

# Geospatial Model Optimization for Mapping Social Vulnerability to Natural Disasters Using Fuzzy Geographically Weighted Clustering and Flower Pollination Algorithm

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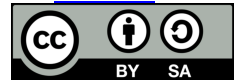
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## ABSTRACT

This study analyzes social vulnerability to natural disasters in Indonesia through a geospatial optimization model integrating Fuzzy Geographically Weighted Clustering (FGWC) with the Flower Pollination Algorithm (FPA). The hybrid FGWC-FPA enhances clustering accuracy by optimizing spatial parameters and addressing the limitations of index-based and non-spatial methods. The model tested two to four clusters, with the optimal configuration producing four distinct vulnerability groups. Cluster 1 (114 districts) exhibits high poverty, weak infrastructure, and low literacy; Cluster 2 (79 districts) reflects demographic pressure and gender-related inequality; Cluster 3 (87 districts) shows low education and poor disaster preparedness; while Cluster 4 (234 districts) represents health- and age-related vulnerability. A comparison with the 2024 Indonesian Disaster Risk Index (IRBI) shows strong spatial consistency, especially in high-risk regions such as Papua, Maluku, and Sulawesi. The FGWC-FPA model provides finer spatial granularity, allowing the identification of region-specific social issues not captured by deterministic index approaches. The findings validate national disaster risk patterns and offer complementary insights for implementing the National Disaster Management Master Plan (RIPB) 2020–2044, supporting regional prioritization, resource allocation, and capacity-building strategies.

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## 1. INTRODUCTION

Indonesia is one of the countries with the highest disaster risk in the world, due to a combination of geological and geographical factors. Geologically, Indonesia is located at the meeting point of four major tectonic plates, namely the Eurasian, Indo-Australian, Philippine, and Pacific plates, making it highly vulnerable to tectonic disasters such as earthquakes, tsunamis, and volcanic eruptions [1], [2]. On the other hand, Indonesia's geographical location in the tropics and between two oceans and two continents also contributes to the high frequency of hydrometeorological disasters, such as floods, landslides, flash floods, extreme weather, coastal erosion, and droughts that have the potential to trigger forest and land fires [3]. In 2024 alone, there were 3,472 natural disasters recorded throughout Indonesia [4]. The impact of these disasters is not only physical, but also social and economic, especially for communities with high vulnerability. In this context, it is important to understand that disaster risk is not only determined by natural threats, but also by the level of social vulnerability and the adaptive capacity of the community [5]. Therefore, effective disaster management planning must include spatial mapping of social

vulnerability as a basis for data-driven decision-making, from the pre-disaster to post-disaster stages.

In the context of natural disaster risk, social vulnerability is one of the main components that determine the level of exposure and impact experienced by the affected population [6]. This vulnerability reflects the complex interaction between social, economic, demographic, and geographical factors that directly affect the capacity of individuals and communities to cope with, respond to, and recover from disasters [7]. Reality shows that the impact of disasters is not evenly distributed; communities with low socioeconomic capacity generally experience more severe impacts and slower recovery processes [8]. Therefore, a deep understanding of the dimensions of social vulnerability and its spatial distribution is very important in developing risk mitigation and disaster adaptation strategies based on social justice [9]. Spatial analysis of social vulnerability not only provides information about who is vulnerable, but also where that vulnerability is concentrated, thereby serving as a basis for more targeted and effective decision-making.

Social vulnerability to natural disasters is a strategic issue in disaster mitigation and risk management efforts in Indonesia, especially given the high number of people exposed and the diversity of socio-economic conditions between regions [10]. This vulnerability reflects the degree of a group's inability to cope with, respond to, and recover from disasters, which is greatly influenced by social structures, access to resources, and the adaptive capacity of communities [11]. Groups with socioeconomic limitations generally experience greater and more sustained impacts from disasters, requiring mitigation strategies based on the precise identification of vulnerable groups [12]. However, mapping social vulnerability in Indonesia still faces a number of challenges, particularly in comprehensively integrating spatial data and geodemographic variables. Due to these limitations, many disaster risk reduction strategies that have been implemented are not fully based on accurate, contextual, and region-based data, resulting in less than optimal policy intervention effectiveness [13].

Identifying and mapping social vulnerability is a crucial step in supporting mitigation strategies and effective disaster management policy planning, especially in vulnerable areas such as those affected by floods and earthquakes [14], [15]. Various approaches have been developed for this purpose, including the use of the Social Vulnerability Index (SoVI) [16], [17], [18], Baseline Resilience Indicators for Communities (BRIC) [19], [20], [21], spatial regression models [22], [23], and multilevel geospatial approaches that integrate socioeconomic indicators with spatial data. In addition, multi-criteria-based methods such as the Analytic Hierarchy Process (AHP) [24], dan Weighted Overlay [25], are also used for social vulnerability mapping. Although these approaches have successfully identified vulnerability patterns and geographic clusters effectively and provided useful information for policymakers, index-based models generally present results in aggregate form. This makes them less sensitive in capturing specific spatial variations between regions [26], [27]. Biswas & Nautiyal [28] emphasize that this kind of approach tends to cause regional homogenization, thereby ignoring local factors that are contextually very influential on vulnerability levels. As a result, the social vulnerability mapping results obtained may be less accurate in representing the actual conditions in each location.

As an alternative to index-based approaches, a number of studies have developed methods for mapping social vulnerability using clustering algorithms. Nur and Abdurakhman [29], applied the K-Median algorithm to group regions in Java based on their vulnerability levels, while Halim and Wijaya [30], combined Principal Component Analysis (PCA) and K-Means at the district level in Indonesia. Clustering methods have proven to be able to identify the specific characteristics of each region more flexibly and independently of linear assumptions between variables [31]. However, conventional clustering approaches do not fully take into account spatial effects, even though social vulnerability is greatly influenced by the geographical interrelationships between heterogeneous regions [14]. In addition, most existing studies are still limited in considering biophysical indicators that directly affect vulnerability, such as housing quality, unemployment rates, home ownership, and access to basic services [32]. These limitations indicate the need for a

new approach that is not only capable of capturing spatial patterns but also pays attention to the diversity of social and biophysical factors in a more comprehensive manner.

In this study, the Fuzzy Geographically Weighted Clustering (FGWC) method was chosen because it has advantages in capturing spatial variations and social data heterogeneity that are often overlooked by index-based approaches and conventional clustering methods [33]. FGWC allows each spatial entity to have a degree of membership in more than one cluster, thereby representing social vulnerability that is gradual, non-binary, and more in line with complex social realities. In addition, FGWC explicitly considers the geographical proximity between regions in the clustering process, so that the resulting vulnerability patterns are more realistic and contextual in accordance with local conditions [34]. However, FGWC has a major limitation in determining the initial center of the cluster, which greatly affects the final results of the clustering process. The selection of an inappropriate initial center can cause the algorithm to get stuck in a local solution, resulting in suboptimal clustering results that are unable to accurately represent spatial patterns [35]. Therefore, integration with an optimization algorithm is needed to help determine the cluster center more effectively, in order to improve the accuracy and quality of the clustering results produced by FGWC.

Although various metaheuristic optimization algorithms have been successfully used to improve the performance of the FGWC algorithm, each has limitations that need to be considered. Particle Swarm Optimization (PSO), which has been applied in mapping social vulnerability on the island of Java, tends to converge prematurely, thus risking getting stuck in local solutions [34]. Similarly, the integration of FGWC with Artificial Bee Colony (FGWC-ABC) shows an increase in accuracy, but the ABC algorithm is known to have slow exploration and unstable solution search efficiency in high-dimensional datasets [36]. Meanwhile, the Gravitational Search Algorithm (GSA) used to map groups with social welfare problems in Central Java [37] has weaknesses in the stability of results and convergence speed, especially when faced with complex and spatial data. Based on these limitations, this study proposes the use of the Flower Pollination Algorithm (FPA) as an optimization approach for FGWC. FPA has a better balance between exploration and exploitation processes through global and local cross-pollination mechanisms [38], as well as advantages in avoiding local solution traps and maintaining solution population diversity [39]. Thus, the integration of FGWC and FPA is expected to produce more accurate and adaptive mapping of social vulnerability clusters to existing spatial and social complexities.

Based on the above explanation, it can be concluded that mapping social vulnerability to natural disasters requires an approach that is not only capable of capturing spatial variations and social complexity, but also supported by effective and adaptive optimization algorithms. The combination of Fuzzy Geographically Weighted Clustering (FGWC) and Flower Pollination Algorithm (FPA) is expected to overcome the limitations of conventional methods and produce more accurate, realistic, and contextual mapping of social vulnerability clusters. This study aims to develop and implement an FGWC-FPA-based geospatial optimization model in the context of mapping social vulnerability to natural disasters in Indonesia, as a tangible contribution to supporting data-driven disaster mitigation planning and policy.

## 2. RESEARCH METHOD

### 2.1. Dataset

This study refers to the conceptual framework of social vulnerability developed by Cutter et al. [16] as the basis for selecting indicators and variables for analysis. A total of eight main indicators were used to represent various dimensions of social vulnerability, which were then broken down into 19 measurable variables. The dataset used covers all administrative regions in Indonesia at the district/city level, with a total of 514 observations. All data were obtained from official sources of the Central Statistics Agency (BPS), which includes social, economic, demographic, and infrastructure data. The indicators and variables used in this study are presented in detail in Figure 1.

## 2.2. Data Preprocessing

Data quality greatly determines the validity of analysis results, making the data preprocessing stage a crucial step before modeling. Without proper data cleaning and preparation, the resulting social vulnerability mapping may be misleading and not reflect the actual conditions in the field. Therefore, in this study, data preprocessing was carried out to ensure that all variables used were in accordance with the format, scale, and structure required by the Fuzzy Geographically Weighted Clustering (FGWC) method and the Flower Pollination Algorithm (FPA) optimization algorithm. The preprocessing process consisted of three main stages, namely data cleaning, data normalization, and data integration. The experiments in this study were designed to develop and test the performance of a social vulnerability mapping model based on the integration of Fuzzy Geographically Weighted Clustering (FGWC) and the Flower Pollination Algorithm (FPA). The experiments were divided into four main stages, namely: (1) FGWC implementation, (2) application of FPA as an optimization algorithm, (3) evaluation of clustering results using the Cluster Validity Index (CVI), and (4) geodemographic analysis of the resulting clusters. The research design can be seen in Figure 2.

## 2.3. Fuzzy Geographically Weighted Clustering

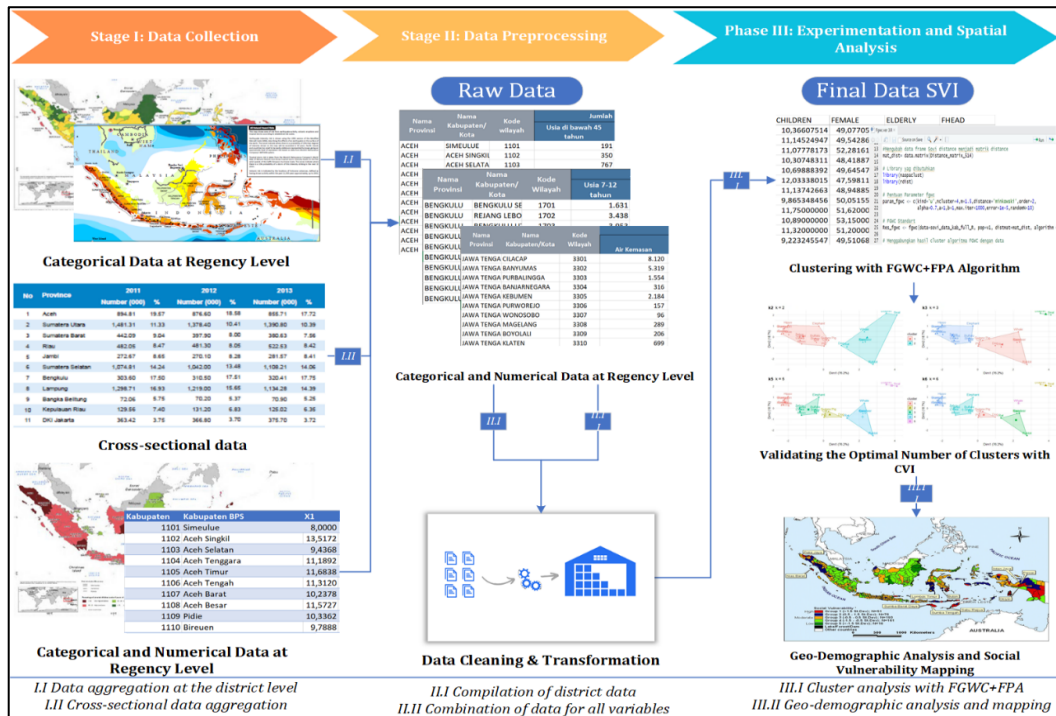
Fuzzy Geographically Weighted Clustering (FGWC) was developed by Mason and Jacobson (2007) as an improvement on the Fuzzy C-Means (FCM) algorithm to address the weaknesses of FCM in the context of geodemographic clustering. FCM does not consider spatial effects and inter-regional relationships in determining cluster membership. To that end, FGWC incorporates geographical elements such as distance between regions and population size into the fuzzy membership weight calculation process, making it more geographically aware [40]. FGWC calculates the influence of one region on another as the product of population size and distance between regions. Thus, regions with large populations and close proximity will have a greater influence on the fuzzy membership of surrounding regions.

## 2.4. Flower Pollination Algorithm

The Flower Pollination Algorithm (FPA) is a metaheuristic optimization algorithm developed by Yang (2012), inspired by the process of cross-pollination in flowering plants. In the context of the algorithm, this process is modeled as a mechanism for searching for optimal solutions through two main strategies, namely global pollination and local pollination, which are executed alternately based on certain probabilities. The main advantage of FPA lies in its ability to maintain a balance between broad exploration of the solution space and intensive exploitation of the best solution area. This makes FPA effective in avoiding local optimum traps, which are often a weakness in conventional algorithms such as Particle Swarm Optimization (PSO) or Artificial Bee Colony (ABC), especially in high-dimensional complex optimization problems [38]. In this study, FPA is used to optimize the cluster center initialization process in the FGWC algorithm. Good initialization is crucial to the quality of the FGWC's final results, as it can minimize the possibility of convergence on local solutions. By integrating FPA into the initial FGWC process, it is hoped that the resulting cluster centers will be more representative and capable of improving the quality of social vulnerability spatial mapping. The optimization process is carried out by setting an objective function that minimizes the total weighted distance between the data and the cluster center by considering the fuzzy membership weight. Convergence is achieved when there is no significant change in the position of the cluster center or when the maximum number of iterations is met.



Figure 1. Framework of social vulnerability indicators and variables derived from Cutter et al. [16]



optimal number of clusters and to evaluate the extent to which the clusters formed have good internal compactness and inter-cluster separation. The indices used include the Partition Coefficient (PC), Classification Entropy (CE), Partition Index (SC), Separation Index (S), Index of Fuzzy Validity (IFV), and Xie-Beni Index (XBI). In general, a good cluster structure is characterized by high PC and IFV values, as both indicate clarity in fuzzy membership distribution. Conversely, low CE, SC, S, and XBI values indicate that clusters have clear boundaries and data membership does not spread ambiguously across multiple clusters. In this study, all of these indices were calculated for each number of clusters from two to four. This approach aims to evaluate the stability of the clustering results and identify the cluster number configuration that consistently provides the best validity index values. By comparing the index results for each cluster number, the optimal number of clusters can be determined in mapping social vulnerability based on geospatial and socioeconomic characteristics.

## 2.6. Geodemographic Analysis

After the clustering process was carried out using FGWC optimized with the Flower Pollination Algorithm (FPA), the next step was to analyze the characteristics of each cluster formed. Geodemographic analysis aims to identify social, economic, and geographical patterns that distinguish one cluster from another, as well as provide substantive interpretation of the results of social vulnerability mapping. In this context, each cluster is analyzed based on its spatial distribution, as well as the average values of the social variables used in the model, such as education level, poverty, population density, and access to basic services. Spatial mapping of the cluster results is also used to see the distribution of areas based on social vulnerability levels, so that priority areas requiring more intensive intervention in disaster mitigation efforts can be identified. By integrating the clustering results and geodemographic analysis, this study not only produces accurate spatial mapping but also provides the contextual information needed by policymakers to design more targeted disaster risk reduction strategies.

## 2.7. Parameter Tuning and Selection

This study employs two types of parameters: those associated with the Fuzzy Geographically Weighted Clustering (FGWC) model and those used in the optimization process of the Flower Pollination Algorithm (FPA). The FGWC parameters control the level of fuzziness, spatial influence, and numerical convergence during the clustering process. The fuzzifier exponent  $m = 2$  was set to regulate the degree of fuzziness in cluster memberships, ensuring smooth transitions between clusters, as recommended by Mason and Jacobson [40]. The population weighting factor  $\alpha = 0.7$  and spatial influence coefficient  $\beta = 0.3$  were empirically adjusted to achieve a balance between cluster compactness and spatial continuity. The distance decay parameter  $b = 1$  and spatial weighting constant  $a = 1$  were adopted from previous studies [34], [35] to maintain consistent spatial effects across different observation points, while the convergence threshold  $\varepsilon = 1e - 6$  lower than that used by Nasution et al. [41], was applied to ensure that the model achieved the best possible solution. Meanwhile, the FPA parameters were configured to optimize the centroid initialization through metaheuristic search. The step-size scaling factor  $\gamma = 1.2$ , Lévy index  $\lambda = 1.5$ , and switch probability  $p = 0.7$  were adopted following prior literature [39], [42], which reported stable convergence and a good balance between global exploration and local exploitation. This parameter configuration provided a reliable trade-off between clustering accuracy, convergence stability, and computational efficiency. The overall workflow of the hybrid FGWC–FPA optimization process is summarized in Algorithm 1, which describes the integration of the Flower Pollination Algorithm for optimizing centroid initialization and updating within the FGWC clustering framework.

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### Algorithm 1. Hybrid Optimization of FGWC using the Flower Pollination Algorithm (FPA)

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Input: Dataset X, spatial distance matrix D, population matrix P, number of clusters C, fuzzifier

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exponent  $m$ , weights  $\alpha$  and  $\beta$ , spatial weighting constant  $a$ , spatial decay coefficient  $b$ , error tolerance  $\varepsilon$ , maximum iteration  $\text{maxIter}$ , number of flowers  $n_x$ , switch probability  $p$ , step-size factor  $\gamma$ , Lévy index  $\lambda$ , and shift  $\delta$ .

Output: Optimized centroids  $V_{\text{opt}}$ , final membership matrix  $\mu_{\text{opt}}$ , minimum objective function value  $f_{\text{opt}}$ , and cluster validity indices (PC, CE, SC, S, XB, IFV).

1. Initialize a set of flower populations  $V = \{v_1, v_2, \dots, v_{n_x}\}$ .
2. For each flower  $v_k$ , compute the initial fitness  $f_k$  using the FGWC objective function:

$$J_m = (V, K) = \sum_{i=1}^n \sum_{k=1}^c \frac{d^2(x_i, v_k)}{\sum_{r=1}^c \left( \frac{d(x_i, v_r)}{d(x_i, v_k)} \right)^{\frac{2}{m-1}}}$$

3. Identify the current global best centroid  $g = \text{argmin}(f_k)$ .
4. Set iteration counter  $t = 0$ .
5. While ( $t < \text{maxIter}$ ) and (convergence not reached):
  - $t \leftarrow t + 1$
  - For each flower  $v_k$ :
    - Generate random number  $r \in [0, 1]$ .
    - If ( $r < p$ ): perform global pollination using Lévy flight:
 
$$v_k(t+1) = v_v(t) + \gamma \times L(\lambda) \times (g - v_k(t))$$
    - Else: perform local pollination:
 select  $v_i$  and  $v_j$  randomly, then update centroid:
 
$$v_k(t+1) = v_k + \varepsilon \times (v_i - v_j)$$
  - Update fuzzy memberships and spatial weighting as:
 
$$u_{ij} = \left[ \sum_{r=1}^c \left( \frac{d(x_i, v_j)}{d(x_i, v_r)} \right)^{\frac{2}{m-1}} \right]^{-1}$$

$$\mu'_{ij} = \alpha \mu_{ij} + \beta \sum_p \omega_{ip} \mu_{pj}$$
- Evaluate  $J_m(V, X)$  and update global best  $g$  if improved.

6. Return optimized centroids  $V_{\text{opt}}$ , membership matrix  $\mu_{\text{opt}}$ , objective value  $f_{\text{opt}}$ , and CVI.

### 3. RESULTS AND DISCUSSION

This section presents the results of the geospatial model optimization for mapping social vulnerability to natural disasters in Indonesia using the integration of FGWC and FPA. The proposed FGWC–FPA approach produced the most optimal clustering outcome, enabling a more accurate representation of social vulnerability distribution at the district level. The analysis focused on grouping regions based on relevant socio-economic indicators to identify critical issues within each cluster. The clustering process was carried out using the previously tuned FGWC and FPA parameters described in the previous section, with the number of clusters tested between two and four. The evaluation results indicated that the optimal configuration produced four distinct clusters, which effectively captured the variation in social vulnerability across regions. This hybrid approach not only improves the accuracy of the model but also reinforces the spatial analytical foundation for supporting the formulation of disaster mitigation policies.

Table 1. Cluster Validity Evaluation for Optimal Cluster Determination

| Cluster | PC             | CE             | SC             | S              | IFV            | XB             |
|---------|----------------|----------------|----------------|----------------|----------------|----------------|
| 2       | <b>0.56241</b> | <b>0.62735</b> | 6.51892        | 2.14567        | 0.55329        | 11.9846        |
| 3       | 0.46137        | 0.91264        | 2.53488        | <b>2.04835</b> | 3.47215        | 9.94281        |
| 4       | 0.35112        | 1.18623        | <b>1.68845</b> | 3.82694        | <b>7.09451</b> | <b>8.21974</b> |

The results of the cluster evaluation in Table 2 show differences in performance between validation indicators. The highest PC and lowest CE values are found in two clusters, indicating a fairly clear membership distribution in a simple scenario. However, the main advantage is seen in four clusters because they have the lowest SC, highest IFV, and lowest XB, thus indicating clearer cluster boundaries, better clarity of fuzzy distribution, and more optimal spatial separation quality. Based on this combination of indicators, four clusters are declared as the most optimal number to describe social vulnerability in this study.

Table 1. Cluster Center Social Vulnerability

| Cluster | X1           | X2           | X3           | X4           | X5           | X6          | X7           | X8          | X9           | X10         |
|---------|--------------|--------------|--------------|--------------|--------------|-------------|--------------|-------------|--------------|-------------|
| 1       | <b>9.60</b>  | 49.49        | 4.49         | 14.01        | <b>4.00</b>  | <b>7.05</b> | 33.58        | 1.40        | <b>13.91</b> | <b>8.83</b> |
| 2       | 9.06         | <b>49.63</b> | 4.22         | <b>15.81</b> | 3.92         | 2.90        | 24.24        | <b>1.57</b> | 8.79         | 5.94        |
| 3       | 9.50         | 49.50        | 4.65         | 14.06        | 3.97         | 6.31        | <b>33.87</b> | 1.36        | 13.56        | 8.62        |
| 4       | 9.45         | 49.50        | <b>4.70</b>  | 14.08        | 3.95         | 5.83        | 33.69        | 1.36        | 13.12        | 8.39        |
| Cluster | X11          | X12          | X13          | X14          | X15          | X16         | X17          | X18         | X19          |             |
| 1       | 98.63        | <b>92.14</b> | 6.00         | <b>20.65</b> | 15.13        | 6.57        | 6.68         | 6.59        | <b>19.21</b> |             |
| 2       | 97.36        | 90.90        | <b>16.38</b> | 8.55         | <b>47.22</b> | <b>7.33</b> | 6.52         | 6.41        | 33.45        |             |
| 3       | <b>98.67</b> | 91.31        | 5.89         | 19.01        | 14.62        | 6.44        | 6.55         | 6.44        | 19.49        |             |
| 4       | 98.66        | 91.60        | 6.10         | 18.03        | 15.01        | 6.41        | <b>6.71</b>  | <b>7.25</b> | 20.33        |             |

An examination of Table 3 reveals clear distinctions in the social vulnerability characteristics of each cluster. Clusters exhibiting the highest average values for specific variables reflect the dominance of vulnerability factors associated with those indicators in the respective districts. The bold values highlight the primary dimensions contributing to the heightened vulnerability within each cluster. These findings suggest that identifying the most vulnerable cluster is not straightforward, as each cluster demonstrates distinct vulnerability patterns shaped by diverse social, demographic, and economic conditions. The novelty of this study lies in the application of Fuzzy Geographically Weighted Clustering (FGWC) optimized with the Flower Pollination Algorithm (FPA), which improves the capacity to capture spatial heterogeneity and uncover nuanced vulnerability profiles.

Based on the evaluation results, the optimal number of clusters was set at four groups. Figure 3 shows the results of social vulnerability mapping using the FGWC method optimized with FPA. These clustering results divide Indonesia into four groups with different vulnerability characteristics. Cluster 1 (red, 114 districts) is dominated by areas with relatively high vulnerability levels, spread across most of Papua, Maluku, Sulawesi, central Kalimantan, and parts of Sumatra. Cluster 2 (blue, 79 districts) represents areas with distinctive vulnerability patterns in North Kalimantan and East Kalimantan. Cluster 3 (light green, 87 districts) shows areas with moderate vulnerability, spread across several regions of Java, Nusa Tenggara, and parts of Sulawesi. Cluster 4 (dark green, 234 districts) is a group with relatively lower vulnerability, dominating the regions of Java, Bali, most of West and South Kalimantan, and several areas in Sumatra.

Cluster 1 is a group of regions with the most prominent social vulnerability characteristics. Based on the average values of the indicators used, the districts/cities included in this cluster exhibit various complex social problems. One of the main characteristics is the high percentage of residents under the age of five, which reflects a high demographic dependency burden and an urgent need for basic services such as maternal and child health and early childhood education. In addition, the average number of family members in a household is relatively large, which may indicate a higher economic burden and limited household capacity to cope with disaster risks. This cluster is also characterized by a high proportion of households without access to electricity, reflecting weak basic infrastructure and low levels of regional development. The high poverty rate in this group is also a significant factor that reinforces the social vulnerability of the community, as it directly affects their ability to survive and recover from disasters. In terms of education, the high

percentage of people who cannot read and write indicates a major obstacle to the dissemination of disaster information and a low level of community preparedness.

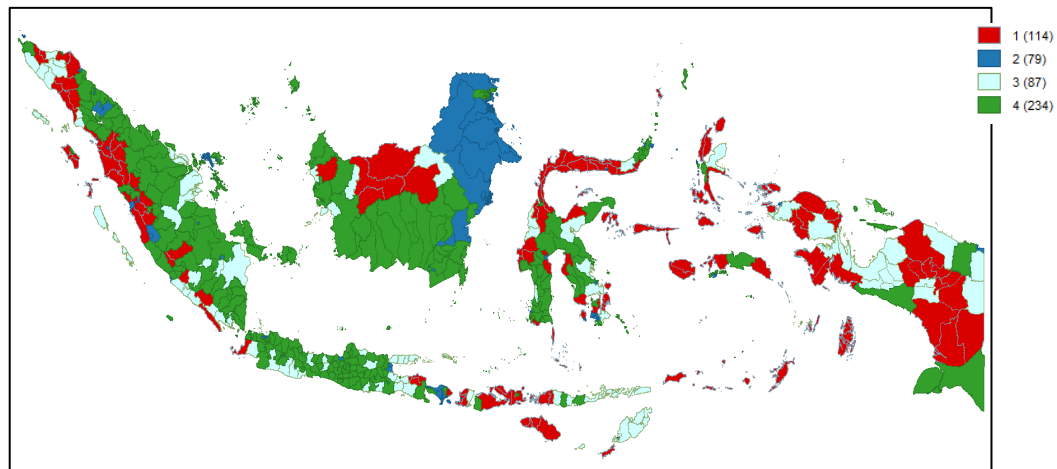


Figure 3. Spatial distribution of social vulnerability in Indonesia generated using the hybrid FGWC–FPA

Furthermore, areas in Cluster 1 also show a high percentage of households living in disaster-prone areas, such as coastal areas, steep slopes, and seasonal flood areas, which increase physical exposure to natural hazards. In addition, the low access to clean water, as reflected in the high percentage of households that do not use piped water, indicates weak sanitation and environmental health services, which can exacerbate the post-disaster impact. Geographically, Cluster 1 is spread across eastern Indonesia, including most of Papua, Maluku, Nusa Tenggara, and several inland areas in Kalimantan, Sulawesi, and the west coast of Sumatra. The high level of social vulnerability in these areas is influenced by low socioeconomic status, limited infrastructure, and unequal access to resources. In addition, geographical constraints are also an important factor that exacerbates the level of social vulnerability in these regions. Areas such as the Central Highlands of Papua and remote islands face major obstacles in terms of accessibility and communication, which have an impact on the slow distribution of aid and difficulties in disaster management. Therefore, it is necessary to allocate special attention and resources to reduce social vulnerability and improve disaster preparedness in regions included in Cluster 1. A multisectoral policy approach that combines social, economic, and infrastructure development is essential to improve community resilience in the long term.

Cluster 2 represents a group of regions with complex social vulnerability linked to demographic dynamics and household socioeconomic instability. These areas are characterized by a high proportion of women and female-headed households, which often indicates gender-related inequalities in access to resources, economic opportunities, and decision-making power. Such conditions make female-headed households particularly vulnerable during disasters due to limited mobility and weaker social safety nets. In addition, high population growth rates in this cluster create increasing pressure on the availability of infrastructure, public facilities, and essential services. Without balanced development, this rapid growth can exacerbate poverty, housing shortages, and disaster exposure. A notable characteristic of Cluster 2 is the high percentage of tenant households, reflecting limited asset ownership and economic insecurity. These households tend to have lower adaptability and higher mobility, making recovery after disasters more challenging. The lack of proper drainage systems further increases exposure to hydrometeorological hazards such as floods and waterlogging, while poor sanitation conditions threaten public health. Economically, the relatively high unemployment rate within this cluster signifies low household productivity and dependence on informal or precarious livelihoods.

Cluster 3 describes areas with social vulnerability closely related to education and community preparedness for disasters. The main characteristic of this cluster is the high percentage of residents with low levels of education, indicating limited access to formal education at both the primary and secondary levels. Low education is one of the factors that hinders the development of

community awareness, understanding, and skills in dealing with disaster risks effectively. This also has implications for limited employment opportunities, income, and participation in community decision-making processes. In addition, areas in Cluster 3 also show a high percentage of residents who have never received disaster response training, either formally from government agencies or through community-based training programs. This condition indicates a weak disaster education system and a lack of community capacity building activities in dealing with and responding to disasters. Low participation in emergency response training has the potential to reduce community preparedness, increase the risk of casualties, and slow down the evacuation and recovery process when a disaster occurs.

Cluster 4 is characterized by social vulnerability strongly associated with health conditions, aging populations, and disability. Regions in this cluster have a high proportion of elderly residents (>65 years) and people with disabilities, reflecting demographic dependency and limited physical mobility that heighten disaster risk. These groups often face challenges in accessing disaster information and emergency services, particularly when reliant on technology-based communication. In addition, the high prevalence of chronic diseases such as hypertension, diabetes, and respiratory disorders further amplifies vulnerability during disruptions to health and evacuation systems. Geographically, Cluster 4 includes both urban areas with aging populations and rural regions affected by youth out-migration, leading to limited local workforce and declining social support. This demographic structure necessitates health-centered and inclusive disaster management policies, including accessible infrastructure, community-based healthcare strengthening, and tailored disaster education for elderly and disabled populations. Without such interventions, these areas remain at risk of more severe disaster impacts and slower recovery compared to other clusters.

Furthermore, the high prevalence of chronic diseases in these clusters is also an important indicator of the vulnerable health conditions of the community. Chronic diseases such as hypertension, diabetes, or lung disease not only limit individuals' daily activities, but also increase the risk of serious complications in disaster situations that disrupt access to medical services, medicines, and other support systems. The geographical distribution of Cluster 4 is generally in areas with aging populations, both in urban areas experiencing demographic stagnation and in rural areas with high out-migration rates. These areas require special attention in the form of policies to protect vulnerable groups, strengthening community-based health care systems, and providing infrastructure and disaster planning that is friendly to the elderly and people with disabilities. Therefore, it is important for policymakers to design inclusive and health-based disaster mitigation strategies, including strengthening medical evacuation systems, building shelters that are accessible to people with disabilities, and developing disaster education programs that are adaptive to older age groups. Without proper intervention, areas in Cluster 4 are at risk of experiencing more severe disaster impacts and slower recovery than other areas.

Overall, the four cluster typology produced by the FGWC-FPA reflects the multidimensional nature of social vulnerability across Indonesia, encompassing variations in socio-economic, demographic, and health related conditions. To further validate these clustering results and assess their consistency with national disaster risk assessments, a comparison was conducted with the Indonesian Disaster Risk Index (IRBI) 2024 [43]. The IRBI integrates three primary components hazard, vulnerability, and capacity to evaluate disaster risk levels across all provinces and districts in Indonesia. The IRBI report shows that Indonesia ranks second globally in disaster risk, with 29.4% of districts categorized as high risk and 70.6% as medium risk. High-risk provinces are concentrated in Maluku, Sulawesi, Sumatra, and Papua, while provinces in Java, Bali, Kalimantan, and Nusa Tenggara are mostly in the medium-risk category. The spatial pattern of high vulnerability regions identified by the FGWC-FPA aligns with the high-risk zones reported in the IRBI, particularly across eastern Indonesia and several coastal areas. Cluster 1 of the FGWC-FPA covering 114 districts, primarily in Papua, Maluku, and parts of Sulawesi corresponds to provinces with consistently high IRBI scores. Meanwhile, clusters with lower vulnerability (Clusters 3 and 4) largely overlap with provinces identified by the IRBI as having medium risk,

such as Java, Bali, and West Kalimantan. This spatial correspondence confirms the consistency between the hybrid clustering framework and the official national disaster risk assessment.

However, unlike the IRBI, which relies on deterministic index aggregation and assumes uniform spatial influence, the FGWC–FPA offers several methodological advantages. By integrating fuzzy membership functions and geographically weighted clustering, it accounts for local variations and overlapping socio-economic conditions that are often obscured in index-based assessments. The inclusion of the Flower Pollination Algorithm (FPA) further enhances centroid optimization, improving convergence stability and reducing subjectivity in parameter weighting. In addition, the FGWC–FPA framework enables the identification of distinct socio-economic and demographic issues within each cluster such as high dependency ratios, gender-based vulnerability, or educational disparities that cannot be explicitly captured through index-based approaches. This ability to reveal underlying social and spatial structures provides deeper diagnostic insights, as also highlighted by previous studies [34], [41]. Consequently, the FGWC–FPA approach not only validates but also extends the national assessment framework by offering a more data-driven, spatially adaptive, and fine-grained representation of social vulnerability across Indonesia. These improvements make the model particularly valuable for regional disaster management planning, where localized differentiation is essential for prioritizing interventions and optimizing resource allocation.

To ensure that the findings have practical implications for national disaster management, the clustering results were further interpreted within the framework of Indonesia's Rencana Induk Penanggulangan Bencana (RIPB) 2020–2044. The RIPB emphasizes four strategic pillars: risk governance, resilience of communities and infrastructure, knowledge management, and investment prioritization for risk reduction. In this context, the four-cluster typology generated by the FGWC–FPA model can serve as an evidence-based reference for prioritizing regional funding and policy interventions in line with RIPB objectives. Cluster 1 characterized by high poverty, poor infrastructure, and limited accessibility should become the primary focus of integrated poverty alleviation, basic service improvement, and infrastructure development programs. Cluster 2, dominated by gender-related and economic vulnerabilities, requires gender-responsive disaster management policies, social protection for female-headed households, and employment diversification initiatives. Cluster 3 highlights the importance of strengthening disaster literacy and inclusive education programs, while Cluster 4 underscores the need for health-based and elderly-inclusive disaster preparedness systems. Accordingly, the FGWC–FPA clustering results provide actionable insights for operationalizing the RIPB 2020–2044 by aligning regional disaster risk management strategies with the specific vulnerability profiles of each cluster. This approach ensures that national investment and mitigation programs are directed toward the most socially and spatially vulnerable regions, thereby enhancing the effectiveness of disaster risk governance in Indonesia.

#### 4. CONCLUSION

This study emphasizes the importance of social vulnerability mapping as a strategic foundation for regional planning and disaster risk management. By integrating FGWC algorithm with FPA, this research successfully identified four optimal clusters that describe the spatial distribution of social vulnerability across Indonesia. The hybrid FGWC–FPA model demonstrated its advantage in capturing spatial variations and local heterogeneity, producing more detailed and adaptive vulnerability patterns compared to index based approaches. The results reveal that each district exhibits distinct social vulnerability characteristics. Cluster 1, covering areas in Papua, Maluku, Nusa Tenggara, and several regions in Sumatra and Kalimantan, shows the highest level of vulnerability, driven by poverty, weak infrastructure, and low literacy rates. Clusters 2 to 4 highlight diverse forms of vulnerability, including gender inequality, demographic dependency, limited preparedness, and health-related risks. These findings are consistent with the Indonesian Disaster Risk Index (IRBI) 2024, particularly in identifying high-risk areas, while providing finer spatial insights that can complement national-scale assessments. From a policy perspective, the four-cluster typology offers actionable evidence to support the implementation of the National Disaster Management Master Plan (RIPB) 2020–2044, particularly in prioritizing regional funding,

capacity-building, and inclusive disaster mitigation programs. Regular updates and applications of this model at finer spatial scales are essential to enhance Indonesia's disaster preparedness, promote equitable development, and strengthen national resilience against future hazards.

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