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# FUZZY GEOGRAPHICALLY WEIGHTED CLUSTERING WITH OPTIMIZATION ALGORITHMS FOR SOCIAL VULNERABILITY ANALYSIS IN JAVA ISLAND

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*ABSTRACT*

*The Social Vulnerability Index (SoVI) measurement assesses social vulnerability. However, the measurement of SoVI can only describe the general conditions without being able to show which factors dominate. Therefore, a clustering approach has been proposed to characterise the dominant social vulnerability factors. Fuzzy Geographically Weighted Clustering (FGWC) is a method that works for this purpose. FGWC is an extension of the Fuzzy C-Means algorithm, which involves geographical influences in calculating membership values. However, the FGWC method is sensitive because the initial initialisation to determine the centroid is randomised, and it will affect the cluster quality. This research uses a metaheuristic approach to overcome the weakness of FGWC by using Particle Swarm Optimisation (PSO) and Artificial Bee Colony (ABC). This study aims to cluster districts/cities in Java Island using the PSO-FGWC and ABC-FGWC methods based on social vulnerability variables and determine the dominant factors of social vulnerability in each region. Optimum cluster selection uses the index of the largest Partition Coefficient (PC) and the smallest Classification Entropy (CE). Clustering social vulnerability in Java Island resulted in the best clustering using the ABC-FGWC method with 5 optimum clusters based on the PC and CE index values of 0.343 and 1.298, respectively. This research found that social vulnerability exists in each region of Java Island. Cluster 1, consisting of 19 districts/cities, is characterized by vulnerabilities in demography and education. Cluster 2, consisting of 33 districts/cities, is characterized by demographic and health vulnerabilities. Cluster 3, which consists of 24 districts/cities, is dominated by education and economic vulnerability factors. Cluster 4, consisting of 14 districts/cities, has the highest social vulnerability characteristics on the unemployment rate and the proportion of house rent. The last one, cluster 5, consists of 29 districts/cities and has a vulnerability problem in the population growth variable.*



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## 1. INTRODUCTION

Recently, various natural disasters have often occurred in Indonesia. Based on records from the National Disaster Management Agency (BNPB), from the beginning of 2023 to December 2023, there were 5,400 disaster events recorded in various regions. This number shows a significant increase, which is an increase of 52.4% when compared to the number of natural disaster events recorded in 2022, where there were only 3,544 events [1]. The majority of natural disasters in 2023 occurred on Java Island, with a total of 1,867 events. In early 2023, a landslide in Bogor City caused severe damage to residential areas and caused considerable losses to the local community. In addition, this landslide also impacted transportation routes, especially the Bogor-Sukabumi railroad line, whose operations were disrupted due to damaged infrastructure. Furthermore, in mid-2023, Bantul Regency was shaken by a magnitude of 6.4 earthquake. This earthquake caused damage to various buildings and infrastructure in the area. Not only that, in mid-2023, there was also a cold lava flood in Lumajang Regency, East Java, caused by the eruption of Mount Semeru. This flood caused damage to the areas it passed through and threatened the local communities living around the area [1].

Natural disasters have a tremendous impact on society, both in terms of health, social, and economic, which can be felt by various groups in society [2] Communities living in disaster-prone areas are often said to be vulnerable communities, where they have the potential to experience loss, damage, or loss that can have a significant effect on their daily lives. These losses and damages often disproportionately affect the most vulnerable people in society, such as those affected by various factors, including poverty, age, gender, and race, which can worsen their conditions amid a disaster [2], [3], [4]. In addition, communities in disaster-affected areas take a long time and process to recover, often facing complex challenges and requiring adequate support [5]. If in these areas, the recovery process is slow or even fails, the impact of the disaster will further worsen the condition of the community so that they will be in an increasingly vulnerable position or exceed their condition before the disaster occurred due to the low capacity they have in dealing with this challenging situation [6].

Understanding and analyzing the social vulnerability of communities in the face of disasters is an essential step in mitigating and preventing disaster impacts, especially in areas with a high risk of disaster events [7], [8], [9]. Such analysis plays a role in identifying the most vulnerable community groups and forms the basis for effective policy planning to minimize material losses and casualties [9]. Various methods have been developed to measure social vulnerability, including the Social Vulnerability Index (SoVI) approach introduced by Cutter in 1996. The process utilizes principal component analysis (PCA) techniques to integrate various socio-economic and demographic variables to provide a comprehensive picture of community vulnerability to disasters [10], [11]. In Indonesia, SoVI measurements were first conducted by Birkman in 2008 to assess the preparedness of local communities for the threat of tsunamis in Padang [12]. The research was then continued by Siagian in 2014, who conducted SoVI measurements throughout Indonesia to explore the factors driving social vulnerability and evaluate the implications of government policies in disaster risk reduction efforts [13]. Based on the research results, disaster mitigation policies are expected to be more targeted and data-based to significantly reduce the impact of disasters, especially for the most vulnerable groups of society.

Measuring social vulnerability using SoVI has several weaknesses, one of which is that it does not take into account the geographical aspects of disaster events [14]. In addition, SoVI only focuses on assessing regional vulnerability without providing an in-depth analysis of the specific impacts of natural disasters in a region. Therefore, this study aims to develop a more comprehensive analysis of social vulnerability by considering geographical aspects, namely through grouping districts/cities in Java Island based on social vulnerability indicators. This step is expected to support more targeted mitigation efforts to minimize the negative impact of disasters. One of the methods used for this purpose is Fuzzy Geographically Weighted Clustering (FGWC) which was first introduced by Mason & Jacobson [15] as a solution to the limitations of simple cluster analysis methods. FGWC is a development of the Fuzzy C-Means algorithm [16], where the regional aspect is taken into account in calculating the membership value [16]. Several previous studies have shown that FGWC is an appropriate algorithm for analysis involving geographical or regional effects [14], [17], [18], [19], [20], [21].

However, the FGWC method has some disadvantages in its iteration, namely limitations in choosing the initial value of the cluster center because it is done randomly and can cause the iteration process to fail to reach the global optimal solution [22]. A possible approach is to add a metaheuristic method to FGWC. Metaheuristic methods have a high chance of achieving better solutions with less computational process or less time than simple heuristic methods or other optimization algorithms [23]. The metaheuristic algorithms that will be used in this research are Particle Swarm Optimisation (PSO) and Artificial Bee Colony (ABC). PSO algorithm is one of the many optimization algorithms that exist. PSO is a distributed artificial intelligence (AI)-based optimization algorithm inspired by nature, which mimics the behavior of flocks of birds or fish [24], [25], [26], [27]. The algorithm starts with initializing a randomly generated population of solutions (called particles). Its current position and velocity values determine the particle's movement. The particle position value represents a possible solution in the optimization case, while the velocity value changes the particle position. The ABC algorithm is an optimization method inspired by nature, namely from the behavior of bee colonies in finding and exploring food sources efficiently. If the optimization solution is described through particles in the PSO algorithm, the ABC algorithm defines the solution of the optimization problem as a food source (nectar) [28]. In general, there are five stages of the ABC algorithm process: the initialization phase, the worker bee phase, the spectator bee phase, the scout bee phase, and the food source selection phase [29].

Therefore, clustered districts/cities in Central Java based on SoVI indicators. We used the FGWC method by adding ABC and PSO optimization methods to optimise the FGWC method. We also used the Partition Coefficient (PC) and Classification Entropy (CE) indexes to get the best cluster. We then conducted Kruskal-Wallis's test to determine the independence of the clusters formed. The rest of the paper is organized as follows. Section 2 describes the dataset and details of the methodology. We apply the FGWC method to social vulnerability indicators to cluster districts in Java Island using PSO and ABC optimisation methods, and discuss the results in Section 3. Section 4 concludes the paper with some final notes.

## 2. RESEARCH METHODS

In this section we divide it into three parts, first we explain the scope of the research, second we explain the methods used, and third the research procedure.

### 2.1 Research Scope

The scope of this study is applying the PSO and ABC algorithms to optimize the social vulnerability cluster using FGWC. The data comes from the publication of BPS-Statistics Indonesia. For the reasons of data availability, this study only used 9 variables. The study area covers all the districts in Java and its surroundings based on 2023 data. The variables used in this study are described in Table 1.

**Table 1. Social Vulnerability Variables**

| Variables | Description |
|---|---|
| Children | Percentage of under 15 years old population |
| Elderly | Percentage of up to 64 years old population |
| Loewdu | Percentage of 15 years old and over population with low education |
| Illiterate | Percentage of the population that cannot read and write |
| Rented | Percentage of households renting a house |
| Unemployment | Percentage of the total labor force that is unemployed but actively seeking employment and willing to work |
| Water | Percentage of households that don't have access to proper drinking water |
| Poverty | Percentage of poor people |
| Popgrowth | Percentage of population change |

***Data source**: Central Bureau of Statistics, 2023*

### 2.2 Fuzzy Geographically Weighted Clustering (FGWC)

Fuzzy Geographically Weighted Clustering (FGWC) Cluster Analysis is one of the analyses that can overcome the weaknesses of another clustering method, namely the Fuzzy C-Means method. Fuzzy Geographically Weighted Clustering analysis was first introduced by [15]. FGWC is an improvement of the Fuzzy Geodemographics algorithm proposed by [30]. The influence of one area on another is considered by

FGWC as a product of the population in that area [22]. At each iteration in the fuzzy clustering grouping, the determination of group membership uses Equation (1) following:

$$\mu_i' = \alpha\mu_i + \beta\frac{1}{A}\sum\nolimits_j^n w_{ij}\mu_j \tag{1}$$

where:

$\mu_i'$ : Value the new members of the object *i*.

$\mu_i$ : The value of the old membership of the object *i*.

$\mu_j$ : The value of the old membership of the object *j*.

$w_{ij}$ : Weighing the size the of several interactions between regions.

$A$ : Value to ensure the weigher value is not more than 1.

α and β are multiplier factors for the value of the old membership and the weighing value of the average membership of other observation units. The α and β values are defined as follows: α + β = 1. The membership weigher ($w_{ij}$) is defined in Equation (2) as follows:

$$w_{ij} = \frac{(m_i m_j)^b}{d_{ij}^a} \tag{2}$$

where:

$m_i$ : Total population of region *i*.

$m_j$ : Total population of the region *j*.

$d_{ij}$ : Distance between region *i* and region *j*.

$a, b$ : User definable parameter, if the population effect is considered as important as the distance $a = b = 1$.

### 2.3 The Improvement of FGWC using ABC and PSO optimization

The FGWC algorithm has some limitations when performing clustering because the FGWC algorithm determines the cluster's center randomly during the iteration process in the initialization stage. The limitation in randomly selecting the cluster center causes the iteration process to fail to reach the optimum local solution. This issue will impact the quality of the clusters generated by FGWC. Optimization algorithms can be used to solve the problem. The basic idea is to use an optimisation algorithm to automatically select several clusters and their centroid in the initialization phase of FGWC clustering. The optimization algorithms used in this study are Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC). These algorithms work by minimizing the value of the FGWC objective function. The objective function of FGWC is defined in Equation (3) following [22]:

$$J_{FGWC}(U,V;X) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m\, |v_i - x_k|^2 \rightarrow \min \tag{3}$$

where $U$ is the membership matrix, $V$ is the matrix for the cluster center, $X$ is a matrix for data, m is an exponential weigher used to determine the degree of fuzziness of a cluster, $v_i$ is the cluster center for i-objects, $u_i$ and is an element of the membership matrix, $x_k$ and is a data point. The center of the cluster is defined in Equation (4) following:

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m} \tag{4}$$

as well as the membership matrix can be calculated using Equation (5):

$$u_i = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|v_i - x_k\|}{\|v_j - x_k\|}\right)^{\frac{2}{m-1}}} \tag{5}$$

## 2.4 Procedure Analysis

PSO-FGWC dan ABC-FGWC algorithms are implemented using R programming languange, and the parameters specified in the two algorithms are obtained from the "nasplacust" packages in R (the initial parameter settings for FGWC in this study are $\alpha = 0.5$; $\beta = 0.5$; a = 1.2; b = 1.2; threshold $\varepsilon = 10^{-6}$; $c_1 = 0.7$; $c_2 = 0.6$; maximum iteration = 1000; $n = \ldots$; the number of clusters ($c$) to be used will be different. It will start from $c = 2$ to 10. Fuzziness ($m$) to be used is $m = 2$. Meanwhile, the initial parameters for the PSO are npar = 15; vmax = 0.8; pso.same = 10; w.inertia = "chaotic"; wmax = 0.8; wmin = 0.3, map = 0.3, and the initial parameters for the ABC are abc.same = 15; nfood = 10; n.onlooker = 5. The step by step improved FGWC algorithms using PSO and ABC optimization algorithms are stated thus:

a. Algorithm 1: PSO-FGWC optimization algorithm

Step 1: Determine the number of clusters $c$, threshold $\varepsilon > 0$ and other parameters such as weighted fuzziness exponent($m$).

Step 2: Set initial value of cluster centers $v_i$ in **Equation (4)** at $t$=0 using Particle Swarm Optimization process by minimizing the objective function in **Equation (3)**. Specify PSO parameters such as maximum iteration and number of swarm particles. Best solution provided by PSO is chosen as the cluster center.

Step 3: Define geographic parameters $\alpha$,$\beta$,$a$,and $b$ which will be used to adjust the partition matrix following by geographical characteristics.

Step 4: The **Equation (5)** is then utilized to determine the fuzzy membership values.

Step 5: Perform geographical cluster modifications using **Equation (1)**, **Equation (2)** and $\alpha + \beta = 1$ to involve the neighbourhood effect.

Step 6: Use PSO and step (1) to compute the cluster centers at $t$+1 by minimizing the objective function in **Equation (3)**.

Step 7: If the error of $\|V(t+1) - V(t)\| \le \varepsilon$ then stop the iterative procedure. Otherwise, assign $V(t) = V(t+1)$ and return to Step 2.

b. Algorithm 2: ABC-FGWC optimization algorithm

Step 1: Determine the number of clusters $c$, threshold $\varepsilon > 0$ and other parameters such as weighted fuzziness exponent($m$).

Step 2: Set initial value of cluster centers $v_i$ in **Equation (4)** at $t$=0 using Artificial Bee Colony process by minimizing the objective function in **Equation (3)**. Number of food sources, employed bees and onlooker bees is defined by number of cluster respectively. The ABC dimension is equal to number of clustering data variable. Best solution provided by ABC is chosen as the cluster center.

Step 3: Define geographic parameters $\alpha$,$\beta$,$a$,and $b$ which will be used to adjust the partition matrix following by geographical characteristics.

Step 4: The **Equation (5)** is then utilized to determine the fuzzy membership values.

Step 5: Perform geographical cluster modifications using **Equation (1)**, **Equation (2)** and $\alpha + \beta = 1$ to involve the neighbourhood effect.

Step 6: Use ABC and setp (1) to compute the cluster centers at $t$+1 by minimizing the objective function in **Equation (1)**.

Step 7: If the error of $\|V(t+1) - V(t)\| \le \varepsilon$ then stop the iterative procedure. Otherwise, assign $V(t) = V(t+1)$ and return to Step 2.

## 3. RESULTS AND DISCUSSION

This section presents the performance of FGWC, PSO-FGWC, and ABC-FGWC. It then analyses the characteristics of social vulnerability in Java Island at the district/city level using the best clustering results.

### 3.1 Comparison of FGWC, PSO-FGWC, and ABC-FGWC

In this section, we consider the evaluation of FGWC, PSO-FGWC, and ABC-FGWC methods by comparing the number of clusters used, which is 2 to 10. Partition Coefficient (PC) and Classification Entropy (CE) are the evaluation methods used. PC index measures how well the data is divided into clusters based on the membership degree in fuzzy clustering. Furthermore, the CE index is used to measure the uncertainty in cluster partitioning. A good clustering aims to have a high PC and a low CE, which means the clustering is clear enough but still retains its fuzzy nature.

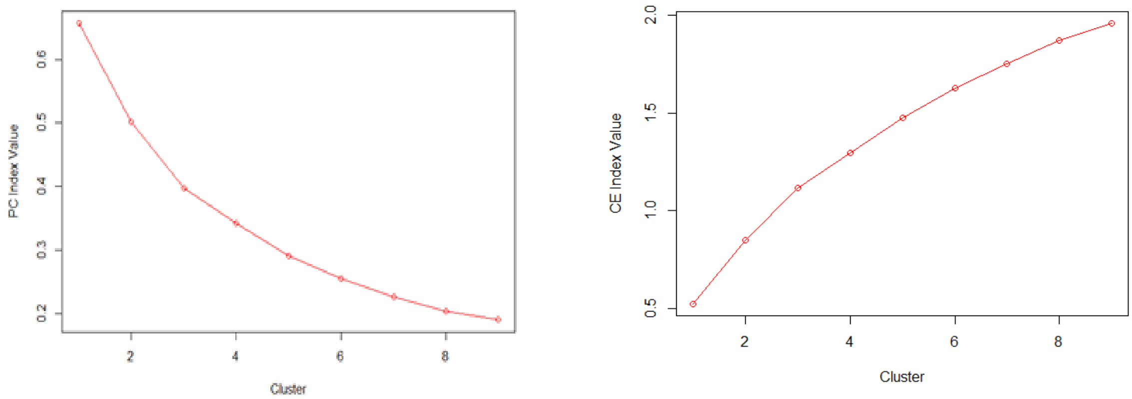
Table 2 compares clustering results using three different algorithms, FGWC, PSO-FGWC, and ABC-FGWC, based on two evaluation metrics, i.e., PC and CE index, for the number of clusters varying from 2 to 10. The ABC-FGWC algorithm has the highest PC value compared to FGWC and PSO-FGWC for all numbers of clusters, indicating that ABC-FGWC is better at forming clearer clusters than the other methods. The PC value decreases as the number of clusters increases, which is common because more clusters will increase the uncertainty in membership [30], [31]. ABC-FGWC has the lowest CE value compared to FGWC and PSO-FGWC for all clusters, which means this method produces partitions with the least uncertainty. The CE value increases as the number of clusters increases, indicating that more clusters lead to more fuzzy partitions [30], [31]. Overall, ABC-FGWC is the most effective method for producing firmer and more accurate clustering than the other methods, and it has the highest PC (clearer clustering) and lowest CE (less uncertainty).

**Table 2. Comparison of FGWC, PSO-FGWC and ABC-FGWC**

| Number of Cluster | PC | | | CE | | |
|---|---|---|---|---|---|---|
| | FGWC | PSO-FGWC | ABC-FGWC | FGWC | PSO-FGWC | ABC-FGWC |
| 2 | 0.648 | 0.653 | **0.657** | 0.533 | 0.527 | **0.521** |
| 3 | 0.494 | 0.500 | **0.502** | 0.865 | 0.856 | **0.850** |
| 4 | 0.381 | 0.387 | **0.398** | 1.147 | 1.137 | **1.116** |
| 5 | 0.317 | 0.319 | **0.343** | 1.346 | 1.343 | **1.298** |
| 6 | 0.276 | 0.278 | **0.290** | 1.510 | 1.506 | **1.478** |
| 7 | 0.247 | 0.245 | **0.254** | 1.649 | 1.651 | **1.628** |
| 8 | 0.215 | 0.217 | **0.226** | 1.789 | 0.783 | **1.752** |
| 9 | 0.199 | 0.200 | **0.204** | 1.889 | 1.889 | **1.874** |
| 10 | 0.186 | 0.186 | **0.189** | 1.984 | 1.983 | **1.962** |

### 3.2 Number of Optimum Clusters

Based on the best algorithm (ABC-FGWC), Figure 1 shows a graph that helps determine the optimal number of clusters based on the PC Index and CE Index. The graph in Figure 1 (a) illustrates that the PC Index decreases as clusters increase. A significant decrease is seen from clusters 2 to 5, then decreases slowly thereafter, suggesting that after a certain number of clusters (around 5), the partitioning becomes increasingly fuzzy, so increasing the number of clusters may not provide significant benefits. In addition, the graph in Figure 1 (b) shows that the CE Index increases as the number of clusters increases. A significant increase occurs up to the 5th cluster, after which the increase continues but at a slower rate. This indicates that adding more clusters leads to more fuzzy partitions and increases the uncertainty in membership. Thus, clustering the social vulnerability of districts/ cities in Java Island selected an optimal number of clusters of 5 by considering both clarity of clustering (high PC) and low uncertainty (low CE).




(a) (b)

**Figure 1. Determination Number of Clusters, (a) PC Index, (b) CE Index**

### 3.3 Clustering Social Vulnerability on The Island of Java Using ABC-FGWC

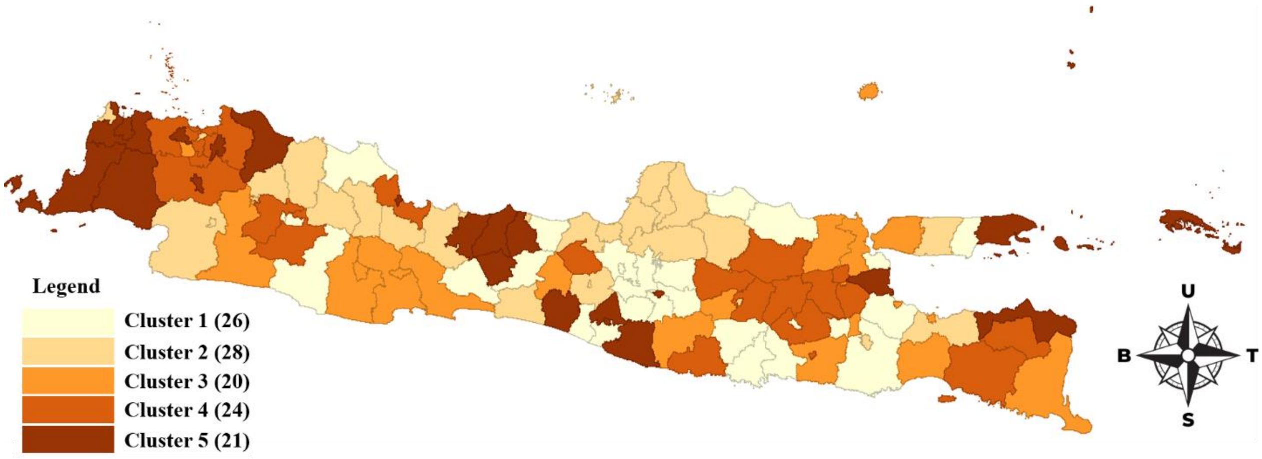
In analyzing social vulnerability clustering in Java Island, ensuring that the clusters formed have significantly different characteristics is essential. To provide this measure, the Kruskal- Wallis' test with a chi-square ($\chi^2$) approach is used to determine whether there are significant differences in the distribution of variables between clusters. In this study, the ABC-FGWC algorithm was compared with the FGWC algorithm to evaluate its effectiveness in forming independent clusters based on social vulnerability indicators in Java Island. The Kruskal- Wallis's test results are presented in Table 3, which shows the significance level of each social vulnerability variable in both algorithms. The results of the Kruskal- Wallis's test, where the results obtained are p-values less than 0.1 for each variable. Testing using a significance of α = 10% provides a decision to reject the null hypothesis. In other words, it can be concluded that the 5 clusters formed from the ABC-FGWC algorithm are mutually independent and produce different characteristics.

**Table 3. Kruskal-Wallis's Test Results of Social Vulnerability**

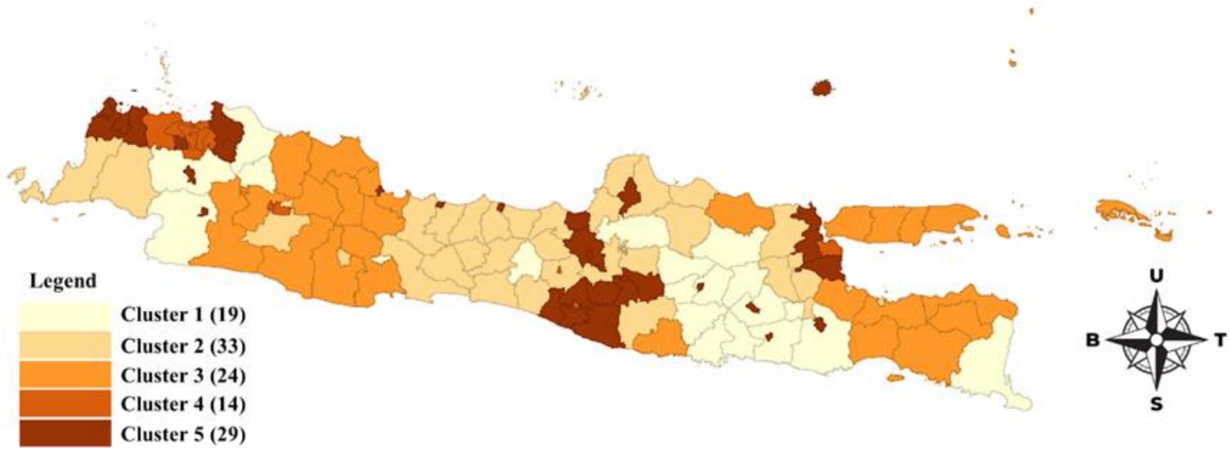
| Variable | FGWC | ABC-FGWC |
|---|---|---|
| Children | 0.023** | 0,060* |
| Elderly | 0.000*** | 0.000*** |
| Lowedu | 0.000*** | 0.000*** |
| Illiterate | 0.000*** | 0.000*** |
| Rented | 0.000*** | 0.000*** |
| Unemployment | 0.081* | 0.033** |
| Water | 0.000*** | 0.000*** |
| Poverty | 0.000*** | 0.000*** |
| Popgrowth | 0.000*** | 0.000*** |

*Significance at level *) 10%; **) 5%; and ***) 1%*

The results of mapping based on the clustering of social vulnerability on the island of Java using FGWC and ABC-FGWC with five clusters are presented in Figure 2. In this study, we only discuss the clustering results with the ABC-FGWC algorithm. Cluster 1 consists of 19 districts, comprising several areas in West Java Province and several districts in East Java Province. This cluster is vulnerable to the impacts caused by natural disasters, especially demographics. Regarding demographics, cluster 1 has a high percentage of elderly people (65 years and above). This is because the elderly usually have chronic diseases, vision, hearing, and motor problems; loneliness and dependence on children are characteristics that make a person more vulnerable in old age. Older people, especially those with poor health or socioeconomic status, are more vulnerable to natural disasters, especially those that occur quickly. Physical problems of the elderly make them vulnerable during all stages of a disaster [32]. Furthermore, in terms of education, the average percentage of people with low education in cluster 1 is the second highest.




**(a)**




**(b)**

**Figure 2. Social Vulnerability Map Based on: (a) FGWC Algorithm and (b) ABC-FGWC Algorithm**

Cluster 2 is the most dominant, as it has the most members compared to the other clusters. This cluster comprises parts of Central Java with the highest social vulnerability characteristics regarding demographics and health. Regarding demographics, cluster 2 has the highest percentage of the population under 15 years of age and the second highest percentage of the elderly population (65 years and above). This indicates a high dependency ratio, which is reflected in the high rate of elderly people (65 years and above) and people under 15 years of age. The region is also characterized by relatively high average population growth. High population growth implies an increase in the child population, increasing the potential for vulnerability. As stated by Cutter et al. [11] and Rufat [33], the high proportion of the child and elderly population contributes to increased responsibilities that must be shouldered by productive age in disaster rescue and recovery efforts. Children are vulnerable to disasters because they lack understanding of what disasters are and how to anticipate them.

Meanwhile, the elderly are vulnerable to disasters related to decreased physical abilities, so they need other people to save themselves [34]. In the health sector, represented by access to safe drinking water sources, districts in cluster 2 have the highest average percentage of households that do not have access to safe drinking water. Decent drinking water plays a vital role in supporting health. When natural disasters occur, areas with lower access require special attention so that it is not increasingly complex to obtain clean water due to damage to clean water infrastructure.

Then, cluster 3 consists of 24 districts/cities, as seen in Figure 2. The main problems in this group occur in the high illiteracy rate, the proportion of the low-educated population, the proportion of the elderly population, and the proportion of the poor population. In macroeconomic variables, the average poverty rate of cluster 3 is the highest, but the unemployment rate is the lowest. This shows that the efficiency of the use of labor in the productive age group does not provide enough income to access a decent life for themselves and the people they cover. In addition, many people still have low levels of education. Therefore, they can only compete in sectors of the economy where wages are relatively lower, such as the real sector. This condition will exacerbate the social vulnerability of the community. People with poor status generally do not have sufficient non-physical assets. When a natural disaster occurs, these assets will be damaged, taking the group longer to recover [13].

Cluster 4 consists of the cities on Java Island with the highest social vulnerability characteristics regarding open unemployment and the proportion of house rent. Member cluster 4 consists of 14 districts/cities, as detailed in Figure 2. Property prices have increased dramatically along with the increasing need for housing due to urbanization in major cities in Indonesia, making low-income people prefer to rent housing [35]. The high level of open unemployment indicates the tight competition in finding a job. The majority of employment in urban areas comes from the industrial and service sectors that require high skills and expertise, followed by a high population density, causing the labor market to be unable to accommodate the entire available labor force, resulting in the inefficiency of labor absorption [36].

Recommendations for addressing vulnerabilities in cluster 4 were pre-employment training and business capital inclusiveness. Cluster 4 has the best level of education, so it is hoped that these methods can provide more sustainable solutions to vulnerabilities. Then, the government can support vulnerability in terms of housing ownership through a simple rental apartment program for low-income people as currently implemented.

Finally, cluster 5 consists of 29 districts/cities with vulnerability problems in the population growth variable. Increased population growth means that the population will increase, causing the population's risk of being exposed to disasters to be higher [9]. Then, in terms of macroeconomic, health, and education variables, cluster 5 tends not to experience significant problems. Thus, in cluster 5, the government must implement policies to educate the community about all possible risks and mitigate disaster impacts. Disaster education should not only be carried out in cluster 5 but also in all clusters and carried out not only at the community level but also in formal education activities.

## 4. CONCLUSIONS

This study aims to cluster districts/cities in Java Island using the PSO-FGWC and ABC-FGWC methods and the Social Vulnerability Index (SoVI) to assess social vulnerability, such as demographic, education, health, and macroeconomic variables. The best clustering method to group districts/cities in Java and its surroundings is FGWC with ABC algorithm to optimize the clustering quality. Using criteria such as the PC and CE indexes results in 5 as the optimum number of clusters. The Kruskal-Wallis test has confirmed that all the variables in each cluster are statistically different. It means that all the clusters aren't identic and do separation of the districts well. This research found that social vulnerability exists in every region of Java and its surroundings. Cluster 1 is characterized by vulnerability in demographics and education. Cluster 2 has vulnerability characteristics in demographics and health. Cluster 3 has dominant vulnerability characteristics in education and economics. Cluster 4 is the cities in Java Island with the highest social vulnerability characteristics from the unemployment rate and the proportion of rental housing. Cluster 5 has vulnerability problems in the population growth variable. The issues faced by each district in Java and its surroundings are different. This is reflected in the different characteristics of the formed clusters. The policy implication should fit with the main vulnerability. Furthermore, the most common problems experienced by the districts are poverty and lower education, meaning the government must preserve job training and financial inclusion programs to help societies avoid vulnerability. Besides, disaster education is needed to help people develop a good strategy for facing disasters.

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