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Application of Fuzzy Logic in PEOPLES Framework for Community Resilience Measurement in Flood Disaster

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Abstrak

Penilaian ketahanan masyarakat memiliki tantangan karena kompleknya faktor yang mempengaruhi. Banyak kerangka kerja, model konseptual, dan teknik penilaian ketahanan yang telah dikembangkan untuk menentukan landasan teoretis dan aplikasi praktis, salah satunya framework PEOPLES. Saat berhadapan dengan ketidakpastian, pemilihan model yang tepat bergantung pada karakteristiknya. Pendekatan probabilistik sering digunakan namun masih tidak mencukupi, model ketidakpastian dapat digunakan. Fuzzy logic memberikan dasar untuk memodelkan ketidakpastian. Penelitian ini untuk menggali ketahanan masyarakat di Kota Bekasi dengan menggunakan proses fuzzifikasi dan fungsi keanggotaan jenis trapesium untuk variabel input yang terdiri kelompok rendah, sedang, dan tinggi. Fungsi keanggotaan jenis segitiga untuk variabel output yang terdiri empat derajat keanggotaan yaitu nilai kelas rendah, sedang, tinggi dan sangat tinggi dengan rentang antara 43-129. Perumusan aturan fuzzy menggunakan fungsi "minimal" dan memiliki aturan dasar sebanyak 2.187. Hasil pengujian memiliki akurasi yang sangat bagus, percobaan pengujian pada 6 segmen wilayah mampu menghasilkan prediksi yang sama dengan penilaian ahli.

Kata kunci: *Fuzzy Logic, Framework PEOPLES, Bencana Banjir, Ketahanan Masyarakat*

Abstract

Assessing community resilience is challenging due to the complexity of influencing factors. Various frameworks and models, such as the PEOPLES framework, have been developed for both theoretical and practical applications. In dealing with uncertainty, selecting the right model is crucial. While probabilistic approaches are common, they can be insufficient. Fuzzy logic, as an uncertainty model, offers a solution. This study explores community resilience in Bekasi City using fuzzification and trapezoidal membership functions for input variables categorized as low, medium, and high. The output uses triangular membership functions with four degrees: low, medium, high, and very high, ranging from 43-129. Fuzzy rule formulation applies the "minimal" function with 2,187 basic rules. The test results show high accuracy, with predictions for six regional segments matching expert assessments.

Keywords : *Fuzzy Logic, PEOPLES Framework, Flood Disaster, Community Resilience*

1. Introduction

Indonesia is a country with various disaster vulnerabilities, one of which is flooding. Flood disaster is a disaster with the highest intensity of occurrence in Indonesia. Based on the Indonesian Disaster Data released by the National Disaster Management Agency (BNPB) in 2023, there were 6,166 floods that occurred in Indonesian districts during the period January 2021 to November 2023. Events such as floods have indicated that extreme events can have a wide impact on society [1]. Flood impacts that tend to increase need good preparation for disaster mitigation planning that is integrated with spatial management [2]. It is therefore necessary that effective disaster mitigation planning should include efforts to improve community capacity to cope with disasters. This needs to be well planned in order to create resilience to flooding.

Disaster resilience is the capacity of potentially disaster-affected communities to withstand disaster conditions [3]. The concept of resilience in flood risk management has contributed to the idea that there is a need to learn to live with floods and should reduce the consequences of disasters and not try to avoid them altogether. Resilience can be seen from various perspectives ranging from individuals, communities, regions and countries [4]. As for community resilience, it is determined by the resilience of individuals in the community itself [5]. Communities geographically have varying levels of vulnerability and resilience which will affect post-disaster recovery [6].

Assessing community resilience is challenging due to the complexity of factors that influence the level of resilience from both the dynamic and complex interactions within the community as well as the environment in which they live. Another challenge is the lack of methods to identify resilience because there is no benchmark that can be used globally [7]. Many frameworks, conceptual models, and community resilience assessment techniques have been developed to determine theoretical foundations and practical applications. These include indicator-based resilience frameworks, other top-down frameworks, quantitative frameworks that focus on community resilience. The PEOPLES framework (Figure 1) addresses community aspects. These aspects are classified in seven community dimensions: Population and demographics (P), Environment and ecosystem (E), Organized government services (O), Physical infrastructure (P), Lifestyle and community competence (L), Economic development (E), and Social-cultural capital (S). Later, the PEOPLES framework was upgraded to a quantitative framework for measuring community resilience [8]-[9]. The PEOPLES framework is adopted as a community resilience framework to determine community resilience through its comprehensive indicators and structure.

Figure 1. PEOPLES Resilience Framework

From the vast literature on quantifying community resilience measurement, there are arguments about which indicators affect resilience and which framework is best. An important aspect that is often overlooked from various resilience measurements is uncertainty. Assessing uncertainty will help understand the system being studied [10]-[12]. Klir and Yuan categorize uncertainty into two basic types: vagueness and ambiguity [13]. In the study Measuring and improving community resilience using a fuzzy approach to measure PEOPLES indicators using descriptive knowledge. The fuzzy approach is able to provide numerical and descriptive input data with different levels of uncertainty, resulting in good resilience estimates [14-15].

The purpose of fuzzy logic is to solve high-level uncertainty problems and to represent fuzzy and ambiguous information. Fuzzy logic is able to solve ambiguity and inaccuracy in uncertainty problems [16]. The purpose of this research is to measure community resilience to flood disasters using the Fuzzy Logic approach in the PEOPLES framework. Some indicators are possible to measure in certain scenarios, fuzzy logic techniques are used as inference to account for uncertainty.

2. Research Method

2.1. Research Variables

The variables used in this study are variables derived from the dimensions of the PEOPLES framework. Based on the results of identification, literature studies, and discussions with experts, the variables used are as in Table 1 while the community resilience class for flood disasters can be seen in Table 2.

Table 1. PEOPLES Framework Dimensions and Variables

Dimension	Variable	Description
Population and demographics (P)	Age	0-11 th=1, 12-25th=2, 26-55 th, > 56 th =4
	Population density	High = 1; Medium =2; Low = 3
	Education level	No School =1, SD-SMA =2, > S1 = 3
	House level	1 Level = 1; 2 Level = 2; 3 Level = 3
	Transportation disruption	Low = 1; Medium =2; High = 3
	Clean water access	Low = 1; Medium =2; High = 3
Environment and ecosystem (E)	Flood height	<1 m = 1; 1-2m =2; >3 m = 3
	Flood damage	High=1; Medium=2; Low=3
	Flood frequency	Rare=1; Occasional =2; Frequent =3
	Water quality	Uncertain = 1; Normal = 2; Good = 3
	Hygiene conditions	Uncertain = 1; Normal = 2; Good = 3
	Proximity to flood source	<100m = 1, 100-200m = 2, >200m =3
	Proximity to shelter	>100m = 1, 50-100m = 2,
	Proximity to Main Road	>100m = 1, 50-100m = 2,
Organized government services (O)	Security service	Low=1; Medium=2; High=3
	Cleaning service	Low=1; Medium=2; High=3
	Fire fighting services	Low=1; Medium=2; High=3
	Legal services	Low = 1; Medium =2; High = 3
	Trauma services	None = 1; May exist = 2; Definitely exist = 3
	Volunteer Provision	None = 1; Possibly present = 2; Definitely present = 3
	Accuracy of Information	Low = 1; Medium =2; High = 3
	Early Warning Effectiveness	Low = 1; Medium =2; High = 3
	Evacuation Planning	Low = 1; Medium =2; High = 3
	Assistance During Disaster	Low = 1; Medium =2; High = 3
	Post Disaster Assistance	Low = 1; Medium =2; High = 3
	Trust in Government	Low=1; Medium=2; High=3
Physical infrastructure (P)	Health services	Low = 1; Medium = 2; High = 3
	Evacuation site	None = 1; May exist = 2; Definitely exist = 3
	Countermeasure plan	None = 1; May be present = 2; Definitely present = 3
Lifestyle and community competence (L)	Community Preparation	Little = 1; Medium = 2, Good = 3
	Decision Making	Low = 1; Medium =2; High = 3
	Women's Participation	Low = 1; Medium =2; High = 3
	Community Connections	Low = 1; Medium =2; High = 3
	Learning Experience	Low = 1; Medium =2; High = 3
	Disaster Mitigation Efforts	Low = 1; Medium =2; High = 3
Economic development (E)	Trust and Expectations	Low=1; Medium=2; High=3
	Personal Income	<2 Million = 1; 2-5 Million = 2; >5 Million = 3
	Diversified sources of income	1 Source =1; 2 Sources = 2, >2 Sources = 3
	Access to health services	Low = 1; Medium = 2; High = 3
	Health insurance ownership	None = 1; Inactive = 2; Active = 3
	Access to education	Low = 1; Medium = 2; High = 3
	Internet access	Low = 1; Medium =2; High = 3
	Savings	Do not have = 1; Have = 2; More than One = 3
Social-cultural capital (S)	Life Satisfaction	Low = 1; Medium =2; High = 3
	Community Awareness	Unaware = 1; Aware but not applied = 2, Aware and applied = 3
	Local Knowledge	None = 1; Present but not applied = 2, Present and applied = 3
	Mutual Cooperation	None = 1; Several times = 2; Often = 3
	Community Cohesiveness	Low = 1; Medium =2; High = 3
	Willingness to Help	Low = 1; Medium =2; High = 3
	Joint Discussion	Low = 1; Medium =2; High = 3

Table 2. Community Resilience Classes for Flood Disasters

Resilience Level	Score
Low	43 – 65
Medium	66 – 86
High	87 – 107
Very High	108 – 129

2.2. Data Sources

Data collection utilizes observation and interview methods. Observation is used to find out how the condition of community resilience can be observed such as livelihoods, housing conditions, accessibility, former flooding, and accessibility. Interviews were conducted with the village government and the community to explore community resilience in the Bekasi City area with 100 samples in 3 kelurahan areas. The sampling technique for data collection was conducted using a cluster random sampling approach. Sampling was divided into 6 segments based on the region. Data validation uses a source triangulation approach where data is validated from interviews with the community combined with interviews with local government and observation results. The valid data results were then analyzed using the scoring method. The experts used as benchmarks in assessing the performance of the fuzzy model are urban and environmental planning experts and public policy experts.

2.3. Fuzzy Model Building

Fuzzy logic provides different membership values ranging between 0 and 1 for variable x indicating the variable's membership to several classes (fuzzy sets). The power of fuzzy logic inference systems relies on two main features namely (i) fuzzy inference systems can handle both descriptive (linguistic) knowledge and numerical data; (ii) fuzzy inference systems use approximate reasoning algorithms to determine the relationship between inputs where uncertainty can be propagated during the process. The application of fuzzy logic as an inference system requires three main steps: 1) fuzzification and membership functions; 2) Fuzzy Inference System (FIS) to combine indicators, and 3) defuzzification (Figure 2). FIS is a computation framework based on the concepts of fuzzy set theory, fuzzy rules, and fuzzy thinking. The process carried out in the development of FIS using attribute data. Then the formation of a fuzzy set is carried out by mapping the input data points into the membership value of the fuzzy set having an interval of zero to one. After forming the fuzzy set, the minimum value of each method based on the rule is sought. The minimum curve value is aggregated to determine the maximum curve value. From the maximum curve value, defuzzification can be determined.

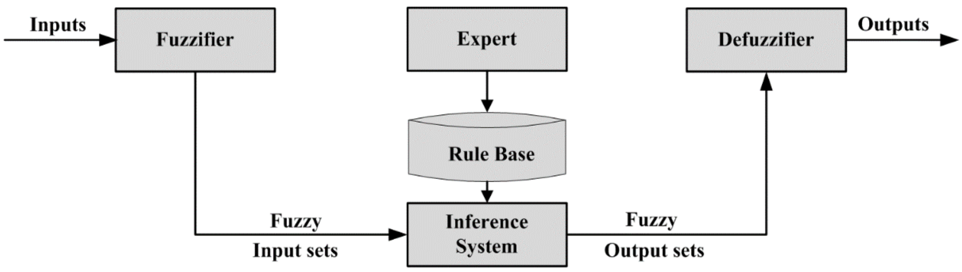

Figure 2. Fuzzy inference system

In making fuzzy logic models, 2 methods are carried out, namely (1) the formation of fuzzy logic models, and (2) comparing the results of fuzzy logic models with actual results.

a. Formation of fuzzy logic model
The data obtained is processed using the Mamdani fuzzy logic model (max-min model). There are several steps to get the output in this model, namely:
    1. Fuzzification of variables, which is to convert variables into fuzzy sets. For each variable, several fuzzy sets are defined, using certain membership functions. In this scientific work, trapezoidal and triangular membership functions will be used.
    2. Formulation of basic rules with reference to previously defined fuzzy sets. A basic rule combines a number of fuzzy membership functions into a logic proposition using conjunctions and "if then" stems. In the formulation of basic rules, the concept of selecting the minimum fuzzy membership degree value is used.
    3. Aggregation, which combines several basic rules into a complex rule using the concept of selecting the maximum fuzzy membership degree value.
    4. Defuzzification is a way to convert the membership degree of each member of the domain of the output variable to the expected final result. In this research, the centroid defuzzification method is used. After verifying the model using existing data, the output variable can be predicted using the appropriate range.

b. Comparing the results of fuzzy logic with statistical processing data to determine the percentage of fit.

3. Literature Study

In the literature on measuring community resilience [17-21], most approaches are indicator-based. Resilience indicators provide a way to address the complexity of community systems and quantify their resilience. Many frameworks, conceptual models, and community resilience assessment techniques have been developed to determine theoretical foundations and practical applications. Among the indicator-based resilience frameworks, the Hyogo Framework for Action (HFA) method [22] is a top-down framework for increasing community resilience through implementing detailed steps at the central level. Another top-down framework is the Baseline Resilience Indicator for Communities (BRIC) [23], a quantitative framework that focuses on community resilience. Cimellaro et al. [17] introduced the PEOPLES framework which also includes top-down aspects that discuss community aspects. The PEOPLES framework was adopted as a community resilience framework to determine community resilience through its comprehensive indicators and structure. Shammin et al. [24] adopted a holistic approach to design community-based adaptation programs to climate change impacts.

Many studies have focused on developing methods to measure community resilience and assess the impact of recovery strategies through probabilistic approaches, such as Bayesian Networks [13]. For example, Cai et al. [25] used Bayesian Network to investigate the interdependence of resilience components and improve disaster resilience. Kameshwar et al. [26] developed a probabilistic decision support framework for community resilience planning. Despite the advantages of the Bayesian Network, such as updating the system when new data becomes available [27]. When dealing with uncertainty, the selection of an appropriate model depends on the uncertainty characteristics presented in the problem description. Generally, probabilistic models are used to characterize random variables and handle uncertainty through statistical data. If data is insufficient, uncertainty models can be used. When little data is available with significant uncertainty, expert knowledge with linguistic judgment is most often needed. Fuzzy set theory provides a basis for modeling uncertainty models that consider fuzzy sets and human knowledge to represent uncertainty. The goal of fuzzy logic is to solve problems of high levels of uncertainty and to represent fuzzy and ambiguous information. The fuzzy set approach can address complex models that are unable to measure conventionally on an indicator. With the reliability of operating on linguistic variables and qualitative system assessment, fuzzy logic will optimally work on cases that cannot be described numerically.

4. Result and Discussion

The programming language used in the data analysis of this study uses Python 3.10. Python is an open source programming language. Although this application is not paid, in terms of programming fuzzy logic modeling, Python is no less good than paid applications such as Matlab. Next, the implementation steps of fuzzy logic will be described.

4.1. Data Adjustment

Information in the form of variable data from the dimensions of P, O, E, P, L, E, S becomes an input variable. The input variable determines the Class of Community Resilience to Flood Disasters. The value of the variable data will form a dimensional value (input variable) with 4 values, namely low, medium, high, and very high. There are 7 input variables and 1 output variable (Community Resilience Class). The following rules are used to adjust the input variables:

a. Input variable P is determined by 6 variables namely Age, Population density, Education level, House level, Transportation disruption, and Access to clean water.
b. The input variable E is determined by 8 variables, namely Flood height, Flood damage, Flood frequency, Water quality, Hygiene condition, Proximity to flood source, Proximity to shelter, and Proximity to Main Road.
c. Input variable O is determined by 12 variables namely Security services, Cleaning services, Fire fighting services, Legal services, Trauma services, Volunteer provision, Information accuracy, Early warning effectiveness, Evacuation planning, Assistance during disaster, Post disaster assistance, and Trust in local government.
d. Input variable P is determined by 3 variables, namely health services, evacuation sites, and disaster management plans.
e. Input variable L is determined by 6 variables, namely Community Preparation, Decision Making, Women's Participation, Community Connection, Learning Experience, and Disaster Mitigation Efforts.
f. The input variable E is determined by 8 variables namely Trust and Expectations, Personal Income, Diversified Sources of Income, Access to health services, Ownership of health insurance, Access to education, Access to internet, and Savings.

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g. Input variable S is determined by 7 variables, namely Life Satisfaction, Community Awareness in Disaster Risk Reduction, Local Knowledge, Mutual Cooperation, Level of Community Cohesiveness, Willingness to Help, and Joint Discussion.

4.2. Data Analysis Using Fuzzy Logic Models

The stages of forming a fuzzy logic model consist of fuzzification of input and output variables, evaluation of fuzzy rules, aggregation of fuzzy rule outputs, and defuzzification. This analysis will produce output in the form of a value range of 43 to 129, the higher the value, the higher the person has a community resilience class to disasters. This output is based on the value of 7 input variables (P, O, E, P, L, E, S). The following will discuss the data processing process in fuzzy logic.

a. Fuzzification of input variables and output variables (converting input/output variables into fuzzy inputs/outputs and their sets), in making the set of input/output variables there is no certain reference in determining the value, so that in determining the set of input/output variables in this study there is an element of subjectivity.

1. Set of input variables

Population and demographics levels are categorized using the concept of fuzzy sets, which consist of low, medium, and high groups. The degree of membership in the Population and demographics group is defined using the following membership function: $\mu p(x)$ for the low group, $\mu p\mathrm{s}(x)$ for the medium group, and $\mu pt(x)$ for the high group. The definition of each fuzzy membership function is as follows:

$$\mu\mathrm{pr}(\mathrm{x}) = \begin{cases} 1 & , x \leq 3 \\ \dfrac{4{,}8 - x}{1{,}8} & , 3 < x < 4 \\ 0 & , x \geq 4 \end{cases}$$

$$\mu\mathrm{ps}(\mathrm{x}) = \begin{cases} 0 & , x \leq 3 \\ \dfrac{x - 3{,}4}{0{,}3} & , 3 < x < 4 \\ 1 & , 4 \leq x \leq 6 \\ \dfrac{6 - x}{0{,}5} & , 6 < x < 7 \end{cases}$$

$$\mu\mathrm{pt}(\mathrm{x}) = \begin{cases} 0 & , 6 \leq x \\ \dfrac{x - 6}{1} & , 6 < x < 7 \\ 1 & , 7 \geq x \end{cases}$$

The membership degrees of the three fuzzy sets of the Population and demographics dimension can be illustrated in Figure 3.

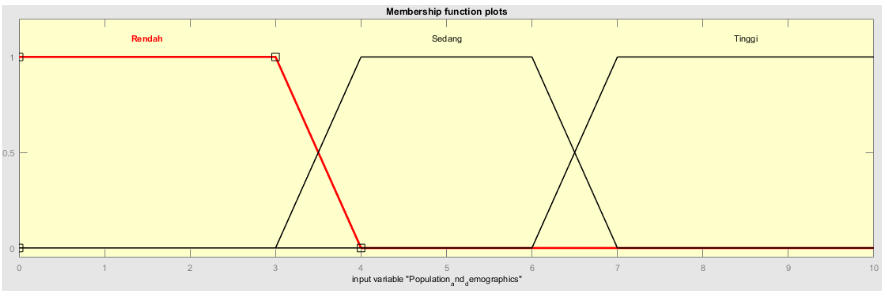

Figure 3. Representation of Population and demographics input variables

For the input variables Environment and ecosystem (E), Organized government services (O), Physical infrastructure (P), Lifestyle and community competence (L), Economic development (E), and Social-cultural capital (S) are categorized using the concept of fuzzy sets, which consist of low, medium, and high groups, like the input variable Population and demographics. The definition of each fuzzy membership function is also the same as the membership function in the Population and demographics input variable.

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Likewise, the membership degrees of the three fuzzy sets of the other six dimensions can be illustrated as in Figure 3.

2. Set of output variables
The output variable is the class of community resilience to disasters. A triangular curve is used to represent the community resilience class variable. $\mu(x)$ is the membership degree of low class values, μs(x) is the membership degree of medium class values, μt(x) is the membership degree of high class values, and μst(x) is the membership degree of very high class values. The fuzzy membership function is defined as follows:

$$\mu\mathrm{r}(\mathrm{x}) = \begin{cases} 0 & , x < 43 \text{ dan } x > 66 \\ \dfrac{x-43}{11} & , 43 \le x \le 54 \\ \dfrac{65-x}{11} & , 54 < x \le 66 \end{cases} \qquad \mu\mathrm{s}(\mathrm{x}) = \begin{cases} 0 & , x < 65 \text{ dan } x > 87 \\ \dfrac{x-66}{10} & , 65 \le x \le 76 \\ \dfrac{86-x}{10} & , 76 < x \le 87 \end{cases}$$

$$\mu\mathrm{t}(\mathrm{x}) = \begin{cases} 0 & , x < 86 \text{ dan } x > 108 \\ \dfrac{x-87}{10} & , 86 \le x \le 97 \\ \dfrac{107-x}{10} & , 97 < x \le 108 \end{cases} \qquad \mu\mathrm{st}(\mathrm{x}) = \begin{cases} 0 & , x < 107 \text{ dan } x > 129 \\ \dfrac{x-108}{10} & , 107 \le x \le 118 \\ \dfrac{129-x}{11} & , 118 < x \le 129 \end{cases}$$

The membership degrees of the four fuzzy sets of community resilience classes can be illustrated in Figure 4.

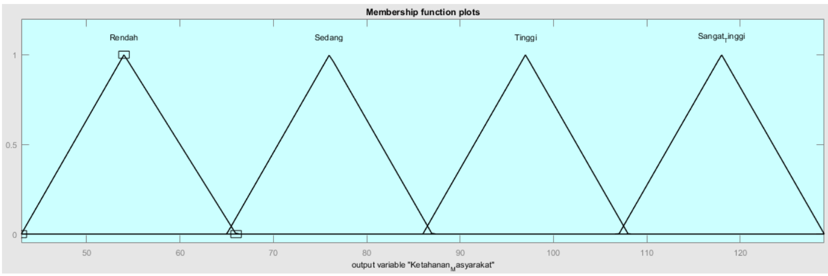

Figure 4. Representation of community resilience class output variables

b. Formulation of fuzzy rules (implications)

At the stage of formulating fuzzy rules using the "minimal" function. if there are r linguistic constants and p input variables, then the number of basic rules is r^p. In this study there are 7 input variables with 3 linguistic constants. The number of basic rules is 3^7 = 2,187 basic rules. The following is a sample of the 3 basic rules used.

Rule 1 = if P['HIGH'] & E['HIGH'] & O['HIGH'] & P['HIGH'] & L['HIGH'] & E['HIGH'] & S['HIGH']
Then Community Resilience level['VERY HIGH']
Rule 1 = if P['HIGH'] & E['HIGH'] & O['HIGH'] & P['HIGH'] & L['LOW'] & E['LOW'] & S['LOW']
Then Community Resilience level['HIGH']
Rule 1 = if P['LOW'] & E['LOW'] & O['LOW'] & P['LOW'] & L['LOW'] & E['LOW'] & S['LOW']
Then Community Resilience level['LOW']

c. Defuzzification

Defuzzification is a mapping of the magnitude of the fuzzy set into the form of a firm set. In this study, the centroid defuzzification method is used to obtain a firm set form. The results of this defuzzification will later become a decision in helping to make decisions. Can be seen in Table 4 in the KM value column (community resilience) is the output of defuzzification.

Table 4. Fuzzy logic model decision results

Region	P	E	O	P	L	E	S	KM

Segmen1	7	7	7	4	5	5	6	86
Segmen2	5	6	6	6	7	7	8	76
Segmen3	5	5	6	7	7	7	8	97
Segmen4	7	5	6	8	6	5	7	76
Segmen5	4	8	7	5	6	7	7	86
Segmen6	5	6	8	7	6	5	8	76

The decision results of the fuzzy logic model in the above model show quite good results. All six segments were successfully assessed correctly. This is shown in Table 5 that by testing 6 assessment segments compared to the assessment by the expert.

Table 5. Comparison of fuzzy and actual results

Region	Valueof KM	Resilience Class	Fuzzy Decision	Actual Decision
Segmen1	86	Medium Class	Yes	Yes
Segmen2	76	Medium Class	Yes	Yes
Segmen3	97	High Class	Yes	Yes
Segmen4	76	Medium Class	Yes	Yes
Segmen5	86	Medium Class	Yes	Yes
Segmen6	76	Medium Class	Yes	Yes

5. Conclusion

This study aims to measure the class of community resilience to flood disasters in Bekasi City using the PEOPLES framework. With seven dimensions consisting of several variables in each dimension and incomplete data, an uncertainty approach technique is needed, namely fuzzy logic. The variable fuzzification process in this study with the membership function used is the trapezoidal type for input variables consisting of low, medium and high groups. triangular type membership function for output variables consisting of four degrees of membership, namely low, medium, high and very high class values with a range between 43 and 129. In the formulation of fuzzy rules using the "minimal" function and has 2,187 basic rules. The results of applying fuzzy logic algorithms to the PEOPLES framework have very good accuracy. Experimental testing on 6 regional segments was able to produce predictions that were all the same as expert judgment. With the increasing number of variables used in measurements, fuzzy logic can be an approach in data processing to make decisions.

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