

# A Spatial Analysis-Based PSI Model for Post-Crisis Social Vulnerability Mitigation Priorities

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## ABSTRACT

Post-crisis social vulnerability is a crucial factor influencing a region's ability to face, respond to, and recover from a disaster. Differences in socioeconomic conditions, access to basic services, demographic characteristics, and adaptive capacity cause variations in the level of social vulnerability between regions. This study aims to develop a social vulnerability mitigation priority model in Medan City by integrating the Preference Selection Index (PSI) method with a sub-district-based spatial analysis approach. The study used 21 sub-districts in Medan City as decision alternatives evaluated based on seven criteria: economic vulnerability, disruption of access to basic services, post-crisis social impacts, demographic vulnerability, community social capital, community recovery capacity, and institutional and mitigation support. Research data were obtained through questionnaires and then aggregated into a decision matrix for the PSI calculation process. The PSI method was used to objectively generate criteria weights and obtain preference index values for each region. Next, the preference index values were transformed into a mitigation priority index using the inverse approach  $PM_i = 1 - \theta_i$ , where a higher PM value indicates a greater need for mitigation interventions. The results of the study indicate that Medan Belawan District has the highest mitigation priority with a PSI value of 0.5556 and a PM value of 0.4444, followed by Medan Labuhan District with a PSI value of 0.5986 and a PM value of 0.4014, and Medan Marelan District with a PSI value of 0.6253 and a PM value of 0.3747. These results indicate that the integration of the PSI method and spatial analysis is able to produce a data-based decision support model to identify priority areas for mitigating social vulnerability more objectively and systematically.

**Keyword :** Social Vulnerability; Preference Selection Index (PSI); Administrative Spatial Analysis; Social Vulnerability Mitigation Priority; Multi-Criteria Decision Making (MCDM).

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## 1. INTRODUCTION

Natural disasters are one of the major factors affecting regional development sustainability because their impacts are not limited to physical damage but also disrupt social conditions, economic activities, and community recovery capacity. In urban contexts, disaster risks become increasingly complex due to population density growth, land-use changes, urbanization, and community dependence on basic service systems. Therefore, disaster impacts are not only determined by hazard characteristics but are also influenced by the level of social vulnerability experienced by exposed communities (Builes-Jaramillo et al., 2025; Martins et al., 2024; Xu et al., 2024).

Social vulnerability describes the condition of a community group that causes differences in its ability to cope with, respond to, and recover from disaster impacts. This concept is generally influenced by several major dimensions, including exposure, socioeconomic sensitivity, and adaptive and recovery capacity (Arunachalam et al., 2023; Lapietra et al., 2023; Painter et al., 2024). Communities with limited economic resources, inadequate access to basic services, low education levels, and weak institutional capacity tend to experience greater impacts when disasters occur. Therefore, modern disaster risk reduction approaches do not only focus on controlling physical hazards but also require an understanding of the social characteristics of affected communities (Arunachalam et al., 2023; Lapietra et al., 2023; Painter et al., 2024).

Floods are one of the hydrometeorological disasters that have significant impacts on urban areas. Increasing flood frequency due to climate change and urban development pressures has led to a growing need for more adaptive and region-based mitigation strategies. Studies on social vulnerability caused by floods indicate that integrating socioeconomic indicators with spatial approaches can provide a more comprehensive understanding of the distribution of communities with high vulnerability levels (Ajtai et al., 2023; Rogers et al., 2025; Roldán-Valcarce et al., 2023). An administrative region-based approach enables the analysis of differences in social vulnerability characteristics between areas, allowing decision-makers to identify districts requiring more appropriate interventions (Chelariu et al., 2024; Guerrero et al., 2023; Lapietra et al., 2024).

Medan City, as one of the largest urban centers in Indonesia, has regional characteristics that face various challenges related to flood risks. Urban growth, population density, land-use changes, and differences in socioeconomic conditions between areas cause disaster impacts to be distributed unevenly. Each district has different social characteristics and recovery capacities, making general mitigation approaches less effective in determining priority areas. Therefore, an analytical model is required that can consider variations in social conditions between regions through a spatial perspective.

Previous studies have developed Social Vulnerability Index (SoVI) approaches to identify areas with high levels of social risk. However, most studies have focused on measuring or mapping vulnerability levels without providing decision-making mechanisms regarding which areas should be prioritized for mitigation interventions (Batista & Passini, 2023; Kalaycioğlu et al., 2023). Vulnerability mapping only provides information regarding risk distribution but does not directly address the practical needs of governments in allocating mitigation resources effectively.

These challenges indicate that social vulnerability analysis requires a decision-making approach capable of integrating multiple indicators with different characteristics. Multi-Criteria Decision Making (MCDM) methods have been widely applied in disaster-related studies because they can combine social, economic, environmental, and regional capacity factors within a single decision evaluation framework (Li et al., 2025; Yahia Meddah et al., 2023). The integration of Geographic Information Systems (GIS) and MCDM methods has been proven to provide more supportive spatial information for mitigation planning because it not only identifies risk locations but also determines priorities based on multiple simultaneously considered criteria (Lin et al., 2026; Yılmaz & Alemdar, 2025).

One MCDM method that can be applied for priority determination is the Preference Selection Index (PSI). The PSI method is characterized by objective criterion weighting based on information contained in the decision matrix without requiring pairwise comparison processes from experts, as used in the Analytical Hierarchy Process (AHP). This approach reduces subjectivity in determining criterion weights and produces a more data-driven ranking process (Mai, 2025; Obeidat et al., 2025). In the context of disaster mitigation, the PSI method can be used to evaluate multiple regions based on several social vulnerability indicators, thereby generating a priority sequence of areas requiring greater attention.

Based on these studies, two research gaps are identified as the foundation of this research. First, previous studies on social vulnerability based on spatial approaches have mostly focused on vulnerability mapping without integrating mechanisms for determining mitigation priorities. Second, decision-making approaches in disaster mitigation often apply expert-based weighting methods that may introduce subjectivity. Therefore, a model is required that integrates spatial analysis with objective weighting methods to produce data-driven mitigation priorities.

This study aims to develop a PSI-Based Spatial Analysis Model for Post-Crisis Social Vulnerability Mitigation Priorities in Medan City. The developed model uses districts as spatial analysis units and socioeconomic indicators as evaluation criteria in the PSI method. The contribution of this study is to provide a data-driven decision support approach capable of objectively identifying priority mitigation areas through the integration of district-based spatial analysis and the MCDM method. The results are expected to support local governments in developing mitigation strategies that are more targeted, effective, and aligned with the social characteristics of each region.

## 2. RESEARCH METHOD

### 2.1 Research stages

This study employs a quantitative approach by integrating spatial analysis based on sub-district administrative boundaries with the Multi-Criteria Decision Making (MCDM) method, specifically the

Preference Selection Index (PSI). This approach is used to develop a decision-support model for prioritizing areas for post-crisis social vulnerability mitigation.

The research process comprises several key stages: problem identification, a literature review, the determination of social vulnerability indicators, primary data collection via community questionnaires, and the processing of sub-district-level data. The research stages are illustrated in Figure 1.

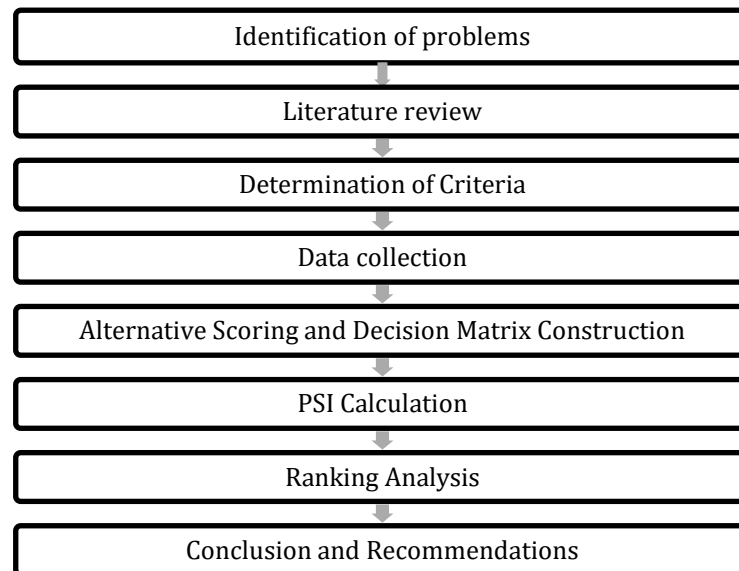


Figure 1. Research Flow of the Spatial Analysis-Based PSI Model for Post-Crisis Social Vulnerability Mitigation Priorities

The research process began with identifying issues related to the distribution of social vulnerability due to urban disaster risk. A literature review was then conducted to determine relevant indicators for measuring social vulnerability. Indicator data was then collected and processed based on sub-districts in Medan City.

Each sub-district served as a decision alternative, evaluated against several social vulnerability criteria. The data was then analyzed using the Social and Infrastructure Assessment (PSI) method to generate objective weights for each criterion and determine priority rankings for mitigation areas.

## 2.2 Research Location and Data Source

The research was conducted in the administrative area of Medan City, North Sumatra Province. Medan City was chosen as the research location due to its urban characteristics with a high level of social complexity and the risk of various disasters, particularly flooding caused by hydrometeorological factors.

Primary data for the study were obtained through questionnaires distributed to residents living in the study area. Respondents were selected because they had direct experience with social and economic conditions, access to basic services, and the characteristics of their residential environments. Community assessments were used to describe the level of social vulnerability in each sub-district in Medan City.

The research instrument used a five-level Likert scale with a range of values from 1 to 5. Each respondent provided an assessment of seven predetermined indicators of social vulnerability. The results of all respondents' assessments in each sub-district were then calculated using the average value to produce an evaluation score for each criterion, which was used as a decision matrix for the PSI method.

The study involved 420 residents spread across 21 sub-districts in Medan City. Each sub-district received a relatively balanced number of respondents, 20, to provide a representative picture of social conditions across regions. Respondents were distributed based on sub-district, taking into account community representation in each study area. Respondents were residents of the sub-district and experienced the social conditions of their neighborhoods.

The research analysis unit was 21 sub-districts in Medan City, which were used as decision alternatives in the Preference Selection Index (PSI) method. The selection of sub-districts as spatial units aimed to illustrate variations in levels of social vulnerability across regions based on community perceptions within each sub-district. Each sub-district received an evaluation score based on the aggregated results of respondents' assessments of social vulnerability indicators.

### 2.3 Preference Selection Index Method

The Preference Selection Index (PSI) method is an objective Multicriteria Decision-Making (MCDM) method used to determine the most preferred alternative based on several evaluation criteria. In this study, each criterion is categorized based on its attribute characteristics, namely cost and benefit. The cost criterion is used for indicators indicating the level of social vulnerability, while the benefit criterion is used for indicators indicating the community's capacity to face and recover from the impact of a crisis.

The PSI method was chosen in this study because it can objectively determine criterion weights without requiring pairwise comparisons or subjective expert judgment. The weights for each criterion are obtained based on information contained in the decision matrix through stages of data normalization, calculation of average values, preference variations, deviation values, and determination of the final weights for each criterion. This approach allows the ranking of regional alternatives to be based on the data characteristics obtained from each evaluation criterion, rather than on the subjective preferences of decision-makers. In this study, the decision matrix was constructed based on the aggregation of questionnaire data from each regional alternative. Each row of the matrix represents a sub-district, while each column shows the social vulnerability indicator values obtained from respondents' measurements. The PSI method was used to process social vulnerability evaluation scores in 21 sub-districts in Medan City into a regional preference index, which reflects the relative performance of each alternative based on a combination of social vulnerability indicators and recovery capacity. These preference index values were then transformed into a mitigation priority index to identify areas requiring greater mitigation intervention.

The following are the calculation steps that apply the PSI method (Amin et al., 2021; Amrullah et al., 2025; Huu-Phan et al., 2019; Minglin & Ren, 2022; Obeidat & Traini, 2020; Pon Bharathi et al., 2022; Puspitasari et al., 2020; Tien et al., 2021), namely:

- Define the problem: define the objectives and identify the attributes and alternatives involved in the decision-making problem.
- Formulate the decision matrix: this step involves creating a matrix based on all available information describing the attributes of the problem. Each row of the decision matrix is allocated to one alternative and each column to one attribute. Therefore, the elements  $X_{ij}$  of the decision matrix  $X$  assign the attribute values to their original values. Thus, if the number of alternatives is  $M$  and the number of attributes is  $N$ , then the decision matrix as an  $NM$  matrix can be represented as (1).

$$X_{ij} = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1n} \\ X_{21} & X_{22} & \dots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (1)$$

- Normalization of decision matrix: if the attribute is typebenefits then the larger value is desired which can be normalized as (2):

$$R_{ij} = \frac{x_{ij}}{x_j^{max}} \quad (2)$$

If the attribute is typecost then a smaller value is desired which can be normalized as (3).

$$R_{ij} = \frac{x_j^{min}}{x_{ij}} \quad (3)$$

Where  $X_{ij}$  is the attribute size ( $i=1, 2, \dots, N$  and  $j=1, 2, \dots, M$ ).

- Calculating the average value of the normalized data: in this step, the normalized data value for each attribute is calculated by (4).

$$N = \frac{1}{n} \sum_{i=1}^n R_{ij} \quad (4)$$

- Calculate the value of perception variation: in this step, the value of preference variation between the values of each attribute is calculated using (5).

$$\phi_j = \sum_{i=1}^n [R_{ij} - N_j]^2 \quad (5)$$

- Determine the deviation in preference values

$$\Omega_j = 1 - \phi_j \quad (6)$$

- Determine the weight of the criteria

$$W_j = \frac{\Omega_j}{\sum_{j=1}^m \Omega_j} \quad (7)$$

The total value of all criteria for the weight of all attributes must be one, for example  $\sum_{j=1}^m \Omega_j$ .

- Calculate PSI: to select the preference index for each alternative, use (8).

$$\theta_i = \sum_{j=1}^m R_{ij} W_j \quad (8)$$

- Select the appropriate alternative for the given application.

#### 2.4. Analisis sistem

The systems analysis in this study was conducted using the Preference Selection Index (PSI) method to evaluate and rank priority areas for post-crisis social vulnerability mitigation in Medan City. The analysis used data from 21 sub-districts as decision-making alternatives, evaluated based on seven social vulnerability criteria: economic vulnerability, disruption of access to basic services, post-crisis social impacts, demographic vulnerability, community social capital, community recovery capacity, and institutional support and mitigation.

These criteria were determined based on the concept of social vulnerability, which encompasses aspects of community sensitivity and adaptive capacity in facing and recovering from the impact of the crisis. Each criterion was categorized based on its characteristics, namely cost and benefit attributes. The cost criterion indicates that a higher value indicates a greater level of vulnerability and therefore needs to be minimized, while the benefit criterion indicates that a higher value indicates a greater regional recovery capacity.

Data from each sub-district was then converted and compiled into a decision matrix as the basis for applying the PSI method. The analysis process consisted of matrix normalization, calculation of preference variation, objective determination of criterion weights, and calculation of the final preference index value. The PSI calculation results in a preference index value that reflects the relative performance of each sub-district based on a combination of social vulnerability and recovery capacity criteria. Because a higher PSI value indicates a relatively better regional condition, this value is then transformed into a mitigation priority index using the inverse approach, i.e.,  $PM_i = 1 - \theta_i$ . A higher mitigation priority value indicates a greater need for intervention. This approach allows the PSI results to be translated into decision-making information that aligns with the research objective, namely identifying areas requiring priority social vulnerability mitigation.

The values in Table 2 are obtained from the aggregation of respondents' responses to seven social vulnerability indicators. Each indicator is scored on a five-level Likert scale, and then all respondents' scores in each sub-district are calculated using the average value, resulting in an initial evaluation value used as the PSI decision matrix.

Table 1. PSI Priority Criteria for Mitigating Post-Crisis Social Vulnerability

| Code | Criteria                  | Questionnaire Indicator                                         | Type    |
|------|---------------------------|-----------------------------------------------------------------|---------|
| C1   | Economic Vulnerability    | Income, poverty, and economic dependency                        | Cost    |
| C2   | Access to Basic Services  | Ease of access to health care, education, and public facilities | Cost    |
| C3   | Post-Crisis Social Impact | Disruption of social activities and vulnerable groups           | Cost    |
| C4   | Demographic Vulnerability | Population density and vulnerable groups                        | Cost    |
| C5   | Social Capital            | Mutual cooperation and social networks                          | Benefit |

|    |                       |                                            |         |
|----|-----------------------|--------------------------------------------|---------|
| C6 | Recovery Capacity     | Community recovery after a crisis          | Benefit |
| C7 | Institutional Support | The role of government/mitigation agencies | Benefit |

The validity of the evaluation criteria in this study was strengthened through alignment with the concept of social vulnerability and the disaster risk reduction framework. Economic vulnerability is used to describe the condition of communities with limited resources in facing the impacts of a crisis, such as poverty levels, economic dependency, and household economic recovery capacity. Disruption of access to basic services reflects the community's limitations in obtaining essential needs such as healthcare, education, basic infrastructure, and public facilities after a crisis. Before being used in primary data collection, the questionnaire instrument was evaluated to ensure its suitability with the research objectives. Questions were formulated based on seven predetermined dimensions of social vulnerability so that each item adequately represented the social conditions of the community in the study area.

Post-crisis social impact is used to measure changes in community social conditions due to disaster disruptions, including disruptions to social activities, an increase in vulnerable groups, and weakened community functions. Demographic vulnerability describes population characteristics that can increase social risks, such as population density, vulnerable age groups, and community social structure. Meanwhile, community social capital, community recovery capacity, and institutional and mitigation support are used as indicators of regional capacity to face and mitigate the impact of a crisis.

The recovery capacity criterion is categorized as a benefit attribute because a higher value indicates a region's greater ability to adapt and recover. Conversely, the criterion describing vulnerability conditions is categorized as a cost attribute because an increase in the value indicates a greater level of social risk. Thus, these seven criteria are able to represent the relationship between the level of community sensitivity and the region's adaptive capacity in determining post-crisis social vulnerability mitigation priorities. Below, you can see the results of the data that has been converted using the initial normalization score based on the indicator index and the initial average data in Table 2. The values in Table 2 are the results of the aggregation of questionnaire scores from all respondents in each sub-district. These values are then converted into average indicator values used as a decision matrix in the PSI method.

Table 2. Initial Score of Social Vulnerability Criteria Evaluation in Sub-districts in Medan City

| No | District         | C1  | C2  | C3  | C4  | C5  | C6  | C7  | Avg  |
|----|------------------|-----|-----|-----|-----|-----|-----|-----|------|
| 1  | Medan Belawan    | 4.8 | 4.7 | 4.9 | 4.5 | 2.3 | 2.4 | 2.5 | 3.73 |
| 2  | Medan Labuhan    | 4.6 | 4.5 | 4.7 | 4.3 | 2.6 | 2.7 | 2.8 | 3.74 |
| 3  | Medan Marelán    | 4.5 | 4.4 | 4.6 | 4.2 | 2.8 | 2.9 | 3.  | 3.77 |
| 4  | Medan Deli       | 4.3 | 4.2 | 4.4 | 4.1 | 3.  | 3.1 | 3.2 | 3.76 |
| 5  | Medan Sunggal    | 3.9 | 3.8 | 4.  | 3.7 | 3.4 | 3.5 | 3.6 | 3.7  |
| 6  | Medan Helvetia   | 3.7 | 3.6 | 3.8 | 3.5 | 3.6 | 3.7 | 3.8 | 3.67 |
| 7  | Medan Tuntungan  | 2.9 | 3.  | 3.1 | 3.  | 4.2 | 4.1 | 4.3 | 3.51 |
| 8  | Medan Johor      | 3.3 | 3.4 | 3.5 | 3.2 | 3.9 | 3.8 | 4.  | 3.59 |
| 9  | Medan Amplas     | 3.8 | 3.7 | 3.9 | 3.6 | 3.5 | 3.6 | 3.7 | 3.69 |
| 10 | Medan Denai      | 4.  | 3.9 | 4.1 | 3.8 | 3.3 | 3.4 | 3.5 | 3.71 |
| 11 | Medan Area       | 3.9 | 4   | 4.1 | 3.7 | 3.4 | 3.3 | 3.5 | 3.7  |
| 12 | Medan Kota       | 3.2 | 3.3 | 3.4 | 3.1 | 4.  | 3.9 | 4.1 | 3.57 |
| 13 | Medan Maimun     | 3.6 | 3.7 | 3.8 | 3.5 | 3.7 | 3.6 | 3.8 | 3.67 |
| 14 | Medan Timur      | 3.5 | 3.4 | 3.6 | 3.3 | 3.8 | 3.9 | 4.  | 3.64 |
| 15 | Medan Perjuangan | 3.4 | 3.5 | 3.6 | 3.4 | 3.7 | 3.8 | 3.9 | 3.61 |
| 16 | Medan Tembung    | 3.6 | 3.5 | 3.7 | 3.6 | 3.6 | 3.7 | 3.8 | 3.64 |
| 17 | Medan Barat      | 3.8 | 3.9 | 4.  | 3.7 | 3.5 | 3.4 | 3.6 | 3.7  |
| 18 | Medan Petisah    | 2.8 | 2.9 | 3.  | 2.8 | 4.3 | 4.2 | 4.4 | 3.49 |
| 19 | Medan Baru       | 2.6 | 2.7 | 2.9 | 2.6 | 4.4 | 4.5 | 4.6 | 3.47 |
| 20 | Medan Polonia    | 2.7 | 2.8 | 3.  | 2.7 | 4.3 | 4.4 | 4.5 | 3.49 |
| 21 | Medan Selayang   | 3.  | 3.1 | 3.2 | 3.  | 4.1 | 4.  | 4.2 | 3.51 |

Figure 2 presents the distribution of initial social vulnerability scores across 21 sub-districts in Medan City before weighting using the Preference Selection Index (PSI) method. The horizontal axis

shows the initial evaluation score based on seven social vulnerability criteria, while the vertical axis shows the alternative regions, namely sub-districts, that were analyzed. This visualization provides an initial overview of the variation in social vulnerability characteristics between regions before objectively calculating criterion weights using the PSI method.

Observations indicate that each sub-district has distinct social vulnerability characteristics based on a combination of indicators of economic vulnerability, access to basic services, post-crisis social impacts, demographic conditions, social capital, recovery capacity, and institutional support. The initial scores reflect the characteristics of each sub-district based on the combination of vulnerability and recovery capacity indicators. Interpretation of vulnerability levels is not determined solely based on the initial average value, as each criterion has distinct cost and benefit attribute characteristics.

However, the initial scores cannot be used directly to determine mitigation priorities because each criterion has different levels of contribution and characteristics in the decision-making process. Therefore, the PSI method is applied to generate objective criterion weights based on the variation in information in the decision matrix. The resulting preference values are then transformed into a mitigation priority index to determine areas with greater intervention needs.

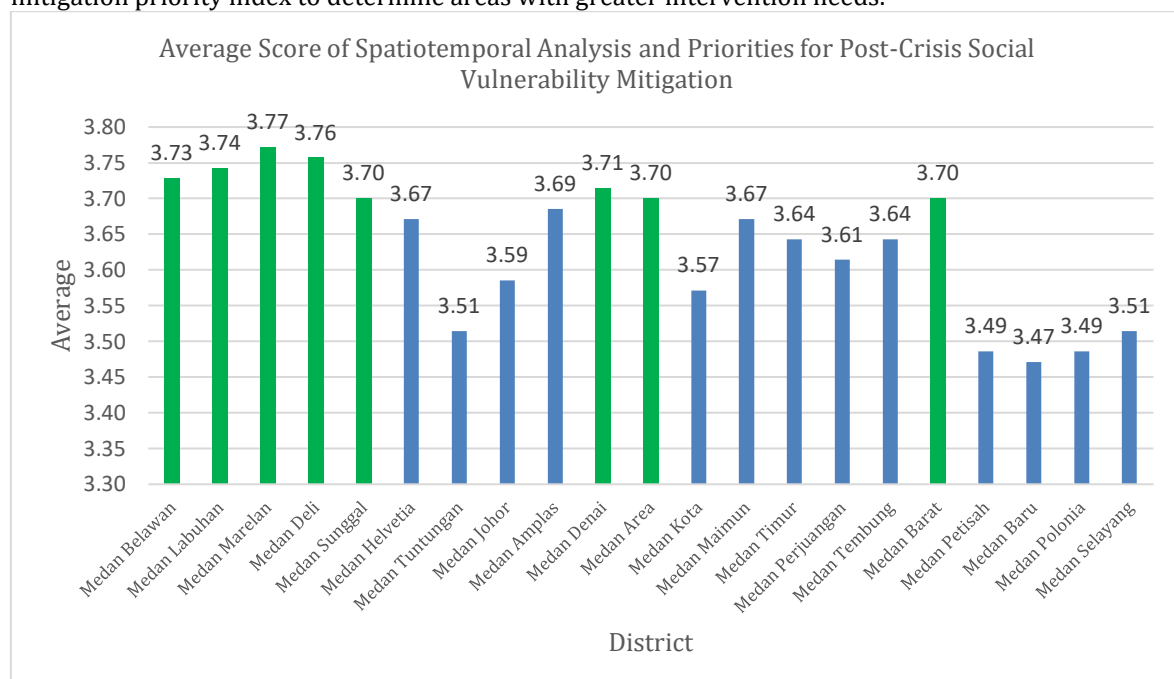


Figure 2. Distribution of Initial Scores of Social Vulnerability Evaluation of Sub-districts in Medan City

As shown in Figure 2, the initial evaluation scores indicate variations in social vulnerability levels across sub-districts in Medan City based on the seven criteria used in the study. These differences in scores illustrate that each region has different social, economic, and demographic characteristics, as well as recovery capacity to deal with the potential impacts of the crisis. Some sub-districts exhibit relatively higher social vulnerability scores due to a more dominant combination of vulnerability factors, while others are relatively better off due to stronger adaptive capacity and institutional support.

These initial scores provide a descriptive overview of the initial conditions of each region before the weighting process using the PSI method. However, the initial average score cannot be used as the primary basis for determining mitigation priorities because each criterion has a different level of importance and varying information. Therefore, the PSI method was applied to objectively calculate the weights for each criterion based on a decision matrix, resulting in a more accurate and data-driven final ranking of priority mitigation areas.

Figure 2 also shows that several sub-districts have relatively close initial score patterns. This situation suggests that social vulnerability characteristics between regions can be similar based on the indicators used. However, similar initial values do not necessarily indicate equal priority levels because each criterion contributes differently to the final decision. By applying the PSI method, variations

between indicators can be mathematically accounted for, resulting in a more objective mitigation priority order.

### 3. RESULTS AND DISCUSSION

#### 3.1. Results of Initial Analysis of Regional Social Vulnerability

An initial analysis was conducted to determine the characteristics of social vulnerability in each sub-district in Medan City before weighting using the Preference Selection Index (PSI) method. Based on the results of processing seven evaluation criteria, each sub-district exhibited distinct vulnerability characteristics. These differences indicate that socioeconomic conditions, access to basic services, demographic characteristics, and community recovery capacity vary across regions.

The results of the initial analysis are visualized in Figure 2, which shows the distribution of social vulnerability scores for each sub-district. Sub-districts with higher vulnerability scores indicate a more dominant combination of social risk factors, while areas with lower scores indicate relatively more adaptive social conditions.

#### 3.2. Results of the Preference Selection Index Calculation

The PSI calculation was applied to a  $21 \times 7$  decision matrix constructed based on the evaluation scores of seven social vulnerability criteria across 21 sub-districts in Medan City. Each row in the decision matrix represents one regional alternative, while each column indicates the value of each evaluation criterion: economic vulnerability (C1), disruption to access to basic services (C2), post-crisis social impacts (C3), demographic vulnerability (C4), community social capital (C5), community recovery capacity (C6), and institutional support and mitigation (C7).

The characteristics of each criterion were considered in the normalization process, with lower values for the cost criterion indicating better conditions, while higher values for the benefit criterion indicating better regional capacity. The normalization results were then used to calculate preference variation, preference deviation, criterion weights, and the final preference index value for each sub-district.

The following are the results of applying the PSI method to the data:

- Create a decision matrix: a decision matrix based on the results of converting alternative values as in (9).

$$\text{Matrix } X_{ij} = \begin{bmatrix} 4.8 & 4.7 & 4.9 & 4.5 & 2.3 & 2.4 & 2.5 \\ 4.6 & 4.5 & 4.7 & 4.3 & 2.6 & 2.7 & 2.8 \\ 4.5 & 4.4 & 4.6 & 4.2 & 2.8 & 2.9 & 3 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 3 & 3.1 & 3.2 & 3 & 4.1 & 4 & 4.2 \end{bmatrix} \quad (9)$$

- Find the maximum and minimum values of each alternative: here is Table 3 which contains the maximum and minimum values for each alternative.

Table 3. Maximum and Minimum Values for Each Evaluation Criteria

| Maximum value | Minimum value |
|---------------|---------------|
| 4.8           | 2.6           |
| 4.7           | 2.7           |
| 4.9           | 2.9           |
| 4.5           | 2.6           |
| 4.4           | 2.3           |
| 4.5           | 2.4           |
| 4.6           | 2.5           |

- Normalization of the decision matrix: in (10)-(30) is the normalization of the alternative value matrix according to its type. Normalization for criterion I:

$$R_{ij} = \frac{X_{ij}}{X_j^{max}}$$

$$R_{ij} = \frac{X_j^{min}}{X_{ij}}$$

Normalization for criterion I:

(10)

$$R_{11} = \frac{x_1^{min}}{x_1} = \frac{2.6}{4.8} = 0.5417 \quad (11)$$

$$R_{21} = \frac{x_1^{min}}{x_2} = \frac{2.6}{4.6} = 0.5652 \quad (12)$$

$$R_{31} = \frac{x_1^{min}}{x_3} = \frac{2.6}{4.5} = 0.5778 \quad (13)$$

$$R_{211} = \frac{x_1^{min}}{x_{21}} = \frac{2.6}{3} = 0.8667 \quad (14)$$

Normalization for criterion II:

$$R_{12} = \frac{x_2^{min}}{x_1} = \frac{2.7}{4.7} = 0.5745 \quad (15)$$

$$R_{22} = \frac{x_2^{min}}{x_2} = \frac{2.7}{4.5} = 0.600 \quad (16)$$

$$R_{32} = \frac{x_2^{min}}{x_3} = \frac{2.7}{4.4} = 0.6136 \quad (17)$$

$$R_{212} = \frac{x_2^{min}}{x_{21}} = \frac{2.7}{3.1} = 0.8710 \quad (18)$$

Normalization for criterion III:

$$R_{13} = \frac{x_3^{min}}{x_1} = \frac{2.9}{4.9} = 0.5918 \quad (19)$$

$$R_{23} = \frac{x_3^{min}}{x_2} = \frac{2.9}{4.7} = 0.6170 \quad (20)$$

$$R_{33} = \frac{x_3^{min}}{x_3} = \frac{2.9}{4.6} = 0.6304 \quad (21)$$

$$R_{213} = \frac{x_3^{min}}{x_{21}} = \frac{2.9}{3.2} = 0.9063 \quad (22)$$

Normalization for criterion IV:

$$R_{14} = \frac{x_4^{min}}{x_1} = \frac{2.6}{4.5} = 0.5778 \quad (23)$$

$$R_{24} = \frac{x_4^{min}}{x_2} = \frac{2.5}{4.3} = 0.6047 \quad (24)$$

$$R_{34} = \frac{x_4^{min}}{x_3} = \frac{2.5}{4.2} = 0.6190 \quad (25)$$

$$R_{214} = \frac{x_4^{min}}{x_{21}} = \frac{2.5}{3} = 0.8667 \quad (26)$$

Normalization for criterion V:

$$R_{15} = \frac{x_{15}}{x_{5max}} = \frac{2.3}{4.4} = 0.5227 \quad (27)$$

$$R_{25} = \frac{x_{25}}{x_{5max}} = \frac{2.6}{4.4} = 0.5909 \quad (28)$$

$$R_{35} = \frac{x_{35}}{x_{5max}} = \frac{2.8}{4.4} = 0.6364 \quad (29)$$

$$R_{215} = \frac{x_{215}}{x_{5max}} = \frac{4.1}{4.4} = 0.9318 \quad (30)$$

Normalization for criterion VI:

$$R_{16} = \frac{x_{16}}{x_{6max}} = \frac{2.4}{4.5} = 0.5333 \quad (31)$$

$$R_{26} = \frac{x_{26}}{x_{6max}} = \frac{2.7}{4.5} = 0.6000 \quad (32)$$

$$R_{36} = \frac{x_{36}}{x_{6max}} = \frac{2.9}{4.5} = 0.6444 \quad (33)$$

$$R_{216} = \frac{x_{216}}{x_{6max}} = \frac{4}{4.5} = 0.8889 \quad (34)$$

Normalization for criterion VII:

$$R_{17} = \frac{x_{17}}{x_{7max}} = \frac{2.5}{4.6} = 0.5435 \quad (35)$$

$$R_{27} = \frac{x_{27}}{x_{7max}} = \frac{2.8}{4.6} = 0.6087 \quad (36)$$

$$R_{37} = \frac{x_{37}}{x_{7max}} = \frac{3}{4.6} = 0.6522 \quad (37)$$

$$R_{217} = \frac{x_{217}}{x_{7max}} = \frac{4.2}{4.6} = 0.9130 \quad (38)$$

(39) is the result of normalizing the overall decision matrix.

$$\text{Matrix } R_{ij} = \begin{bmatrix} 0.5417 & 0.5745 & 0.5918 & 0.5778 & 0.5227 & 0.5333 & 0.5435 \\ 0.5652 & 0.6000 & 0.6170 & 0.6047 & 0.5909 & 0.6000 & 0.6087 \\ 0.5778 & 0.6136 & 0.6304 & 0.6190 & 0.6364 & 0.6444 & 0.6522 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0.8667 & 0.8710 & 0.9063 & 0.8667 & 0.9318 & 0.8889 & 0.9130 \end{bmatrix} \quad (39)$$

- Calculate the average value of the matrix: add up the average values of the matrix of each attribute as in (40).

$$N = \frac{1}{N} \sum_{i=1}^n R_{ij} = [15.5509 \ 16.0261 \ 16.4844 \ 15.9668 \ 17.1364 \ 16.8667 \ 17.1304] \quad (40)$$

Calculate the average value of the results obtained above, namely:

$$N = \frac{1}{N} \sum_{i=1}^n R_{ij} = \frac{1}{21} \times 15.5509 = 0.7405 \quad (41)$$

$$N = \frac{1}{N} \sum_{i=1}^n R_{ij} = \frac{1}{21} \times 16.0261 = 0.7631 \quad (42)$$

$$N = \frac{1}{N} \sum_{i=1}^n R_{ij} = \frac{1}{21} \times 16.4844 = 0.7850 \quad (43)$$

$$N = \frac{1}{N} \sum_{i=1}^n R_{ij} = \frac{1}{21} \times 15.9668 = 0.7613 \quad (44)$$

$$N = \frac{1}{N} \sum_{i=1}^n R_{ij} = \frac{1}{21} \times 17.1364 = 0.8160 \quad (45)$$

$$N = \frac{1}{N} \sum_{i=1}^n R_{ij} = \frac{1}{21} \times 16.8667 = 0.8032 \quad (46)$$

$$N = \frac{1}{N} \sum_{i=1}^n R_{ij} = \frac{1}{21} \times 17.1304 = 0.8157 \quad (47)$$

- Calculating the preference variation value: determine the preference variation value in relation to each criterion using (38). The following is the preference variation value ( $\emptyset_j$ ) as in (48).

$$\emptyset_j = \begin{bmatrix} 0.0395 & 0.0356 & 0.0373 & 0.0337 & 0.0860 & 0.0728 & 0.0741 \\ 0.0307 & 0.0266 & 0.0282 & 0.0245 & 0.0507 & 0.0413 & 0.0429 \\ 0.0265 & 0.0224 & 0.0239 & 0.0202 & 0.0323 & 0.0252 & 0.0268 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0.0159 & 0.0116 & 0.000428 & 0.0111 & 0.0134 & 0.0073 & 0.0095 \end{bmatrix} \quad (48)$$

Then add up the results of the ranking values in the preference variation matrix ( $\emptyset_j$ ). The results of adding up the preference variation matrix are as in (49):

$$\emptyset_j = [0.3432 \ 0.2822 \ 0.2841 \ 0.2718 \ 0.3315 \ 0.2798 \ 0.2832] \quad (49)$$

- Determining the preference deviation value: here the preference deviation value is as in (48)-(52):

$$\Omega_j = 1 - 0.3432 = 0.6568 \quad (48)$$

$$\Omega_j = 1 - 0.2822 = 0.7178 \quad (49)$$

$$\Omega_j = 1 - 0.2841 = 0.7159 \quad (50)$$

$$\Omega_j = 1 - 0.2718 = 0.7282 \quad (51)$$

$$\Omega_j = 1 - 0.3315 = 0.6685 \quad (52)$$

$$\Omega_j = 1 - 0.2798 = 0.7202 \quad (53)$$

$$\Omega_j = 1 - 0.2832 = 0.7168 \quad (54)$$

In (55) is the result of reducing the preference values which consist of:

$$\Omega_j = [0.6568 \ 0.7178 \ 0.7159 \ 0.7282 \ 0.6685 \ 0.7202 \ 0.7168] \quad (55)$$

Calculate the total value as in (56):

$$\sum \Omega_j = 0.6568 + 0.7178 + 0.7159 + 0.7282 + 0.6685 + 0.7202 + 0.7168 = 4.9242 \quad (56)$$

- Determine the weight criteria: the formula used in calculating the weight criteria is as in (57)-(63):

$$W_j = \frac{\Omega_j}{\sum_{j=1}^m \Omega_j} = \frac{0.6568}{4.9242} = 0.1334 \quad (57)$$

$$W_j = \frac{\Omega_j}{\sum_{j=1}^m \Omega_j} = \frac{0.7178}{4.9242} = 0.1448 \quad (58)$$

$$W_j = \frac{\Omega_j}{\sum_{j=1}^m \Omega_j} = \frac{0.7159}{4.9242} = 0.1454 \quad (59)$$

$$W_j = \frac{\Omega_j}{\sum_{j=1}^m \Omega_j} = \frac{0.7282}{4.9242} = 0.1479 \quad (60)$$

$$W_j = \frac{\Omega_j}{\sum_{j=1}^m \Omega_j} = \frac{0.6685}{4.9242} = 0.1358 \quad (61)$$

$$W_j = \frac{\Omega_j}{\sum_{j=1}^m \Omega_j} = \frac{0.7202}{4.9242} = 0.1463 \quad (62)$$

$$W_j = \frac{\Omega_j}{\sum_{j=1}^m \Omega_j} = \frac{0.7168}{4.9242} = 0.1456 \quad (63)$$

The results of the calculation of the overall value of the  $W_j$  weighting criteria are as in (64):

$$W_j = [0.1334 \ 0.1448 \ 0.1454 \ 0.1479 \ 0.1358 \ 0.1463 \ 0.1456] = 1 \quad (64)$$

- Calculate the PSI value: to get the largest preference index value, use (65). The result of the multiplication calculation on the matrix  $\phi_i$  is as in (65):

$$\phi_i = \begin{bmatrix} 0.0722 & 0.0837 & 0.0860 & 0.0854 & 0.0710 & 0.0780 & 0.0791 \\ 0.0754 & 0.0875 & 0.0897 & 0.0894 & 0.0802 & 0.0878 & 0.0886 \\ 0.0771 & 0.0894 & 0.0916 & 0.0916 & 0.0864 & 0.0943 & 0.0949 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0.1156 & 0.1270 & 0.1317 & 0.1282 & 0.1265 & 0.1300 & 0.1329 \end{bmatrix} \quad (65)$$

- Select the appropriate alternative for the given application: the final step is to find the ranking value in Table 4. To see the ranking results that have been achieved using PSI more clearly, they can be seen in Figure 3 in visual form.

Table 4. Social Vulnerability Mitigation Priority Ranking of Medan City Districts Based on the Mitigation Priority Index

| No | Code       | District               | PSI Value ( $\theta_i$ ) | Mitigation Priority Value (PMi) | Ranking |
|----|------------|------------------------|--------------------------|---------------------------------|---------|
| 1  | A01        | Medan Belawan          | 0.5556                   | 0.4444                          | 1       |
| 2  | A02        | Medan Labuhan          | 0.5986                   | 0.4014                          | 2       |
| 3  | A03        | Medan Marelan          | 0.6253                   | 0.3747                          | 3       |
| 4  | A04        | Medan Deli             | 0.6585                   | 0.3415                          | 4       |
| 5  | A05        | Medan Sunggal          | 0.7344                   | 0.2656                          | 8       |
| 6  | A06        | Medan Helvetia         | 0.7754                   | 0.2246                          | 11      |
| 7  | <b>A07</b> | <b>Medan Tuntungan</b> | <b>0.9139</b>            | 0.0861                          | 18      |
| 8  | A08        | Medan Johor            | 0.8319                   | 0.1681                          | 15      |
| 9  | A09        | Medan Amplas           | 0.7546                   | 0.2454                          | 9       |
| 10 | <b>A10</b> | <b>Medan Denai</b>     | 0.7147                   | 0.2853                          | 5       |
| 11 | A11        | Medan Area             | 0.7170                   | 0.2830                          | 6       |
| 12 | A12        | Medan Kota             | 0.8556                   | 0.1444                          | 16      |
| 13 | A13        | Medan Maimun           | 0.7749                   | 0.2251                          | 10      |
| 14 | A14        | Medan Timur            | 0.8191                   | 0.1809                          | 14      |
| 15 | A15        | Medan Perjuangan       | 0.8057                   | 0.1943                          | 13      |
| 16 | A16        | Medan Tembung          | 0.7811                   | 0.2189                          | 12      |
| 17 | A17        | Medan Barat            | 0.7339                   | 0.2661                          | 7       |
| 18 | <b>A18</b> | <b>Medan Petisah</b>   | <b>0.9458</b>            | 0.0542                          | 19      |
| 19 | <b>A19</b> | <b>Medan Baru</b>      | <b>1.0000</b>            | 0.0000                          | 21      |
| 20 | <b>A20</b> | <b>Medan Polonia</b>   | <b>0.9700</b>            | 0.0300                          | 20      |
| 21 | A21        | Medan Selayang         | 0.8919                   | 0.1081                          | 17      |

Based on the mitigation priority index results, the five regions with the highest intervention needs are Medan Belawan District (PM=0.4444), Medan Labuhan (PM=0.4014), Medan Marelan (PM=0.3747), Medan Deli (PM=0.3415), and Medan Denai (PM=0.2853). These five regions are characterized by relatively higher levels of economic vulnerability, disruption of basic services, social impacts, and demographic vulnerability compared to other regions.

Figure 3 visualizes the final PSI preference index values based on the results of the social vulnerability mitigation priority ranking presented in Table 4. The horizontal axis shows the PSI preference index values ranging from 0 to 1, while the vertical axis shows alternative regions, namely sub-districts in Medan City, and their rankings. This visualization illustrates the differences in mitigation priority levels based on a combination of seven social vulnerability criteria that have been objectively weighted using the PSI method.

The ranking results indicate that the PSI index values and the mitigation priority index have an inverse relationship. A high PSI value indicates a relatively better regional condition based on a combination of social vulnerability indicators and recovery capacity, while a high PM value indicates a greater need for mitigation interventions. Based on the transformation results, Medan Belawan District is the area with the highest mitigation priority, with a PM value of 0.4444. This condition indicates that the area has a more dominant combination of social vulnerability factors compared to other areas.

These results demonstrate that the PSI method is capable of producing objective regional rankings based on the contribution of each criterion. Unlike using an initial average score, which only provides a general overview of regional conditions, the PSI index considers the importance of each criterion through a mathematical weighting process, thus providing a more accurate basis for decision-making in determining post-crisis social vulnerability mitigation priorities.

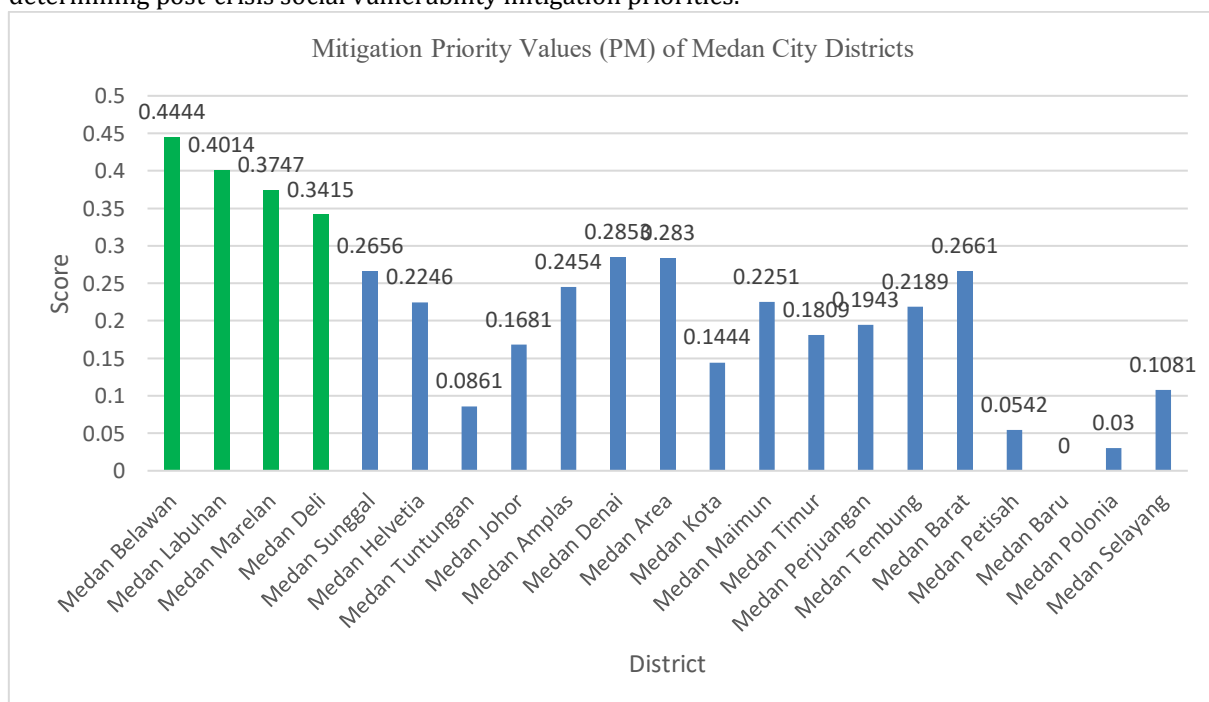


Figure 3. Social Vulnerability Mitigation Priority Index for Medan City Districts

Figure 3 shows the distribution of mitigation priority index (PM) values in 21 districts of Medan City. The horizontal axis shows the mitigation priority values resulting from the PSI index transformation, while the vertical axis shows the alternative areas analyzed. Higher PM values indicate areas with greater need for mitigation interventions.

### 3.3 Transforming the PSI Index into a Mitigation Priority

The PSI preference index value essentially indicates the alternative with the best performance based on all the criteria used. Therefore, to align the interpretation with the research objective of

determining social vulnerability mitigation priorities, the PSI value was transformed into a mitigation priority index. The transformation was performed by subtracting the PSI preference value from the maximum value, as follows:

$$PMi = 1 - \theta_i$$

Description:

- $PMi$  = mitigation priority value of the  $i$ -th alternative
  - $\theta_i$  = PSI preference index value of the  $i$ -th alternative
- The higher the  $PMi$  value, the greater the area's need for mitigation interventions.

#### 4. CONCLUSION

Based on the results of the research that has been conducted, the Preference Selection Index (PSI) model based on spatial analysis of administrative areas can be used to determine post-crisis social vulnerability mitigation priorities in 21 sub-districts in Medan City. The developed approach integrates social vulnerability indicators and community recovery capacity into a data-driven decision-making model, so that each region can be evaluated based on different social characteristics. The results of the PSI method application show that each sub-district has a different level of mitigation priority based on seven evaluation criteria, namely economic vulnerability, disruption of access to basic services, post-crisis social impacts, demographic vulnerability, community social capital, community recovery capacity, and institutional and mitigation support. The weighting process using the PSI produces objective criteria weights based on information in the decision matrix without relying on subjective expert assessments. Based on the results of the mitigation priority index ranking, Medan Belawan Sub-district is the area with the highest need for mitigation interventions with a mitigation priority value of 0.4444, followed by Medan Labuhan Sub-district at 0.4014 and Medan Marelan Sub-district at 0.3747. These results indicate that areas with higher levels of social vulnerability require greater attention in developing mitigation strategies tailored to the social characteristics of the local community. The resulting model can serve as a decision-support approach for local governments in prioritizing area-based mitigation interventions. Further research can be developed by adding more diverse socioeconomic variables, expanding the scope of the study area, and integrating more detailed spatial data to produce a more comprehensive social vulnerability analysis.

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