

RESEARCH ARTICLE

Mobile Based IoT System for Real -Time Soil Monitoring and Machine Learning Predictive Irrigation in Smart Agriculture

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Abstract

Water scarcity and inefficient irrigation remain problems in agriculture. This study developed and tested an IoT-based irrigation system with a mobile application and machine learning prediction for rice paddy water management. Soil moisture, air temperature, and relative humidity sensors were connected to an ESP32 microcontroller, which collected data and sent them to a cloud platform. A total of 8,640 valid observations were collected over 30 days from two plots at 10-minute intervals. Four algorithms (Decision Tree, Random Forest, Support Vector Machine, and Gradient Boosting) were trained and compared to predict irrigation need from current and historical conditions. The mobile application showed real-time readings, irrigation predictions, and historical data, and allowed manual pump control. The system reached a data transmission success rate of 98.7% and an average response time of 3.8 s. Random Forest gave the highest accuracy (94.3%), with a precision of 92.1%, a recall of 90.8%, and an F1-score of 91.4%. Compared with threshold-based irrigation, the predictive strategy used 20.8% less water (1,016.8 L vs. 1,284.6 L) and 18.4% fewer irrigation events (151 vs. 185), and soil moisture varied less (SD 5.7% vs. 7.4%). These results come from a 30-day trial with two plots at one site and were not tested statistically. Future work includes multi-depth soil sensing, weather forecast integration, solar-powered operation, and multi-season field validation.

Keywords

Internet of Things; Smart Agriculture; Predictive Irrigation; Machine Learning; Mobile Application.

1 | INTRODUCTION

Agriculture plays a fundamental role in global food production and economic development, yet the sector is increasingly challenged by water scarcity, climate variability, and the growing demand for efficient resource use. Irrigation is among the most important agricultural activities, because inappropriate water management can lead to excessive water consumption, higher operational costs, and unfavorable soil conditions for crop growth. Conventional irrigation is often based on fixed schedules or farmers' manual observations, which may not respond to dynamic changes in soil and environmental conditions (Mohammed *et al.*, 2025; Rachdi *et al.*, 2026). Irrigation systems that support data-driven and adaptive decisions are therefore needed (Bwambale *et al.*, 2022; Nsoh *et al.*, 2024).

The Internet of Things (IoT) offers new opportunities for agricultural monitoring and irrigation management. Interconnected sensors can continuously measure soil moisture, air temperature, and relative humidity, and the data can be transmitted to cloud platforms for storage, visualization, and analysis (Eze *et al.*, 2025; Obaideen *et al.*, 2022). The ESP32 microcontroller is widely used as the hardware platform for such systems because it balances processing capability and efficiency (Abdulrasaq *et al.*, 2026; Rachdi *et al.*, 2026). Reviews have reported that IoT-based irrigation reduced water use by roughly 20–40% and increased crop yields by 10–25% (Dutta *et al.*, 2026), and that AI- and sensor-driven scheduling typically reduced water use by 15–40% (Mohammed *et al.*, 2025). One ESP32-based drip irrigation system that sent soil moisture, temperature, and humidity data to a cloud platform for remote monitoring and pump control reported a 70% reduction in water consumption (Jaiswal *et al.*, 2025). These figures come from different crops, systems, and conditions and are not directly comparable with one another. Mobile applications add an accessible interface through which farmers and agricultural managers can monitor field conditions and adjust irrigation schedules remotely (Abdulrasaq *et al.*, 2026; Eze *et al.*, 2025).

Although IoT-based irrigation systems are increasingly adopted, many still activate irrigation according to predefined thresholds, particularly soil-moisture thresholds. Such rules are simple and practical, but a fixed threshold may not capture the complex and dynamic relationships among soil conditions, environmental variables, crop requirements, and irrigation history. Reviews have contrasted machine learning algorithms that analyze sensor data for irrigation scheduling with fixed threshold-based control (Nsoh *et al.*, 2024) and have highlighted the limited adaptive capacity of fixed or manual scheduling (Mohammed *et al.*, 2025). Soil moisture, air temperature, relative humidity, temporal information, and previous irrigation activities can serve as input features for models that estimate whether irrigation is required and, potentially, for how long or how much (Del-Coco *et al.*, 2024; Younes *et al.*, 2024). The potential of machine learning is considerable, although model generalization, data quality, system robustness, operational cost, and interoperability remain open concerns (Dutta *et al.*, 2026; Li *et al.*, 2026; Mohammed *et al.*, 2025). The absence of standardized benchmarks and open datasets also limits the transition from pilot studies to large-scale adoption (Jaiswal *et al.*, 2025).

Existing studies have mostly examined individual technological components, and the interoperability of integrated architectures that combine real-time IoT sensing, machine learning-based prediction, automated irrigation control, and mobile interaction has received less systematic examination (Dutta *et al.*, 2026). Sustainability-related outcomes such as water use are also not consistently quantified across studies (Rahayu *et al.*, 2026). Whether an integrated predictive approach offers measurable advantages over conventional irrigation strategies therefore requires practical evaluation. Such an evaluation should consider not only prediction accuracy but also agricultural indicators such as water consumption, soil moisture stability, system response time, and irrigation efficiency (Adeyemi *et al.*, 2017; Bwambale *et al.*, 2022).

This study therefore developed and evaluated a mobile-based IoT system for real-time soil and environmental monitoring combined with machine learning-based predictive irrigation. The system collects soil moisture, air temperature, and relative humidity data from IoT sensors and transmits them to a cloud-based platform for storage and analysis. Machine learning algorithms then predict irrigation requirements from real-time and historical environmental data, and the results are delivered through a mobile application that allows users to monitor field conditions, receive irrigation recommendations, and remotely control the irrigation pump. The main contribution of this study is an integrated framework that combines these components. Unlike threshold-based irrigation, the proposed approach bases irrigation decisions on multiple soil and environmental parameters. Its performance was compared with a conventional threshold-based strategy in terms of prediction performance, water consumption, soil moisture stability, and irrigation efficiency.

2 | BACKGROUND THEORY

IoT-based irrigation systems are usually built from sensing, communication, processing, and user-interface layers. Soil moisture, air temperature, and relative humidity sensors connect to a microcontroller, commonly an ESP32, which sends the readings to a cloud platform for storage, visualization, and analysis (Eze *et al.*, 2025; Obaideen *et al.*, 2022; Rachdi *et al.*, 2026). The cloud platform can return control commands to a pump and present

real-time data to users through a mobile application, such as a Blynk dashboard (Abdulrasaq *et al.*, 2026; Jaiswal *et al.*, 2025). Hybrid edge–cloud designs, in which part of the processing takes place near the field, have also been proposed for real-time irrigation optimization (Mohammed *et al.*, 2025). In such systems, the irrigation decision can be made by a fixed threshold or by a machine learning model that uses sensor data, and the latter is the approach evaluated in this study (Nsoh *et al.*, 2024).

Decision-tree-based algorithms are widely used for classification because they require relatively few parameters to be estimated and allow a high degree of automation (Boateng *et al.*, 2020). A Random Forest combines many decision trees, whereas Gradient Boosting builds an ensemble in which decision trees serve as common base learners that are added sequentially to correct the errors of the earlier ones (Natekin & Knoll, 2013). Support Vector Machines are another established classifier family that has been compared with Random Forest in terms of robustness, stability, sensitivity to noise, tuning effort, and accuracy (Boateng *et al.*, 2020). In this study, a Decision Tree, a Random Forest, a Support Vector Machine, and Gradient Boosting were used to classify whether irrigation was required.

Classifier performance is commonly reported with accuracy, precision, recall, and the F1-score. These metrics are the most frequently used for binary and multi-class classifiers, although their use is not standardized across studies and each has limitations (Grandini *et al.*, 2020; Naidu *et al.*, 2023). The F1-score is the harmonic mean of precision and recall and is used to find a balance between the two (Grandini *et al.*, 2020). When classes are unequally distributed, the classifier tends to favor the dominant class, and accuracy alone may therefore give a misleading picture; precision, recall, F1-score, G-mean, and the area under the curve are then used to complement it (Altalhan *et al.*, 2025; Branco *et al.*, 2016; Tanha *et al.*, 2020). F1-score is particularly useful on unbalanced datasets (Naidu *et al.*, 2023). Accordingly, this study reported accuracy, precision, recall, and F1-score for the selected model.

3 | METHOD

This study used a quantitative experimental design to develop and evaluate an irrigation system that integrates Internet of Things (IoT) sensing, machine learning-based prediction, automated irrigation control, and mobile-based monitoring. The experiment tested whether predictive irrigation based on multiple soil and environmental variables could provide measurable improvements over conventional threshold-based irrigation. The study was conducted from June 2026 to August 2026 in an agricultural cultivation area in Denpasar, Bali, Indonesia. The work followed a structured sequence of IoT system development, sensor calibration and deployment, real-time data collection, machine learning model development, predictive irrigation implementation, and comparative performance evaluation. Combining sensing, prediction, and control in this way is consistent with existing reviews of IoT- and machine learning-based irrigation (Nsoh *et al.*, 2024; Obaideen *et al.*, 2022).

The study population consisted of time-series observations collected from the agricultural environment rather than human participants. Soil moisture, air temperature, relative humidity, temporal information, and irrigation activity were recorded automatically at 10-minute intervals over the experimental period. The data came from two experimental plots with comparable crop, soil, and irrigation conditions. Only complete and valid observations were retained; records affected by sensor malfunction, communication failure, missing values, or physically implausible measurements were excluded. Before deployment, the sensors were calibrated and repeatedly tested against appropriate reference measurements to improve measurement reliability. An ESP32 microcontroller transmitted the sensor data over Wi-Fi to a cloud-based platform, where they were stored and synchronized with irrigation event records. Soil moisture and environmental sensing as the basic inputs follow established IoT-based smart irrigation architectures (Eze *et al.*, 2025; Obaideen *et al.*, 2022; Rachdi *et al.*, 2026).

Before model development, the dataset was preprocessed by removing duplicate and incomplete records, handling missing values, detecting abnormal values, normalizing the data where required, and engineering features. The predictive features were soil moisture, air temperature, relative humidity, time of measurement, previous irrigation status, and previous irrigation duration. The irrigation requirement was defined with an independent irrigation reference based on crop water requirements, observed soil moisture conditions, and agronomic irrigation recommendations, so that the model would not simply reproduce the soil moisture threshold used in the conventional approach. Using several soil and environmental variables follows data-driven irrigation approaches that aim to improve decisions beyond fixed thresholds (Del-Coco *et al.*, 2024; Nsoh *et al.*, 2024; Younes *et al.*, 2024).

The dataset was divided chronologically into 80% training data and 20% testing data to minimize information leakage and preserve the temporal structure of the observations. Decision Tree, Random Forest, Support Vector Machine, and Gradient Boosting were trained and compared to identify the most suitable model for irrigation prediction. Multiple algorithms have been applied to irrigation scheduling, and model performance and generalizability remain key considerations in practice (Del-Coco *et al.*, 2024; Nsoh *et al.*, 2024; Umutoni & Samadi, 2024). Model development and analysis were conducted in Python with the Scikit-learn library. The best-performing

model was integrated into the IoT irrigation system for real-time operation. Sensor data were collected continuously and sent to the processing platform, where the trained model predicted whether irrigation was needed. When irrigation was predicted to be necessary, the system sent a control signal to the irrigation actuator, which consisted of a water pump and a solenoid valve, and the irrigation event was recorded in the cloud database. Predictions, real-time sensor readings, and irrigation status were delivered to a mobile application developed with Blynk, which allowed users to monitor field conditions, receive irrigation recommendations, and interact with the irrigation system remotely.

The proposed predictive approach was evaluated against a conventional threshold-based irrigation method that used the same crop type, a comparable cultivation area, and similar environmental conditions during the experimental period. The models were assessed with accuracy, precision, recall, and F1-score (Grandini *et al.*, 2020; Naidu *et al.*, 2023), and, where regression models applied, with the mean absolute error (MAE) and the root mean square error (RMSE). Practical performance was assessed with water consumption, soil moisture stability, irrigation efficiency, and system response time. These indicators were chosen because the effectiveness of irrigation systems should be judged by water-management outcomes and field applicability, and not only by prediction accuracy (Adeyemi *et al.*, 2017; Bwambale *et al.*, 2022). Differences between the predictive and threshold-based approaches were tested statistically at a significance level of 0.05, using Python with the Pandas, NumPy, Scikit-learn, and SciPy libraries. Possible limitations arising from sensor accuracy, environmental variability, data availability, network connectivity, and model generalizability were addressed through sensor calibration, data quality monitoring, systematic preprocessing, chronological data splitting, and standardized experimental procedures. These factors matter because data quality, system integration, field variability, communication reliability, and generalizability are known challenges for IoT- and machine learning-based irrigation (Del-Coco *et al.*, 2024; Dutta *et al.*, 2026; Li *et al.*, 2026; Nsoh *et al.*, 2024).

4 | RESULTS AND DISCUSSION

4.1 Results

The system monitored soil and environmental conditions continuously for 30 days. A total of 8,640 valid observations were collected from two experimental plots at 10-minute intervals (Table 1). Soil moisture ranged from 28.4% to 68.7%, air temperature from 23.8 °C to 34.6 °C, and relative humidity from 47.2% to 96.4%. The mean values were 43.8% for soil moisture, 28.9 °C for air temperature, and 73.6% for relative humidity. The data transmission success rate was 98.7%, and the average time from sensor measurement to irrigation actuation was 3.8 s. The mobile application displayed real-time soil moisture, air temperature, relative humidity, irrigation predictions, and irrigation status.

Table 1. IoT monitoring results

Indicator	Result
Total observations	8,640
Observation period	30 days
Sampling interval	10 min
Soil moisture range	28.40–68.70%
Air temperature range	23.80–34.60 °C
Relative humidity range	47.20–96.40%
Mean ± SD, soil moisture (predictive plot)	43.80 ± 5.70%
Mean ± SD, air temperature	28.90 ± 1.70 °C
Mean ± SD, relative humidity	73.60 ± 10.80%
Data transmission success	98.70 ± 1.20%
Average response time	3.80 ± 0.90 s

Random Forest gave the best predictive performance of the four algorithms (Table 2, Figure 1). It reached an accuracy of 94.3%, a precision of 92.1%, a recall of 90.8%, and an F1-score of 91.4%, which is the harmonic mean of precision and recall. Gradient Boosting reached 93.1% accuracy, Support Vector Machine (SVM) 89.7%, and Decision Tree 87.6%.

Table 2. Classification performance of the evaluated models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Decision Tree	87.60	—	—	—
SVM	89.70	—	—	—
Gradient Boosting	93.10	—	—	—
Random Forest	94.30	92.10	90.80	91.40

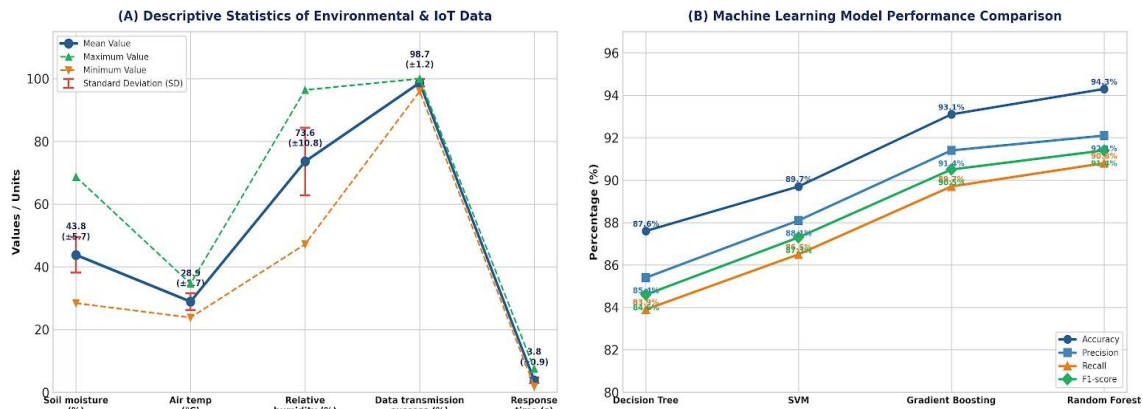


Figure 1. Environmental and IoT monitoring results and comparison of machine learning model performance.

The predictive strategy used less water and fewer irrigation events than the conventional threshold-based strategy (Table 3, Figure 2). Water consumption fell from 1,284.6 L to 1,016.8 L (Equation 1), and irrigation events fell from 185 to 151 (Equation 2). Mean soil moisture was 43.8% under the predictive strategy and 42.1% under the conventional one, and the standard deviation was 5.7% and 7.4%, respectively.

$$\text{Water reduction (\%)} = \frac{W_{\text{conv}} - W_{\text{ML}}}{W_{\text{conv}}} \times 100\% = \frac{1,284.60 - 1,016.80}{1,284.60} \times 100\% = 20.8\%$$

$$\text{Irrigation event reduction (\%)} = \frac{185 - 151}{185} \times 100\% = 18.38\%$$

Table 3. Irrigation performance of the conventional and predictive strategies

Indicator	Conventional	Predictive
Water consumption (L)	1,284.60	1,016.80
Water reduction (%)	—	20.80
Irrigation events	185	151
Irrigation event reduction (%)	—	18.38
Mean soil moisture (%)	42.10	43.80
Soil moisture SD (%)	7.40	5.70

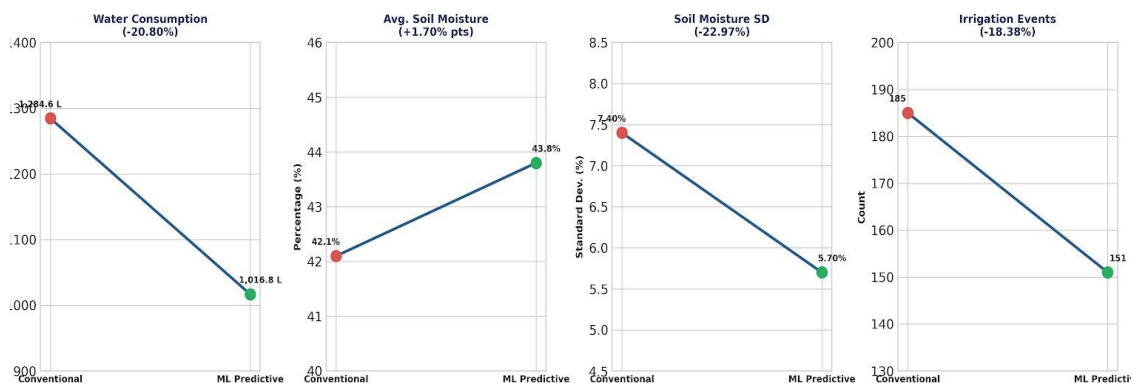


Figure 2. Comparison of irrigation performance between conventional and machine learning-based predictive approaches.

The prototype (Figure 3) was installed in a rice paddy field. An ESP32 board and a relay module were housed in an IP65 junction box on a wooden stake on an earthen embankment. Two capacitive soil moisture sensors and a temperature probe were placed in the flooded root-zone soil. A submersible pump in the adjacent water channel delivered water through a hose to the soil near the sensors, and the node transmitted its data by cellular IoT connectivity. The mobile interface (Figure 4) was developed on Blynk 2.0. A switch changes between manual control and ML predictive mode. A gauge shows soil moisture (43.8%), and readouts show air temperature (28.9 °C) and relative humidity (73.6%). A status card shows the Random Forest output ("IRRIGATION NOT NEEDED"), a trend chart shows historical readings, and the manual pump button is locked in ML predictive mode.

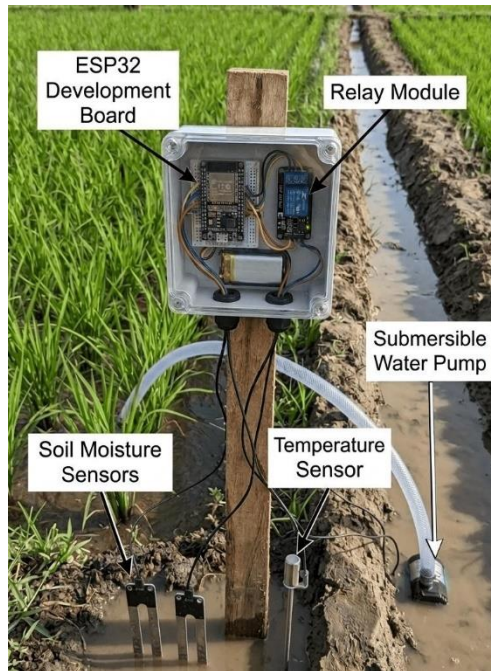


Figure 3. Prototype of the IoT irrigation node.



Figure 4. Mobile interface.

4.2 Discussion

The monitoring infrastructure worked reliably during the experiment. A transmission success rate of 98.7% and a response time of 3.8 s show that the system could support near-real-time monitoring and actuation. Connectivity limits, sensor drift, and proprietary architectures remain reported barriers for smart irrigation (Mohammed *et al.*, 2025), and a single 30-day record cannot show long-term reliability. Random Forest performed best among the four models. This may be because an ensemble of trees can represent nonlinear relations among soil moisture, weather, time, and irrigation history. Other studies report different best models. Random Forest was best in Glória *et al.* (2021), with an accuracy of 84.6%. XGBoost was best in Sahu and Tripathi (2025), with 99.96% accuracy, where LightGBM and Random Forest were comparable, and in Wang *et al.* (2025) for cherry tomatoes in greenhouses. Because data, crops, and labels differ, these accuracies are not comparable with 94.3%. XGBoost was not tested here, so Random Forest was best only among the four models compared. Reviews note that Random Forest and SVM are among the algorithms commonly compared for adaptive irrigation scheduling (Oğuztürk, 2025; Umutoni & Samadi, 2024). Khomri *et al.* (2026) found only moderate soil moisture prediction by Random Forest and the best results from LSTM and GRU, so sequence models are worth testing.

The predictive strategy used 20.8% less water than the threshold-based one and 18.38% fewer irrigation events, while soil moisture was less variable (SD 5.7% vs. 7.4%). This saving is at the lower end of reported ranges: 15–40% for AI- and sensor-driven scheduling (Mohammed *et al.*, 2025), 30–50% in a meta-analysis (Oğuztürk, 2025), 25% (Sahu & Tripathi, 2025), 30% for maize and 27% for wheat (Nasar *et al.*, 2026), and up to 60% in a 90-day trial (Glória *et al.*, 2021). Reviews also report that ML generally outperforms conventional approaches (Umutoni & Samadi, 2024; Younes *et al.*, 2024). Baselines differ among these studies, and the present one was a soil-moisture threshold and not a fixed schedule, so a smaller saving is plausible. The mean soil moisture difference of 1.7 percentage points is small. Energy use and equipment wear were not measured, so fewer irrigation events are only a possible benefit. Nasar *et al.* (2026) did measure energy and runoff reductions in their field validation.

The study had limits. It covered 30 days, two plots, and one site, and the water comparison is one total per

strategy, which prevents a statistical test. If each strategy ran on a separate plot, plot differences cannot be separated from the strategy effect. ML irrigation in the field is also limited by data availability, uncertainty quantification, and generalization (Li *et al.*, 2026; Umutoni & Samadi, 2024). Standardization, validation across crops and regions, and sensor calibration protocols are further needs (Oğuztürk, 2025). Future work should use several growing seasons, replicated plots, other crops and soils, and models such as XGBoost and LSTM, and should measure crop yield, energy use, cost, and long-term reliability.

5 | CONCLUSIONS

This study developed and tested an IoT-based irrigation system that combines an ESP32 node, soil and environmental sensors, machine learning prediction, automated pump control, and a mobile dashboard for rice paddy water management. Random Forest gave the highest accuracy of the four algorithms tested (94.30%), with a precision of 92.10%, a recall of 90.80%, and an F1-score of 91.40%. Gradient Boosting, Support Vector Machine, and Decision Tree reached accuracies of 93.10%, 89.70%, and 87.60%, respectively. Compared with the conventional threshold-based strategy, the predictive strategy reduced water consumption by 20.80%, from 1,284.60 L to 1,016.80 L, and irrigation events by 18.38%, from 185 to 151. Mean soil moisture was 43.80% under the predictive strategy and 42.10% under the conventional one, and its standard deviation was lower (5.70% vs. 7.40%). The cellular IoT link achieved a data transmission success rate of 98.70% and an average response time of 3.80 s for the mobile dashboard. These results come from a 30-day trial with two plots at one site, so they should be confirmed under wider conditions. Future work will test the system over several growing seasons and evaluate its effect on paddy yield, energy use, and economic return. Planned improvements include solar power for remote fields, soil moisture sensing at 10, 20, and 30 cm depths to capture water movement in the root zone, and rainfall forecasts as a model input to avoid watering before expected rain.

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