

Article

Assessing Sustainable Development in Community Welfare and Economic Resilience to Extreme Weather in Indonesia

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Abstract: In recent decades, Indonesia has experienced a surge in natural disasters, resulting in increased casualties and disruptions to economic growth and welfare. This study investigates the impact of various types of natural disasters, focusing on how economic growth (measured by provincial GDP) and welfare levels (measured by the Human Development Index, HDI) influence the number of victims affected by extreme weather. Data on gross regional domestic product and the Human Development Index for each province in Indonesia were obtained from Statistics Indonesia. We employed multivariable negative binomial regression to analyze the relationships between the number of victims affected by extreme weather, provincial HDI, and provincial GDP. The results indicate significant correlations between provincial GDP, HDI, and the number of victims. Higher HDI correlates with fewer victims, whereas higher GDP is associated with an increase in victims. Additionally, we used the Self-Organizing Map (SOM) method, identifying two clusters as the optimal model. Cluster 1 comprises 31 provinces, while Cluster 2 comprises 3 provinces, with the latter highlighting the provinces with the highest disaster risk. Consequently, provinces such as West Java, Central Java, and East Java require heightened attention from various stakeholders involved in disaster management efforts. By examining these relationships, our study contributes to the understanding of sustainable development and resilience against natural disasters. It underscores the importance of improving welfare and economic policies to mitigate the impacts of extreme weather events.

Keywords: extreme weather; Human Development Index; gross domestic product; disaster resilience; sustainable development



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1. Introduction

Indonesia's geographic location within the Pacific Ring of Fire, the world's most active seismic zone, contributes to its high frequency of natural disasters [1,2], placing the country among those with the highest disaster risks globally. Indonesia is continuously threatened by seismic and volcanic activities due to its position at the convergence of tectonic plates. Effective disaster management plans are crucial to mitigating the impacts of this volatile region, which also produces a variety of both typical and unpredictable natural hazards. Over the past decade, Indonesia has experienced an increasing number of natural disasters (i.e., extraordinary events), accompanied by a rising toll of losses and fatalities [3]. In addition to genuine vulnerabilities brought on by population growth, uneven economic development, urbanization, a lack of social and environmental considerations in the development process, and other factors, the country's high exposure to a variety of geophysical and hydrometeorological risks is the primary cause of this risk [4].

The Indonesian National Board for Disaster Management (BNPB) officially recorded 35,034 natural disaster events in Indonesia over the past ten years, from 2014 to 2023. In addition to the official records of over 5.4 million people being evacuated and over 9000 deaths, the BNPB also documented significant economic losses. These figures highlight the critical need for comprehensive disaster risk reduction and preparedness programs. In 2022, a series of natural disaster events resulted in economic losses amounting to IDR 1.06 trillion, which is significantly lower than the IDR 11.06 trillion losses reported in 2021 [5]. This striking difference draws attention to the annual variations in the impacts of disasters.

Indonesia, a Southeast Asian nation, is highly susceptible to a wide range of natural calamities, including earthquakes, volcanic eruptions, tsunamis, and extreme weather [6]. Extreme weather refers to unusual or uncommon weather and climate events that are increasing in frequency due to natural phenomena [7]. A significant extreme weather phenomenon that frequently affects Indonesia is the El Niño-Southern Oscillation (ENSO), a naturally occurring climatic cycle that influences the Pacific Ocean and has a major impact on global weather patterns [8]. Heatwaves, tropical cyclones, floods, and droughts are just some of the extreme weather phenomena that can occur in Indonesia. In addition, extreme weather can cause both financial losses (i.e., damage to structures and other properties that are replaceable or repairable) and nonfinancial losses (i.e., deaths, health effects, and irreversible damage, such as ecosystem degradation, coastal erosion, and social effects) [9]. Figure 1, which shows the total number of victims—deaths, lost, harmed, and impacted/evacuated—raises grave concerns due to its widespread distribution across the Indonesian territory.



Figure 1. Indonesia’s number of extreme weather victims in 2018–2022.

The assessment of vulnerability following disasters often emphasizes economic growth as a strategy for reducing risks. Community well-being refers to a situation in which the necessities of existence are met. The Human Development Index (HDI) offers a more comprehensive perspective for evaluating human welfare by measuring the following three aspects: purchasing power, health, and education. Economic growth per capita is influenced by people’s purchasing power, and as purchasing power increases, so does people’s ability to maintain their standard of living [10]. In this context, maximizing economic growth is an effective way to enhance human well-being. An area with strong public finances, a high GDP per capita, and a robust economy will handle an extreme weather catastrophe far better than a nation already facing sustainability issues, such as

an aging population [11]. Moreover, higher welfare levels are associated with increased awareness of natural disaster events, since welfare correlates with longevity, healthy living, knowledge, and a decent standard of living.

Based on Figure 2a,b, the comparison of GDPs reveals a slight similarity in the visualized mapping, suggesting that high GDP may correlate with a higher number of victims. Conversely, the evenly distributed data for the HDI implies that higher HDI levels may be associated with fewer victims. The amount of Gross Regional Domestic Product (GRDP) indicates an area's rising economic growth; as the GRDP level increases, the community will have more opportunities to access better education and healthcare. Thus, as an area's economy grows, the community will have more resources to direct toward the health and education sectors [12].

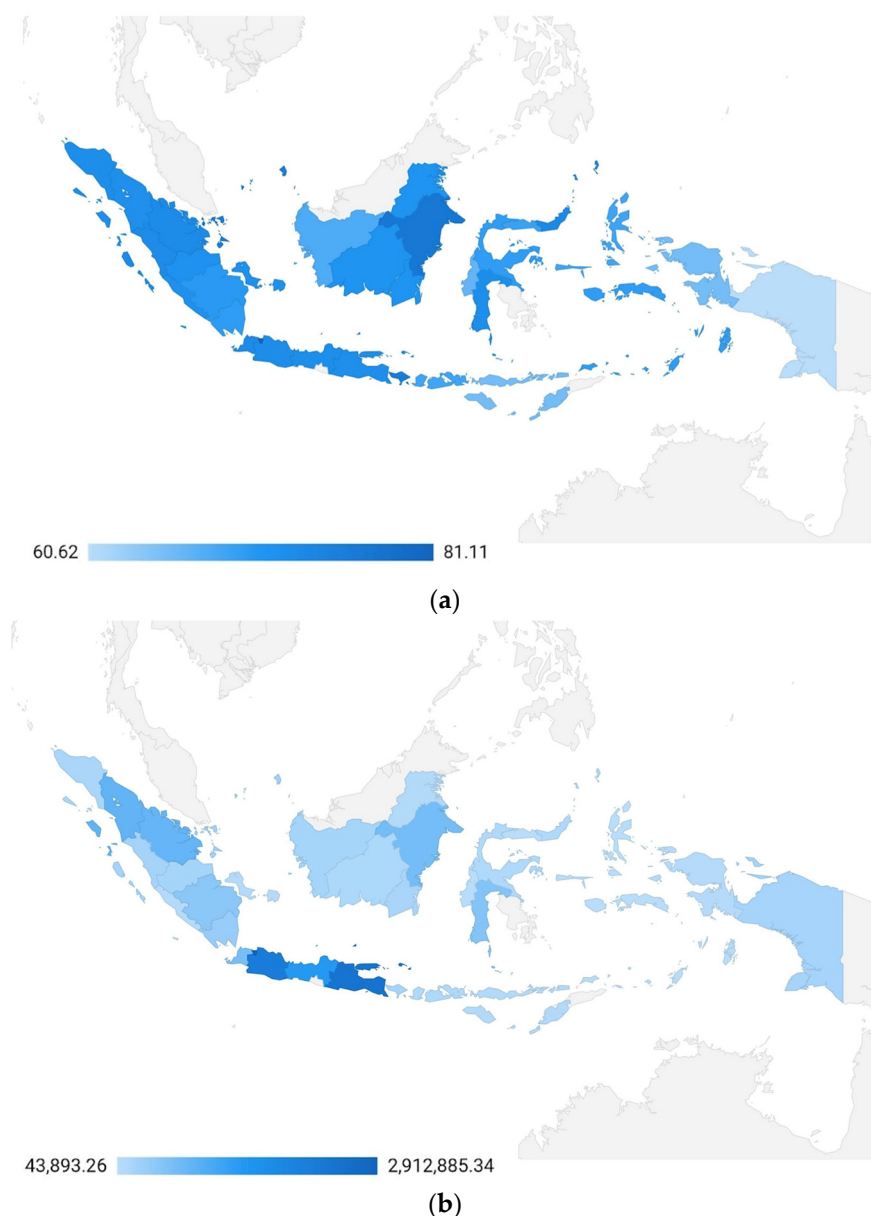


Figure 2. Geographic representation of Indonesia's provincial community welfare and economic resilience: (a) Indonesia's Provincial Human Development Index in 2021; (b) Indonesia's provincial gross domestic product in 2021.

The impact of welfare and economic growth on the total number of human victims—those who die, go missing, are injured, or are affected/evacuated—remains unclear. The

number of victims is chosen as an outcome measure to demonstrate the effectiveness of disaster preparedness. Given this background, it is crucial to determine whether welfare increases or decreases the effects of a disaster to manage risks effectively. Economic growth is also included in the study to understand its impact on the effects of natural disasters. This research aims to explore the relationship between welfare, economic growth, and the effects of disasters. We utilized secondary data, including the Provincial Human Development Index and provincial economic growth of Indonesia, as well as the number of victims, sourced from Statistics Indonesia for the required period. The primary method employed in the data analysis is the count data regression. Furthermore, we also use clustering analysis to visualize mapping vision. The findings from this study and mapping are essential for enhancing Indonesia's current disaster management efforts, particularly in improving preparedness for natural disaster events and developing contingency plans. By assessing the interplay between community welfare, economic resilience, and disaster impacts, this research contributes to the broader understanding of sustainable development in Indonesia, particularly in the context of extreme weather events.

2. Materials and Methods

2.1. Data Source and Variables

Our study investigates the relationship between welfare and the number of victims (including those who are deceased, missing, injured, or otherwise impacted) across 34 Indonesian provinces affected by natural disasters, specifically extreme weather events. We obtained data from Statistics Indonesia (Badan Pusat Statistik or BPS), which provides information on gross regional domestic product and the Human Development Index (HDI) at the provincial level in Indonesia. Additionally, we acquired data on the number of victims related to extreme weather, categorized as deceased, missing, injured, or impacted. This study focuses on extreme weather incidents that occurred between 2018 and 2022, as such events have become increasingly frequent and severe in Indonesia [13].

The primary outcome of interest, or the dependent variable, is the 'number of victims' resulting from deaths, missing persons, injuries, and those otherwise impacted. This is represented by the annual average number of victims (DnM), calculated by dividing the total number of victims by the number of years in which extreme weather events occurred and rounding to the nearest integer. The independent variables are the Human Development Index (HDI) and the Gross Regional Domestic Product (GDP) at the provincial level for 2021, which serve as proxies for welfare and economic conditions, respectively. We chose 2021 as the reference year because it is the only year between 2018 and 2022 in which every province in Indonesia was affected by at least one extreme weather event.

2.2. Negative Binomial Regression

Considering that the outcome variable is in the count format, the most widely used count regression models commonly applied in count data analysis include zero-inflated models, Poisson, and negative binomial models [14]. In this study, we employ negative binomial regression analysis as our analytical technique. Negative binomial regression is a type of Generalized Linear Model (GLM) that describes the relationship between predictor variables and response variables [15,16]. The negative binomial regression model is derived from the Poisson-gamma mixture distribution [17]. While the Poisson regression model is often utilized, we choose negative binomial regression due to the presence of overdispersion. To detect overdispersion in the Poisson model, dispersion statistics based on Pearson residuals can be used as a diagnostic tool [18]. Overdispersion in a Poisson model refers to a situation in which the variance of the dependent variable exceeds the predictions made by the Poisson distribution [15]. The probability density used in Equation (1) and the conditional mean and conditional variance used in Equations (2) and (3) form the basis for fitting the model. In these equations, α represents the dispersion parameters, while β_0 , β_1 , and β_2 are regression parameters, with the province indices denoted by i ($i = 1, 2, \dots, 34$). For clarity, V_i represents the number of victims in each province, and

μ_i denotes the average number of victims for each province. Below are the probability density function displayed in Equation (1), the conditional mean in Equation (2), and the conditional variance in Equation (3):

$$f(V_i|HDI_i, Ln_GDP_i) = \frac{\Gamma(V_i + \alpha^{-1})}{V_i! \Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i} \right)^{\alpha^{-1}} \left(\frac{\mu_i}{\alpha^{-1} + \mu_i} \right)^{V_i}, V_i = 0, 1, 2, \dots \quad (1)$$

$$E(V_i|HDI_i, Ln_GDP_i) = \mu_i = \exp(\beta_0 + \beta_1 HDI_i + \beta_2 Ln_GDP_i) \quad (2)$$

$$Var(V_i|HDI_i, Ln_GDP_i) = \mu_i(1 + \alpha\mu_i) \quad (3)$$

when a Poisson regression model exhibits overdispersion—meaning that the variance exceeds the mean—negative binomial regression is employed as an alternative [19]. The maximum likelihood estimation method was used to estimate the regression parameters. For statistical inference, we adopted a significance level of 5%. All data analyses were conducted using R statistical software, specifically RStudio version 2023.12.0+369.

2.3. Self-Organizing Maps (SOMs) Clustering

In this study, we utilized both negative binomial regression analysis and the Self-Organizing Map (SOM) clustering method. Cluster analysis is a key technique in multivariate analysis that aims to categorize objects based on their characteristics. It involves grouping individuals or research objects so that those with the most similar characteristics are placed in the same cluster. Objects within a cluster have very similar (i.e., homogeneous) characteristics, while objects in different clusters have dissimilar (i.e., heterogeneous) characteristics. This clustering is optimized based on the identified variables [20].

The Self-Organizing Map (SOM) algorithm was first introduced by Kohonen in 1982 [21]. Kohonen popularized SOM using an artificial neural network (ANN) training technique that operates on a winner-take-all basis, meaning that only the winning neuron updates its weights [22]. SOM is an artificial neural network technique that aims to visualize data by reducing their dimensionality using self-organizing artificial neural networks, allowing humans to interpret high-dimensional data represented as low-dimensional data. This unsupervised learning method operates without guidance from input-target data, enabling SOM to summarize a systematically structured topology into individual class or cluster units [23,24]. The Kohonen SOM structure consists of the following two layers: the input layer and the output layer. Each neuron in the input layer is connected to each neuron in the output layer, where each neuron in the output layer represents a cluster of the given input [25]. In Kohonen SOM, the input layer (first) is connected to the competitive layer (second), indicating that each input unit is connected to each output unit, with associated weights (weighting values) [26].

The steps in the Kohonen SOM JST algorithm begin with step 0, where weight initialization (w_{ij}) is performed by inputting the learning rate parameter (α) and the input topological neighborhood parameters (R). If the stop condition is not met (i.e., false), the following actions are performed. For each vector x ($x_i, i = 1, 2, \dots, n$), the next actions are taken. For each index j ($j, i = 1, 2, \dots, m$), calculate the Euclidean distance, as shown in Equation (4).

$$D(j) = \sum_{i=1}^n (w_{ij} - x_i)^2 \quad (4)$$

Identify the winning unit (index j), which is the unit with the closest (minimum) distance $D(j)$. The next step is to calculate the new values of w_{ij} using the following formula: $w_{ij}(new) = w_{ij}(old) + \alpha [x_i - w_{ij}(old)]$. Update the learning rate with $\alpha(new) = 0.5\alpha(old)$. Then, reduce the radius of the neighborhood function at the specified time (i.e., epoch). For reference, N represents the total number of data points, y_i is the actual value of the i -th

data point, and $\hat{y}_i$ is the value predicted by the model for the the i -th data point. Finally, test the termination condition, as shown in Equation (5).

$$MSE = \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{N} \quad (5)$$

Consistency between the previous iteration and the current one is crucial for understanding the current iteration. If all the w_{ij} values change only slightly, this indicates that the iteration has reached a convergence point, allowing for verification [27].

3. Results

3.1. Negative Binomial Regression Analysis

Table 1 presents the results of the negative binomial regression analysis examining the relationship between the Gross Regional Domestic Product (GDP) at the provincial level, the Provincial Human Development Index (HDI), and the number of victims from deaths and missing persons. Both independent factors were found to be significantly related to the number of victims, although to varying degrees. At a 5% significance level, both the HDI and GDP demonstrated substantial relationships with the number of victims.

Table 1. Regression model for number of victims.

	Intercept	HDI	Ln_GDP	Likelihood Ratio Test Prob. (>Chisq)	Dispersion
Estimate	6.647	−0.00275	1.090×10^{-6}	0.0002145	0.8868 ^a
Standard error	3.633	0.05164	2.863×10^{-7}		1609.874 ^b
Wald statistics (z)	1.830	−0.053	3.808		
Prob (> z)	0.00067	0.00958	0.00014		

^a Dispersion parameter for the binomial negative regression model. ^b Dispersion statistics when data fitted to the Poisson regression model.

The results indicate significant correlations between the Provincial Human Development Index (HDI) and the number of disaster victims. Specifically, provinces with higher HDI scores tend to experience fewer casualties and injuries during natural disaster events. This finding suggests that improved welfare, as reflected by a higher HDI, may enhance disaster preparedness and resilience, thereby reducing the adverse effects of such events. The regression analysis also revealed noteworthy insights regarding the role of economic growth. Provinces with higher economic growth rates exhibited a mixed impact on disaster outcomes. While some high-growth regions demonstrated better disaster management and lower victim counts, others did not show a significant reduction in the number of victims. This variation indicates that economic growth alone may not be a sufficient indicator of disaster preparedness and response effectiveness; other factors, such as infrastructure development and governance, may also play crucial roles.

The findings from our analysis underscore the importance of integrating welfare improvement and economic growth strategies into disaster management policies. Higher welfare levels, as indicated by the HDI, are associated with better disaster outcomes, highlighting the need for continued investment in human development. The mixed results regarding economic growth suggest that while economic prosperity can contribute to disaster resilience, it must be complemented by robust infrastructure and effective governance to optimize disaster preparedness and response.

3.2. Self-Organizing Maps (SOMs) Clustering Analysis

The values of the Connectivity Index, Silhouette, and Dunn Index demonstrate the cluster validation for the Self-Organizing Map (SOM) clustering method. In cluster 2, the Connectivity Index has the smallest value of 4.8690, the Dunn Index has the largest value of 0.5041, and the value of the index Silhouette is 0.8265, which is close to 1. The number of clusters chosen for the clustering technique in this study was two, as it effectively groups

the 34 provinces of Indonesia based on the number of victims (including deaths, missing persons, injuries, and those impacted) caused by extreme weather events. The cluster validation results indicate that the optimal cluster value was two. The cluster analysis using the Self-Organizing Map (SOM) method produced two clusters, as shown in Figure 3.

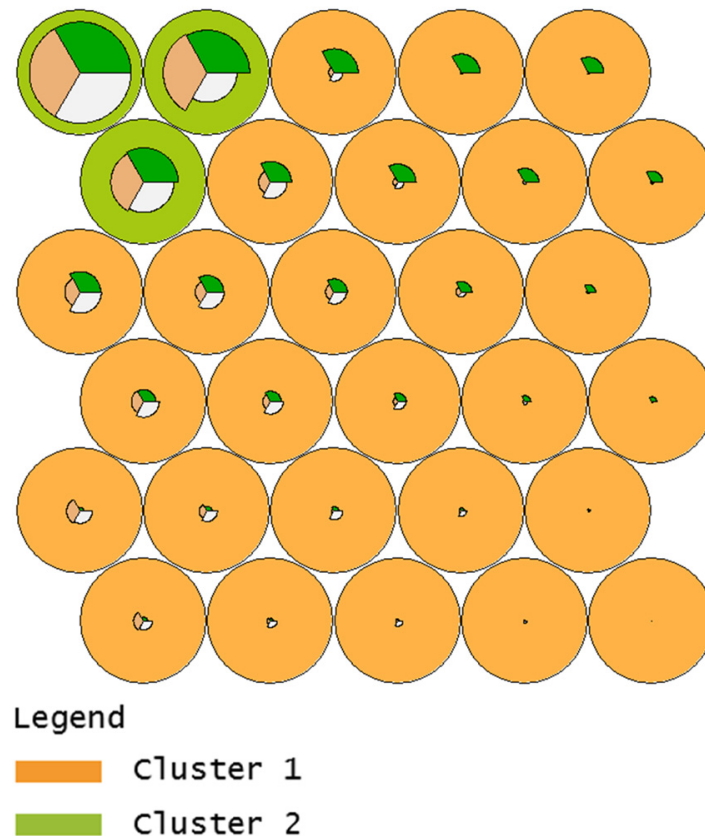


Figure 3. Diagram of self-organizing map (SOM).

The cluster analysis using the Self-Organizing Map (SOM) method produced two clusters, each consisting of thirty hexagonal designs on a 56-grid layout. The total input consisted of 34 districts and cities; however, only 56 pattern multiplications were employed to generate 30 patterns, while the remaining 4 patterns were not formed but were still recorded in the SOM data output. The SOM algorithm allows for interpretation when a diagram is colored and specified by vectors displayed in a mapping plot, as shown in the image. The primary variables represented by each circle are the number of deaths and the number of people impacted, as indicated in the results presented in Figure 3. Nearly every cluster formation pattern or circle is dominated by these two variables. The two distinct colors represent the status of each formed cluster, with the first cluster associated with an orange circle and the second with a green circle. Table 2 below provides a comprehensive overview of the specific members assigned to each cluster, offering additional insights into the distribution and characteristics of the clusters.

Using the Self-Organizing Map (SOM) method, two clusters were created, as shown in Figure 4. The first cluster, represented by an orange color, consists of 31 member provinces that typically exhibit lower values for the number of deaths, impacted individuals, injuries, and missing victims compared to the second cluster, which is represented in green and consists of 3 member provinces.

Table 2. Self-organizing maps cluster's member.

Cluster	Total	Province
1	31	Aceh Province, North Sumatra Province, West Sumatra Province, Riau Province, Jambi Province, South Sumatra Province, Bengkulu Province, Lampung Province, Bangka Belitung Islands Province, Riau Islands Province, DKI Jakarta Province, DI Yogyakarta Province, Banten Province, Bali Province, West Nusa Tenggara Province, East Nusa Tenggara Province, West Kalimantan Province, Central Kalimantan Province, South Kalimantan Province, East Kalimantan Province, North Kalimantan Province, North Sulawesi Province, Central Sulawesi Province, South Sulawesi Province, Southeast Sulawesi Province, Gorontalo Province, Province West Sulawesi, Maluku Province, North Maluku Province, West Papua Province and Papua Province
2	3	West Java Province, Central Java Province, and East Java Province

**Figure 4.** Indonesian provinces' clustering map membership.

The interpretation of the grouping results using the Self-Organizing Map (SOM) method is presented in Table 3, which displays the average values of the variables in each cluster for a comprehensive understanding of the clustering outcomes.

Table 3. Averages of the victim categories for each cluster.

Category	Cluster 1	Cluster 2
Number of missing and dead victims	3	20
Number of injured victims	14	190
Number of impacted victims	4237	40,920

4. Discussion

This study aims to investigate the relationship between economic growth, welfare, and the impact of extreme weather events, specifically concerning the number of victims who

are deceased, missing, injured, or otherwise affected. The study examines whether welfare influences the number of victims and how economic growth affects this figure. The study hypothesizes that natural disasters significantly negatively impact Indonesia's economic growth. Furthermore, it posits that the severity of a natural disaster is positively correlated with the magnitude of economic losses. Additionally, it suggests that regions with higher welfare levels experience relatively lower economic losses from natural disasters compared to those with lower welfare levels.

Based on Table 1, the regression model indicates a very significant correlation between the number of victims—those deceased, missing, injured, and affected—and both provincial GDP and HDI. Specifically, there is a positive correlation between a province's GDP and the number of fatalities, missing persons, injured individuals, and those impacted. Conversely, higher HDI levels correlate with a decreased number of victims from death, missing, injured, and affected categories. This outcome reveals the following intriguing discovery: while economic factors that determine provincial GDP generally govern Indonesia's ability to respond to extreme weather events, higher provincial GDP—which is characteristic of well-developed regions—might experience the most significant impacts from such events. In contrast, advancements in human development, such as improved health and education, may help reduce the number of fatalities among victims. Economic growth indicators, including GDP growth rates, employment rates, and income levels, are utilized to provide a comprehensive picture of the economic context. In addition, welfare indicators such as the Human Development Index (HDI), poverty rates, and access to healthcare and education are employed to capture the multifaceted nature of community well-being.

Our findings offer an alternative viewpoint, suggesting that areas experiencing slower economic growth may also have a higher victim count during periods of severe weather. However, our research indicates that victims are more common in areas with faster economic growth. While economic expansion has long been seen as a major driver of advancement and development, it is increasingly understood to contribute to disaster risk [28]. Developed areas may be particularly vulnerable to natural catastrophes, as they are often the centers of socioeconomic activity, housing concentrated populations and high-value assets [29]. These regions suffer greatly due to the high economic risks they face. The built infrastructure can affect how buildings and other characteristics respond to natural disasters [30]. Although improved socioeconomic conditions can mitigate these effects, they cannot entirely prevent casualties during catastrophes [28]. Research suggests that emerging countries may be more resilient than affluent ones when assessing the financial impact of natural disasters [31]. Indonesia's explosive economic expansion has significantly aided infrastructure development and socioeconomic advancement. However, the negative effects of growth are reflected in increased risk and vulnerability to natural disasters, particularly extreme weather events. Economically developed regions tend to have more complex infrastructure, yet they are also more susceptible to disasters such as floods, landslides, and hurricanes.

In terms of welfare, as measured by the Human Development Index (HDI), regions or countries with higher HDI values typically possess stronger healthcare systems, higher educational attainment, and generally better population well-being [32]. These factors are related to greater awareness of extreme weather occurrences. Awareness of potential disasters and preparedness are essential for preventing fatalities, including loss of life and damage to infrastructure [33]. It is crucial to educate everyone—from residents to government representatives—about natural catastrophes. Community-based early warning systems are vital for mitigating the effects of emergencies and natural disasters. These systems rely on networks, local knowledge, and resources to provide at-risk populations with timely and relevant information [34]. According to the HDI, a measure of well-being, higher levels of welfare can reduce the likelihood of fatalities during natural disasters. Increased income is associated with greater resources and public awareness in disaster scenarios, including improved early warning systems and more robust emergency response infrastructure.

Despite these advantages, Indonesia continues to face significant challenges in responding to natural disasters, particularly those exacerbated by extreme weather. The high death toll and destruction caused by such disasters indicate that many regions in Indonesia still lack adequate preparation and response measures. Efforts to enhance disaster preparedness and rapid response must be better integrated with sustainable economic growth. This requires a comprehensive strategy that prioritizes not only economic development but also the creation of disaster-resistant infrastructure, enhancing community resilience and improving disaster preparedness.

Figure 4 illustrates that businesses in the alternative cluster—wealthy urban centers with dense populations—are more vulnerable to the severe impacts of extreme weather events. In contrast, businesses in the first cluster experience lower casualty rates and may be more resilient overall, even if they still face certain risks.

Based on the results of this cluster analysis, Indonesia needs to adjust its approach to improve the effectiveness of mitigation and response to natural disasters arising from extreme rainfall events. Regions in the first cluster should focus on strengthening emergency response systems and developing awareness campaigns about the risks of disastrous rainfall events. Meanwhile, regions in the alternative group should prioritize bolstering early warning systems, investing in disaster-resilient infrastructure, and increasing public education and awareness regarding disasters. Enhanced collaboration between relevant government agencies and organizations is essential to ensure efficiency in these efforts.

Currently, Indonesia is working to improve its preparedness and response to natural disasters caused by extreme weather across all provinces. By applying the insights from this cluster analysis, resources can be allocated more efficiently, and disaster management strategies can be tailored to meet the specific needs of each cluster. This approach not only enhances the effectiveness of disaster mitigation and response but also ensures that the most vulnerable communities receive the necessary attention and support. Consequently, Indonesia can reduce the loss of life and economic damages due to disasters while increasing the resilience of communities in the most vulnerable areas.

These results have several important implications. To reduce financial losses, catastrophe planning and mitigation measures should be given top priority by policymakers. Investing resources into emergency response plans and robust infrastructure can help lessen the damage that comes with natural disasters. In order to decrease vulnerability, the study highlights the necessity of economic diversification in areas that are prone to disasters. Encouraging investment in industries less vulnerable to natural disasters can improve the stability of the economy. The results also highlight the significance of welfare programs and social safety nets in disaster-affected areas. Providing communities with timely recovery and long-term economic hardship mitigation can be achieved by guaranteeing access to basic services and support. Resilience can be further increased by incorporating sustainability into catastrophe preparedness and encouraging ecologically friendly behavior. By concentrating on both sustainable development and immediate relief, communities are able to recover from disasters more successfully and establish a better foundation for future resilience.

5. Conclusions

This research explores the relationship between economic growth, welfare, and the impact of extreme weather events, specifically focusing on the number of individuals who are dead, missing, injured, or affected. We utilized Gross Domestic Product (GDP) and the Human Development Index (HDI) as indicators of economic conditions and welfare, respectively. A multivariable negative binomial regression model and clustering analysis using Self-Organizing Maps (SOMs) were applied to the obtained data. Our study confirms that an increase in economic growth, as represented by provincial GDP, is directly proportional to a higher number of deaths, missing persons, injuries, and affected individuals during extreme weather events. While economic growth has long been considered a key driver of development and progress, it is increasingly recognized as a

contributor to high disaster risk. This highlights the importance of balancing economic growth with efforts to enhance community resilience, as communities with high capacity to respond to risk may have lower vulnerability to disasters.

Furthermore, improvements in well-being, as indicated by the HDI, correlate with reductions in the numbers of casualties resulting from extreme weather. Regions with higher HDI values tend to demonstrate greater awareness of extreme weather, as their residents generally have higher levels of education and access to better healthcare. Disaster awareness and preparedness are crucial for minimizing casualties, including loss of life and damage to infrastructure. Our study also employed the SOM method for clustering, revealing that the optimal number of clusters is two. Cluster 1 includes 31 provinces with lower values for the number of impacted, injured, and missing victims, while Cluster 2 comprises West Java, Central Java, and East Java, which exhibit higher values for these categories.

By integrating economic and human development indicators, policymakers can better allocate resources and implement targeted interventions to enhance community resilience against extreme weather events. This comprehensive approach not only promotes immediate disaster preparedness but also fosters long-term sustainable development by ensuring that communities are better equipped to adapt to and recover from future environmental challenges. While this analysis provides valuable insights, it primarily focuses on extreme weather and does not consider other types of natural disasters. Additionally, the use of aggregated data over time may mask nuanced patterns. To build on these findings, future research could broaden its scope to encompass a wider range of natural disasters and adopt a panel data approach, thereby offering a more detailed and comprehensive understanding of the impacts over time.

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