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Atmospheric Water Harvesting System With Smart Irrigation Integration

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Abstract: The growing pressures of climate change, water scarcity, and the need for sustainable agricultural practices have driven significant research into smart irrigation and machine learning–based solutions. Agriculture, as one of the most water-intensive sectors, faces the dual challenge of maximizing crop yields while minimizing resource consumption. Recent advancements in sensor technologies, Internet of Things (IoT) systems, predictive analytics, and atmospheric water harvesting have enabled data-driven approaches to irrigation management, offering precise control over water delivery based on real-time environmental and crop conditions. Machine learning, in particular, has emerged as a transformative tool, enabling accurate predictions of soil moisture, evapotranspiration, and rainfall patterns, as well as adaptive decision-making for diverse agricultural contexts.

Keywords – Machine Learning, IoT, Agriculture, Smart Irrigation.

I. INTRODUCTION

Agriculture, being one of the most water-intensive sectors, consumes nearly 70% of the world's freshwater resource. With the growing challenges of climate change, erratic rainfall, and groundwater depletion, the availability of water for irrigation is becoming increasingly scarce. Traditional irrigation methods often result in overuse of water and soil degradation, making them unsustainable in the long run. This situation calls for innovative solutions that ensure efficient water management and sustainable farming practices to secure future food production [1-3].

Recent advancements in Internet of Things (IoT), sensors, and machine learning (ML) have paved the way for smart irrigation systems that deliver water based on real-time soil and environmental conditions. Machine learning models can predict soil moisture, rainfall patterns, and evapotranspiration, enabling adaptive irrigation scheduling . Such data-driven approaches not only conserve water but also help maximize crop yield and improve resilience to climate variability. Meanwhile, innovations in atmospheric water harvesting (AWH) offer a renewable and decentralized alternative water source by condensing moisture from the air . When combined with smart irrigation, AWH has the potential to address water scarcity in arid and semi-arid regions effectively [3-5].

This research focuses on integration of atmospheric water harvesting, smart irrigation, and machine learning into a unified system [4, 5]. The proposed model collects atmospheric water, stores it, and intelligently irrigates crops using ML-based decision-making and IoT-enabled controls. By optimizing both water collection and usage, the system reduces dependence on conventional water sources while promoting sustainable agriculture [1, 2]. This work contributes to advancing water-efficient farming practices and highlights a scalable approach for addressing global agricultural water challenges[3, 6].

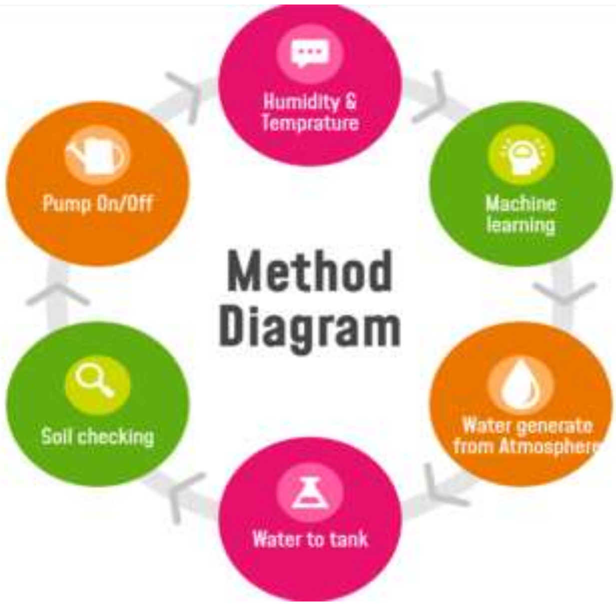

Figure 1 *Process of Smart Irrigation*

II. LITERATURE REVIEW

Campos et al. (2019) demonstrated that a machine learning–enabled IoT irrigation system using Gradient Boosted Regression Trees (GBRT) could accurately predict soil moisture and optimize water use. Through advanced data preprocessing and localized model training, their system achieved up to 90.4% water savings, providing a scalable and highly efficient solution for smart irrigation[7].

In the same year, Mohapatra et al. (2019) developed a neural network and fuzzy logic–based smart decision support system (DSS) for real-time irrigation control in precision agriculture. By evaluating both crop and environmental parameters through hybrid intelligence, the DSS delivered adaptive and efficient water management, further contributing to sustainable farming practices.

Jaramillo et al. (2020) expanded the application of water-efficient practices through pilot water-harvesting interventions in Nicaragua and Mexico. By converting rainfed cropland into irrigated systems using reservoirs and optimized agronomic methods, their approach doubled to quadrupled crop yields. The study demonstrated that small-scale, runoff-capturing reservoirs combined with smart crop management can substantially enhance agricultural productivity [1].

Ahmed et al. (2023) emphasized the significance of smart irrigation technologies in improving water productivity in dryland regions affected by climate change. By integrating sensor-based systems, data analytics, and decision-support tools, they underscored the potential of these approaches to enhance both water use efficiency and agricultural sustainability [2].

That same year, Entezari et al. (2023) reviewed sorption-based atmospheric water harvesting (SAWH) as a decentralized freshwater production method for arid regions. Highlighting its versatility across various sectors, they advocated for integrating SAWH with existing agricultural and energy systems to address interconnected global challenges in food, water, and energy security[4].

Del-Coco et al. (2024) highlighted both the promise and challenges of applying machine learning in smart irrigation. While noting its potential to significantly improve efficiency, they identified obstacles such as limited datasets, data heterogeneity, and interpretability issues. They recommended the future use of advanced models graph neural networks, transformers, and digital twins—to create scalable, robust, and explainable irrigation solutions [5].

Lai Chee Sern et al. (2025) advanced sustainable practices by developing a Sustainable Smart Irrigation System (SIS) for indoor plants . Addressing the drawbacks of manual watering, their system offered an integrated, cost-effective, and eco-friendly approach aligned with affordable and clean energy goals [8].

Similarly, D. Balamurali et al. (2025) examined smart irrigation systems integrating Internet of Things (IoT) technologies, aerosol-based rainfall forecasting, and solar photovoltaic (PV) power . Their study demonstrated how real-time environmental monitoring and predictive analytics can improve irrigation precision while relying on renewable energy sources [6].

Belarbi and El Younoussi (2025) reinforced the transformative role of machine learning in agriculture by showing its effectiveness in enhancing evapotranspiration prediction and real-time decision-making. Their synthesis of current research demonstrated how ML optimizes water use, supports resilient agricultural practices, and offers scalable, data-driven solutions to tackle water scarcity and climate variability [3].
Addressing water scarcity from an alternative angle, Barletta et al. (2025) explored atmospheric water harvesting (AWH) using ion deposition membranes (IDM). Their system achieved yields of up to 354 ml/day, and multilayer perceptron (MLP) models predicted water yield with 89% accuracy [10]. Forecasts for Jeddah revealed strong potential for IDM-based AWH as a viable, data-driven solution for arid regions [9][10].

Table 1: *Summary of recent studies on smart irrigation and water harvesting technologies.*

Author & Year	**Focus of Study**	**Method/Technology Used**	**Key Findings/Results**
Campos et al. (2019)	ML-enabled IoT irrigation system	Gradient Boosted Regression Trees (GBRT), data preprocessing, localized model training	Achieved up to 90.4% water savings; scalable & highly efficient irrigation system.
Mohapatra et al. (2019)	Smart DSS for precision irrigation	Neural networks + fuzzy logic hybrid intelligence	Adaptive and efficient real-time water management; sustainable farming practices.
Jaramillo et al. (2020)	Water-harvesting interventions in Nicaragua & Mexico	Small-scale runoff reservoirs + optimized agronomic practices	Crop yields doubled to quadrupled; proved potential of rainfed → irrigated conversion.
Ahmed et al. (2023)	Smart irrigation in dryland regions under climate change	Sensor-based systems, data analytics, decision-support tools	Improved water productivity and agricultural sustainability in vulnerable regions.
Entezari et al. (2023)	Sorption-based atmospheric water harvesting (SAWH)	Sorption materials integrated with agri & energy systems	Highlighted SAWH as a decentralized freshwater source; links to food-water-energy security.
Del-Coco et al. (2024)	Challenges & future of ML in irrigation	Identified limits: small datasets, heterogeneity, interpretability; proposed GNNs, transformer, twins	Emphasized need for advanced, explainable ML models for scalable irrigation solutions.
Lai Chee Sern et al. (2025)	Sustainable Smart Irrigation System (SIS) for indoor plants	IoT-enabled automated irrigation, eco-friendly design	Provided affordable, clean energy–aligned solution to replace manual watering.
D. Balamurali et al. (2025)	IoT-enabled smart irrigation with renewable integration	IoT + aerosol-based rainfall forecasting + solar PV power	Real-time monitoring improved irrigation precision while reducing reliance on non-renewables.

The above table summarizes key contributions from recent research, highlighting the methodologies employed and the outcomes achieved in the domain of smart irrigation and water harvesting systems.

III. TOOLS & TECHNIQUES

This section outlines the key hardware components and methodological approaches employed in the development of the Atmospheric Water Harvesting System integrated with smart irrigation. The aim is to ensure resource efficiency, automation, and sustainability, particularly in water-scarce or off-grid regions.

3.1Tools

- **DHT22 Sensor:** Utilized for real-time measurement of ambient temperature and relative humidity, both critical parameters for determining the feasibility of atmospheric water generation. Accurate sensing ensures that the Atmospheric Water Generator (AWG) is activated only under optimal environmental conditions.
- **Soil Moisture Sensor:** Deployed at root-level depth to monitor the volumetric water content of the soil. This sensor facilitates efficient irrigation by initiating water delivery only when moisture levels fall below predefined crop-specific thresholds, thereby preventing over-irrigation.
- **Water Level Sensor:** Installed in the water reservoir to track the available water volume. It safeguards the pump by enabling operation only when sufficient water is present, thus avoiding dry-running and potential hardware damage.
- **ESP32 Microcontroller:** Functions as the central processing unit of the system. It collects sensor data, processes it using embedded machine learning (ML) models, and controls relays for operating both the AWG and the irrigation pump.
- **Thermoelectric Cooling (TEC) Condenser:** A vital component of the AWG that facilitates condensation of atmospheric moisture into liquid water. It operates based on the Peltier effect and plays a key role in water generation.
- **Reservoir with Filtration Unit:** Harvested water is stored in a reservoir equipped with a basic filtration system (e.g., mesh or UV) to ensure a clean water supply suitable for agricultural use.
- **DC Water Pump with Relay Control:** A low-voltage water pump managed via relay by the ESP32. It delivers stored water to the irrigation system only when conditions are met, optimizing energy and water usage.
- **Drip Irrigation Setup:** Ensures precise and localized delivery of water to plant roots, minimizing evaporation losses and enhancing water-use efficiency.
- **Solar Panel with Battery Backup:** Provides sustainable, off-grid power to the entire system. The battery ensures uninterrupted operation during low solar availability, enhancing system reliability.

3.2Techniques:

- **Data Acquisition and Pre-processing:** Environmental and soil data are continuously collected from sensors. Pre-processing techniques such as moving average filtering are applied to reduce noise and enhance data reliability for downstream decision-making.
- **Machine Learning-Based Prediction:** A lightweight ML model trained on historical data (temperature, humidity, and water yield) predicts favourable atmospheric conditions for water harvesting. This enables dynamic adaptation to climatic and seasonal variations.
- **Relay-Based System Automation:** The ESP32 microcontroller operates relays to control the AWG and water pump. Actuation is based on sensor readings and ML outputs, ensuring the system functions only under suitable conditions to optimize resource use.
- **Soil Moisture Thresholding:** Irrigation is automated based on real-time soil moisture data. Water delivery is initiated only when levels fall below defined thresholds, ensuring plants receive water when genuinely needed.
- **Closed-Loop Feedback System:** System parameters such as humidity, temperature, soil moisture, reservoir level, and pump activity are logged in real time. This data is used both for monitoring and iterative retraining of ML models, enhancing predictive accuracy over time.
- **Energy Optimization Strategy:** The system integrates sensor data, predictive modeling, and control logic to minimize unnecessary operation of energy-intensive components. Coupled with solar power integration, this approach ensures both operational efficiency and long-term sustainability.

IV. RESEARCH METHODOLOGY

The below diagram shows the complete architecture of developing Atmospheric Water Harvesting System with smart irrigation integration system.

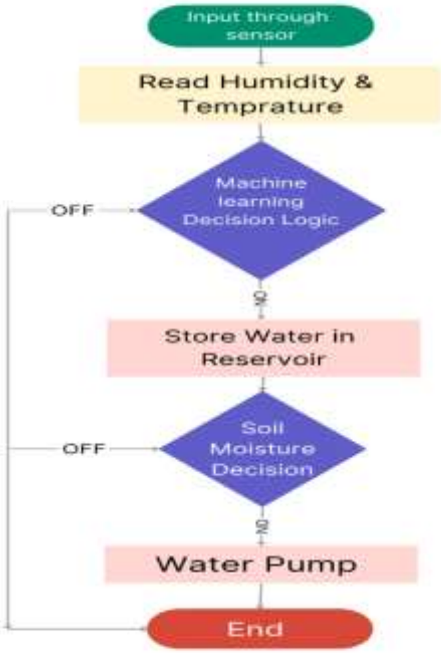

Figure 1 General Architecture

Step 1 – Sense the Environment

The system begins with environmental data acquisition using the DHT22 sensor, which is responsible for measuring real-time temperature and relative humidity from the surrounding air [7, 10]. These parameters are vital because atmospheric water generation is highly dependent on humidity levels—higher humidity results in better condensation efficiency [4, 9] . The sensor readings are collected by the ESP32 microcontroller at regular intervals, and a simple data smoothing technique (such as moving average filtering) is applied to remove sudden fluctuations or noise. This ensures that the system works on stable and reliable data instead of reacting to short-lived variations, creating a strong foundation for accurate decision-making in subsequent steps [3, 5, 6, 9].

Step 2 – Machine Learning Decision Logic (When to Harvest Water)

Once the environmental data is available, it is processed through a lightweight machine learning model embedded in the ESP32[5, 6]. The model, trained on historical datasets of humidity, temperature, and corresponding water yield, predicts whether the atmospheric conditions are suitable for water generation. Instead of relying on fixed thresholds, the ML model learns patterns, making the system adaptive to different climates and seasonal variations. If the model predicts unfavourable conditions, such as very low humidity or excessively high temperatures, the atmospheric water generator remains off to save electricity. However, when the prediction indicates favourable conditions, the ESP32 activates the AWG unit through a relay switch, ensuring that the system only works when the chances of generating water are high, thereby maximizing efficiency.

Step 3 – Water Harvesting and Storage

When activated, the atmospheric water generator condenses water vapour present in the air using a thermoelectric cooling (TEC) condenser setup[4, 9]. The cooled surface of the TEC unit attracts moisture, which forms droplets that are collected and directed into a storage reservoir . A simple filtration stage, such as mesh or UV purification, can be included to ensure that the collected water remains clean and safe for agricultural use [1, 2]. The reservoir plays a central role in the system, acting as a buffer that stores harvested water until it is needed for irrigation. To further enhance system intelligence, the water level in the reservoir can also be monitored, which prevents the irrigation pump from running in the absence of adequate water supply.

Step 4 – Monitoring Soil Condition

Parallel to atmospheric sensing, a soil moisture sensor is embedded in the cultivation zone, usually at the root depth of the plants [7, 10]. This sensor continuously monitors the volumetric water content of the soil, providing a direct measure of plant water availability. Since crops differ in their water requirements, the system can be programmed with crop-specific moisture thresholds, ensuring that the irrigation cycle aligns with the biological needs of the chosen plant. The data collected is analyzed by the ESP32, and just like in atmospheric monitoring, smoothing techniques are applied to prevent false triggers caused by sudden changes. This makes the soil sensing reliable, reducing unnecessary pump activations and water wastage.

Step 5 – Irrigation Decision (When to Pump Water)

Based on soil moisture readings, the system decides whether irrigation is necessary [5, 7]. If the soil already contains sufficient water, the irrigation cycle remains inactive, avoiding overwatering and preserving the limited harvested water. If the soil moisture drops below the predefined threshold, the ESP32 checks the availability of stored water in the reservoir before making the final decision to irrigate. This double-check ensures that the pump never runs dry, which not only prevents damage to the pump but also maintains operational efficiency [2, 3, 10]. By combining environmental sensing, machine learning predictions, and soil condition monitoring, this step ensures that irrigation decisions are made intelligently, balancing crop needs with resource availability.

Step 6 – Irrigation Execution

When all conditions are satisfied, the ESP32 triggers the water pump through a relay, drawing water from the reservoir and delivering it directly to the crop root zone[7, 8]. The irrigation continues until one of two conditions is met: either the soil moisture sensor detects that the soil has reached the target moisture range, or the system reaches a maximum time/volume cut-off, acting as a failsafe against overwatering [5, 10]. This ensures precision irrigation, delivering just the right amount of water to maintain soil health while conserving resources. After irrigation is completed, the pump is automatically turned off, and the system allows a short pause before rechecking soil conditions to confirm that the cycle achieved its purpose.

Step 7 – Feedback and Continuous Cycle

At the end of each irrigation cycle, the system records key data including humidity, temperature, water yield predictions, AWG runtime, reservoir level, soil moisture readings, pump activity, and energy consumption. This logged data serves two purposes: it provides real-time monitoring for the user and also creates a dataset that can be used to retrain and improve the machine learning model for better decision-making in the future. The cycle then restarts from the environmental sensing step, creating a continuous and self-regulating loop of monitoring, decision-making, harvesting, storage, and irrigation. Over time, this feedback-driven cycle adapts to changing weather conditions, crop requirements, and seasonal variations, ensuring sustainable water use with minimal human intervention [5, 6, 9].

V. CONCLUSION

The proposed Atmospheric Water Harvesting System integrated with Smart Irrigation and Machine Learning presents an innovative and sustainable approach to addressing water scarcity in agriculture. By combining environmental sensing, predictive ML models, and intelligent irrigation control, the system ensures that water is harvested and used only when necessary. This reduces wastage of resources and energy consumption, while also increasing crop resilience to climate change.

The integration of renewable energy sources, such as solar power, further enhances the system's suitability for rural and off-grid areas. Continuous data logging and feedback make the system adaptive over time, improving decision-making accuracy in varying conditions.

Overall, this paper demonstrates the potential of low-cost, technology-driven solutions to achieve water-efficient and climate-resilient farming. It highlights a scalable approach to sustainable agriculture and long-term food security in regions facing severe water challenges.

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