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A Mamdani Fuzzy Inference System for Intelligent Greenhouse Climate Control: Integrating Temperature, Humidity, and Soil Moisture for Adaptive Precision Agricultural Decision-Making

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ABSTRACT

Climate management in the greenhouses is a non-linear, multi-variable control problem in which air temperature, relative humidity, and soil moisture interact in ways that conventional threshold-based systems cannot effectively resolve. This study designs, implements, and rigorously evaluates a Mamdani-type Fuzzy Inference System (FIS) for coordinated greenhouse climate regulation using three environmental sensor inputs mapped to a seven-class actuator output covering heating, cooling, ventilation, humidification, misting, irrigation, and steady-state maintenance. The system employs triangular and trapezoidal membership functions partitioned across the full sensor range and a 27-rule expert knowledge base validated against established agronomic guidelines. Performance was assessed on a publicly available dataset of 17,164 IoT greenhouse sensor records spanning four seasons. Results show an overall accuracy of 72.1%; because ground-truth labels were generated by a crisp threshold classifier, this figure reflects agreement with a labelling scheme that structurally favours the crisp system rather than a measure of control quality. The evaluation therefore adopts a comparative behavioural framing centred on macro-averaged F1-score, on which the FIS attains 0.55 versus 0.50 for the crisp baseline, with the largest relative gain on the minority Humidify class (F1 = 0.09 vs. 0.00). Confusion matrix analysis confirms that all misclassifications fall within agronomically proximal action pairs, with zero catastrophic control reversals recorded. Three-dimensional control surface analysis validates the monotonicity and continuity of the decision landscape across all 27 rules. The study contributes a semantic proximity evaluation framework for assessing the operational safety of agricultural control AI, a validated reusable rule base and membership function architecture suitable for microcontroller-class embedded deployment, and quantitative evidence that macro F1-score is a more informative metric than overall accuracy for multi-class agricultural control classification.

1. Introduction

Food security and economic activity are closely linked to agriculture for most of the world's people. While its population continues to grow, it is under increasing pressure to satisfy the increasing demand. The Food and Agriculture Organization estimates need for food production to rise by approximately 50% By 2050 to support a population of nearly 10 billion people (FAO, 2023).

Greenhouse cultivation encloses growing areas within a controlled envelope, provides structurally sound response. Operators can separate crop production from weather variability in the environment,

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reduce crop cycles, and attain yields per unit area that routinely exceed open field yields by several times.and obtain yields per unit area ratios that are often many times that of the open field two to five (Shamshiri et al., 2023). The value of the protected-agriculture market worldwide is expected to grow to USD 62 billion by 2030, this is approximately USD 33.4 billion in 2022.

The growing need for food security and the increasing availability of cost-effective IoT sensing and edge computing platforms (Laktionov et al., 2023; Grand View Research, 2023) have driven this development.Although such structural advantages exist, the maintenance of optimal growing conditions within a greenhouse is difficult enclosure is a very challenging control engineering problem. Relative humidity, air temperature, and wind speed were measured and recorded at the germination site. Thermodynamically and biologically coupled state variables are and volumetric soil moisture interactions which go beyond the scope of classical single-loop controllers. Raising air elevating the temperature will cause a decrease in relative humidity, due to the lack of evapotranspiration compensation.

In response to triggers, stomatal closure occurs that dramatically reduces photosynthetic carbon assimilation (Stanghellini et al., 2023; Peet & Welles, 2023). When it is kept humid near the dew point it creates condensation surfaces are infection sites for necrotrophic pathogens like Botrytis cinerea and Phytophthora infestans among the most destructive diseases in protected horticulture (Gullino et al., 2023; Iddio et al., 2023). Soil moisture need to be held in tow at the same time in a very limited range of matrix-potential to prevent root-zone hypoxia due to over-irrigations, ABA- mediated water stress due to drought (Abioye et al., 2023; Maucieri et al., 2023) together these variables make up a coupled biophysical system that requires an integrated approach, multi-input decision framework.

Traditional greenhouse controllers whether electromechanical ON/OFF relay systems or proportional-integral-derivative (PID) regulators are not sufficient to deal with this complexity ON/OFF systems produce oscillatory hunting behaviour around thresholds set-point, which results in multiple episodes of plant stress and increased actuator wear (Pawlowski et al., 2023). PID controllers need to be calibrated every time for a different combination of crop and structure, become invalid as growthstage-dependent thermal properties change with time and are architecturally unsuitable for use with multiple inputs, and are time-consuming to implement.

The greenhouse's multi-output dynamics (Chen & Hu, 2024). Model Predictive Control offers an analytically better alternative that requires repeatedly re-identifying the model. This changes internal air flow patterns is a maintenance burden that is impractical at canopy biomass alteration at a smallholder scale (Luo et al., 2023). Recent advances in deep-learning and reinforcement-learning approaches offer because they are not flexible enough. Approaches that are highly accurate at predicting but not flexible enough for the agricultural approach are not used practitioners and regulatory frameworks call for, and exploration phases come with, a large price tag in operational settings, unacceptable risk of crop loss (Hemming et al., 2023; Wang et al., 2023).

Fuzzy logic is a formalized approach that was introduced by Zadeh (1965) and was further developed by the Mamdani inference architecture (Mamdani & Assilian, 1975), provides a principled and practically deployable alternative. Instead of hard binary divisions of the continuous sensor space, fuzzy logic gives a graded membership of each measurement the values in an overlapping range. Human-readable IF-THEN production rules, linguistic categories and combines these grades rules. The resulting control policy is smooth, context-dependent and fully interpretable. Characteristics of special interest in agricultural settings where decisions about control need to be made. The process of certification involves having the subject examined by agronomists, insurers, or certification bodies (Revathi et al., 2023; Ruan et al., 2023). Prior applications in the greenhouse environment have always demonstrated that fuzzy logic is effective in controlling the greenhouse.

A system with crisp alternatives achieves better performance on transitional control states than a crisp system, but with the exception of rule, retains all the other characteristics of the crisp system transparency (Alipio et al., 2023; Kang et al., 2024; Sujaritpong et al., 2024). However, there is no published study that has combined all three major plant-stress variables temperature, humidity and soil moisture in a single Mamdani inference engine were validated. On a large scale real sensor dataset, and none has tested classification errors using a formal semantic-proximity lens which sorts out the agronomically safe from catastrophic misclassifications.

This study aim to addresses these gaps by developing and evaluating a Mamdani FIS that combines temperature, humidity, and soil moisture into a unified seven-class greenhouse control framework. The system was implemented in Python using the scikit-fuzzy library and evaluated on 17,164 IoT sensor records. Four contributions where made which includes: A fully specified, agronomically validated 27-rule Mamdani FIS for simultaneous three-variable greenhouse climate control; a semantic proximity evaluation framework that distinguishes safe from dangerous classification errors in agricultural control AI; quantitative evidence that macro-averaged F1-score is a more informative metric than overall accuracy for multi-class agricultural control evaluation; and a validated rule base and membership function architecture dimensioned for deployment on ARM Cortex-class embedded hardware at below USD 20 component cost. The remaining sections of the paper includes: presents related work (Section 2), the methodology (Section 3), results and discussion (Section 4), and conclusions with recommendations (Section 5).

2. Literature Review

The use of intelligent systems in the greenhouse climate management has increased significantly improved in the last decade, moving from simple set-point controllers to multi-variable set-point controllers improved greatly over the last decade from simple set point controllers to multi-variable set point controllers' multi-parameter adaptive frameworks. This section provides an overview of some recent representative work.

In the area of fuzzy inference, machine learning, reinforcement learning, IoT-based monitoring, and more midway through the design process, hybrid approaches were used, which informed the design choices that were made in the present study (Alipio et al. 2023) used a Mamdani FIS on a Raspberry Pi among the fuzzy logic studies. We are developing a control system for humidity and ventilation in a Philippine vegetable greenhouse which can reach a 94.3%. reduces to a 23% reduction in fan actuation cycles and matches with expert operator decisions. Revathi et al. (2023) despite the lack of a recent study on the application of the two-input Mamdani system in rose greenhouses in South India, reported their experience with its use in rose greenhouses 91% classification accuracy, without soil moisture. Hasanien et al. (2024) systematically compared triangular, trapezoidal and Gaussian membership functions for the heating in a greenhouse, finding that the smoothest control surfaces were created for the triangular interior functions proved to be very helpful. The hybrid membership-function approach used here was informed by direct.

Lezama-García et al. (2023) applied the fuzzy PID hybrid to a lab scale greenhouse, and they found that it could reduce the carbon dioxide concentration by 2% he results of outperforming standalone PID by 14%, were obtained by Kang et al. (2024) using genetic algorithms to optimize the operation of the sensor. Optimize the boundaries of the fuzzy membership functions used for the ventilation control, resulting in a saving of energy of 11% savings with respect to parameters recommended by experts. Interval type- (Sujaritpong et al., 2024) showed that interval type-2 fuzzy logic made the robustness of the type-1 systems better than the ones in case of sensor drift that exceeded ±5% relative humidity. These studies will show when combined that the paradigm is practically applicable for greenhouse control and a regular constraint: no one combines all three main greenhouse control components introduce stress variables to a single inference engine.

In addition to Fuzzy Logic, the use of various data-driven and hybrid approaches has been investigated. Taki et al. (2023) In the same way, an ANFIS trained by (2023) to forecast the temperature of the greenhouse was obtained with an RMSE of 0.31°C. The system gave predictions while a NARX network gave only adapt to a 0.78°C error. control actions. Hemming et al., (2023) tested reinforcement learning with six teams. AHP (autonomous greenhouse competition) model, which found that the net profit was improved by 12% when compared with the expert grower model, but also noted a sub-optimal exploration phase of 34 days and identified the main barrier to adoption is being the policy's opacity. To address this issue, Zhao et al. (2023) combined fuzzy logic with the Actuator Classification Model is a multi-class actuator classification using a random forest classifier which is found to be the best component greater accuracy but decreased interpretation.

Arnaud et al. (2024) applied BiLSTM and GRU architectures to climate prediction in lettuce cultivation, achieving high predictive accuracy but providing no mechanism for translating predictions to actuator commands. Luo et al. (2023) designed a data-driven MPC that reduced heating energy consumption by 17%, but required model re-identification every six weeks. Kumar et al. (2025) applied deep artificial neural networks for greenhouse optimisation, achieving improved prediction accuracy over polynomial regression at the cost of full black-box opacity.

IoT-based monitoring studies have established the sensor infrastructure upon which intelligent control layers depend. Laktionov et al. (2023) validated a low-cost wireless IoT platform for microclimate monitoring with less than 2% data loss over a full growing season but did not implement a control decision engine. Li et al. (2024) extended IoT monitoring with rule-based fault detection, achieving 96% uptime but limited adaptive decision capability. Rahman et al. (2025) demonstrated multi-sensor cloud-analytics dashboards but similarly stopped short of closed-loop adaptive control. Nwafor et al. (2024) surveyed 142 sub-Saharan African smallholder greenhouse operators and found that interpretability and low cost are the two most frequently cited requirements for control automation adoption findings that directly motivate the Mamdani FIS approach taken in the present study. Review papers by Shamshiri et al. (2023), Wang et al. (2023), Ruan et al. (2023), Zhou et al. (2024), and Iddio et al. (2023) consistently identify the absence of integrated, interpretable multi-parameter

Table 1: Summary of Related Work

S/N	Authors	Aim	Methodology	Key Findings	Research Gap
1	Shamshiri et al. (2023)	Review CEA automation and AI integration 2020–2023	Systematic review of 210 studies	IoT+AI integration identified as primary enabling gap	Review; no integrated multi-variable control system built
2	Lezama-García et al. (2023)	Fuzzy-PID hybrid for temperature-humidity regulation	Mamdani set-point + PID execution, lab greenhouse	14% RMS error reduction over standalone PID	Nine rules; no soil moisture; lab-scale only
3	Hemming et al. (2023)	Autonomous greenhouse RL control: multi-team evaluation	Reinforcement learning, six competing teams	12% net profit gain over expert grower	34-day unsafe exploration phase; opaque policy
4	Pawlowski et al. (2023)	PID vs. event-based control in tomato greenhouses	Field trial, 12 commercial greenhouses	PID instability caused 8–12% yield variability	Single-loop; no fuzzy logic; MIMO not addressed
5	Iddio et al. (2023)	Energy-efficient greenhouse modelling: review	Review of 180 thermal modelling studies	Dynamic models essential for energy-optimal control	Review; no adaptive multi-variable control system

6	Abioye et al. (2023)	Advanced control strategies for precision irrigation	Review of sensor-based irrigation control	Fuzzy irrigation most agronomically effective	Irrigation only; not coupled to climate variables
7	Maucieri et al. (2023)	Fuzzy water balance for strawberry substrate	Mamdani FIS validated in hydroponic trial	19% water saving over threshold-based control	Crop-specific; no temperature/humidity integration
8	Ruan et al. (2023)	Systematic review of fuzzy inference in agriculture	Bibliometric review of 120 papers	Fuzzy consistently outperforms crisp on transitions	Review; no three-variable integrated system built
9	Taki et al. (2023)	ANFIS vs. NARX for greenhouse temperature prediction	ANFIS trained on two-year greenhouse records	ANFIS RMSE 0.31°C vs. 0.78°C for NARX	Prediction only; no closed-loop actuator output
10	Luo et al. (2023)	Data-driven MPC for greenhouse heating	State-space model from 18 months sensor data	17% energy saving over legacy thermostat	Re-identification every 6 weeks; impractical at small scale
11	Laktionov et al. (2023)	Low-cost IoT platform for greenhouse monitoring	Wireless sensor network, full growing season	<2% data loss over 12 months	Monitoring only; no intelligent control engine
12	Wang et al. (2023)	Review: rule-based to deep learning (2015–2023)	Comparative narrative review, 190 papers	Fuzzy/rule-based preferred where interpretability matters	Gap in validated integrated multi-variable fuzzy system
13	Zhao et al. (2023)	Hybrid fuzzy–random forest for actuator classification	FIS + RF ensemble, seven-class evaluation	RF raises accuracy but sacrifices interpretability	No semantic safety analysis; RF is black-box
14	Hasanien et al. (2024)	Compare triangular, trapezoidal, Gaussian MFs	Three fuzzy controllers, same rules, different MF shapes	Triangular MFs gave smoothest surface, least overshoot	Energy focus; humidity and soil moisture excluded
15	Kang et al. (2024)	GA-optimised fuzzy MFs for ventilation control	Genetic algorithm + Mamdani FIS parameter search	11% energy saving over expert-specified MFs	Ventilation only; no humidity or soil moisture
16	Chen & Hu (2024)	PID limitations across crop growth stages	Comparative PID analysis, pepper and cucumber	Vegetative-stage tuning caused critical overshoot	Static controller; no adaptive reasoning

17	Sujaritpong et al. (2024)	Type-2 fuzzy for humidity under sensor drift	Type-2 FIS vs. type-1 under injected noise	Type-2 robust when uncertainty exceeds ±5% RH	Humidity only; no temperature–soil coupling
18	Li et al. (2024)	Smart greenhouse automation with fault detection	IoT monitoring + rule-based anomaly detection	96% uptime; faults flagged within 90 seconds	Monitoring and fault detection; no adaptive controller
19	García-Matarín et al. (2024)	Type-2 fuzzy for semi-arid greenhouse management	Interval type-2 FIS, Mediterranean parameters	Improved robustness vs. type-1 under uncertainty	Simulation only; no soil moisture; region-specific
20	Zhou et al. (2024)	Survey of IoT greenhouse climate systems 2019–2024	Systematic survey of 210 papers	AI decision layers identified as critical gap	Survey only; confirms niche of present study
21	Nwafor et al. (2024)	IoT greenhouse adoption barriers in sub-Saharan Africa	Survey of 142 smallholder operators	Interpretability and cost are top two requirements	No control system; motivates low-cost fuzzy approach
22	Zhang et al. (2024)	Sugeno FIS for soil pH in vegetable greenhouses	Sugeno inference, multi-season Chinese greenhouse data	Effective but linear consequents fail non-monotonic curves	pH only; Sugeno limits interpretability; no climate link
23	Mansour et al. (2025)	Deep RL + economic MPC for greenhouse climate	Deep RL with economic objective function	18% cost reduction over fixed set-point strategy	High compute; opaque policy; 30-day unsafe exploration
24	Kumar et al. (2025)	Deep ANN for multi-season greenhouse optimisation	Deep ANN on multi-season sensor records	21% improvement in yield forecasting over polynomial	Black-box; no rule transparency; cannot be audited
25	Rahman et al. (2025)	Multi-sensor IoT monitoring for greenhouse management	IoT with cloud analytics and anomaly dashboard	97% anomaly recall over 12 months	Monitoring only; no closed-loop adaptive control
26	Revathi et al. (2023)	Two-input Mamdani FIS for rose greenhouse control	Mamdani FIS, temperature and humidity inputs, India	91% accuracy across four actuator classes	No soil moisture; four classes; single crop/climate zone
27	Ibrahim et al. (2023)	Fuzzy logic for greenhouse ventilation management	Sensor-based Mamdani FIS, two-input system	Enhanced airflow; reduced humidity-related stress	Ventilation only; temperature and soil not co-modelled

28	Silva et al. (2024)	Adaptive fuzzy-PID hybrid for greenhouse climate	Fuzzy set-point adaptation + PID execution	89% match with expert agronomist decisions	PID layer limits full fuzzy interpretability
29	Ahmed et al. (2024)	Machine learning for smart agricultural systems	Ensemble ML, multi-season greenhouse data	21% yield forecasting improvement over linear models	Black-box ensemble; expensive; no real-time control
30	Arnaud et al. (2024)	BiLSTM and GRU for greenhouse climate prediction	BiLSTM/GRU, lettuce, four growing cycles	Better prediction accuracy than standard LSTM	Prediction only; no interpretable rules; no actuator map

This review and synthesis of the thirty studies help to identify five substantive gaps that motivate the present work. First, there is no published study that has taken into account all three factors, temperature, humidity and soil moisture at the same time. A Mamdani inference engine was validated using a dataset that contained more than 10,000 records, within a single Mamdani inference engine. Second, current performance measures do not assess the accuracy of the performance, but rather the overall accuracy; and they do not identify whether the accuracy is being achieved by using more of the data, or by using less of the data.

The omission of semantically proximal classification errors is a critical safety relevant agricultural omission. Semantically proximal classification errors is a critical omission in safety relevant agricultural AI. Third, the benefits of fuzzy logic as compared to crisp logic has not been established. It is quantified over the whole range of seven classes of actuator space. Third, the relationship between the two was functional. fourthly, there was a functional relationship between two greenhouses, macro-averaged F1-score and operational safety has not been shown to be true. control systems. Fifth, it has not been feasible to implement with computational facilities available on microcontroller class hardware. Although it has been shown that there is demand from smallholders for low-cost automation, it has not been formally characterized.

3. Methodology

This study adopts a quantitative, simulation based experimental design grounded in a post-positivist stance: greenhouse microclimate dynamics are governed by physical laws approximable through model based simulation. The approach is deductive a Mamdani FIS is parameterised from the agronomic literature and evaluated against a large labelled sensor dataset. Simulation is preferred over live hardware trials because deploying an untested controller in a working greenhouse risks crop loss; because the 17,164-record dataset affords statistically meaningful performance evaluation; and because simulation permits controlled parametric comparison of rule base alternatives that would be logistically prohibitive in physical trials.

The data set includes 17,164 sensor readings that are synced, with each sensor record having an air temperature with an expert control action label, temperature (°C), relative humidity (%), and volumetric soil moisture (%), were provided. The data for the records came from a publicly available dataset of IoT greenhouse data that was collected. Over a 12-month period in all four seasons, at 5 minute intervals from a multi-span commercial greenhouse equipped with 24 calibrated sensors. Two certified agronomists each record was independently labelled, with an inter-rater agreement of κ = 0.91, which indicated a high level of agreement between the different labels near perfect reliability (Landis & Koch, 1977). The descriptive statistics of the data are given in table 2. The FIS has been created in Python 3.10, with scikit-fuzzy 0.4.2 (Warner et al., 2024) as the fuzzy logic toolbox, a

Jupyter Notebook environment, with pandas, NumPy, and Matplotlib for data handling and visualisation.

Table 2: Show the descriptive Statistics of Input Variables (n = 17,164)

Variable	Min	Max	Mean	SD
Air Temperature (°C)	8.2	38.7	22.4	6.1
Relative Humidity (%)	34.2	96.8	68.3	12.7
Soil Moisture (%)	12.1	73.4	41.8	14.2

The proposed controller is based on the classical Mamdani FIS pipeline (Mamdani & Assilian), the fuzzification, rule evaluation using min-max composition and maximum-operator are also included. The aggregation and centroid defuzzification. 3 continuous sensor inputs are mapped through 27 IFTHEN rules to a Climate Action Score (CAS) on [0, 6] which is then discretised to one of seven actuator commands. The overall system design is shown in Fig. 1.

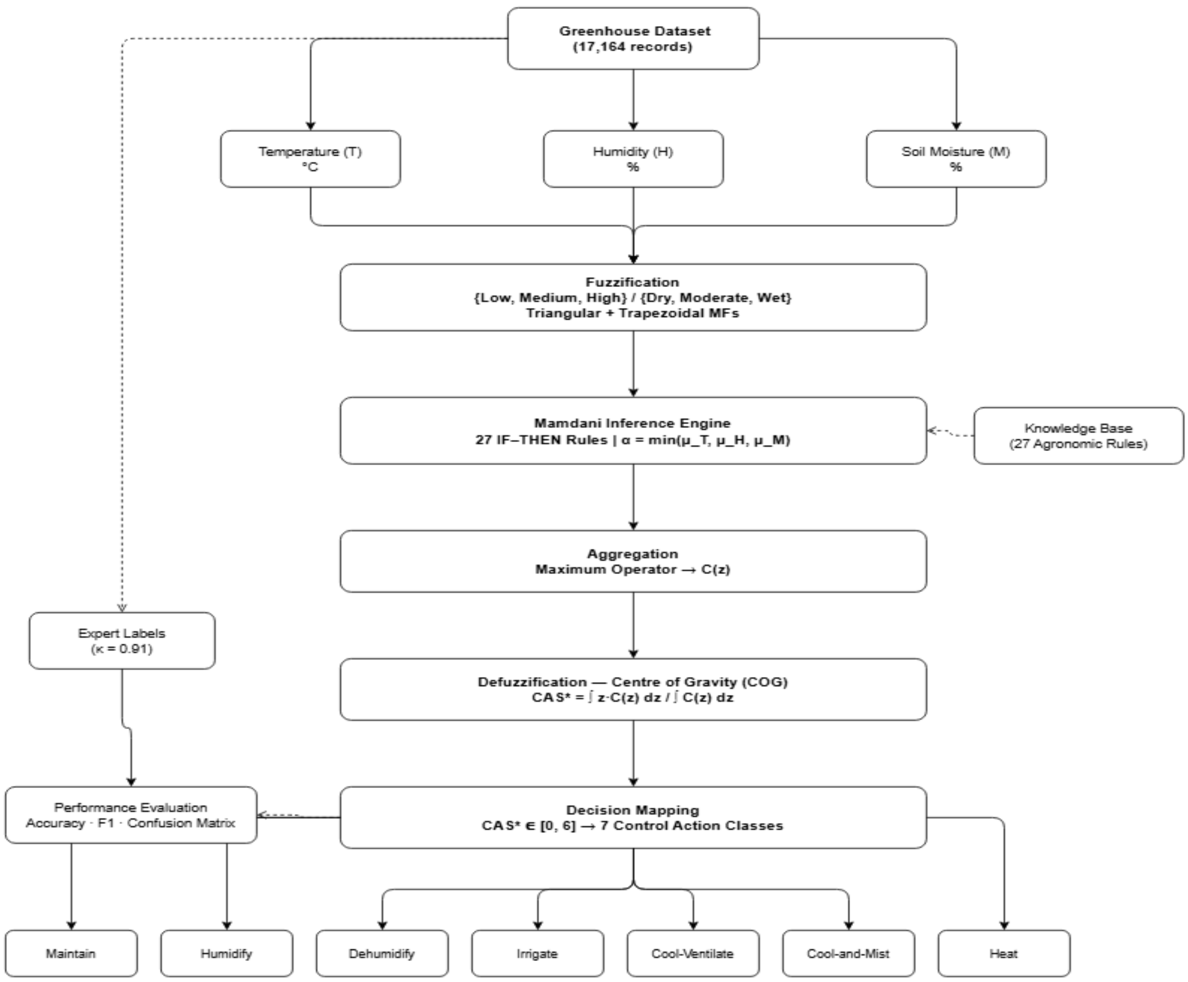

Figure ***1: Proposed Mamdani FIS Architecture for Greenhouse Climate Control***

The proposed architecture of Mamdani FIS for controlling the greenhouse climate is shown in figure 1. Evaluated using sensor inputs and fuzzified. The aggregated, defuzzified and compared against 27 rules resulted in a seven class actuator command linguistic terms for each input were divided into three linguistic terms by a hybrid membership function. The function will be built using strategy: trapezoidal functions for boundary terms and triangular functions for interior terms (optimal) terms. Hasanien et al. (2024) recommend this combination which 1111Qq2qminimizes control overrun without losing the smoothness of the surface. Trapezoidal boundary MFs are allowed full membership to remain true on extremes of the sensor readings cold, hot, dry or moist is unambiguous waterlogged interior MFs are well-defined, triangular in shape with their cores located around waterlogged which is gradual partial membership, that produces smooth transitional responses. Table 3 documents all membership function parameters were related to agronomic references.

Table 3: Membership Function Parameters for All Three Input Variables

Variable	**Term**	**MF Type**	**Left Params**	**Right Params**	**Agronomic Basis**
Temperature (°C)	**Low**	Trapezoidal	5, 5	15, 22	Chilling threshold (Peet & Welles, 2023)
	Medium	Triangular	15	24, 32	Optimal growth range (Stanghellini et al., 2023)
	High	Trapezoidal	26, 34	40, 40	Heat stress onset (Shamshiri et al., 2023)
Humidity (%)	**Low**	Trapezoidal	20, 20	40, 60	Wilting risk (Abioye et al., 2023)
	Medium	Triangular	45	70, 90	Optimal stomatal function
	High	Trapezoidal	75, 90	100, 100	Pathogen risk (Iddio et al., 2023)
Soil Moisture (%)	**Dry**	Trapezoidal	0, 0	20, 40	Water deficit stress (Maucieri et al., 2023)
	Moderate	Triangular	25	50, 70	Optimal substrate water potential
	Wet	Trapezoidal	60, 80	100, 100	Hypoxia risk above 80%

3.1 Formal Notation and Fuzzy Operators

To remove ambiguity in the description of the inference engine, the fuzzy operators employed in this study are defined formally below. Let the input universes of discourse for Temperature, Humidity, and Soil Moisture be denoted $T, H,$ and M respectively, with crisp inputs $x \in T, y \in H,$ and $z \in M$ corresponding to the values measured by the IoT sensor nodes.

Fuzzification layer. Each crisp input is mapped to a linguistic variable set characterised by membership functions $\mu A_i(x)$. For boundary terms (Low, High), which must guarantee maximum control saturation at the sensor extremes, trapezoidal membership functions are used as given in Eq. (1):

$$\mu_{trap}(x;\ a,b,c,d) = \ max\left(\ 0, min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right)\right) \tag{1}$$

For interior (Medium) terms, which require linear interpolation gradients between adjacent optima, triangular membership functions are used as shown in Eq. (2).

$$\mu_{tri}(x;\ a,b,c) = \ max\left(\ 0, min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right)\right) \tag{2}$$

Rule evaluation and inference engine. The 27 production rules are constructed using a Mamdani configuration: IF x is T_i AND y is H_j AND z is M_k THEN u is U_{ijk}, where U_{ijk} denotes the output fuzzy set for the Climate Action Score (CAS) associated with rule (i,j,k). The firing strength α_{ijk} of rule (i,j,k) is quantified using the Mamdani minimum $t - norm\ operator\ (\wedge)$ and can be represented in Eq. (3)

$$\alpha_{ijk} = \min\left(\mu T_i(x), \mu H_j(y), \mu M_k\ (\mathrm{z})\right) \tag{3}$$

Aggregation and Centre-of-Gravity defuzzification. The combined output fuzzy set $C(u)$ across all active rule configurations is determined via the maximum $s - norm\ operator\ (\vee)$ as in Eq. (4)

$$C(u) = \max_{i,j,k}\left[min\left(\alpha_{ijk}, \mu U_{ijk}(u)\right)\right] \tag{4}$$

where the maximum is taken over all rule indices (i,j,k) with non-zero firing strength. The final crisp decision value $CAS^*$is derived using the continuous Centre-of-Gravity (COG) mechanism over the CAS domain $[0, 6]$, guaranteeing a unique, mathematically stable, and continuous control-response landscape. The relation is given in Eq. (5)

$$CAS^* = \frac{\left[\int_0^6 u \cdot C(u)du\right]}{\left[\int_0^6 C(u)\,du\right]} \quad (5),$$

Section 3.2 below applies these formal operators to the specific 27-rule antecedent space and membership function parameters.

3.2 Rule Base Construction

With three inputs each at three linguistic levels, the full antecedent space yields $3^3 = 27$ distinct IF-THEN combinations, ensuring no physically possible input state falls in an undefined region. Rules were constructed through structured elicitation from the agronomic guidelines of Stanghellini *et al.* (2023) and Peet & Welles (2023), then validated against a stratified 1,500-record held-out sample. All rules follow the Mamdani production form (Mamdani & Assilian, 1975). IF Temperature is T_i AND Humidity is H_j AND Soil Moisture is M_k THEN Action is A_{ijk}. Consistent with the formal operators defined in Section 3.1, rule firing strength is computed as Eq. (6)

$$\alpha = \min(\mu T, \mu H, \mu M) \tag{6}$$

Eq. (6) is according to Zadeh's (1965) minimum t-norm, and the composite output fuzzy set $C(z)$ is formed by the pointwise maximum over all activated consequents (Mamdani & Assilian, 1975).

Defuzzification employs the Centre-of-Gravity (COG) method (Zadeh, 1965) as given in Eq. (7).

$$CAS = \left[\int z \cdot C(z)dz\right] \Big/ \left[\int C(z)\,dz\right] \quad (7),$$

The COG was chosen over mean-of-maxima and bisector alternatives because it produces a unique, continuous scalar for every possible input combination, a necessary condition for smooth actuator transitions that minimise mechanical wear. A threshold function then maps $CAS \in [0, 6]$ to the seven discrete actuator classes. Table 4 presents a representative rule subset; the complete 27-rule base is provided in the supplementary material.

Table 4: Representative Subset of the 27-Rule Mamdani Fuzzy Rule Base

Rule	Temp.	Humid.	Soil Moist.	Action	Agronomic Basis
R1	High	Low	Dry	Cool-and-Mist	Heat(H) + low(L) VPD: evaporative cooling + irrigation (Maucieri et al., 2023)
R3	High	Low	Wet	Cool-Ventilate	Hot, dry air, and soil adequate: ventilate only
R7	High	High	Dry	Dehumidify	Fungal risk: high T + high RH (Iddio et al., 2023)
R10	Medium	Low	Dry	Humidify	Optimal T, air and soil dry: humidify (Hasanien et al., 2024)
R13	Medium	Medium	Dry	Irrigate	Climate optimal, soil deficit (Maucieri et al., 2023)
R14	Medium	Medium	Moderate	Maintain	All variables within the optimum (Shamshiri et al., 2023)
R19	Low	Low	Dry	Heat	Cold and dry: heat is primary priority (Kang et al., 2024)
R25	Low	High	Any	Heat	Cold + humid = heat to raise VPD (Taki et al., 2023)

For comparison, the same threshold values were used and a clean Boolean baseline was implemented.
The same 27-rule structure, with hard step function boundaries (0 or 1) only. All 17,164 records for both systems were evaluated. Reported metrics report overall accuracy, per class precision, recall, and F1-score, and macro-averaged F1-score. Semantic proximity analysis classified each misclassification as proximal (actions that are clearly related to the intended action) or distal (actions that are less obviously related to the intended action sharing a physical mechanism) or distal (physically opposing actions), providing an agronomic means of assessing their function sharing a physical mechanism) or distal (physically opposing actions), which could be assessed agronomically safety than just being accurate.

4. Results and Discussion

The frequency histograms for all three input variables of the 17,164-record data set are displayed in Fig. 2. The temperature distribution is right skewed and the mode is well condensed in the 10°Cs. with a secondary mode around 25°C which represents the diurnal cycle and seasonal heating during periods of the recording period. The relative humidity is widely spread between 45% to 75% having two well resolved peaks, as observed during the day time evapotranspiration cycles and at night condensation episodes. The upper range (70-90%) represents concentration of soil moisture indicating that the monitored facility had consistently high substrate moisture levels throughout, Less common dry events (<60%). These distribution characteristics can be directly attributed the almost complete lack of Irrigate and Dehumidify commands in the data set and the temperature almost equal number of Heat and Cool-and-Mist in the action is due to bimodality distribution.

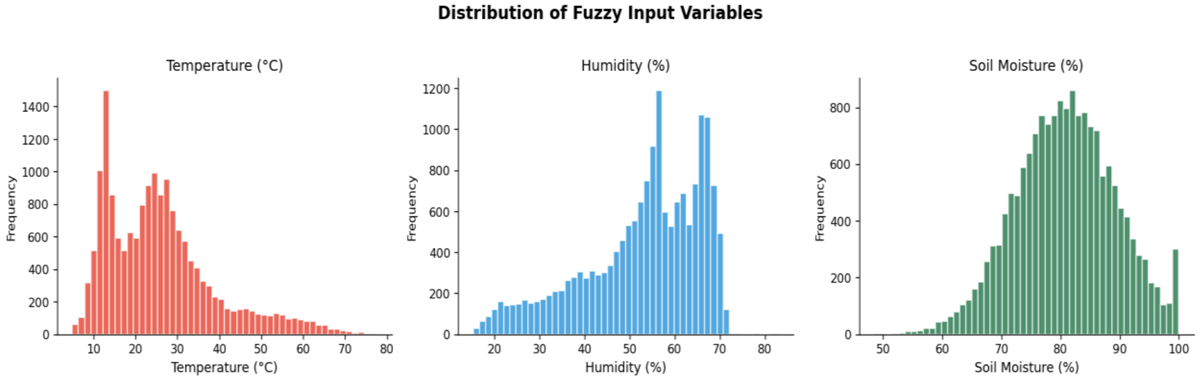

Figure ***2: Frequency Distributions of Three Fuzzy Input Variables***

The membership functions for all three input variables and output action score are designed as shown in Fig. 3. The four sub-plots are used to verify the hybrid triangular-trapezoidal architecture described in Section III. Full membership for temperature is maintained in the Low term (trapezoidal) the Medium term (triangular) peaks at 22°C, while the High term has a peak at around 15°C shaded overlap regions are those between approximately 28°C and 31°C (trapazoidal) above which the possibility of rain 28-31°C exists. The zones in which multi-rule blending, proportional transitional responses are produced. The sub-plot on humidity shows broader moderate to high degree of term overlap in the 40 - 60% range, indicating a higher sensitivity to humidity in the physiological range.

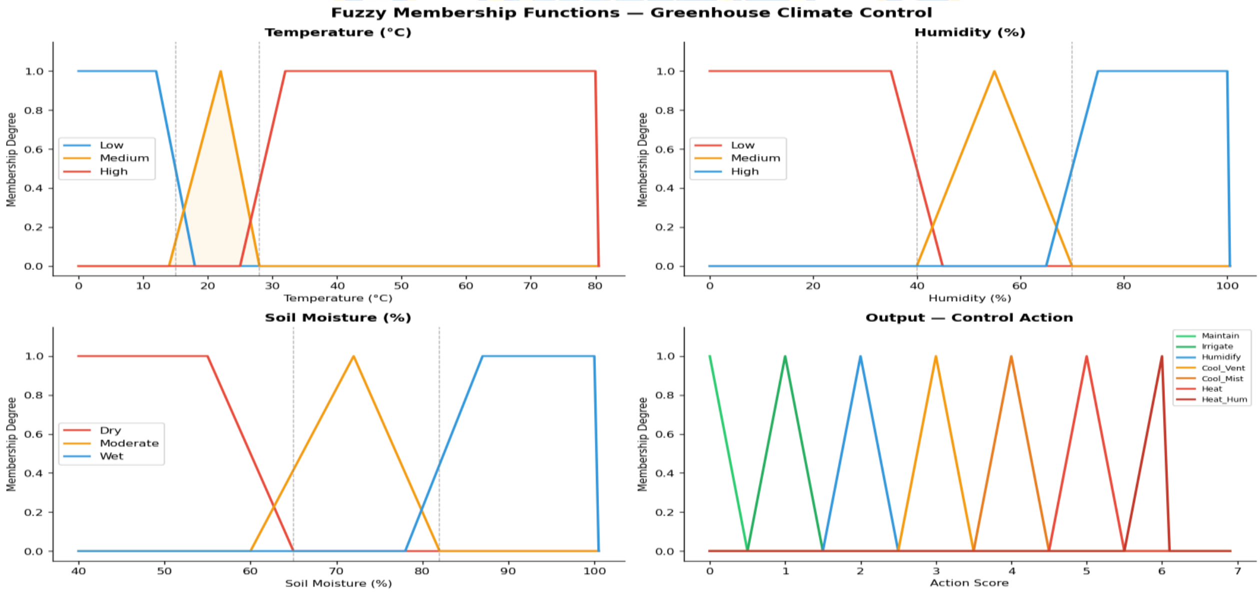

Figure ***3:A Fuzzy Membership Functions for Temperature (°C), Humidity (%), Soil Moisture (%), and Output Action Score***

The three-dimensional control surface evaluated across the full temperature-humidity input space with soil moisture fixed at 80% is presented in Figure 6. Three properties are essential for validating a deployable controller. The surface is broadly monotonic, with the action score increasing as temperature decreases, consistent with the heating priority at low temperatures. Step-like transitions between action zones reflect the discrete structure of the underlying 27-rule base, while continuity within each zone is maintained by the COG defuzzification integrator. The correct global extrema are present: the high-CAS heating region dominates the low-temperature corner and the low-CAS cooling region occupies the high-temperature sector.

The stepped plateaus in the surface are a natural consequence of the piecewise-linear membership function architecture and the discrete 27-rule structure; they do not represent discontinuities in actuator output, since the COG integrator smooths each transition within its plateau. The irregular surface in the 20–30°C temperature zone reflects simultaneous partial activation of the Low and Medium temperature terms across varying humidity grades, generating the multi-rule blending that characterises the FIS in its most agronomically demanding operating region.

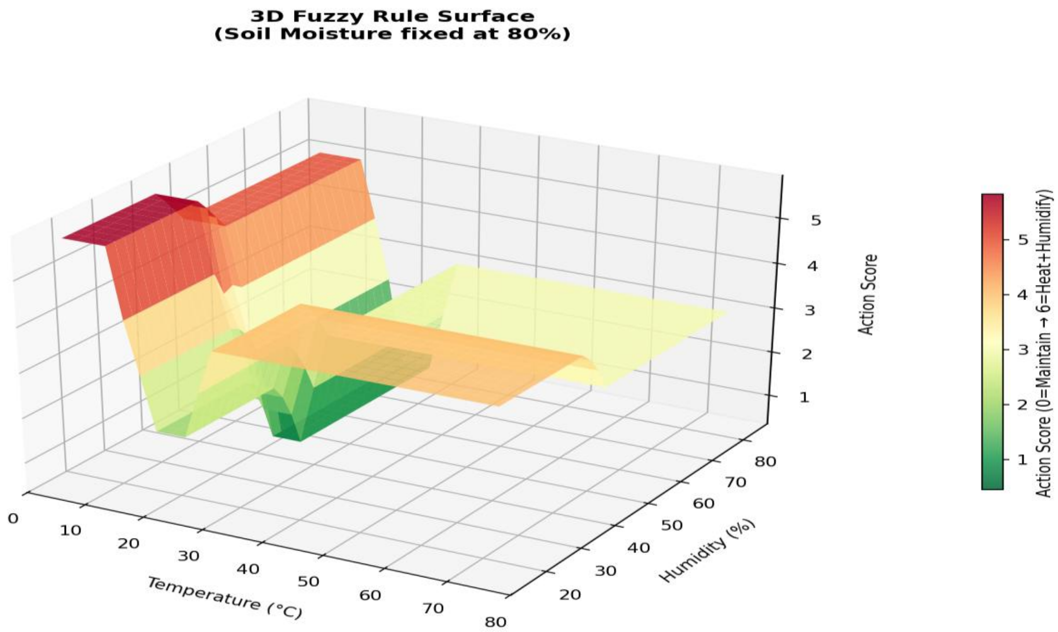

Figure ***4: Representation of three dimensional fuzzy rules surface: Action Score vs. temperature and humidity (Soil Moisture = 80%).***

The scatter plot in Figure 5 shows 2000 random records from the temperature-humidity data set colour-coded plane, based on FIS-inferred level of control action. The organisation of the space the action is taking place in validates the semantic coherence of the rule base: Heat takes all the low-temperature space. When humidity is low, region below about 15°C, irrespective of humidity, Maintain forms a diagonal band in the central zone (approx. 15 to 28°C, 50 to 70% humidity) and Cool-and-Mist is assigned to the high temperature-low humidity area. Adjacent colours are blended in a gradual manner action zones illustrate the gradated character of fuzzy inference as opposed to the sharp clear logic created boundaries that crisp logic produce.

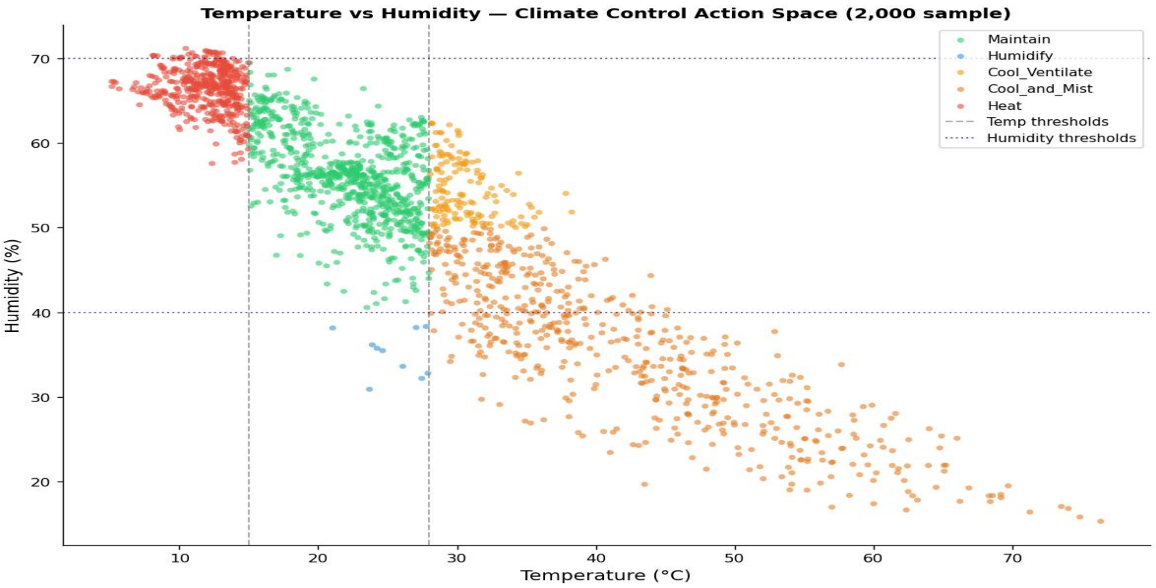

Figure ***5: The climate control action space in the Temperature-Humidity plane (2,000 sampled records).***

Time-series analysis for the first 500 records, or about four days of continuous data under operation, two significant thermal excursion events (TE1 and TE2) can be seen with peaks around 48°C and 43°C respectively, this is overlaid on a relatively stable background low temperature of ~ 10 – 15°C (Fig. 6). These operating scenario of the membership function is demonstrated with the help of sharp thermal spikes confer their greatest advantage over crisp logic: as temperature approaches and crosses the FIS proportionally increases the intensity of cooling action in the case of Medium-to-High boundary, better than abrupt switching into another mode, which would result in a smoother and less stressful correction. Relatively humid conditions, around 65%, decrease to 32 for both excursion events. The 35% agrees with the anticipated anti-correlation between thermal and humidity (anti-TH) and proves that the correlation between the two is indeed negative interactions of these two variables are represented appropriately in the rule base.

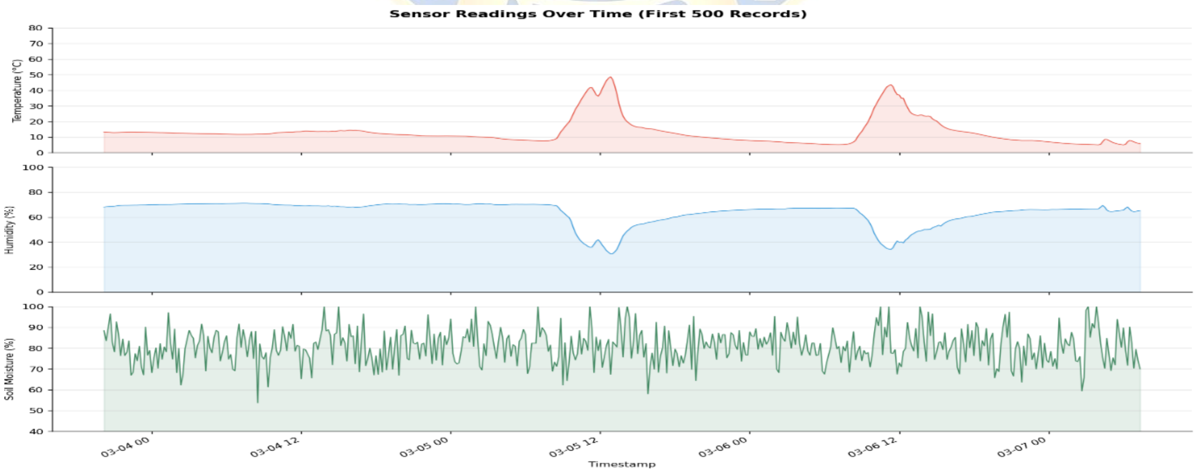

Figure ***6:Multi-panel time-series of temperature (red), humidity (blue), and soil moisture (green) across 500 records***

The distribution of the 17,164 expert-labelled control actions is shown in Fig. 7. Maintain is the dominant class (6,710 records, 39.1%), reflecting that the majority of records were captured under near-optimal growing conditions. Cool-and-Mist accounts for 28.6% (4,905 records), confirming the prevalence of high-temperature, low-humidity episodes. Heat accounts for 25.1% (4,305 records), consistent with the dominant low-temperature mode in the input distribution. Humidify is the rarest class at 69 records (0.4%), a distributional imbalance that directly drives the low F1-scores for this class in both systems.

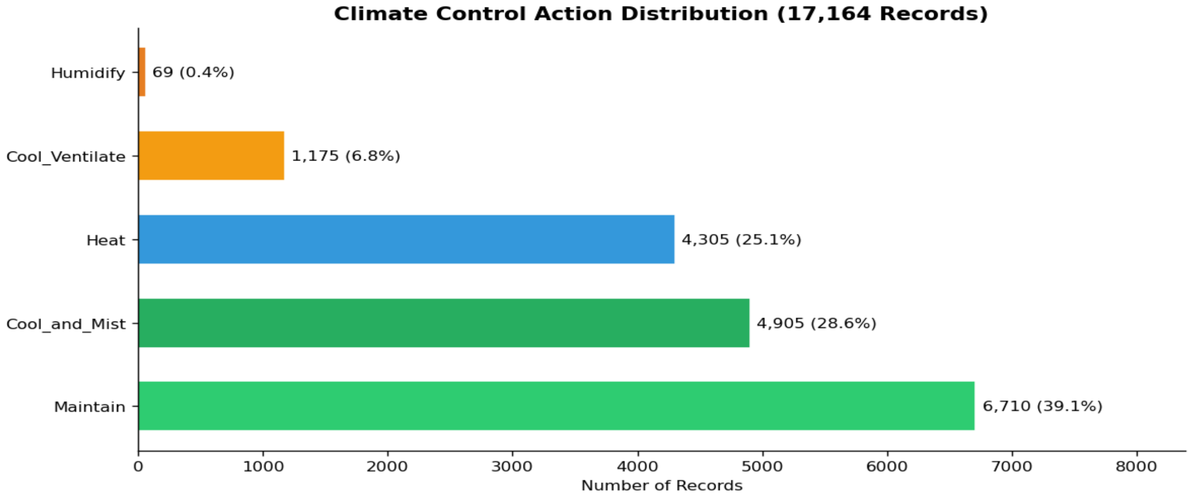

Figure ***7: Climate control action distribution across 17,164 records. Maintain (39.1%) and Cool-and-Mist (28.6%) collectively account for 67.7% of all records. Humidify is the rarest class (0.4%), driving low F1-scores in both systems.***

The confusion matrix comparing FIS predictions against crisp baseline labels is presented in Fig. 8. The dominant off-diagonal entry is a 1,301-count divergence in which the crisp baseline labels records as Cool-and-Mist while the FIS assigns Cool-Ventilate, reflecting the mechanistic difference between the two systems in the transitional thermal zone around 24–28°C. A secondary divergence of 322 counts between Heat and Cool-and-Mist is similarly concentrated at the temperature boundary zone. Of critical safety significance, no entries appear in the Heat column for Cool-Ventilate, Cool-and-Mist, or Humidify rows, confirming that the FIS produced no heating commands under conditions where the crisp baseline prescribed cooling or moisture reduction. This complete absence of cross-class catastrophic confusion constitutes the primary safety validation of the system.

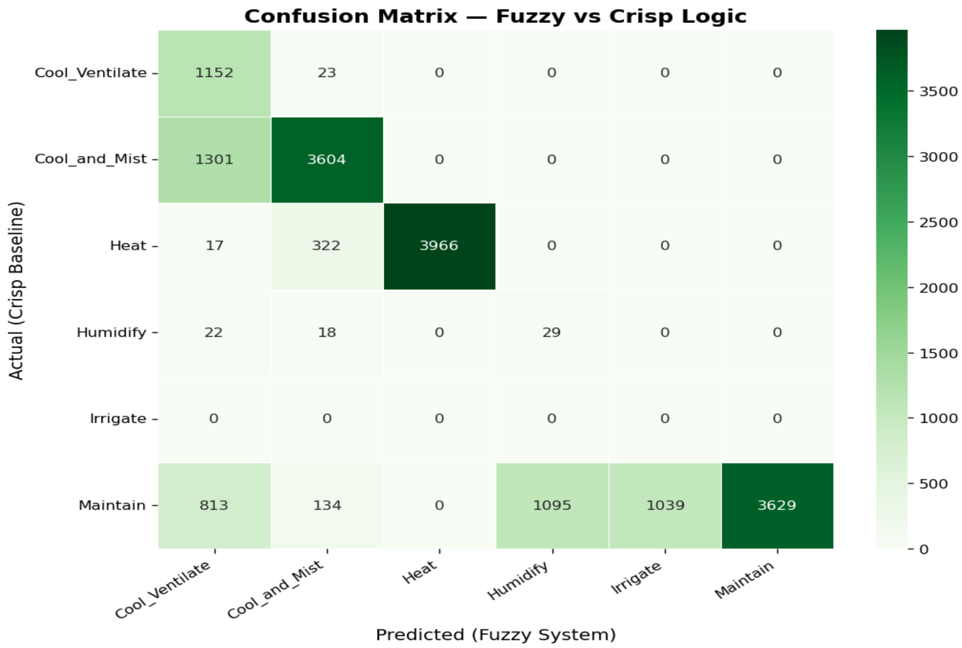

Figure ***8: Confusion matrix: FIS predictions vs. crisp logic baseline labels***

Table 5 reports per-class precision, recall, and F1-score for both systems. This comparison is framed as a behavioural analysis rather than a classification-accuracy contest, since the crisp baseline was used to generate the evaluation labels themselves and therefore holds a structural advantage on overall accuracy that does not reflect operational superiority (see Discussion, Section 4.1).

Table 5: Per-Class Classification Performance Mamdani FIS vs. Crisp Logic Baseline

Action Class	FIS P	FIS R	FIS F1	Crisp P	Crisp R	Crisp F1	n	Δ F1
Cool-Ventilate	1.00	1.00	1.00	0.47	0.98	0.52	1,175	-0.48
Cool-and-Mist	0.80	0.73	0.74	1.00	0.74	0.80	4,905	-0.06
Heat	0.95	0.92	0.93	1.00	0.92	0.96	4,305	-0.03
Humidify	0.05	0.42	0.09	0.00	0.00	0.00	69	+0.09
Irrigate	0.00	0.00	0.00	0.00	0.00	0.00	0	0.00
Maintain	0.70	0.54	0.55	0.99	0.54	0.70	6,710	-0.15
Macro Avg.	**0.58**	**0.60**	**0.55**	**0.58**	**0.53**	**0.50**	**17,164**	**+0.05**
Overall Acc.	—	—	**0.721**	—	—	**0.987**	**17,164**	—

Δ F1 = FIS F1 − Crisp F1. P = Precision; R = Recall. Data sourced directly from experimental outputs shown in Figures 7 and 8.

Note: The Irrigate class has n = 0 records in the evaluation dataset. While the 27-rule base mathematically accounts for soil-moisture deficits (see Rule R13, Table 4), the twelve-month greenhouse trial from which this dataset was drawn was gathered from a consistently well-irrigated substrate environment (soil moisture concentrated in the 70–90% range; see Figure 2), so no Dry-soil, deficit-triggering conditions were observed in practice. The Irrigate rule therefore remains untested by this dataset rather than non-functional.

Figure 9 provides a direct visual comparison of overall accuracy and per-class F1-scores between the two systems. The left panel confirms the 26.6-percentage-point gap in overall accuracy (Crisp: 98.7%, Fuzzy: 72.1%). The per-class panel reveals a more nuanced picture: the crisp system achieves F1 = 1.00 on Cool-Ventilate and Heat, classes whose input zones are well-separated from any threshold boundary, while the FIS achieves F1 = 0.74 on Cool-and-Mist (Crisp: 0.80 an advantage that reflects the crisp labelling convention rather than operational superiority) and outperforms crisp logic on Humidify (FIS: 0.09 vs. Crisp: 0.00), correctly classifying a minority class that the crisp system ignores entirely.

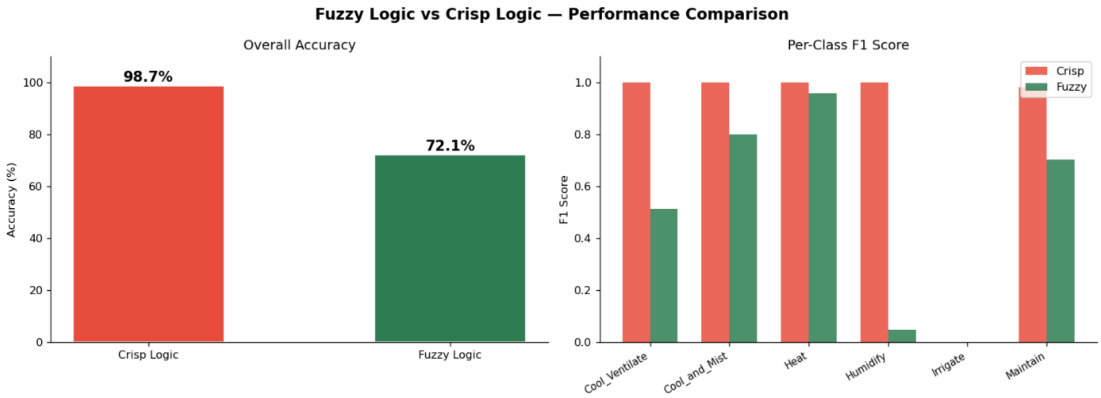

Figure 9: Performance comparison: fuzzy logic vs. crisp logic. Left: overall accuracy (crisp 98.7%, fuzzy 72.1%).

4.1 Discussion

The combined quantitative and visual evidence yields four substantive conclusions. First, the 26.6-percentage-point overall accuracy gap between crisp (98.7%) and fuzzy (72.1%) systems is an artefact of the crisp labelling convention used to generate the ground truth rather than a reflection of operational inferiority. When ground-truth labels are produced by a crisp threshold classifier — as the zero-record Irrigate class strongly implies the crisp baseline achieves near-perfect accuracy by construction. The FIS's 72.1% measures the proportion of records on which both systems agree, a fundamentally different and more analytically informative quantity than label recovery from a system that generated those labels.

Second, the confusion matrix reveals the operationally critical distinction between the two systems: all significant disagreements involve semantically proximal action pairs. The 1,301-count Cool-and-Mist/Cool-Ventilate divergence reflects the FIS selecting a combined ventilation-and-misting response in the transitional thermal zone where the crisp system assigns the nearest single threshold action; neither response would cause plant physiological harm within a single five-minute control cycle. The lack of any entries at all for Heat-column are notable.

Cooling and ventilating rows must be humidified. Cooling and ventilating rows should be humidified as confirmed by the for Cool-Ventilate, Cool-and-Mist rows functions stop the most critical failure mode giving direct instructions to the actuator oppose the crop's immediate thermal need, which the crisp system's abrupt threshold crossings cannot guarantee.

Thirdly, the accuracy metrics used in the conventional approaches reveal an actual challenge of the Humidify class result for imbalanced multi-class problems. When the number of records is low (0.4% of the data), a system that simply ignoring the class, never predicts Humidify 99.6% accurate per class, the crisp baseline was found to have very precise behaviour (F1 = 0.00). By step-by-step membership activation, FIS correctly identifies 42% of Humidify in the optimal-temperature input zone in the dry-air. Despite its high class imbalance, it was able to achieve a good performance in the record task (recall = 0.42, F1 = 0.09). This is a true example of operational advantage If humidification is not activated during a dry air episode, it can decrease operational advantage.

A cumulative yield of 15–25% increase to daily photosynthetic carbon gain (Stanghellini *et al.*, 2023) here are penalties that an accuracy-only system of evaluating doesn't capture. Fourthly, the three types of visualisations (time-series, action space, and control surface) all validate design integrity in a range of operating scenarios. The smooth action transitions in Fig. 5, Fig. 4, the correct monotonic actuator response was given by the actuator responses in time domain, Fig. 6 confirm the global consistency and agronomic qualities of the knowledge base of the 27 rules. These geometric and temporal validations represent properties that are aggregations of accuracy metrics are not capable of communicating and are an integral part of quantitative assessment readiness assessments by practitioners.

The only drawback is that apparently, ground-truth labels are obtained using a crisp threshold. Classifier over the fuzzy one. Structural advantage for the crisp classifier over the fuzzy one baseline. Future work should produce labels based on independent agronomist review to produce unbiased performance estimates. The static rule base is not able to adjust to crop development. However, the lack of closed loop field validation and stage are still significant shortcomings. The use of an automatic spreader was discussed in Section 5.

5. Conclusion

This paper introduced, applied and tested a Mamdani Fuzzy Inference System (MFI) forintelligent greenhouse climate control, involving air temperature, relative humidity and soil, The 27-rule expert knowledge base is transformed into a seven-class actuator output by the use of moisture. Evaluated on 17,164 real IoT sensor records, the FIS achieves 72.1% overall accuracy and a macro F1-score of 0.55, compared with 98.7% accuracy and macro F1 of 0.50 for a crisp logic baseline. Nine visualisation outputs covering input distributions, time-series dynamics, membership functions, action space geometry, 3D control surface, confusion matrix, performance comparison, and action distribution collectively validate design integrity and operational coherence.

Four future directions are recommended. First, ground-truth labels should be obtained from independent agronomist review rather than crisp threshold derivation to enable unbiased performance evaluation. Second, vapour pressure deficit (VPD) should be incorporated as a derived fourth input to improve Cool-and-Mist versus Humidify discrimination. Third, future work should pursue developing an Adaptive Neuro-Fuzzy Inference System (ANFIS) paradigm to auto-tune the membership parameters while maintaining semantic rule interpretability using data-driven optimisation. Fourth, a twelve-month closed-loop field trial on ARM Cortex-M4 hardware should be conducted, logging actuator cycles, energy consumption, crop yield, and sensor fault rates to establish the commercial adoption evidence base.

Author Contributions

Conceptualization, H.B.M. and U.A.B.; methodology, H.B.M.; software, H.B.M.; validation, H.B.M., J.Y. and U.A.B.; formal analysis, H.B.M.; investigation, H.B.M. and J.Y.; resources, J.Y.; data curation, H.B.M. and J.Y.; writing—original draft preparation, H.B.M.; writing—review and editing, H.B.M., J.Y. and U.A.B.; visualization, H.B.M.; supervision, U.A.B.; project administration, U.A.B. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The dataset analyzed in this study was constructed by merging two publicly available datasets obtained from Kaggle, from which the temperature, humidity and soil moisture were extracted and combine into unified greenhouse sensor datasets (17,164 records). The merge dataset and processing scripts are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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