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MODELING DISASTER RISK IN INDONESIA: A LATENT VARIABLE MODELING APPROACH TO HEVA ASSESSMENT

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ABSTRACT

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Indonesia, as the world's largest archipelagic nation, faces significant disaster risks due to its position at the convergence of three major tectonic plates. This study employs Generalized Linear Latent Variable Models (GLLVM) to analyze relationships among 12 Hazard, Exposure, and Vulnerability Assessment (HEVA) indicators across 34 Indonesian provinces. The HEVA dataset used in this study was obtained from the United Nations University – Institute for Environment and Human Security (UNU-EHS), which provides harmonized global risk indicators for hazard intensity, exposure levels, and socioeconomic–environmental vulnerability. Unlike conventional approaches assuming variable independence, GLLVM captures complex dependency structures through latent variables, providing deeper insights into multidimensional disaster risk patterns. Model-based ordination analysis reveals distinct spatial risk patterns. Eastern provinces (Papua, Maluku) demonstrate high physical vulnerability and exposure despite lower hazard levels, while Java provinces show moderate hazards but lower vulnerability due to better infrastructure and governance. A notable negative correlation ($r < -0.70$) between hazard levels and vulnerability indicators suggests that regions frequently exposed to disasters develop stronger adaptation capacity. Conversely, vulnerability indicators show very strong positive correlations ($r > 0.90$), indicating interconnections requiring holistic interventions. Incorporating geographical covariates such as population, number of islands, and provincial areas reveals significant relationships with HEVA indicators. Population shows negative associations with physical and environmental vulnerability but positive relationships with climate and geophysical hazards, i.e., the corresponding 95% CIs do not contain zero, reflecting urbanization's dual nature. The number of islands positively correlates with multiple vulnerability indicators, highlighting structural challenges in archipelagic disaster management, including limited accessibility and infrastructure connectivity. Provincial areas demonstrate positive relationships with vulnerability indicators but negative associations with economic exposure, indicating concentrated economic activities in urban centers. These findings emphasize differentiated spatial approaches for disaster mitigation.

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1. INTRODUCTION

As the world's largest archipelagic nation, Indonesia possesses unique geographical complexity with approximately 17,504 islands scattered across an area of 1.9 million km² of land (22.9%) and 6.9 million km² of waters (83.1%), along with a coastline stretching 108,000 km [1]. Indonesia's strategic position at the intersection of three major tectonic plates (Australian, Pacific, and Eurasian) and its location along the equator creates significant duality: on one hand, it presents abundant natural resource diversity, but on the other hand, it places the country in a high-risk zone for geological disasters (earthquakes, tsunamis, volcanic eruptions) and hydrometeorological disasters (floods, droughts, extreme weather, coastal erosion, forest and land fires) [2].

Over the past decade, thousands of disaster events have struck various regions of Indonesia, triggered by climate change and environmental degradation, causing multidimensional impacts including loss of life, economic losses, infrastructure damage, and disruption of community social activities [3, 4]. Although disaster risk makes mitigation and preparedness crucial aspects of national development, studies in Surabaya and various Indonesian regions reveal that disaster risk management has not been comprehensively integrated into spatial planning due to limited data and coordination among stakeholders [3, 5, 6]. Development that ignores disaster aspects has been proven to increase regional vulnerability and worsen disaster impacts [7], making in-depth understanding of disaster risk factors essential to reduce impacts and enhance community resilience.

The complexity of disaster risk in Indonesia involves multifactor interactions among geographical, demographic, socio-economic, and infrastructure characteristics that are simultaneously interconnected [8], making conventional analysis approaches that assume independence among variables inadequate. To address this challenge, this research employs Generalized Latent Variable Models (GLLVM) as the primary methodological framework. GLLVM is chosen for its ability to model complex dependency structures among variables through unobserved latent variables simultaneously [9]. This capability is particularly urgent in the context of HEVA indicators, which are inherently correlated due to shared underlying processes such as environmental degradation, population pressure, and spatial exposure patterns. Without jointly modeling these dependencies, important cross-variable relationships would be overlooked, leading to biased interpretations of disaster risk patterns across provinces. In addition to that, GLLVM enables identification of hidden patterns and interacting risk factors [10], providing a more robust analytical foundation for data-driven decision-making in disaster mitigation strategies and ultimately strengthening community resilience against future disaster threats.

2. METHODS

Definition

Hazard refers to phenomena or processes that have the potential to cause harm, such as loss of life, injury, property damage, social and economic disruption, or environmental degradation [11]. Hazards can be natural, such as earthquakes, floods, and volcanic eruptions; or man-made, such as chemical spills and industrial accidents. It is important to distinguish between hazard and disaster; a hazard is a potential threat, while a disaster occurs when that hazard significantly impacts society or the environment.

Vulnerability refers to physical, social, economic, and environmental characteristics that make individuals, communities, assets, or systems susceptible to the negative impacts of hazards. This vulnerability can be caused by various factors, such as poverty, inadequate infrastructure, lack of access to information and resources, and inability to cope with and recover from disasters [12]. Understanding the level of vulnerability in a community helps in identifying effective mitigation strategies to reduce disaster impacts.

Exposure refers to situations where people, infrastructure, buildings, systems, or other assets are located in zones vulnerable to specific hazards. The level of exposure is determined by the quantity and value of assets situated in at-risk areas. The more population or assets that are exposed, the higher the potential losses if a disaster occurs [7]. Therefore, spatial management and development planning that consider hazard risks are essential to minimize exposure.

Data

The data used in this research is sourced from the United Nations, where the levels of hazard, vulnerability, and exposure are measured using the HEVA (Hazard, Exposure, and Vulnerability Assessment) method [13]. The HEVA method uses 12 main indicators to measure the levels of hazard, exposure, and vulnerability. These indicators can be seen in Table 1. The data obtained are averaged, and standardized scores are calculated for the 12 HEVA indicators based on the constituent attributes for each indicator across 34 provinces in 2023. For example, the score of climate-related hazards from a certain area was obtained by averaging the standardized scores from the measured attributes, such as extreme heat hazard level and flood hazard area.

Table 1. HEVA indicators a few examples of measured attributes

Variabel	Indicator	Examples of measured attributes
Hazard	Climate-related hazards	Extreme heat hazard level Flood hazard area
	Livelihood shocks	Dengue incidence Malaria incidence
	Geophysical hazards	Earthquake hazard level Number of active volcanoes
Exposure	People and their livelihoods	Share of elderly Share of children
	Environmental assets	Environmental area exposed to earthquake, tsunami, volcano, flood, flash floods, landslide, extreme waves and abrasion, extreme weather, droughts
	Economic activities	Number of villages with MSMEs
	Physical assets	Number of airports Railway length Road length
Vulnerability	Human and Social	Gini Coefficient Share of population not using internet
	Physical	Number of villages without road or transportation access
	Environmental	Unprotected forest area
	Economic	Number of villages without bank
	Institutional	Number of villages without evacuation route

Therefore, in this research, the 12 HEVA indicators are used as response variables whose relationships will be analyzed. Additionally, the researcher uses other variables such as area size, population, and number of islands to understand their relationships with the HEVA indicators. The collected data is sourced from the Statistics Indonesia and has been adjusted to match the year when these indicators were calculated. The selection of these three variables is based on theoretical and empirical considerations in disaster risk studies.

Population is a crucial indicator that reflects the level of exposure to disaster threats. The larger the population in an area, the higher the potential for casualties and socio-economic impacts when disasters occur [14]. This variable is also related to settlement density, pressure on natural resources, and the complexity of infrastructure systems that can affect an area's vulnerability [15]. The number of islands becomes a highly relevant variable in the context of Indonesia as an archipelagic nation. Geographic fragmentation due to numerous islands creates particular challenges in disaster management, including accessibility difficulties for evacuation and aid distribution, limited inter-island infrastructure, and geographical isolation that can slow emergency response [16]. Small islands also tend to be more vulnerable to hydrometeorological disasters such as tidal flooding, coastal erosion, and climate change impacts. The third variable is provincial area size, which reflects the spatial dimension of disaster risk that affects threat diversity, management complexity, and geographical condition heterogeneity within a region. Larger areas generally have greater variability in topography, climate, and disaster types, thus requiring more comprehensive mitigation strategies. Furthermore, area size is related to public service coverage, early warning system effectiveness, and local government capacity in conducting disaster monitoring and response.

Generalized Linear Latent Variable Models (GLLVM)

In this research, the Generalized Linear Latent Variable Model (GLLVM), which is an extension of Generalized Linear Models (GLM), is used to model the relationships among HEVA indicators. In the ecological community, GLLVM is often used to build joint models on abundance data such as absence-presence, counts, or biomass from various locations [17, 18]. In this research, GLLVM is used as an explanatory tool where the estimated latent variables are plotted to illustrate differences in HEVA indicator composition across provinces. This analysis is referred to as model-based ordination analysis. One important assumption in using the GLLVM model is the dependency among response variables, in this case, the HEVA indicators. This assumption is considered highly relevant given that HEVA indicators are closely interconnected with one another. For example, areas with high levels of geophysical hazard tend to also have high levels of exposure and vulnerability, or vice versa. However, if HEVA indicators are considered independent, the analysis can be conducted separately using GLM, producing m separate and independent regression equations.

The general framework of GLLVM can be found in [9], where response variables come from a specific distribution with a known mean-variance relationship. Let $\boldsymbol{y_{ij}}$ denote response variable of $\boldsymbol{j}$th indicator from $\boldsymbol{i}$th province for $\boldsymbol{i = 1, \ldots, n}$ and $\boldsymbol{j = 1, \ldots, m}$. GLLVMs model the mean of response variable $(\boldsymbol{\mu_{ij}})$ against a number of latent variables of size $\boldsymbol{p < m}$, i.e., $\boldsymbol{u_i = \{u_{il}; l = 1, \ldots, p\}}$, and a number of independent variables $\boldsymbol{x_i = \{x_{ik}; l = 1, \ldots, K\}}$ through a known link function, namely:

$$g(\mu_{ij}) = \eta_{ij} = \tau_i + \beta_{0j} + x'\beta_j + u_i'\lambda_j, \tag{1}$$

where λ_j or factor loading, denotes the coefficient of latent variables, β_j is the regression coefficient of the corresponding independent variable, and τ_i is the site effect [18]. The component $u_i'\lambda_j$ is a component that models residual correlation in the response variable that is not captured by the observed independent variables. The latent variable u_i is often assumed to be identically independent and comes from a standard normal distribution,

$$u_i \sim \mathrm{N_p}(0, I_p), \tag{2}$$

where I_p is an identity matrix of size $p \times p$. Additionally, it is assumed that the upper triangular matrix elements of λ are zero, i.e., $\lambda_{ij} = 0$ for $j > i$, and the diagonal elements are set to be positive to ensure the model rotation is not unique and the parameters can be identified.

In this research, the chosen link function, $g(.)$, is the identity function since the response variables are assumed to follow multivariate normal distribution. Therefore, the joint distribution of the response variables is given by the following equation:

$$f(y_{ij}|u_i, \theta) = \prod_{j=1}^{m} f(y_{ij}|u_i; \theta) f(u_i; \sigma^2), \tag{3}$$

where θ contains all the estimated model parameters. The marginal log-likelihood function of the GLLVM model is obtained by performing a dimensional integral of $p + 1$ on the latent variable, which in this case is unobserved and considered as a random variable such that:

$$l(\theta) = \sum_{i=1}^{n} \left(\int \prod_{j=1}^{m} f(y_{ij}|u_i; \theta) f(u_i; \sigma^2)\, du_i \right). \tag{4}$$

In practice, this integral cannot be solved explicitly, so various approaches are used. In this research, we use the gllvm() package from R [19] to estimate model parameters and perform ordination, where this package allows approaches such as Laplace approximation and variational approximation to solve the integral. Specifically, parameter estimation in the GLLVM framework relies on maximum likelihood estimation, where both observed responses and latent variables contribute jointly to the likelihood function as defined in Eq. (4), ensuring that dependency structures are captured in a statistically coherent manner. Computationally, the model is fitted using numerical optimization routines such as the optim() function in R or similar Quasi-Newton algorithms, which iteratively maximize the approximated likelihood while simultaneously estimating regression coefficients, latent factor loadings, and dispersion parameters.

3. RESULTS

Explorative Data Analysis

The hazard level is measured through three types of indicators: climate-related hazard, geophysical hazard, and livelihood shocks. Each of these indicators is calculated based on several constituent attributes whose final scores are standardized so that the values range from 0 to 3. Heva classifies these scores into four categories: (i) 0 – 0.49 (very low/no risk), (ii) 0.5 – 1.49 (low), (iii) 1.5 – 2.49 (moderate risk), and (iv) 2.5 – 3.0 (high) [13]. Based on Figure 1, we can observe that 34 provinces in Indonesia have moderate climate hazard levels, and most provinces have low to moderate livelihood hazard levels. However, we can also see that there are several provinces with high geophysical hazard levels. The attributes measuring geophysical hazard include earthquake frequency, tsunami hazard level, landslide risk, and volcanic activity. There are more than 10 provinces with high geophysical hazard categories, such as Aceh, Bengkulu, West Java, and North Sulawesi.

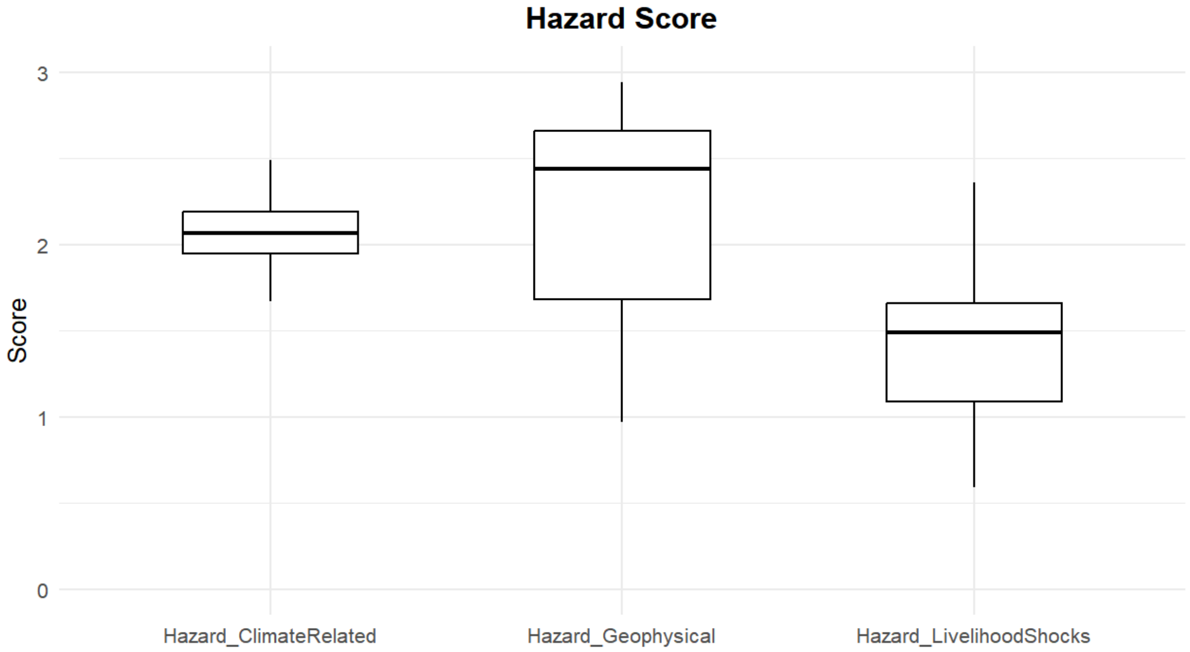

Figure 1. The distribution of hazard levels measured from three main indicators: climate-related hazard, geophysical hazard and livelihood and shocks hazard.

Figure 2 shows the distribution of exposure levels measured from four main indicators: economic exposure, physical exposure, environmental exposure, and people and livelihoods exposure. These four indicators show similar distributions, where exposure levels vary from the negligible category to provinces with high exposure. However, in general, the exposure levels of provinces in Indonesia for these four indicators are in the moderate category. The indicators used to measure the vulnerability of an area are five: economic vulnerability, environmental vulnerability, physical vulnerability, institutional vulnerability, and human and social vulnerability.

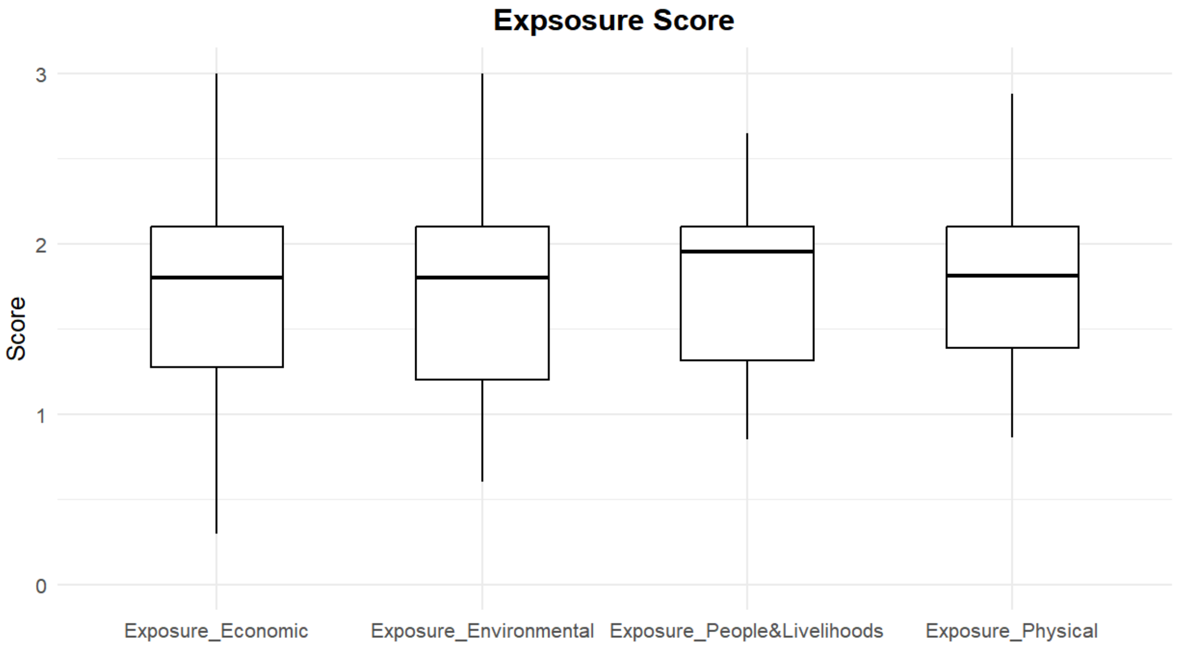

Figure 2. The distribution of exposure levels measured from four main indicators: economic exposure, physical exposure, environmental exposure, and people and livelihoods exposure.

Figure 3 shows the distribution of these five indicators across various provinces. Aside from human and social vulnerability, the 34 provinces in Indonesia have vulnerability levels that vary from negligible to high. The estimated median shows that the average vulnerability level of provinces in Indonesia is in the moderate category (1.5 – 2.49). However, attention should still be given to provinces with high vulnerability, such as Papua, which has high vulnerability levels in human and social, physical, and institutional indicators.

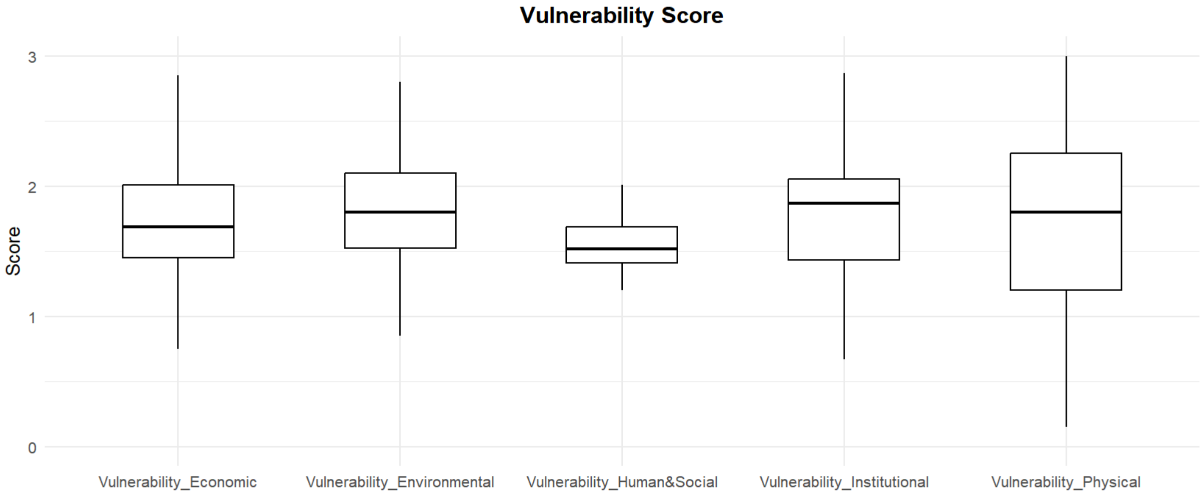

Figure 3. The distribution of vulnerability levels measured from five main indicators: economic vulnerability, physical vulnerability, environmental vulnerability, insitutional vulnerability, human and social vulnerability.

Data Analysis Using GLLVMs

Next, we will build a GLLVM model to understand more deeply and illustrate the differences in HEVA indicator composition across provinces. The model used to obtain the ordination plot is:

$$g(\mu_{ij}) = \eta_{ij} = \beta_{0j} + \boldsymbol{u}_i'\boldsymbol{\lambda}_j, \tag{5}$$

for $i = 1, \dots, 34$ and $j = 1, \dots, 12$. See Eq (1) and (2) for the explanation of the parameters. The researcher further assumes that the number of latent variables used for ordination is two ($p = 2$) and row effects are not included in the model ($\tau_i = 0$ for each i). In this analysis, the response variables are assumed to follow a normal (Gaussian) distribution, and the method used to estimate all model parameters is the variational approximation method [18]. Variational approximation (VA) is an efficient likelihood-based method used to approximate intractable integrals that arise in latent variable models such as GLLVM. Instead of evaluating the full likelihood, which requires integrating over high-dimensional latent variables, VA replaces the true posterior distribution with a simpler, tractable distribution and optimizes it by minimizing the Kullback-Leibler divergence. The use of VA is motivated by its computational efficiency and accuracy, particularly when dealing with high-dimensional multivariate data where methods like Laplace approximation or Monte Carlo integration become computationally expensive or unstable. [18] demonstrates through extensive simulation studies that VA provides more robust, more accurate, and more computationally scalable parameter estimates for GLLVM compared to competing approximations. For these reasons, VA is adopted in this study to ensure reliable estimation of regression coefficients, factor loadings, and latent variables while maintaining computational feasibility for the 34-province, 12-indicator HEVA dataset.

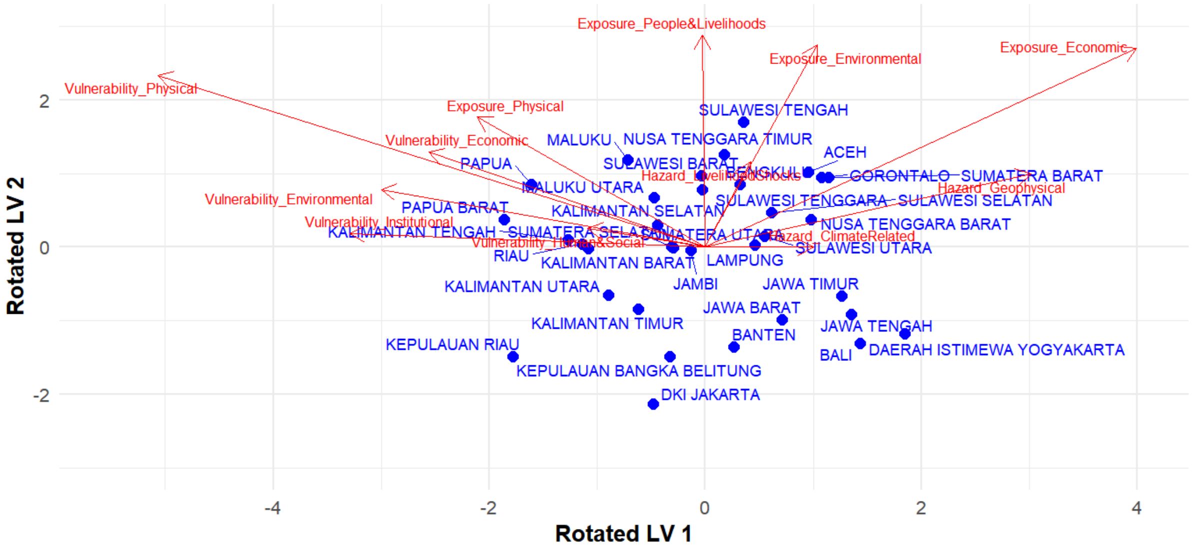

Figure 4. Ordination plot of 12 HEVA indicators showing the relationship patterns among hazard, exposure, and vulnerability indicators across provinces.

Model-based ordination analysis as displayed in Figure 4 uses the Generalized Linear Latent Variable Model (GLLVM) approach. The GLLVM method through estimated latent variables allows us to reduce the dimensionality of multidimensional data from 12 HEVA indicators into two main latent axes: Rotated LV1 (horizontal) and Rotated LV2 (vertical), as shown in Figure 4. This method enables visualization of relationships between variables (arrow vectors) and objects (provincial points) in two-dimensional space. In this context, HEVA indicators include hazard (climate hazard, geophysical hazard, and livelihood shocks), exposure (exposure of human assets, environment, economy, and physical infrastructure), and vulnerability (physical, economic, environmental, institutional, and human and social vulnerability), which are measured across 34 Indonesian provinces to assess disaster risk spatially.

This biplot reveals spatial patterns of disaster risk in Indonesia, where eastern provinces and remote islands tend to show more complex risk profiles compared to Java provinces. Arrows indicate the direction of indicator contributions to the dimensions. Long vectors (for example, physical vulnerability) have strong influence, and/or short vectors (for example, climate-related hazards) are weaker. Angles between vectors show correlations: vectors pointing in the same direction have positive correlation, while opposite vectors have negative correlation.

Based on the position of provincial points relative to the vectors, the biplot can be divided into four main quadrants.

1. Quadrant I: Upper-Right (LV1 > 0, LV2 > 0) Provinces located in this quadrant include East Nusa Tenggara (NTT), Aceh, West Sumatra, West Nusa Tenggara, and almost all provinces on Sulawesi Island. These provinces are close to environmental exposure, economic exposure, and geophysical and climate hazard vectors, which show a positive and aligned relationship, indicating high risk levels on these indicators.
2. Quadrant II: Lower-Right (LV1 > 0, LV2 < 0) Provinces included in this quadrant are East Java, Central Java, West Java, DI Yogyakarta, Bali, and Banten. In this quadrant, there are no close vectors, but they are still aligned with the same vectors as in Quadrant I, indicating a positive relationship with those indicators but not as strong as the relationship in Quadrant I.
3. Quadrant III: Upper-Left (LV1 < 0, LV2 > 0) This quadrant is an area close to vulnerability vectors (physical, economic, environmental, institutional, human and social) and physical exposure vector. Provinces included in this quadrant are provinces in the eastern region, namely Papua, West Papua, Maluku, and North Maluku. This shows high physical exposure and vulnerability (infrastructure to floods or coastal erosion) even though hazards are relatively low due to having an opposite relationship. The high combination of physical exposure and vulnerability makes eastern provinces hotspots.
4. Quadrant IV: Lower-Left (LV1 < 0, LV2 < 0) This quadrant has similar characteristics to Quadrant II, where there are no hazard, exposure, or vulnerability vectors close to the provinces in this quadrant. This area reflects overall low risk, similar to Quadrant II.

In general, Java provinces have high adaptation to climate hazards (urban flooding) and geophysical hazards (earthquakes). A clear negative relationship exists where hazards are moderate (score 1.5-2.49), but vulnerability is low (<0.5), due to national mitigation priorities. This relationship is more clearly illustrated through the correlation matrix calculated from factor loadings given by the following equation and shown in Figure 5:

$$\boldsymbol{\Sigma} = \boldsymbol{\lambda}'\boldsymbol{\lambda},$$

where $\boldsymbol{\Sigma}$ denotes variance-covariance matrix of size 12×12. In Figure 5, there is a negative relationship between vulnerability levels and hazard levels (climate-related and geophysical hazards). In the context of HEVA (Hazard, Exposure, Vulnerability Assessment), this can be rationalized by considering how areas with high hazards tend to have low vulnerability due to better adaptation and mitigation capacity, while areas with low hazards often have high vulnerability due to lack of attention or resources. The negative relationship implies that when hazard levels increase (for example, score 2.5-3.0, "high" category), vulnerability levels tend to decrease (score in "low" category), and vice versa. In the HEVA framework, hazard refers to potential dangers (for example, floods, earthquakes), exposure to populations or assets that are exposed, and vulnerability to the system's inability to cope with impacts.

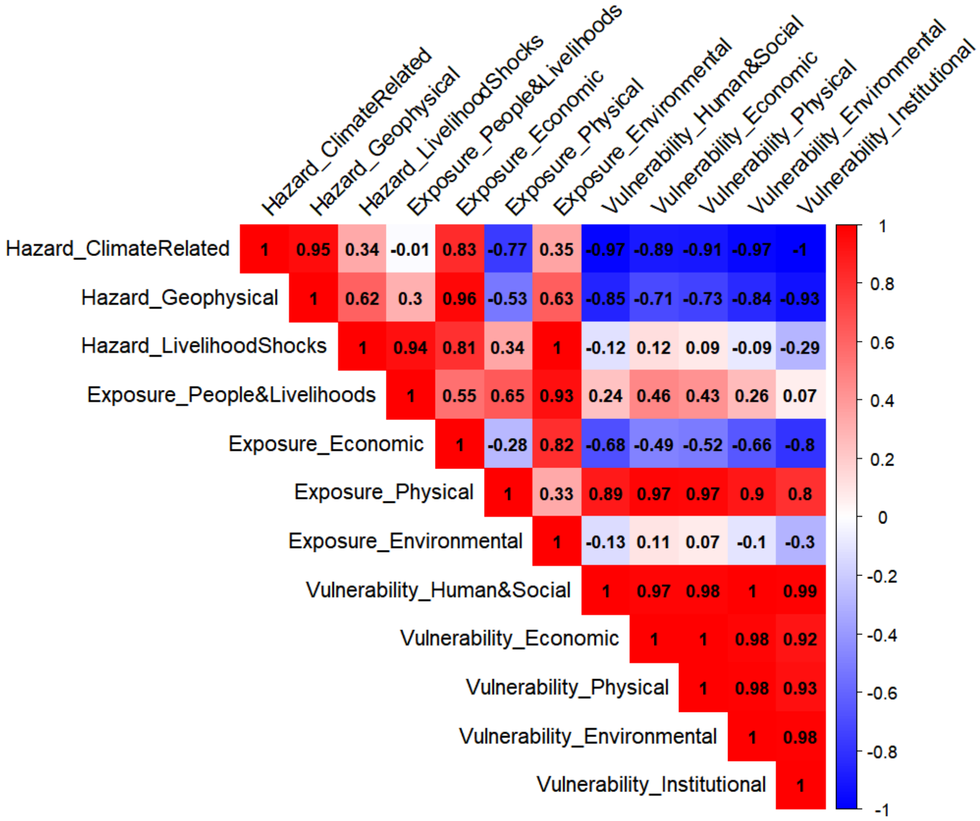

Figure 5. Correlation matrix of 12 HEVA Indicators derived from GLLVM

It can be further explained that areas frequently facing climate-related hazards (floods, storms, droughts) or geophysical hazards (earthquakes, landslides) tend to develop better adaptation capacity, reducing vulnerability. As an illustration, in the human and social indicator, the measured attributes include poor health and well-being, lack of education and skills, and lack of assistance. Areas with high hazards often have better access to health services due to mitigation priorities (for example, disaster-resistant hospitals), thus reducing health vulnerability. On the other hand, disaster preparedness education programs in high-hazard areas improve community skills, lowering vulnerability [8]. High hazards in an area imply that the area often becomes the focus of humanitarian aid or government programs, reducing vulnerability due to lack of assistance. Therefore, cities in earthquake zones (high geophysical hazard, score 2.5-3.0), such as Central Java and West Java have better health infrastructure, disaster education, and strong governance, resulting in low vulnerability (<1.5). Another illustration can explain that areas with low hazards (score 0.5-1.49) often receive less mitigation attention, so vulnerability remains high. For example, agriculture dependent on rainfall without adequate irrigation increases vulnerability in low-hazard areas.

On the other hand, we can also see that vulnerability indicators have high positive correlations. This indicates that these vulnerability indicators are closely interconnected with one another. Rationally, this strong positive relationship shows that an increase in one aspect of vulnerability (for example, economic, environmental, or social) tends to be followed by an increase in other aspects. This condition reflects systemic interconnection, where each dimension of vulnerability does not stand alone but rather influences each other in forming the total vulnerability level of an area or population. Thus, vulnerability reduction efforts need to be carried out holistically, because intervention on one indicator alone will likely not be effective without considering the interconnections among other factors.

Next, a few independent variables are included in the model to evaluate the relationships of these variables with all HEVA indicators. In this research, the independent variables used include population (*Penduduk*), number of islands (*Pulau*), and provincial area size (L). To determine the optimal number of latent variables, the Akaike Information Criterion (AIC) is used. Table 2 shows the AIC values for various numbers of latent variables, ranging from 2 to 6. The analysis results show that the optimal number of latent variables, indicated by the smallest AIC value, is three. Therefore, further inference is conducted using the model with three latent variables.

Table 2. AIC values for different number of latent variables

p	**AIC**
2	432,07
3	427,77
4	451,68
5	439,12
6	524,60

Figure 6 shows the parameter estimates of the three independent variables (area size, population, and number of islands) along with confidence intervals calculated at a 95% confidence level for the 12 response variables (HEVA indicators). Parameters that are significant at a 5% significance level are shown by plots that are far from the vertical axis at zero, indicating that the confidence intervals do not include zero.

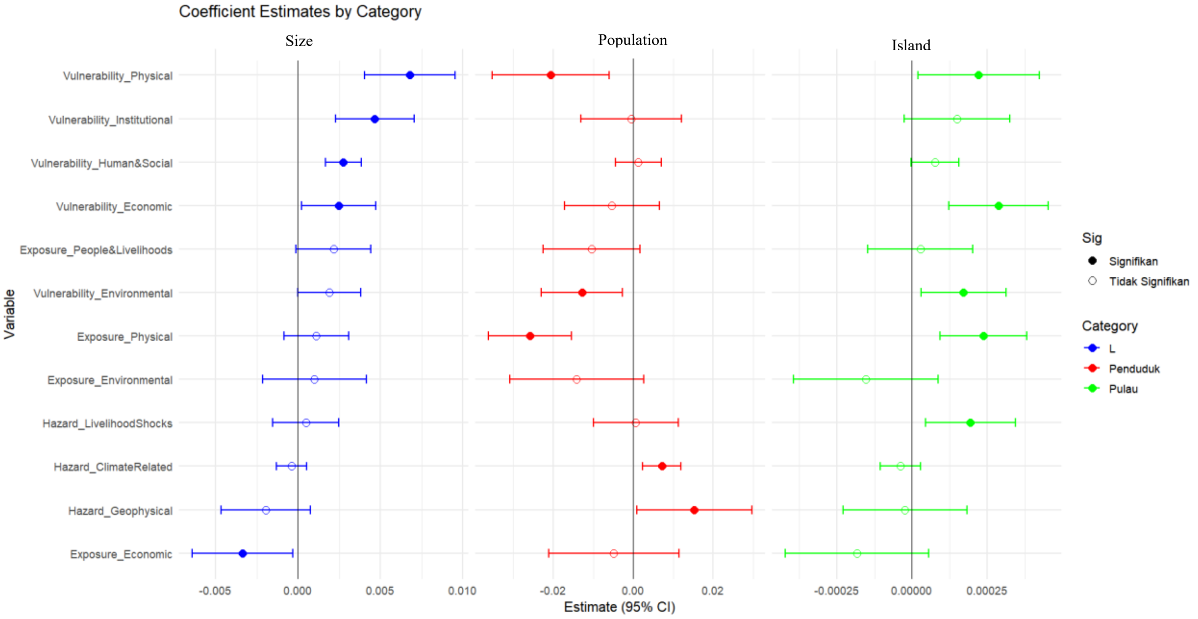

Figure 6. Parameter Estimates of regression coefficients for area size, population and number of islands

The independent variable, Size, shows mostly small coefficient magnitudes, with several estimates centered near zero. Only a few indicators, such as *Vulnerability_Physical* and *Exposure_Economic*, show coefficients that are statistically different from zero. The population variable shows statistically similar effects across the HEVA indicators to the area size variable. Several indicators, including *Hazard_ClimateRelated*, and *Hazard_Geophysical,* have significant positive coefficients, indicated by red-filled points with CIs not crossing zero. However, the population variable also exhibits negative significant coefficients for some vulnerability indicators, such as *Vulnerability_Physical, Vulnerability_Environmental,* and *Exposure_Physical*. Finally, the number of islands shows small coefficient magnitudes and many non-significant effects (open circles). However, many vulnerability indicators, including *Vulnerability_Physical, Vulnerability_Economic,* and *Vulnerability_Economic* display significant positive coefficients.

4. DISCUSSION

The provincial area size variable shows significant influence on five HEVA indicators: physical vulnerability, institutional vulnerability, human and social vulnerability, economic vulnerability, and economic exposure. A positive relationship is found in four vulnerability indicators (physical, institutional, human-social, and economic), showing that the larger a province's area, the higher its vulnerability level to disasters. This finding is consistent with research [20] explaining that larger areas tend to have greater geographical heterogeneity, increased management complexity, and challenges in equitable resource and infrastructure distribution. In the Indonesian context, provinces with large areas such as Papua and East Kalimantan face difficulties in emergency response coordination, limited public service coverage, and development disparities between regions that increase overall vulnerability [21].

Conversely, a negative relationship is found between area size and economic exposure, indicating that provinces with larger areas tend to have lower economic exposure. This phenomenon can be explained through the concentration of economic activities that tend to be centered in certain urban areas, so that economic asset value per unit area becomes lower in larger provinces. Studies in Kalimantan show that despite its large area, economic concentration only occurs in a few growth centers, while other areas have low economic density [22].

The population variable shows diverse patterns of influence on HEVA indicators. A significant negative relationship is found in physical and environmental vulnerability as well as physical exposure, indicating that provinces with larger populations tend to have better infrastructure and environmental management systems, resulting in relatively lower physical and environmental vulnerability. This finding aligns with research in Java showing that areas with high populations generally have greater infrastructure investment, better drainage systems, and higher adaptation capacity [23].

Conversely, a positive relationship is found between population and climate and geophysical hazards, showing that the larger the population, the higher the hazard level toward hydrometeorological and geological dangers. This can be explained by increased land pressure, land use changes, and settlement expansion into high-risk areas such as riverbanks and hillsides [24]. Studies in Jakarta and surrounding areas confirm that rapid population growth has driven development in flood and landslide hazard zones, increasing community exposure and hazard vulnerability to disasters [25].

The number of islands variable shows a significant positive relationship with several vulnerability indicators: physical vulnerability, economic vulnerability, environmental vulnerability, physical exposure, and livelihood and shocks hazard. Geographic fragmentation caused by numerous islands creates structural challenges in disaster management, including accessibility difficulties, limited inter-island infrastructure connectivity, and geographical isolation that slows emergency response [26].

Archipelagic provinces such as Maluku, Nusa Tenggara, and the Riau Islands face higher vulnerability due to dependence on sea transportation for logistics distribution, evacuation, and SAR team mobilization, which can be hindered by poor weather conditions [27]. Additionally, small islands have limited economic resources, limited institutional capacity, and high vulnerability to climate change impacts such as sea level rise and coastal ecosystem degradation.

5. CONCLUSIONS

These findings underscore the importance of a differential spatial approach in disaster mitigation strategies in Indonesia. Provinces with different geographical characteristics (area size, population density and archipelagic fragmentation) require interventions tailored to their specific risk profiles. Archipelagic regions require special investment in emergency communication systems, maritime logistics, and local capacity, while large areas need decentralization of emergency response capacity and strengthening of coordination between regencies/cities.

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