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Flood Vulnerability Mapping in Cepu Subdistrict Using Mamdani Fuzzy Inference System for Disaster Risk Reduction

Joko Handoyo[1,2], Anton Yudhana[2], Sunardi[2]
[1]Sekolah Tinggi Teknologi Ronggolawe, Blora, Indonesia
[2]Universitas Ahmad Dahlan, Yogyakarta, Indonesia

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ABSTRACT

Floods pose a persistent and serious threat to Cepu Subdistrict, frequently causing significant economic loss, resident displacement, and damage to critical infrastructure. In response to this issue, and aligned with the National Disaster Management Agency's (BNPB) efforts to enhance landscape monitoring, a comprehensive analytical study was conducted. The purpose of this research was to assess and map the flood vulnerability levels across 17 villages in Cepu Subdistrict, categorizing them to facilitate more effective disaster response planning and resource allocation. The research method employs the Mamdani Fuzzy Inference System, an advanced computational approach that is adept at handling nonlinear relationships between environmental variables. This system enabled a detailed analysis of the complex interactions among key factors influencing floods, including rainfall intensity, watershed area, elevation, slope, and population density. The results of the quantitative research conducted in 17 villages of the Cepu Subdistrict indicate that Ngelo Village has the highest score of 65.16, categorized as a "high" risk level. In contrast, most other villages, such as Ngroto, Karangboyo, and Cabean, fell into the "medium" risk category, with varying scores ranging from 55.0 to 63.93. The model's accuracy was validated by evaluation metrics, with a Mean Absolute Error (MAE) of 8.67 and a Root Mean Squared Error (RMSE) of 10.29, indicating satisfactory predictive performance. The conclusion of this study emphasizes the urgent need for comprehensive and adaptive mitigation strategies, including early warning systems and community preparedness programs, to protect Cepu Subdistrict from future flood threats.

Corresponding Author:

Joko Handoyo, +62859-5161-2944,
Faculty of Industrial Technology, Doctoral Program in Informatics,
Universitas Ahmad Dahlan, Yogyakarta, Indonesia,
Email: 2437083009@webmail.uad.ac.id

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1. INTRODUCTION

Local background and the importance of flood mitigation, because floods frequently occur in Cepu Subdistrict, especially during heavy rainfall and river overflow. The primary factors contributing to floods include extreme rainfall intensity, blocked river flows, and inadequate drainage systems. Human activities such as the construction of settlements along riverbanks and the disposal of waste into water streams further exacerbate the flood risk [1]. According to the report from the Blora District Disaster Management Agency (BPBD), in 2022, severe flooding affected the Cepu Subdistrict, submerging at least five villages. In response to this, the government is focusing on mitigation and monitoring efforts along the River Basin as part of the ecosystem-based disaster risk reduction strategy [?]. To support this effort, a flood vulnerability analysis system is needed that utilizes spatial data and computational logic-based modeling to enhance disaster preparedness and response at the local level [2].

Literature review and research gaps indicate that various previous studies have developed flood prediction systems that combine fuzzy inference techniques to assess the spatial impact of floods based on a combination of hazard, exposure, and vulnerability. This system is capable of displaying flood impact predictions interactively and in real-time [3]. For example, a study applying the Mamdani FIS method in Garut Regency showed an accuracy rate of up to 92.30% in assessing flood vulnerability [2]. Additionally, the use of fuzzy logic has also been applied in flood detection systems based on weather and rainfall data to support smart cities [4]. The validity of the Mamdani method in measuring vulnerability levels was also confirmed in a study in Pangkalpinang City, with a good MAPE value [5]. Another study compared the performance of various AI paradigms, such as ANN, Fuzzy Logic, and ANFIS, in predicting flood events [6]. Research based on the Delhi Weather Data dataset revealed that the model achieved an accuracy of 63.29%, a precision of 62.44%, a recall of 66.7%, and an F1 score of 64.49%. [7]. However, most of these studies have not specifically addressed the need for localized flood vulnerability mapping, such as in the Cepu Subdistrict. Several approaches, such as AHP, Random Forest, and SVM, have been used in flood risk assessment (for example, in susceptibility analysis and spatial classification) [8]. However, these approaches usually require complete and clean numerical data, and have limitations in handling uncertainty and linguistic variables such as drainage conditions or subjective rainfall intensity [9]. Therefore, fuzzy logic, particularly the Mamdani method, was chosen because it is more adaptive to uncertain and qualitative local data, and it can represent expert reasoning more intuitively. Classification methods, such as Decision Trees and SVMs, tend to work optimally on complete, numerical, and noise-free data. In this context, the data used has uncertainty and is of a linguistic nature, such as 'high rainfall' or 'gentle slope'. Fuzzy logic allows for linguistic rule-based interpretations that are closer to the thinking of field experts and more communicative for decision-makers in the region [10].

The difference between this study and previous research is that although many studies have shown the effectiveness of the Mamdani FIS in assessing and predicting flood vulnerability, this research distinguishes itself by specifically targeting flood vulnerability mapping in the Cepu Subdistrict. To enhance real-time flood forecasting, this paper proposes a Takagi-Sugeno fuzzy inference system, known as the Sugeno flood model. A total of 12 input parameters were used to develop two fuzzy flood models, Mamdani and Sugeno [6]. Unlike some previous studies that emphasized the comparison of AI methods to understand and predict flood frequency in general [11], this research is more focused on detailed and localized vulnerability classification. By considering input variables such as rainfall, watershed area, land slope, elevation, population density, and risk level [7], Descriptive statistical analysis is used to analyze vulnerability in social, economic, physical, and environmental aspects, as well as community resilience to floods [12]. This granular approach provides more targeted and applicable mitigation strategies for the Cepu area. Although this research does not propose a new fuzzy method, its contribution lies in the application and validation of the Mamdani fuzzy inference system in the local context of Cepu Subdistrict, which has not been extensively explored. The novelty of this study compared to previous studies lies in integrating spatial and socioeconomic variables into a single classification system that can be applied to risk mapping based on local data.

The aim and contribution of this research are to develop a flood vulnerability mapping system in the Cepu Subdistrict using the Mamdani FIS method. This system is designed to support decision-making in early disaster mitigation and evacuation. By integrating spatial and environmental variables, this system is capable of providing easily understandable vulnerability classification results, making it usable by policymakers and local communities. The primary contribution of this research is the development of a scientifically tested and applicable fuzzy logic-based approach in the local context, thereby strengthening data- and technology-based disaster preparedness at the sub-district level.

2. RESEARCH METHOD

A flowchart or flow diagram is a diagram that displays the steps and decisions involved in executing a process within a program. Each step is depicted in diagram form and connected by lines or arrows [?]. Flowcharts play a crucial role in determining the steps or functionalities in a program development project involving multiple stakeholders. Additionally, using a process flowchart for a program makes it clearer, more concise, and reduces the likelihood of misinterpretation [13]. The use of flowcharts in programming is also an effective way to bridge the gap between technical and non-technical requirements [?]. Flowcharts that detail the fuzzy inference system methodology applied to assess flood vulnerability have been widely used in decision support systems and spatial modeling [14]. This process is designed to systematically map various environmental and demographic inputs, as shown in Figure 1 below.

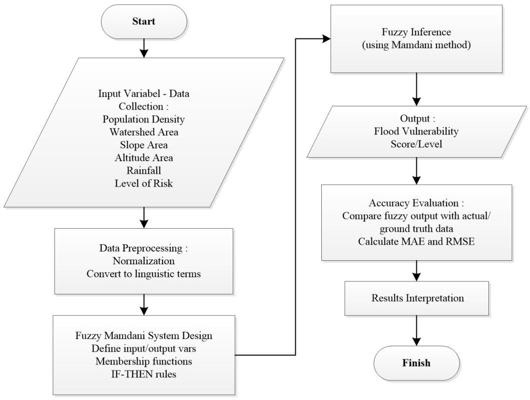


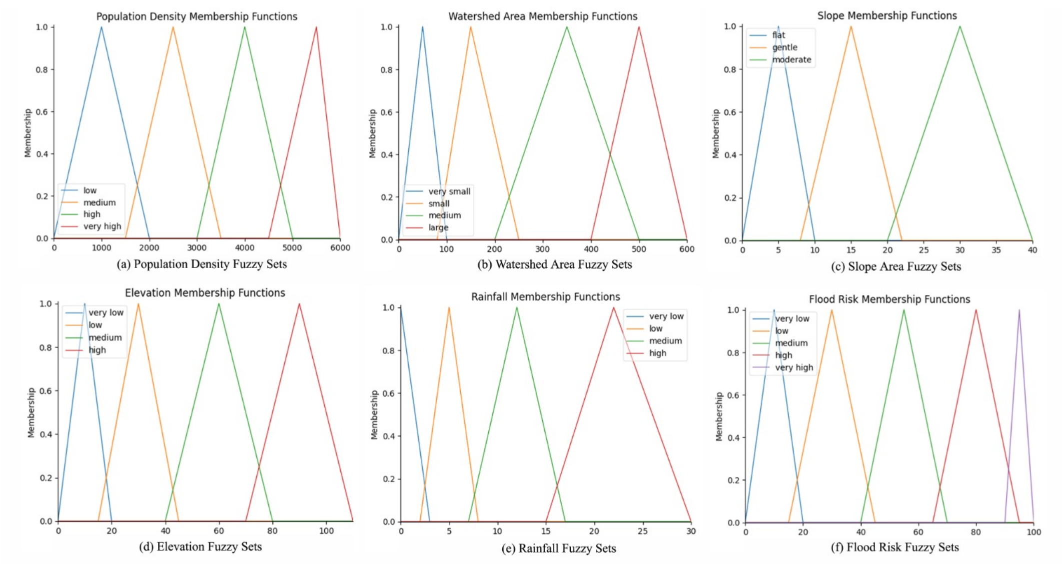
Figure 1. Research design

Figure 1 explains the process of determining flood vulnerability levels using the Mamdani fuzzy system. The process begins with the collection and preprocessing of variable data such as population density and rainfall. This data is then used to design the fuzzy system by determining variables, membership functions, and IF-THEN rules. Next, fuzzy inference is performed to generate flood vulnerability scores, followed by an accuracy evaluation and the interpretation of the results. Evaluating flood-prone areas is essential for disaster mitigation, but is often complicated by the presence of qualitative and uncertain variables like population density and drainage conditions [15]. Traditional mathematical models struggle with such uncertainties, making FIS a suitable alternative. The Mamdani method captures expert-like reasoning and processes linguistic terms (e.g., "low", "high") to yield realistic risk assessments [16], making it highly applicable for spatial and dynamic flood risk mapping [?].

2.1. Input Variabel and Data Collection

In flood vulnerability analysis based on fuzzy inference systems, various environmental, climatological, and socio-economic factors that influence flood risk are represented as fuzzy sets. This representation aims to quantify the level of risk more flexibly and comprehensively, especially when the available data is uncertain, incomplete, or vague [17]. Each input variable is defined through a range of values (domain) and a specific fuzzy membership function, which describes the extent to which the input value contributes to the level of flood risk. The use of fuzzy logic allows for realistic modeling of uncertainty and ambiguity in environmental data and is adaptive to local conditions [18]. The following are some of the main inputs commonly used in fuzzy-based flood vulnerability assessment systems, including population density, which has a significant impact on the potential social and economic effects of flooding. Areas with high population density tend to have a greater level of exposure and face challenges in evacuation and emergency response [?].

Several key environmental and demographic factors significantly influence flood risk and are commonly incorporated into fuzzy inference systems for risk assessment. Population density plays a crucial role in determining the potential social and economic impacts of floods; densely populated areas face greater exposure and more challenges in evacuation and emergency response, and are thus classified into low, medium, and high categories using fuzzy membership functions as shown in Figure 2(a) [19]. The watershed area affects the volume of rainwater collected and channeled; larger areas generally accumulate more water, heightening flood potential if drainage capacity is inadequate, as shown in Figure 2(b) [20]. Similarly, the slope area influences surface runoff velocity and soil infiltration. Steep slopes tend to accelerate flow and erosion, increasing the risk of flash floods, which necessitates slope angle-based classification, as illustrated in Figure 2(c) [21]. The height of a region above sea level determines its vulnerability, as low-lying areas are more susceptible to water accumulation and flooding, particularly when situated near natural drainage channels, as shown in Figure 2(d) [22]. Rainfall characteristics, both in terms of intensity and duration, are fundamental flood triggers; short, intense rain or prolonged moderate rainfall can both result in hazardous runoff, as shown in Figure 2(e) [?]. All these variables feed into the calculation of the vulnerability level, which serves as the final fuzzy output and is categorized into low, moderate, and high levels, providing essential input for prioritizing disaster response and mitigation strategies, as shown in Figure 2(f) [23]. This final value can be used to set priorities in flood disaster mitigation and response planning. To determine the value limits for each variable, the membership function of each fuzzy set variable is obtained by referring to Figure 2, which displays the various fuzzy set graphs.



(a) Population Density Fuzzy Sets (b) Watershed Area Fuzzy Sets (c) Slope Area Fuzzy Sets
(d) Elevation Fuzzy Sets (e) Rainfall Fuzzy Sets (f) Flood Risk Fuzzy Sets

Figure 2. Fuzzy sets

Figure 2 shows the fuzzy membership functions for six variables in flood risk assessment, namely population density, watershed area, land slope, elevation, rainfall, and flood risk as the output. Each variable is classified into linguistic categories such as low, medium, and very high, based on certain value ranges. This function enables the fuzzy system to convert numerical data into linguistic information, supporting decision-making in flood mitigation. This triangular shape demonstrates linear transitions and overlaps between categories, indicating that a value can possess partial membership degrees in more than one set. The value boundaries for each of these fuzzy sets, as detailed in Table 1, precisely define the scope and range for the linguistic terms associated with each factor.

Table 1. Value Limits for Each Fuzzy Set of Input and Output Variables

Function Type	Input	Unit	Fuzzy Set	Min	Peak	Max
Input	Population Density	(people/km^2)	Low	0	1000	2000
			Medium	1500	2500	3500
			High	3000	4000	5000
			Very High	4500	5500	6000
	Watershed Area	(km^2)	Very Small	0	50	100
			Small	80	150	250
			Medium	200	350	500
			Large	400	500	600
	Elevation	(m)	Very Low	0	10	20
			Low	15	30	45
			Medium	40	60	80
			High	70	90	110
	Slope Area	Percent (%)	Flat	0	5	10
			Gentle	8	15	22
			Moderate	20	30	40
	Rainfall	(mm/hour)	Very Low	0	0	3
			Low	2	5	8
			Medium	7	12	17
			High	15	22	30
Output	Level of Risk	(0–100)	Very Low	0	10	20
			Low	15	30	45
			Medium	40	55	70
			High	65	80	95
			Very High	90	95	100

Table 1 presents the value limits for each fuzzy set of the input and output variables. The input variables include Population Density, Watershed Area, Elevation, Slope Area, and Rainfall, each with fuzzy sets such as ”Low,” ”Medium,” ”High,” or ”Very Small,” along with specific value ranges (Min, Peak, Max). The output variable is the Level of Risk, which is also divided into fuzzy sets ranging from ”Very Low” to ”Very High,” complete with value ranges from 0 to 100, indicating how the input values are processed to produce a certain level of risk in a fuzzy logic system.

2.2. Fuzzification

Fuzzification is the crucial first step in any fuzzy logic system. It's the process of converting sharp, precise numerical (or ”crisp”) input values into fuzzy values. These fuzzy values aren't single numbers; instead, they represent the degree of membership an input has in one or more predefined fuzzy sets [30]. Commonly used membership functions include triangular, trapezoidal, and Gaussian functions. Although this research does not propose a new fuzzy method, its contribution lies in the application and validation of the Mamdani fuzzy inference system in the local context of Cepu Subdistrict, which has not been extensively explored. This study also integrates spatial and socio-economic variables into a single classification system that is applicable for risk mapping based on local data. The function of the triangular curve can be seen in Figure 3.

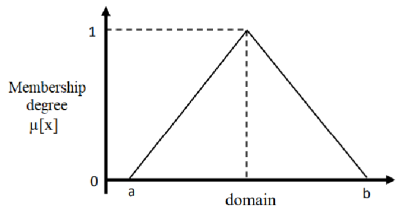


Figure 3. Representation of a triangular curve

Conceptually, Figure 3 displays a triangular membership function graph. One of the most common and intuitive ways to define these degrees of membership is by using triangular membership functions. Three parameters define a triangular membership function [24] : (lower limit): The point where the membership degree starts to increase from 0. (peak): The point where the membership degree reaches its maximum of 1. (upper limit): The point where the membership degree decreases back to 0. Graphically, this forms a triangle. For any given crisp input value, its membership degree in a fuzzy set defined by a triangular function can be calculated using the following piecewise linear formula 1.

$$\mu(x) = \begin{cases} 0 & \text{if } x \leq a \\ \dfrac{x-a}{b-a} & \text{if } a < x \leq b \\ \dfrac{c-x}{c-b} & \text{if } b < x < c \\ 0 & \text{if } x \geq c \end{cases} \tag{1}$$

2.3. Application of function implication

After the input values have been fuzzified, the next step is to apply function implication. At this stage, the fuzzy rules (IF-THEN) that have been created will be evaluated. Each rule activates its fuzzy output based on the membership degree of the input. The Mamdani method typically uses the MIN or PRODUCT operator to calculate the degree of truth of the ”IF” (antecedent) part of a rule [24]. If a rule states ”IF Input1 is A AND Input2 is B THEN Output is C,” then the truth degree of this rule (α) is calculated as:

$$\alpha = min(\mu_A(\text{Input 1}), \mu_B(\text{Input 2}))(\text{For the MIN operator})$$

or

$$\alpha = \mu_A(\text{Input 1}) \times \mu_B(\text{Input 2})(\text{For the PRODUCT operator})$$

Then, this α value is used to prune the membership function of the output C (consequent). If using the MIN operator, the membership function of the output will be pruned at the α value.This means that the area under the output membership function curve will be trimmed at the membership level α, reflecting how strongly the rule is activated.

$$\mu_{c'}(y) = min(\alpha, \mu_c(y)) \tag{2}$$

2.4. Composition Rules

Composition rules are the process of combining all fuzzy outputs from each activated rule to form an aggregate fuzzy output set. Since each rule can produce different fuzzy outputs, there needs to be a mechanism to integrate all these outputs into a single final representation. The methods commonly used in Mamdani FIS are the MAX (maximum) or SUM (summation) methods [25]. If several rules produce fuzzy outputs for the same fuzzy set, then the aggregate fuzzy output set ($\mu_A gregat(y)$) will take the maximum value of all overlapping fuzzy outputs. This creates a single combined fuzzy set that represents all contributions from the activated rules.

$$\mu_{Agregat}(y) = max(\mu_{c1'}(y), \mu_{c2'}(y), \ldots, \mu_{cn'}(y)) \tag{3}$$

2.5. Defuzzification

Defuzzification is the final stage to convert the aggregate fuzzy output set back into a single numerical (crisp) value representing the flood vulnerability level. There are several defuzzification methods, with the Center of Gravity (COG) or Centroid Method being the most popular and commonly used in Mamdani FIS [25]. The formula for the Center of Gravity (COG) method is Equation 4.

$$COG = \frac{\sum_{i=1}^{n} \mu(yi)yi}{\sum_{i=1}^{n} \mu(yi)} \tag{4}$$

2.6. Output

The defuzzification process in the Mamdani FIS converts fuzzy outputs into single numerical values that represent the level of flood vulnerability. These numerical values are then categorized into linguistic terms such as ”very low” to ”very high” based on specified thresholds [24]. Conceptually, the numerical value resulting from defuzzification (e.g., 65 on a scale of 0-100) is mapped to linguistic categories based on the fuzzy output set. For example, a value of 65 may have a high membership degree in the z”High” category and a low membership degree in the ”Moderate” category. This numerical output provides clear and measurable information about flood risk potential, which is crucial for decision-makers in formulating mitigation and adaptation strategies. The application of the Mamdani FIS method enables flood vulnerability analysis to be more comprehensive and accurate [25].

2.7. Accuracy Evaluation

Mean Absolute Error (MAE) is an evaluation metric that calculates the average absolute difference between predicted values and actual values, resulting in a value in the same units as the original data, making it easy to interpret. MAE is widely used in flood prediction studies due to its ability to provide a clear picture of the average error without amplifying the impact of outliers [26]. It is used to assess the accuracy of the ConvLSTM model in predicting tidal heights, while other research uses it to evaluate the timing of flood peak arrival [**?**]. Another study recommends MAE as the primary metric in evaluating machine learning models for flood risk prediction due to its stable and communicative interpretation [27].

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{5}$$

Root Mean Squared Error (RMSE) is an evaluation metric that calculates the square root of the average of the squared differences between predicted and actual values. RMSE is more sensitive to large errors because the squaring process gives more weight to outliers. In studies predicting water levels and rainfall, RMSE is often used to assess the accuracy of machine learning models because it can reflect the significant impact of extreme errors [28]. Other research also indicates that RMSE is a crucial indicator in evaluating LSTM and ANN models, particularly in flood prediction systems. RMSE is usually used alongside MAE to provide a more balanced picture regarding the accuracy and sensitivity of the model [29].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

3. RESULT AND ANALYSIS

This research requires several data points to determine the level of flood vulnerability. The data needed for this study are population density data, slope gradient, and elevation from the website of the Central Bureau of Statistics (BPS) of Cepu Subdistrict. River basin area (DAS) data were obtained from the Bengawan Solo River Basin Office (BBWS) of Central Java Province. Rainfall data was obtained from the Hydrology and Water Quality Information System of the Bengawan Solo River Basin Office. Flood risk level data was obtained from the Regional Disaster Management Agency (BPBD) of Blora District. The following data was obtained from 17 villages in Cepu Subdistrict as shown in Table 2 and Table 3.

Table 2. Input Variables for Cepu Subdistrict Data

No	Villages Name	Population Density	Watershed Area	Elevation	Slope Area	Rainfall
1	Cabean	747	0.5	38	17	12.8
2	Gadon	540	0.6	35	2	12.8
3	Getas	710	1.8	32	2	12.8
4	Jipang	952	4	33	2	12.8
5	Kapuan	1173	0.2	40	2	12.8
6	Kentong	265	0.6	35	17	12.8
7	Merunng	500	0.8	61	17	12.8
8	Mulyorejo	947	2.74	38	17	12.8
9	Nglanjuk	165	6.8	33	2	12.8
10	Ngloram	642	1.6	34	2	12.8
11	Sumberpitu	152	0.23	32	2	12.8
...	...	...	...	...	...	...
17	Tambakromo	847	8.92	39	17	12.8

Table 2 presents the input variable data for 17 villages or urban areas in Cepu District. This table has six columns: ”No”, ”Village Name”, ”Population Density”, ”Watershed Area”, ”Elevation”, ”Slope Area”, and ”Rainfall”. Each row contains specific data for each village, such as Population Density, Watershed Area, Elevation, Slope Area, and Rainfall, which vary between villages. Although most rainfall data was recorded the same, data for other variables such as population density and watershed area showed significant differences between villages, from the most densely populated (Balun, Cepu) to the least populated (Sumberpitu, Nglanjuk).

Table 3. Cabean Villages Data

Variables	Cabean
Population Density	747 (People/km^2)
Watershed Area	0.5 (km2)
Elevation	38 (%)
Slope Area	17 (m)
Rainfall	12.80 (mm/day)
Level of Risk (Risk Index)	55.00 %

Table 3 presents a summary of variable data for Cabean Village. This table consists of two main columns, namely ”Variables” and ”Cabean,” which detail six different variables along with their values. The data presented include population density (747 people/km^2), River Basin Area (0.5 km^2), Elevation (38 m), Slope Gradient (17%), and Rainfall (12.80 mm/day). Additionally, this table displays the results of the analysis and calculations, specifically the Level of Risk with a value of 55.00%, which is likely a result of processing the input variable data mentioned above.

3.1. Analysis

In the manual calculation process, a simulation was conducted in Cepu Subdistrict to illustrate the application of the fuzzy inference system. The purpose of this simulation is to validate whether the fuzzy logic method can represent the actual conditions in the study area. By applying manual calculations, the results can later be compared with the software-based output to ensure accuracy. This step also helps to understand better how each variable interacts within the system. The following are the calculation steps for Cepu Subdistrict using the Mamdani FIS as the chosen inference method.

3.2. Determine Fuzzy Sets

This stage is known as fuzzification, which involves determining the degree of membership of each input value in each relevant fuzzy set, as shown in Table 1. The fuzzification process transforms clear numerical data into linguistic variables that the system can process. In this study, triangular and trapezoidal membership functions are used, as they are commonly applied due to their simplicity and effectiveness. Each input parameter, such as population density, slope, elevation, and rainfall, is assigned to one or more fuzzy sets depending on its value. Through this process, real-world quantitative data can be expressed in qualitative terms for further processing in a fuzzy system.

3.3. Implication

This stage applies fuzzy rules (IF-THEN rules) to connect input conditions with output categories. Each fuzzy rule acts as a bridge that links the degree of membership from the input fuzzy set to the corresponding output fuzzy set. The rules are formulated based on expert knowledge and literature review, ensuring that they represent logical relationships between variables. For instance, if the population density is high and rainfall is heavy, then the flood risk level is categorized as high. A complete list of fuzzy rules is provided in this section to illustrate the implication process in detail, as can be seen in Figure 4.

```
rule1=ctrl.Rule((population_density['low']&watershed_area['verysmall']&elevation['high']&slope['moderate']&rainfall['verylow']),flood_risk['verylow'])
rule2=ctrl.Rule((population_density['medium']|watershed_area['medium']|elevation['medium']|slope['gentle']|rainfall['medium']),flood_risk['medium'])
rule3=ctrl.Rule((population_density['high']&watershed_area['large']&elevation['low']&slope['flat']&rainfall['high']),flood_risk['veryhigh'])
rule4=ctrl.Rule((population_density['veryhigh']|watershed_area['large']|elevation['verylow']|slope['flat']|rainfall['high']),flood_risk['veryhigh'])
rule5=ctrl.Rule((population_density['low']&watershed_area['small']&elevation['medium']&slope['gentle']&rainfall['low']),flood_risk['low'])
rule6=ctrl.Rule((population_density['medium']&watershed_area['large']&elevation['low']&slope['flat']&rainfall['medium']),flood_risk['high'])
rule7=ctrl.Rule((population_density['low']&watershed_area['large']&elevation['verylow']&slope['flat']&rainfall['high']),flood_risk['high'])
flood_risk_ctrl = ctrl.ControlSystem([rule1, rule2, rule3, rule4, rule5, rule6, rule7])
flood_risk_simulation = ctrl.ControlSystemSimulation(flood_risk_ctrl)
```

Figure 4. Python Code Define Fuzzy Rules

To connect the input variables with the flood risk level, a set of fuzzy rules written in Python program code is used. This rule states the logical conditions based on a combination of population density, watershed area, elevation, slope, and rainfall values, which are then mapped to specific flood risk categories. The implementation of these rules is shown in Figure 4, which contains the definitions of the seven main fuzzy rules, as well as the process of forming the control system and simulating flood risk.

3.4. Composition Rule

At the composition or aggregation stage, the outputs of all membership functions generated by fuzzy rules are merged into a single output, as presented in Table 4. This integration ensures that the influence of every activated rule is included in constructing the final fuzzy set. Since multiple rules may often be triggered simultaneously, aggregation is necessary to combine their partial outputs. By doing so, the system forms a comprehensive and consistent fuzzy representation that improves the accuracy and reliability of the fuzzy inference process.

Table 4. Results of Fuzzification in Cabean Villages

Variables	Fuzzy Sets	Range (Min - Max)	Calculation (μ)
Population Density	Low	0 - 0 1000 - 2000	(747 - 0) / (1000 - 0) = 0.747
747	Medium	1500 - 2500 - 3500	μ = 0.000
	High	3000 - 4000 - 5000	μ = 0.000
Watershed Area	Very Small	0 - 50 - 100	(0.5 - 0) / (50 - 0) = 0.010
0.5	Small	80 - 150 - 250	μ = 0.000
	Medium	200 - 350 - 500	μ = 0.000
Elevation	Low	15 - 30 - 45	(45 - 38) / (45 - 30) = 0.467
38	Medium	40 - 60 - 80	(40 - 38) / (40 - 30) = 0.200
	Very Low	0 - 10 - 20	μ = 0.000
Slope	Gentle	8 - 15 - 22	(22 - 17) / (22 - 15) = 0.714
17	Moderate	20 - 30 - 40	μ = 0.000
	Flat	0 - 5 - 10	μ = 0.000
Rainfall	Medium	07/12/2017	(17 - 12.8) / (17 - 12) = 0.840
12.8	High	15 - 22 - 30	(15 - 12.8) / (15 - 12) = 0.200
	Low	02/05/2008	μ = 0.000

Table 4 presents the results of the fuzzification process for the variable data of Cabean Village. This table consists of four columns: "Variables," "Fuzzy Sets," "Range (Min - Max)," and "Calculation (μ)." The "Variables" column lists the numerical values for Population Density (747), River Basin Area (0.5), Elevation (38), Slope Gradient (17), and Rainfall (12.8). The "Fuzzy Sets" column shows the relevant fuzzy sets for each variable, and the "Range (Min - Max)" column provides the range of values for each set. The "Calculation (μ)" column displays the results of the membership function calculations for each variable value against its fuzzy set. For example, for a Population Density of 747, the membership degree is 0.747 in the 'Low' fuzzy set, while for the 'Medium' and 'High' sets, the values are 0.000. This table provides an overall explanation of how the precise numerical values of the input variables for Cabean Village are transformed into membership values in fuzzy sets, the initial step in fuzzy logic analysis.

3.5. Defuzzification

In the defuzzification stage, the final step is to convert fuzzy membership values into real numbers (decisions). The conversion is performed by returning the fuzzy values to definite values based on the specified membership function so that the output remains a linguistic variable. In this process, all fuzzy areas obtained from the composition of rules are combined, and then the center point of the rules is taken to obtain the optimal result. Figure 5 shows the calculation process of the centroid method.

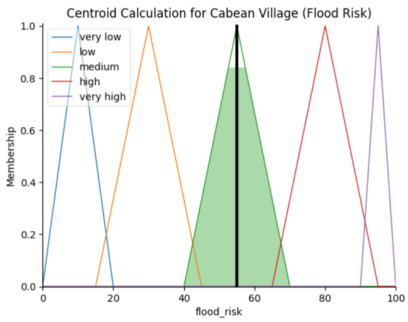


Figure 5. Centroid calculation for cabean village (Flood Risk)

Figure 5 illustrates the defuzzification process to determine the flood risk level in Cabean Village. This graph illustrates five triangular membership functions that represent fuzzy sets for flood risk: 'very low', 'low', 'medium', 'high', and 'very high'. Each membership function has a membership value between 0.0 and 1.0 on the y-axis and flood risk values (ranging from 0 to 100) on the x-axis. The green-shaded area indicates the active fuzzy sets considered in the calculation, which seem to be centered around the 'medium' set. The thick vertical black line on the graph indicates the final result of the centroid calculation, which falls right in the middle of the shaded area, signifying that the defuzzified output value (flood risk index) for Cabean Village is approximately 55.The simulation results of the program, which utilize all the data in Table 1, produce the calculation results shown in Table 5.

Table 5. Applications of calculation results Mamdani FIS

Index	Villages Name	Predicted Level of Risk (Score)	Predicted Level of Risk (Category)
14	Ngelo	65.16	high
15	Ngroto	63.93	medium
13	Karangboyo	62.18	medium
1	Gadon	62.18	medium
2	Getas	62.18	medium
8	Nglanjuk	62.18	medium
9	Ngloram	62.18	medium
3	Jipang	62.18	medium
4	Kapuan	62.18	medium
10	Sumberpitu	62.18	medium
12	Cepu	62.18	medium
0	Cabean	55.0	medium
5	Kentong	55.0	medium
7	Mulyorejo	55.0	medium
6	Meruung	55.0	medium
11	Balun	55.0	medium
16	Tambakromo	55.0	medium

Table 5 presents the final results of flood risk level predictions for various villages. This table details the calculation results produced by the Mamdani Fuzzy Inference System (Mamdani FIS). There are four columns: ”Index”, ”Village Name”, ”Predicted Level of Risk (Score)”, and ”Predicted Level of Risk (Category)”. The ”Predicted Level of Risk (Score)” column displays the numerical value resulting from defuzzification, while the ”Predicted Level of Risk (Category)” column categorizes that value into risk categories. The data shows variations in risk levels among villages; for example, Ngelo Village has the highest score of 65.16 with a ”high” category, while most other villages, including Ngroto, Karangboyo, and Cabean, fall into the ”medium” category despite having different numerical scores, ranging from 63.93 to 55.0. This data collectively illustrates the final output of an analysis process that combines various geographical and demographic parameters to estimate the flood risk level in each area. Other risk levels occur with lower frequencies, each at least once or more, as shown in the data comparison graph in Figure 6.

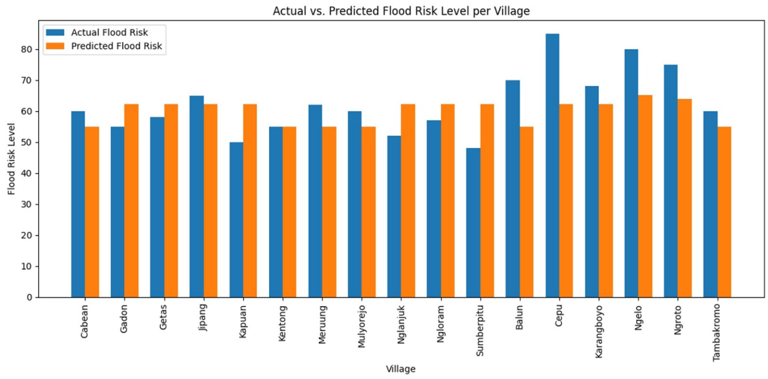


Figure 6. Data actual risk vs predicted flood risk level per village

Figure 6 compares the actual flood risk levels with the predicted flood risk levels for each village. The horizontal axis of the graph displays the names of the villages, while the vertical axis represents the flood risk levels in numerical scores (0 to 100). Each pair of bars represents one village, with the blue bars indicating ”Actual Flood Risk” and the orange bars indicating ”Predicted Flood Risk.” In general, this graph shows that although there are variations, the predicted scores (orange bars) tend to be close to or slightly different from the actual scores (blue bars) for most villages. However, for some villages, such as Cepu, Karangboyo, and Balun, there is a noticeable difference between the actual and predicted values. To see the Results of the Prediction Accuracy Evaluation, refer to Table 6.

Table 6. Results of Prediction Accuracy Evaluation

No	Villages Name	Level of Risk (Risk Index)	Predicted Level of Risk (Numeric)	Squared Error
1	Cabean	60	55.00	250000
2	Gadon	55	62.18	515524
3	Getas	58	62.18	174724
4	Jipang	65	62.18	79524
5	Kapuan	50	62.18	1483524
6	Kentong	55	55.00	0.0000
7	Meruung	62	55.00	490000
8	Mulyorejo	60	55.00	250000
9	Nglanjuk	52	62.18	1036324
10	Ngloram	57	62.18	268324
11	Sumberpitu	48	62.18	2010724
12	Balun	70	55.00	2250000
13	Cepu	85	62.18	5207524
14	Karangboyo	68	62.18	338724
15	Ngelo	80	65.16	2202256
16	Ngroto	75	63.93	1225449
17	Tambakromo	60	55.00	250000

Table 6 presents the results of the accuracy evaluation of flood risk prediction levels for 17 villages. This table contains comparative data between the actual risk values and the predictions. The columns consist of ”No”, ”Village Name”, ”Level of Risk (Risk Index)” which shows the actual risk value, ”Predicted Level of Risk (Numeric)” which shows the predicted risk value, and

"Squared Error" which calculates the squared difference between the actual and predicted values. The data in the table show that the predicted values do not always match the actual values exactly, and the varying "Squared Error" values reflect the degree of mismatch between the predicted results and the actual data for each village, with some villages, such as Cepu and Sumberpitu, showing quite large squared errors—evaluation Results.

$$MAE = \frac{\text{Total Selisih Absolut}}{34} = \frac{294.90}{34} \approx 8.673529411764704$$

Mean Absolute Error (MAE): 8.67

$$RMSE = \sqrt{105.928076} \approx 10.29116$$

Root Mean Squared Error (RMSE): 10.29

The results of this accuracy evaluation show that the MAE value of 8.67 and the RMSE value of 10.29 are within a relatively low range of prediction errors, although there are some villages, such as Cepu and Sumberpitu, that exhibit quite large errors. This finding aligns with research using similar prediction methods, which obtained an MAE of X and an RMSE of Y in the case of flood risk prediction [30], indicating that the method used has a consistent level of accuracy. Additionally, other research has also reported that although the RMSE value tends to be greater than the MAE, this difference is common because RMSE is more sensitive to large errors [31]. Thus, the results of this study reinforce the evidence that the prediction model used can provide reasonably reliable flood risk estimates. However, improvements are needed in areas with high error rates.

4. CONCLUSION

This study concludes that the Mamdani Fuzzy Inference System (FIS) method can be effectively used to analyze the flood vulnerability levels in Cepu Subdistrict. The analysis results show variations in risk levels among villages. Analysis of the 17 villages in the Cepu sub-district shows that Ngelo Village has the highest score of 65.16 and is categorized as having a "high" risk level. Meanwhile, most of the other villages, including Ngroto, Karangboyo, and Cabean, fall into the "medium" category, although their scores range from 63.93 to 55.0. The accuracy of this model is reinforced by evaluation results using two error metrics: a Mean Absolute Error (MAE) of 8.67 and a Root Mean Squared Error (RMSE) of 10.29, which indicate that the system's performance is quite good in mapping flood risk both quantitatively and qualitatively. The application designed by the researcher using Python programming has successfully achieved the research objectives, as it effectively provides information on flood disaster vulnerability levels in the selected area. For future research, it is recommended that researchers explore other types of fuzzy logic methods to compare the results. Additionally, it is hoped that the application can be further enhanced with features allowing users to edit fuzzy set parameters or rules, and to save calculation results for reviewing previous analyses. As part of its contribution to scientific development, this study offers a significant scholarly contribution to the literature on flood mitigation, particularly through the application of a localized approach using the Mamdani Fuzzy Inference System. This approach not only enriches the technical references for flood vulnerability mapping but also provides a practical framework that can be applied in data-driven emergency planning in flood-prone areas such as the Cepu Subdistrict. However, this study has certain limitations that should be acknowledged, including the use of limited spatial and meteorological data as well as assumptions made during the fuzzification process, which may affect the accuracy of vulnerability classification. These limitations have both policy and technical implications, including the potential for biased results and the necessity for periodic field verification. Therefore, at the policy and operational levels, decision-makers need to integrate these analytical results with real-time data and local community participation to enhance the effectiveness of the proposed mitigation strategies.

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6. DECLARATIONS

AI USAGE STATEMENT

The authors utilized ChatGPT (OpenAI) to enhance the clarity of the manuscript. All text was subsequently reviewed, revised, and remains the sole responsibility of the authors.

AUTHOR CONTIBUTION

Joko Handoyo: Conceptualization, Methodology, Original Draft Writing, Resources, Results Discussion. **Anton Yudhana**: Methodology, Supervision, Results Discussion, Resources, Oversight. **Sunardi**: Review Writing and Editing, Final Text Approval.

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COMPETING INTEREST

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