forecasts are sufficiently reliable.

Forecasting applications in RWH are especially valuable because they can help balance two competing goals: preserving storage capacity for future rainfall while maximizing immediate water use. AI models are well suited to this task because they can continuously update predictions as weather and demand conditions change.

2.3. AI for Smart Operation and Adaptive Control

A key shift in literature is the move from passive collection systems to active, sensor-driven systems. A smart RWH framework described in the literature includes physical, monitoring, data-transfer, and data-processing layers. That architecture uses sensors for water flow, tank level, and leak detection, and it incorporates weather and user data to support real-time decisions. The authors frame the system to monitor water quality, water level, and leakage while improving harvesting efficiency at the neighborhood scale [7].

This architecture shows that AI depends on upstream digital infrastructure. AI does not replace the RWH system; rather, it interprets sensor and contextual data so the system can make more informed operational choices. For example, if rainfall is forecast soon, an AI-enabled controller may delay drainage to preserve capacity for the next storm. If a leak or anomaly is detected, the system can trigger alerts or corrective actions [7].

From an operational standpoint, this integration of sensing and AI is one of the most important developments in the field because it shifts RWH from a static infrastructure model to a dynamic water-management system.

2.4. AI for Water Quality and Leak Monitoring

Water quality remains a persistent issue in RWH because contamination can arise from roof materials, gutters, pipes, storage tanks, and local environmental conditions. The smart RWH literature identifies quality monitoring as a core capability of future systems and describes sensor-based monitoring for flow, level, and quality as part of the platform design. This is especially relevant where harvested rainwater is intended for non-potable or treated potable use [7].

Leak detection is another practical AI use case. Sensor-based monitoring can identify abnormal water loss, malfunctioning distribution components, or unwanted flow behavior in indoor and household networks. In the smart RWH architecture described by Judeh et al., leak detection is explicitly treated as a monitored variable, and the processing layer is used to clean, analyze, and visualize data before decisions are made [7].

In this context, AI contributes to reliability as well as efficiency. Systems that detect contamination or leakage early can reduce operational risk, protect water quality, and improve user confidence in harvested rainwater.

2.5. Why AI Improves RWH Performance

The main advantage of AI in RWH is adaptability. Traditional designs generally assume average rainfall patterns and fixed demand conditions, whereas AI can continuously update predictions from new data. This enables better timing of storage, more efficient use of available tank capacity, improved retention of stormwater, and earlier detection of operational problems. The strongest practical evidence currently comes from smart cistern studies and ML-based suitability mapping, both of which show measurable gains over static approaches [5,6].

AI also improves the decision layer of RWH systems by combining multiple information streams: rainfall forecasts, historical usage, tank status, and system health. In that sense, the value of AI is not only predictive but also integrative; it helps unify planning and operation into one adaptive framework [7].

At a broader level, these developments align with the growing emphasis in the water literature on data-driven, decentralized, and resilient infrastructure. RWH is particularly suited to AI because its performance is highly dependent on local variability, which is exactly the type of problem ML methods are designed to address.

3. Current Limitations

Despite its promise, AI in RWH remains constrained by several issues. Many RWH systems are small, decentralized, and poorly instrumented, so long-term datasets are limited. Sensor noise and missing data can reduce model reliability. In addition, models trained in one climate or building type may not generalize well to other settings because roof area, runoff behavior, rainfall regime, and user demand vary substantially. Many AI-based solutions also remain at prototype scale and have not yet been evaluated widely in real-world deployments. These limitations are consistent with broader hydrological ML literature, which emphasizes that no single model is universally best across all catchments and conditions [3].

Another limitation is that many published studies demonstrate technical feasibility but provide limited evidence on lifecycle cost, maintenance burden, or user acceptance. For AI-enabled RWH to move from research to practice, these implementation issues will need more attention.

4. Research Gaps and Future Directions

Future research should prioritize field validation, standardized datasets, low-cost IoT hardware, and hybrid approaches that combine physics-based hydrology with ML. Edge computing could make AI-enabled RWH more accessible for households and small communities, while explainable AI would help users and engineers trust operational recommendations, especially when systems affect water security and public health. More comparative studies across climates and building types are also needed to establish generalizable performance benchmarks [2].

5. Conclusion

AI is beginning to reshape rainwater harvesting from a static conservation method into an adaptive, sensor-driven water management system. Current evidence shows promising results in suitability mapping, weather-informed cistern control, and real-time monitoring of level, quality, and leakage. The field is still developing, however, and broader adoption will depend on stronger datasets, lower-cost sensing, and more real-world validation. Even so, the literature clearly indicates that AI can make RWH systems more efficient, resilient, and responsive to changing hydrologic conditions [6,7].

References

[1] Siva Rama Krishnan S, Nallakaruppan MK, Chengoden R. Smart water resource management using artificial intelligence—A review. *Sustainability*. 2022;14(20):13384, https://doi.org/10.3390/su142013384.

[2] Yildirim G, Alim MA, Rahman A. Review of rainwater harvesting research by a bibliometric analysis. *Water*. 2022;14(20):3200, https://doi.org/10.3390/w14203200.

[3] Mohammadi B. A review on the applications of machine learning for runoff modeling. *Sustainable Water Resources Management*. 2021;7:98, https://doi.org/10.1007/s40899-021-00584-y.

[4] Hasan MM, Talha M, Akter MM, Ferdous MT, Mojumder P, Roy SK, et al. Assessing the performance of machine learning and analytical hierarchy process (AHP) models for rainwater harvesting potential zone identification in hilly region, Bangladesh. 2024, https://doi.org/10.1016/j.jaesx.2024.100189.

[5] Asrade TM, Abebe SA, Tadesse KB. Rainwater harvesting potential zone identification using GIS–machine learning approach and comparison of their performance. *Agricultural Water Management*. 2026, 10.1016/j.agwat.2026.110134.

[6] Oberascher M, et al. Examining how a smart rainwater harvesting system connected to a green roof can improve urban stormwater management. *Water*. 2022;14(14):2216, https://doi.org/10.3390/w14142216.

[7] Judeh T, Shahrour I, Comair F. Smart rainwater harvesting for sustainable potable water supply in arid and semi-arid areas. *Sustainability*. 2022;14(15):9271, https://doi.org/10.3390/su14159271.