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Spatial Framework for Multi-Hazard Vulnerability Assessment and Sustainable Agricultural Risk Mitigation in Batu City: Integrating Social, Economic, Physical, and Ecological Perspectives

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ABSTRACT

Agrarian regions exposed to multiple natural hazards exhibit complex and interrelated vulnerabilities, necessitating a holistic and integrated assessment approach. This study develops a spatial framework to evaluate multi-hazard agricultural vulnerability in Batu City, East Java, by integrating the Social Vulnerability Index (SoVI) and Self-Organizing Map (SOM) methodologies. Assessments were conducted at the village level to generate multidimensional vulnerability indices and clusters across social, economic, physical, and ecological variables. Data were standardized using z-score transformation, analyzed through Principal Component Analysis (PCA), and clustered using SOM to identify non-linear typological vulnerability profiles. The primary objective of this research is to spatially map multidimensional vulnerabilities to various hazards in Batu City, supporting sustainable disaster risk mitigation strategies and evidence-based policymaking in the agricultural sector. The findings reveal significant spatial heterogeneity Sisir Village consistently exhibited high vulnerability indeces over the past three years (2.92 to 6.19 to5.50), while Junrejo Village maintained consistently low vulnerability levels (1.16 to -0.29 to -1.30). Dominant vulnerability drivers varied across clusters, namely number of farmers (Cluster 1), access to communication (Cluster 2), and proportions of migrants and young children (Cluster 3). Subsequently, the derived indices and clusters were integrated with seismic amplification maps (Vs30), landslide susceptibility maps, and volcanic hazard maps related to Mount Arjuna-Welirang. Overlay analysis revealed significant overlap between areas of high vulnerability and zones of pronounced physical hazard, underscoring the urgent need for structural reinforcement, spatial planning controls, and prioritized resource allocation in agrarian disaster risk reduction efforts.

Keywords: Multidimensional vulnerability, Social Vulnerability Index (SoVI), Self-Organizing Map (SOM), Multi-Hazard, Kota Batu.

INTRODUCTION

Disaster risk is a systemic outcome of the interplay between hazard, exposure, and vulnerability a conceptual triad central to contemporary disaster risk science (UNISDR, 2009). While natural hazards such as earthquakes, volcanic eruptions, landslides, and hydro-meteorological events are geophysical or climatological phenomena beyond human control, their societal impacts are largely shaped by underlying conditions of vulnerability. The

Sendai Framework for Disaster Risk Reduction (SFDRR) explicitly emphasizes the need for integrated, multi-hazard, and multi-dimensional assessments that account for physical, social, economic, and environmental vulnerabilities, particularly in regions where cascading and compound risks threaten development gains (UNDRR, 2015). Despite this global mandate, many studies remain confined to single-hazard or single-dimension analyses, thereby failing to capture the interconnected nature of real-world risk dynamics (Spence et al., 2005; Wilson et al., 2010; Maharani et al., 2016; Kelman et al., 2016; Karuppusamy et al., 2021).

Multi-hazard risk assessment involves evaluating the cumulative and interactive effects of multiple natural hazards whether concurrent, sequential, or synergistic on exposed elements (Kappes et al., 2012). Complementing this, multi-vulnerability refers to the dynamic and interrelated set of vulnerabilities across systems, defined as "a set of interconnected and dynamic vulnerabilities among exposed elements" (Terzi et al., 2019). This perspective acknowledges that interventions targeting one hazard may inadvertently increase vulnerability to another a phenomenon known as risk synergy. For instance, elevated stilt houses reduce flood risk but can amplify seismic vulnerability (de Ruiter et al., 2021), highlighting the necessity of holistic, cross-hazard planning.

Agricultural systems are especially susceptible to multi-hazard environments due to their dependence on stable climatic conditions, fertile soils, functional infrastructure, and socio-economic stability. In Indonesia, Law No. 24 of 2007 defines vulnerability comprehensively, encompassing geological, biological, hydro-meteorological, social, cultural, political, economic, and technological dimensions. Yet implementation remains fragmented, particularly at sub-national levels where technical capacity and data integration constrain effective DRR governance.

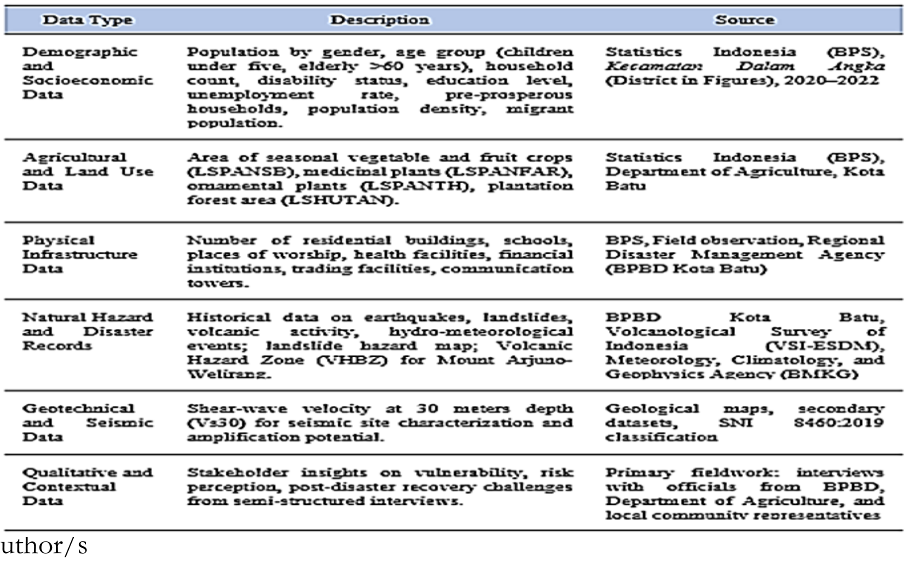
Batu City, East Java, exemplifies a high-risk agrarian region confronting converging threats from earthquakes, landslides, volcanic activity (Mount Arjuno-Welirang), and extreme rainfall. With over 100 landslide incidents annually and recurring seismic events including the M6.7 offshore earthquake in April 2021 the city faces escalating disaster pressures (BPBD Kota Batu, 2022). Its economy relies heavily on horticulture (e.g., apples, vegetables, ornamental flowers), rendering it highly sensitive to disruptions in land productivity, water supply, and market access. However, post-disaster recovery lacks standardized technical guidance and coordinated institutional responses (Tate & Drakes, 2022; Pagliacci & Russo, 2019), undermining long-term resilience.

This study addresses a critical gap in operationalizing multi-hazard vulnerability assessments within agricultural contexts by developing a spatially explicit, multidimensional index using a hybrid method combining the Social Vulnerability Index (SoVI) and Self-Organizing Map (SOM) clustering. Unlike traditional additive models, this approach enables pattern recognition and non-linear relationships among vulnerability drivers, facilitating nuanced classification of villages into distinct vulnerability profiles. By integrating social, economic, physical, and ecological dimensions, the research advances scientific understanding of multi-vulnerability while providing actionable insights for local DRR planning. The findings contribute directly to SFDRR Priorities 1 (Understanding Risk) and 4 (Enhancing Preparedness), offering a replicable framework for other mountainous, agrarian cities across Southeast Asia facing similar complex risk landscapes.

DATA AND METHODS

The research utilizes a combination of primary and secondary data sources to conduct a comprehensive multi-hazard and multi-vulnerability assessment in Batu City, East Java. All data are collected at the village (desa/kelurahan) level across the three administrative districts: Batu, Junrejo, and Bumiaji. The following table summarizes the types of data used and their respective sources.

Table 1. Data Type, Description dan Source



Data Type	Description	Source
Demographic and Socioeconomic Data	Population by gender, age group (children under five, elderly >60 years), household count, disability status, education level, unemployment rate, pre-prosperous households, population density, migrant population.	Statistics Indonesia (BPS), *Kecamatan Dalam Angka* (District in Figures), 2020–2022
Agricultural and Land Use Data	Area of seasonal vegetable and fruit crops (LSPANSB), medicinal plants (LSPANFAR), ornamental plants (LSPANTH), plantation forest area (LSHUTAN).	Statistics Indonesia (BPS), Department of Agriculture, Kota Batu
Physical Infrastructure Data	Number of residential buildings, schools, places of worship, health facilities, financial institutions, trading facilities, communication towers.	BPS, Field observation, Regional Disaster Management Agency (BPBD Kota Batu)
Natural Hazard and Disaster Records	Historical data on earthquakes, landslides, volcanic activity, hydro-meteorological events; landslide hazard map; Volcanic Hazard Zone (VHBZ) for Mount Arjuno-Welirang.	BPBD Kota Batu, Volcanological Survey of Indonesia (VSI-ESDM), Meteorology, Climatology, and Geophysics Agency (BMKG)
Geotechnical and Seismic Data	Shear-wave velocity at 30 meters depth (Vs30) for seismic site characterization and amplification potential.	Geological maps, secondary datasets, SNI 8460:2019 classification
Qualitative and Contextual Data	Stakeholder insights on vulnerability, risk perception, post-disaster recovery challenges from semi-structured interviews.	Primary fieldwork: interviews with officials from BPBD, Department of Agriculture, and local community representatives

Primary data were collected through semi-structured interviews and field observations conducted with key stakeholders, including personnel from the Regional Disaster Management Agency (BPBD), the Department of Agriculture, and local farmers. These inputs were crucial for contextualizing indicator relevance, validating statistical trends, and ensuring socio-cultural accuracy in the vulnerability framework. Secondary data were obtained from official publications and institutional databases, with spatial adjustments made where necessary to align with village-level boundaries.

Methods

This study employs an integrated analytical framework combining two advanced techniquesSelf-Organizing Map (SOM) and Social Vulnerability Index (SoVI) to assess multidimensional vulnerability in a multi-hazard agricultural context. The methodological approach follows a taxonomic classification system, which moves beyond demographic-based assessments by capturing the structural characteristics that render communities differentially susceptible to disasters. Unlike purely additive indices, this hybrid model enables both quantitative scoring and qualitative profiling of vulnerability archetypes across social, economic, physical, and ecological dimensions. The analysis begins with data standardization using z-score transformation:

$$Z = \frac{X - \mu}{\sigma} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where X is the raw value, μ is the mean, and σ is the standard deviation.

Standardization ensures comparability across variables with differing scales and units, a prerequisite for multivariate integration. Following normalization, the SoVI methodology, originally developed by Cutter et al. (2003), is applied to construct a composite social vulnerability index. Principal Component Analysis (PCA) with varimax rotation is used to extract latent components that explain maximum variance in the dataset. Components with eigenvalues greater than 1 are retained, following Kaiser's criterion (Kaiser, 1974). Prior to PCA, the suitability of the correlation matrix is verified using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (threshold ≥ 0.5) and Bartlett's Test of Sphericity ($p<0.001$), ensuring sufficient inter-variable correlations for valid factor extraction (Hutcheson et al., 1999; Tabachnick & Fidell, 2007). The resulting component loadings are used to compute a linear composite index representing relative social vulnerability across administrative units, where higher positive scores indicate greater vulnerability.

To complement SoVI and uncover non-linear patterns and hidden structures within the data, an unsupervised artificial neural network the Self-Organizing Map (SOM) is implemented. Developed by Teuvo Kohonen (1982), SOM performs dimensionality reduction while preserving topological relationships between high-dimensional input vectors. In this study, a hexagonal 2D lattice with hexagonal neighborhood topology is employed, optimized based on quantization error (QE) and topographic error (TE) lower values indicating better representation of input space (Kiviluoto, 1996). During training, each input vector is matched to its Best Matching Unit (BMU) through Euclidean distance calculation:

$$d_j = ||X - W_j|| = \sqrt{\sum_{i=1}^{M} (x_i - w_{ij})^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Neighboring neurons around the BMU are updated iteratively to become more similar to the input, creating a self-organized map that reflects clustering tendencies in the original data. The final SOM output is visualized using the U-matrix (Unified Distance Matrix) , which highlights cluster boundaries via grayscale intensity: dark regions represent large distances (cluster edges), while light areas indicate homogeneity (Ultsch, 1993). Component planes further illustrate the spatial distribution of individual variables across the map, enabling identification of dominant drivers within each cluster.

Hierarchical agglomerative clustering and k-means algorithms are applied to the SOM codebook to define meaningful vulnerability clusters. The optimal number of clusters is determined using the Davies-Bouldin Index (DBI), where lower values indicate compact, well-separated groups (Vesanto et al., 2000). This clustering process allows for the identification of distinct vulnerability profiles such as "high socioeconomic but low physical vulnerability" or "ecologically fragile yet socially cohesive" that provide actionable insights for targeted interventions.

The integration of SoVI and SOM offers significant advantages over conventional vulnerability assessments. While SoVI provides a statistically robust, interpretable ranking of vulnerability levels, SOM reveals complex interactions among variables and enables typology-based understanding of systemic weaknesses. This dual approach supports not only comparative analysis but also spatial profiling, facilitating evidence-based decision-making in disaster risk reduction (DRR) planning.

Additionally, seismic hazard is modeled using Vs30 the average shear-wave velocity in the top 30 meters of soil as a proxy for site amplification. Lower Vs30 values indicate softer soils that amplify ground shaking during earthquakes, increasing structural damage risk. This parameter is incorporated into the overall risk landscape to enhance physical exposure context.

The overall research workflow is illustrated in Figure 1, which presents the complete flowchart of the data analysis process based on Figure 4.2 from the dissertation. The diagram outlines the sequential and iterative stages of the study: (1) data collection (primary and secondary), (2) data preprocessing and standardization, (3) construction of the Social Vulnerability Index (SoVI) using PCA, (4) application of Self-Organizing Maps (SOM) for clustering and pattern recognition, and (5) integration with geotechnical data (Vs30) for multi-hazard vulnerability mapping. This structured workflow ensures transparency, reproducibility, and alignment with the research objectives.

By synthesizing these methods, the research advances a holistic, spatially explicit framework for assessing multi-hazard agricultural vulnerability in Batu City. The resulting Multi-Hazard Agricultural Vulnerability Index (MHAVI) integrates statistical rigor with machine learning-driven pattern recognition, offering a replicable model for other agrarian cities facing converging natural hazards in Southeast Asia and beyond.

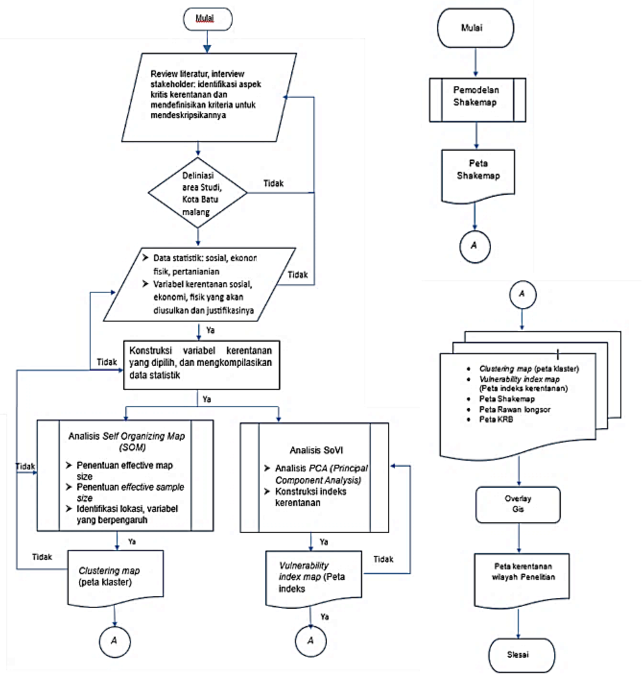


Figure 1. Flowchart of the data analysis process.

By synthesizing these methods, the research advances a holistic, spatially explicit framework for assessing multi-hazard agricultural vulnerability in Batu City. The resulting Multi-Hazard Agricultural Vulnerability Index (MHAVI) integrates statistical rigor with machine learning-driven pattern recognition, offering a replicable model for other agrarian cities facing converging natural hazards in Southeast Asia and beyond.

RESULT AND DISCUSSION

Vulnerability Index in Batu City, 2021

The multidimensional vulnerability analysis of Batu City in 2021 reveals significant spatial heterogeneity across villages and urban wards. The results are presented in Table 2, which displays vulnerability scores for each administrative unit based on social, economic, physical, and ecological dimensions key components widely recognized in disaster risk science (UNISDR, 2009).

A key finding is the high disparity within Bumiaji Subdistrict. Tulungrejo Village recorded the highest vulnerability score (+4.50), classified as very high, driven by high population density, strong dependence on agriculture, and limited access to basic services factors consistently linked to increased social vulnerability in agrarian communities (Wisner et al., 2004). In contrast, Gunungsari Village had the lowest index (–3.29), indicating relatively high resilience despite its proximity to the Mount Arjuno-Welirang hazard zone, underscoring that exposure alone does not determine overall risk (Cardona et al., 2012).

Table 2. Vulnerability Index of Batu City, 2021

Subdistrict	Village/Ward	Vulnerability Index 2021
Bumiaji	Pandanrejo	-1,44
	Bumiaji	-0,52
	Bulukerto	-1,08
	Gunungsari	-3,29
	Punten	-2,59
	Tulungrejo	4,50
	Sumbergondo	-2,73
	Giripurno	2,98
	Sumber Brantas	2,00
Batu	Oro-oro Ombo	3,27
	Temas	-0,32
	Sisir	2,92
	Ngaglik	-0,92
	Pesanggrahan	2,68
	Songgokerto	2,26
	Sumberejo	-0,59
	Sidomulyo	-2,11
Junrejo	Tlekung	0,01
	Junrejo	1,16
	Mojorejo	-1,58
	Torongrejo	-1,90
	Beji	-1,26
	Pendem	1,01
	Dadaprejo	-2,47

In Batu Subdistrict, Sisir Ward emerged as the most vulnerable (+3.29), while Sidomulyo and Ngaglik were categorized as low vulnerability. Junrejo Subdistrict showed greater stability, with Dadaprejo Village being the most resilient (–2.47), followed by Mojorejo, Beji, and Pendemall exhibiting low vulnerability levels due to better infrastructure and diversified livelihoods. This spatial pattern is visualized in Figure 2, which classifies areas into five categories very low, low, moderate, high, and very high.

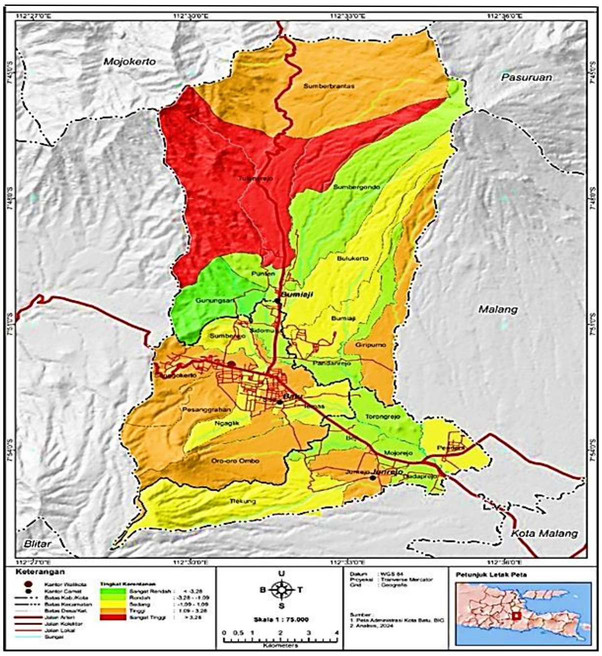


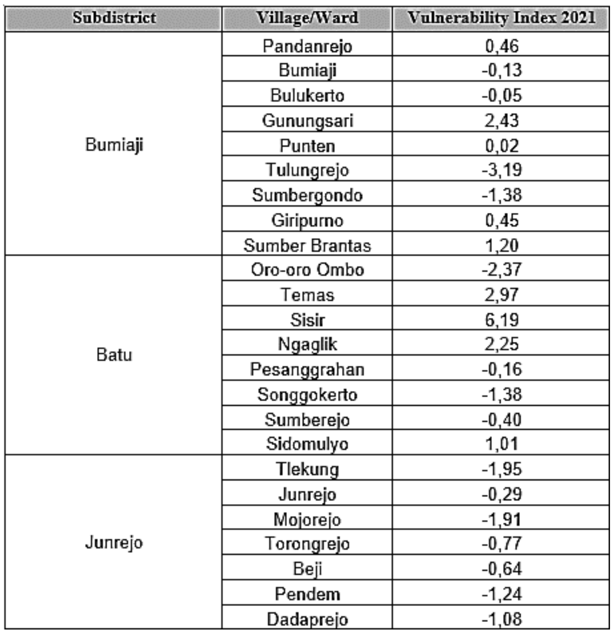
Figure 2. Vulnerability Index Map of Batu City, 2021

The map shows that northern and central areas (Bumiaji and Batu) are predominantly yellow to red, reflecting high vulnerability. In contrast, southern areas (Junrejo) are mostly green, indicating lower vulnerability due to better infrastructure access and more diversified local economies a pattern observed in other mountainous urban-agricultural interfaces in Indonesia.

Vulnerability Index in Batu City, 2022

The multidimensional vulnerability assessment for Batu City in 2022 reveals significant spatial variation across its three sub-districts. Results are presented in Table 3, which displays the vulnerability index at the village/ward level based on social, economic, physical, and ecological dimensions.

Table 3. Vulnerability Index of Batu City, 2022



Subdistrict	Village/Ward	Vulnerability Index 2021
Bumiaji	Pandanrejo	0,46
	Bumiaji	-0,13
	Bulukerto	-0,05
	Gunungsari	2,43
	Punten	0,02
	Tulungrejo	-3,19
	Sumbergondo	-1,38
	Giripurno	0,45
	Sumber Brantas	1,20
Batu	Oro-oro Ombo	-2,37
	Temas	2,97
	Sisir	6,19
	Ngaglik	2,25
	Pesanggrahan	-0,16
	Songgokerto	-1,38
	Sumberejo	-0,40
	Sidomulyo	1,01
Junrejo	Tlekung	-1,95
	Junrejo	-0,29
	Mojorejo	-1,91
	Torongrejo	-0,77
	Beji	-0,64
	Pendem	-1,24
	Dadaprejo	-1,08

A striking pattern emerges: while several villages in Bumiaji Subdistrict show low vulnerability—most notably Tulungrejo (–3.19) and Sumber Brantas (–2.37) indicating improved resilience, others exhibit high vulnerability. In contrast, Sisir Ward (Batu Subdistrict) recorded the highest index (+6.19), reflecting a sharp increase from 2021 (+2.92) and highlighting growing systemic fragility driven by population pressure, land-use change, and limited adaptive capacity common drivers in rapidly urbanizing agrarian landscapes (Ward et al., 2021). This shift is visualized in Figure 3 , the Vulnerability Index Map of Batu City, 2022, which classifies areas into five categories: very low, low, moderate, high, and very high.

The map confirms that northern and central zones remain hotspots of high vulnerability, particularly Sisir and parts of Bumiaji. Meanwhile, southern areas especially in Junrejo Subdistrict such as Tlekung (–1.95), Mojorejo (–1.91), and Beji (–0.64) maintain low to moderate vulnerability, supported by better infrastructure and diversified livelihoods. Notably, Tulungrejo's vulnerability dropped drastically from +4.50 in 2021 to –3.19 in 2022, suggesting effective local mitigation efforts, including environmental conservation and community-based disaster preparedness strategies emphasized in the Sendai Framework for Disaster Risk Reduction (UNDRR, 2015). Conversely, Sisir's surge underscores the risks posed by unregulated urbanization and agricultural dependency in hazard-prone settings, where economic marginalization exacerbates exposure (Tate & Drakes, 2022).

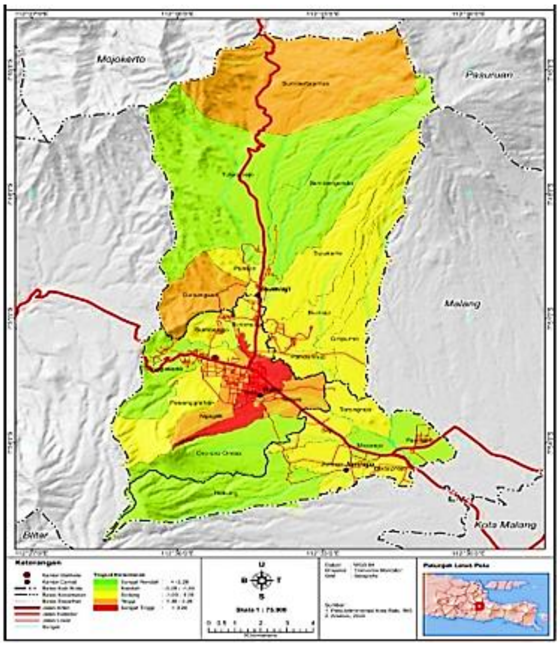


Figure 3. Vulnerability Index Map of Batu City, 2022

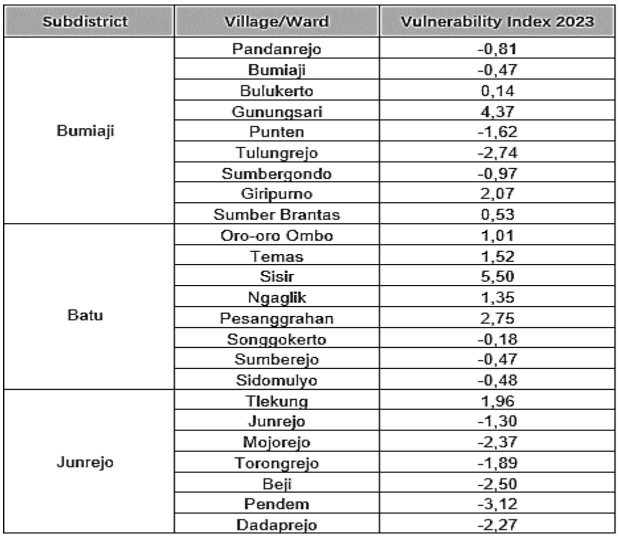
These findings demonstrate that vulnerability is dynamic, shaped by both structural conditions and policy interventions. Continuous monitoring through annual index assessments is therefore critical for evidence-based disaster risk reduction and sustainable urban planning

Vulnerability Index in Batu City, 2023

The 2023 multidimensional vulnerability assessment reveals persistent spatial disparities across Batu City's villages and wards. Results presented in Table 4 show that Gunungsari (Bumiaji Subdistrict) recorded the highest vulnerability index (+4.37), reflecting a continuous upward trend from previous years (+2.43 in 2022; –3.29 in 2021). This indicates deepening systemic fragility driven by high population density, limited access to health and communication infrastructure, and economic dependence on subsistence agriculture.

In contrast, Tulungrejo, once the most vulnerable village in 2021 (index +4.50), has significantly improved its resilience, with an index of –2.74 in 2023. As confirmed by local officials (Mr. Suliyono and Ms. Eka), this transformation is attributed to livelihood diversification where farming is no longer the primary income source but supplemented by tourism, trade, and wage labor. This shift highlights the critical role of economic resilience in reducing social vulnerability (Cutter et al., 2008; Cutter et al., 2012)

Table 4. Vulnerability Index of Batu City, 2023



Subdistrict	Village/Ward	Vulnerability Index 2023
Bumiaji	Pandanrejo	-0,81
	Bumiaji	-0,47
	Bulukerto	0,14
	Gunungsari	4,37
	Punten	-1,62
	Tulungrejo	-2,74
	Sumbergondo	-0,97
	Giripurno	2,07
	Sumber Brantas	0,53
Batu	Oro-oro Ombo	1,01
	Temas	1,52
	Sisir	5,50
	Ngaglik	1,35
	Pesanggrahan	2,75
	Songgokerto	-0,18
	Sumberejo	-0,47
	Sidomulyo	-0,48
Junrejo	Tlekung	1,96
	Junrejo	-1,30
	Mojorejo	-2,37
	Torongrejo	-1,89
	Beji	-2,50
	Pendem	-3,12
	Dadaprejo	-2,27

Despite ome improvements, Sisir Ward (Batu Subdistrict) remains highly vulnerable (+5.50), although slightly reduced from 2022 (+6.19). It continues to face structural challenges, including dense settlements on steep slopes and weak disaster awareness, despite being exposed to high seismic hazard. These temporal dynamics are visualized in Figure.4, which maps the trend of vulnerability from 2021 to 2023.

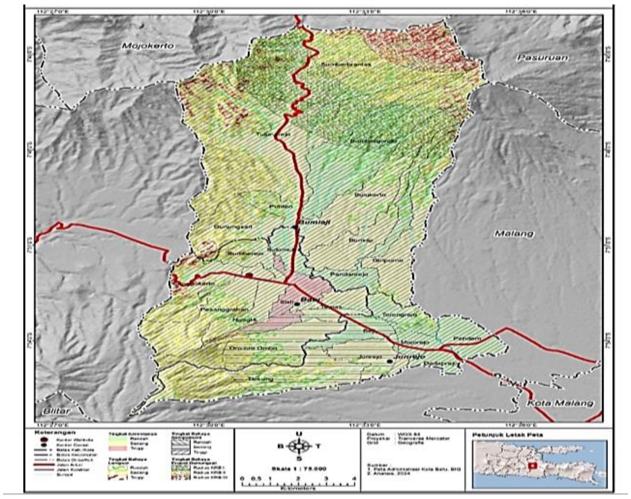


Figure 4. Map of Vulnerability Index in Batu City 2023

The map shows that southern areas—such as Pandanrejo, Beji, Dadaprejo, Mojorejo, and Pendem consistently exhibit low vulnerability (green zones), due to better infrastructure, lower population pressure, and stronger institutional support. In contrast, northern and central zones remain red-hotspots, indicating chronic vulnerability, often associated with topographic exposure and limited governance reach (Kelman et al., 2016.

This longitudinal analysis confirms that vulnerability is not static, but evolves in response to socioeconomic changes, policy interventions, and environmental pressures. The case of Tulungrejo demonstrates that targeted development can rapidly reduce vulnerability, while Gunungsari and Sisir underscore the risks of unchecked urbanization in hazard-prone agrarian landscapes.

Vulnerability Index Trends in Batu City (2021–2023)

A temporal analysis of the vulnerability index in Batu City from 2021 to 2023 reveals significant spatial dynamics at the village/urban ward level. Overall, four areas demonstrate notable shifts worth examining. Junrejo Village shows a consistent decline in vulnerability (2021 = 1.16; 2022 = -0.29; 2023 = -1.30), indicating an improvement in local adaptive capacity. Tulungrejo Village (Bumiaji District) underwent a dramatic transition from high vulnerability (2021 = 4.50) to substantial resilience (2022 = -3.19; 2023 = -2.74), reflecting the effectiveness of policy and community-based interventions (Supriyanto et al., 2022). Sisir Urban Ward experienced sharp fluctuations, with a spike in vulnerability in 2022 (6.19) following a baseline of 2.92 in 2021. Although the index dropped slightly in 2023 (5.50), the area remains a priority for risk mitigation (Sutanto & Wulandari, 2023). Gunungsari Village recorded a rising trend from a resilient condition (-3.29 in 2021) to heightened vulnerability in 2023 (4.37), highlighting sustainability challenges in risk management. To provide a spatial visualization of the vulnerability trend from 2021 to 2023, the data is presented in Figure 5

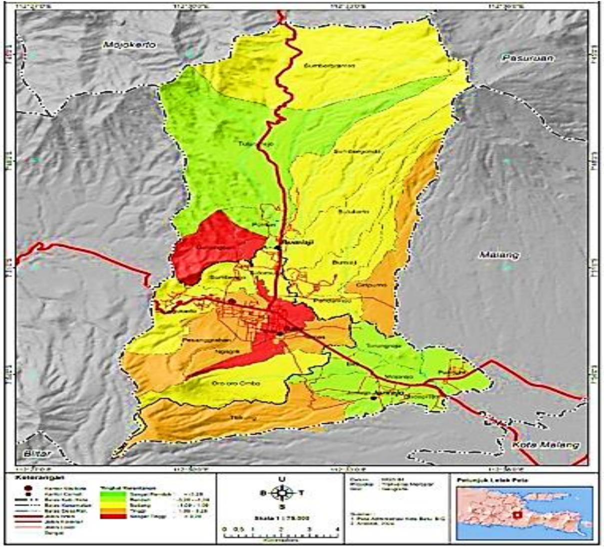
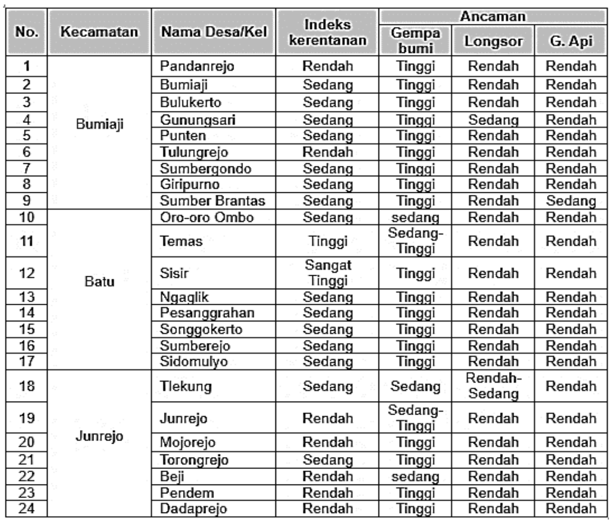


Figure 5. Map of Vulnerability Index Trends in Batu City from 2021 to 2023

Figure 5 includes an overlay of hazard levels for earthquakes, landslides, and volcanic eruptions. To further elaborate the spatial relationship between vulnerability and hazard exposure in Batu City, the composite data is presented in Table 5

Table 5. Summary of Vulnerability Index and Multihazard Assessment for 2021–2023



No.	Kecamatan	Nama Desa/Kel	Indeks kerentanan	Ancaman		
				Gempa bumi	Longsor	G. Api
1	Bumiaji	Pandanrejo	Rendah	Tinggi	Rendah	Rendah
2		Bumiaji	Sedang	Tinggi	Rendah	Rendah
3		Bulukerto	Sedang	Tinggi	Rendah	Rendah
4		Gunungsari	Sedang	Tinggi	Sedang	Rendah
5		Punten	Sedang	Tinggi	Rendah	Rendah
6		Tulungrejo	Rendah	Tinggi	Rendah	Rendah
7		Sumbergondo	Sedang	Tinggi	Rendah	Rendah
8		Giripurno	Sedang	Tinggi	Rendah	Rendah
9		Sumber Brantas	Sedang	Tinggi	Rendah	Sedang
10	Batu	Oro-oro Ombo	Sedang	sedang	Rendah	Rendah
11		Temas	Tinggi	Sedang-Tinggi	Rendah	Rendah
12		Sisir	Sangat Tinggi	Tinggi	Rendah	Rendah
13		Ngaglik	Sedang	Tinggi	Rendah	Rendah
14		Pesanggrahan	Sedang	Tinggi	Rendah	Rendah
15		Songgokerto	Sedang	Tinggi	Rendah	Rendah
16		Sumberejo	Sedang	Tinggi	Rendah	Rendah
17		Sidomulyo	Sedang	Tinggi	Rendah	Rendah
18	Junrejo	Tlekung	Sedang	Sedang	Rendah-Sedang	Rendah
19		Junrejo	Rendah	Sedang-Tinggi	Rendah	Rendah
20		Mojorejo	Rendah	Tinggi	Rendah	Rendah
21		Torongrejo	Sedang	Tinggi	Rendah	Rendah
22		Beji	Rendah	sedang	Rendah	Rendah
23		Pendem	Rendah	Tinggi	Rendah	Rendah
24		Dadaprejo	Rendah	Tinggi	Rendah	Rendah

Clustering of Vulnerability in Batu City, 2021

The Self-Organizing Map (SOM) clustering for 2021 reveals a non-random, spatially structured pattern of vulnerability in Batu City, driven by interconnected socio-ecological and geographic factors. As shown in Figure 6, villages are grouped into three clusters: Cluster 3 (high vulnerability) including Sisir and Temas exhibits high population density, agricultural dependence, and hazard exposure. Cluster 1 (low vulnerability), in light gray, comprises resilient southern villages (e.g., Mojorejo, Beji, Dadaprejo) with better infrastructure and diversified economies. Cluster 2 (moderate vulnerability), in medium gray, includes transitional areas like Junrejo and Pendem. The spatial clustering underscores the need for targeted, context-specific disaster risk reduction strategies (Wisner et al., 2003; UNDRR, 2015).

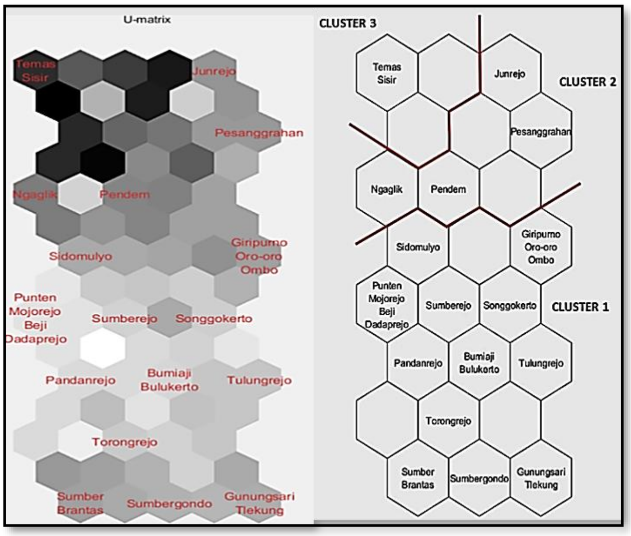


Figure 6. U-Matrix and Clustering of Vulnerability in Batu City, 2021

Dominant Variables in Batu City, 2021

The analysis of dominant variables for 2021 identified key factors influencing the vulnerability characteristics within each cluster. In Cluster 1 (low vulnerability), the PETANI (Farmers) variable (12.55%) was dominant, reflecting the region's economic dependence on the agricultural sector, which is susceptible to climate fluctuations, commodity price volatility, and disaster threats. Cluster 2 (medium vulnerability) was redominantly influenced by KOMUNKS (Communication) (10.25%), indicating challenges related to access and the quality of communication infrastructure, which limits connectivity and information dissemination, particularly in remote areas. Cluster 3 (high vulnerability) was primarily driven by the "pendatang" (Migrant Population) variable (7.19%), highlighting that population migration and mobility dynamics significantly contribute to vulnerability, particularly concerning disaster preparedness. The visualization of these dominant variables is presented in Figure 7 while the spatial cluster map for 2021 is shown in Figure 8.

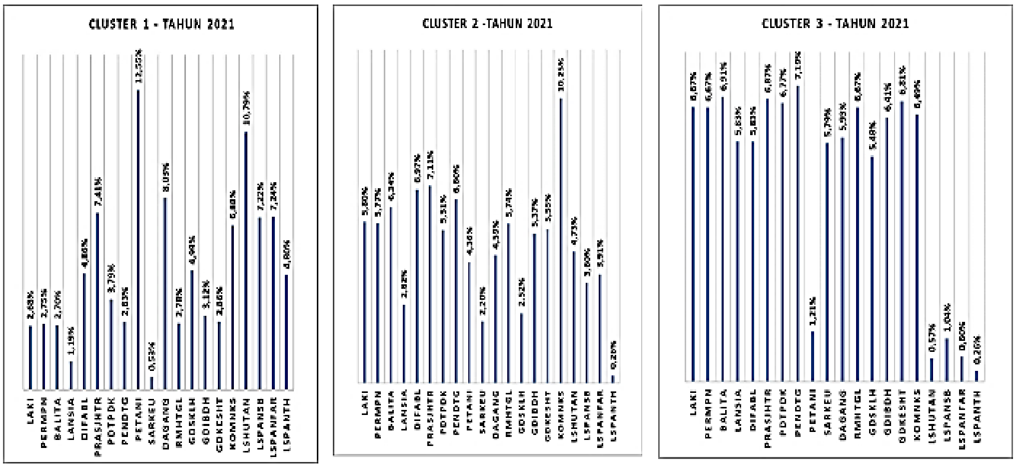


Figure 7. Bar Chart Showing Dominant Variables for Each Cluster in 2021

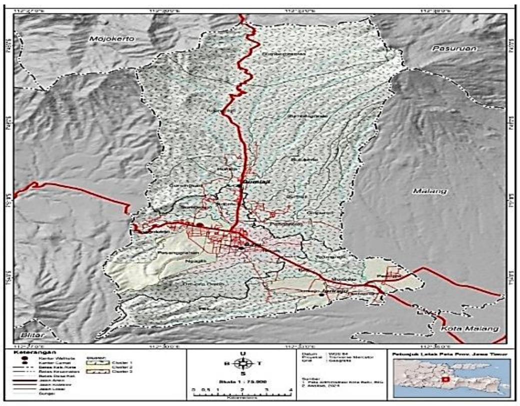


Figure 8. Cluster Map for 2021

Clustering of Vulnerability in Batu City, 2022

The 2022 vulnerability cluster analysis for Batu City, using the Self-Organizing Map (SOM) method and visualized through the U-Matrix (Figure 9), revealed distinct spatial patterns of risk. Areas in Cluster 1 (low vulnerability) are represented by desa-desa with light grey to white colors on the U-Matrix, including Pandanrejo, Bulukerto, Songgokerto, Gunungsari, Punten, Sumber Brantas, Torongrejo, Sumbergondo, and Tlekung. These areas demonstrate better resilience. Conversely, areas in high vulnerability clusters are indicated by darker colors, concentrated mainly in the northern part of the map, such as Temas, Sisir, Pendem, Pesanggrahan, Junrejo, Ngaglik, Giripuno, and Oro-oro Ombo. The darker hues signify a combination of complex threats, including geographically prone conditions and significant economic challenges (Kohonen, 2001; Wisner et al., 2012). This systematic pattern highlights that vulnerability is clustered based on shared socio-economic and ecological characteristics.

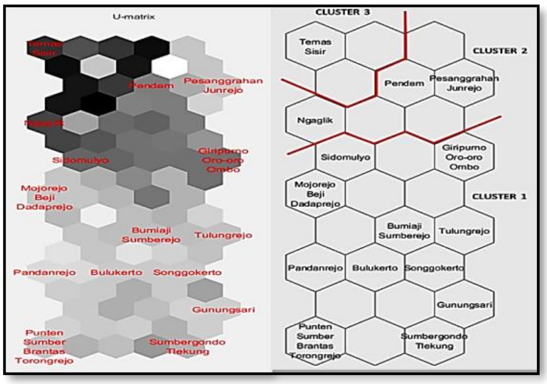


Figure 9. U-Matrix and Clustering of Vulnerability in Batu City, 2022

The spatial distribution of these clusters is visualized in Figure 10.

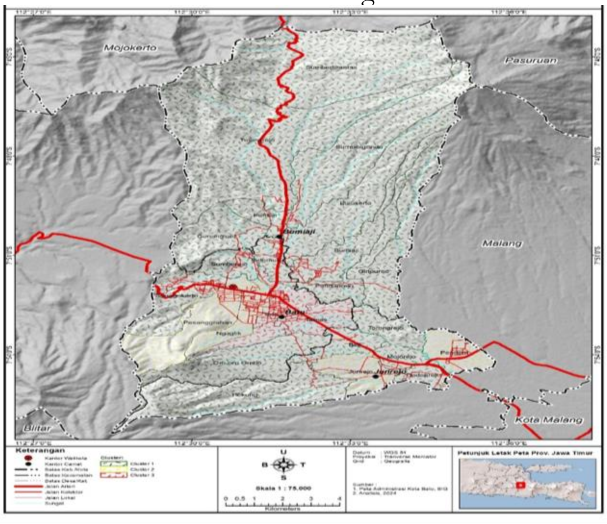


Figure 10. Cluster Map for 2022

A Comparative Study of Vulnerability Clusters in Batu City from 2021 to 2022

visualized using the Self-Organizing Map (SOM), illustrates marked spatial and temporal shifts in disaster risk. Consistently high-risk areas such as Sisir and Temas remained critical, while others like Tulungrejo showed a drastic reduction in vulnerability. The central region presented contrasting dynamics: Sidomulyo and Bumiaji demonstrated improved resilience likely linked to infrastructure upgrades, whereas Mojorejo and Beji experienced increased risk—potentially due to population pressure and environmental decline. These nuanced transitions highlight the SOM's capability to detect evolving spatial vulnerabilities (de Gouvêa et al., 2023; Ultsch, 2003).

. The study confirms that SOM-based analysis can inform strategic planning by distinguishing between regions requiring urgent action and those maintaining low risk. Continuous spatial monitoring is essential to prevent regression, especially in dynamically evolving urban cores (Suprapto et al., 2022; Panchal et al., 2022).

Dominant Variables in Batu City, 2022

The dominant variable in Cluster 1 for the year 2022 remained consistent with 2021, namely "Farmer (PETANI)", although its contribution declined from 12.55% to 11.49%. This reduction not only reflects a modest improvement in farmers' socioeconomic conditions but also signals a broader structural transformation within the region's economic landscape. Similarly, Cluster 2 continued to be characterized by "communication (KOMUNKS)", contributing 8.12%, while Cluster 3 was dominated by the "migrant population (PENDATANG)" at 7.19%. These patterns suggest that Batu City retains its core socioeconomic characteristics across both years. The visualization of these dominant variables is presented in Figure 11.

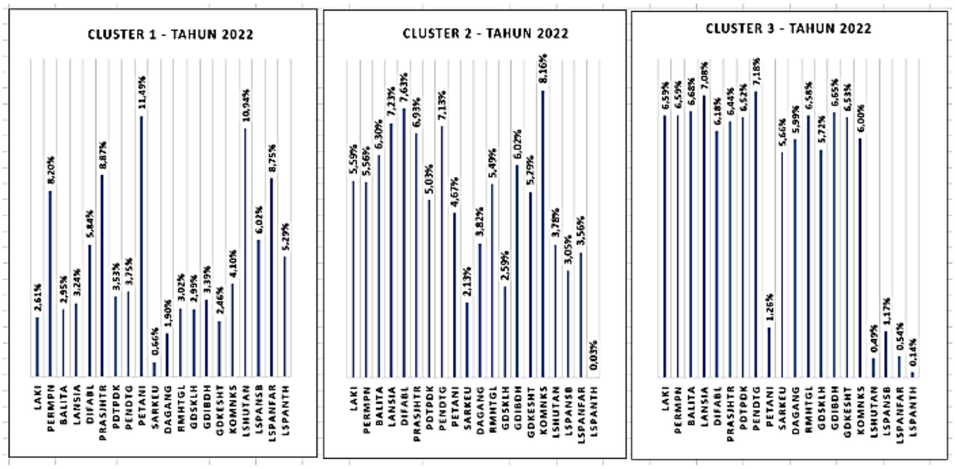


Figure 11. Bar Chart Showing Dominant Variables for Each Cluster in 2022

Clustering of Vulnerability in Batu City, 2023

The 2023 cluster pattern reveals that vulnerability in Batu City is not randomly distributed, but follows a systematic pattern with clear inter-regional connectivity. High vulnerability cluster regions, such as clusters 2 and 3 comprising villages Tema, Sisir, Pendem, Pesanggrahan, Junrejo, Ngaglik, Giripuno, and Oro-oro Ombo, form a cluster with darker to very dark colors indicating moderate to very high vulnerability levels, reflecting complex threat combinations including inadequate infrastructure, high population density, difficult accessibility, and geographically disaster-prone locations (Turner et al., 2003). Cluster 1 covering Pandanrejo, Bulukerto, Dadaprejo, Songgokerto, Gunungsari, Punten, Sumber Brantas, Torongrejo, Sumbergondo, Tulungrejo, Sidomulyo, Mojorejo, Beji, Bumiaji, Sumberejo, and Tlelung displays lighter colors, indicating relatively low vulnerability levels, with better resilience against threats through improved infrastructure development and more stable environmental conditions (Adger, 2006).

The central region functions as a transition zone, where vulnerability levels remain significant but have potential for enhanced resilience if appropriate interventions are implemented. Several areas such as Sidomulyo and Bumiaji show increased resilience with lighter colors compared to previous years, indicating stronger infrastructure improvements or economic diversification. However, regions like Mojorejo and Beji appear darker, reflecting increased risk due to rising population density or environmental degradation. Some areas such as Gunungsari and Torongrejo even demonstrate improved resilience with lighter colors compared to previous years, reflecting better vulnerability level stability. U-Metrix visualization and clustering are presented in Figure 12.

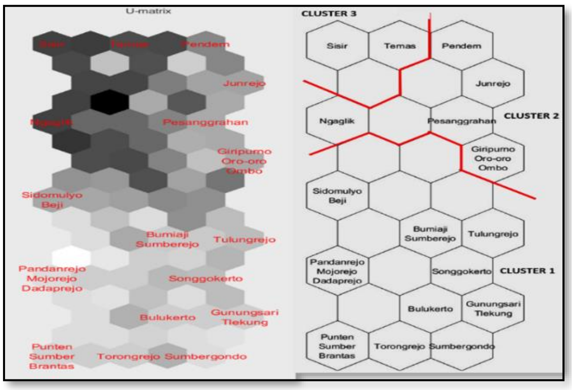


Figure 12. U-Matrix and Clustering of Vulnerability in Batu City, 2023

The spatial distribution of these clusters is visualized in Figure 13.

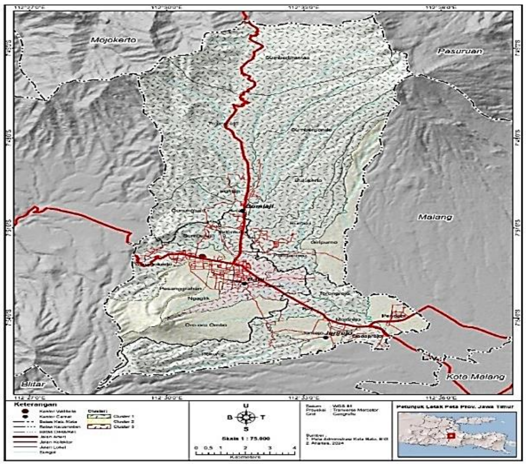
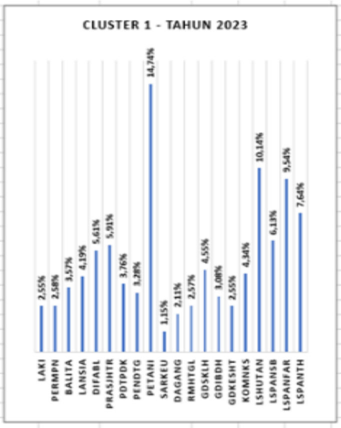


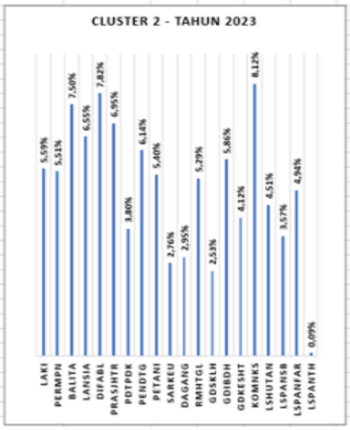
Figure 12. Cluster Map for 2023

Dominant Variables in Batu City, 2023

The dominant variable in Cluster 1 for 2023 remains consistent with 2021 and 2022, namely FARMERS. However, the contribution value of the "Farmers" factor has changed from year to year: 12.55% in 2021, 11.49% in 2022, and 14.74% in 2023. This change reflects the complex dynamics within the agricultural sector and community conditions in Cluster 1. Cluster 2's dominant variable remains the same as in 2021 and 2022, namely "communication (KOMUNKS)" with a contribution of 8.12%, while Cluster 3 in 2023 experienced a shift in the dominant variable from "migrants (PENDATANG)" at 7.19% to "toddlers (BALITA) with a contribution of 7.21%. Toddlers are not only vulnerable to social, economic, or general health threats, but also specifically vulnerable to natural disasters (UNISDR, 2009. The visualization of these dominant variables is presented in Figure 12.

The shift in dominant variables in Cluster 3 from Migrants to Toddlers reflects a significant transformation in the vulnerability dynamics of Cluster 3, particularly in the context of natural disasters.





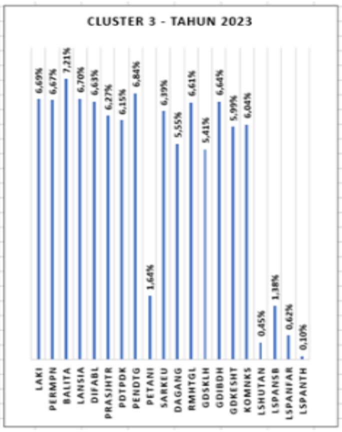


Figure 13. Bar Chart Showing Dominant Variables for Each Cluster in 2023

CONCLUSION

This study presents a comprehensive, spatially explicit framework for assessing multidimensional agricultural vulnerability in multi-hazard environments, using Batu City, East Java, as a case study. By integrating Social Vulnerability Index (SoVI) and Self-Organizing Map (SOM), the research demonstrates the synergistic power of statistical and neural-based approaches in capturing both linear and non-linear patterns of vulnerability across social, economic, physical, and ecological dimensions. The temporal analysis from 2021 to 2023 reveals dynamic shifts in vulnerability profiles, with certain areas (e.g., Tulungrejo and Junrejo) exhibiting marked improvements due to livelihood diversification, while others (e.g., Sisir and Gunungsari) show persistent or escalating risk linked to urban pressure, structural fragility, and limited adaptive capacity.

Overlaying vulnerability indices with seismic amplification (Vs30), landslide susceptibility, and volcanic hazard zones reinforces the existence of compounded risk hotspots—particularly in central and northern subdistricts—where social fragility intersects with physical hazard exposure. The clustering analysis offers typological insights that enable place-specific interventions, underscoring the value of integrated methodologies for disaster risk reduction planning.

Overall, the Multi-Hazard Agricultural Vulnerability Index (MHAVI) developed herein provides a replicable model for other agrarian and mountainous cities facing cascading hazards. It aligns with the Sendai Framework's call for risk-informed development and contributes to the evolving paradigm of multi-hazard, multi-vulnerability governance.

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