

Article

Measuring Temporal Socioeconomic Resilience to Earthquakes Using the Adjusted Mazziotta–Pareto Index: Evidence from Indonesia

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Abstract

Indonesia is one of the world's most seismically active countries, experiencing frequent earthquakes that make assessing regional resilience essential for disaster risk reduction. This study dynamically evaluates socioeconomic resilience in 28 regencies/municipalities affected by destructive earthquakes between 2016 and 2022. Resilience was quantified using the Adjusted Mazziotta–Pareto Index (AMPI) at three periods: pre-event (T_0), during the event (T_1), and post-event (T_2). Index changes were interpreted as resistance ($\Delta_1 = T_1 - T_0$), recovery ($\Delta_2 = T_2 - T_1$), and adaptive capacity ($\Delta_3 = T_2 - T_0$). Results show substantial regional differences in resilience trajectories: some areas experienced only minor declines during the earthquake, while others were heavily affected but recovered quickly. Cluster analysis revealed distinct typologies, including consistently high-resilience regions, rapid-recovery regions, and persistently vulnerable regions. These disparities are associated with variation in economic capacity, social vulnerability, labor market conditions, and access to health services. Overall, the findings highlight the value of a multidimensional, time-sensitive approach to measuring socioeconomic resilience. The study advances an AMPI-based temporal measurement framework and offers policy insights for development planning and disaster mitigation.

Keywords: Adjusted Mazziotta–Pareto Index (AMPI); earthquake disaster; regional resilience; resistance; recovery; adaptability



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1. Introduction

Natural disasters adversely affect regional development, community well-being, and macroeconomic conditions in both the short and long term [1,2]. Beyond physical destruction, disasters disrupt economic activity, generate social stress, and strain public service systems, often extending recovery periods. Consequently, strengthening regional resilience has become a core priority in the global development agenda, reflected in Sustainable Development Goal (SDG) 11's focus on disaster-resilient settlements and SDG 13's emphasis on adaptive capacity to disaster risks [3]. This commitment is further reinforced by the Sendai

Framework for Disaster Risk Reduction 2015–2030, which calls for systemic approaches to enhance the capacity of regions to absorb, respond to, and recover from disasters.

Globally, the frequency of natural disasters has risen, with Asia recording the highest incidence over the past two decades [4]. Although hydrometeorological events such as floods and storms occur most frequently, geological hazards—especially earthquakes—pose a particularly severe threat, often causing extensive infrastructure damage, large economic losses, and prolonged social disruption [5]. The Emergency Events Database (EM-DAT) data indicate that earthquakes from 2005 to 2024 resulted in 25,495 deaths, affected 6.6 million people, and produced average annual economic losses of about US\$40 billion [4]. The disparity between event frequency and impact severity underscores the importance of evaluating the capacity of regional systems to withstand high-intensity shocks [6–10].

Indonesia ranks among the most earthquake-prone countries globally [11], owing to its position at the convergence of the Eurasian, Indo-Australian, Philippine, and Pacific plates [12,13]. This tectonic setting generates high seismicity, particularly along subduction zones that can produce large and destructive earthquakes [11,14]. Major events include the 2004 Aceh, 2005 Nias, 2009 Padang, 2018 Lombok, 2018 Palu, and 2022 Cianjur earthquakes. These disasters not only damage the built environment but also disrupt regional economic activity and public services while increasing social vulnerability. Indonesia's 2022–2026 Disaster Risk Assessment estimates that earthquake hazard zones cover 192,473,068 hectares, with 272,405,410 people exposed and potential physical and economic losses reaching Rp1,111.32 trillion [15].

Regional disparities in economic structure, socioeconomic conditions, institutional capacity, and adaptation mechanisms lead to substantial variation in resilience [16]. Areas with strong and diversified economies, higher levels of well-being, and adequate basic services tend to recover more quickly and steadily [2,17]. Conversely, places with constrained fiscal capacity, high poverty, and weak social infrastructure are more likely to suffer greater losses and experience slower recovery [18,19]. Given the wide heterogeneity across Indonesian regencies and municipalities, earthquake resilience is expected to differ markedly, warranting systematic empirical assessment.

Although scholarship on disaster resilience has progressed, important gaps remain. Much of the existing work emphasizes vulnerability, risk, or loss [20–22], while quantitative measurement of regional resilience is still relatively limited. Prior studies have operationalized resilience using diverse indicator sets [2,23–28]. In earthquake-specific research, assessments often prioritize physical damage [29] or rely on single metrics such as labor force indicators [30] or GRDP [31]. Bruneau et al. [32] proposed a widely cited framework that evaluates earthquake resilience through economic losses and recovery speed, structured around four dimensions (technical, organizational, social, and economic) and five systems (global, electricity, water, hospitals, and response and recovery).

Methodologically, multiple approaches have been used to quantify disaster resilience, including composite indices [2,28] and multi-criteria techniques such as Gray Relational Analysis (GRA) [27,33], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [27,34], Rank Sum Ratio (RSR) [27] and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [33,35–37]. However, these methods are typically compensatory, allowing poor performance in one indicator to be offset by strong performance in others during aggregation. This can bias resilience estimates by obscuring imbalances across dimensions. More robust composite approaches—particularly the Adjusted Mazziotta–Pareto Index (AMPI), which reduces aggregation bias by penalizing indicator imbalance—remain rarely applied in disaster resilience research. In addition, most empirical studies assess resilience at national or provincial scales [2,27,30,38], leaving sub-provincial measurement underexplored.

This study responds to these gaps in two ways. First, it applies AMPI to measure regional socioeconomic resilience to earthquakes—an approach that remains underdeveloped in the disaster literature. Second, it proposes a regency/municipality-level assessment framework that integrates economic and social indicators to reveal spatial disparities in resilience capacity. By placing resilience at the center of analysis, the study also extends to a field historically dominated by vulnerability- and risk-oriented perspectives.

Accordingly, this research evaluates regional social and economic resilience to earthquakes using AMPI, focusing on destructive seismic events in Indonesia. It aims to identify how regional socioeconomic resilience changes following major earthquakes. The results are intended to support evidence-based planning for disaster risk mitigation and management, with relevance for both national and broader policy contexts.

The remainder of the article is structured as follows. The introduction presents the background, problem statement, and objectives. The literature review discusses key concepts and measurement approaches in disaster resilience. The methodology section explains indicator construction and the AMPI procedure, including scope and limitations. The empirical analysis examines regency/municipality-level earthquake resilience in Indonesia, highlighting spatial patterns and potential drivers. The conclusion summarizes the findings and provides strategic recommendations to strengthen regional resilience and reduce earthquake risk in Indonesia.

2. Materials and Methods

This study proposes a framework to measure regional socio-economic resilience to earthquakes across 28 Indonesian regencies and municipalities affected between 2016 and 2022. The framework assesses resilience patterns across three phases—pre-disaster, during the disaster, and post-disaster—using the Adjusted Mazziotta–Pareto Index (AMPI) approach.

2.1. Study Area

The study covers 28 Indonesian regencies and municipalities affected by destructive earthquakes between 2016 and 2022, as shown in Table 1 and Figure 1. This period was chosen based on Post-Disaster Rehabilitation and Reconstruction Plan (RRRP) proposals submitted by local governments and published by the National Disaster Management Agency (BNPB). Using these criteria, 28 regencies/municipalities across 15 provinces were identified. The dataset is event-based and cross-sectional: each observation corresponds to an earthquake event in a given area during a specific period, and therefore the data are neither panel data nor a time series.

Table 1. Earthquake characteristics and affected regions used as the study area.

Earthquake	Date	Mw	Depth (km)	Epicenter	Study Areas (Regencies/Municipalities)
Aceh (Pidie Jaya)	7 December 2016	6.5	10	Offshore Pidie Jaya Regency, Aceh Province	Bireuen, Pidie, Pidie Jaya
Poso	29 May 2017	6.6	11	Southeast of Poso Regency, Central Sulawesi Province	Poso
West Java	15 December 2017	6.9	105	Indian Ocean, south of Java (offshore Tasikmalaya)	Garut, Ciamis, Pangandaran, Tasikmalaya Regency, Tasikmalaya City, Cilacap
Lebak	23 January 2018	6.1	64	Indian Ocean, southwest of Lebak Regency, Banten Province	Lebak

Table 1. Cont.

Earthquake	Date	Mw	Depth (km)	Epicenter	Study Areas (Regencies/Municipalities)
Banjarnegara	18 April 2018	4.4	4	Kalibening District, Banjarnegara Regency, Central Java Province	Banjarnegara
Lombok	5 and 19 August 2018	6.9	10–15	North of Lombok Island, West Nusa Tenggara Province	North Lombok, West Lombok, East Lombok, Central Lombok, Mataram City
Palu–Donggala	28 September 2018	7.5	10	North of Donggala Regency, Central Sulawesi	Donggala, Sigi, Palu City
Ambon	26 September 2019	6.5	10	Mountainous Donggala Regency, Central Sulawesi Province	Central Maluku, West Seram, Ambon City
Majene–Mamuju	15 January 2021	6.2	10	Northeast of Ambon Island, Maluku Province	Majene, Mamuju
Karangasem	16 October 2021	4.8	10	Rendang District, Karangasem Regency, Bali Province	Karangasem
Pasaman	25 February 2022	6.1	4	West Pasaman Regency (Talamau District), West Sumatra Province	Pasaman
Cianjur	21 November 2022	5.6	11	Cugenang District, Cianjur Regency, West Java Province	Cianjur

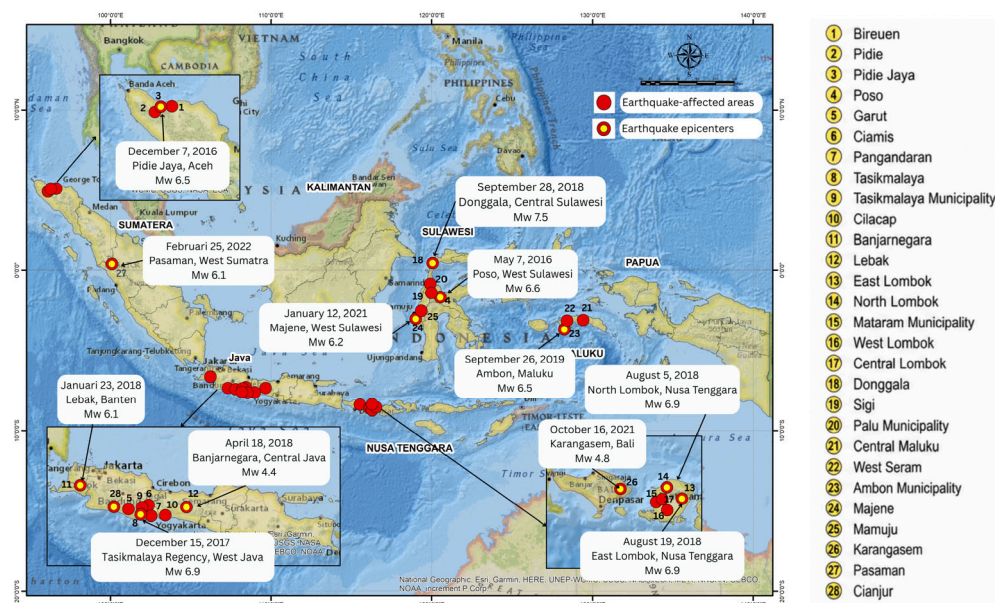


Figure 1. Geographical distribution of the 28 earthquake-affected regencies and municipalities in Indonesia. Red dots represent the earthquake-affected areas, while red circles with yellow centers denote the earthquake epicenters.

These locations were impacted by 12 major earthquakes and are situated in active tectonic settings shaped by interactions among the Indo-Australian, Eurasian, Pacific, and Philippine plates, resulting in high seismic vulnerability PusGen [39]. In western Indonesia, the 7 December 2016 Pidie Jaya earthquake affected Bireuen, Pidie, and Pidie Jaya Regencies and was associated with the Sumatran Fault system and the active Sunda

subduction zone; local alluvial plains and folded hills contribute to seismic-wave amplification [40]. The 25 February 2022 Pasaman earthquake also occurred along the Sumatra Fault, affecting the Sumpur and northern Sianok segments [40]. On Java, Garut, Tasikmalaya Regency, Tasikmalaya City, Ciamis, Pangandaran, Cilacap, and Cianjur are influenced by the southern Java subduction zone and active local faults, with young volcanic materials and unconsolidated sediments that elevate liquefaction and landslide potential. Lebak and Banjarnegara combine steep terrain with complex geological structures, heightening secondary hazards such as landslides.

In central and eastern Indonesia, Poso, Donggala, Sigi, and Palu City are affected by the Palu-Koro Fault—an active strike-slip system with high deformation rates—and by alluvial valley conditions that promote wave amplification and liquefaction, particularly in Palu [41]. The 2021 Mw 6.2 Mamuju earthquake in West Sulawesi was linked to the Makassar Strait Thrust, where complex fault interactions contribute to elevated seismic hazard [42]. The August 5 and 19, 2018 Lombok earthquake sequence was triggered by the Flores Back-Arc Thrust north of Lombok, producing shallow, damaging events [43]. Central Maluku, Western Seram, and Ambon City lie within a complex convergence zone involving multiple microplates, generating frequent seismicity. Karangasem reflects combined influences from Mount Agung's volcanic activity and the southern Bali subduction zone. Overall, the study areas share proximity to active seismic sources and geological and geomorphological conditions that increase earthquake hazards and their impacts.

This study examined twelve destructive earthquakes that varied in magnitude, focal depth, and hazard characteristics, all of which produced substantial socioeconomic impacts across the affected regencies and municipalities. Higher-magnitude earthquakes, such as the Palu–Donggala (Mw 7.5) and Lombok (Mw 6.9) events, resulted in extensive damage due to intense ground shaking and cascading hazards, including tsunamis and liquefaction. In contrast, lower-magnitude earthquakes, such as the Cianjur (Mw 5.6) and Banjarnegara (Mw 4.4) events, also caused considerable damage because of their shallow focal depths, proximity to densely populated areas, and unfavorable local geological conditions. These findings highlight that earthquake impacts are determined not only by magnitude but also by the interaction between hazard characteristics, exposure, vulnerability, and local environmental conditions.

For this analysis, the study area encompasses diverse geomorphological settings, including coastal plains (Pangandaran, Majene, and Ambon City), volcanic hills and valleys (Garut, Banjarnegara, and Karangasem), and active mountain regions (Cianjur, North Lombok, and Poso). Differences in elevation, landform, and distance to seismic sources lead to spatial variation in hazard levels and the potential for ground-motion amplification. This variability is further intensified by major and local geological structures—such as the Palu–Koro fault zone, the Lembang fault, other faults in West Java, and active fault systems in Seram and Ambon—resulting in heterogeneous risk across regions. These contrasts are important for interpreting differences in physical damage, vulnerability patterns, and post-disaster response capacity.

Demographically, the 28 study areas include both urban and rural contexts with distinct socioeconomic profiles. Urban centers (e.g., Palu City, Mataram City, Ambon City, and Tasikmalaya City) typically have denser economic activity, more developed public-service infrastructure, and higher levels of urbanization. In contrast, regencies such as North Lombok, West Seram, Majene, Pidie Jaya, and Sigi tend to have lower population density, more limited health-service access, and weaker fiscal capacity. Gaps in education, preparedness, and self-rescue capacity are especially pronounced in regency-level areas, which can magnify the social consequences of earthquakes.

Economically, the study area is similarly varied. Agriculture and fisheries dominate in Pangandaran, Pidie, Pidie Jaya, and Majene; industry and services are more prominent in Palu, Mataram, and Ambon; and tourism plays a central role in Lombok, Pangandaran, and Karangasem. While some areas function as regional growth centers, mitigation infrastructure, access to recovery resources, and fiscal capacity remain uneven. These disparities complicate long-term resilience building, underscoring the need to strengthen seismic resilience to support sustainable development and post-earthquake stability.

2.2. Indicators of Regional Earthquake Resilience

Indicator selection for measuring regional earthquake resilience was carried out in two stages. First, we reviewed the literature on regional resilience indices for natural hazards generally and earthquakes in particular. Second, the indicators were adjusted to the Indonesian context and to the availability of regency- and municipality-level data published by the Central Statistics Agency (BPS). This process resulted in seven indicators for constructing the regional earthquake resilience index, along with their expected direction of influence, as shown in Table 2.

Previous studies show that a region's socioeconomic characteristics strongly shape disaster resilience. Lower socioeconomic capacity is associated with greater vulnerability and slower recovery [16,44]. Socioeconomic conditions therefore reflect a region's capacity to absorb shocks, sustain essential functions, and rebound after a disaster.

Accordingly, this study measures resilience through economic and social dimensions. The ecological dimension is not included due to limited and inconsistent regency- or municipality-level data. The institutional dimension is also excluded because disaster management institutions tend to change slowly and in broadly similar ways across regions within the same period. Economic and social indicators are therefore the most suitable for capturing changes over time in regional resilience capacity.

The explanatory variables were selected based on two criteria: (1) strong theoretical relevance to socioeconomic resilience as identified in previous studies, and (2) the availability of consistent, comparable, and complete data for all study areas and observation periods. Several potentially important dimensions of resilience, including social capital, institutional capacity, governance effectiveness, community preparedness, access to insurance, and emergency response capability, were not included because standardized datasets covering all regencies/municipalities and earthquake events were not available. Their exclusion should not be interpreted as indicating limited importance; rather, it reflects current data constraints. Consequently, the identified resilience pathways should be interpreted within the scope of the selected socioeconomic dimensions. Future studies incorporating these additional dimensions may provide a more comprehensive understanding of regional resilience and reveal complementary resilience pathways that could not be examined in the present study.

Table 2. Regional earthquake resilience indicators.

Dimension	Indicator ^a	Description	Polarity	Source
Economy	GRDP per capita	GRDP at constant prices divided by the population of a region each year (Millions of rupiah/persons)	+	BPS
	GRDP	Percentage change in real GRDP from one year to the next (%)	+	BPS
	Adjusted Per Capita Expenditure	Average expenditure per person per month (Thousand Rupiah/Person/Year)	+	BPS

Table 2. *Cont.*

Dimension	Indicator ^a	Description	Polarity	Source
Social	Poverty	Rate Percentage of the population with average monthly per capita expenditure below the poverty line (%)	—	BPS
	Unemployment Rate	Percentage of the unemployed labor force relative to the total labor force (%)	—	BPS
	Doctor	Number of doctors per 100,000 population	+	BPS
	Health Workers	Number of health workers per 100,000 population	+	BPS

Note: ^a sources: [23,26,36,45–55]. “+” is for positive polarity indicators, and “—” is for negative polarity indicators. BPS; Statistics Indonesia.

The economic dimension is measured using GRDP per capita, GRDP growth, and adjusted per capita expenditure. Together, these indicators represent regional prosperity, economic stability, and purchasing power, which shape an area’s capacity to withstand disaster losses and recovery. The social dimension is assessed through poverty and unemployment rates and the availability of health personnel, indicated by the numbers of doctors and healthcare workers. These measures reflect socioeconomic vulnerability and the ability of social and health systems to manage emergencies and support recovery.

To maintain comparability within the Adjusted Mazziotta–Pareto Index (AMPI) framework, this study applies the same socioeconomic indicators across the pre-disaster, disaster, and post-disaster phases, while assigning them different analytical roles in each period. In the pre-disaster phase, the indicators represent baseline capacity, using averages from the two years preceding the event. During the disaster phase, they reflect the stress and disruption affecting the socioeconomic system. In the post-disaster phase, they assess recovery and adaptive capacity, using averages from the two years following the event. Resilience is therefore measured as temporal change in a consistent set of indicators, ensuring continuity of measurement over time.

Drawing on a resilience conceptual framework and the availability of regency and municipality-level data, this study constructed a composite regional earthquake resilience index using the Adjusted Mazziotta–Pareto Index (AMPI), encompassing two core dimensions: economic resilience and social resilience.

2.3. Method

Resilience refers to a region’s socio-economic capacity to cope with earthquakes. It comprises three core dimensions: resistance (withstanding shocks), recovery (returning to pre-disaster conditions), and adaptability (adjusting to post-disaster change). These dimensions are assessed using regency or municipality-level macroeconomic indicators observed across three phases—before, during, and after the earthquake.

To measure resilience dynamics, this study applies the Adjusted Mazziotta–Pareto Index (AMPI), a non-compensatory composite indicator proposed by Mazziotta and Pareto [56–59]. AMPI is designed to represent multidimensional phenomena while preserving balance among indicators, so strong performance in one area cannot fully offset weaknesses in another. This property is well suited to resilience assessment, because structural vulnerabilities (e.g., high poverty or limited health capacity) remain visible in the overall score through AMPI’s penalty mechanism. Given that socio-economic resilience is inherently multidimensional and only partially compensatory, a non-compensatory approach is therefore more appropriate.

AMPI also supports consistent comparisons across regions and over time, in both relative and absolute terms, making it suitable for evaluating changes in resilience before, during, and after an earthquake [60,61]. Compared with approaches such as Principal

Component Analysis (PCA), which depends on statistical variance, AMPI is generally more sensitive to multidimensional socio-economic disparities and avoids excessive simplification. It has been widely used in applied socio-economic research, including studies of well-being, social investment, and regional resilience [57,62,63].

Since AMPI is explicitly spatiotemporal, it enables analysis of both inter-regional differences and resilience trajectories over time. Accordingly, the study is organized into three periods: the average of the two years before the earthquake, the earthquake year, and the average of the two years after. This three-phase design captures resilience as a dynamic process—mapping to anticipatory, absorptive, and adaptive/transformational capacities—thereby identifying critical points in the disaster cycle that static, cross-sectional measures may miss.

AMPI computation follows two main steps. First, each indicator is normalized to ensure a time-independent scale. Second, the normalized indicators are aggregated into a single composite score representing a region's earthquake resilience [57,64–66].

Step 1. Indicators Normalization

The first step in AMPI calculation is to normalize the variables. This involves selecting 7 indicators (Table 1) for 28 regencies/municipalities at 3 time points. The unscaled data matrix $X = (x_{ij})$ is transformed into a scaled matrix $R = (r_{ij})$, where $i = 1, \dots, n$ denotes affected regencies/municipalities and $j = 1, \dots, p$ the resilience indicators. Normalization depends on indicator polarity: positive polarity means higher values raise the composite index, negative polarity means they lower it [57,67]. In this study, per capita GRDP, GRDP growth, adjusted per capita expenditure, and numbers of doctors and health workers have positive polarity, reflecting greater resilience at higher values. Poverty and unemployment rates have negative polarity, so higher values indicate lower resilience.

The AMPI method applies the min-max transformation to convert the original data (x_{ijt}) into standardized values (r_{ijt}) according to the following formula:

$$r_{ijt} = \left(\frac{(x_{ijt} - \min(x_j))}{\max(X_j) - \min(X_j)} \right) 60 + 70; \text{ if indicator } j \text{ has positive polarity} \quad (1)$$

$$r_{ijt} = \left(\frac{(\max(x_j) - x_{ijt})}{\max(x_j) - \min(X_j)} \right) 60 + 70; \text{ if indicator } j \text{ has negative polarity} \quad (2)$$

The minimum and maximum values of the indicator x_j , denoted $\min(x_j)$ and $\max(x_j)$, serve as the boundaries for the normalization process. This transformation scales the original data to the range 70–130, centering the normalized indicator values at 100 [57,68]. The selection of the constants 60 and 70 is arbitrary; however, it does not influence the rankings among units and has been widely adopted in the literature [65,67]. This normalization process enhances the Mazziotta–Pareto Index (MPI) method by enabling the capture of absolute changes over time [68].

By defining Ref_{x_j} as the reference value of the j th indicator, the goalposts are defined as:

$$\begin{cases} \text{Min}_{x_j} = \text{Ref}_{x_j} - \Delta x_j \\ \text{Max}_{x_j} = \text{Ref}_{x_j} + \Delta x_j \end{cases} \quad (3)$$

where Ref_{x_j} is the average value of the indicator and calculated using Formula (4):

$$\text{Ref}_{x_j} = \sum x_i / n \quad (4)$$

where Δx_j is defined as half the difference between the overall maximum value ($\text{Sup}(x_j)$) and the overall minimum value ($\text{Inf}(x_j)$), as given by Formula (5).

$$\Delta x_j = \frac{\text{Sup}(x_j) - \text{Inf}(x_j)}{2} \quad (5)$$

By substituting these values into the normalization formula, when the raw value of an indicator equals the base-year average, it will be converted to a normalized score of 100; the overall maximum will be 130; and the overall minimum will be 70.

Step 2. Indicator aggregation

After the indicators are normalized, the regional earthquake resilience index is computed for each reGENCY or city i at time t . If the composite index is positive—so higher values indicate improvement in the phenomenon (e.g., greater resilience)—the AMPI version using the subtraction operator is applied. If the composite index is negative—so higher values indicate deterioration—the AMPI version using the addition operator is used. In both cases, disparities among indicators reduce the resulting index. Therefore, this study applies the subtraction operator, as presented in Equation (6).

$$ERI_{it} = Mr_{it} - (S_{r_{it}} \cdot cv_i) \quad (6)$$

where ERI_{it} is the earthquake resilience index for region i at time t , and Mr_{it} is the average of the normalized indicator values as shown in Equation (7).

$$Mr_{it} = \frac{1}{m} \sum_{j=1}^m r_{ijt} \quad (7)$$

$S_{r_{it}}$ is the standard deviation of the normalized indicator value as shown in Formula (8).

$$S_{r_{it}} = \sqrt{\frac{1}{m} \sum_{j=1}^m (r_{ijt} - Mr_{it})^2} \quad (8)$$

and $cv_{r_{it}}$ is the coefficient of variation in the normalized indicator value, as shown in Formula (9).

$$cv_i = \frac{S_{r_{it}}}{Mr_{it}} \quad (9)$$

The aggregation formula has two parts: a mean component and an imbalance component. The imbalance term penalizes regions with larger disparities among indicator values, consistent with the Mazziotta–Pareto Index (MPI) framework underlying the AMPI calculation used by Higgs et al. [67]. The key distinction of the AMPI-based approach is its normalization procedure, which converts each region's indicator values across different time points into time-independent values. This enables consistent within-period analysis of changes in a region's earthquake resilience index and its constituent indicators.

Changes in the regional earthquake resilience index were assessed in three ways: (1) during-disaster minus pre-disaster to measure resistance; (2) post-disaster minus during-disaster to measure recovery speed; and (3) post-disaster minus pre-disaster to measure adaptability. Descriptive statistics were computed for both raw and normalized indicator values, as well as for the regional earthquake resilience index under pre-, during-, and post-disaster conditions and for the corresponding changes in indices and indicators.

Since AMPI normalization places all indicators on a common scale, it allows direct comparison of indicator changes over time. The analysis also identified the two regions with the largest increases and decreases in earthquake resilience, and radar plots were used

to highlight which indicators drove these changes. Radar plots provide a single view for comparing multiple variables simultaneously.

AMPI decomposes each unit's score into two main components: the mean M_{r_i} and a penalty term ($S_{r_i} \cdot cv_i$). The penalty term captures variability in the indicators relative to their average (horizontal variability) and lowers the index for units that show uneven performance across indicators. In doing so, the method assigns greater value to units that achieve the same mean level with a more balanced indicator profile.

The Adjusted Mazziotta–Pareto Index (AMPI) shares the key properties of the Mazziotta–Pareto Index (MPI), but it allows each unit's score to be computed independently, whereas MPI depends on the mean and standard deviation of each indicator. This makes AMPI suitable for aggregating indicators with different degrees of variability. Moreover, normalizing indicators to a common scale tends to reduce differences in variability compared with the original measures, facilitating valid comparisons across units and over time [56].

2.4. Analysis of Changes in the Earthquake Resilience Index and Application of K-Means Cluster Analysis

The regional earthquake resilience index for each regency or city was calculated across three temporal phases: pre-earthquake, during the earthquake, and post-earthquake. Variations in the index across these phases represent the principal dimensions of regional resilience. The resistance dimension is defined as the difference between the index values during the earthquake and in the pre-earthquake phase, reflecting a region's capacity to withstand the initial impact of a disaster. The recovery dimension is determined by the difference between the post-earthquake and during-earthquake index values, which illustrates the region's ability to recover following disruption. The adaptability dimension is measured as the difference between the post- and pre-earthquake index values, indicating the region's capacity to adapt and achieve a condition equal to or better than its pre-disaster state.

In the next stage, a k-means clustering analysis will be conducted. K-means clustering is an unsupervised machine learning approach that aims to identify patterns or structures within large, unexplored datasets. In this study, the k-means clustering method was used to group regencies/municipalities based on their resistance, recovery, and adaptability values into a number of ' K ' clusters. Prior to performing the k-means clustering analysis, the resistance, recovery, and adaptability values were standardized [69] using a z-score, as shown in Formula (10):

$$Z = \frac{(x - \mu)}{\sigma} \quad (10)$$

where Z is the normalization result; x is the resistance, recovery and adaptability value in each 28 regency/municipality; μ is the average resistance/recovery/adaptability of 28 regencies/municipalities and σ is the standard deviation of resistance/recovery/adaptability of 28 regencies/municipalities.

K-means clustering is suitable for identifying similarities and patterns among objects with similar characteristics [69]. Using the K-means algorithm, a set of observations is grouped into k clusters based on similar attributes. By measuring the degree of similarity among observations, this algorithm divides the data into several segments based on these similarities. In this study, the optimal number of clusters in the K-means method was determined using the elbow method introduced by Robert L. Thorndike. The elbow method uses the within-cluster sum of squares (WCSS) as a measure of internal variation within each cluster, reflecting the degree of closeness among data points within the same group. The smaller the WCSS value, the more homogeneous the members within a cluster, making the clustering process more representative. As the number of clusters increases,

the WCSS value tends to decrease. However, the main objective of the analysis is not merely to minimize the WCSS but to obtain a number of clusters that can represent the data structure efficiently and meaningfully. Therefore, a balance is needed between the level of homogeneity within clusters and the number of clusters formed so that the clustering results remain informative and not excessive.

The elbow method provides a solution by identifying the “elbow” point, that is, the point where the decrease in WCSS begins to slow significantly. This point reflects the optimal condition, in which adding more clusters subsequently yields only a relatively small improvement in clustering quality. Thus, the number of clusters chosen at the elbow point can be considered the most optimal number, as it effectively accommodates data variation while maintaining model simplicity.

2.5. Methodological Approach for Robustness Assessment

A robustness analysis was conducted to assess the reliability and stability of regional resilience index measurements for earthquake disasters. The primary method used was the Adjusted Mazziotta–Pareto Index (AMPI). Two alternative aggregation methods were also compared: the arithmetic mean and the median. These methods were used by Myftiu & Scalise [62], Scaccabarozzi et al. [70], Mazziotta & Pareto [57]. This analysis examines how sensitive the results are to changes in assumptions during indicator aggregation.

The arithmetic mean is a fully compensatory aggregation method. In this method, a high value on one indicator can offset a low value on another. Mathematically, the arithmetic mean is calculated as follows:

$$\text{Arithmetic means } i^t = \frac{1}{m} \sum_{j=1}^m y_{ij}^t \quad (11)$$

where y_{ij}^t represents the value of either the normalized simple indicator j (in the first step) or the value of pillar j (in the second step) for unit i , with m representing the number of normalized simple indicators or pillars to be aggregated

The median is a non-compensatory method that identifies the middle value in a sorted list of numbers. Because it is not influenced by extreme values, the ME provides a measure of central tendency without compensating for higher and lower values.

For an odd number of observations, the median is:

$$\text{Median } i^t = y_{ij(\frac{m}{2}+1)}^t \quad (12)$$

For an even number of observations, the median is:

$$\text{Median } i^t = \frac{y_{ij(\frac{m}{2})}^t + y_{ij(\frac{m}{2}+1)}^t}{2} \quad (13)$$

The choice of normalization techniques for calculating the arithmetic mean and median aims to enable absolute comparisons over time. Indicators are normalized using the min–max procedure. Suppose the value of indicator j for unit i at time t is y_{ij}^t , and it has positive polarity. The min–max procedure calculates the normalized value as follows [71]:

$$y_{ij}^t = \frac{x_{ij}^t - \min_i(x_{ij})}{\max_i(x_{ij}) - \min_i(x_{ij})} \quad (14)$$

where $\min_i(x_{ij})$ and $\max_i(x_{ij})$, called goalposts, represent the minimum and maximum values for indicator j . These goalposts are based on the indicator’s minimum and maximum values across all observations. This includes periods before, during, and after the

earthquake. If indicator j has a negative polarity, the numerator in Equation (15) changes to:

$$\max_i(x_{ij}) - x_{ij}^t \quad (15)$$

thereby

$$y_{ij}^t = \frac{\max_i(x_{ij}) - x_{ij}^t}{\max_i(x_{ij}) - \min_i(x_{ij})} \quad (16)$$

Data processing and statistical analyses in this study were conducted using Microsoft Excel 365 (Microsoft Corporation, Redmond, WA, USA) and IBM SPSS Statistics for Windows, Version 22.0 (IBM Corp., Armonk, NY, USA). Spatial data processing and map visualization were performed using ArcGIS Desktop 10.5 (Esri, Redlands, CA, USA)

3. Results and Discussion

3.1. Temporal Dynamics of the Regional Resilience Index

Table 3 presents the results of a comparison of AMPI rankings across the three phases of the analysis. The comparison of AMPI rankings indicates that regional resilience to earthquakes undergoes significant changes during the pre-shock, during-shock, and post-shock phases. Some regions maintained their relative positions throughout the disaster phases, whereas others experienced significant increases or decreases in their rankings. These changes in ranking indicate that a region's resilience capacity is not static but varies according to each area's ability to cope with disruptions, maintain regional functions, and carry out post-disaster recovery.

Table 3. Comparative analysis of AMPI before, during, and after the earthquake.

Regency/Municipality	Pre-Shock		During-Shock		Post-Shock		Δ AMPI		
	AMPI	Rank	AMPI	Rank	AMPI	Rank	Resistance	Recovery	Adaptability
Bireuen	98.10	13	97.48	21	101.38	10	−0.62	3.90	3.28
Pidie	98.24	12	97.80	19	98.63	15	−0.44	0.83	0.38
Pidie Jaya	95.72	23	94.60	26	98.04	18	−1.12	3.44	2.32
Poso	96.05	19	100.38	10	102.78	8	4.32	2.40	6.73
Garut	95.41	24	95.18	25	96.46	21	−0.23	1.29	1.06
Ciamis	97.92	14	99.96	12	102.34	9	2.04	2.38	4.42
Pangandaran	95.83	22	99.61	14	100.92	12	3.78	1.31	5.10
Tasikmalaya	96.01	20	98.52	17	97.99	19	2.50	−0.53	1.97
Tasikmalaya Minicpality	100.50	8	103.32	5	100.79	13	2.82	−2.53	0.29
Cilacap	104.82	4	106.01	3	105.85	5	1.19	−0.16	1.03
Lebak	99.55	10	97.65	20	98.41	17	−1.90	0.76	−1.14
Banjarnegara	96.92	17	100.24	11	97.13	20	3.33	−3.12	0.21
East Lombok	96.35	18	98.40	18	92.35	25	2.06	−6.06	−4.00
North Lombok	90.33	27	89.78	28	85.53	28	−0.56	−4.25	−4.80
Mataram Municipality	115.47	1	117.33	2	120.39	1	1.86	3.05	4.91
West Lombok	99.46	11	96.25	24	92.91	24	−3.21	−3.34	−6.55
Central Lombok	95.27	25	98.85	15	90.91	26	3.58	−7.93	−4.36
Donggala	95.96	21	96.77	23	95.83	22	0.81	−0.94	−0.13
Sigi	97.86	16	99.62	13	98.44	16	1.76	−1.18	0.57
Palu Municipality	114.06	2	121.31	1	113.84	2	7.25	−7.47	−0.23
Central Maluku	95.20	26	97.25	22	93.41	23	2.05	−3.84	−1.79
West Seram	90.15	28	92.27	27	89.43	27	2.12	−2.84	−0.72
Ambon Municipality	106.32	3	102.21	8	99.43	14	−4.11	−2.78	−6.89
Majene	97.88	15	98.55	16	101.06	11	0.67	2.52	3.19
Mamuju	103.89	5	105.78	4	108.91	3	1.89	3.14	5.02
Karangasem	102.93	6	102.95	6	106.55	4	0.02	3.60	3.62
Pasaman	100.63	7	102.64	7	103.89	6	2.00	1.25	3.25
Cianjur	100.19	9	100.72	9	102.85	7	0.52	2.14	2.66

Several regions maintained highly stable rankings across the disaster phases. Mataram City and Palu City were particularly consistent: Mataram ranked first in the pre- and post-shock phases and second during the shock phase, while Palu ranked first during the shock phase and second in both the pre- and post-shock phases. This pattern suggests that regions with stronger socio-economic capacity, infrastructure, and governance are better able to preserve development stability during and after earthquakes. This finding extends previous evidence reported by Lu et al. [2] and W. Liu et al. [72]. Rather than merely indicating that economically developed regions are more resilient, the results highlight that economic capacity and health infrastructure strengthen both the ability to absorb earthquake impacts and the capacity to restore essential services. Consequently, socio-economic indicators, particularly per capita GRDP and health facility availability, emerge as key drivers of regional resilience in the Indonesian context [50]. These findings suggest that strengthening local economic capacity and healthcare systems should be prioritized as key strategies for improving earthquake resilience in disaster-prone regions.

By contrast, some regions improved notably during the shock and post-shock phases, including Poso, Pangandaran, and Ciamis. Poso rose from 19th (pre-shock) to 10th (shock) and then to 8th (post-shock). Pangandaran and Ciamis likewise improved after the event. These upward shifts indicate that certain regions have sufficient adaptive capacity to sustain performance and even strengthen outcomes following earthquake-related disruption.

Conversely, other regions experienced pronounced declines, particularly Ambon City, West Lombok, and Central Lombok. Ambon fell from third (pre-shock) to 14th (post-shock), while Central Lombok dropped from 15th (shock) to 26th (post-shock). Such declines indicate difficulties in maintaining development stability and achieving effective recovery, suggesting that structural vulnerability and limited adaptive capacity can extend earthquake impacts on regional systems.

Overall, the varied ranking trajectories point to substantial spatial heterogeneity in earthquake responses across Indonesia. While some regions maintained or improved post-disaster conditions, others saw diminished resilience in the post-shock phase. These results suggest that resilience depends not only on initial development levels but also on a region's capacity to adapt, recover, and transform after disruption. Accordingly, changes in AMPI rankings provide a more comprehensive representation of regional resilience dynamics.

These findings also support an evolutionary resilience perspective, which conceptualizes resilience as a dynamic, adaptive process rather than a simple return to pre-disaster conditions. In disaster contexts, evolutionary resilience highlights adaptive learning, institutional change, and the gradual strengthening of long-term capacity across stages from initial impact to adjustment and system enhancement [73,74]. In this framing, temporal shifts in resilience indices reflect trajectories of shock, adaptation, recovery, and transformation that differ across regions.

3.2. *Dynamic Trajectories of Resistance, Recovery, and Adaptability*

Table 2 indicates that regional earthquake resilience followed distinct temporal patterns across resistance, recovery, and adaptability. Overall, 71.43% of regions were resistant to earthquake shocks, 50% recovered rapidly, and 64.29% showed greater adaptability. As shown in Figure 2, Palu City and Poso Regency recorded the highest resistance scores, suggesting a stronger capacity to sustain socioeconomic stability in the immediate aftermath of an earthquake. Such resistance is shaped by institutional capacity [75], government support, and prior experience in managing crises [76–78], all of which enhance response capability. In Palu City, mitigation initiatives—including mapping hazard-prone areas, strengthening community preparedness, and implementing community resilience programs—have further increased resilience [75,79]. Consistent with earlier studies, high resilience in sub-

districts such as Mantikulore and East Palu is closely linked to social preparedness and adaptive settlement choices that reduce earthquake impacts [75]. These findings suggest that strengthening disaster preparedness and institutional capacity before an earthquake occurs is likely to be more effective in enhancing regional resistance than relying solely on post-disaster recovery measures.

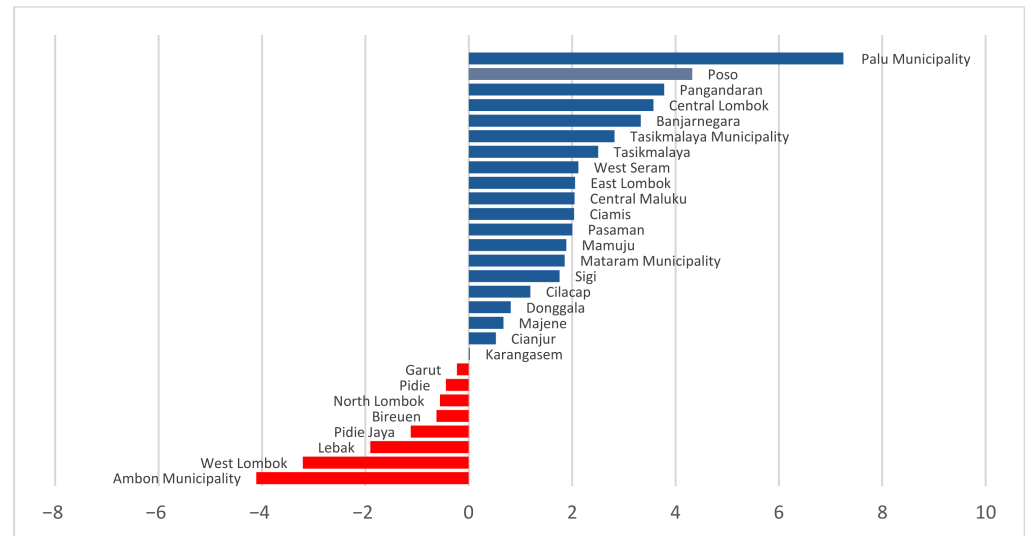


Figure 2. Changes in regional resistance to earthquakes Blue indicates positive resistance values, where the during-disaster resilience index is higher than the pre-disaster resilience index, while red indicates negative resistance values, where the during-disaster resilience index is lower than the pre-disaster resilience index.

In contrast, as shown in Figure 3, several regions—including Ambon City and West Lombok—experienced an immediate decline in the index during the earthquake phase. This pattern suggests that areas with more vulnerable socioeconomic conditions and weaker institutional capacity tend to contract more sharply when earthquakes occur. In West Lombok, low resistance is associated with the dominance of soft-sediment layers and high peak spectral acceleration (PSA) values, which can intensify ground shaking and increase infrastructure vulnerability [80,81]. The West Lombok event also triggered approximately 10,521 landslides, affecting about 1850 km², with a total landslide area of roughly 28.0 km² [82]. The scale of impacts further strained local economic activity, infrastructure, and basic public service capacity.

Figure 4 shows changes in regional resilience from the pre-disaster to post-disaster phase. Karangasem and Bireuen recorded the highest positive recovery scores, indicating relatively rapid post-disaster recovery. This aligns with Adry et al. [83], who found that these regions had lower seismic impact indices than Palu City and Central Lombok, resulting in less disruption to socioeconomic conditions and infrastructure. By contrast, Palu City and Central Lombok displayed the lowest recovery rates, reflecting severe structural damage and limited capacity for economic rebound PusGen [84]. These findings indicate that high resilience does not necessarily translate into effective recovery when disaster impacts are systemic and widespread across sectors. Sriyono et al. [85] further reported that low community preparedness for the 2018 Lombok earthquake and weak household coping capacity—shaped by income and educational background—slowed recovery. The situation was compounded by the emergence of the COVID-19 pandemic early in the post-disaster period, adding pressure to regional socioeconomic conditions. Together, these shocks produced a multiplier effect that impeded recovery and contributed to a “resilience trap,” in which repeated disturbances limit a region’s ability to regain optimal recovery

capacity. Such conditions can erode response and recovery capability, pushing a region toward a critical threshold that may either trigger broader systemic failure or, alternatively, catalyze adaptation and transformation toward greater resilience [86].

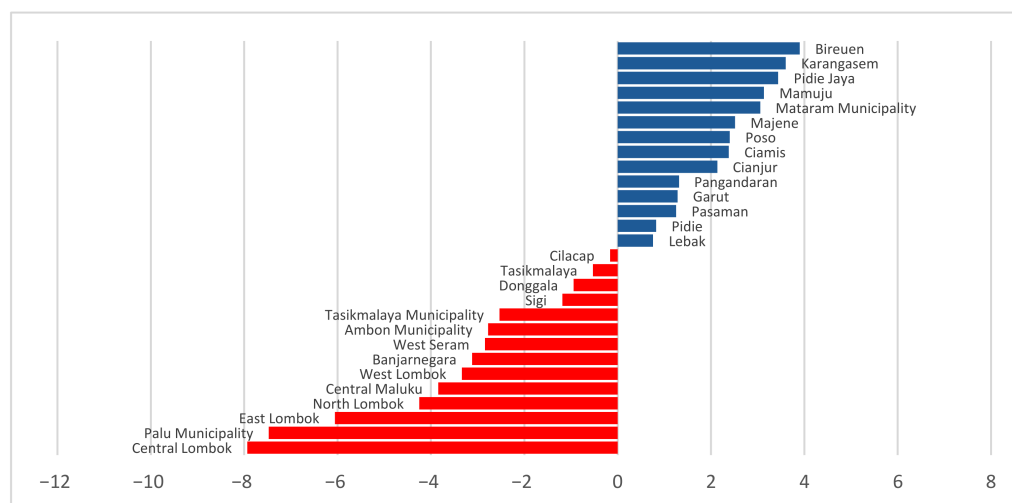


Figure 3. Changes in regional recovery to earthquakes. Blue indicates positive recovery values, where the post-disaster resilience index is higher than the during-disaster resilience index, while red indicates negative recovery values, where the post-disaster resilience index is lower than the during-disaster resilience index.

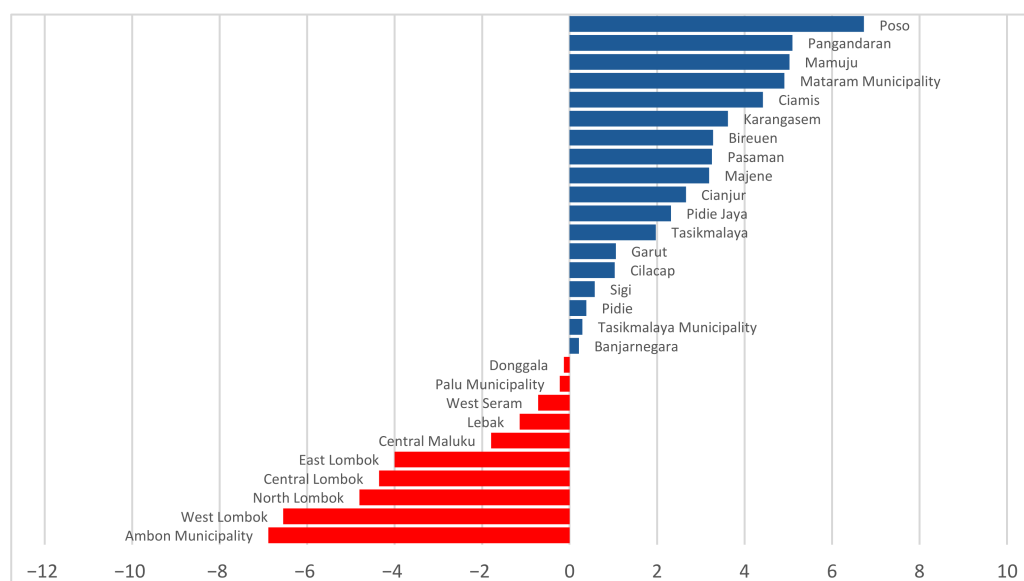


Figure 4. Changes in regional adaptability to earthquakes. Blue indicates positive adaptability values, where the post-disaster resilience index is higher than the pre-disaster resilience index, while red indicates negative adaptability values, where the post-disaster resilience index is lower than the pre-disaster resilience index.

Figure 5 shows that Poso (Figure 5a) and Pangandaran (Figure 5b) have the highest adaptability among the regions studied. This suggests strong post-disaster transformative capacity, reflected in efforts to strengthen communities, diversify local economies, and revise development policies. In Poso, adaptability is reinforced by a comprehensive understanding of regional seismic characteristics, improving the effectiveness of risk management and mitigation strategies [87]. Pangandaran, in contrast, demonstrates robust adaptation by incorporating local knowledge into earthquake-resistant building designs

and the development of sustainable tourism infrastructure. Moreover, community capacity-building through disaster education and simulation exercises has improved preparedness, while broader dissemination of risk information has enhanced earthquake resilience [88,89]. Effective risk communication helps communities understand emergency response procedures and fosters a local culture of preparedness [90]. Accurate risk perception also shapes adaptive behaviors, reducing vulnerability during disasters [89].

Ambon and West Lombok showed the lowest negative adaptability, suggesting limited capacity to implement long-term structural transformations and, consequently, persistent regional vulnerability. In West Lombok, the earthquake caused widespread damage and a 7.01% economic contraction, which was compounded by a further 13.32% contraction during the COVID-19 pandemic [91]. The tourism-dependent economy was hit particularly hard: visitor numbers fell sharply following the disasters and the pandemic, contributing to steep declines in hotel occupancy and the loss of about 15,000 jobs [92].

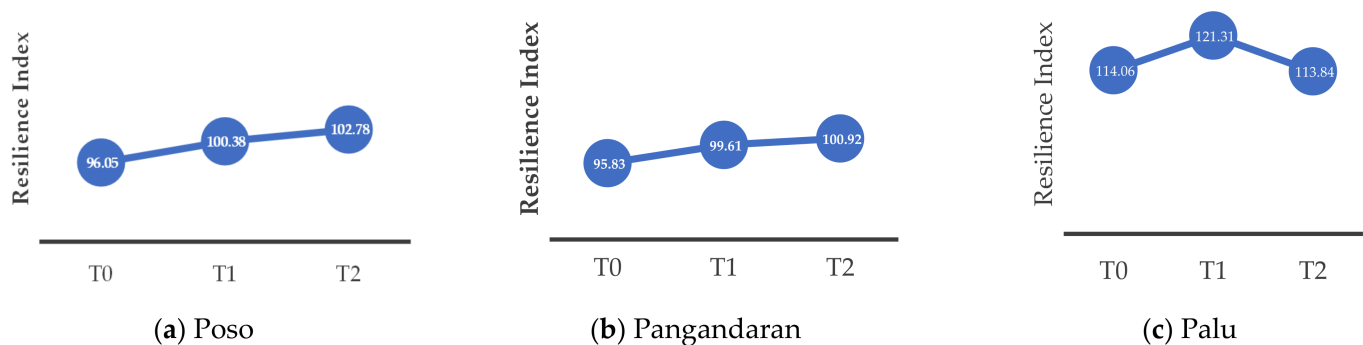


Figure 5. Temporal trajectories of resilience index across the pre-shock, shock, and post-shock phases in (a) Poso, (b) Pangandaran, and (c) Palu.

In Ambon City, adaptation after earthquakes has been constrained by limited preparedness, weak early warning systems, and socio-psychological pressures. Low disaster information literacy, insufficient integration of historical knowledge into preparedness strategies, and high levels of mental and emotional distress have all undermined Ambon's capacity to adapt to seismic hazards [93–95]. In addition, substantial economic losses from building damage, inadequate reconstruction resources, and seismically vulnerable infrastructure further slow recovery and weaken regional resilience [96,97].

From a policy perspective, strengthening earthquake resilience requires a multidimensional approach that reduces immediate impacts while also enhancing recovery and adaptive capacity. This can be pursued through improved governance, economic diversification, resilient health systems, stronger institutional capacity, and expanded social protection [98–100]. Overall, these findings reinforce that earthquake resilience should be understood within a multi-hazard framework and as inherently temporal: strong resistance does not automatically lead to effective long-term recovery and adaptation, particularly under compound shocks [101,102].

3.3. Dynamic Resilience Typology

The optimal number of clusters was identified using the Elbow method by evaluating the within-cluster sum of squares (WCSS) for k values from 2 to 12. As shown in Figure 6, WCSS drops steeply for small k —most notably from $k = 2$ to $k = 4$ —then declines more gradually beyond $k = 4$. This leveling off indicates that additional clusters provide only minor improvements in within-cluster cohesion. Accordingly, the elbow occurs at $k = 4$, implying that four clusters best capture the underlying structure by balancing within-cluster similarity and between-cluster separation. The 4-cluster solution also yields a more

even distribution of observations and clearer, more stable interpretations than $k = 5$ or $k = 6$, where some clusters contain too few members. Therefore, four clusters were selected as optimal for this study.

The clustering results in Table 4 indicate that the groups differ across resilience, recovery, and adaptability. Cluster 2 exhibits the strongest resilience, with the highest recovery and adaptability scores and an overall positive resilience score. In contrast, Cluster 4 shows the weakest resilience, with negative scores across all dimensions, especially adaptability. Clusters 1 and 3 further suggest that the ability to withstand immediate disaster impacts does not necessarily align with longer-term recovery and adaptive capacity, highlighting the multidimensional and dynamic nature of regional resilience.

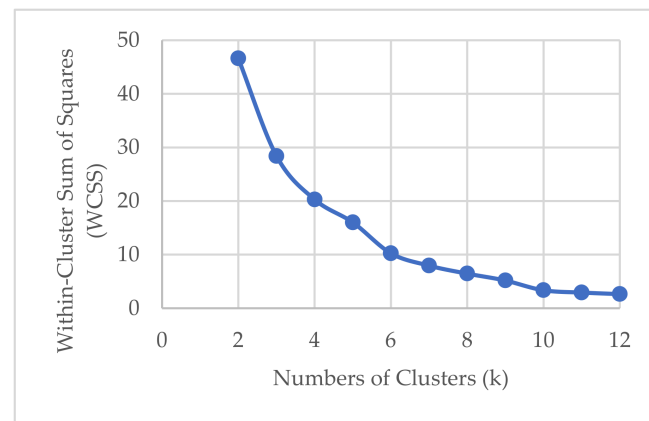


Figure 6. Elbow method for optimal cluster.

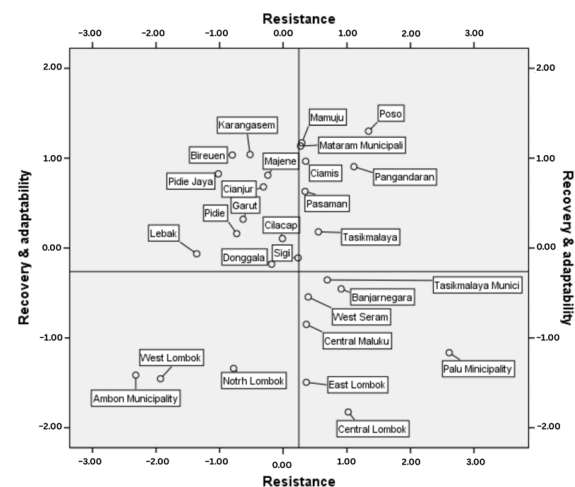
Table 4. Final cluster centers.

	Cluster			
	1	2	3	4
Resistance	0.91	0.61	−0.51	−1.68
Recovery	−1.28	0.71	0.60	−0.87
Adaptability	−0.63	1.08	0.24	−1.93

Table 5 and Figure 7 summarize the regional clustering results across resistance, recovery, and adaptability. Cluster 1 comprises Palu Municipality, Central Lombok, Banjarnegara, Tasikmalaya Municipality, West Seram, East Lombok, and Central Maluku. This group records the highest resistance score (0.91) but comparatively low recovery (−1.28) and adaptability (−0.63) scores. Overall, these regions appear able to sustain socioeconomic stability in the immediate aftermath of a disaster, yet they face substantial difficulties with longer-term recovery and adaptation. Possible drivers include weak infrastructure resilience, limited compliance with seismic standards, complex socio-political contexts, and disaster management systems with insufficient capacity to support reconstruction and strengthen adaptive capacity [11,103]. Socioeconomic conditions—particularly welfare and governance capacity—also shape adaptability; regions with stronger economic and institutional capacity tend to recover and adapt more effectively [104]. Consistent with this, Tope et al. [105] report slow post-disaster progress in Palu City, with socioeconomic recovery reaching only 44.2% one year after the event, highlighting the earthquake’s enduring impacts.

Table 5. Region cluster membership based on resistance, recovery and adaptability.

Cluster	Region	n (%)
1	Palu Municipality, Central Lombok, Banjarnegara, Tasikmalaya Municipality, West Seram, East Lombok, Central Maluku	7 (25%)
2	Poso, Pangandaran, Tasikmalaya, Ciamis, Pasaman, Mamuju, Mataram Municipality	7 (25%)
3	Sigi, Cilacap, Donggala, Majene, Cianjur, Karangasem, Garut, Pidie, Bireuen, Pidie Jaya, Lebak	11 (39.7%)
4	North Lombok, West Lombok, Ambon Municipality	3 (10.7%)

**Figure 7.** Mapping of resistance, recovery and adaptability.

Poso, Pangandaran, Tasikmalaya, Ciamis, Pasaman, Mamuju, and Mataram City fall into Cluster 2. This cluster shows the strongest regional resilience, reflected in the highest recovery (0.71) and adaptability (1.08) scores and a positive resistance score (0.61). These results suggest that the regions can sustain socioeconomic stability in the initial disaster phase and rebound quickly, supported by relatively strong adaptive capacity. Empirical studies indicate that high resilience is often driven by community-based approaches, multistakeholder collaboration, and the use of local wisdom in disaster risk reduction and post-disaster rehabilitation and reconstruction [106,107]. Evidence from post-2018 Lombok earthquake recovery in West Nusa Tenggara and the application of indigenous knowledge in mitigation further highlights the value of strengthening local capacity and collaborative governance to improve seismic resilience [108,109].

Cluster 3 comprises Sigi, Cilacap, Donggala, Majene, Cianjur, Karangasem, Garut, Pidie, Bireuen, Pidie Jaya, and Lebak. While recovery (0.60) and adaptability (0.24) are generally positive, resistance is negative (−0.51). This pattern indicates heightened vulnerability at the onset of disasters—marked by stronger immediate physical and socioeconomic shocks—followed by relatively good capacity to recover and adjust after the event. BPS data show that earthquakes in several of these areas have been associated with economic contraction and rising poverty and unemployment. Nevertheless, the positive recovery and adaptability scores suggest that communities and local governments can mobilize to accelerate recovery and recalibrate socioeconomic systems under post-disaster conditions.

Cluster 4 includes North Lombok, West Lombok, and Ambon City and records negative scores across all dimensions—resistance (−1.68), recovery (−0.87), and adaptability (−1.93)—signaling the lowest overall resilience. In North and West Lombok, repeated

earthquake exposure, fragile geological conditions, and infrastructure damage from the 2018 events elevate future risk [80,110–112]. Limited preparedness, weak infrastructure, socioeconomic and psychological vulnerability, and low economic diversification further constrain recovery and long-term adaptation [113–118]. Governance gaps, weak policy implementation, environmental pressures, and climate change also intensify vulnerability [118]. In Ambon City, low resistance, slow recovery, and limited adaptability are linked to strike-slip fault complexity and frequent aftershocks that damage infrastructure and disrupt socioeconomic activity [119–121]. Strengthening infrastructure, updating hazard maps, improving seismic monitoring, and expanding preparedness and community participation are therefore critical to building long-term resilience.

Overall, the clustering results show that regional resilience is highly heterogeneous, with distinct profiles across clusters. This implies that resilience-building strategies should be differentiated rather than uniformly applied. A cluster-based approach can therefore support the design of adaptive, targeted, and context-specific regional development policies.

3.4. Robustness Assessment Results of the Resilience Index

To evaluate the robustness of aggregation methods for constructing regional earthquake resilience indices, this study compares the rankings produced by three aggregation methods: the Adjusted Mazziotta–Pareto Index (AMPI), Arithmetic Mean (AM), and Median (ME). Index robustness is tested using Spearman’s Rank Correlation to assess the consistency of rankings across aggregation methods, and Absolute Rank Differences to identify the magnitude of changes in each region’s position due to changes in aggregation method.

Table 6 shows the results of the Spearman rank correlation between the aggregation methods in the pre-, during-, and post-shock phases. Consistently, the correlation between AMPI and the arithmetic mean (AM) is higher than that between AMPI and the median across all time phases. In the pre-phase, the AMPI–AM correlation of 0.76 indicates strong rank agreement, whereas the AMPI–median correlation is only 0.53. In the during-phase, the AMPI–AM correlation increases to 0.99, indicating an almost identical rank structure, whereas the correlation with the median remains low (0.52). A similar pattern is observed in the post-phase, with an AMPI–AM correlation of 0.98 and an AMPI–median correlation of 0.69. Overall, these results show that AM produces the most consistent ranking structure relative to AMPI, whereas the ME produces a relatively more divergent ranking.

Table 6. Spearman’s rank correlation matrix before, during and after shock.

Method	Pre Shock			During Shock			Post Shock		
	AMPI	AM	ME	AMPI	AM	ME	AMPI	AM	ME
AMPI	1.00	0.76	0.53	1.00	0.99	0.52	1.00	0.98	0.69
AM	0.76	1.00	0.60	0.99	1.00	0.52	0.98	1.00	0.72
Median	0.53	0.60	1.00	0.52	0.52	1.00	0.69	0.72	1.00

Note: AMPI, adjusted Mazziotta–Pareto index; AM, arithmetic mean; ME, median.

Table 7 shows that AM consistently produces smaller rank differences than AMPI does for the ME across all observation periods. The AMPI–AM rank gap is very low during the phase (0.79) and remains small in the post-phase (1.07), whereas the median exhibits a larger and more stable deviation (approximately 5–6). The same pattern is reflected in the coefficient of variation, where AM shows higher conformity to AMPI than ME, although the variation increases in the during and post-phases. Accordingly, all sensitivity indicators (Spearman, absolute rank differences, and CV) consistently indicate that AM has the highest structural rank similarity to AMPI, whereas ME yields more divergent rankings. These results affirm that AMPI produces a relatively stable structure but remains

sensitive to inter-indicator imbalances, making it more suitable for measuring regional earthquake resilience.

Table 7. Spearman’s rank correlation matrix, before, during and after earthquake.

Absolute Rank Differences	Mean	SD	CV
Pre			
AMPI_AM	4.21	3.64	0.86
AMPI_ME	5.89	5.10	0.87
During			
AMPI_AM	0.79	0.98	1.24
AMPI_ME	6.00	5.22	0.87
Post			
AMPI_AM	1.07	1.19	1.11
AMPI_ME	5.04	3.90	0.78

Note: AMPI, adjusted Mazziotta–Pareto index; AM, arithmetic mean; ME, median; SD, standard deviation; CV, coefficient of variation.

Tables 8–10 present a comparison of the regional resilience index obtained using the Adjusted Mazziotta–Pareto Index (AMPI), arithmetic mean (AM), and median (ME) across the pre-shock, during-shock, and post-shock periods. This analysis aims to evaluate the robustness of the aggregation methods to changes in the regional ranking structure and to identify the most robust method for measuring regional resilience.

Table 8. Regional resilience index by summary method, pre-earthquake.

Region	AMPI		AM		ME		Ranks Difference	
	Value	Ranks	Value	Ranks	Value	Ranks	AMPI—AM	AMPI—ME
Bireuen	98.10	13	33.52	26	26.63	17	−13	−4
Pidie	98.24	12	33.77	24	27.14	15	−12	−3
Pidie Jaya	95.72	23	32.45	27	28.61	14	−4	9
Poso	96.05	19	42.86	10	26.19	18	9	1
Garut	95.41	24	37.95	18	24.62	21	6	3
Ciamis	97.92	14	36.24	21	16.87	26	−7	−12
Pangandaran	95.83	22	38.88	17	15.95	27	5	−5
Tasikmalaya	96.01	20	36.06	22	15.95	27	−2	−7
Tasikmalaya Municipality	100.50	8	45.54	7	41.33	5	1	3
Cilacap	104.82	4	53.13	3	47.67	4	1	0
Lebak	99.55	10	39.62	15	32.46	11	−5	−1
Banjarnegara	96.92	17	40.17	12	24.44	22	5	−5
East Lombok	96.35	18	39.25	16	29.87	13	2	5
North Lombok	90.33	27	34.79	23	17.26	25	4	2
Mataram Municipality	115.47	1	73.53	1	79.85	1	0	0
West Lombok	99.46	11	45.36	8	48.77	3	3	8
Central Lombok	95.27	25	37.89	19	27.03	16	6	9
Donggala	95.96	21	40.06	13	34.53	10	8	11
Sigi	97.86	16	41.38	11	30.09	12	5	4
Palu Municipality	114.06	2	68.19	2	58.65	2	0	0
Central Maluku	95.20	26	33.74	25	36.66	9	1	17
West Seram	90.15	28	27.39	28	17.77	24	0	4
Ambon Municipality	106.32	3	48.71	6	24.17	23	−3	−20
Majene	97.88	15	39.86	14	37.29	8	1	7
Mamuju	103.89	5	51.30	4	40.82	6	1	−1
Karangasem	102.93	6	50.72	5	40.05	7	1	−1
Pasaman	100.63	7	42.98	9	25.72	19	−2	−12
Cianjur	100.19	9	37.76	20	25.21	20	−11	−11

Note: AMPI, Adjusted Mazziotta–Pareto Index; AM, arithmetic mean; ME, median.

Table 9. Regional resilience index by summary method, during-earthquake

Region	AMPI		AM		ME		Ranks Difference	
	Value	Ranks	Value	Ranks	Value	Ranks	AMPI—AM	AMPI—ME
Bireuen	97.48	21	38.53	23	26.80	20	−2	1
Pidie	97.80	19	40.45	18	35.91	12	1	7
Pidie Jaya	94.60	26	33.75	26	31.79	15	0	11
Poso	100.38	10	43.62	10	28.94	18	0	−8
Garut	95.18	25	35.11	25	24.62	23	0	2
Ciamis	99.96	12	42.94	12	20.45	26	0	−14
Pangandaran	99.61	14	42.77	13	19.60	28	1	−14
Tasikmalaya	98.52	17	40.42	19	25.16	22	−2	−5
Tasikmalaya Municipality	103.32	5	48.71	7	50.40	4	−2	1
Cilacap	106.01	3	56.81	3	59.29	3	0	0
Lebak	97.65	20	39.02	20	20.16	27	0	−7
Banjarnegara	100.24	11	43.16	11	26.56	21	0	−10
East Lombok	98.40	18	40.86	17	31.02	16	1	2
North Lombok	89.78	28	30.50	28	23.25	24	0	4
Mataram Municipality	117.33	2	77.80	2	84.36	2	0	0
West Lombok	96.25	24	38.86	21	41.19	6	3	18
Central Lombok	98.85	15	41.57	15	34.29	13	0	2
Donggala	96.77	23	38.62	22	36.64	11	1	12
Sigi	99.62	13	42.53	14	32.94	14	−1	−1
Palu Municipality	121.31	1	81.28	1	86.07	1	0	0
Central Maluku	97.25	22	38.40	24	40.40	8	−2	14
West Seram	92.27	27	30.79	27	21.01	25	0	2
Ambon Municipality	102.21	8	51.71	5	28.07	19	3	−11
Majene	98.55	16	41.30	16	37.12	10	0	6
Mamuju	105.78	4	53.06	4	41.59	5	0	−1
Karangasem	102.95	6	49.89	6	38.91	9	0	−3
Pasaman	102.64	7	47.37	9	29.86	17	−2	−10
Cianjur	100.72	9	48.14	8	40.53	7	1	2

Note: AMPI, adjusted Mazziotta–Pareto index; AM, arithmetic mean; ME, median.

Table 10. Regional resilience index by summary method, post-earthquake.

Region	AMPI		AM		ME		Ranks Difference	
	Value	Ranks	Value	Ranks	Value	Ranks	AMPI—AM	AMPI—ME
Bireuen	101.38	10	45.08	12	27.71	21	−2	−11
Pidie	98.63	15	40.85	17	35.55	12	−2	3
Pidie Jaya	98.04	18	39.87	18	34.70	13	0	5
Poso	102.78	8	48.00	9	31.99	15	−1	−7
Garut	96.46	21	37.23	22	18.13	26	−1	−5
Ciamis	102.34	9	46.87	10	29.15	19	−1	−10
Pangandaran	100.92	12	44.90	13	26.99	22	−1	−10
Tasikmalaya	97.99	19	39.64	19	26.99	22	0	−3
Tasikmalaya Municipality	100.79	13	43.79	14	27.95	20	−1	−7
Cilacap	105.85	5	56.85	4	49.60	4	1	1
Lebak	98.41	17	41.65	15	37.20	11	2	6
Banjarnegara	97.13	20	37.89	20	29.54	18	0	2
East Lombok	92.35	25	33.96	24	30.99	17	1	8
North Lombok	85.53	28	26.50	27	16.48	28	1	0
Mataram Municipality	120.39	1	81.26	1	88.78	1	0	0
West Lombok	92.91	24	35.13	23	17.60	27	1	−3
Central Lombok	90.91	26	33.21	25	20.00	25	1	1
Donggala	95.83	22	37.78	21	37.92	10	1	12
Sigi	98.44	16	41.37	16	32.28	14	0	2

Table 10. *Cont.*

Region	AMPI		AM		ME		Ranks Difference	
	Value	Ranks	Value	Ranks	Value	Ranks	AMPI—AM	AMPI—ME
Palu Municipality	113.84	2	71.18	2	66.51	2	0	0
Central Maluku	93.41	23	31.99	26	39.53	9	−3	14
West Seram	89.43	27	25.73	28	21.02	24	−1	3
Ambon Municipality	99.43	14	48.05	8	42.29	7	6	7
Majene	101.06	11	45.28	11	40.51	8	0	3
Mamuju	108.91	3	57.94	3	46.11	5	0	−2
Karangasem	106.55	4	54.17	5	43.05	6	−1	−2
Pasaman	103.89	6	49.34	7	31.94	16	−1	−10
Cianjur	102.85	7	50.25	6	53.99	3	1	4

Note: AMPI, adjusted Mazziotta–Pareto index; AM, arithmetic mean; ME, median.

The analysis results show that the AM method yields a ranking structure most consistent with AMPI across the entire observation period. This is evident from the small absolute rank differences between the two methods in most regions. During the shock and post-shock periods, several regions display identical rankings between AMPI and AM, such as the Palu Municipality, Mataram Municipality, Cilacap, and Mamuju. These findings indicate that both methods demonstrate a high level of consistency in capturing regional resilience patterns.

Nevertheless, the ME method produces a ranking structure that is relatively different from both AMPI and AM. This difference is evident in the substantial changes in ranking positions for several regions. For example, the Ambon Municipality ranked third in the pre-shock period based on AMPI but dropped to 23rd when using the ME. A similar pattern is also observed for Central Maluku and West Lombok, which experienced considerable ranking changes between aggregation methods. This condition indicates that the median method is more sensitive to the distribution of indicators and tends to reduce the influence of extreme values; therefore, regions with unbalanced indicator performance undergo significant ranking shifts.

The analysis results also show the stability of regional resilience in urban areas and administrative centers. The Mataram and Palu municipalities consistently occupy the top positions across all aggregation methods and throughout the observation periods. Similarly, regions such as Cilacap, Mamuju, and Karangasem maintain relatively high positions before, during, and after the shock. This stability indicates that regions with stronger fiscal, institutional, and infrastructure capacities tend to have higher and more stable levels of regional resilience against changes in external conditions.

Conversely, peripheral regions and areas with limited development capacity exhibit higher sensitivity to changes in aggregation methods. For example, regions such as Central Maluku, Donggala, Pangandaran, and the Ambon Municipality experience considerable ranking fluctuations, especially when using the median method. These findings indicate disparities among the dimensions of regional resilience, in which some indicators progress more favorably than others.

From a methodological perspective, these results reinforce the argument that AMPI is a more robust aggregation method for constructing a regional resilience index. AMPI not only produces a ranking structure that is relatively stable and consistent compared to compensatory methods such as the arithmetic mean but also remains capable of capturing imbalances in the distribution between indicators that are not fully reflected in simple average methods. Thus, the use of AMPI is considered more appropriate for measuring multidimensional phenomena such as regional resilience, especially in the context of regions with high socioeconomic heterogeneity and institutional capacity.

4. Conclusions

This study applies the Adjusted Mazziotta–Pareto Index (AMPI), a non-compensatory composite index, to quantify regional resilience, enabling comparisons across regions and time while providing an interpretable tool for decision makers. The composite approach is well suited to the study's aim of capturing variation in resistance, recovery, and adaptive capacity across earthquake-affected areas in Indonesia.

The research findings indicate that 71.43% of regions exhibit positive resistance to earthquake shocks, 50% of regions demonstrate relatively rapid recovery capabilities, and 64.29% of regions show good adaptability in the post-disaster phase. Notably, these three dimensions do not always develop concurrently. The city of Palu and Poso Regency exhibit the highest levels of resistance, whereas Karangasem and Bireuen demonstrate superior recovery capabilities. In contrast, Poso Regency and Pangandaran display the highest levels of adaptability, while Ambon City and West Lombok Regency have the lowest adaptability scores. These results suggest that regions capable of maintaining socio-economic functions during disasters do not necessarily possess equally strong recovery or long-term transformation capabilities.

Cluster analysis identified four regional resilience typologies, each reflecting distinct capacity characteristics. Notably, Cluster 2 displayed the most balanced integration of resistance, recovery, and adaptability, thereby representing regions with the highest resilience levels. In contrast, Cluster 4 exhibited deficiencies across all resilience dimensions, while Clusters 1 and 3 demonstrated capacity imbalances across disaster phases. These findings suggest that resilience enhancement strategies should not adopt a uniform approach but rather be tailored to address the specific weaknesses in each region's resilience dimensions, whether by strengthening shock resistance, expediting recovery, or facilitating the build-back-better process. Furthermore, the robustness analysis results indicated that the ranking structure generated by AMPI remained consistent with that produced by the arithmetic mean method, thereby affirming the reliability of the research outcomes.

The present study is limited by the lack of indicators that represent institutional aspects, disaster risk financing, and community participation at the regency or municipality level. Consequently, future research should incorporate these indicators and broaden the scope to include various regions and disaster types. This approach will facilitate a more comprehensive understanding of the determinants of regional resilience and the effectiveness of disaster risk reduction policies.

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