

Integrating Fuzzy Rule-Based Reasoning with Machine Learning for Intelligent and Scalable Irrigation Control

Bharati Wukkadada,¹ Pradeep Kachakayala,² Padma Nilesh Mishra,³ Aditi Srivastava,⁴ T. Prem Chander,⁵ Saiprasad Potharaju,⁶ and Ali Khwaldeh⁷

¹Department of Data Science and Technology, K J Somaiya Institute of Management, Somaiya Vidyavihar University, Mumbai, India

²Cloud Engagement Manager, Insight Enterprises, Arizona, USA

³Master of Computer Applications, Thakur Institute of Management Studies, Career Development and Research, Maharashtra, India

⁴Master of Business Administration, ABES Business School, Ghaziabad, India

⁵Department of CSE, Matrusri Engineering College, Saidabad, Hyderabad, Telangana, India

⁶Computer Science and Engineering, Symbiosis Institute of Technology, Symbiosis International (Deemed University), Pune, India

⁷Communications and Computer Engineering Department, Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman, Jordan

(Received 10 August 2026; Revised 06 September 2026; Accepted 21 September 2026; Published online 30 October 2026)

Abstract: This study presents a hybrid intelligent irrigation decision support system that integrates fuzzy logic and Random Forest (RF) regression to support irrigation decision-making in agriculture. A fuzzy inference engine was designed using expert-defined rules based on soil moisture, air temperature, and rainfall. This system generated irrigation recommendations on a scale of 0–10 using Mamdani-type fuzzy logic. An RF model was trained on the same inputs with the fuzzy output as the target to evaluate how accurately a data-driven model can reproduce the fuzzy decision mapping. Using five-fold cross-validation, the RF achieved a root mean squared error (RMSE) of 0.2459 ± 0.1399 , mean absolute error (MAE) of 0.0801 ± 0.0434 , and coefficient of determination (R^2) of 0.9682 ± 0.0282 , indicating strong alignment with fuzzy decision logic. This hybrid approach offers a transparent, data-driven, and scalable solution, effectively bridging the gap between interpretability and prediction accuracy. The system has the potential to support precision irrigation and informed water management decisions and was evaluated using one year of daily aggregated Internet of Things (IoT) sensor observations from Narrabri, Australia.

Keywords: decision support; environmental conditions; fuzzy logic; irrigation; machine learning

I. INTRODUCTION

Efficient water management in agriculture has become a pressing global concern due to increasingly unpredictable climate patterns, declining freshwater availability, and the growing demand for food [1,2]. In many regions, especially those prone to arid and semi-arid climates, water scarcity significantly affects crop yields, soil quality, and the long-term sustainability of farming practices. Conventional irrigation systems, which are often based on fixed schedules, manual control, or farmer intuition, do not adequately account for dynamic environmental conditions such as real-time changes in soil moisture, rainfall, and ambient temperature [3]. As a result, they frequently lead to either over-irrigation wasting valuable water resources and causing soil nutrient leaching or under-irrigation, which can induce plant stress and reduce agricultural productivity.

To overcome these challenges, it was decided to develop the smart irrigation system, which was motivated by environmental sensing technologies integration with the artificial intelligence (AI) technologies [4,5]. The aim of these systems is to take decisions based on real-time data and usage to balance the water use from usage perspective with maintaining ecosystem or crop yield [6,7]. Among all the various AI tools, the complex nonlinear relationship between data and the predictions can be effectively discovered by machine learning (ML) models [8,9]. However, the ‘black box methods’ that fall into this classification category of neural networks or ensemble learners [10,11] have the characteristic of being not interpretable. These systems have to be transparent and explainable to be used by stakeholders like farmers, agronomists, and policy-makers for critical decision-making tasks in agriculture. On the other hand, fuzzy logic systems (FLSs) lend themselves very well because of their rule-based nature that imitates human reasoning with linguistic variables and logical rules [12]. Fuzzy systems are highly interpretable, and they are especially suited in the situations where it is easy to express the domain knowledge in the process of decision-making [13]. They are the perfect tools for

*Corresponding author: Padma Nilesh Mishra (e-mail: mishrapadma1988@gmail.com).

using imprecise or uncertain input conditions, as required in environmental monitoring [14,15]. But the conventional fuzzy systems are static and expert-dependent and are less flexible to handle large-scale datasets and changing environmental patterns. A major research gap currently exists in the literature: although ML and fuzzy logic techniques have been implemented in irrigation decision-making, little has been done to integrate them into an integrated framework. Existing systems are based on opaque ML models, which lack interpretability, or on fixed-rule fuzzy systems, which have no learning ability and adaptation. Furthermore, there are few studies that study the trade-off between interpretability and performance or apply the ML technique to validate and replicate the fuzzy logic controller's decisions. The opportunity to employ the ML models as evaluative tools in fuzzy systems is not fully explored. Based on the above, the research purpose of the present research is to develop and test a hybrid intelligent irrigation decision support system which takes the advantages of both fuzzy logic and ML. The system is designed to be two-fold. First, the fuzzy inference engine is developed based on expert defined IF-THEN rules, which are given as input to the fuzzy inference engine: soil moisture, air temperature and rainfall, and output as daily irrigation need recommendations between 0 and 10. The rules are designed to mimic real-world decision-making in the presence of uncertainty and variance in the field.

In that, the input of a model called Random Forest (RF) regression is the same as in the first step, while the output of the fuzzy system is the target variable. This model is not intended to replace the fuzzy system, but to check, understand, and know how the ML system would behave, and if it could make the same rule-based decisions. An RF learning with the capability to keep interpretability by fuzzy logic is used in both methods, which gives the robustness and generalization ability. This research offers novelty in the fuzzy logic world that provides the transparency and high performance seamlessly, for explainable fuzzy reasoning with ML validator. It is one of the rare applications that use crisp or fuzzy irrigation decisions based on predictions made by the RF algorithm on real-world environmental sensor data and a practical, scalable, and smart solution in the field of precision agriculture. AI has been applied to agriculture and has resulted in the development of precision irrigation systems [16]. Fuzzy logic has been extensively applied due to its capabilities to deal with uncertainty and represent the knowledge of experts in terms of IF-THEN rules [17]. For example, fuzzy systems for the management of a greenhouse [18] have been developed, soil condition analysis [19], and crop health monitoring [20]. These systems will, however, have to be constructed by hand and are not very flexible. Agricultural forecasting tasks have shown excellent results with ML models like RF, support vector machines, and neural networks. RF stand out in particular because of its robustness and contains key insights. But there are issues with the difficulty of these models' interpretation [21].

Although some hybrid systems have tried to combine AI techniques, there is limited research on how to evaluate fuzzy systems based on models obtained by ML, trained directly with the fuzzy outputs. This study fills this gap by using an RF model as a validation tool for a rule-based fuzzy system in smart irrigation. In motor control studies [22], fuzzy logic is used to develop a decision support system for automatic assessment of the wide range of motor control to assist the motor control practitioner in motor control assessment. The use of fuzzy logic in a healthcare setting aims at improving the accuracy and the interpretation of the diagnosis. Since the Mamdani Fuzzy Inference System (Mamdani FIS) is used to

model complex medical decision-making process that has imprecise or uncertain medical data, it also provides nuanced assessments. In [24], we have developed intelligent decision support system (IDSS) based on fuzzy logic to support the chemical process company to decide on the suppliers selection. The fuzzy-based model can be used to convert the uncertainties and subjectivity in supplier evaluation into quantitative criteria, which can then be used in a more intelligent and reasonable decision-making process. Developed with the fuzzy inference system (FIS, a precision irrigation controller is developed that takes into account the deviation from the reference soil moisture and the crop coefficient. These inputs are processed in a 28-rule base, and the optimal incremental control of irrigation volume is computed by the FIS accuracy matching Discrete Linear Quadratic Regulator (DLQR) with significantly lower computational complexity, making it suitable for real-time applications for IoT [25]. A fuzzy logic controller is proposed to process the inputs like soil moisture, ambient temperature, and the level of water tank, so as the status of the water pump can be determined in which the smart irrigation system can give the optimal irrigation for balcony plants [26]. In the proposed hybrid AC/DC microgrid operating in stand-alone mode with an integrated EV charging station, a fuzzy logic-based decision-making system manages power distribution by evaluating the state of charge (SOC) of the energy storage system (ESS) and solar irradiance levels. This method could improve the reliability of the system by switching its operating modes to utilize energy resources in a more efficient way while maintaining uninterrupted operation through environmental changes [27]. While previous research used fuzzy logic in isolation for particular applications such as ergonomic evaluation, medical diagnosis, supplier selection, or hardware-based control (e.g. irrigation, microgrid), this proposed system has a hybrid decision support architecture that combines fuzzy logic and RF ML into one holistic model. This is further discussed in the next section.

II. METHODOLOGY

The proposed hybrid system consists of two main components:

1. An FIS to simulate expert-based irrigation decisions.
2. An RF model to learn from and validate the fuzzy outputs.

These components deliver an intelligent and explainable irrigation decision support system. The overall architecture is depicted in Fig. 1, and its components are described below.

A. FUZZY INFERENCE SYSTEM (FIS)

The fuzzy system models irrigation decision-making through expert-defined rules applied to environmental inputs: Inputs: In this system, the attributes (inputs) are environmental factors collected via IoT sensors. These form the basis for decision-making. Attributes used:

1. Soil Moisture (%VWC) – Indicates how much water is currently in the soil.
2. Air Temperature (°C) – Higher temperatures increase evaporation, indicating greater irrigation needs.
3. Rainfall (mm) – Recently recorded rainfall reduces irrigation requirements.

These attributes are fed into the fuzzy system for interpretation.

Fuzzification: Inputs are transformed into fuzzy linguistic variables using triangular membership functions (TMFs) in this

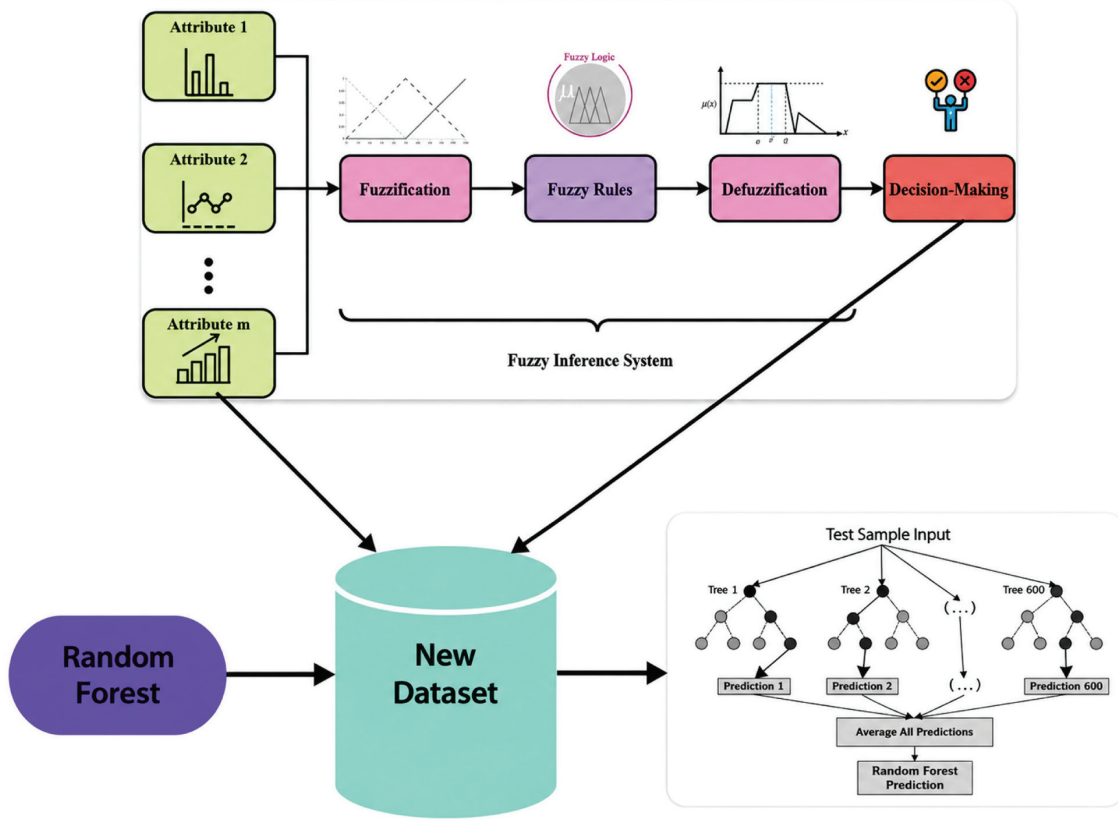


Fig. 1. System architecture.

Algorithm: Hybrid Fuzzy Random Forest Irrigation System

Input:

- Environmental dataset with attributes:
SoilMoisture, AirTemperature, Rainfall

Output:

- Irrigation Need Recommendation (Low, Medium, High)

BEGIN

// Step 1: Load and Preprocess Dataset

Read dataset from sensor logs or Excel file

FOR each record IN dataset DO

 Extract input values: $SM \leftarrow \text{SoilMoisture}$
 $TEMP \leftarrow \text{AirTemperature}$
 $RAIN \leftarrow \text{Rainfall}$

END FOR

// Step 2: Fuzzy Inference System (FIS)

Define fuzzy membership functions for:

 SoilMoisture: Low, Medium, High
 AirTemperature: Low, Medium, High
 Rainfall: Low, Medium, High

Define output variable: IrrigationNeed (range: 0–10)

Define fuzzy rules (R1 to R8) based on expert knowledge

FOR each input sample DO

 Fuzzify Inputs:

 Compute μ_{SM} , μ_{TEMP} , μ_{RAIN} using triangular MFs

Algorithm: (continued)

Rule Evaluation:

 FOR each rule R_i DO

 Compute rule activation μ_{R_i} using fuzzy AND
 (min operator)

 Clip output fuzzy set accordingly

 END FOR

Aggregation:

 Combine all clipped fuzzy outputs (max operator)

Defuzzification:

 Compute crisp output using Centroid method

 Save crisp output as FuzzyIrrigationNeed

END FOR

// Step 3: Train and Validate Regression Models

Create five folds using KFold ($n_splits = 5$, $shuffle = True$,
 $random_state = 42$)

FOR each fold: train RandomForestRegressor using inputs [SM,
TEMP, RAIN] and target [FuzzyIrrigationNeed]; predict the held-
out fold

Repeat the same five folds for Linear Regression and Support
Vector Regression baselines

Evaluate all models:

Compute RMSE, MAE, and R^2 for each fold; report mean $\pm$
standard deviation

// Step 4: Decision Recommendation

(continued)

(Ahead of Print)

(continued)

Algorithm: (continued)

```

FOR each predicted output DO
  IF output  $\leq 3$  THEN
    Recommendation  $\leftarrow$  "Low (No Irrigation Needed)"
  ELSE IF output  $\leq 6$  THEN
    Recommendation  $\leftarrow$  "Medium (Moderate Irrigation)"
  ELSE
    Recommendation  $\leftarrow$  "High (Full Irrigation)"
  END IF
END FOR

```

stage. Each crisp input (numeric value) is converted into linguistic variables using membership functions as per Table I.

Fuzzy Rule Base: The FIS was constructed using a Mamdani-type rule base derived from expert agronomic knowledge as per Table II. A total of eight IF-THEN rules were defined based on combinations of the three environmental inputs: soil moisture, air temperature, and rainfall. Each rule maps input conditions to a linguistic output representing irrigation needs.

Rule Development and Validation: The eight rules were formulated from agronomic reasoning and the relationships reported in prior smart irrigation studies [25,26]. Soil moisture was treated as an indicator of available soil water, air temperature as an indicator of evaporative demand, and rainfall as natural water replenishment. The rule base was used as an expert-informed rule set in the present study; however, it was not independently validated by a separate agricultural expert. Independent expert validation is therefore retained as a limitation and future direction.

Defuzzification: It converts fuzzy output values (like partial degrees of Low, Medium, High) into a crisp scalar value. The most commonly used method is the centroid method, also called center of gravity.

Before Defuzzification, let's see the Fuzzification Process for Sample Input

To demonstrate the fuzzification process, consider an accurate environmental input sample:

1. Soil Moisture = 31.0 %VWC
2. Air Temperature = 40.0 °C
3. Rainfall = 0.0 mm

Each input variable is mapped to fuzzy linguistic terms using TMFs defined over their respective domains.

1. Soil Moisture Fuzzification

Membership functions:

Low: Triangular MF with range [30,30,35]

Medium: Triangular MF with range [33,35,37]

High: Triangular MF with range [35,40,40]

Calculation:

Low (μ_{low}):

$$\mu_{Low}(31.0) = 35 - 31.0/35 - 30 = 4/5 = 0.80$$

Medium (μ_{medium}):

$31.0 < 33 \rightarrow$ Outside support $\rightarrow$

$$\mu_{Medium}(31.0) = 0.0$$

High (μ_{high}):

$31.0 < 35 \rightarrow$ Outside support $\rightarrow$

$$\mu_{High}(31.0) = 0.0$$

Result:

$$\mu_{Low} = 0.80$$

$$\mu_{Medium} = 0.0$$

$$\mu_{High} = 0.0$$

2. Air Temperature Fuzzification

Membership functions:

Low: Triangular MF with range [5,5,20]

Medium: Triangular MF with range [15,25,35]

High: Triangular MF with range [30,45,45]

Table I. Membership functions

Input/output variable	Low	Medium	High	Membership type
Soil moisture (%VWC)	[30,30,35]	[33,35,37]	[35,40,40]	Triangular
Air temperature (°C)	[5,5,20]	[15,25,35]	[30,45,45]	Triangular
Rainfall (mm)	[0, 0, 10]	[5,20,35]	[30,60,60]	Triangular
Irrigation need (0–10)	[0, 0, 4]	[3,5,7]	[6,10,10]	Triangular

Table II. The fuzzy rules

Rule no.	IF conditions	THEN output	Justification
1	Soil Moisture is Low AND Air Temperature is High AND Rainfall is Low	Irrigation Need is High	Hot and dry conditions with low moisture require urgent irrigation.
2	Soil Moisture is Low AND Rainfall is Medium	Irrigation Need is Medium	Moderate rainfall partially compensates for dry soil.
3	Soil Moisture is Low AND Rainfall is High	Irrigation Need is Low	High rainfall offsets the low soil moisture.
4	Soil Moisture is Medium AND Air Temperature is Medium AND Rainfall is Low	Irrigation Need is Medium	Moderate weather with low rain requires careful irrigation.
5	Soil Moisture is Medium AND Rainfall is High	Irrigation Need is Low	Rainfall supports existing soil moisture.
6	Soil Moisture is High	Irrigation Need is Low	High moisture eliminates need for irrigation.
7	Rainfall is High	Irrigation Need is Low	Heavy rainfall satisfies water demand independently.
8	Air Temperature is Low AND Soil Moisture is Medium	Irrigation Need is Low	Low evaporation preserves medium soil moisture.

Calculation:

Low (μ_{low}):

$40 > 20 \rightarrow$ Outside support

$\mu_{Low}(40.0) = 0.0$

Medium (μ_{medium}):

$40 > 35 \rightarrow$ Outside support

$\mu_{Medium}(40.0) = 0.0$

High (μ_{high}):

$\mu_{Hig}(40.0) = 40.0 - 30/45 - 30 = 10/15 = 0.67$

Result:

$\mu_{Low} = 0.0$

$\mu_{Medium} = 0.0$

$\mu_{High} = 0.67$

3. Rainfall Fuzzification

Membership functions:

Low: Triangular MF with range [0, 0, 10]

Medium: Triangular MF with range [5,20,35]

High: Triangular MF with range [30,60,60]

Calculation:

Low (μ_{low}):

$\mu_{Low}(0.0) = 1.0$

Medium (μ_{medium}):

$0.0 < 5 \rightarrow$ Outside support $\rightarrow$

$\mu_{Medium}(0.0) = 0.0$

High (μ_{high}):

$0.0 < 30 \rightarrow$ Outside support $\rightarrow$

$\mu_{Hig}(0.0) = 0.0$

Result:

$\mu_{Low} = 1.0$

$\mu_{Medium} = 0.0$

$\mu_{High} = 0.0$

For the given input of Soil Moisture = 31.0 %VWC, Air Temperature = 40.0°C, and Rainfall = 0.0 mm, the system evaluated the membership of each variable in its respective fuzzy categories. The soil moisture input was 31.0 which was mainly located in the “Low” fuzzy set, and the membership degree (μ) of the “Low” fuzzy set is 0.80. The membership of 31.0 in the defined intervals “Medium” or “High” is essentially zero because it is well below those intervals. The air temperature of 40.0°C was compared with the “High” fuzzy set, and the membership value of 40.0°C was

calculated as 0.67, with the membership value for the “Low” and “Medium” categories being 0, because the temperature is not in the support sets of the “Low” and “Medium” fuzzy sets. Finally, the amount of rainfall input was 0.0 mm and produced a membership grade of 1.00 in the “Low” fuzzy set and 0.0 in the “Medium” and “High” fuzzy sets. These fuzzified values Soil Moisture (Low: 0.80), Air Temperature (High: 0.67), and Rainfall (Low: 1.00) are then fed into the fuzzy inference engine for evaluation of the rules. In this stage, the degree of activation of each rule is computed with fuzzy logic operators. If the rule is an AND rule (like Rule 1 for this system), the degree of activation is calculated as the minimum (min) of the degrees of membership to the inputs. Thus, for Rule 1, the final degree of activation is calculated as $\mu = \min(0.80, 0.67, 1.00) = 0.67$. The centroid method was applied over the clipped output fuzzy set representing the “High” irrigation need. This resulted in a crisp value of 6.8, calculated by numerically integrating the product of each point and its membership value across the domain of 6 to 10. This output falls in the “High” irrigation category, validating the decision inferred by the activated fuzzy rule.

Decision-Making: The output score is interpreted as:

Low (0–3): No irrigation required;

Medium (>3–6): Moderate irrigation;

High (>6–10): Full irrigation needed.

The crisp output of 6.8 is greater than 6.0 and therefore falls within the “High” irrigation decision range (>6–10) as per Fig. 2, indicating a high/full irrigation recommendation for this illustrative case.

A Random Forest Regressor was trained using the same environmental inputs to assess how well ML can replicate fuzzy logic. The fuzzy output served as the target variable. The model was evaluated using root mean squared error (RMSE), mean absolute error (MAE), and R^2 .

In order to complement the rule-based interpretability of the FIS, an RF regression model was trained with the same environmental inputs soil moisture, air temperature, and rainfall and a fuzzy system’s crisp outputs as labels. The model was trained and simulated with the expert specified FLS in order to evaluate the consistency of the FLS derived decision mapping from the FIS and to determine the degree of consistency with which the FIS-generated decision mapping could be replicated under the observed environmental variability. The model is scalable, generalizable, adaptable, and unlike traditional fuzzy systems, is not static, so making it suitable for dynamic agricultural conditions. This mixed integration is a new method that combines the interpretation of fuzzy logic and the prediction of ML and forms a decision-making support system that is powerful and intelligent for precision irrigation. Random Forest Configuration and Validation: The Random Forest Regressor was configured with 100 trees ($n_{estimators} = 100$), $max_depth = None$, $min_samples_split = 2$, $min_samples_leaf = 1$, $max_features = 1.0$, $bootstrap = True$, and $random_state = 42$. Five-fold cross-validation with KFold ($n_splits = 5$, $shuffle = True$, $random_state = 42$) was used instead of 70:30 split. To compare the results, Linear Regression (LR) and Support Vector Regression (SVR) were tested with the same folds. Within the training pipeline, SVR employed a radial basis function kernel with a C value of 10, an epsilon of 0.1, a gamma of scale, and feature standardization. Each fold was computed for RMSE, MAE, and the coefficient of determination (R^2), and then the mean $\pm$ standard deviation was determined. The fuzzy inference output is used for the training of the ML class, and the regression metrics are used to calculate the accuracy of the models with respect to the decision surface generated with FIS. They are not

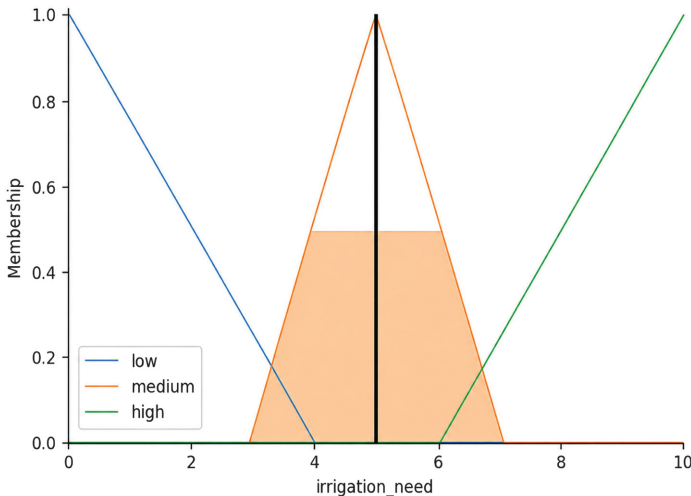


Fig. 2. Irrigation needed range as per membership function.

a measure of the actual effectiveness of irrigation, water saved, or crop production improvement.

III. EXPERIMENTAL RESULTS

A. DATASET DESCRIPTION

The study is based on real-time environmental data acquired from the Internet of Things (IoT) sensor nodes deployed in an agricultural environment in Narrabri, Australia. The data were obtained from the IEEE DataPort dataset “IoT Sensor Node Data” by Waqas Afridi [28] (DOI: 10.21227/m66w-vh45). The file “1 Year Node-4, Narrabri.xlsx” contains 366 dated daily observations covering 10 October 2022 to 10 October 2023. IEEE DataPort states that the aggregated raw data were cleaned, scaled, and converted to a per-day basis; therefore, the sampling frequency used in this study is one observation per day. The public dataset metadata does not specify the pre-aggregation raw sensor acquisition interval. Data includes daily measurements of: soil moisture (%VWC) at 20 cm depth, air temperature ($^{\circ}\text{C}$), and rainfall (mm).

1). DESIGN FUZZY LOGIC MODEL. A Mamdani-type FIS was designed. Three linguistic terms were used to fuzzify the inputs (Low, Medium, and High), and the output (Irrigation Need) was defined in the range of 0–10. Eight expert-informed rules were developed to control the irrigation recommendations. Table III presents 20 representative environmental conditions and their output and recommendation by the FIS. In the same way, all 366 daily observations and their FIS outputs were considered for the ML analysis.

Here is the Justification of FIS.

Case 1:

The results are Soil Moisture = 35.91 %; Air Temperature = 17.7°C ; Rainfall = 0.0 mm; and Fuzzy Output = 3.69 which is considered to be the medium (Moderate Irrigation)

recommendation. This scenario has moderately moisture soil and has no rainfall with cool air temperature. The soil has a fair supply of moisture (just below “High”) but no rainfall and moderate transpiration at this temperature, which means that crops could start to experience water stress over time. This balance of environmental conditions is fairly interpreted by the fuzzy system and moderate irrigation is recommended in order to keep the moisture of soil without excess watering. It is a preventive measure in water management – something which is key to sustainable farming.

Case 2:

Based on the above information, the soil moisture level is 35.23 % and the air temperature is 18.1°C , while the rainfall is 20.4 mm, the fuzzy output is 1.88, which translates to “Low (No Irrigation Needed).”

Here, moderate soil moisture, a relatively low air temperature, and heavy rainfall are recorded. More than 20 mm of rainfall have fallen recently, which means that there is a good supply of natural water for the soil and artificial irrigation is not necessary at this time. In addition, cooler temperatures reduce evapotranspiration and help to hold available water for longer periods. Given this, the FLS gives an irrigation score of 1.88, suggesting that no irrigation should be provided. This shows the system’s capability to downregulate irrigation needs with natural precipitation matching real agronomic practices. The graphical interpretation of the influence of the three variables to the fuzzy output is shown in Fig. 3.

B. RF MODEL

The consistency and generalizability of the FIS were tested by a Random Forest Regressor with all 366 daily observations. The environmental input parameters, soil moisture, air temperature, and rainfall were used as the independent input variables, with the fuzzy output parameter (0–10) treated as the target variable. A five-fold cross-validation method was used rather than the usual 70:30 split of

Table III. Fuzzy inference system output and its recommendation

Soil moisture	Air temp ($^{\circ}\text{C}$)	Rainfall (mm)	Fuzzy output (0–10)	Recommendation
35.91	17.7	0	3.69	Medium (Moderate irrigation)
35.48	18.95	0	4.33	Medium (Moderate irrigation)
35.9	20.25	0	4.08	Medium (Moderate irrigation)
33.68	22.92	0.2	5	Medium (Moderate irrigation)
33.35	24	0.2	5	Medium (Moderate irrigation)
33.49	26.99	0	5	Medium (Moderate irrigation)
33.29	31.38	0	6.21	High (Full irrigation)
34.12	27.37	0	5	Medium (Moderate irrigation)
33.24	27.17	0	5	Medium (Moderate irrigation)
33.85	25.17	0	5	Medium (Moderate irrigation)
35.23	18.1	20.4	1.88	Low (No irrigation needed)
34.3	16.5	0	3.05	Medium (Moderate irrigation)
33.91	15.65	0	2.36	Low (No irrigation needed)
33.72	15.1	0	1.8	Low (No irrigation needed)
34.14	6.85	0	1.5	Low (No irrigation needed)
35.02	12.15	0.2	1.54	Low (No irrigation needed)
34.75	13.95	0	1.63	Low (No irrigation needed)
34.54	13.35	0	1.6	Low (No irrigation needed)
34.37	11.4	4.2	1.5	Low (No irrigation needed)
34.18	17.4	0	3.65	Medium (Moderate irrigation)

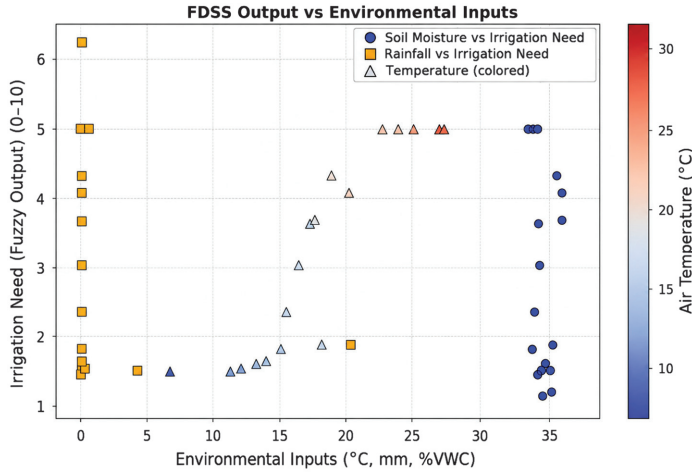


Fig. 3. Fuzzy decision support system output with environmental inputs

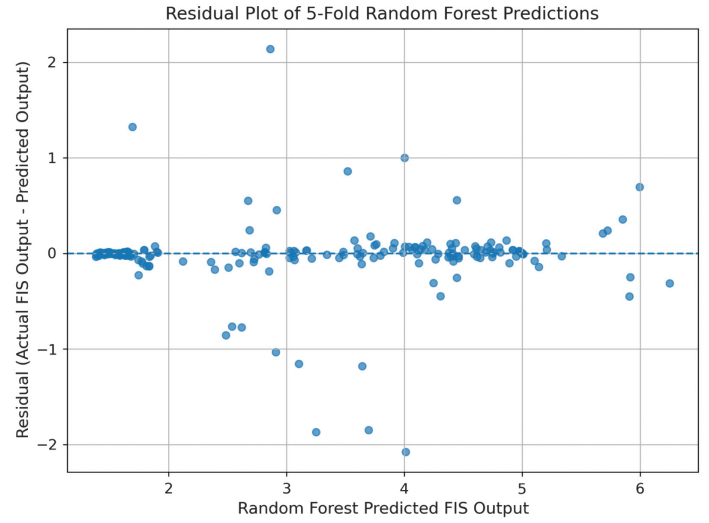


Fig. 5. Residual plot of five-fold Random Forest predictions.

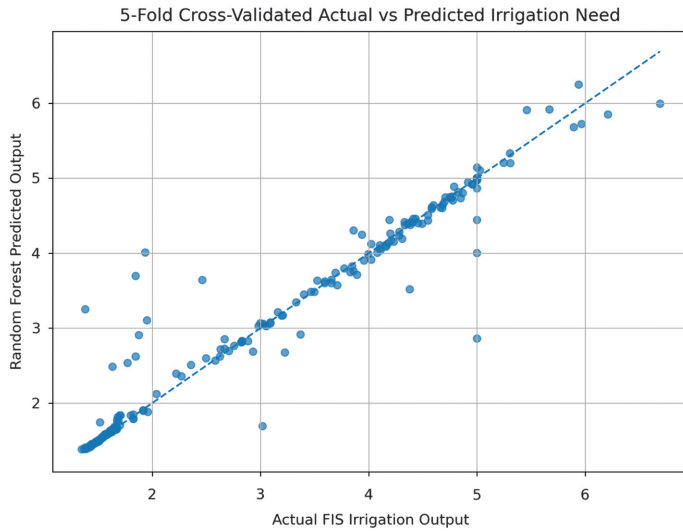


Fig. 4. Five-fold cross-validated actual versus predicted irrigation need.

the data, and the same folds were used with the RF, LR, and SVR. The results for the folds are reported in Table IV, and the mean $\pm$ standard deviation comparison is reported in Table V. The five-fold cross-validated actual-versus-predicted output, residual plot, and RF feature importance are shown in Figs. 4–6, respectively.

Evaluation parameters were RMSE, MAE, and R^2 . From the five-fold results, it is seen that the overall mean performance was

Table IV. Fold-wise five-fold cross-validation performance of the regression models

Model	Fold	RMSE	MAE	R^2
Linear Regression	1	0.643153	0.539121	0.815108
Linear Regression	2	0.609208	0.473195	0.853802
Linear Regression	3	0.677483	0.612504	0.817027
Linear Regression	4	0.635401	0.524229	0.835300
Linear Regression	5	0.620193	0.517461	0.820633
Support Vector Regression	1	0.290840	0.187568	0.962191
Support Vector Regression	2	0.312392	0.184842	0.961557
Support Vector Regression	3	0.287345	0.170558	0.967085
Support Vector Regression	4	0.321114	0.193754	0.957935
Support Vector Regression	5	0.314950	0.146703	0.953744
Random Forest	1	0.382907	0.114726	0.934464
Random Forest	2	0.376405	0.117763	0.944189
Random Forest	3	0.135885	0.044920	0.992639
Random Forest	4	0.262127	0.100108	0.971970
Random Forest	5	0.072226	0.022829	0.997567

best for RF and the fold-to-fold variability in RMSE was the lowest for SVR.

Across five folds, RF obtained $RMSE = 0.2459 \pm 0.1399$, $MAE = 0.0801 \pm 0.0434$, and $R^2 = 0.9682 \pm 0.0282$. LR obtained

Table V. Mean $\pm$ standard deviation performance across five-folds

Model	RMSE Mean $\pm$ SD	MAE Mean $\pm$ SD	R^2 Mean $\pm$ SD
Linear Regression	0.6371 ± 0.0261	0.5333 ± 0.0506	0.8284 ± 0.0163
Support Vector Regression	0.3053 ± 0.0152	0.1767 ± 0.0188	0.9605 ± 0.0050
Random Forest	0.2459 ± 0.1399	0.0801 ± 0.0434	0.9682 ± 0.0282

The comparative results indicate that Linear Regression is insufficient to reproduce the full nonlinear FIS mapping, whereas both SVR and Random Forest provide strong agreement. Random Forest achieved the lowest average RMSE and MAE and the highest average R^2 . Its larger RMSE standard deviation reflects greater fold-to-fold variation than SVR, which showed more uniform performance. Because the target values are generated by the FIS, these results quantify rule-replication fidelity rather than field-level irrigation effectiveness.

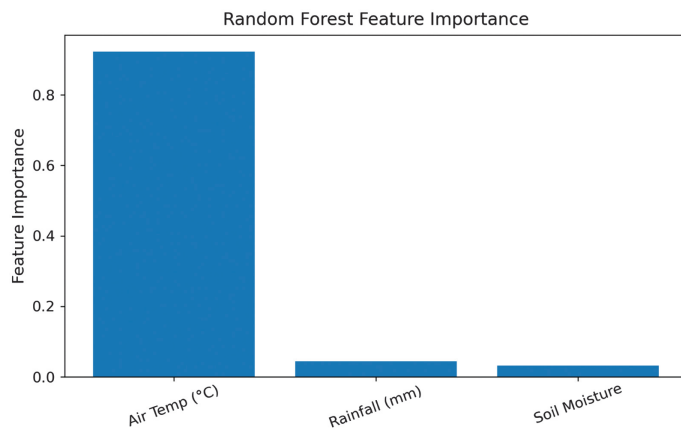


Fig. 6. Random Forest feature importance for the FIS surrogate model.

RMSE = 0.6371 ± 0.0261 , MAE = 0.5333 ± 0.0506 , and $R^2 = 0.8284 \pm 0.0163$, while SVR obtained RMSE = 0.3053 ± 0.0152 , MAE = 0.1767 ± 0.0188 , and $R^2 = 0.9605 \pm 0.0050$. The results indicate that the irrigation scores from the nonlinear FIS generated by the RF algorithm are the most similar to the actual irrigation scores on average, while the irrigation scores generated by the SVR algorithm are the most similar to the actual irrigation scores in a uniform manner across the folds.

The importance of the RF results is especially relevant as this model is able to capture the nonlinear relationship among environmental variables, is noise resistant by averaging the results across the ensemble of trees, and offers feature-importance estimates. For this dataset, air temperature was the most important feature to be used for the surrogate model, with rainfall and soil moisture also being very important (see Fig. 6). The importance values reflect the fit of the surrogate model and are not necessarily agronomic causal.

IV. CONCLUSION

This research successfully developed and evaluated a hybrid intelligent irrigation decision support system that combines the interpretability of fuzzy logic with the predictive capability of an RF regression model. The FIS was built upon expert-defined rules using environmental parameters such as soil moisture, air temperature, and rainfall. The system generated interpretable irrigation recommendations by means of rule-based reasoning and centroid-based defuzzification. Five-fold cross-validation over the one-year daily dataset showed that RF achieved the strongest overall replication of the FIS output, with $R^2 = 0.9682 \pm 0.0282$, RMSE = 0.2459 ± 0.1399 , and MAE = 0.0801 ± 0.0434 , outperforming LR and SVR on average. These results demonstrate agreement with the fuzzy-generated decision logic rather than direct field-level irrigation effectiveness. With this approach, the study provides a robust, scalable, and explainable framework for smart irrigation decision support.

Future work will be extended to incorporate further agronomic parameters like evapotranspiration, soil type, and crop growth stages to improve further on the supported decision-making process. Independent validation of the fuzzy rule base by agricultural experts and field experiments using actual irrigation volume, water consumption, crop stress, and crop yield measurements will be required to evaluate agronomic effectiveness and potential water

savings. The presentation also allows that ML-based feedback can be harnessed to perform dynamic or adaptive fuzzy rule learning, auto-tuning membership functions, and rule sets over time. Finally, the real-time implementation will be discussed through the use of IoT platforms and edge computing before we deploy this system in the real farm environments. Future work in the development of next-generation precision irrigation system includes empowering climate models through predictive models and incorporating other ensemble learning techniques as well as fuzzy optimization for further resilience and intelligence.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest to report regarding the present study.

REFERENCES

- [1] H. Muzammal *et al.*, "Climate change impacts on water resources and implications for agricultural management," in *Transforming Agricultural Management for a Sustainable Future*. World Sustainability Series, S. Kanga, S. K. Singh, K. Shevkani, V. Pathak, and B. Sajan, Eds. Cham: Springer, pp. 21–45, 2024, DOI. [10.1007/978-3-031-63430-7_2](https://doi.org/10.1007/978-3-031-63430-7_2)
- [2] P. Mehta, "The Impact of Climate Change on the Environment, Water Resources, and Agriculture: A Comprehensive Review," in *Climate, Environment and Agricultural Development. Advances in Geographical and Environmental Sciences*, P. K. Rai and S. Rai, Eds. Singapore: Springer, pp. 189–201, 2024, DOI. [10.1007/978-981-97-8363-2_12](https://doi.org/10.1007/978-981-97-8363-2_12)
- [3] E. A. Abioye *et al.*, "A review on monitoring and advanced control strategies for precision irrigation," *Comput. Electron. Agric.*, vol. 173, p. 105441, 2020, DOI. [10.1016/j.compag.2020.105441](https://doi.org/10.1016/j.compag.2020.105441)
- [4] H. Wei *et al.*, "Irrigation with Artificial Intelligence: Problems, premises, promises," *Hum.-Cent. Intell. Syst.*, vol. 4, pp. 187–205, 2024, DOI. [10.1007/s44230-024-00072-4](https://doi.org/10.1007/s44230-024-00072-4)
- [5] K. Obaideen *et al.*, "An overview of smart irrigation systems using IoT," *Energy Nexus*, vol. 7, p. 100124, 2022, DOI. [10.1016/j.nexus.2022.100124](https://doi.org/10.1016/j.nexus.2022.100124)
- [6] R. Thangamani *et al.*, "AI green revolution: Reshaping agriculture's future," in *Intelligent Robots and Drones for Precision Agriculture. Signals and Communication Technology*, S. Balasubramanian, G. Natarajan, and P. R. Chelliah, Eds. Cham: Springer, pp. 421–461, 2024, DOI. [10.1007/978-3-031-51195-0_19](https://doi.org/10.1007/978-3-031-51195-0_19)
- [7] M. Ratnam, "Water supply mapping for a sustainable future: Data-driven efforts in decision making," *Smart Internet Things*, vol. 2, no. 1, pp. 1–10, 2025, DOI. [10.22105/siot.vi.56](https://doi.org/10.22105/siot.vi.56)
- [8] H. Tao *et al.*, "Groundwater level prediction using machine learning models: A comprehensive review," *Neurocomputing*, vol. 489, pp. 271–308, 2022, DOI. [10.1016/j.neucom.2022.03.014](https://doi.org/10.1016/j.neucom.2022.03.014)
- [9] A. N. Ahmed *et al.*, "Machine learning methods for better water quality prediction," *J. Hydrol.*, vol. 578, p. 124084, 2019, DOI. [10.1016/j.jhydrol.2019.124084](https://doi.org/10.1016/j.jhydrol.2019.124084)
- [10] A. V. Konstantinov and L. V. Utkin, "Interpretable machine learning with an ensemble of gradient boosting machines," *Knowl.-Based Syst.*, vol. 222, p. 106993, 2021, DOI. [10.1016/j.knsys.2021.106993](https://doi.org/10.1016/j.knsys.2021.106993)
- [11] X. Li *et al.*, "Interpretable deep learning: Interpretation, interpretability, trustworthiness, and beyond," *Knowl. Inf. Syst.*, vol. 64, pp. 3197–3234, 2022, DOI. [10.1007/s10115-022-01756-8](https://doi.org/10.1007/s10115-022-01756-8)
- [12] A. K. Ali and M. M. Mahmoud, "Methodologies and applications of Artificial Intelligence in systems engineering," *Int. J. Robot. Control Syst.*, vol. 2, no. 1, pp. 201–229, 2022, DOI. [10.31763/ijrcs.v2i1.532](https://doi.org/10.31763/ijrcs.v2i1.532)

- [13] X. Wang *et al.*, “Fuzzy-clustering and fuzzy network based interpretable fuzzy model for prediction,” *Sci. Rep.* vol. 12, p. 16279, 2022, DOI. [10.1038/s41598-022-20015-y](https://doi.org/10.1038/s41598-022-20015-y)
- [14] A. Bressane *et al.*, “Fuzzy Machine Learning applications in environmental engineering: Does the ability to deal with uncertainty really matter? *Sustainability*, vol. 16, no. 11, p. 4525, 2024, DOI. [10.3390/su16114525](https://doi.org/10.3390/su16114525)
- [15] H. H. Tang and N. S. Ahmad, “Fuzzy logic approach for controlling uncertain and nonlinear systems: A comprehensive review of applications and advances,” *Syst. Sci. & Control Eng.*, vol. 12, no. 1, Art No. 2394429, 2024, DOI. [10.1080/21642583.2024.2394429](https://doi.org/10.1080/21642583.2024.2394429)
- [16] K. Sharma and S. K. Shivandu, “Integrating artificial intelligence and internet of things (IoT) for enhanced crop monitoring and management in precision agriculture,” *Sens. Int.*, vol. 5, p. 100292, 2024, DOI. [10.1016/j.sintl.2024.100292](https://doi.org/10.1016/j.sintl.2024.100292)
- [17] A. Kalra, “Introduction to Fuzzy logic and its applications in Machine Learning,” in S. Mahajan, Á. Rocha, A. K. Pandit, P. Chawla, Eds. vol 22. Cham: Springer, pp. 1–15, 2025, DOI. [10.1007/978-3-031-76152-2_1](https://doi.org/10.1007/978-3-031-76152-2_1)
- [18] V. Thomopoulos *et al.*, “Application of fuzzy logic and IoT in a small-scale smart greenhouse system,” *Smart Agric. Technol.*, vol. 8, p. 100446, 2024, DOI. [10.1016/j.atech.2024.100446](https://doi.org/10.1016/j.atech.2024.100446)
- [19] M. Gohil, D. Mehta, and M. Shaikh, “An integration of geospatial and fuzzy-logic techniques for multi-hazard mapping,” *Results Eng.*, vol. 21, p. 101758, 2024, DOI. [10.1016/j.rineng.2024.101758](https://doi.org/10.1016/j.rineng.2024.101758)
- [20] S.K. Nagothu *et al.*, “Advancing aquaculture: Fuzzy logic-based water quality monitoring and maintenance system for precision aquaculture,” *Aquacult. Int.*, vol. 33, p. 32, 2025, DOI. [10.1007/s10499-024-01701-2](https://doi.org/10.1007/s10499-024-01701-2)
- [21] B. Mutale *et al.*, “A performance evaluation of random forest, artificial neural network, and support vector machine learning algorithms to predict spatio-temporal land use-land cover dynamics: a case from lusaka and colombo,” *Front. Environ. Sci.*, vol. 12, p. 1431645, 2024, DOI. [10.3389/fenvs.2024.1431645](https://doi.org/10.3389/fenvs.2024.1431645)
- [22] A. R. Govindan and X. Li, “Fuzzy logic-based decision support system for automating ergonomics risk assessments,” *Int. J. Ind. Ergon.*, vol. 96, p. 103459, 2023, DOI. [10.1016/j.ergon.2023.103459](https://doi.org/10.1016/j.ergon.2023.103459)
- [23] M. S. Basvant *et al.*, “Fuzzy Logic based decision support systems for medical diagnosis,” *Int. J. Intell. Syst. Appl. Eng. IIISAE*, vol. 12, no. 155, pp. 01–07, 2024.
- [24] A. Ramathilagam and P. Pitchipoo, “Modeling and development of fuzzy logic-based intelligent decision support system,” *Rom. J. Inf. Sci. Technol.*, vol. 25, no. 1, pp. 58–79, 2022.
- [25] M. Bukhari *et al.*, “A Fuzzy logic-based smart irrigation controller for precision agriculture,” *IEEE Internet Things J.*, vol. 11, pp. 37257–37268, 2024, DOI. [10.1109/JIOT.2024.3440200](https://doi.org/10.1109/JIOT.2024.3440200)
- [26] J. Simon, “Internet of Things and Fuzzy logic based smart balcony plant care system from a renewable resources,” *Interdiscip. Descr. Complex Syst.: INDECS*, vol. 22, no. 3, pp. 317–328, 2024, DOI. [10.7906/indexs.22.3.7](https://doi.org/10.7906/indexs.22.3.7)
- [27] A. Jagan *et al.*, “A fuzzy-logic-based smart power management strategy for reliability enhancement of energy storage system in a hybrid AC-DC microgrid with EV charging station,” *Int. J. Emerg. Electr. Power Syst.*, vol. 25, no. 3, pp. 405–419, 2024, DOI. [10.1515/ijeeps-2023-0128](https://doi.org/10.1515/ijeeps-2023-0128)
- [28] W. Afridi, “IoT sensor node data,” *IEEE DataPort*, 2024, DOI. [10.21227/m66w-vh45](https://doi.org/10.21227/m66w-vh45).