Journal of Artificial Intelligence and Engineering Applications

Website:https://ioinformatic.org/

June 2026. Vol. 5. No. 3; e-ISSN: 2808-4519

Application of the Tsukamoto Fuzzy Inference System Method for Rainfall Prediction in the Adolina Area

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Abstract

Rainfall is one of the key elements in the climate system that significantly affects various sectors, such as agriculture, spatial planning, and disaster mitigation. Adolina, a region with tropical weather characteristics and highly fluctuating rainfall, requires an accurate prediction system to support informed decision-making. This study applies the *Fuzzy Inference System* (FIS) Tsukamoto method to predict rainfall based on input variables such as air temperature, humidity, and wind speed. The Tsukamoto method is chosen for its capability to handle uncertainty and produce crisp output values through inference and defuzzification processes based on a set of fuzzy rules. The results show that the Tsukamoto FIS provides reasonably accurate and consistent rainfall predictions with a low error rate. Therefore, this approach can serve as an effective alternative in weather decision-support systems for the Adolina area.

***Keywords**: Rainfall Prediction, Fuzzy Inference System, Tsukamoto, Weather, Adolina*

1. Introduction

Global climate change occurring in recent decades has had a significant impact on weather patterns worldwide, including in Indonesia. One of the most noticeable impacts is the increasingly erratic rainfall patterns, both in terms of intensity and distribution. In several regions, including Adolina, North Sumatra, rainfall shows high variability, impacting various sectors, particularly agriculture, water resource management, and mitigating natural disasters such as floods and landslides. This uncertainty makes it difficult for farmers to determine optimal planting and harvesting times, and for local governments to design appropriate mitigation strategies [1].

In the Adolina region, unstable rainfall patterns often cause flooding during the rainy season and drought during the dry season. This directly impacts the agricultural sector, one of the region's primary sectors. When rainfall is too high, crops can fail due to excessive waterlogging. Conversely, when rainfall is low, irrigation water availability is limited, resulting in decreased agricultural productivity. Furthermore, uncertainty in rainfall patterns also impacts spatial planning and infrastructure, making drainage planning and water management more complex due to unpredictable variability. Therefore, accurate rainfall prediction is a key requirement for increasing resilience to the impacts of climate change and supporting the sustainability of affected sectors.

Conventional methods have often been used to predict rainfall, such as the algebraic average, which calculates average rainfall based on historical data. Furthermore, manual measuring instruments such as ombrometers are still commonly used to record daily rainfall amounts. While these methods offer advantages in terms of simplicity and manual accuracy, their limitations are clear in the face of increasingly dynamic climate change. Ombrometers can only measure rainfall at specific points in time, thus failing to capture real-time changes in rainfall. Furthermore, conventional methods fail to account for the complex relationships between meteorological variables such as temperature, humidity, and air pressure, all of which contribute to rainfall formation.

To overcome the limitations of conventional methods, a more intelligent and adaptive approach to rainfall prediction is needed. One promising method is the Tsukamoto Fuzzy Inference System (FIS). This method uses a fuzzy logic approach that can better handle uncertainty in data. In the Tsukamoto FIS, weather data with uncertain or ambiguous characteristics can be categorized into various fuzzy membership functions, allowing the model to adapt to changing weather conditions. The main advantage of this method is its ability to handle non-linear relationships between various meteorological parameters, resulting in more accurate predictions than conventional statistical methods [4].

However, in implementing the Tsukamoto FIS, several challenges remain. One of these is determining optimal parameters, including the membership functions and fuzzy rules used in the system. If the parameters used are inappropriate, the prediction results can be inaccurate. Therefore, in-depth analysis is required in developing the Tsukamoto FIS model to produce better rainfall predictions. Furthermore, although this method is more flexible than conventional methods, the model's accuracy still depends on the quality of the data used. Good data processing and the selection of appropriate input variables significantly impact the performance of this prediction system.

Based on these problems, this study aims to apply and test the Tsukamoto Fuzzy Inference System (FIS) method to predict rainfall in the Adolina area, North Sumatra. By utilizing this method, it is hoped that a more accurate and reliable rainfall prediction model can be obtained, thereby assisting in better decision-making, both in the agricultural sector, water resource management, and disaster mitigation. This research is also expected to contribute to the development of a more sophisticated and adaptive artificial intelligence-based rainfall prediction system, thus being able to face the increasingly complex challenges of climate change in the future [6].

2. Literatur Riview

Rainfall is a crucial component of the hydrological cycle that impacts various human activities, particularly in agriculture, water resources management, and natural disaster mitigation. Accurate rainfall predictions enable better planning and risk mitigation for natural disasters such as floods and droughts (L. A. Zadeh, n.d.).

Evaluation is a crucial process for assessing the performance of a model or system to ensure it performs as expected and meets its stated objectives. It involves using various metrics and techniques to measure the model's effectiveness in making predictions or decisions.

Adolina is a sub-district in Serdang Bedagai Regency, North Sumatra Province, Indonesia. It is strategically located on the Trans-Sumatra Highway, connecting Medan with other areas in Sumatra. Covering an area of approximately 118.97 km², Adolina has a dense and diverse population, comprising various ethnicities, including Malay, Batak, Javanese, and Minangkabau.

Economy: Adolina is the center of economic activity in Serdang Bedagai, with trade, services, and agriculture as its backbone. Traditional markets in Adolina are the center of buying and selling, while the agricultural sector is dominated by oil palm, rice, and rubber.

Tourism: Adolina is also close to coastal tourist areas such as Cermin Beach and Gudang Garam Beach, which attract both local and out-of-town tourists.

Infrastructure: Adolina's infrastructure is well developed, with adequate education, healthcare, and transportation facilities. Access to Medan is easy, making it a strategic transit and residential area for commuters.

Demographics: Adolina has an ethnically and culturally diverse population, with a majority Muslim population. Social life in the area is relatively harmonious, with tolerance among ethnic and religious groups.

Adolina is known as a rapidly developing region, both in economic and social aspects, with potential that continues to grow thanks to its strategic location and diverse human resources.

2.3. Data Pre-Processing

Data preprocessing is a crucial initial step in this research, as the data used will significantly impact the rainfall prediction results. At this stage, several processes are carried out to ensure the data is clean, consistent, and ready to be used as input for the Tsukamoto Fuzzy Inference System (FIS) method. The data preprocessing steps carried out in this research include handling missing data and data normalization (Mathematics, Faculty of Science and Technology, 2017).

2.3.1. Handling Missing Data (Missing Value)

Missing data (missing value) is a condition where an attribute in the data has no value. The presence of missing data can cause calculation results to be inaccurate and disrupt the modeling process (L. A. Zadeh, n.d.). The process of handling missing data can be done by deleting data rows that have blank values in one of the variables, namely air temperature, air humidity, wind speed, or rainfall. This method was chosen because the amount of available data is quite large, so that deleting some data does not affect the representativeness of the dataset as a whole.

2.3.2 Data Aggregation

After the data cleaning process is complete, the next step is to perform data aggregation. Data aggregation is performed to simplify daily observation data into monthly data for easier analysis and adjustment to the needs of the Tsukamoto FIS modeling. At this stage, the cleaned air temperature, air humidity, wind speed, and rainfall data are calculated for monthly average values for each month from January to December 2024. The results of this aggregation process produce 12 monthly data sets that represent the average weather conditions for each month (Melanie, 1999).

2.3.3 Normalization

Data normalization is the process of changing the scale of data values into a specific range so that each variable has a balanced scale.

Normalization is necessary to prevent the dominance of one variable over another in the calculation process, particularly in fuzzy logic-based methods (Farismana et al., 2024).

The normalization method used in this study is Min–Max Scaling, which converts data values into the range 0 to 1 (Farismana et al., 2024). The Min–Max Scaling normalization formula is shown in the following equation:

$$x^{\iota} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Information:
xι : normalized value x : original data value
x_min : minimum value of a variable x max : maximum value of a variable

By using this normalization, all input variables such as air temperature, air humidity, and wind speed are on the same scale, so they can be optimally processed in the fuzzification stage of the Tsukamoto FIS method (Insani et al., 2020). The results of this normalization process are then used as direct input to the fuzzification process, fuzzy rule formation, and defuzzification to produce rainfall predictions.

2.4 Fuzzy Logic

Fuzzy Logic is a computational approach used to handle uncertainty in decision making (Sa'dan et al., 2019). Unlike classical logic which only recognizes values 0 or 1 (true or false), fuzzy logic allows a value to have a membership level between 0 and 1, making it more flexible in handling uncertain or vague data (Untuk & Skripsi, 2024). For example, in a rainfall prediction system, an air temperature of 28°C can be considered "warm" with a membership level of 0.6 and "hot" with a membership level of 0.4, depending on the membership function used (Muhammad Ricky Aryansah. B et al., 2024).

2.5 Tsukamoto's Fuzzy Inference System (FIS) method

Tsukamoto's Fuzzy Inference System (FIS) is a fuzzy inference method introduced by Tsukamoto (Kasim et al., 2025). This method uses if-then rules based on fuzzy logic with output in the form of crisp variables obtained through defuzzification. Each fuzzy rule in Tsukamoto's FIS is represented by a fuzzy set with a monotonic membership function (Ardianto et al., 2017).

3. Research Methodology

3.1 Research Location

This research was conducted at the Meteorology, Climatology, and Geophysics Agency (BMKG) Deli Serdang Office, North Sumatra. BMKG was chosen because it is an official agency that has the authority to observe and provide accurate meteorological, climatological, and geophysical data. Rainfall data used in this study include rainfall, air temperature, air humidity, and wind speed obtained from BMKG Deli Serdang for the Adolina area, Perbaungan District, which is relevant because it has a fairly high level of rainfall variability. With the research location at BMKG Deli Serdang, it is expected that the data obtained will be able to support the application of the Tsukamoto Fuzzy Inference System (FIS) method so that it produces more accurate rainfall predictions and is beneficial for the community and related sectors. Research Stages

The research stages are structured systematically to ensure the research proceeds according to its stated objectives. Generally, the research stages include data collection, data preprocessing, application of the Tsukamoto Fuzzy Inference System (FIS) method, and evaluation of the results. Each stage plays a crucial role in ensuring that the developed predictive model performs effectively and produces useful information.

3.1.1. Data collection

The initial stage of this research is data collection, obtained from the Deli Serdang Meteorology, Climatology, and Geophysics Agency (BMKG). The data collected consists of daily rainfall data in the Adolina area, Perbaungan District. This rainfall data was chosen because it is closely related to climate and weather conditions, which significantly impact various sectors, particularly agriculture and disaster mitigation. This data will be used as the main variable in developing a Tsukamoto FIS-based prediction model.

3.1.2. Research Flowchart

A research flowchart is used to illustrate the overall flow of research stages. The research diagram is shown in Figure 3.1.

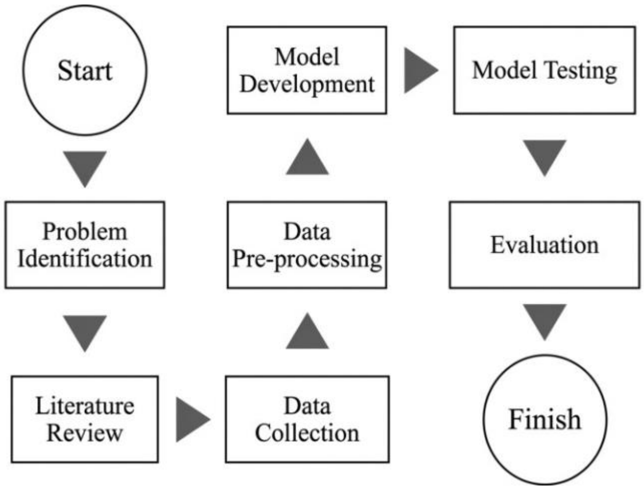

Fig. 1: Research Diagram

4. Results Discussion

This chapter will explain how to process data and implement the Tsukamoto Fuzzy Inference System method for Rainfall Prediction in the Adolina Area.

4.1. Data Description

This stage involved data collection and processing as the basis for applying the Tsukamoto Fuzzy Inference System (FIS) method to predict rainfall in the Adolina area. The data used was secondary data obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG) in Excel format.

The data consisted of four variables: air temperature, air humidity, wind speed, and rainfall. The universe of discourse in this study was obtained by examining the lowest and highest values for each variable. An explanation of each variable is provided in the following table:

Table 1: Description of Research Variables and Universe of Discussion

No	Variable Name	Information	Satuan	Universe of Conversations
1.	Air temperature	The level of hot/cold air	°C	Low : (0-37) Medium : (37-49) Height : (49-92)
2.	Air Humidity	Percentage of water vapor permeability in the atmosphere	%	Dry : (<43%) Medium : (43-50%) Humidity: 100%)
3.	Wind velocity	Wind movement rate	m/s	Weak : (<0.1m/s) Medium : (5m/s) Fast : (84m/s)
4.	Rainfall	Amount of rainfall during the observation period	mm	Low : (<0 mm) Medium : (0-89 mm) High : (>89 mm)

4.2. Data Preprocessing

Before being used in calculations using the Tsukamoto Fuzzy Inference method, the data first undergoes a preprocessing stage. This stage aims to ensure the data used is clean, consistent, and on a uniform scale, thus ensuring more accurate and stable prediction results. The data preprocessing stages are as follows :

4.2.1. Data Cleansing

In this stage, the entire dataset, totaling 52,847 rows, was checked to ensure there were no duplicate data, recording errors, or missing values. Based on the results of the check, it was found that 5,053 rows of data were unusable because they contained blank values for one or more variables, such as air temperature, humidity, wind speed, or rainfall. Thus, the total number of data used in the next stage was 47,794 rows.

4.2.2. Data Aggregation (Monthly Average)

After the data cleaning process, data aggregation was performed by calculating monthly averages from the cleaned daily data. This aggregation aims to provide an overview of weather and rainfall patterns in the Adolina region from January to December 2024. The monthly averages were obtained from all daily data for the respective months and are presented in the following table.

Table 2: Monthly Average Data

Month	Rainfall	Air temperature	Wind velocity	Humidity
January	4.8	27.64	2.8	87.97
February	1.42	28.63	1.6	83.76
March	7.1	28.73	4.3	84.06
April	0.81	29.56	3.2	82.4
May	6.3	29.3	0.9	84.2
June	2.91	29.3	2.1	84.2
July	9.6	29.11	5.4	82.54
August	3.5	27.94	3.7	86.11
September	5.64	28.3	1.8	85.44
October	2.09	28.03	4.1	86.27
November	8.4	27.49	5.0	88.54
December	4.2	27.58	0.6	87.86

The data above is single data, many data because the data is even and divisible by 4 so finding Q1 temperature variable is Q1=(x(12/4)+x(12/4+1))/2=(x3+x4)/2 So we get Q1=(Q3+Q4)/2=(2.09+2.91)/2=5/2=2.5. Finding Q2 temperature variable is, Q2=(x(12/2)+x(12/2+1))/2=(x6+x7)/2 So we get Q2=(Q6+Q7)/2=(4.2+4.8)/2=4.5 Finding Q3 temperature variable is, Q3=(x(3.12/4)+x(3.12/4+1))/2=(x9+x10)/2. So we get Q3=(Q9+Q10)/2=(6.3+7.1)/2=6.7. In the same way, we will get Q1, Q2, Q3 for the variables of air temperature, wind speed, and air humidity. The air temperature variable is obtained Q1 = 27.79, Q2 = 28.47 and Q3 =
29.21. The wind speed variable is obtained Q1 = 1.7, Q2 = 3.0 and Q3 = 4.2. And the air humidity variable is obtained Q1 = 83.91, Q2 =
84.82 and Q3 = 86.19 and from the domain, the membership function of each variable can be determined. The following is presented in Table 4.3 to represent the fuzzy set.

Table 3: Fuzzy Sets

Variable Name	Fuzzy Set	Universe of Conversations	Domain
Air temperature	low	[22,49, 37,92]	[22 .49, 27.79]
	medium		[27.79, 29.21]
	high		[29.21, 37.92]
Wind velocity	low	[0,1, 5,84]	[0.1, 1.7]
	medium		[1.7, 4.2]
	high		[4.2, 5.84]
Air Humidity	low	[43,55, 100]	[43.55, 83.91]
	medium		[83.91, 86.19]
	high		[86.19, 100]
Rainfall	low	[0, 10]	[0, 2.5]
	medium		[2.5, 6.7]
	high		[6.7, 10]

4.3. Website Interface View

This section explains the visual form of a website-based system that interacts directly with users, from the opening page to the final result display.

4.3.1. Initial View of Rainfall Prediction System

Displays the website's opening page, general information, and a guide on how to use the system.

Fig. 2: Initial View of the Rainfall Prediction System

Figure 2 displays the application's homepage, which serves as a system introduction interface with a modern design based on the Home, Variables & Rules, and Rainfall Prediction navigation. This page provides an educational explanation to users regarding the use of the Tsukamoto Fuzzy Inference System (FIS) method in processing weather parameters such as temperature, humidity, and wind speed into rainfall prediction values (mm). Through this display, users can understand that the system aims to produce low, medium, or high rainfall classifications to support decision-making in the agricultural and environmental sectors.

4.3.1.1. Tsukamoto Fuzzy Variables

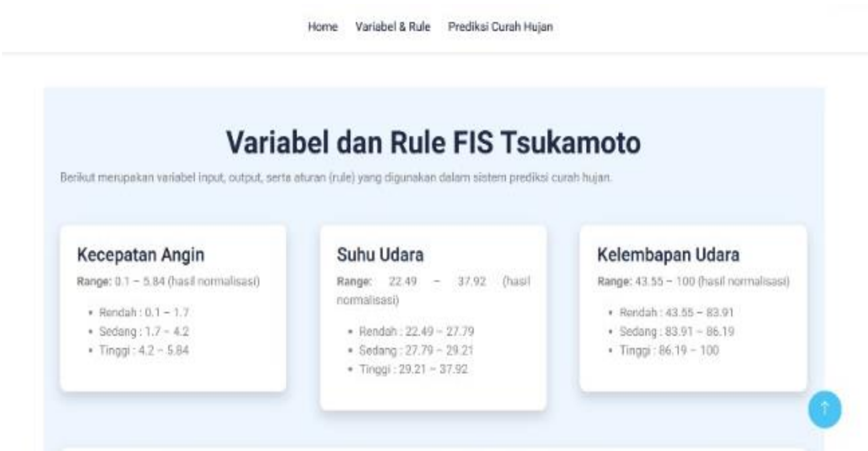

Fig. 3: Tsukamoto Fuzzy Variables

Figure 3 presents the Tsukamoto FIS Variables and Rules page interface, detailing the main input parameters used by the system to predict rainfall. Three input variables are mapped in the form of information cards: Wind Speed (range 0.1–5.84), Air Temperature (range 22.49–37.92), and Air Humidity (range 43.55–100), each of which has undergone a data normalization process. Each variable has three fuzzy set classifications—Low, Medium, and High—with specific numerical value limits that will serve as references in the process of calculating membership functions and applying rules in the Tsukamoto method.

4.3.1.2. Fuzzy Rules (If-Then Rules)

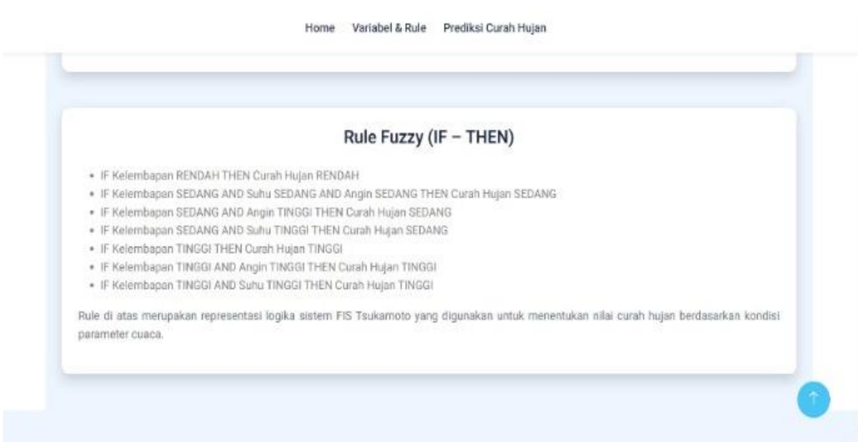

Fig. 4: Fuzzy Rules (If – Then Rules)

Figure 4 presents the Fuzzy Rule (IF-THEN) section, which is the knowledge base or brain of the expert system in determining rainfall prediction results. This section contains a list of logical rules that connect various combinations of input variables, such as humidity, temperature, and wind speed, to produce a conclusion (consequence) regarding rainfall intensity, whether low, medium, or high. The application of this If-Then rule represents the logic of the Tsukamoto FIS system, where each met weather parameter condition will be processed through an inference stage to calculate an accurate output value based on the weighting of each rule.

4.1.3.3. Rainfall Prediction Home Page

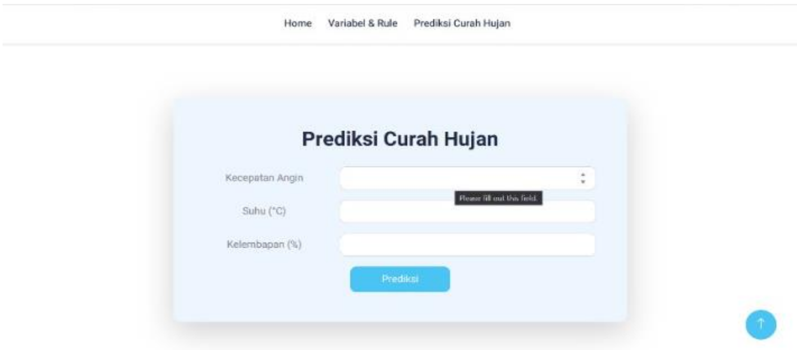

Fig. 5: Rainfall Prediction Page

Figure 5 displays the Rainfall Prediction page, which serves as the primary input interface for users to perform prediction calculations. This page provides a data entry form consisting of three weather parameters: Wind Speed, Temperature (°C), and Humidity (%), designed with validation controls to ensure all data is filled in before processing. Users can click the Predict button to execute calculations using the Tsukamoto Fuzzy Inference System (FIS) method, which will then automatically process the input values into rainfall classification information.

4.1.3.4. Rainfall Output

Fig. 6: Rainfall Output

Figure 6 displays the Rainfall Prediction Results interface that appears after the user clicks the prediction button on the previous page. This section presents the final output in the form of a numerical rainfall value in millimeters (mm) and a classification category, such as low, medium, or high, based on the fuzzy logic calculations performed. These results provide users with concise and clear information to aid decision-making regarding weather conditions in agriculture and the environment.

4.1.3.5. Rainfall Prediction Results

Fig. 7: Rainfall Prediction Results

Figure 7 presents the Rainfall Prediction Results interface, the final output of the Tsukamoto FIS method calculation process after the user has input weather parameter data. This page displays very specific information in the form of a quantitative rainfall value of 11.95 mm along with its qualitative interpretation, which falls into the Light category. This simple and straightforward data presentation makes it easy for users to quickly understand the system's analysis results for decision-making purposes in agriculture and environmental monitoring.

5. Conclusion and Recommendations

5.1. Conclusion

Based on the results of research and testing that has been carried out, it can be concluded that:

1. The Tsukamoto Fuzzy Inference System (FIS) method can be applied to predict rainfall in the Adolina area using air temperature, humidity, and wind speed as input variables, and generates numerical rainfall prediction values.
2. Based on the evaluation using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), the rainfall prediction results obtained were MAE 0.2657 mm and RMSE 0.3173 mm, indicating a fairly good level of accuracy, thus the Tsukamoto FIS method is suitable for use as an approach in rainfall prediction in the Adolina area.

5.2. Recommendations

Based on the results of this study, there are several suggestions that can be given:

1. Real-Time System Development it is recommended that the prediction system be further developed into a real-time system by integrating automatic weather data from sensors or the BMKG API. This will improve the accuracy and speed of prediction responses.
2. Broader Scale Applicability the method used in this study can be applied not only to the Adolina area but also to other regions with different climatic conditions. Therefore, it is necessary to recalibrate the membership functions and fuzzy rules based on each local characteristic.

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