Proceeding of International Conference on Advanced Technologies, Innovations and Science
Vol 1, No 1, June 2026, Page 75-88
ISSN XXXX-XXXX (Media Online)
https://journals.adaresearch.or.id/icatis

Comparison of the Performance Fuzzy Mamdani, Sugeno, and Tsukamoto in Weather Data Modeling

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Submitted: **01/06/2026**; Accepted: **12/06/2026**; Published: **30/06/2026**

Abstract−Weather forecasting is an essential component in various sectors, including agriculture, transportation, disaster mitigation, and environmental management, as it supports more effective planning and decision-making processes. The dynamic, nonlinear, and uncertain nature of weather data makes weather modeling a complex task. One of the widely adopted approaches for handling such uncertainty is the Fuzzy Inference System (FIS), which is capable of representing expert knowledge through linguistic rules and membership functions. This study aims to compare the performance of the Fuzzy Mamdani, Fuzzy Sugeno, and Fuzzy Tsukamoto methods in weather data modeling using an identical experimental configuration. The dataset consists of 96,453 historical weather records, with Temperature, Humidity, Wind Speed, and Pressure serving as input variables and Weather Condition as the output variable. The research process includes data preprocessing, membership function design, rule base construction, fuzzy model implementation, and performance evaluation. A total of 56 identical fuzzy rules were applied to all methods to ensure an objective comparison. Performance evaluation was conducted using Accuracy, Precision, Recall, F1-Score, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The results indicate that the Mamdani method achieved the best performance, with an Accuracy of 81.04%, Precision of 65.68%, Recall of 81.04%, F1-Score of 72.55%, MAE of 0.264113, and RMSE of 0.642724. These findings demonstrate that all three fuzzy methods are effective for weather data modeling; however, the Mamdani method provides slightly superior performance compared to the Sugeno and Tsukamoto methods.

Keywords: Weather Modeling; Fuzzy Mamdani; Fuzzy Sugeno; Fuzzy Tsukamoto; Weather Forecasting

1. INTRODUCTION

Weather forecasting plays a crucial role in modern society because weather conditions directly influence agriculture, transportation, disaster mitigation, energy management, tourism, environmental sustainability, and public safety, making accurate weather information essential for effective planning and decision-making processes (Song et al., 2021)(Tauhid et al., 2025). The increasing frequency of extreme weather events and climate variability has further intensified the need for reliable weather prediction systems capable of modeling complex atmospheric behavior and supporting timely responses to environmental challenges (Reports, 2026) (Studies, 2026) (Amin et al., 2026). Weather data modeling has therefore become a significant research domain because meteorological variables such as temperature, humidity, pressure, precipitation, and wind speed interact dynamically and nonlinearly, creating uncertainty that is difficult to represent using conventional deterministic approaches (Zhang et al., 2025)(Pidduck et al., n.d.)(Amin et al., 2026). Various approaches have been developed to model weather data and improve forecasting accuracy, ranging from traditional statistical techniques to advanced artificial intelligence methods (Wu & Xue, 2024)(Tauhid et al., 2025). Statistical and numerical prediction models have historically been employed to estimate atmospheric conditions; however, their performance is often limited when dealing with highly nonlinear and uncertain weather patterns (Song et al., 2021)(Wu & Xue, 2024)(Bonavita, 2024). Recent developments in machine learning have introduced more sophisticated forecasting techniques capable of learning hidden relationships from large-scale meteorological datasets (Cnn et al., 2022)(Amin et al., 2026). Deep learning architectures, including convolutional neural networks, probabilistic learning frameworks, and data-driven weather prediction models, have demonstrated substantial improvements in prediction accuracy and computational efficiency compared with conventional forecasting approaches (Reports, 2026)(Zhang et al., 2025)(Cnn et al., 2022). Furthermore, intelligent forecasting systems have been expanded into various domains through hybrid prediction frameworks, uncertainty-aware models, and advanced computational intelligence techniques that integrate weather information into broader forecasting applications (Kernel et al., 2025)(Mehrotra et al., 2026)(Barón-velandia, 2026). Despite these advances, machine learning and deep learning approaches still exhibit several limitations when applied to weather forecasting problems (Bonavita, 2024)(Studies, 2026). Many models operate as black-box systems, making their decision-making processes difficult to interpret and validate from an expert perspective (Bonavita, 2024)(Studies, 2026). Moreover, uncertainty, vagueness, and linguistic ambiguity inherent in meteorological observations are often difficult to represent effectively using purely numerical learning models (Mohanta, 2026)(Rejabov et al., 2026). Consequently, researchers have explored fuzzy-based intelligent systems as an alternative paradigm capable of handling uncertainty while maintaining interpretability through linguistic reasoning and rule-based inference mechanisms (Mehrotra et al., 2026)(Amin et al., 2026). The effectiveness of fuzzy approaches has also been demonstrated in diverse prediction, forecasting, recognition, and intelligent decision-support applications, including time-series forecasting, hybrid neural-fuzzy systems, rainfall prediction, and pattern recognition problems (Reports, 2026)(Nugroho et al., 2024).

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ISSN XXXX-XXXX (Media Online)
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Among fuzzy inference approaches, the Mamdani, Sugeno, and Tsukamoto methods are the most widely adopted because of their ability to transform expert knowledge into interpretable IF–THEN rules while handling uncertain data effectively The Mamdani method has been extensively applied in rainfall prediction, weather forecasting, environmental monitoring, and decision-support systems due to its intuitive linguistic representation and strong interpretability (Rohman, 2024)(Studies, 2026)(Mehrotra et al., 2026). Similarly, Mamdani-based approaches have demonstrated promising performance in production planning, weather prediction, and classification tasks because they can represent expert reasoning in a transparent manner (Surorejo et al., 2024)(Murtopo et al., 2024)(Amin et al., 2026)(Putra, 2024). In contrast, the Sugeno method offers computational efficiency through mathematical consequents and weighted-average outputs, making it suitable for prediction systems requiring rapid execution and integration with optimization algorithms (Reports, 2026)(Amin et al., 2026). Meanwhile, the Tsukamoto method generates crisp outputs from each rule using monotonic membership functions, enabling stable and continuous predictions in forecasting and control applications (Murtopo et al., 2024)(Aslam et al., 2025). Numerous studies have attempted to compare the performance of fuzzy inference systems across different application domains (Matematika, 2024)(Suryadi & Romansyah, 2024). Comparative analyses involving Mamdani, Sugeno, and Tsukamoto have been conducted in production optimization, agricultural productivity, environmental prediction, rainfall forecasting, greenhouse control systems, and employee selection decision support systems (Engineering et al., 2025)(Zhang et al., 2025). Several studies reported that Mamdani achieved superior performance because of its comprehensive aggregation and defuzzification mechanisms conversely, other studies concluded that Sugeno produced better predictive performance due to its computational simplicity and numerical output representation (Kendari et al., 2024). Additional investigations found that Tsukamoto generated lower prediction errors and more stable outputs in several forecasting scenarios (Burhanuddin, 2023)(Pattiradjawane, 2024). Similar inconsistencies were also observed in comparative evaluations of fuzzy inference systems designed for uncertainty handling and intelligent decision-making applications (Pattiradjawane, 2024). Although previous studies have provided valuable insights regarding fuzzy inference systems, their findings remain inconclusive concerning which fuzzy method performs best for weather data modeling (Tauhid et al., 2025)(Kazim et al., 2026). A critical limitation of existing research is that most comparisons employ different datasets, different numbers of rules, different membership functions, different parameter configurations, and different evaluation metrics, making it difficult to determine whether observed performance differences originate from the inference mechanisms themselves or from variations in experimental settings (Kendari et al., 2024)(Pattiradjawane, 2024)(Engineering et al., 2025). Consequently, an objective and controlled comparison among Mamdani, Sugeno, and Tsukamoto under identical modeling conditions remains largely unexplored, particularly in the context of weather data modeling and forecasting applications (Matematika, 2024)(Suryadi & Romansyah, 2024). To address this research gap, this study proposes a comprehensive comparative evaluation of the Fuzzy Mamdani, Fuzzy Sugeno, and Fuzzy Tsukamoto methods using the same weather dataset, identical membership functions, identical fuzzy rule bases, and identical performance evaluation metrics. By maintaining a consistent experimental configuration across all models, the resulting performance differences can be attributed directly to the inference mechanisms of each fuzzy method rather than to external experimental factors. This approach establishes a more objective benchmark for evaluating fuzzy inference systems in weather data modeling and provides a fair assessment of their respective strengths and limitations. The novelty of this study lies in the implementation of a controlled comparison framework in which the dataset, preprocessing procedures, membership functions, fuzzy rules, and evaluation metrics are standardized across all fuzzy models. Unlike previous studies that compared fuzzy methods under heterogeneous experimental settings, this research isolates the influence of the inference mechanism itself, thereby producing a more reliable evaluation of Mamdani, Sugeno, and Tsukamoto performance in weather data modeling. Therefore, the objective of this study is to compare the performance of the Fuzzy Mamdani, Fuzzy Sugeno, and Fuzzy Tsukamoto methods in weather data modeling and to identify the most effective fuzzy inference approach for representing weather patterns and supporting forecasting tasks. The contributions of this research include providing an objective comparative benchmark for fuzzy weather modeling, offering empirical evidence regarding the relative strengths of three widely used fuzzy inference methods, and supporting future development of interpretable and uncertainty-aware weather forecasting systems based on fuzzy logic.

2. RESEARCH METHODS

2.1 Research Framework

The research framework in this study was designed using an experimental approach to compare the performance of three widely used fuzzy inference methods, namely Fuzzy Mamdani, Fuzzy Sugeno, and Fuzzy Tsukamoto, in weather data modeling. The proposed framework consists of a systematic sequence of stages, beginning with weather dataset preparation and continuing through data preprocessing, fuzzy model development, prediction generation, and performance evaluation. To ensure an objective comparison, all fuzzy methods were implemented using the same dataset, input-output variables, membership functions, rule base, and evaluation metrics. This experimental design enables the observed performance differences to be attributed primarily to the inference mechanisms of each fuzzy method rather than variations in the experimental configuration. The overall research framework adopted in this study is presented in Figure 1.

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ISSN XXXX-XXXX (Media Online)
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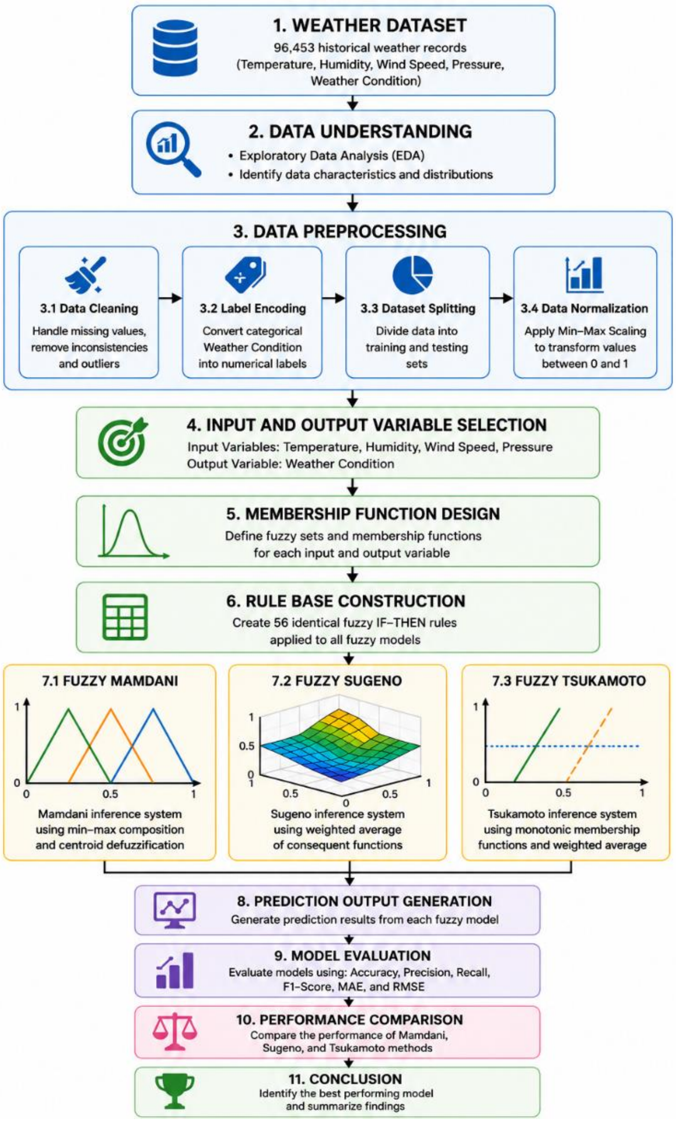

Figure 1. Research Framework

As illustrated in Figure 1, the research process begins with the collection of historical weather data containing meteorological variables such as temperature, humidity, wind speed, pressure, and weather conditions. The dataset is then examined through a data understanding stage to identify its characteristics and distributions before undergoing preprocessing procedures, including data cleaning, label encoding, dataset splitting, and normalization. Subsequently, the relevant input and output variables are selected to support the fuzzy modeling process. Membership functions are then designed to represent the linguistic characteristics of each variable, followed by the construction of a fuzzy rule base consisting of identical IF–THEN rules applied to all models. The developed rule base and membership functions are subsequently implemented within the Fuzzy Mamdani, Fuzzy Sugeno, and Fuzzy Tsukamoto inference systems. Each model generates prediction outputs that are evaluated using several performance metrics, including Accuracy, Precision, Recall, F1-Score, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The resulting performance values are then compared to determine the relative effectiveness of each fuzzy method and to identify the most suitable approach for weather data modeling. Finally, conclusions are drawn based on the comparative analysis results and the overall findings of the study.

2.2 Dataset Description

The weather dataset used in this study consists of several meteorological variables that represent atmospheric conditions and are commonly employed in weather forecasting systems. These variables were selected because they have a direct influence on weather formation and can provide important information for fuzzy inference modeling. Four variables were used as input attributes, namely Temperature, Humidity, Wind Speed, and Pressure, while Weather Condition was used as the target output variable. The dataset used in this study was obtained from a publicly available weather dataset repository and contains 96,453 historical weather records. The dataset can be accessed through the following link: https://drive.google.com/file/d/1K_4g1bUH1j-YFbpzXhh4_fSZ39X9LTVg/view?usp=sharing.The complete description of the dataset attributes is presented in Table 1.

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Table 1. Weather Dataset

Variable	Type	Description
Temperature	Input	Air temperature (°C)
Humidity	Input	Relative humidity (%)
Wind Speed	Input	Wind velocity (km/h)
Pressure	Input	Atmospheric pressure (millibars)
Weather Condition	Output	Weather classification

Table 1 presents the variables utilized in this study for weather data modeling. Temperature, Humidity, Wind Speed, and Pressure were selected as input variables because they represent key meteorological parameters that influence atmospheric behavior and weather changes. Temperature reflects the thermal condition of the atmosphere, Humidity indicates the amount of moisture present in the air, Wind Speed describes air movement intensity, and Pressure represents atmospheric pressure conditions. Meanwhile, Weather Condition serves as the output variable and represents the weather category to be predicted by the fuzzy models. The combination of these variables provides sufficient information for constructing fuzzy inference systems and evaluating the performance of the Mamdani, Sugeno, and Tsukamoto methods in weather classification tasks.

2.3 Data Preprocessing

Data preprocessing was performed to improve data quality and prepare the dataset for fuzzy modeling. The preprocessing stage consists of data cleaning, label encoding, dataset splitting, and normalization. The workflow of the preprocessing stage is illustrated in Figure 2.

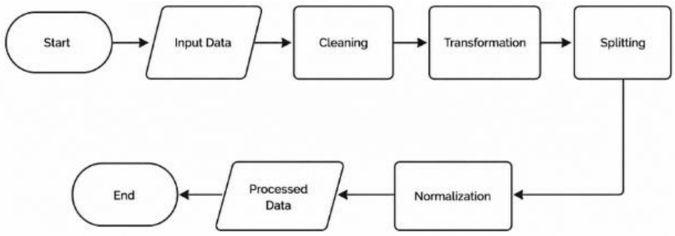

Figure 2. Data Preprocessing Workflow

Figure 2 shows the sequence of preprocessing activities conducted in this research. The process starts with raw weather data, followed by cleaning and transformation procedures. The resulting processed dataset is then used as input for fuzzy model development.

2.3.1 Data Cleaning

The data cleaning stage was conducted to identify missing values and ensure dataset consistency before further processing. The results of the cleaning process are presented in Table 2.

Table 2. Cleaning Process Result

Attribute	Number
Temperature (°C)	0
Humidity	0
Wind Speed (km/h)	0
Pressure (millibars)	0
Summary	0
Weather_Condition	0

Table 2 shows that all attributes contain zero missing values. This indicates that the dataset has good quality and can be directly used for subsequent preprocessing and modeling stages without additional imputation procedures.

2.3.2 Label Encoding

The Weather Condition variable originally contained categorical values. Therefore, label encoding was applied to convert categorical weather classes into numerical representations. The result of the label encoding process is presented in Table 3.

Table 3. Label Encoding Result

Weather Condition	Encoded Value
Breezy	0
Breezy and Dry	1
Breezy and Foggy	2

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Weather Condition	Encoded Value
Breezy and Mostly Cloudy	3
Breezy and Overcast	4
Breezy and Partly Cloudy	5
Clear	6
Dangerously Windy and Partly Cloudy	7
Drizzle	8
Dry	9
Dry and Mostly Cloudy	10
Dry and Partly Cloudy	11
Foggy	12
Humid and Mostly Cloudy	13
Humid and Overcast	14
Humid and Partly Cloudy	15
Light Rain	16
Mostly Cloudy	17
Overcast	18
Partly Cloudy	19
Rain	20
Windy	21
Windy and Dry	22
Windy and Foggy	23
Windy and Mostly Cloudy	24
Windy and Overcast	25

Table 4 demonstrates the successful transformation of categorical weather conditions into numerical labels. This conversion enables the output variable to be processed and evaluated efficiently by the fuzzy models.

2.3.3 Dataset Splitting

Dataset splitting was performed to separate training data and testing data. The training dataset was used for fuzzy model development, while the testing dataset was used to evaluate prediction performance. The dataset splitting result is shown in Table 4.

Table 4. Dataset Splitting Result

Dataset	Number of Records
Training Data	77,162
Testing Data	19,291

Table 5 shows that the dataset has been successfully divided into training and testing data. This stage is important to ensure that the developed model can generalize effectively and produce reliable predictions when applied to unseen data.

2.3.4 Data Normalization

Data normalization was performed using the Min-Max Scaling technique to transform numerical values into a common range between 0 and 1. This process prevents variables with larger numerical scales from dominating the fuzzy inference process. The normalization formula used in this study is given in Equation (1).

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Equation (1) transforms each numerical value into a range between 0 and 1 by considering the minimum and maximum values of the corresponding attribute. Through this transformation, all variables contribute proportionally during the fuzzy modeling process, resulting in more stable and reliable prediction performance. The results of the normalization process are presented in Table 5.

Table 5. Data Normalization Result

No	Temperature (°C)	Humidity	Wind Speed (km/h)	Pressure (millibars)
0	0.506975	0.89	0.221130	0.970135
1	0.505085	0.86	0.223399	0.970613
2	0.505445	0.89	0.061523	0.970909
3	0.487805	0.83	0.220877	0.971358
4	0.495365	0.83	0.172970	0.971454
5	0.502925	0.85	0.218608	0.971597

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No	Temperature (°C)	Humidity	Wind Speed (km/h)	Pressure (millibars)
6	0.478805	0.95	0.193646	0.971655
7	0.495635	0.89	0.221634	0.971769
8	0.528845	0.82	0.177257	0.972276
9	0.576636	0.72	0.196167	0.972132

Table 6 Data Normalization Result shows that the numerical data were successfully normalized into a balanced value range. This stage is important to ensure that the modeling process runs more optimally and produces more reliable prediction results.

2.4 Fuzzy Mamdani Model

The Mamdani method is one of the most widely used Fuzzy Inference System (FIS) approaches because it can effectively represent expert knowledge through easily interpretable IF–THEN linguistic rules. The Mamdani inference process consists of four main stages: fuzzification, rule evaluation, aggregation, and defuzzification. During the rule evaluation stage, the firing strength is calculated using the minimum operator, as expressed in Equation (2).

$$\alpha i = min(\mu A(x), \mu B(y), \mu C(z), \mu D(w)) \tag{2}$$

The firing strength represents the degree of activation of a fuzzy rule based on the combination of membership degrees of all input variables. A higher firing strength indicates a greater influence of the corresponding rule on the final system decision. After all rules have been evaluated and aggregated, the defuzzification process is performed using the centroid method, as shown in Equation (3).

$$z^* = \frac{\int z\mu(z)dz}{\int \mu(z)dz} \tag{3}$$

The centroid method determines the center of gravity of the aggregated fuzzy output set, allowing all information generated by the fuzzy rules to be considered during the decision-making process. Consequently, the Mamdani method often produces outputs that are both stable and easy to interpret.

2.5 Fuzzy Sugeno Model

The Sugeno method employs a rule structure similar to that of the Mamdani method; however, the consequent part of each rule is represented by either a constant value or a mathematical function. This characteristic makes the computational process simpler and more efficient. The firing strength in the Sugeno method is calculated using Equation (4).

$$\alpha i = min\big(\mu A(x), \mu B(y), \mu C(z), \mu D(w)\big) \tag{4}$$

The firing strength values are subsequently used as weights in the computation of the final output. The final output of the Sugeno method is obtained through a weighted average of all activated rules, as expressed in Equation (5).

$$z = \frac{\sum_{i=1}^{n} \alpha_i z_i}{\sum_{i=1}^{n} \alpha_i} \tag{5}$$

This weighted averaging mechanism enables the Sugeno method to perform inference efficiently while maintaining satisfactory prediction performance, making it particularly suitable for applications that require high computational speed.

2.6 Fuzzy Tsukamoto Model

The Tsukamoto method utilizes monotonic membership functions in the consequent part of each rule, allowing every rule to produce a crisp output. This characteristic enables the system to generate more detailed and continuous outputs. The firing strength is calculated using Equation (6).

$$\alpha i = \min\big(\mu A(x), \mu B(y), \mu C(z), \mu D(w)\big) \tag{6}$$

After the firing strength has been determined, the crisp output value for each rule is calculated based on the monotonic membership function, as shown in Equation (7).

$$\mu C(zi) = \alpha i \tag{7}$$

The final output of the Tsukamoto method is obtained through a weighted average of all crisp outputs, as expressed in Equation (8).

$$z = \frac{\sum_{i=1}^{n} \alpha_i z_i}{\sum_{i=1}^{n} \alpha_i} \tag{8}$$

Unlike the Mamdani method, which relies on centroid defuzzification, the Tsukamoto method generates a crisp output for each rule before applying the weighted averaging process. This approach allows the system to produce more measurable outputs and is particularly suitable for prediction and numerical decision-making applications.

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ISSN XXXX-XXXX (Media Online)
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3. RESULTS AND DISCUSSION

This section presents the implementation results and evaluation of the Fuzzy Mamdani, Fuzzy Sugeno, and Fuzzy Tsukamoto methods for weather data modeling. All methods were developed using the same dataset, membership functions, and rule base to ensure that any performance differences observed were solely attributable to their respective inference mechanisms. The analysis was conducted in several stages, including membership function evaluation, rule base analysis, classification performance comparison, error analysis, and comparison with previous studies. This approach enables a more objective assessment of the strengths and limitations of each fuzzy method. Furthermore, the findings provide a basis for determining the most appropriate fuzzy method for weather data modeling applications.

3.1 Membership Function Analysis

Membership functions are a fundamental component of fuzzy systems because they transform numerical data into linguistic representations that can be processed through fuzzy inference mechanisms. The design of membership functions plays a critical role in determining the quality of the decisions produced by a fuzzy system. In this study, all methods employed identical membership functions to ensure a fair and consistent comparison. The input variables consisted of Temperature, Humidity, Wind Speed, and Pressure, while the output variable was Weather Condition. The membership function analysis was conducted to verify that each variable adequately represented the characteristics of the weather dataset. Membership functions were used to convert numerical values into linguistic representations suitable for fuzzy processing. To maintain consistency throughout the evaluation process, the same membership functions were applied to all fuzzy methods. The input variables included Temperature, Humidity, Wind Speed, and Pressure, whereas the output variable represented Weather Condition. The complete set of membership functions used in this study is presented in Figure 7.

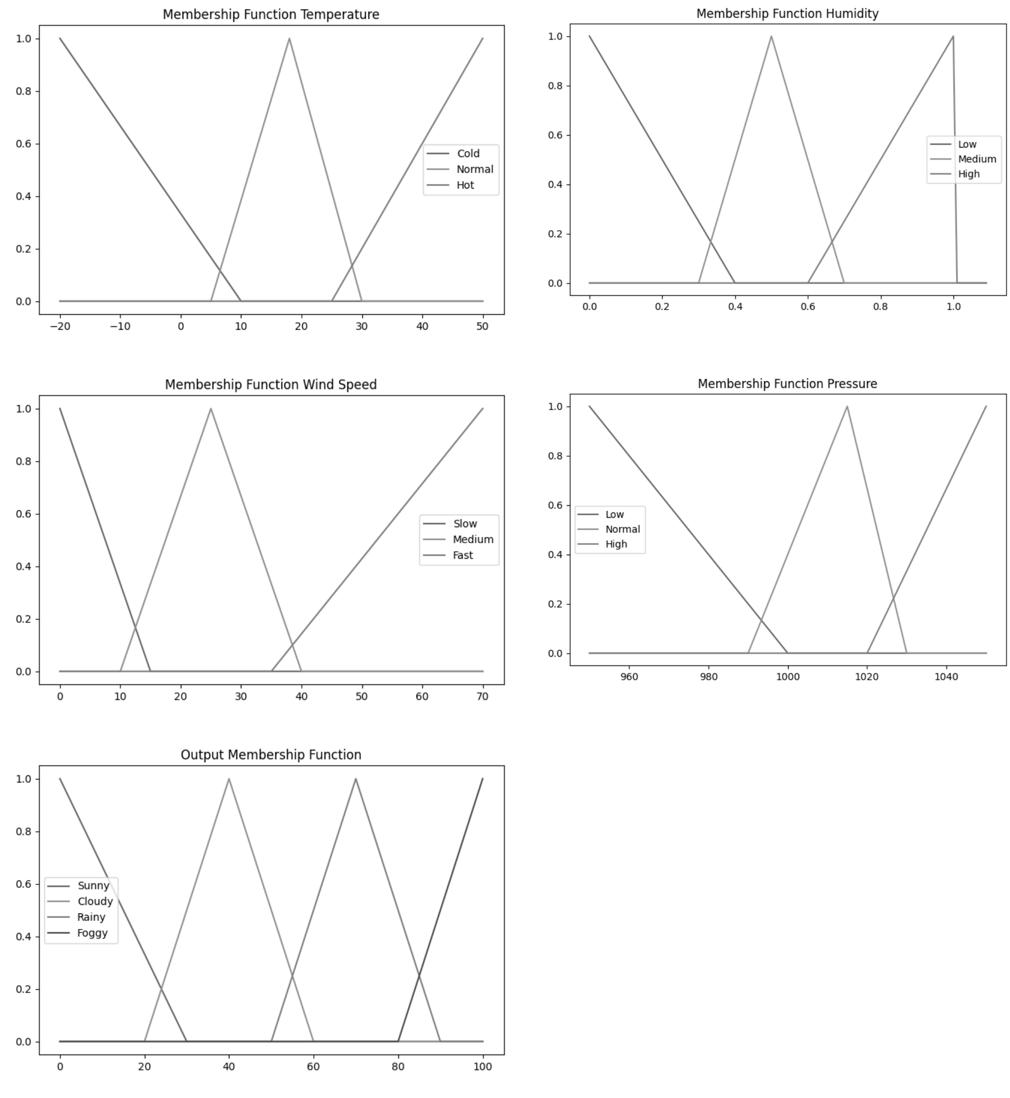

Figure 7. Membership Functions of Temperature, Humidity, Wind Speed, Pressure, and Weather Condition

Based on Figure 7, each input variable is represented by three overlapping fuzzy sets. Temperature is categorized into Cold, Normal, and Hot; Humidity into Low, Medium, and High; Wind Speed into Slow, Medium, and Fast; and Pressure

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into Low, Normal, and High. The presence of overlapping regions allows a single value to belong to more than one fuzzy set simultaneously, enabling the system to represent uncertainty in weather data more effectively. The output variable, Weather Condition, is represented by four categories: Sunny, Cloudy, Rainy, and Foggy. Using identical membership functions across all methods ensures that any differences observed during the evaluation process are attributable solely to the inference mechanisms of Mamdani, Sugeno, and Tsukamoto rather than differences in membership function design.

3.2 Rule Base Analysis

The rule base is a fundamental component of a Fuzzy Inference System, serving to establish relationships between input variables and output variables through IF–THEN linguistic rules. In this study, the rule base was constructed based on the relationships among Temperature, Humidity, Wind Speed, and Pressure with respect to Weather Condition. The same set of rules was applied to the Mamdani, Sugeno, and Tsukamoto methods to ensure an objective comparison. A total of 56 fuzzy rules were developed to represent various atmospheric conditions contained in the historical weather dataset. Specific combinations of meteorological parameters were mapped into weather categories such as Sunny, Cloudy, Rainy, and Foggy. Several representative rules used in this study are presented in Table 6.

Table 7. Representative Fuzzy Rules

Rule	Temperature	Humidity	Wind Speed	Pressure	Weather Condition
R1	Normal	High	Slow	Normal	Cloudy
R2	Normal	Medium	Slow	Normal	Cloudy
R3	Cold	High	Slow	Normal	Cloudy
R4	Cold	High	Medium	Normal	Cloudy
...	...	...	...	...	...
R53	Hot	Low	Slow	High	Sunny
R54	Normal	Medium	Slow	Normal	Cloudy
R55	Cold	High	Medium	Low	Rainy
R56	Cold	High	Slow	Low	Foggy

Based on Table 7, different combinations of temperature, humidity, wind speed, and atmospheric pressure produce different weather condition outputs. For example, a combination of normal temperature, high humidity, low wind speed, and normal pressure results in a Cloudy condition. In contrast, high temperature combined with low humidity and high pressure tends to produce a Sunny condition. The use of an identical rule base across all three fuzzy methods ensures that each model receives the same information during the inference process. Therefore, any differences in performance observed during the evaluation stage can be attributed solely to the inference mechanisms of the respective methods, enabling a fair and objective comparison.

3.3 Comparative Performance Evaluation

The performance evaluation stage was conducted to compare the capabilities of the Fuzzy Mamdani, Fuzzy Sugeno, and Fuzzy Tsukamoto methods in weather data modeling. All methods were tested using the same dataset, membership functions, and rule base, ensuring that the evaluation results objectively reflect the impact of their respective inference mechanisms on model performance. Performance was assessed using Accuracy, Precision, Recall, and F1-Score, which are widely used metrics for classification model evaluation. The experimental results are presented in Table 7.

Table 7. Comparative Performance Evaluation Results

Metode	Accuracy	Precision	Recall	F1-Score
Mamdani	0.810378	0.656788	0.810378	0.725544
Sugeno	0.809860	0.656777	0.809860	0.725329
Tsukamoto	0.810015	0.656767	0.810015	0.725385

Based on Table 8, the three fuzzy methods demonstrate relatively similar performance across all evaluation metrics. Nevertheless, the Mamdani method achieved the highest values for Accuracy, Precision, Recall, and F1-Score. These results indicate that the Mamdani inference mechanism provides slightly better performance than the Sugeno and Tsukamoto methods when applied to the weather dataset used in this study. A more detailed analysis of each metric is presented in Figure 8.

Figure 8. Comparison of Fuzzy Method Performance

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Based on Table 7 and Figure 8, all three fuzzy methods exhibit comparable performance across the evaluation metrics. However, the Mamdani method consistently achieved the highest values for Accuracy, Precision, Recall, and F1-Score. Although the observed differences are relatively small, the consistently superior results indicate that Mamdani is more effective in utilizing the information embedded within the membership functions and rule base. The performance pattern presented in Figure 8 provides important insights into the behavior of the three fuzzy inference mechanisms when applied to weather data modeling. Although the numerical differences among the methods appear relatively small, the consistent superiority of the Mamdani approach across Accuracy, Precision, Recall, and F1-Score suggests that its inference structure is more capable of capturing the complex relationships among meteorological variables.

Weather conditions are inherently uncertain because atmospheric variables often interact in nonlinear ways and rarely exhibit clear boundaries between classes. Under such conditions, the ability of a fuzzy system to integrate information from multiple activated rules becomes critically important. One possible explanation for the superior performance of Mamdani lies in its aggregation mechanism. Unlike Sugeno and Tsukamoto, Mamdani aggregates all activated fuzzy output sets before performing the final defuzzification process. As a result, the final decision reflects the collective contribution of all relevant rules rather than relying primarily on numerical consequents or individual crisp rule outputs. This characteristic enables the system to preserve more uncertainty information during inference and may lead to a more balanced representation of atmospheric conditions.

The centroid defuzzification process also contributes to the effectiveness of the Mamdani model. By calculating the center of gravity of the aggregated fuzzy output set, the centroid method incorporates information from the entire output distribution. Consequently, the final prediction is influenced by all activated membership functions rather than by a limited set of dominant rules. This mechanism can be particularly beneficial in weather modeling because meteorological observations frequently contain overlapping characteristics associated with multiple weather categories simultaneously. The Sugeno method achieved performance very close to that of Mamdani, indicating that its weighted-average mechanism remains highly effective for weather classification tasks. However, because Sugeno uses constant or functional consequents, some linguistic information represented in the fuzzy output space may be simplified during inference. While this simplification improves computational efficiency, it can slightly reduce the model's ability to represent subtle transitions between weather conditions.

Similarly, the Tsukamoto method produced results that were highly competitive but marginally lower than those of Mamdani. The requirement for monotonic consequent membership functions causes each rule to generate a crisp output before aggregation. Although this mechanism provides stable numerical predictions, it may reduce flexibility when representing complex weather patterns characterized by overlapping atmospheric states. Overall, the findings suggest that the inference mechanism plays an important role in determining classification performance, even when membership functions and rule bases remain identical. The results indicate that comprehensive aggregation and centroid-based defuzzification provide a slight advantage in extracting useful information from weather data. Therefore, Mamdani appears particularly suitable for weather data modeling applications where interpretability, uncertainty representation, and classification accuracy are simultaneously required.

3.3.1 Accuracy Analysis

Accuracy measures the proportion of correctly classified instances among all testing samples. This metric provides a general overview of a model's capability to classify weather conditions correctly. A high Accuracy value indicates that the model effectively captures the relationships between meteorological variables and weather conditions. According to Table 7, the Mamdani method achieved an Accuracy of 81.04%, while Tsukamoto and Sugeno obtained Accuracy values of 81.00% and 80.99%, respectively. These results indicate that the three methods possess nearly equivalent classification capabilities. Nevertheless, Mamdani consistently outperformed the other methods. This advantage may be attributed to its fuzzy aggregation process and centroid defuzzification mechanism, which consider the contributions of all fuzzy rules before producing the final decision. Such a mechanism enables a more comprehensive utilization of information derived from the rule base, resulting in more stable classification outcomes. Overall, Accuracy values exceeding 80% indicate that fuzzy approaches are effective for weather classification tasks using historical weather data.

3.3.2 Precision Analysis

Precision evaluates the correctness of the predictions generated for a particular class. A high Precision value indicates that most predicted instances correspond to their actual classes, thereby minimizing false-positive classifications. Based on Table 7, the Mamdani method achieved a Precision value of 65.68%, while Sugeno and Tsukamoto obtained values of approximately 65.67%. The extremely small differences indicate that all three methods possess nearly identical predictive precision. Nevertheless, Mamdani still achieved the highest value. This finding suggests that the Mamdani inference process is slightly more effective in handling weather conditions characterized by overlapping class boundaries. This advantage may result from its fuzzy aggregation mechanism, which simultaneously considers all activated rules before the defuzzification stage. The lower Precision values compared with Accuracy indicate the existence of some classification errors among specific weather categories. This phenomenon is common in weather datasets because atmospheric conditions often do not have sharply defined boundaries. Nevertheless, all three methods maintained satisfactory predictive precision through the consistent use of membership functions and fuzzy rules.

Proceeding of International Conference on Advanced Technologies, Innovations and Science
Vol 1, No 1, June 2026, Page 75-88
ISSN XXXX-XXXX (Media Online)
https://journals.adaresearch.or.id/icatis

3.3.3 Recall Analysis

Recall measures the ability of a model to correctly identify actual instances belonging to a particular class. A high Recall value indicates that the model successfully recognizes most of the existing weather conditions within the testing dataset. Based on Table 7, the Mamdani method achieved the highest Recall value of 81.04%, followed by Tsukamoto with 81.00% and Sugeno with 80.99%. These results indicate that all three fuzzy methods possess strong capabilities in detecting weather condition patterns contained in the dataset. Although the differences are relatively small, Mamdani consistently achieved the best Recall performance. Overall, the high Recall values demonstrate the effectiveness of fuzzy inference systems in weather data modeling.

3.3.4 F1-Score Analysis

F1-Score is a performance metric that combines Precision and Recall into a single value, providing a balanced assessment of classification performance. This metric is particularly useful when evaluating models that require both accurate positive predictions and comprehensive detection of actual classes. Based on Table 7, the Mamdani method achieved the highest F1-Score of 72.55%, followed closely by Tsukamoto with 72.54% and Sugeno with 72.53%. The small differences among the three methods indicate that all fuzzy inference systems exhibit comparable classification performance. However, the slightly higher F1-Score obtained by Mamdani suggests a better balance between Precision and Recall, contributing to its overall superior performance in weather data modeling.

3.4 Error Analysis

In addition to classification metrics, this study evaluated the performance of the Fuzzy Mamdani, Fuzzy Sugeno, and Fuzzy Tsukamoto methods using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These metrics were employed to quantify the discrepancy between predicted and actual values. Lower error values indicate that the predictions are closer to the actual observations. Therefore, MAE and RMSE were used to complement the classification metrics and provide a more comprehensive performance assessment.

Table 8. Error Performance Comparison

Metode	MAE	RMSE
Mamdani	0.2641	0.6427
Sugeno	0.2645	0.6429
Tsukamoto	0.2644	0.6429

The results presented in Table 9 indicate that all three fuzzy methods produced relatively low error values. However, the Mamdani method consistently achieved lower MAE and RMSE values than Sugeno and Tsukamoto. These findings suggest that Mamdani generates predictions are closer to the actual weather conditions represented in the dataset.

3.4.1 MAE Analysis

Mean Absolute Error (MAE) measures the average absolute difference between predicted and actual values. This metric provides an estimate of overall prediction accuracy without assigning additional penalties to large errors. According to Table 8, the Mamdani method achieved the lowest MAE value of 0.264113, followed by Tsukamoto with 0.264424 and Sugeno with 0.264527. These results indicate that Mamdani produced the smallest average prediction error among the evaluated methods. Although the differences in MAE values are relatively small, Mamdani consistently maintained the lowest error level. This finding suggests that the Mamdani inference mechanism is more effective in utilizing information from the membership functions and rule base to generate outputs that closely match the actual conditions.

3.4.2 RMSE Analysis

Root Mean Square Error (RMSE) measures prediction error while assigning greater penalties to larger deviations. Consequently, RMSE is commonly used to evaluate model stability and robustness. Based on Table 8, the Mamdani method achieved an RMSE value of 0.642724, which is lower than those obtained by Sugeno and Tsukamoto, both of which recorded RMSE values of 0.642885. These results indicate that Mamdani is slightly more effective in reducing large prediction errors. The nearly identical RMSE values obtained by all three methods indicate that each model exhibits a high degree of stability when applied to weather data modeling.

However, Mamdani's consistent achievement of the lowest RMSE further supports the previous findings that identified it as the best-performing method across multiple evaluation metrics. Overall, the MAE and RMSE analyses indicate that Mamdani provides the best performance in minimizing prediction errors. These findings are consistent with the Accuracy, Precision, Recall, and F1-Score results, which also ranked Mamdani as the top-performing method. Therefore, Mamdani not only excels in classification performance but also generates predictions that are closer to the actual weather conditions than those produced by Sugeno and Tsukamoto.

3.5 Comparative Analysis of Fuzzy Methods

Although the three fuzzy inference systems share the same conceptual foundation, important differences exist in their inference mechanisms and output generation processes. These differences influence both predictive performance and practical applicability in weather data modeling. The Mamdani method employs fuzzy consequents and performs aggregation before centroid defuzzification. This structure provides a highly interpretable inference process because the resulting decisions can be directly associated with linguistic weather concepts. The aggregation mechanism allows multiple rules to contribute simultaneously to the final prediction, enabling richer uncertainty representation. The Sugeno method differs by replacing fuzzy consequents with numerical constants or mathematical functions. As a result, the final output is generated using a weighted-average calculation.

This approach reduces computational complexity and is particularly suitable for real-time applications. However, the simplification of fuzzy output representations may slightly reduce the system's ability to model subtle atmospheric transitions. The Tsukamoto method introduces monotonic consequent membership functions that produce crisp outputs for each activated rule. These outputs are then aggregated using a weighted-average mechanism. This structure enables smooth numerical predictions and stable decision-making. Nevertheless, the monotonic constraint may limit flexibility when representing complex weather patterns involving highly overlapping classes. The experimental results indicate that all three methods achieved very similar performance levels. This observation suggests that the membership functions and rule base exert substantial influence on classification performance.

Nevertheless, Mamdani consistently achieved the highest values across all evaluation metrics. The results imply that comprehensive aggregation and centroid defuzzification provide a slight advantage in extracting meaningful information from weather data. Therefore, Mamdani appears to offer the best balance between interpretability, uncertainty handling, and predictive accuracy, whereas Sugeno provides superior computational efficiency and Tsukamoto offers stable numerical output generation.

3.6 Statistical Interpretation of Results

From a statistical perspective, the performance differences among the three fuzzy methods are relatively small. The maximum difference in Accuracy is less than one tenth of one percent, while Precision, Recall, and F1-Score values differ only in the third or fourth decimal place. Such small variations indicate that all methods possess highly comparable classification capabilities when implemented under identical experimental conditions. The similarity of the results demonstrates the stability of fuzzy inference systems in weather data modeling. Because the same dataset, membership functions, and rule base were applied, the observed differences can be attributed primarily to the inference mechanisms rather than to external experimental factors.

This finding supports the assumption that fuzzy system performance depends not only on the selected inference method but also on the quality of membership function design and rule construction. The low MAE and RMSE values further indicate that prediction errors remain relatively small across all methods. Moreover, the consistency of these error metrics suggests that the models generate stable outputs and do not exhibit substantial performance fluctuations. In practical applications, such stability is highly desirable because weather prediction systems must maintain reliable performance across varying atmospheric conditions.

Although Mamdani achieved the best overall results, the small performance margins imply that the selection of a fuzzy method should also consider computational requirements, interpretability, and application objectives. Therefore, the statistical interpretation indicates that all three methods are suitable for weather data modeling, with Mamdani providing a modest but consistent performance advantage.

3.7 Discussion with Previous Studies

The findings of this study are generally consistent with previous investigations that reported strong performance of fuzzy inference systems in weather prediction and environmental modeling applications. Earlier studies demonstrated that fuzzy logic is highly effective for handling uncertainty, nonlinear relationships, and ambiguous boundaries among weather conditions. The present study confirms these observations by achieving classification accuracy above 80% across all evaluated methods. Several earlier investigations found that the Mamdani method frequently outperformed alternative fuzzy approaches due to its comprehensive aggregation process and centroid-based defuzzification mechanism.

The results obtained in this research support that observation, as Mamdani consistently achieved the highest Accuracy, Precision, Recall, F1-Score, and the lowest prediction error values. These findings provide additional empirical evidence that Mamdani remains a highly competitive approach for weather-related classification problems. At the same time, previous studies have also reported situations in which Sugeno or Tsukamoto achieved superior performance. Such inconsistencies may be explained by differences in datasets, membership function configurations, rule base structures, input variables, and evaluation procedures. In many previous comparisons, experimental settings varied substantially among models, making it difficult to determine whether performance differences originated from the inference mechanism itself or from other factors.

A key contribution of the present study is the use of a controlled experimental design. By employing identical datasets, membership functions, and fuzzy rules across all methods, the influence of external variables was minimized. Consequently, the resulting performance differences can be interpreted as reflecting the actual characteristics of the inference mechanisms. The results indicate that when experimental conditions are standardized, the performance gap among Mamdani, Sugeno, and Tsukamoto becomes relatively small, although Mamdani still maintains a slight advantage. This finding contributes to a more objective understanding of fuzzy inference system behavior and provides useful guidance for future weather data modeling research.

4. CONCLUSION

This study presented a comprehensive comparison of the Fuzzy Mamdani, Fuzzy Sugeno, and Fuzzy Tsukamoto methods for weather data modeling using historical meteorological data consisting of Temperature, Humidity, Wind Speed, and Pressure as input variables and Weather Condition as the output variable. To ensure an objective evaluation, all methods were implemented using identical datasets, membership functions, fuzzy rules, preprocessing procedures, and evaluation metrics. This experimental design allowed the observed performance differences to be attributed primarily to the inference mechanisms of the respective fuzzy approaches. The experimental results demonstrate that the three fuzzy methods achieved satisfactory overall classification performance. However, the results indicate that the models were more effective in recognizing the dominant weather class than minority classes, suggesting the presence of class imbalance within the dataset. The Mamdani method achieved the best overall performance, obtaining an Accuracy of 81.04%, Precision of 65.68%, Recall of 81.04%, F1-Score of 72.55%, MAE of 0.264113, and RMSE of 0.642724. The Sugeno and Tsukamoto methods produced highly competitive results with only marginal differences across all evaluation metrics. These findings indicate that the three fuzzy inference systems possess comparable capabilities for weather classification; however, Mamdani provides a consistent advantage in both classification performance and prediction error reduction. The study contributes to the literature by providing a controlled comparison framework in which the effects of dataset characteristics, membership functions, and rule bases were standardized. As a result, the findings offer a more objective assessment of the influence of fuzzy inference mechanisms on weather data modeling performance. Nevertheless, several limitations remain, including the use of a single weather dataset, fixed membership functions, manually constructed rule bases, and the absence of optimization procedures. Future research should investigate adaptive membership function optimization, automated rule generation, class-balancing techniques, and hybrid approaches such as Fuzzy–Genetic Algorithms, Fuzzy–Particle Swarm Optimization, and Adaptive Neuro-Fuzzy Inference Systems. These developments may further improve prediction accuracy, model robustness, and generalization capability for real-world weather forecasting applications.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the lecturers and the entire academic community of the Information Systems Study Program for their guidance, support, and valuable feedback throughout the course of this research. The authors also appreciate all parties who contributed to the provision of data, academic discussions, and technical assistance required for the completion of this study. Their support and contributions were invaluable to the successful accomplishment of this research.

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