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COMMUNITY VULNERABILITY ASSESSMENT AGAINST LANDSLIDE HAZARD POTENTIAL IN TANAH DATAR REGENCY, INDONESIA

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Abstract

Many disasters have occurred in the hilly and mountainous areas along active faults in the western part of Sumatra Island, influenced by tectonic, volcanic, and anthropogenic activities that indirectly impact community life. The first step in understanding the impact of natural hazards, such as landslides, is to assess community vulnerability. This study aimed to assess community vulnerability factors in an integrated manner using the Analytic Hierarchy Process approach to parameters such as population density, age <14 years, age >44 years, number of women, number of health facilities, and number of education facilities. Vulnerability assessment, with a scientific evidence approach, provides better information for visualizing vulnerability, and can be used in disaster risk reduction, enhancing community adaptive capacity, and strengthening governance. Moreover, maximizing capacity for preparedness, community response, recovery, and adaptive building reconstruction can be achieved through sustainable spatial planning management.

Keywords: Assessment, Community Vulnerability, Social Data, Disaster Risk Reduction

1. INTRODUCTION

One of the important elements in landslide risk reduction is to educate at-risk communities about the potential occurrence of landslide hazards in specific locations [1], [2]. This involves self-preparation and attention to land conditions vulnerable to landslides as well as the provision of ground motion detection systems [3]. Although simple, the process of preparing at-risk neighborhoods for events poses challenges for public officials in recognizing potential vulnerabilities to different types of ground motion hazard sources [4]. Information on uncertainties in the location and frequency of events as well as the high temporal-spatial variability of population dynamics is considered crucial [5]. The development of an effective ground motion hazard preparedness strategy requires a sound understanding of potential ground motion hazards and the individuals vulnerable to them, including interexposure strengths, sensitivities, mobility issues, communication barriers, and adaptive capacity of the community [6].

The decision to delineate a single evacuation zone is often rooted in the desire to prepare communities for worst-case ground motion scenarios that will react appropriately in multiple zones [7]. However, the spatial extent of potential ground motion in upland communities and the timing of ground mass arrival can vary dramatically with additional influences from earthquakes or volcanic eruptions [8]. The response of at-risk populations is expected to vary depending on the threat, ranging from self-evacuation to localized sources of ground motion hazard due to the effects of earthquakes and volcanoes [9],[10].

In support of hydrometeorological disaster education and preparedness efforts, attempts have been made by several scientists to characterize population vulnerability to hydrometeorological disasters in recent years. This includes exposure assessments, pedestrian route evaluations, demographic sensitivities, and the identification of open evacuation sites[11],[12]. Together, these efforts contribute to understanding whether sufficient time for evacuation is available for low-risk populations [13]. However, efforts to characterize the vulnerability of populations to ground motion, focusing only on residents, can be problematic for upland communities that are geomorphologically more prone to disasters [14]. Based on ground motion sources, hazard mapping, and evacuation routes for local communities are reflective of a worst-case scenario or maximum zone that covers the needs of local communities [15].

The present work focuses on the primary assessment to address the issue of local investigation to identify landslide-prone areas in the neighborhood of community activities. This assessment considers various social aspect criteria that are affected by value and uncertainty. To tackle the challenges of imprecision and uncertainty in decision making, this study employs a multi-criteria decision-making approach with the Analytic Hierarchy Process (AHP) method, aiming to represent the consistency of subjectively constructed knowledge. The main objective of this research is to apply geographic information systems and remote sensing to assess the social vulnerability of communities to potential landslide hazards in the Tanah Datar Regency in the western region of Sumatra Island, Indonesia.

2. RESEARCH METHOD

2.1. Site location

The Tanah Datar Regency is one of the regions in West Sumatra Province. The topographic conditions of the area, featuring hills, allow the transformation of land into a highly agricultural sector [16]. Several mountains, including Mt. Marapi, Mt. Sao, Mt. Singgalang, and Mt. Tandikek, were found in the study area, with the highest altitude reaching 2,891 m above sea level. The boundaries of the study area were determined by geospatial agencies (Geospatial Information Agency) and covered an area of 1,375 square kilometers. The study area is illustrated in Figure 1.

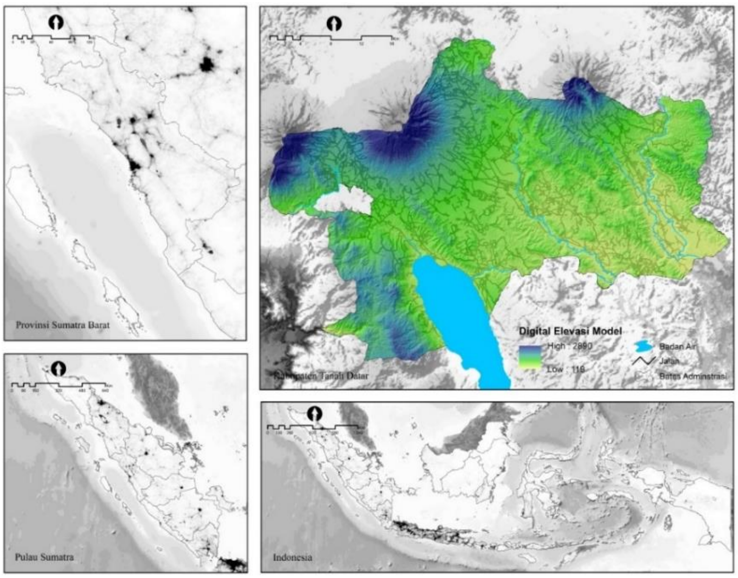

Figure 1. Location of Observation

2.2. Data collection

The selection and acquisition of data representing key indicators, such as resilience, exposure, and capacity, involves a process based on literature review, expert arguments, and data availability. The principal indicators chosen for this study were derived from various definitions and frameworks of vulnerability established in recent research. The extensive literature on disaster vulnerability has spawned diverse approaches and adaptability terms within communities (Table 1). In the Tanah Datar District, the collection of vulnerability data is rooted in the social data obtained from the Central Bureau of Statistics Subdistricts in Figures 2022. This dataset encompasses factors such as population density, age distribution (<14 years and >44 years), number of women, health facilities, Base Transceiver Stations, and education facilities (see Tables 1 and 2). Additionally, building data referenced in the research conducted by [17], [18] utilizing 10m resolution Sentinel-2 satellite imagery with projections to WGS 84 UTM zone 47S, is integral to the study's comprehensive approach.

Table 1. Explanation of parameters that represent observation indicators

Variable	Description	Correlation	Reference
Population Density (per hectare)	The risk level of disaster vulnerability is represented by population density. High-density population activity will lead to increased risk, and vice versa at low densities.	(+)	[19]
Age <14 Years (total)	Children aged less than 14 years represent the most vulnerable segment of the population in terms of both life knowledge capacity and the availability of equipment to respond to disaster activities.	(+)	[20]
Age >44 Years (total)	In the elderly population, health limitations are experienced by most, necessitating special care and assistance from those around them.	(+)	[21]
Number of Women (total)	In physical, social, and economic dimensions, the ability to recover from the effects of disasters is influenced by women. Women's vulnerability is heightened by fewer resources and increased barriers.	(+)	[22]
Health facilities (total)	A crucial facility, health services, can be affected during a disaster. The operation of a large number of service facilities can disrupt and negatively impact the community's vulnerability to disasters,	(-)	[23]
Education facilities (total)	Similar to healthcare facilities, many deaths and injuries can result from building damage in high-density residential structures such as schools.	(+)	[24]

Table 2. Parameter of community vulnerability

District	Population Density	Age <14th	Age >44th	Women	Health facilities	Education facilities
Batipuh	222	6913	10779	15981	7	32
Batipuh Selatan	137	2439	3804	1977	4	14
Lima Kaum	766	8250	12864	26427	10	41
Lintau Buo	4459	4328	6748	9864	4	17
Lintau Buo Utara	2485	8186	12763	19199	5	44
Padang Ganting	177	3169	4941	7496	3	16
Pariangan	273	4498	7013	10615	5	24

Rambatan	292	8129	12675	18925	5	35
Salimpaung	5261	5171	8062	12085	4	23
X Koto	308	10074	15708	21769	8	47
Sungai Tarab	6171	7148	11146	16519	9	32
Sungayang	3861	4077	6356	9846	5	19
Tanjung Baru	4537	3153	4916	7251	4	13
Tanjung Emas	228	5511	8593	12597	6	22

2.3. Analytical hierarchy process

The weighting stage of the community vulnerability criteria begins with the provision of an assessment questionnaire to each expert, and these assessments are then aggregated into a range for each criterion using the Analytical Hierarchy Process approach [25]. Expert assessments, based on a scale ranging from 1 to 9 and involving pairwise comparisons, form the basis of this process. The AHP procedure for evaluating criteria factors based on their influence on community vulnerability is shown in the following table. The AHP assessment construction aims to compare sub-criteria assessments through pairwise comparisons, resulting in weighted coefficients for each criterion [26]. To assess the most influential criteria for community vulnerability to potential landslide hazards, interviews were conducted with five experts. The values for the pairwise comparison scale in the Analytical Hierarchy Process method (Table 3).

Table 3. AHP pairwise comparison scale criteria

Value	Description
1	X is equally important as Y
3	X is slightly more important than Y
5	X is obviously more important than Y
7	X is clearly more important than Y
9	X is absolutely more important than Y
2,4,6,8	When in doubt, choose between two adjacent values

The consistency of multiple comparison-based selectors was assessed using decision parameters [27]. The consistency value is calculated using the consistency index with the following parameters.

$$CI = \frac{\lambda max - n}{n-1} \quad (1)$$

Where CI is the Consistency Index, which is the most crucial element in the multiple comparison matrix, a and n denotes the parts of the comparison matrix. Although inconsistency may be exhibited in AHP judgments, this can be addressed through emphasis settings. The Consistency Ratio (CR) is defined as follows.

$$CR = \frac{CI}{RI} \quad (2)$$

Where the CI value is represented as the consistency index and RI is the random index. The consistency ratio was considered acceptable if it was less than 0.1 (10%). If the threshold is exceeded, the expert assessment is deemed unacceptable, necessitating reassessment. Once the criterion weight values are available, the other sub-criteria for vulnerability can be identified. The subsequent step involves calculating the score of each sub-criterion in the geographic information system software. Each score was derived by multiplying the weighted criteria values. The values for each sub-criterion were obtained from several studies. Notably, no software was used in the analysis. The obtained results are the scores input into the polygon, ranging from the smallest score to the highest score [28]. The following equation was used to determine community vulnerability zoning.

$$I = \frac{c-b}{k} \quad (3)$$

In Part I, the distance between the intervals is represented, where c is the highest score, b is the lowest score, and k is the desired number of community vulnerability classes.

3. RESULTS AND ANALYSIS

Before combining them using the linear weight summation technique to map community vulnerability to landslide hazards, each vulnerability factor was weighted. A CR tolerance of approximately 0.0523 (<0.1) was indicated in the community vulnerability map for the observation area (Figure 3), considering factors such as population density, age <14 years, age >44 years, number of women, education facilities, and health facilities. The ranking of each class was determined based on the value of the influence weight between the pixels that were indicated to be vulnerable and those that had no effect. Using the ranking values, the class weights for each class of community vulnerability causal factors were determined using an Analytical Hierarchy Process (Figure 2).

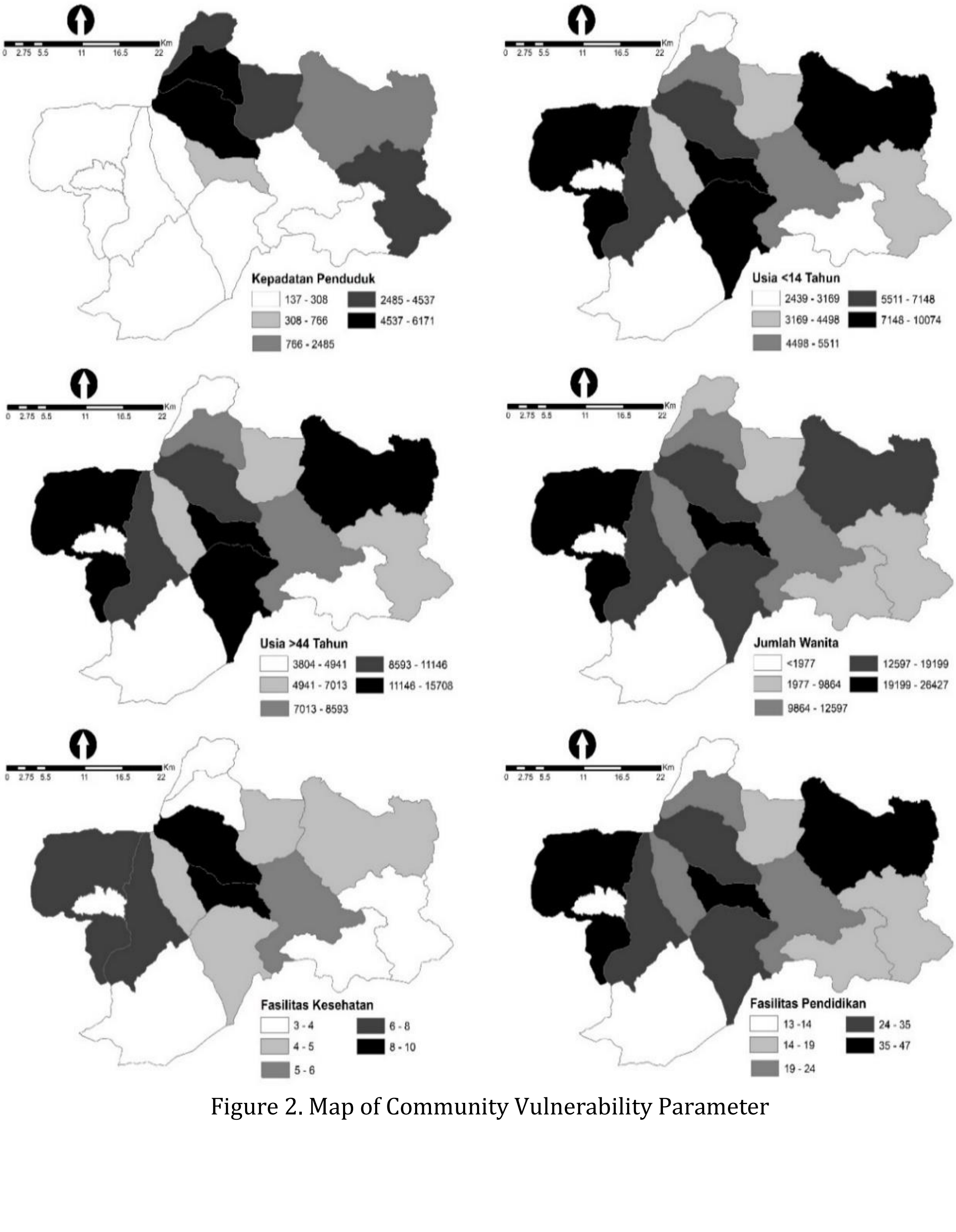

Figure 2. Map of Community Vulnerability Parameter

Based on the AHP results, the impact of each factor on landslide vulnerability was ranked according to the assigned weights. First, population density was identified as the factor with the highest weight (0.383), as indicated by the assessment results. Uneven population distribution has implications for varying vulnerability levels in different regions. The number of people affected will certainly differ in areas with high and low population densities [29]. Thus, population density is deemed one of the key factors determining the vulnerability level of an area. Next, the age of the population below 14 years was categorized as having a low capacity to deal with disasters. This factor was assigned a weight of 0.25, which is below the population density. Age influences the sensitivity of a population to disasters. Finally, the population aged >44 years is considered an elderly population that has passed productive years. Assuming that they have had previous experience, this age group is categorized as no more vulnerable than those aged <14 years.

Furthermore, women are categorized as one of the groups vulnerable to disasters alongside children and the elderly [30]. One appropriate mitigation measure is to increase public awareness through educational programs, particularly for vulnerable groups [31]. For this reason, educational facilities, in this case schools, are factors that are influenced by the level of vulnerability. Similar to educational facilities, health facilities play an important role in providing support during disasters. Therefore, health facilities are also a factor for assessing the level of vulnerability (Table 4).

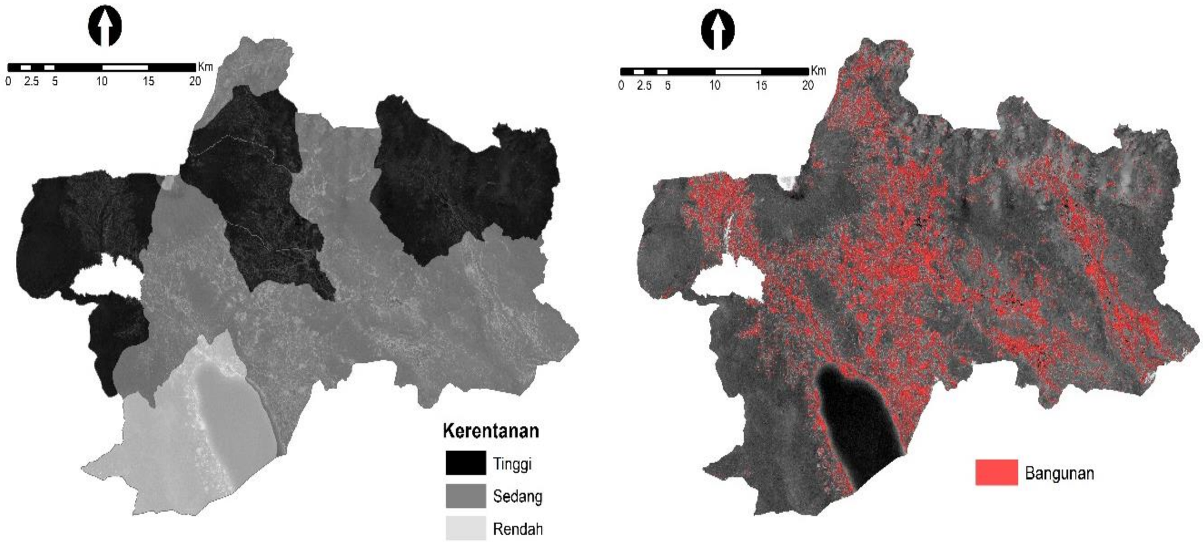

Figure 3. Vulnerability and existing buildings in Tanah Datar Regency

AHP is a Multiple Criteria Decision-Making (MCDM) method used to determine the importance of factors based on expert judgment [32]. The least influential category was assigned a value of 1, and the most influential category was assigned a value of 9 [33]. The results of the AHP assessment were integrated with GIS to produce a map of vulnerability levels, grouped based on the weights from the AHP. Following the principle of classification using natural breaks, three classes were formed: areas with high, medium, and low vulnerability [34]. The relationship between causal factors and landslide occurrence was indicated by the results of AHP analysis. Subsequently, the vulnerability analysis results were juxtaposed with the building map to observe the exposure of the area based on the intensity of building density. The level of vulnerability in an area is influenced by the population. Assuming that the presence of buildings reflects the population density of an area, areas vulnerable to landslides are indicated by the results of this analysis based on the presence of the population (Figure 3).

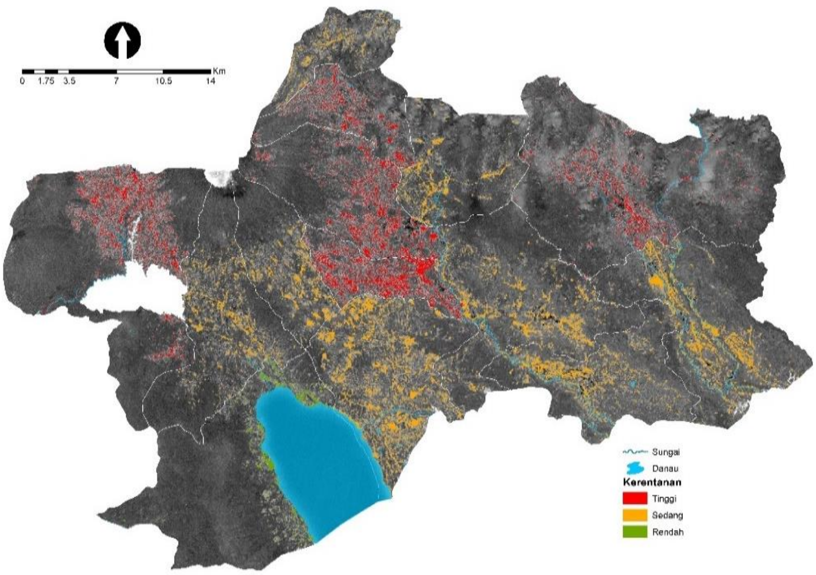

Figure 4. Community Vulnerability based on existing buildings

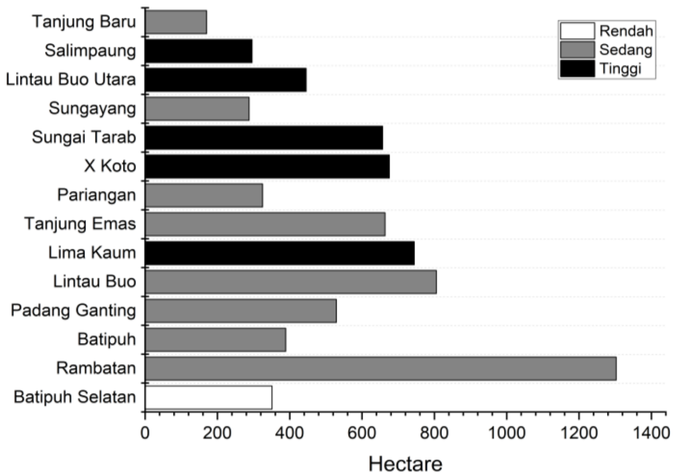

Figure 5. The area of distribution of community vulnerability in each sub-district

The spatial distribution of community vulnerability in Figure 4 visualizes the susceptibility of the Tanah Datar Regency to landslides based on the presence of existing buildings. Similar to the previous classification, vulnerability levels were categorized into three classes: areas with high, medium, and low vulnerability. More specifically, areas experiencing high vulnerability in the Tanah Datar District include Lima Kaum, X Koto, and Sungai Tarab. The likelihood of landslides occurring is increased by the presence of these sub-districts, which are primarily located in mountainous areas.

Landslide risk is the result of the interaction between landslides and buildings [10]. Therefore, an area with high building density is more vulnerable to landslides. Identified as the district with the highest vulnerability level, Lima Kaum district has a population density of 776 people/km2, making it the district with the highest population density in the Tanah Datar Regency (Figure 5). The substantial population activity in Lima Kaum district renders it vulnerable to landslides. Similarly, X Koto and Sungai Tarab district, where both areas exhibit high population densities based on BPS data from Tanah Datar District, are prone to landslides. The population and socioeconomic characteristics of the local population are still inadequate, resulting in a low community capacity to deal with disasters and, consequently, a higher vulnerability level in the area.

Disaster vulnerability assessment is an essential step that needs to be undertaken as part of disaster risk analysis and to determine directions for disaster mitigation. In this study, the vulnerability assessment was based solely on the distribution of buildings in the Tanah Datar

Regency. Areas with high building density are considered more vulnerable to landslides, assuming that the presence of buildings indicates high human activity. However, more detailed building characteristics were not considered in this study in order to determine the vulnerability of each structure. Therefore, future research should be conducted with more detailed consideration of the conditions and characteristics of buildings.

3. CONCLUSION

Based on the analysis conducted, regional vulnerability to disasters can be assessed using information systems to depict the spatial distribution of disaster-prone areas. The potential for disasters and the community's capacity, as indicated by the socioeconomic conditions of the community, are the main determinants of the vulnerability level of an area. The presence of a population, as depicted by the existence of buildings, is also a factor that needs to be considered when determining the vulnerability of the area.

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REFERENCES

[1] Y. Park, A. M. S. Pradhan, U. Kim, Y. T. Kim, and S. Kim, “Development and Application of Urban Landslide Vulnerability Assessment Methodology Reflecting Social and Economic Variables,” Advances in Meteorology, vol. 2016, 2016, doi: 10.1155/2016/4572498.

[2] I. H. Diva et al., “Investigation Volcanic Land Form and Mapping Landslide Potential at Mount Talang,” Sumatra Journal of Disaster, Geography and Geography Education, vol. 2, no. 1, p. 16, 2018, doi: 10.24036/sjdgge.v2i1.130.

[3] S. Saha et al., “Measuring landslide vulnerability status of Chukha, Bhutan using deep learning algorithms,” Sci Rep, vol. 11, no. 1, Dec. 2021, doi: 10.1038/s41598-021-95978-5.

[4] D. Kumar and R. Kumar Bhattacharjya, “Study of Integrated Social Vulnerability Index SoVIint of Hilly Region of Uttarakhand, India,” Environmental and Climate Technologies, vol. 24, no. 1, pp. 105–122, Jan. 2020, doi: 10.2478/rtuect-2020-0007.

[5] B. Ahmed and I. Kelman, “Measuring Community Vulnerability to Environmental Hazards: A Method for Combining Quantitative and Qualitative Data,” Nat Hazards Rev, vol. 19, no. 3, Aug. 2018, doi: 10.1061/(asce)nh.1527-6996.0000290.

[6] L. D. Bhatta, E. Udas, B. Khan, A. Ajmal, R. Amir, and S. Ranabhat, “Local knowledge based perceptions on climate change and its impacts in the Rakaposhi valley of Gilgit-Baltistan, Pakistan,” Int J Clim Chang Strateg Manag, vol. 12, no. 2, pp. 222–237, Mar. 2020, doi: 10.1108/IJCCSM-05-2019-0024.

[7] R. Roslee, T. A. Jamaludin, and N. Simon, “Landslide Vulnerability Assessment (LVAs): A case study from Kota Kinabalu, Sabah, Malaysia,” Indonesian Journal on Geoscience, vol. 4, no. 1, pp. 49–59, 2017, doi: 10.17014/ijog.4.1.49-59.

[8] M. W. A. Ramli et al., “Spatial multidimensional vulnerability assessment index in urban area- A case study Selangor, Malaysia,” Progress in Disaster Science, vol. 20, Dec. 2023, doi: 10.1016/j.pdisas.2023.100296.

[9] L. J. Bowman and K. B. Henquinet, “Disaster risk reduction and resettlement efforts at San Vicente (Chichontepec) Volcano, El Salvador: Toward understanding social and geophysical vulnerability,” Journal of Applied Volcanology, vol. 4, no. 1, Dec. 2015, doi: 10.1186/s13617-015-0031-0.

[10] T. Raduszynski and M. Numada, “Measure and spatial identification of social vulnerability, exposure and risk to natural hazards in Japan using open data,” Sci Rep, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-27831-w.

[11] R. Moorthy, G. Benny, and S. S. Gill, “Disaster communication in managing vulnerabilities,” Jurnal Komunikasi: Malaysian Journal of Communication, vol. 34, no. 2, pp. 51–66, 2018, doi: 10.17576/JKMJC-2018-3402-04.

[12] S. Sekhri, P. Kumar, C. Fürst, and R. Pandey, “Mountain specific multi-hazard risk management framework (MSMRMF): Assessment and mitigation of multi-hazard and climate change risk in the Indian Himalayan Region,” Ecol Indic, vol. 118, Nov. 2020, doi: 10.1016/j.ecolind.2020.106700.

[13] G. Gomes, V. Marchezini, and M. Sato, "(In)visibilities About the Vulnerabilities of People with Visual Impairments to Disasters and Climate Change: A Case Study in Cuiabá, Brazil," International Journal of Disaster Risk Science, vol. 13, no. 1, pp. 38–51, Feb. 2022, doi: 10.1007/s13753-022-00394-6.

[14] A. B. Ndah and J. O. Odihi, "A Systematic Study of Disaster Risk in Brunei Darussalam and Options for Vulnerability-Based Disaster Risk Reduction," International Journal of Disaster Risk Science, vol. 8, no. 2, pp. 208–223, Jun. 2017, doi: 10.1007/s13753-017-0125-x.

[15] J. Maes et al., "Social multi-criteria evaluation to identify appropriate disaster risk reduction measures: application to landslides in the Rwenzori Mountains, Uganda," Landslides, vol. 16, no. 9, pp. 1793–1807, Sep. 2019, doi: 10.1007/s10346-018-1030-0.

[16] E. A. Giofandi et al., "Potential Land Suitability For Spatial Planning of Wheat Commodity (Triticum Aestivum) In Tanah Datar Regency," Jurnal Geografi, Edukasi, dan Lingkungan (JGEL), vol. 6, no. 2, pp. 101–112, 2022.

[17] Y. Zha, J. Gao, and S. Ni, "Use of normalized difference built-up index in automatically mapping urban areas from TM imagery," Int J Remote Sens, vol. 24, no. 3, pp. 583–594, Feb. 2003, doi: 10.1080/01431160304987.

[18] E. A. Giofandi and D. Sekarjati, "Persebaran Fenomena Suhu Tinggi melalui Kerapatan Vegetasi dan Pertumbuhan Bangunan serta Distribusi Suhu Permukaan," Jurnal Geografi : Media Informasi Pengembangan dan Profesi Kegeografian, vol. 17, no. 2, pp. 56–62, 2020, doi: 10.15294/jg.v17i2.24486.

[19] S. K. Aksha, L. Juran, L. M. Resler, and Y. Zhang, "An Analysis of Social Vulnerability to Natural Hazards in Nepal Using a Modified Social Vulnerability Index," International Journal of Disaster Risk Science, vol. 10, no. 1, pp. 103–116, Mar. 2019, doi: 10.1007/s13753-018-0192-7.

[20] O. L. Azzimonti, M. Colleoni, M. De Amicis, and I. Frigerio, "Combining hazard, social vulnerability and resilience to provide a proposal for seismic risk assessment," J Risk Res, vol. 23, no. 9, pp. 1225–1241, 2020, doi: 10.1080/13669877.2019.1646308.

[21] I. Frigerio et al., "A GIS-based approach to identify the spatial variability of social vulnerability to seismic hazard in Italy," Applied Geography, vol. 74. Elsevier Ltd, pp. 12–22, Sep. 01, 2016. doi: 10.1016/j.apgeog.2016.06.014.

[22] S. Ronoh, J. C. Gaillard, and J. Marlowe, "Children with Disabilities and Disaster Risk Reduction: A Review," International Journal of Disaster Risk Science, vol. 6, no. 1, pp. 38–48, Jan. 2015, doi: 10.1007/s13753-015-0042-9.

[23] R. Robat Mili, K. Amini Hosseini, and Y. O. Izadkhah, "Developing a holistic model for earthquake risk assessment and disaster management interventions in urban fabrics," International Journal of Disaster Risk Reduction, vol. 27, pp. 355–365, Mar. 2018, doi: 10.1016/j.ijdrr.2017.10.022.

[24] A. Banica, L. Rosu, I. Muntele, and A. Grozavu, "Towards urban resilience: A multi-criteria analysis of seismic vulnerability in Iasi City (Romania)," Sustainability (Switzerland), vol. 9, no. 2, 2017, doi: 10.3390/su9020270.

[25] N. Afzal, A. Ahmad, S. A. Shirazi, I. Younes, and L. T. T. Ha, "GIS-based Landslide Susceptibility Mapping using Analytical Hierarchy Process : A Case Study of Astore Region, Pakistan," EQA - International Journal of Environmental Quality, vol. 48, no. 2, pp. 27–40, 2022, doi: 10.6092/issn.2281-4485/12600.

[26] L. Gupta and J. Dixit, "A GIS-based flood risk mapping of Assam, India, using the MCDA-AHP approach at the regional and administrative level," Geocarto Int, vol. 37, no. 26, pp. 11867–11899, 2022, doi: 10.1080/10106049.2022.2060329.

[27] T. Xiong, I. G. B. Indrawan, and D. P. Eka Putra, "Landslide Susceptibility Mapping Using Analytical Hierarchy Process, Statistical Index, Index of Enthropy, and Logistic Regression Approaches in the TinalahWatershed, Yogyakarta," Journal of Applied Geology, vol. 2, no. 2, p. 67, 2017, doi: 10.22146/jag.39983.

[28] Muzani, A. I. Setianingsih, and S. S. Wahyudi, "ANALYSIS OF THE CAUSE OF LANDSLIDE DISASTER IN SUKABUMI , INDONESIA (USING ANALYTICAL HIERARCHY PROCESS) 印度尼西 亚须 文滑坡灾害的原因分析 （ 使用 层 次分析法 ）," JOURNAL OF SOUTHWEST JIAOTONG UNIVERSITY, vol. 56, no. 1, pp. 13–23, 2021.

[29] G. Dhungana, R. Ghimire, R. Poudel, and S. Kumal, "Landslide susceptibility and risk analysis in Benighat Rural Municipality, Dhading, Nepal," Natural Hazards Research, vol. 3, no. 2, pp. 170–185, Jun. 2023, doi: 10.1016/j.nhres.2023.03.006.

[30] Y. Xiao, X. Tang, Y. Li, H. Huang, and B. W. An, "Social vulnerability assessment of landslide disaster based on improved TOPSIS method: Case study of eleven small towns in China," Ecol Indic, vol. 143, Oct. 2022, doi: 10.1016/j.ecolind.2022.109316.

[31] S. Malakar and A. K. Rai, "Estimating seismic vulnerability in West Bengal by AHP-WSM and AHP-VIKOR," Natural Hazards Research, vol. 3, no. 3, pp. 464–473, Sep. 2023, doi: 10.1016/j.nhres.2023.06.001.

[32] F. El Bchari, B. Theilen-Willige, and H. Ait Malek, "Landslide hazard zonation assessment using GIS analysis at the coastal area of Safi (Morocco)," Proceedings of the ICA, vol. 2, pp. 1–7, Jul. 2019, doi: 10.5194/ica-proc-2-24-2019.

[33] S. Sharma and A. K. Mahajan, "Comparative evaluation of GIS-based landslide susceptibility mapping using statistical and heuristic approach for Dharamshala region of Kangra Valley, India," Geoenvironmental Disasters, vol. 5, no. 1, Dec. 2018, doi: 10.1186/s40677-018-0097-1.

[34] D. Asmare, "Application and validation of AHP and FR methods for landslide susceptibility mapping around choke mountain, northwestern ethiopia," Sci Afr, vol. 19, Mar. 2023, doi: 10.1016/j.sciaf.2022.e01470.