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Landslide Disaster Risk for Small and Medium Agricultural Enterprises (SMAEs)

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ABSTRACT

Small and Medium Agricultural Enterprises (SMAEs) are crucial for economic development in many developing countries, particularly in rural areas. Following a disaster, SMAEs experience the most profound impacts on their capital, logistics, workforce, and marketing operations. This study examines the impact of landslides on SMAEs in Selopamioro village, Bantul Regency of Special Region Yogyakarta. The study focused on the economic sensitivity of SMAEs and assessed their spatial distribution and classifications using drone aerial imagery and a village landslide database from 2010 to 2024. A total of 120 SMAEs were identified and classified by type in accordance with Indonesian laws. A representative sample of 60 SMAEs was validated using the Slovin formula. The study employed a hybrid survey methodology, combining interviews with village and hamlet leaders and on-site surveys using standardized questionnaires. The results showed that SMAEs in all hamlets of Selopamioro village have relatively low sensitivity, indicating that recent landslides have had limited effects on their sustainability. The village's disaster response capacity was moderate, but the study identified deficiencies in planning for potential future landslides. This study provides valuable insights for SMAEs and local governments regarding proactive risk mitigation strategies.

HIGHLIGHTS

The study provides valuable insights into the economic impacts of landslides on SMAEs and highlights the need for proactive measures to build resilience and reduce vulnerability in landslide-prone areas.

1. INTRODUCTION

Small and medium agricultural enterprises (SMAEs) play a crucial rolerural employment and economic development in developing countries such as Indonesia (FAO, 2012). They contribute significantly to employment generation and Gross Domestic Product (GDP) growth (Eskesen et al., 2014), and their success in meeting the demand for

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rice (Anggreini and Asyikin, 2023) is closely linked to social security, economic stability (Nurhaedah, 2022), political stability, and national security. SMAEs are essential for economic sustainability in both developed and developing nations (Radović-Marković et al., 2017) and they continuously strive to mitigate disaster impacts while working toward autonomous recovery (Satpathy et al., 2025). However, SMAEs are highly vulnerable to disasters, which can severely affect their capital, logistics, labor, and marketing sectors (Morrish and Jones, 2020). To enhance the income of SMAEs', governments should support small business development (Nasution et al., 2022; Ebrahim et al., 2023).The impact of landslides on agriculture differs between SMAEs and larger agricultural enterprises, as SMAEs often lack financial resilience and alternative resources. Landslides can result in long-term soil degradation, reduced crop yields, and disruptions in supply chains, disproportionately affecting smallholder farmers. I particular, road blockages caused by landslides hinder transportation and market access, further exacerbating economic losses. Alstadt et al. (2012) argues that investments in transportation infrastructure are essential for improving labor market ensuring efficient goods distribution, which, fosters economic growth.

Accessibility is crucial for business development, especially in rural areas where slope stability is at risk (Raza et al., 2022). Agricultural land use, such as monocropping and terraced farming, significantly influences slope stability, surface flow regulation, and vegetation loss due to erosion (Garcia-Chevesich et al., 2021). Landslides cause damage to land and agricultural infrastructure, including irrigation systems, dams, farm roads, and production facilities (Kainthola et al., 2021; Manurung et al., 2016). Climate change has been increasing the likelihood of landslides, indirectly affecting SMAEs. Slope stability depends on various factors, with precipitation being the most significant (Gallage et al., 2021; Jemec et al., 2023). Climate change can alter the frequency and severity of extreme precipitation globally, escalating risks associated with rainfall-induced landslides (Gariano and Guzzetti, 2022; Jakob, 2022). Landslides result in significant human and economic losses in China (Lin et al., 2020) and Indonesia (Sharif, 2021; Utami et al., 2021). Hilly areas often experience landslides, particularly in low-lying areas between hills, which can adversely impact on humans and the environment (Intarat et al., 2024; Lau and Zawawi, 2021). Landslides in remote areas have the potential to cause unexpected ecological and social damage (Putra et al., 2021). Various landslide studies have been conducted globally, categorized into landslide inventories (Hong et al., 2020; Ngadisih et al., 2017), hazard assessment (Mersha and Meten, 2020), and risk assessment (Wubalem, 2020).

The study utilizes landslide inventory to assess the age, activity, depth, and velocity of landslides in a village. However, this method faces challenges such as spectral differences, object-based classification, difficulty in obtaining bi-temporal imagery, and less accuracy when applied to other areas (Gariano and Guzzetti, 2022; Lin et al., 2020; Sukristiyanti et al., 2021). It also suffers from frequent classification errors. The study aims to assess the risks of SMAEs in a village and evaluate the risks of disasters affecting their sustainability. This study aims to assess the risks faced by SMAEs in a village and evaluate the risks of disasters affecting their sustainability. It seeks to develop a landslide disaster risk assessment method that integrates physical and socio-economic aspects at the village level, filling a gap in previous research that has primarily focused on larger administrative units. By incorporating SMAEs, which play a vital yet often overlooked role in rural economies, this study provides a more comprehensive risk evaluation. The modified approach supports a bottom-up disaster risk reduction strategy, contributing to the Sustainable Development Goals (SDGs), particularly in the areas of poverty alleviation and rural resilience. The novelty of this study lies in the risk assessment concept that integrates both physical and socio-economic aspects at the smallest administrative level (i.e., village). Previous studies have primarily focused on risk assessment at the district or sub-district level. To support the achievement of the SDGs through a bottom-up approach that begins at the village level, we have modified existing risk assessment methods. Accordingly, this study adopts several parameters commonly used for risk assessment at the district/provincial level and adapts them to the village level.

2. METHODOLOGY

2.1 Study site

Selopamioro Village, located in Imogiri District, Bantul Regency, is the research area with a history of landslides and a large number of SMAEs. The village spans 2,275 hectares (ha), including lowlands at an altitude of 100 meters above sea level. The topography consists of 30% flat to wavy areas and

70% wavy to hilly, which limits the land available for cultivation by farmers. The topography consists of 30% flat to wavy areas and 70% wavy to hilly, making land cultivation by farmers relatively small. The village is divided into several hamlets, including Lenteng I, Lenteng II, Lemahrubuh, Jetis, Kedungjati, Nogosari, Nawungan I, Nawungan II, Kajor Wetan, Kajor Kulon, Siluk I, Siluk II, Pelemantung, Putat, Kalidadap I, Kalidadap II, and Srunggo I. Selopamioro Village was chosen because it is identified as the poorest and most disaster-prone village in the district. Strengthening SMAEs is expected to drive economic growth and help the village escape poverty through disaster risk reduction-based development.

2.2 Data collection

2.2.1 Landslides inventory

Landslide distribution and classifications were determined manually from aerial images obtained by a drone flight in 2022. The aerial photographs provided a comprehensive view of the affected areas and facilitated the mapping of the landslides. Additionally, historical landslide data was obtained from the village office, which has maintained a database of landslide occurrences since 2010. The landslide inventory technique was also used by Thongley and Vansarochana (2021) in Bhutan. It uses a workflow consisting of landslide inventory, preparation factors, NGO (Non-Government Organization) development, and then validating the data. To classify landslides, visual identification is used without orthomapping. The image capture technique used is oblique aerial photography. This technique provides a distinctive landslide viewpoint compared to using vertical (orthogonal) aerial photography. Another advantage of aerial photography is the 20 MP image resolution, which can help landslide observations. Thus, aerial photography can be used to determine the characteristics of landslides based on visual appearance (Figure 1).

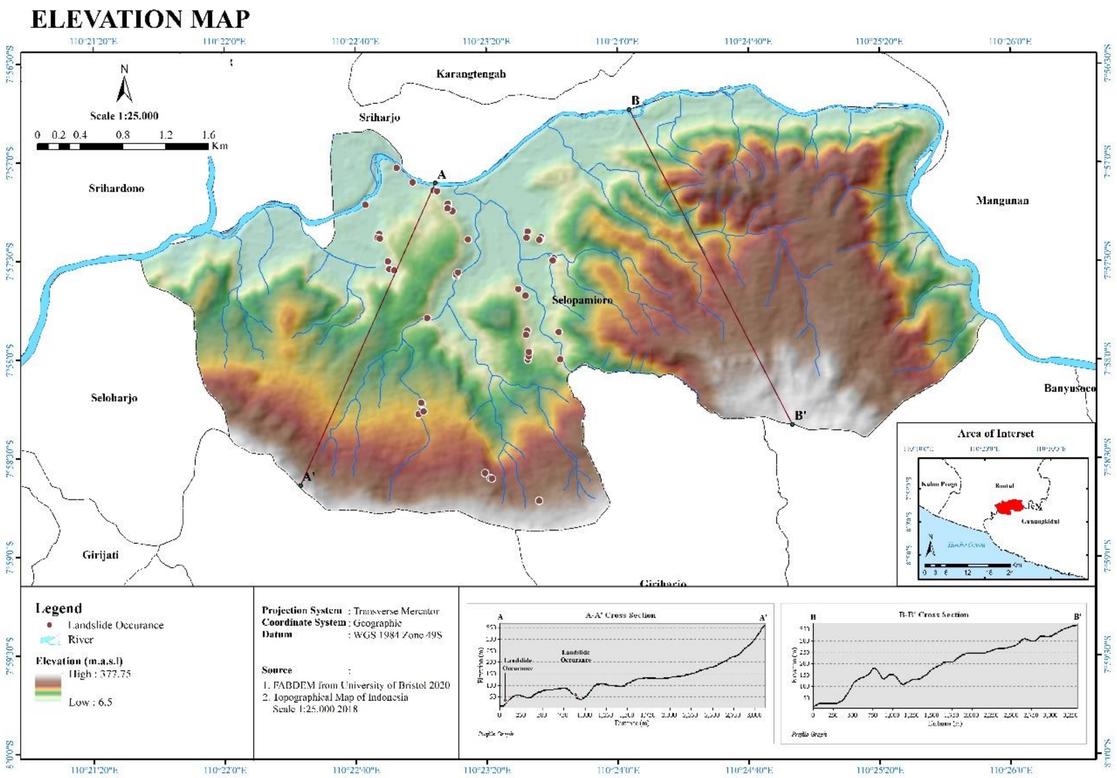

Figure 1. Elevation map of the village Selopamioro, including spots of observed landslide occurrence

2.2.2 SMAEs data acquisition

Information regarding the number and categories of SMAEs was obtained from the village administration, including a detailed listing of SMAEs operating in the region, categorized according to the stipulations outlined in Law No. 20 of 2008 concerning Micro, Small, and Medium Enterprises, which define the classification of such businesses in Indonesia. During the initial mapping phase, 120 SMAEs were identified.

2.2.3 Selection of samples

The Slovin formula was used to determine the sample size from 120 identified SMAEs, resulting in 60 SMAEs. The capacity assessment included 19 respondents, including village officials and their staff.

The equation (1) was used to determine the sample size from a known population (Sugiyono, 2017). The sample was validated through consultations with village and hamlet leaders to confirm the current status of the SMAEs, leading to adjustments in the data. This study aimed to assess the vulnerability of SMAEs actors in Selopamioro to landslides.

$$n = \frac{N}{1 + Ne^2} \quad (1)$$

Where; n=sample size; N=population size; e=Allowance for inaccuracy due to tolerable sampling error, then squared.

The value of e=0.1 (10%) is used for large populations. The value of e=0.2 (20%) is used for small populations. In this study, we used the value of e=0.2 because the sample population was small.

(1) Capacity and Hazard Assessment

A survey was conducted to assess disaster capacity in SMAEs, involving interviews with village and hamlet leaders. The index technique (Table 1) was used to evaluate the resilience of SMAEs to landslides, incorporating input from local leadership. The study focuses on regional capacity, represented by the village government administration unit. Village-level policy makers are needed for SMAE resilience. The hazard evaluation used the frequency ratio method to examine historical and geographic elements contributing to landslide hazards.

Table 1. Disaster capability index

Component	Value (%)	Class		
		Low	Medium	High
		(0-0.333)	(0.334-0.666)	(0.667-1)
Regional resilience	40	Value transformation 0-0.40	Value transformation 0.41-0.80	Value transformation 0.81-1
Community preparedness	60	<0.33	0.34-0.66	0.67-1

(2) SMAEs actor survey

A survey was conducted on the proprietors and managers of 60 selected SMAEs, based on field updates. Many reductions were due to profession changes, address changes, and deceased business actors. Data was collected using a structured survey tool to assess understanding of landslide hazards, readiness, and vulnerability. An interview instrument with a Likert scale was used to quantify responses (Table 2).

Table 2. Likert scale

Class	Description
1	Very unsuitable
2	Unsuitable
3	Quite suitable
4	Suitable
5	Very suitable

2.3 Data analysis

2.3.1 Hazard assessment

In this study, 60% of the data inventory was collected and used for model training, while the remaining 40% was reserved to test the accuracy level. The data distribution was plotted into the parameters of the landslide hazard model. The parameters used in this study include water related factors such as Stream Power Index (SPI) and Topographic Wetness Index (TWI), along with topographic factors like slope, aspect, plan curvature, profile curvature, and elevation (Al'Afif et al., 2024; Samodra et al., 2017). All water-related and topographic factors are compiled using FABDEM with a spatial resolution of 30×30 meter. Additional factors used include geological formation, distance to faults, distance to roads, distance to rivers, and land use sourced from the 2018 Indonesia Topographic Map at a scale of 1:25,000. Twelve factors influencing landslides were analyzed in raster format with a 30×30 resolution, adjusted to the spatial resolution of FABDEM (Figure 2).

The frequency ratio method (equation 2) was used to assess landslide threat in a site study. This method identifies future landslide events using the same conditions as past ones. The ratio between landslide area and total area, along with the probability of a landslide event occurring compared to its absence for a given attribute factors, are crucial elements. The greater the ratio, the stronger the relationship between landslide events and related factors. This method helps identify regions of elevated risk (Pratiwi, 2018).

$$FR = \frac{LAi/LDi}{\sum LAi/\sum LDi} \quad (2)$$

Where; FR=frequency ratio; LAi=number of pixels of containing landslide in the i-th variable class; LDi=number of pixels of each class in the whole area in the i-th variable class; ∑LAi=total number of pixels of containing landslide in the i-th variable class; ∑LDi=total number of pixels of whole area in the i-th variable class.

The FR values were standardized to a probability value range of [0, 1] as relative frequency (RF) in the subsequent stage. The RF values are obtained by dividing the FR value by the total sum of FR values within a single parameter.

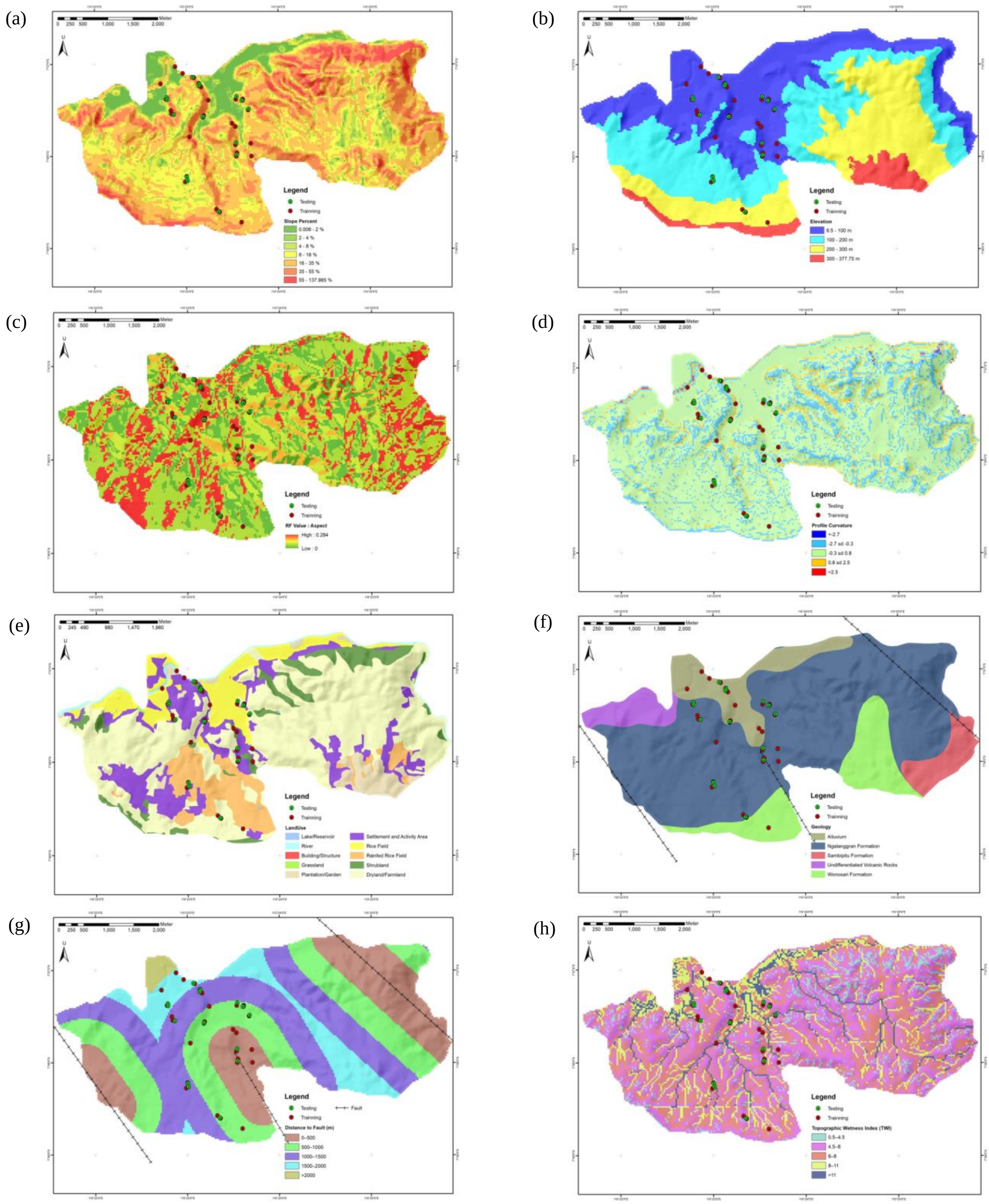

Figure 2. Maps of landslide controlling factors: (a) slope, (b) elevation, (c) aspect, (d) profile curvature, (e) land use, (f) geology, (g) distance to fault, (h) TWI, (i) distance to river, (j) distance to road, (k) SPI, and (l) plan curvature

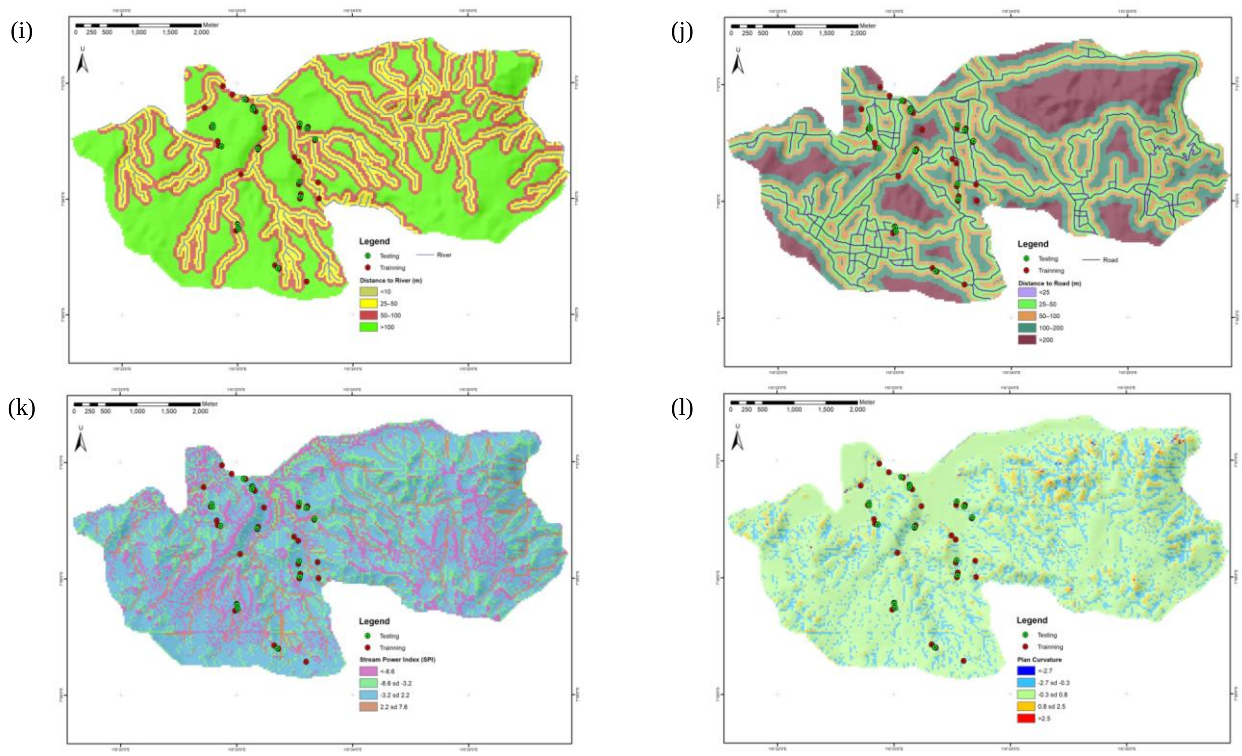

Figure 2. Maps of landslide controlling factors: (a) slope, (b) elevation, (c) aspect, (d) profile curvature, (e) land use, (f) geology, (g) distance to fault, (h) TWI, (i) distance to river, (j) distance to road, (k) SPI, and (l) plan curvature (cont.)

The RF still has the limitation of treating all conditioning elements equally after equalization. To overcome this limitation and consider the interdependencies among the independent variables, the prediction rate (PR) was generated for the evaluation of each conditioning component using the training data set (Youssef et al., 2023). Equation (3) was used to get the PR for each class:

$$\mathrm{PR} = \frac{(\mathrm{RF\,max} - \mathrm{RF\,min})}{(\mathrm{RF\,max} - \mathrm{RF\,min})\mathrm{min}} \tag{3}$$

The PR of each component and the RF of each class were then combined to form the landslide susceptibility index (LSI), as illustrated below:

$$\mathrm{LSI} = \sum(\mathrm{RF} \times \mathrm{PR}) \tag{4}$$

The vulnerability map for landslides is generated using the LSI value, ensuring accuracy and reliability. The model's success rate is evaluated using the Receiver Operating Characteristic (ROC) from 60% of training data and 40% of testing data, with the AUC value above 0.5 or 50% indicating a successful model.

(3) Vulnerability and capacity index

Vulnerability indices are crucial in assessing the susceptibility of communities to hazards. These indices include social, economic, physical, and environmental factors. Environmental vulnerability is not considered due to the absence of protected area land use, and regional geography, infrastructure, and historical exposure are not considered. The disaster vulnerability index is strengthened by considering these factors. The susceptibility and capability of SMAEs are assessed using an index approach that consolidates data from surveys. Vulnerability indices include social vulnerability, economic vulnerability, and physical vulnerability. Social vulnerability includes factors like gender, age, age group, disability group, and income level. Economic vulnerability includes business capital size, while physical vulnerability refers to the value of business buildings. In this study, environmental vulnerability is not considered due to the absence of protected area land use.

(4) Risk evaluation

The overall risk to SMAEs from landslides was determined by integrating the hazard, vulnerability, and capacity assessments into a unified risk index. The risk was spatially mapped, providing a clear visual representation of the most vulnerable areas. Disaster risk studies can be carried out using the equation (3) and the flow diagram of this research is presented in Figure 3.

$$\mathrm{Risk} = \mathrm{Hazard} \times \frac{\mathrm{Vulnerability}}{\mathrm{Capacity}} \tag{5}$$

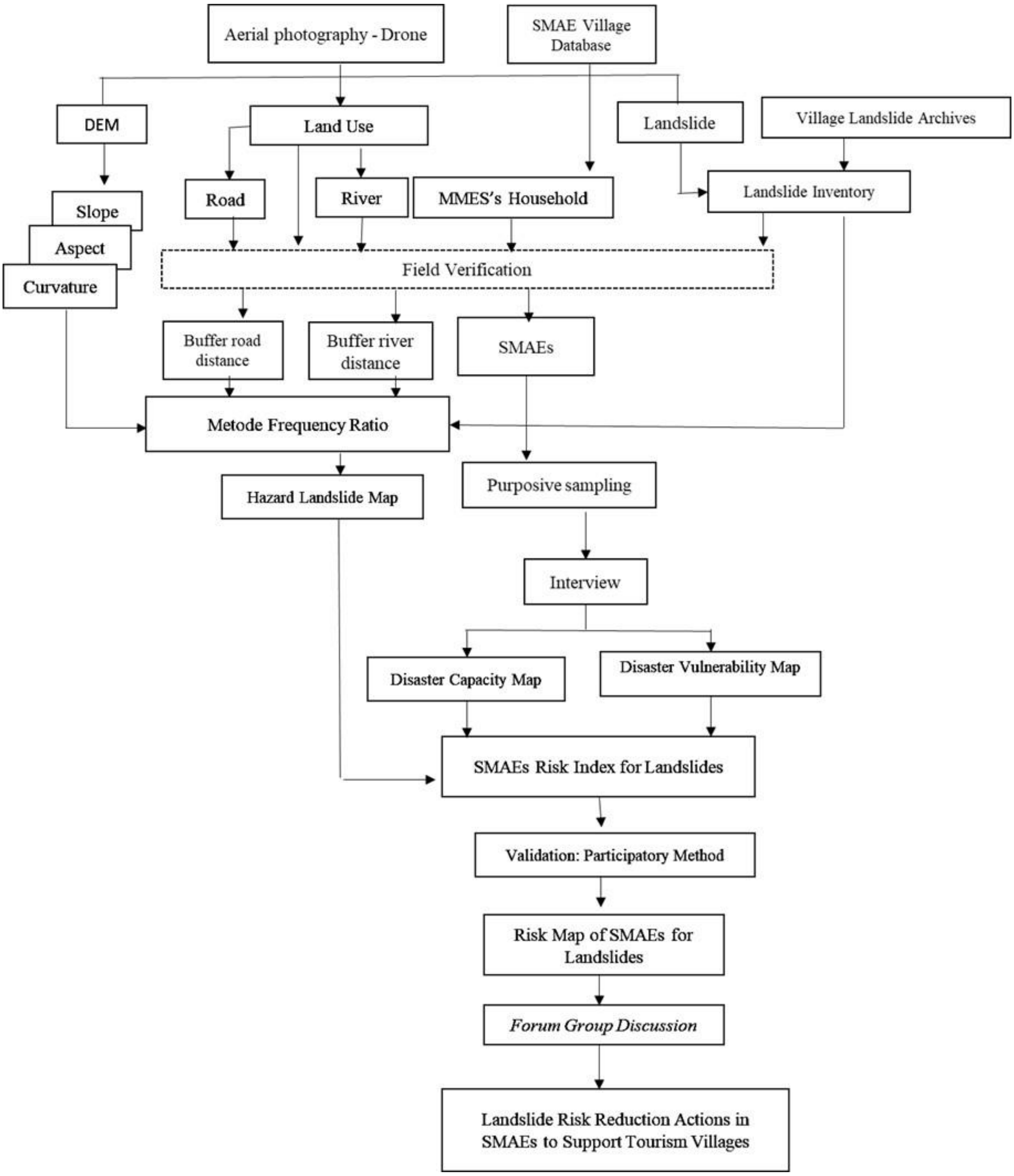

Figure 3. Method's flow chart

3. RESULTS AND DISCUSSION

3.1 Landslide inventory

The preliminary inventory in Selopamioro village identifies multiple landslide sites and scars caused by natural and anthropogenic factors, such as deforestation and poor agricultural practices (Fadilah et al., 2019). The inventory was compiled through field surveys and image analysis using remote sensing imagery from 2010 to 2020. Selopamioro Village has a slope gradient ranging from flat to moderate, with some hamlets having a gentle slope. Landslide points are dispersed throughout the village area, aligning with research by Damayanti et al. (2023) indicating Selopamioro Village has the highest level of landslide vulnerability in Imogiri Sub-district, after Wukirsari Village, with a vulnerability area of 364.4 hectares. Landslide inventory is presented on the map in Figure 4.

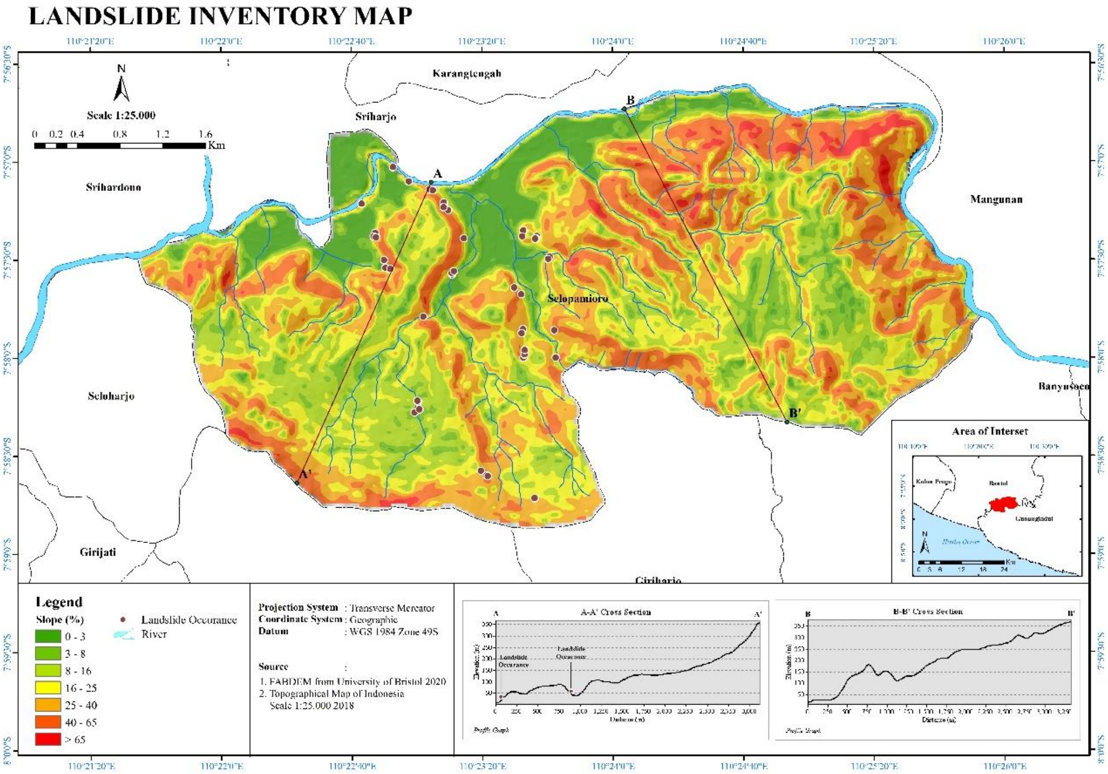

Figure 4. Landslide inventory map

3.2 Distribution SMAEs

SMAEs in this study is categorized into three sectors: Upstream Agroindustry, Downstream Agroindustry, and Primary Sector. Upstream industry produces agricultural tools and machinery and the production facility industry used in the agricultural cultivation process. The Downstream industry processes agricultural products into raw materials or goods that are ready to be consumed or is a post-harvest industry and agricultural product processing (Pratiwi et al., 2017). The SMAEs sector in Selopamioro Village is predominantly composed of Downstream Agroindustry in each hamlet. As shown in Figure 5, the hamlet with the most downstream SMAEs is Siluk I, followed by Pelemantung, Jetis, Lemahrubuh, and Nawungan I. Siluk I Hamlet is located in a relatively flat area, such as soil type, water drainage, and human activities, can also play a role in mitigating or exacerbating the risk in flat areas with no landslide points, as are Pelemantung, Lemahrubuh, and Nawungan I. In contrast, Jetis Hamlet, despite being located on a steep slope, has no recorded landslide points, according to the inventory data, which has allowed for the construction of many SMAEs in the area. Srunggo II Hamlet, located on a moderate slope, has a considerable number of landslide points, which has limited the number of SMAEs built there. Similarly, Kajor Wetan Hamlet is located in an area with a high level of landslide hazard, affecting the number of same in that location. Research by Nagara and Wibowo (2024) indicates that steeper land has greater potential for landslides, leading to higher difficulties and costs associated with land acquisition, including in the construction of SMAEs.

3.3 Vulnerability assessment

The study used a disaster vulnerability index for SMAEs in Selopamioro village, focusing on physical, social, and economic components. The analysis revealed that all SMAEs had low overall vulnerability to landslides, suggesting a low risk of landslide impacts on these enterprises (Table 3). Disaster vulnerability is linked to property damage and human casualties, and higher vulnerability can result in increased damage or prolonged recovery periods (Heryawan et al., 2016). The vulnerability indices analyzed were social vulnerability, economic vulnerability, and physical vulnerability. Social vulnerability, which includes factors like gender, age, disability group, and income level, emerged as the most significant contributor to overall SMAE vulnerability in Selopamioro. However, the study by Febriani (2020) found that economic vulnerability was higher in certain regions of Selopamioro Village, while social vulnerability was more moderate. This discrepancy may be due to the focus on SMAEs actors as the unit of analysis, rather than village administration.

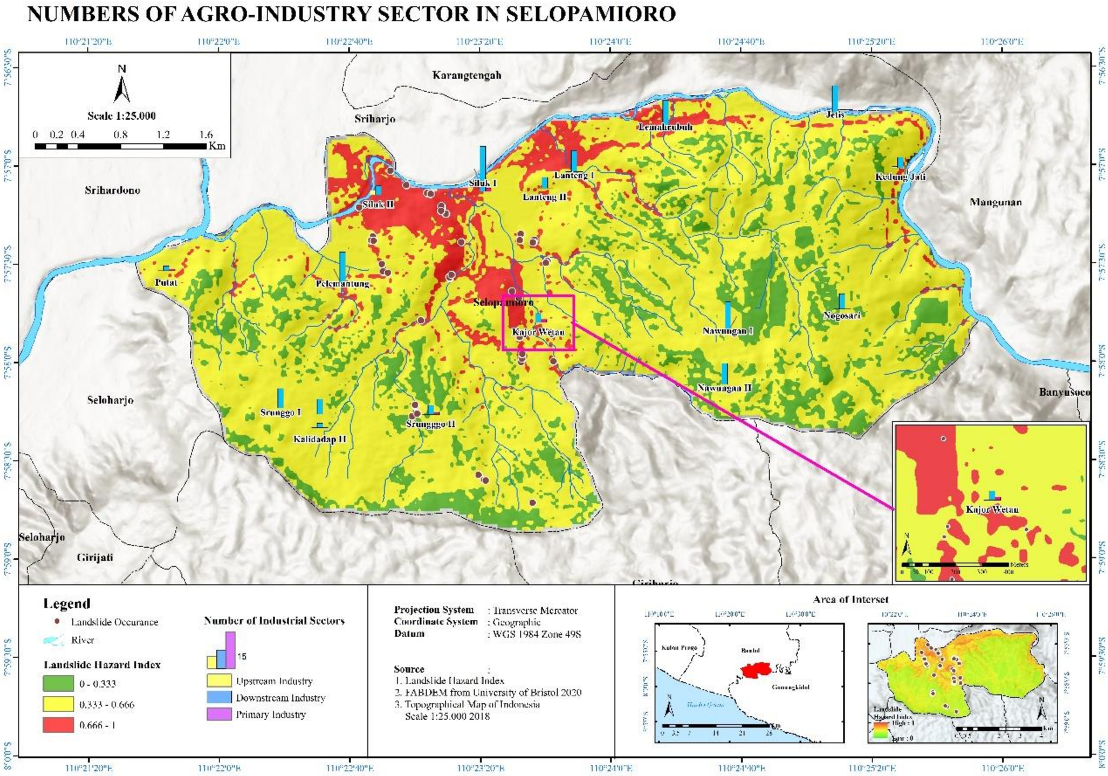

Figure 5. SMAEs distribution in Selopamioro

Table 3. Total vulnerability table of Selopamioro Village

No	Hamlet	Social vulnerability		Economy vulnerability		Physics vulnerability		Total vulnerability	
		Volume	Class	Volume	Class	Volume	Class	Volume	Class
1	Jetis	1.4	Low	0.6	Low	0.4	Low	0.81	Low
2	Kajor Kulon	1.5	Low	0.6	Low	0.4	Low	0.85	Low
3	Kajor Wetan	1.5	Low	0.6	Low	0.4	Low	0.85	Low
4	Kalidadap I	1.5	Low	0.6	Low	0.4	Low	0.85	Low
5	Kalidadap II	1.6	Low	0.6	Low	0.4	Low	0.89	Low
6	Kedung Jati	1.5	Low	0.6	Low	0.4	Low	0.85	Low
7	Lanteng I	1.4	Low	0.6	Low	0.4	Low	0.81	Low
8	Lanteng II	1.5	Low	0.6	Low	0.4	Low	0.85	Low
9	Lemahrubuh	1.4	Low	0.6	Low	0.4	Low	0.81	Low
10	Nawungan I	1.4	Low	0.6	Low	0.4	Low	0.81	Low
11	Nawungan II	1.4	Low	0.6	Low	0.4	Low	0.81	Low
12	Nogosari	1.5	Low	0.6	Low	0.4	Low	0.85	Low
13	Pelemantung	1.4	Low	0.6	Low	0.4	Low	0.81	Low
14	Putat	1.4	Low	0.6	Low	0.4	Low	0.81	Low
15	Siluk I	1.4	Low	0.6	Low	0.4	Low	0.81	Low
16	Siluk II	1.5	Low	0.6	Low	0.4	Low	0.85	Low
17	Srunggo I	1.5	Low	0.6	Low	0.4	Low	0.85	Low
18	Srungggo II	1.4	Low	0.6	Low	0.4	Low	0.81	Low
Class index		Low	1-1.6						
		Medium	1.7-2.3						
		High	2.4-3.0						

3.4 Capacity index analysis

The Capacity Index Analysis was used to evaluate the preparedness of 18 hamlets in Selopamioro Village for mitigating landslide risk. The results showed a "Medium" capacity level, indicating a lack of resilience to disasters (Table 4). The index ranged from 0.4 to 0.8, indicating significant gaps in preparedness measures. One example was the absence of an early warning system for disasters, indicating that while some measures are in place, there are still significant gaps that need to be addressed.

Selopamioro Village has a "Medium" capacity level for landslide preparedness, but its priority index for all hamlets is low (Figure 6). Factors contributing to this include insufficient policies and regulations related to landslide prevention and mitigation, inadequate coordination and resource allocation in the disaster response framework, and the absence of comprehensive landslide risk evaluations for specific regions. Currently, comprehensive landslide risk evaluations for particular regions within the village are missing under Integrated Risk Assessment and Planning, regarding the main barriers to conducting comprehensive landslide evaluations, including insufficient data, lack of expertise, and limited resources. These evaluations are not fully incorporated into the village's development plans. In the Information System Development, Training, and Logistics domain, early warning systems, communication protocols, and public awareness campaigns regarding landslides are inadequate. Training programs for homeowners and emergency workers on landslide preparedness and response are also limited. The absence of equipment or vital resources for disaster mitigation can hinder response operations. Specific methods for mitigating landslide hazards in highly sensitive village regions are lacking. Current mitigation strategies, including slope stabilization and drainage improvement, are inadequate and require further development. Purnamasari et al. (2024) with their research in Central Java added that the material layer is very important for sustainable land management strategies aimed at controlling landslides. In addition, the potential depth of the sliding plane is managed through effective environmental management practices, including proper disposal of household waste and minimizing steep slope cutting.

Table 4. Total capacity table of Selopamioro Village

No	Hamlet	Priority index					Hamlet capacity index	Capacity level
		Strengthening policies and institutions	Risk assessment and integrated planning	Information system development, training and logistic	Thematic handling of disaster-prone areas	Increasing the effectiveness of disaster prevention and mitigation		
1	Jetis	1.6	0.6	0.2	0.5	0.5	0.74	Medium
2	Kajor Kulon	1.4	0.6	0.2	0.5	0.2	0.65	Medium
3	Kajor Wetan	1.7	0.6	0.2	0.5	0.5	0.76	Medium
4	Kalidadap I	1.5	0.6	0.2	0.5	0.4	0.64	Medium
5	Kalidadap II	1.5	0.3	0.2	0.25	0.25	0.53	Medium
6	Kedung Jati	1.7	0.5	0.2	0.5	0.5	0.74	Medium
7	Lanteng I	1.4	0.6	0.2	0.5	0.3	0.67	Medium
8	Lanteng II	1.6	0.6	0.2	0.5	0.5	0.74	Medium
9	Lemahrubuh	1.5	0.6	0.2	0.5	0.4	0.69	Medium
10	Nawungan I	1.7	0.6	0.2	0.5	0.5	0.76	Medium
11	Nawungan II	1.4	0.6	0.1	0.3	0.5	0.6	Medium
12	Nogosari	1.2	0.6	0.1	0.2	0.5	0.53	Medium
13	Pelemantung	1.4	0.3	0.1	0.5	0.4	0.6	Medium
14	Putat	1.7	0.3	0.2	0.5	0.5	0.7	Medium
15	Siluk I	1.5	0.5	0.2	0.2	0.5	0.59	Medium
16	Siluk II	1.7	0.6	0.2	0.25	0.4	0.66	Medium
17	Srunggo I	1.4	0.6	0.2	0.5	0.3	0.67	Medium
18	Srungggo II	1.7	0.4	0.2	0.5	0.2	0.67	Medium

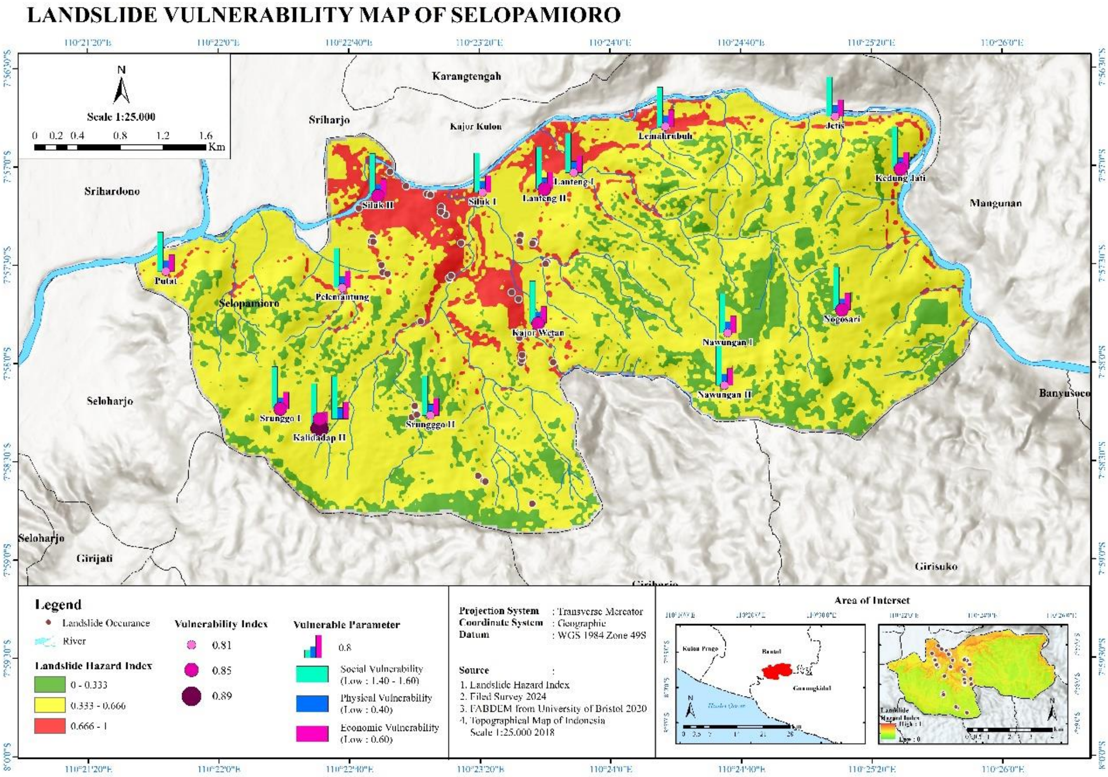

Figure 6. Landslide Vulnerability in Selopamioro

3.5 Hazard analysis

A key step in landslide susceptibility modeling is identifying the connection between previous landslides and their contributing factors. Based on calculations in Table 5, the factors of elevation, geological formation, profile curvature, and plane curvature had the highest values compared to other landslide determining factors. Meanwhile, land use, SPI, distance to roads, slope, TWI, distance to faults, aspect, and distance to rivers had the lowest values.

Table 5. Frequency ratio (FR), Relative frequency (RF) for each class, and the prediction rate (PR) for each conditioning factor

Factor	Class code	Class	Class pixels	Percent class pixels	Hotspot pixels	Percent hotspot pixels	FR	RF	PR
Land use	1	Water body	340	1.5	0	0.0	0.00	0.00	1.6
	2	Building/structure	2	0.0	0	0,0	0.00	0.00	
	3	Grassland	13	0.1	0	0.0	0.00	0.00	
	4	Plantation/garden	1,148	5.0	3	0.1	0.02	0.28	
	5	Settlement and activity Areas	3,664	16.0	15	0.6	0.03	0.44	
	6	Paddy field	2,290	10.0	1	0.0	0.00	0.05	
	7	Rainfed paddy field	2,256	9.8	1	0.0	0.00	0.05	
	8	Shrubland	1,571	6.9	2	0.1	0.01	0.14	
	9	Cultivated land	11,637	50.8	5	0.2	0.00	0.05	
		Total	22,921		27		0.08	1.00	
Elevation (m)	1	6.5-100	7,962	34.7	22	0.8	0.02	0.79	2.8
	2	100-200	7,219	31.5	2	0.1	0.00	0.08	
	3	200-300	6,273	27.4	3	0.1	0.00	0.14	
	4	300-377.75	1,467	6.4	0	0.0	0.00	0.00	
		Total	22,921		27		0.03	1.00	

Table 5. Frequency ratio (FR), Relative frequency (RF) for each class, and the prediction rate (PR) for each conditioning factor (cont.)

Factor	Class code	Class	Class pixels	Percent class pixels	Hotspot pixels	Percent hotspot pixels	FR	RF	PR
Slope (%)	1	0-2	1,640	7.2	0	0.0	0.00	0.00	1.3
	2	2-4	685	3.0	0	0.0	0.00	0.00	
	3	4-8	1,657	7.2	1	0.0	0.01	0.13	
	4	8-16	4,771	20.8	4	0.1	0.01	0.18	
	5	16-35	8,692	37.9	15	0.6	0.01	0.36	
	6	35-55	4,418	19.3	7	0.3	0.01	0.33	
	7	>55	1,058	4.6	0	0.0	0.00	0.00	
		Total	22,921		27		0.04	1.00	
Aspect	1	North	5,916	25.8	6	0.2	0.01	0.10	1.0
	2	Northeast	4,241	18.5	7	0.3	0.01	0.17	
	3	East	2,770	12.1	3	0.1	0.01	0.11	
	4	Southeast	1,087	4.7	3	0.1	0.02	0.28	
	5	South	769	3.4	0	0.0	0.00	0.00	
	6	Southwest	1,486	6.5	2	0.1	0.01	0.14	
	7	West	2,731	11.9	3	0.1	0.01	0.11	
	8	Northwest	3,921	17.1	3	0.1	0.01	0.08	
		Total	22,921		27		0.08	1.00	
Plan curvature	1	<-2.7	16	0.1	0	0.0	0.00	0.00	1.8
	2	-2.7 to -0.3	4,213	18.4	8	0.3	0.02	0.51	
	3	-0.3 to 0.8	17,463	76.2	18	0.7	0.01	0.27	
	4	0.8 to 2.5	1,211	5.3	1	0.0	0.01	0.22	
	5	>2.5	18	0.1	0	0.0	0.00	0.00	
		Total	22,921		27		0.03	1.00	
Profile curvature	1	<-2.7	15	0.1	0	0.0	0.00	0.00	2.4
	2	-2.7 to -0.3	4,993	21.8	3	0.1	0.01	0.11	
	3	-0.3 to 0.8	16,300	71.1	18	0.7	0.01	0.20	
	4	0.8 to 2.5	1,563	6.8	6	0.2	0.03	0.69	
	5	>2.5	50	0.2	0	0.0	0.00	0.00	
		Total	22,921		27		0.05	1.00	
Stream power index (SPI)	1	<-8.6	3,900	17.0	1	0.0	0.00	0.05	1.5
	2	-8.6 to -3.2	4,053	17.7	7	0.3	0.01	0.32	
	3	-3.2 to 2.2	13,276	57.9	15	0.6	0.01	0.21	
	4	2.2 to 7.6	1,692	7.4	4	0.1	0.02	0.43	
		Total	22,921		27		0.05	1.00	
Topographic wetness index (TWI)	1	0.5-4.5	1,525	6.7	3	0.1	0.02	0.28	1.2
	2	4.5-6	9,889	43.1	11	0.4	0.01	0.16	
	3	6-8	7,158	31.2	9	0.3	0.01	0.18	
	4	8-11	3,133	13.7	1	0.0	0.00	0.04	
	5	>11	1,216	5.3	3	0.1	0.02	0.35	
		Total	22,921		27		0.06	1.00	
Geology	1	Alluvium	2,288	10.0	10	0.4	0.04	0.76	2.4
	2	Undifferentiated Volcanic Rocks	1,050	4.6	0	0.0	0.00	0.00	
	3	Formasi Ngalanggran	15,475	67.5	16	0.6	0.01	0.18	
	4	Sambipitu Formation	1,150	5.0	0	0.0	0.00	0.00	
	5	Wonosari Formation	2,958	12.9	1	0.0	0.00	0.06	
		Total	22,921		27		0.05	1.00	

Table 5. Frequency ratio (FR), Relative frequency (RF) for each class, and the prediction rate (PR) for each conditioning factor (cont.)

Factor	Class code	Class	Class pixels	Percent class pixels	Hotspot pixels	Percent hotspot pixels	FR	RF	PR
Distance to fault (m)	1	0-500	5,467	23.9	7	0.3	0.01	0.25	1.1
	2	500-1,000	6,886	30.0	8	0.3	0.01	0.22	
	3	1,000-1,500	7,511	32.8	7	0.3	0.01	0.18	
	4	1,500-2,000	2,727	11.9	5	0.2	0.02	0.35	
	5	>2,000	330	1.4	0	0.0	0.00	0.00	
		Total	22,921		27		0.04	1.00	
Distance to road (m)	1	<25	2,604	11.4	8	0.3	0.03	0.46	1.5
	2	25-50	5,464	23.8	12	0.4	0.02	0.33	
	3	50-100	5,307	23.2	4	0.1	0.01	0.11	
	4	100-200	5,123	22.4	1	0.0	0.00	0.03	
	5	>200	4,423	19.3	2	0.1	0.00	0.07	
		Total	22,921		27		0.06	1.00	
Distance to river (m)	1	<10	1,849	8.1	3	0.1	0.01	0.31	1.0
	3	25-50	4,526	19.7	6	0.2	0.01	0.25	
	4	50-100	5,523	24.1	7	0.3	0.01	0.24	
	5	>100	11,023	48.1	11	0.4	0.01	0.19	
		Total	22,921		27		0.04	1.00	

Based on the results of the analysis using the frequency ratio, the landslide hazard index value in the study area ranges from 0-1 (Figure 7). The closer the value is to 1, the higher the level of danger. Landslides in the study area strongly influenced by topographic conditions where landslides occur in areas with an altitude of 0-100 m with a slope of 16-55%. Although the soil moisture level is at 4.5-6, the dominant surface material of the landslide is in the Nglanggaran geological formation, which is old volcanic material that has weathered so that landslides are easy to occur. This is not much different from the research of Radjah et al. (2020) in Karangkobar. Their research shows that the highest FR value is found in the distance of the area from the highway in the range of 0-25 m, the distance from the river in the range of 100-125 m, flat curvature and use of garden land.

An accuracy test was conducted to determine the level of accuracy between landslide maps and landslide distribution (Figure 8). From the AUC calculation, the success rate value obtained from the training data was a value of 0.887 (Figure 9). While the prediction rate value from the testing data was 0.849. From both values, it can be concluded that the level of accuracy is good.

Hazard is one of the variables used to calculate the risk level. The determination of the index class is based on the Landslide Hazard Map obtained from the official website of the Center for Volcanology and Geological Disaster Mitigation (PVMBG). The landslide map classifies the hazard index class into three classes, namely low, medium, and high. Tian et al. (2017) identified three factors contributing to landslides: (1) terrain data (elevation, slope angle, slope aspect, curvature, slope position, distance to drainage); (2) geological data (lithology); and (3) seismic data (seismic intensity, peak ground acceleration, and distance to the causative source). Fadilah et al. (2019) asserted that landslides mostly result from gravitational pressures on steep slopes, with contributing factors including excessive rainfall, improper land use, and geological formations.

The level of landslide hazard is classified into three classes (Figure 7). Selopamioro Village has 59.2% high hazard zones, 21.8% medium hazard zones and 19% low hazard zones. The high landslide hazard in Selopamioro Village is affected by its steep slope. The higher the hazard and vulnerability level, the higher the area's risk level. In line with research by Budha et al. (2020), which states that the class of factors that have a greater influence on higher landslide hazards include land with an altitude range of 1,000 m to 1,500 m and slopes steeper than 30°.

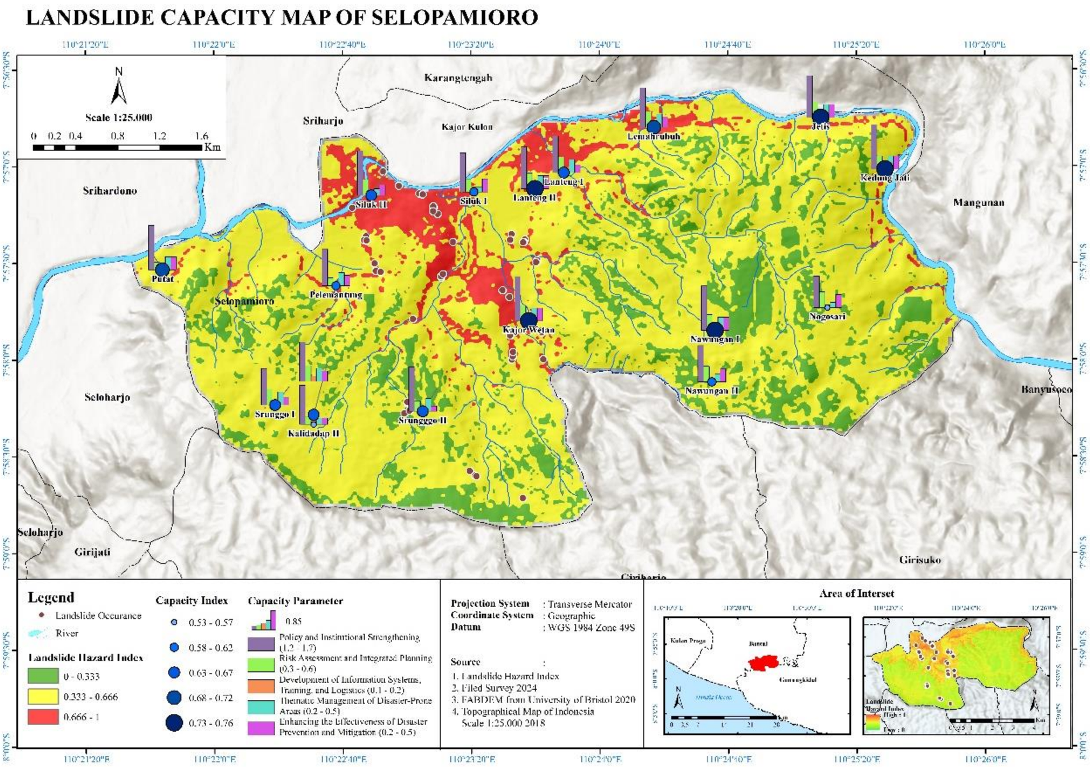

Figure 7. Landslide capacity map of Selopamioro

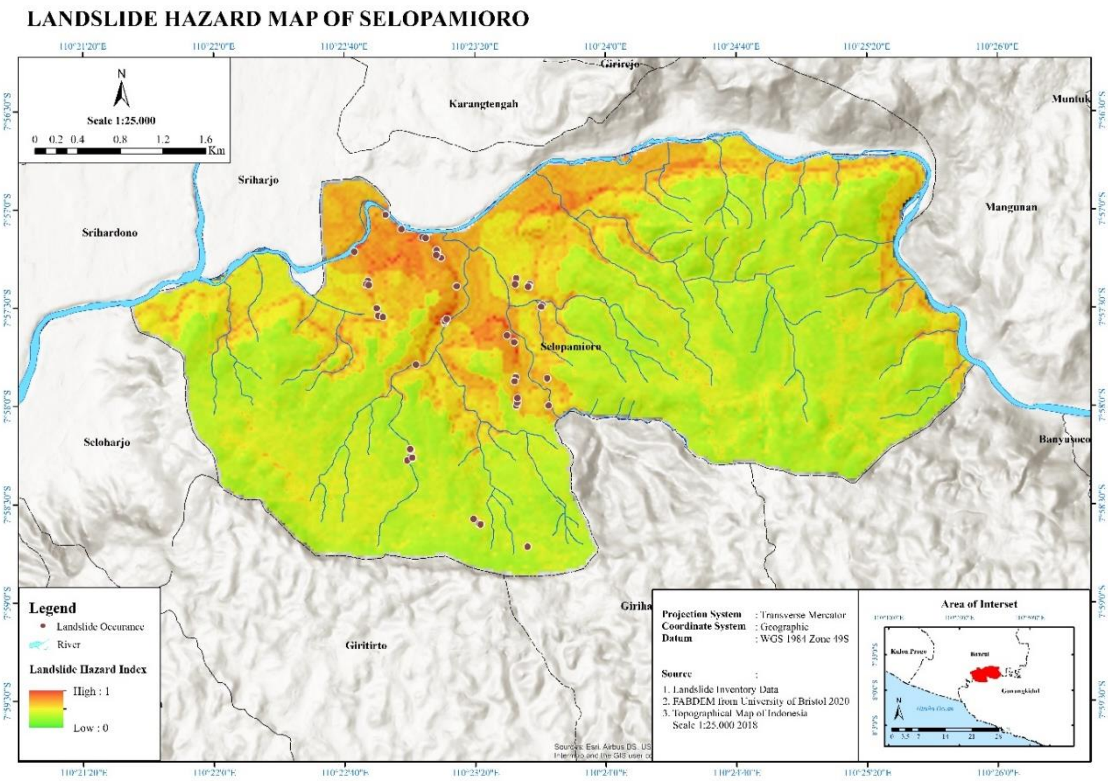

Figure 8. Landslide hazard maps with frequency ratio

Based on the analysis of the map in Figure 7, the hazard risk in Selopamioro Village ranges from moderate to high. The dominant risk level is high, which covers Pelemantung Hamlet, Kalidadap I, Kalidadap II, Kajor Kulon, Kajor Wetan, and Jetis. In areas with a high level of danger, based on the Landslide Inventory, there are landslide points in each area. Based on the distribution of SMAEs, areas with a high level of danger are areas with a low number of SMAEs. Landslides are one of the most destructive hazard processes causing loss of life and damage to the built environment (Luo et al., 2023). Therefore, the establishment of business buildings in areas with high landslide hazard levels is very risky for the sustainability of SMAEs. Establishing business infrastructure in high-risk zones poses significant challenges to the sustainability of SMAEs. Policymakers must prioritize comprehensive land-use planning, integrating slope stabilization projects and drainage improvements to enhance safety and minimize risk (Cheung, 2021).

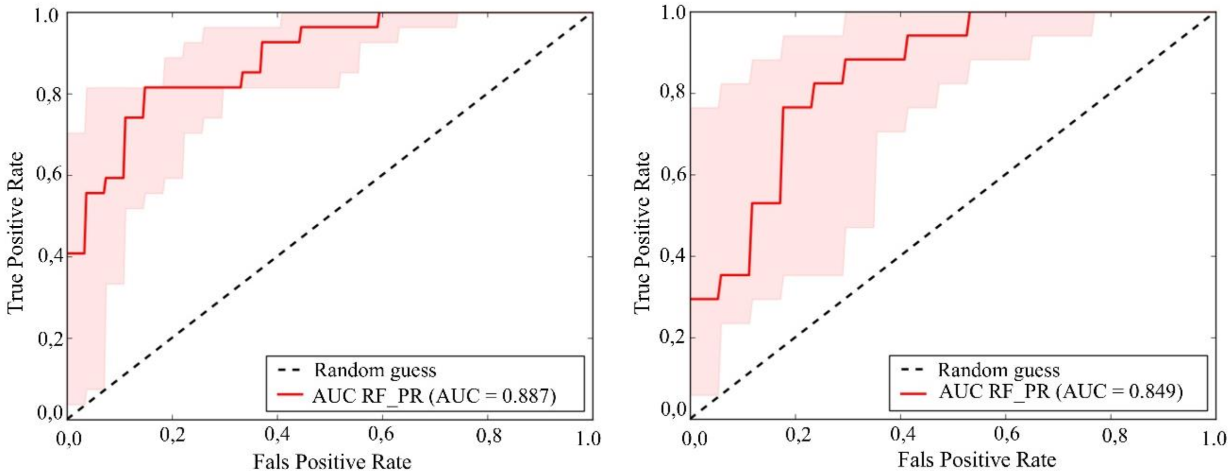

Figure 9. (a) Succes rate training data sample, (b) Prediction rate testing data sample

The study emphasizes the significance of community-based disaster risk management (CBDRM) in addressing landslide hazards. It suggests that local communities should be involved in participatory planning processes to develop effective mitigation strategies. The village government and villagers have been implementing mitigation measures such as strengthening slopes and forming the Disaster Risk Reduction Forum (FPRB). The study also highlights the role of climate change in exacerbating landslide hazards (Holcombe et al., 2013). Rainfall induces changes in surface and groundwater dynamics that reduce the slope stability conditions and cause landslides (Guzzetti et al., 2022). The study suggests that integrating modern technologies like remote sensing, GIS, and AI for hazard prediction and management is crucial. CNN-based landslide susceptibility mapping has demonstrated high accuracy in predicting vulnerable areas (Yi et al., 2020).

Future research should focus on the socio-economic impacts of landslides on SMAE and explore long-term strategies to increase resilience. Steps such as terracing, improving land use practices, and vegetation restoration can significantly reduce risk (Mujiyo et al., 2024). By implementing these recommendations, policymakers and stakeholders can support sustainable development in disaster-prone rural areas. For example, in Sambak Village, Magelang, research conducted by Wibawanti et al. (2023) has implemented mitigation activities in controlling landslides vegetatively. This program is called “Climate Village Program (ProKlim)” involves planting vegetation in landslide-prone areas. This activity can serve as a reference for Selopamioro Village.

4. CONCLUSION

This study assessed the risk of landslides to small and medium agro-industry enterprises (SMAEs) in Selopamioro village, Indonesia. The findings indicate that the current level of vulnerability of SMAEs to landslides is relatively low across the village, suggesting that existing landslides do not significantly impact the sustainability of these businesses. However, the capacity for disaster response in Selopamioro village is only moderate, highlighting a potential gap in preparedness for future landslides.

These findings offer valuable insights for both SMAEs and local authorities. While the current vulnerability of SMAEs appears low, proactive measures to mitigate future landslide risks are still recommended. SMAEs can explore options such as improving infrastructure resilience, implementing early warning systems, and developing evacuation plans. Local authorities should focus on strengthening disaster preparedness efforts in Selopamioro Village. This may involve capacity building initiatives for local communities, investing in critical infrastructure, and developing comprehensive landslide risk management plans. The hazard risk in Selopamioro Village ranges from moderate to high. The dominant risk level is high, which covers Pelemantung Hamlet, Kalidadap I, Kalidadap II, Kajor Kulon, Kajor Wetan, and Jetis.

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AUTHORS CONTRIBUTION

Experimental run and Data Collection Ngadisih, Ismi N. Puspitaningrum; Methodology, Validation, Supervision and Writing Original Draft Preparation Ngadisih, Bambang Purwantana, Devi Yuni Susanti, Guruh Samodra, Peter Strauss; Formal Analysis Ngadisih, Guruh Samodra, Ismi N. Puspitaningrum; Data Curation, Visualization, Writing - Review and Editing, Ngadisih, Guruh Samodra; other authors are SMAEs supervisors.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no conflict of interest.

REFERENCES

Al'Afif M, Sartohadi J, Samodra G. Impact of landslide on geoheritage: Opportunities through integration, geo-morphological classification and machine learning. International Journal of Geoheritage and Parks 2024; 12(2):333-51.

Alstadt B, Weisbrod G, Cutler D. Relationship of transportation access and connectivity to local economic outcomes: Statistical analysis. Transportation Research Record 2012;2297(1):154-62.

Anggreini RR, Asyikin N. Protection of MSMEs in the agriculture and plantation sector in anticipating the global recession. National Law Magazine 2023;53(2):262-95 (in Indonesian).

Budha PB, Rai P, Katel P, Khadka A. Landslide hazard mapping in panchase mountain of central Nepal. Environment and Natural Resources Journal 2020;18(4):387-99.

Cheung RWM. Landslide risk management in Hong Kong. Landslides 2021;18(1):3457-73.

Damayanti F, Sabri L, Wahyuddin Y. Implementation of geographic information system for identification of landslide prone areas (case study: Kapanewon Dlingo and Kapanewon Imogiri, Bantul Regency). Journal of Geodesy, Diponegoro University 2023;12(2):101-10 (in Indonesian).

Ebrahim EA, Toy A, Kassim YH. The factors that influence the growth and performance of micro and small-scale enterprises in dessie town administration. Frontiers in Sustainable Cities 2023;5:Article No.1296605.

Eskesen A, Agrawal R, Desai N. Small and Medium Enterprises in Agriculture Value Chain: Opportunities and Recommendations. United Kingdom: Oxfam International; 2014.

Fadilah N, Arsyad U, Soma AS. Analysis of landslide vulnerability level analysis using frequency ratio method in Bialo river basin. Perennial Journal 2019;15(1):42-50.

Food and Agriculture Organization (FAO). Cost-Effective Management Tools for Ensuring Food Quality and Safety for Small and Medium Agro-Industrial Enterprises. Rome: Food and Agriculture Organization; 2011.

Febriani FNI. Analysis of Social and Economic Vulnerability of Landslide Disasters in Imogiri District, Bantul Regency [dissertation]. Yogyakarta, Universitas Muhammadiyah Surakarta; 2020.

Gallage C, Abeykoon T, Uchimura T. Instrumented model slopes to investigate the effects of slope inclination on rainfall-induced landslides. Soils and Foundations 2021;61(1):160-74.

Garcia-Chevesich P, Wei X, Ticona J, Martínez G, Zea J, García V, et al. The impact of agricultural irrigation on landslide triggering: A review from Chinese, English, and Spanish literature. Water 2021;13(10):1-17.

Gariano SL, Guzzetti F. Mass-movements and climate change. In: Shroder JF, editor. Treatise on Geomorphology. Amsterdam: Elsevier; 2022. p. 1-13.

Guzzetti F, Gariano SL, Peruccacci S, Brunetti MT, Melillo M. Rainfall and Landslide Initiation. Rainfall: Modeling, Measurement and Applications. Amsterdam: Elsevier; 2022. p. 427-50.

Heryawan A, Fauzi A, Hidayat A. Economic analysis and natural resources policy of West Java Province. Journal of Agriculture, Resource and Environmental Economics 2016;1(2):1-11 (in Indonesian).

Holcombe E, Anderson M, Holm-Nielsen N. Community-based landslide risk reduction: Managing disasters in small steps. In: Margottini C, Canuti P, Sassa, editors. Learning by Doing: Community Based Landslide Risk Reduction. Berlin: Springer; 2013.

Hong H, Liu J, Zhu AZ. Modeling landslide susceptibility using LogitBoost alternating decision trees and forest by penalizing attributes with the bagging ensemble. Science of The Total Environment 2020;718:Article No.137231.

Intarat K, Yoomee P, Hussadin A, Lamprom W. Assessment of landslide susceptibility in the intermontane basin area of northern Thailand. Environment and Natural Resources Journal 2024;22(2):158-70.

Jakob M. Landslides in a Changing Climate. In: Davi, editor. Landslide Hazards, Risks, and Disasters. 2nd ed. Amsterdam: Elsevier; 2022. p. 505-79.

Jemec AM, Bezak N, Šegina E, Frantar P, Gariano SL, Medved A, et al. Climate change increases the number of landslides at the juncture of the Alpine, Pannonian and Mediterranean regions. Scientific Reports 2023;13(1):Article No. 23085.

Kainthola A, Sharma V, Pandey VHR, Jayal T, Singh M, Srivastav A, et al. Hill slope stability examination along Lower Tons valley, Garhwal Himalayas, India. Geomatics, Natural Hazards and Risk 2021;12(1):900-21.

Lau PHM, Zawawi AA. Analysis of landslide occurrence using DTM-based weighted overlay: A case study in tropical mountainous forest of cameron highlands, Malaysia. Environment and Natural Resources Journal 2021;19(5): 358-70.

Lin Q, Wang Y, Glade T, Zhang J, Zhang Y. Assessing the spatiotemporal impact of climate change on event rainfall characteristics influencing landslide occurrences based on multiple GCM projections in China. Climatic Change 2020;162:761-79.

Luo HY, Zhang LM, Zhang LL, He J, Yin KS. Vulnerability of buildings to landslides: The state of the art and future needs. Earth Science Review 2023;238:Article No. 104329.

Manurung R, Surjandari NS, Djarwati N. Slope stability analysis based on 3 consecutive days of rain in Tirtomoyo watershed (case study of Damon village, Hargorejo, Wonogiri). Civil Engineering Matrix 2016;4(1):97-105 (in Indonesian).

Radović-Marković M, Farooq MS, Marković D. Strengthening the resilience of small and medium-sized enterprises. Management, Enterprise and Benchmarking in the 21st Century; Budapest: Óbuda University; 2017. p. 345-56.

Mersha T, Meten M. GIS-based landslide susceptibility mapping and assessment using bivariate statistical methods in Simada Area, Northwestern Ethiopia. Geoenvironmental Disasters 2020;7(1):1-22.

Morrish SC, Jones R. Post-disaster business recovery: An entrepreneurial marketing perspective. Journal of Business Research 2020;113(1):83-92.

Mujiyo M, Pratingkas TM, Cahyono O, Ariyanto DP. Landslides hazard assessment using soil physics approaches as a determinant factor on agricultural land in Hilly Area. Journal of Natural Resources and Environmental Management 2024;14(3):566-73 (in Indonesian).

Nagara RP, Wibowo A. The influence of slope on the development of built-up land in Serang Regency, Banten Province. Journal of Regional and Rural Development Planning 2024;8(2):116-31 (in Indonesian).

Nasution RHA, Deswindi L, Indrajaya D. Identification of factors affecting the productivity of medium small micro enterprises (MSMEs). International Journal Of Economics Development Research 2022;3(3):227-35 (In Indonesian).

Ngadisih, Samodra G, Bhandary NP, Yatabe R. Landslide Inventory: Challenge for Landslide Hazard Assessment in Indonesia. Berlin: Springer; 2017. p. 135-59.

Putra AN, Nita I, Jauhary MRA, Nurhutami SR, Ismail MH. Landslide risk analysis on agriculture area in pacitan regency in east Java Indonesia using geospatial techniques. Environment and Natural Resources Journal 2021;19(2): 141-52.

Nurhaedah N. Development of MSMEs in the development of industrial agriculture in Makassar City. Bata Ilyas Educational Management Review 2022;2(2):79-84.

Pratiwi NA, Harianto H, Daryanto A. The role of upstream and downstream agroindustry in the economy and income distribution in Indonesia. Journal of Management and Agribusiness 2017;14(2):127-37 (in Indonesian).

Pratiwi LHK. Landslide Vulnerability Mapping Using Frequency Ratio Method in Tlogosono Village and Surrounding Area, Gebang District, Purworejo Regency, Central Java Province [dissertation]. Yogyakarta, Gadjah Mada University; 2018.

Purnamasari ANC, Hartantyo E, Junun S, Hafahzah H. Mapping subsurface and surface characteristics of the recent Pesanggrahan landslide, Central Java, Indonesia, for landslide hazard management. Environment and Natural Resources Journal 2024;23(1):1-13.

Radjah VYG, Suryatmojo H, Ngadisih. Landslide susceptibility zone using frequency ratio method in Karangkobar catchment, Merawu watershed, Banjarnegara District, Central Java Province. IOP Conference Series: Earth and Environmental Science 2020;451:Article No. 012087.

Raza A, Safdar M, Zhong M, Hunt JD. Analyzing spatial location preference of urban activities with mode-dependent accessibility using integrated land use-transport models. Land 2022;11(8):Article No. 1139.

Samodra G, Chen G, Sartohadi J. Comparing data-driven landslide susceptibility models based on participatory landslide inventory mapping in Purwosari area, Yogyakarta, Java. Environmental Earth Science 2017;76:Article No. 184.

Satpathy AS, Sahoo SK, Mohanty A, Mohanty PP. Strategies for enhancements of MSME resilience and sustainability in the post-COVID-19 era. Social Sciences and Humanities Open 2024;11:Article No. 101223.

Sharif BA. The impact of natural disasters on small and medium enterprises (SME) in Bangladesh. Open Access Library Journal 2021;8(6):1-15.

Sugiyono. Quantitative and Qualitative Research Methods R&D. Bandung: Alfabeta; 2017. p. 50.

Sukristiyanti S, Wikantika K, Sadisun IA, Yayusman LF, Jevon A, Telaumbanua JA. Polygon-based landslide inventory for Bandung basin using google earth. Indonesian Journal of Geography 2021;53(2):285-94.

Thongley T, Vansarochana C. Spatial zonation of landslide prone area using information value in the geologically fragile region of Samdrup Jongkhar-Tashigang National Highway in Bhutan. Environment and Natural Resources Journal 2021;19(2): 121-31.

Tian Y, Chen J, Xu C, Lingling S. Geometrical characteristics of earthquake-induced landslides and correlations with control factors: A case study of the 2013 Minxian, Gansu, China, Mw 5.9 event. Landslides 2017;14(6):1915-27.

Utami, Dyah I, Santosa I, Vidya LMR. Priority resilience strategy for micro, small, and medium enterprises for dealing with natural disasters. International Journal of Disaster Risk Reduction 2021;55:Article No. 102074.

Wibawanti E, Sartohadi J, Ngadisih, Setiawan MA, Mardianto D. The effectiveness of “ProKlim” in controlling landslide by vegetative method in the Sambak village, Kajoran, Magelang. AgriTech 2023;43(2):105-15.

Wubalem A. Modeling of landslide susceptibility in a part of Abay Basin, Northwestern Ethiopia. Open Geosciences 2020; 12(1):1440-67.

Yi Yaning, Zhang Z, Zhang W, Jia H, Zhang J. Landslide susceptibility mapping using multiscale sampling strategy and convolutional neural network: A case study in Jiuzhaigou Region. Catena 2020;195:Article No. 104851.

Youssef B, Bouskri I, Brahim B, Kader S, Brahim I, Abdelkrim B, et al. The contribution of the frequency ratio model and the prediction rate for the analysis of landslide risk in the Tizi N'tichka area on the national road (RN9) linking Marrakech and Ouarzazate. Catena 2023;232:Article No. 107464.