GIS-BASED LANDSLIDE HAZARD ZONATION MODEL IN HIGHLAND CITY (CASE OF PADANG PANJANG CITY, INDONESIA)

(Model Zonasi Bahaya Longsor Berbasis GIS di Kota Dataran Tinggi Kasus di Kota Padang Panjang, Indonesia)

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ABSTRACT

This study presents a GIS-based landslide hazard zonation model that integrates remote sensing data with key physical parameters influencing landslide occurrence in Padang Panjang City, Indonesia. The methodology involves spatial analysis to assess critical environmental factors, including slope, soil type, rainfall, and land use changes. The dataset comprises DEMNAS for topographic information, CHIRPS rainfall data from two periods (2002–2012 and 2013–2022), and Landsat 7 ETM+ and Landsat 8 OLI imagery from 2012 to 2022. The analysis begins with a spatial classification of land use changes to identify trends in land cover transformation. Landslide hazard zonation is determined using a multi-criteria weighting method that integrates various physical factors. The model's accuracy is evaluated using the area under the curve (AUC) metric, incorporating historical landslide occurrence data. The results indicate an expansion of cultivated land for community activities. Additionally, within the landslide hazard zones, both low hazard and high hazard categories have shown an increase in area. The accuracy assessment of the landslide hazard zonation model, based on AUC calculations, achieved 95% for the 2012 event data and approximately 92% for the 2022 event data. The analysis delineates three distinct landslide hazard zones, emphasizing the necessity for proactive disaster risk management policies and increased public awareness, particularly in high potential areas. GIS-based landslide hazard zonation serves as a valuable tool for enhancing risk management and spatial planning in upland urban areas, ultimately contributing to the development of safer and more resilient communities.

Kata kunci: landslide hazard model, GIS, remote sensing, physical factors

ABSTRAK

Penelitian ini membahas model zonasi bahaya longsor berbasis SIG, yang mengintegrasikan data penginderaan jauh serta parameter fisik utama yang mempengaruhi terjadinya longsor di Kota Padang Panjang, Indonesia. Metode yang digunakan dalam penelitian ini melibatkan analisis spasial untuk mengevaluasi faktor lingkungan utama, yaitu kemiringan, jenis tanah, curah hujan, dan perubahan penggunaan lahan. Data yang digunakan mencakup DEMNAS untuk topografi, data curah hujan CHIRPS dalam dua periode (2002-2012 dan 2013-2022), serta citra Landsat Landsat 7 ETM and 8 OLI untuk tahun 2012-2022. Proses analisis diawali dengan kajian perubahan penggunaan lahan yang diklasifikasikan secara spasial untuk mengidentifikasi tren perubahan tutupan lahan. Zonasi bahaya longsor ditentukan dengan metode pembobotan multi-kriteria yang menggabungkan berbagai faktor fisik. Akurasi model diuji menggunakan area under curve (AUC) dengan historis data kejadian longsor. Hasil penelitian menunjukkan bahwa terjadi peningkatan lahan budidaya yang dimanfaatkan untuk aktivitas masyarakat. Sebaliknya, pada zona bahaya longsor, kategori zona bahaya rendah dan tinggi mengalami peningkatan luasan. Selain itu, penilaian akurasi model zonasi bahaya longsor, yang menggunakan perhitungan area under curve (AUC) untuk data kejadian tahun 2012, mencapai 95%, sedangkan untuk data kejadian tahun 2022, akurasi tersebut berkisar 92%. Berdasarkan hasil analisis, diperoleh tiga zona bahaya longsor yang berbeda. Perlunya kebijakan manajemen risiko bencana yang proaktif serta peningkatan kesadaran masyarakat terhadap bahaya longsor, terutama di zona dengan potensi tinggi. Zonasi bahaya longsor berbasis GIS memberikan informasi yang penting untuk meningkatkan manajemen risiko dan perencanaan di kawasan perkotaan dataran tinggi, serta berkontribusi pada terciptanya komunitas yang lebih aman dan tangguh.

***Keywords**: model bahaya longsor, GIS, penginderaan jauh, faktor fisik*

INTRODUCTION

Landslides are ranked as the third most significant natural disaster globally regarding their potential to cause catastrophic impacts (Huang et al., 2023). Similar to many other developing countries, Indonesia frequently experiences various natural hazards, including landslides. Besides the extensive Indus alluvial plain, which renders much of the population vulnerable to major floods, Indonesia is characterized by geomorphologically active mountainous terrain (Kanwal et al., 2017). Landslides are particularly common in mountainous areas and are highly destructive to both the environment and human settlements (Gupta et al., 2022). The occurrence and frequency of landslides in a region depend on the interplay between triggering factors and natural conditions. Several phenomena influence slope stability and contribute to landslides, including rainfall, temperature fluctuations, seismic activity, volcanic eruptions, and various human activities (Małka, 2022). Comprehensive regional landslide occurrence data, along with an understanding of the relationship between landslide distribution and influencing factors, are essential for evaluating regional landslide hazard potential and elucidating the role of landslides in landscape evolution (Affandi et al., 2023). Landslide attribution data, which include details about the location, number of events, and spatial distribution of landslides, are critical for ensuring objectivity and accuracy in subsequent research (Regmi & Agrawal, 2022).

Over the past decades, numerous researchers have employed various methods for landslide hazard mapping (LSM) using GIS technology, utilizing both qualitative and quantitative approaches (El Jazouli, Barakat, & Khellouk, 2019; Devara et al., 2021). Landslide hazard maps are vital tools for land management, land-use planning, and reducing landslide-associated costs (Suprapto et al., 2022). Additionally, landslide hazard assessments serve as critical components of early warning system engineering and are foundational for comprehensive landslide hazard and risk assessments (Sharma & Mahajan, 2018). The literature provides extensive evidence of GIS being applied to mass debris research (Tewari & Misra, 2019). Various techniques are utilized to study landslide susceptibility, including empirical, statistical, and deterministic approaches, particularly in large-scale engineering geology projects (Mardiah et al., 2017; Saha et al., 2022).

The high hazard of landslides is not solely attributable to natural factors but is often exacerbated by anthropogenic activities such as rapid urbanization and unregulated land-use changes (Kohno et al., 2022). Urbanization has resulted in the encroachment of steep slopes previously serving as water catchment areas, thereby increasing the risk of erosion and landslides (Fang et al., 2023). Furthermore, deforestation in areas surrounding agricultural and built-up regions has stripped away vegetation layers that act as natural soil stabilizers, rendering slopes more susceptible to land movement. Without appropriate science-based interventions, this risk will continue to escalate, threatening the safety and livelihoods of local communities (Mardiah, 2021). Geographic Information Systems (GIS) provide an effective solution to these challenges. GIS facilitates the integration of multiple spatial data sources to develop more accurate and detailed hazard zoning models. Addressing spatial problems often involves consideration of numerous criteria and is significantly influenced by the value judgments and uncertainties of investigators (Ullah et al., 2022). To mitigate decision-making imprecision and uncertainty, this study employs a multi-criteria decision-making approach that allows for the consistent representation of subjective perceptions and numerical analyses to mathematically formulate knowledge (Thanh et al., 2022). Landslide risk is influenced not only by physical and environmental factors but also by socio-economic conditions that determine a community's vulnerability and resilience (Pal & Karnjana, 2021). The researchers recognize that factors such as population mobility, population growth, livelihoods, and local community understanding were not included in determining vulnerability zones (Perera et al., 2020). These socio-economic aspects play a crucial role in disaster risk assessment, as they directly influence community resilience and adaptive capacity in landslide-prone areas (Xu et al., 2018).

Padang Panjang City, located in the highlands of West Sumatra, is highly susceptible to landslides due to its steep topography and high annual rainfall (Z. Umar, Pradhan, Ahmad, Jebur, & Tehrany, 2014). As a densely populated urban area situated within a volcanic mountainous landscape, Padang Panjang has experienced multiple landslide events in recent years, resulting in significant disruptions to infrastructure, agricultural productivity, and local livelihoods (Faris & Fawu, 2014). Historical records indicate that landslides frequently occur along major transportation routes, cutting off access between districts and causing economic losses (Purnawan & Khairah, 2021). Furthermore, the combination of rapid urbanization and land-use changes such as deforestation and slope modifications for settlement expansion has exacerbated the risk of slope failures (Johnston et al., 2021). The lack of comprehensive spatial assessments has led to inadequate mitigation measures, leaving many communities vulnerable to landslide hazards (Triyatno et al., 2020). Given these conditions, Padang Panjang is an important case study for developing a GIS-based landslide hazard zoning model, which can help inform sustainable urban planning and disaster preparedness efforts.

The primary objective of this research is to apply a spatial approach, leveraging GIS technology, to produce a landslide hazard map for the highlands of Padang Panjang City, West Sumatra. To achieve this objective, the study examines key aspects such as land-use changes from 2012 to 2022 and a detailed landslide hazard assessment within the Padang Panjang City area, located in the highlands of Sumatra Island. The landslide hazard zonation model developed in this study has significant implications. Beyond providing a scientific basis for spatial planning, it serves as a decision-support tool for disaster risk mitigation, thereby enhancing preparedness for natural disasters.

METHOD

Study Area

Our case study focuses on one of the cities in the West Sumatra region, located in the highlands of West Sumatra (**Figure 1**). Padang Panjang City is characterized by mountainous topography and high rainfall, making it particularly susceptible to natural disasters, especially landslides. Various human activities, particularly in the land development sector, play a significant role in meeting daily needs. With an elevation of approximately 539 meters above sea level, the area supports thriving horticultural crops and a robust agricultural sector. However, the population size is relatively small compared to typical urbanized areas. Despite being administratively categorized as a city, the population, according to the 2022 census, was recorded at 57,850 people (BPS, 2021).

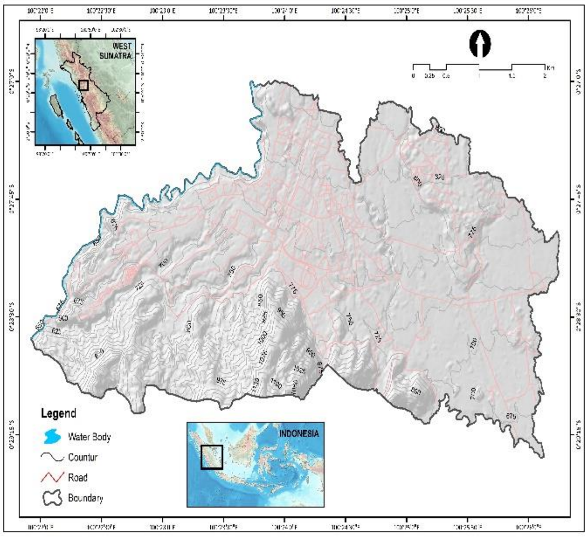

Figure 1. Research location.

Datasets

Measuring landslide movement hazards is crucial for managing hydrometeorology-related disasters and assessing damage risks. Landslide hazards, particularly in upland areas, have significant impacts on urban regions, including infrastructure damage, socio-economic disruption, threats to public safety, and extensive environmental degradation. A landslide hazard analysis was conducted for the upland areas within the administrative boundaries of Padang Panjang City, Indonesia. This analysis employed four main criteria, encompassing various physical characteristics of landslide-prone environments. The datasets used include the Digital Elevation Model Nasional (DEMNAS) obtained from the Geospatial Information Agency (tanahair.indonesia.go.id), soil type data from the Indonesian Center for Agricultural Land Resources Research and Development (sdlp.bsip.pertanian.go.id), and rainfall data categorized into two periods (2002–2012 and 2013–2022) sourced from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) website (www.chc.ucsb.edu). Additionally, Landsat 7 ETM and 8 OLI imagery was retrieved from the United States Geological Survey (USGS) Earth Explorer platform (earthexplorer.usgs.gov), while event data were recorded by regional disaster management agencies.

Given the varying resolutions and scales of these datasets, the final landslide hazard zonation map was standardized to a spatial resolution of 30 meters, ensuring consistency across all raster-based analyses. The soil type data, initially available as a vector dataset at a scale of 1:50,000, were converted into a raster format within the GIS environment to align with other spatial datasets. To maintain consistency, a resampling process was applied, interpolating the vector data into a 30-meter raster grid. This transformation enabled seamless integration with other raster-based datasets, such as slope, rainfall, and land use. The resampling method was carefully selected to preserve the spatial integrity of the original dataset while minimizing potential distortions, ensuring accuracy in the landslide hazard modeling process.

Similarly, rainfall data, originally available as a raster dataset with a spatial resolution of 1 km, were processed to match the 30-meter resolution used in the final analysis. This adjustment was necessary to maintain consistency across all spatial datasets and facilitate accurate integration within the GIS-based landslide hazard zonation model. The resampling process was performed using bilinear interpolation, a technique that smooths transitions between adjacent pixel values while preserving the spatial gradient of precipitation distribution. This method was chosen to ensure precipitation variability across the study area was accurately represented, minimizing distortions in the downscaled data. By standardizing the resolution of all datasets to 30 meters, this study ensures that all contributing factors including topography, soil type, land use, and rainfall are analyzed at the same spatial scale, thereby enhancing the reliability and accuracy of the final landslide hazard zonation map. The detailed criteria and data sources utilized in the analysis are summarized in **Table 1.**

Table 1. Catalog of datasets applied in the research.

Datasets	Type	Resolution/ Scale	Sources
Incident	Vector	1:1.000	Regional Disaster Management Agency
Slope	Raster	8 meters	Geospatial Information Agency
Soil type	Vector	1:50.000	Indonesian Center for Agricultural Land Resources Research and Development
Rainfall	Raster	1km	Climate Hazards Group InfraRed Precipitation with Station data
Land use 2012 and 2022	Raster	30 meters	United States Geological Survey

In GIS-based spatial analysis, the choice of map scale plays a crucial role in determining accuracy and precision. Map-based studies should explicitly declare and discuss the scale used, as not all map scales allow for accurate area calculations. The selected map scale also affects the precision and reliability of spatial analysis, especially when integrating multiple datasets.

The overlay and combination of different maps must consider variations in boundary delineation methods. Climatic maps often rely on interpolation techniques, soil maps are typically interpretative based on landform characteristics, while slope maps are generated using pixel-based calculations. Since these datasets employ different boundary delineation approaches, their direct integration in GIS analysis may introduce inconsistencies. Furthermore, considering the accuracy assessment results based on the Area Under the Curve (AUC) method, it is possible that the obtained accuracy levels may be coincidental rather than fully representative of actual hazard conditions.

Analysis

The distribution of landslide's potential hazard is the result of a combination of soil movement activities and the unstable hydrological cycle (Afzal et al., 2022). Generally, the disaster occurs bond to the topographical category that is steep to a very deep, and can also be rather steep with open surface cover without a barrier on the surface (Vojteková & Vojtek, 2020). In this study, statistical analysis of the physical characteristics of the potential for landslides was supported by a review of relevant literature and adapted to the conditions of the Padang Panjang City area, West Sumatra. The parameter information used in the study is as follows (**Table 2**):

Table 2. Parameters used in research.

No	Parameters	Sub-parameters	Score	Weight
1	Slope	0-8%	0.02	
		8-15%	0.07	
		15-25%	0.15	40%
		25-40%	0.32	
		>40%	0.45	
2	Type of Soil	Mediterranean	0.30	20%
		Cambisol	0.20	
3	Rainfall (mm/month)	0-100mm	0.40	
		100-200mm	0.30	10%
		>200mm	0.20	
4	Land Use	Forest	0.01	
		Paddy Field	0.06	
		Settlement	0.09	30%
		Mixed Plantation	0.21	
		Dryland farming	0.38	

Source: (Amaluddin et al., 2020)

Findings from landslide hazard zones with sub-parameter factors studied will produce relatively appropriate results in providing disaster spatial information. Where the slope > 25% is prone to landslides, and the mediterranean soil type has soil characteristics that have an influence on the occurrence of landslides in a land (Zhao et al., 2022). Differences in land use types have different impacts on landslides. While climatological factors help accelerate the occurrence of landslides by carrying out soil erosion on the characteristics of open land cover and land with weak tree roots. This will suggest in planning a land use that is safe and reducing the risk from various human activities on the land (Li et al., 2022).

Assessment of Accuracy

The accuracy assessment stage is an essential component of spatial data analysis. This research employs two primary methods for accuracy evaluation: the confusion matrix and the Area Under the Curve (AUC) approach. The AUC method, introduced by Swets (1988), is widely utilized for assessing accuracy in spatial modeling (Swets, 1988). Land use data requires an evaluation of classification accuracy to ensure its applicability for subsequent analysis, particularly in landslide hazard model assessments.

The process begins with the collection of geographical coordinates for land use across various years, using a total of 400 samples derived from high-resolution imagery. The accuracy of the landslide hazard model is then evaluated using the Receiver Operating Characteristics (ROC) curve. Historical landslide event data was sourced from the archives of the regional disaster management agency, with 37 events recorded up to 2012 and 45 events recorded from 2013 to 2022. Geographical coordinates were collected through field surveys and supplemented with imagery from Google Earth. To enhance the analysis, external tools were incorporated into Python-based machine learning algorithms to generate the AUC values. Finally, the classification results of the landslide hazard model are calculated in this section, with the AUC graph serving as the output to represent the accuracy assessment.

RESULTS

Land use change in 2012-2022

Land use change reflects the dynamics of land utilization influenced by various factors, including population growth, urbanization, and shifts in agricultural practices. In the context of geography and sustainability, analyzing land use change is essential for understanding the environmental, social, and economic impacts of land conversion processes, as well as the implications of hydrometeorological natural disasters (Giofandi et al., 2024).

In 2012, the region was predominantly characterized by forest land and agricultural land, including dryland farming and mixed agriculture. Built-up areas were relatively limited, indicating that the majority of the land was utilized for agricultural activities and the preservation of forest ecosystems. This diverse land use pattern reflects traditional practices that support local sustainability and food security while highlighting potential conflicts between development needs and environmental conservation (Ambarwulan et al., 2023). However, by 2022, a significant transformation in land use distribution had occurred. The region experienced rapid urbanization, as evidenced by a notable increase in built-up areas (marked in red), particularly in the city center and surrounding regions (**Figure 2**). This transition not only signifies economic growth and infrastructure development but also introduces new challenges related to environmental sustainability, such as habitat loss, soil degradation, and increased pressure on water resources

The phenomenon of increasing land use is evident in the drastic reduction of forest areas during this period. In 2012, forests covered 535.58 hectares, but much of this land was converted into built-up areas and other agricultural land by 2022 (**Table 3**). Additionally, mixed agricultural land experienced a decline, while paddy fields showed significant expansion. This reduction in forest and mixed agricultural land highlights increasing pressure on land resources, which can have adverse effects on biodiversity and disrupt the balance of local ecosystems. The growth of paddy fields, attributed to the conversion of dryland and mixed-use areas, illustrates agricultural intensification but also underscores the trade-offs between land conservation and agricultural development. Built-up areas expanded rapidly, covering an additional 422 management to strike a balance between urban development and environmental preservation. These findings underscore the importance of sustainable land use planning to

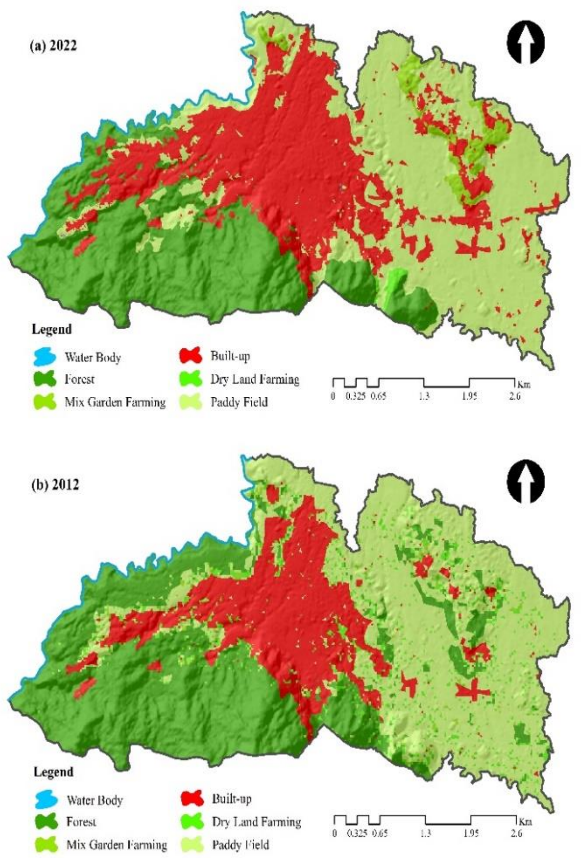

Figure 2. Land use of the research area in (a) 2022, and (b) 2012.

Table 3. Land use changes in the Padang Panjang City for the period 2012-2022.

Category	2012		2022		Change	
	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)
Forest	725	35.04	588	28.42	-137	-6.62
Mixed garden	16	0.77	55	2.66	39	1.88
Dry land farming	98	4.74	8	0.39	-90	-4.35
Paddy field	808	39.05	785	37.94	-23	-1.11
Built-up	422	20.40	633	30.59	211	10.20

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Table 4. User accuracy (UA) and producer accuracy (PA) of LULC category for 2012-2022.

Category	2012		2022	
	UA (%)	PA (%)	UA (%)	PA (%)
Forest	95.65	91.67	92.68	97.44
Mixed garden	86.47	88.36	80.00	82.28
Dry land farming	85.71	85.71	88.24	89.36
Paddy field	89.47	96.23	97.92	90.38
Built-up	92.31	85.71	92.86	95.12
Overall Accuracy	92.03	-	94.16	-
Kappa Coefficient	93.07	-	96.24	-

minimize environmental degradation while meeting the needs of the population.

The accuracy assessment stage plays a crucial role in evaluating land use mapping, as it provides insight into how well the classifications derived from remote sensing imagery align with actual ground conditions. For land use analysis in 2012 and 2022, the User Accuracy (UA) and Producer Accuracy (PA) metrics measure the reliability of the classifications and their effectiveness in identifying specific land use types (**Table 4**). These accuracy evaluations were based on 400 samples taken from high-resolution imagery (Google Earth), offering a robust foundation for analysis

For forest areas, the high UA (95.65%) and PA (91.67%) in 2012 indicate strong classification accuracy, meaning most areas identified as forests were indeed forests in reality. However, by 2022, while the PA improved to 97.44%, the UA slightly declined to 92.68%, suggesting some misclassification between forests and other vegetated areas due to land cover transitions. This shift is consistent with the decreasing forest cover observed in the study, where small forest patches may have been misidentified as mixed agriculture or degraded land due to spectral similarities in satellite imagery.

The classification of mixed agricultural land posed a greater challenge, as indicated by lower UA (86.47%) and PA (88.36%) in 2012, which further declined in 2022 (UA: 80.00%, PA: 82.28%). This reduction highlights increasing classification ambiguity, likely due to overlapping spectral characteristics between different agricultural types (e.g., mixed cropping and dryland farming). The fragmentation of agricultural landscapes and seasonal land use variability may have contributed to classification inconsistencies, requiring more refined spectral differentiation techniques in future studies.

The paddy field classification exhibited consistent improvements, with UA increasing from 89.47% in 2012 to 97.92% in 2022, while PA slightly decreased from 96.23% to 90.38%. This indicates that the classification process became more effective in correctly identifying paddy fields, but some areas may have been misclassified as wetlands or agricultural fields due to seasonal water fluctuations. Given that paddy fields expanded significantly during the study period, maintaining classification accuracy is essential for analyzing agricultural land use impacts on hydrological dynamics.

Built-up areas demonstrated reliable classification accuracy, with UA of 92.31% and PA of 85.71% in 2012, improving to UA of 92.86% and PA of 95.12% in 2022. The increase in PA suggests better identification of urbanized regions, while consistent UA values confirm that most built-up areas were accurately detected. However, slight misclassifications may have occurred between urban and industrial land uses, requiring further refinement in classification algorithms to distinguish between different types of built environments.

The overall classification accuracy improved from 92.03% in 2012 to 94.16% in 2022, with the Kappa coefficient increasing from 93.07 to 96.24, indicating a high level of agreement between classified land use types and reference data. These improvements reflect advancements in data processing techniques, the use of high-resolution reference samples, and refined classification methods, making the land use dataset a reliable basis for landslide hazard assessment.

Landslide Hazard Model

The parameters used in this assessment include slope, soil type, monthly rainfall, and land use (**Figure 3**). A thorough understanding of these parameters facilitates decision-making related to risk mitigation, spatial planning, and environmental preservation (Mersha & Meten, 2020). Data collected over different periods, such as rainfall data from 2002–2012 and 2013–2022, as well as land use data from 2012 and 2022, provide a comprehensive overview of the changes occurring in the study area.

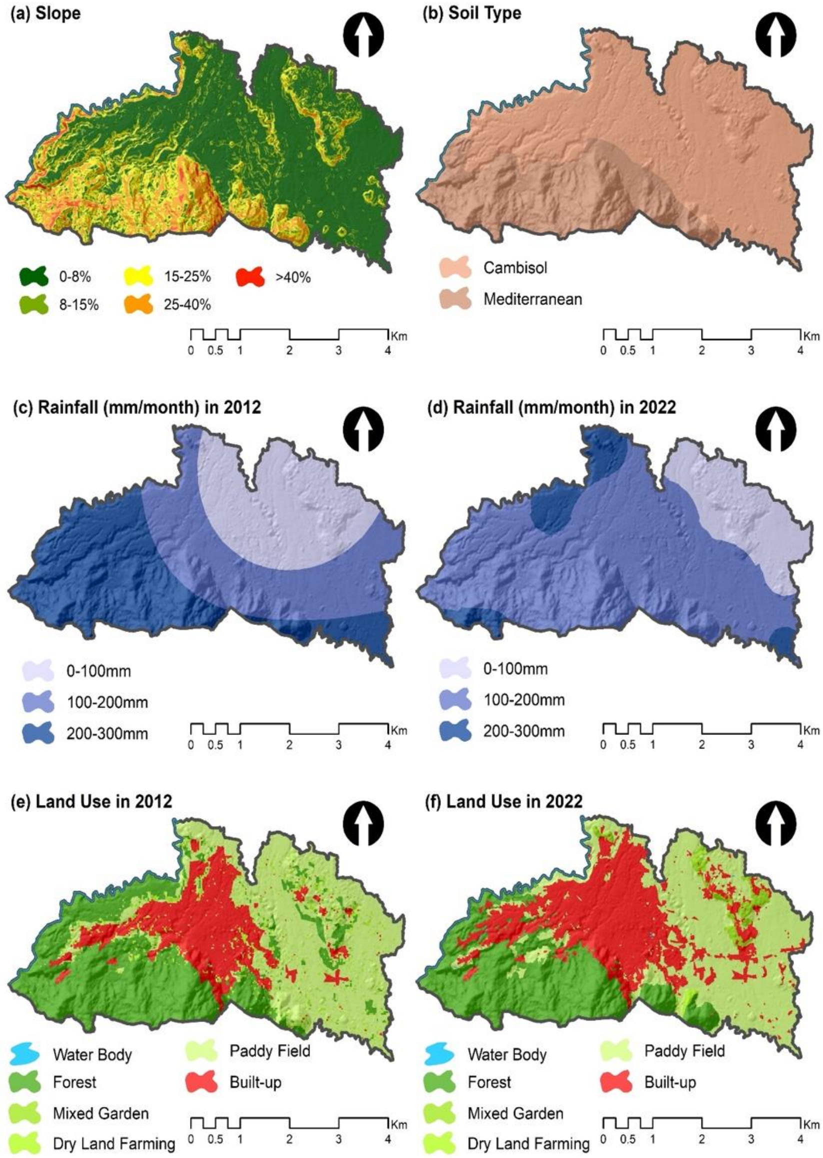


Figure 3. The parameters used in the study include (a) slope; (b) soil type; (c) rainfall in 2012; (d) rainfall in 2022, (e) land use in 2012, and (f) land use in 2022.

In landslide studies, hazard refers to the probability of landslide occurrence based on physical factors such as slope, soil type, and rainfall. However, landslide hazard potential is influenced by the interaction of these physical factors with environmental changes, particularly land use modifications. The slope parameter reveals that most of the area falls within the 0–8° slope category, which accounts for 54.57% of the total area (**Table 5**). This indicates that relatively flat slopes have a lower potential for landslide hazards. Conversely, the 8–15° and 15–25° slope categories account for 15.66% and 15.47%, respectively, suggesting a moderate hazard of landslides in these steeper areas. However, the more extreme slope categories, such as 25–40° and above 40°, represent smaller proportions of 12.71% and 1.59%, respectively. This finding indicates that although there are high-hazard areas, most of the region does not have sufficient slope steepness to significantly increase landslide hazard potential.

The analysis of soil types is also critical in landslide hazard assessments. According to the data, Cambisols dominate, covering 67.86% of the area, while Mediterranean soils account for 32.14%. Cambisols, known for their favorable physical and chemical properties for agriculture, may contribute to landslide hazard potential if not managed appropriately, particularly on steep slopes. Thus, understanding these soil types is essential for planning effective mitigation measures.

Monthly rainfall data indicate significant differences between the 2002–2012 and 2013–2022 periods. During the 2002–2012 period, rainfall in the 200–300 mm range accounted for 42.19%, highlighting a high frequency of rainfall capable of triggering landslides. In contrast, during the 2013–2022 period, the 100–200 mm range dominated, comprising 71.77%, indicating a shift in rainfall patterns. The decrease in extreme rainfall events (0–100 mm) during the latter period suggests a potential reduction in landslide hazard potential.

Table 5. Area and percentage of parameters in research.

No	Parameters	Categories	Area (ha)	Percentage (%)
1	Slope (%)	0-8	1,129	54.57
		8-15	324	15.66
		15-25	320	15.47
		25-40	263	12.71
		>40	33	1.59
2	Type of Soil	Mediterranean	665	32.14
		Cambisol	1,404	67.86
3	Rainfall (mm/month) in 2002-2012	0-100mm	374	18.08
		100-200mm	1,485	71.77
		200-300mm	210	10.15
4	Rainfall (mm/month) in 2013-2022	0-100mm	374	18.08
		100-200mm	1,485	71.77
		200-300mm	210	10.15
5	Land Use in 2012	Forest	657	31.75
		Mixed Plantation	60	2.90
		Dryland Farming	433	20.93
		Paddy Fields	8	0.39
		Settlement	905	43.74
		Water Body	6	0.29
6	Land Use in 2022	Forest	657	31.75
		Mixed Plantation	60	2.90
		Dryland Farming	433	20.93
		Paddy Fields	8	0.39
		Settlement	905	43.74
		Water Body	6	0.29

In the context of landslide studies, risk is a function of hazard, vulnerability, and capacity. Hazard refers to the probability of landslide occurrence based on physical factors such as slope, rainfall, and soil type. Vulnerability, on the other hand, describes the susceptibility of elements at risk (e.g., populations, infrastructure, and ecosystems) to the impacts of a landslide (He et al., 2024). Capacity represents the ability to mitigate or adapt to these hazards through structural and non-structural measures (Broquet et al., 2024). When a region experiences increased hazard potential such as high rainfall variability without adequate mitigation measures to reduce vulnerability, the overall landslide risk increases (Ceccato et al., 2024). Therefore, although fluctuations in rainfall patterns may not directly translate to an immediate increase in hazard, they can influence the frequency and intensity of landslides over time, particularly in areas with high vulnerability and low adaptive capacity. However, significant fluctuations in rainfall still pose a hazard, emphasizing the importance of continuous monitoring. Land use changes between 2012 and 2022 have likely influenced landslide hazards. In 2012, forests covered 35.04% of the area, but by 2022, this had decreased to 28.42%. Conversely, settlement areas increased significantly from 20.40% to 30.59% over the same period. The reduction in forest area heightens landslide hazard potential due to the loss of vegetation that stabilizes soil. Additionally, the decline in dry agricultural land and the increase in mixed land use reflect a shift in land use patterns that may affect soil stability.

Based on the analysis of parameters influencing landslide hazards, it is evident that the combination of slope, soil type, rainfall, and land use changes significantly contributes to the potential for landslides in the area. The reduction in forest cover and the expansion of settlement areas are particularly concerning in terms of landslide hazard mitigation. Furthermore, changes in rainfall patterns over time underscore the importance of data-driven mitigation planning. A comprehensive understanding of these environmental changes is crucial for identifying areas at high hazard of landslides (Dai et al., 2022). Considering these parameters, the next step is to conduct landslide hazard zonation, which will classify and map areas with varying degrees of landslide hazard across the study area.

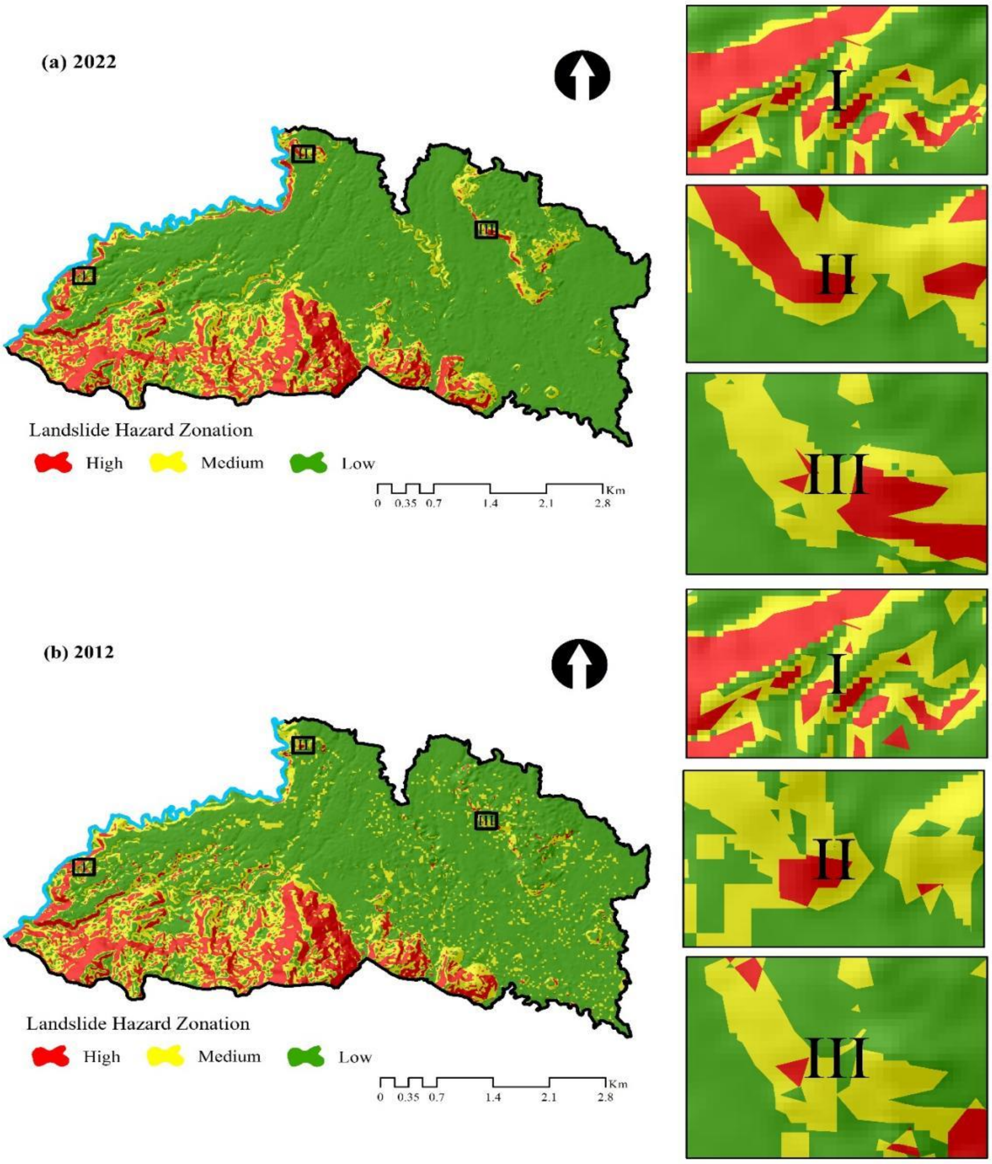


Figure 4. Landslide hazard zone in Padang Panjang City in (a) 2012, and (b) 2022

Table 6. Area and percentage of parameters in research.

Category	Area (ha)		Percentage (%)	
	2012	2022	2012	2022
High	281	301	13.58	14.55
Medium	406	341	19.62	16.48
Low	1,382	1,427	66.80	68.97

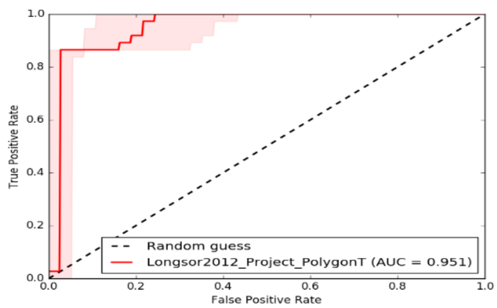
Landslide hazard zonation, based on parameters such as slope, soil type, rainfall, and land use, provides a systematic perspective on areas vulnerable to disasters. Data from 2012 and 2022 illustrate changes in landslide hazard zonation, reflecting environmental dynamics that may affect regional stability (**Figure 4**). The landslide hazard zonation mapping was conducted by integrating multiple spatial parameters, including slope, soil type, rainfall, and land use. Given the scale and resolution of the available data, a generalization process was applied to ensure consistency and accuracy in the delineation of hazard zones. This process involved smoothing and aggregating smaller hazard patches that may have resulted from high resolution spatial variations, preventing over fragmentation in hazard classification (Reichenbach et al., 2018).

Additionally, the mapping scale influenced the level of detail in hazard classification, where finer-resolution data would potentially yield more fragmented zonation (Shano et al., 2020). However, the adopted methodology ensures that the final hazard zonation represents a balanced interpretation between detail and practical usability, minimizing excessive complexity while maintaining spatial accuracy.

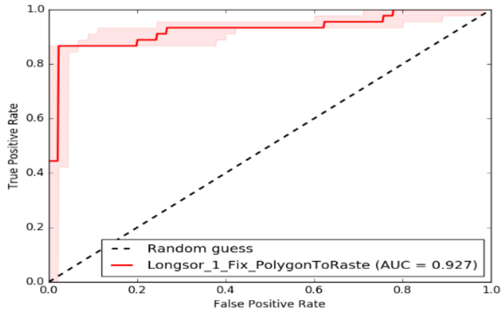
In 2012, areas classified as having a high landslide hazard accounted for 13.58% of the total area (**Table 6**). Although the overall change in landslide hazard zonation appears to be less than 5%, this variation still holds significance from a hazard management perspective. Even minor increases in high hazard zones may indicate localized environmental degradation, particularly in areas undergoing deforestation and urban expansion (Depicker et al., 2021). Additionally, small changes in hazard classification can have substantial implications for communities, infrastructure planning, and early warning systems. Therefore, while the numerical percentage change is relatively low, its spatial distribution and underlying causes warrant further attention in landslide hazard mitigation strategies.

These zones typically include regions with steep slopes, erosion-prone soil types, and high rainfall. The medium hazard zone covered 19.62%, while the low hazard zone dominated at 66.80%. In landslide studies, hazard and risk are distinct yet interconnected concepts. Landslide hazard refers to the probability of a landslide occurring in a specific area, based on physical and environmental factors such as slope, soil type, and rainfall. However, risk is a function of both hazard and vulnerability, where vulnerability encompasses exposure and the inability of affected elements (e.g., infrastructure, population, and ecosystems) to cope with or recover from landslide impacts (Shah et al., 2023). Thus, even in areas classified as low hazard zones, risk can still be significant if the vulnerability is high, such as in densely populated settlements or regions with inadequate mitigation measures. The large proportion of low hazard zones suggests that a substantial portion of the area experiences relatively low landslide hazard potential.

In 2022, the high landslide hazard zone expanded to 14.55%, reflecting an increase in high hazard areas. This growth is attributed to land use changes, such as reduced forest cover and increased settlement areas, which exacerbate the potential hazard of landslides. The medium hazard zone decreased to 16.48%, while the low hazard zone rose to 68.97%. The increase in low-hazard zones suggests that mitigation measures, such as vegetation restoration or erosion control, may have been implemented to reduce landslide potential.



(a)



(b)

Figure 5. Area under curve landslide hazard zone in (a) 2012, and (b) 2022.

The accuracy of landslide hazard zonation mapping is another important indicator of the reliability of zoning results. In 2012, the mapping accuracy reached 95%, indicating that most of the hazard classifications aligned with actual field conditions (**Figure 5**). This accuracy slightly decreased to 92% in 2022, remaining within the excellent category. The decline may be attributed to increasingly dynamic changes in rainfall patterns and land use, which could affect zonation classification results. The integration of landslide hazard parameter analysis—including slope, soil type, rainfall, and land use changes—with landslide hazard zonation offers a comprehensive view of landslide hazard potential within the area. The slight increase in high hazard zones by 2022 underscores the urgency for more intensive mitigation efforts.

DISCUSSION

Landslide hazard zoning is a highly important tool for planning and disaster mitigation in landslide-prone regions. By using a GIS approach, landslide hazard mapping enables the identification of areas most vulnerable to landslide threats (Aydin et al., 2022). The use of GIS also offers advantages in accurate and efficient spatial visualization, which greatly assists stakeholders in making data-driven decisions (Liu et al., 2022). This model can integrate various environmental parameters such as slope gradient, soil type, land use, and rainfall to produce comprehensive zoning maps. Its application allows for the integration of data from multiple sources, making it a highly effective tool for developing prevention and mitigation strategies (Nohani et al., 2019).

Landslide hazard zoning specifically focuses on identifying areas susceptible to landslides based on physical and environmental factors, without directly accounting for social vulnerability or coping capacity (Pourghasemi et al., 2018). Understanding this distinction is crucial for effective disaster reduction strategies, as risk assessment requires an integrated approach that includes vulnerability analysis and capacity building (Nanehkaran et al., 2023).

The results of landslide hazard zoning have significant implications for urban spatial planning.

Padang Panjang City, as a highland area, faces major challenges in disaster management. This zoning maps high hazard, medium hazard, and low hazard areas, providing critical input for local governments in regulating development. For example, high hazard areas should ideally be designated as conservation zones or allocated for low hazard uses, such as protected forests or green zones. Meanwhile, low hazard areas are more suitable for infrastructure development and residential expansion. In other words, this zoning helps align spatial plans with natural realities and potential disaster, enabling sustainable development.

Landslide hazard mapping also plays a crucial role in enhancing disaster preparedness. By delineating hazard prone areas, this mapping allows decision makers to prioritize mitigation efforts and allocate resources efficiently (Sun et al., 2022). High hazard zones can be targeted for early warning systems, slope stabilization projects, and community-based disaster risk reduction programs (Zeng et al., 2021). Additionally, hazard maps provide essential information for land use planning, ensuring that new developments do not encroach on unstable areas (Tjahjono et al., 2024). By integrating hazard zoning into policy frameworks, local governments can strengthen resilience and minimize potential losses.

Landslide hazard zoning models must also consider social and economic dimensions. Areas identified as high-risk zones require greater attention in the form of mitigation policies, such as restrictions on development, relocation of residents living in vulnerable areas, or stricter enforcement of environmental regulations (Firmansyah et al., 2019). Additionally, educating communities living in high-risk areas is crucial to raising awareness of potential disasters and preventive measures (Ahyuni et al., 2022). This will reduce material and non-material losses that may arise from disasters. On the other hand, governments can also use this zoning to design sustainable economic development policies while prioritizing community safety and well-being (Umar et al., 2019).

Furthermore, the GIS-based approach to landslide hazard modeling emphasizes the importance of environmental dynamics in the zoning process (Xiong et al., 2017). Changes in land use, forest degradation, or increased rainfall due to climate change can affect soil stability and increase landslide hazard potential. Therefore, it is essential to regularly update zoning data to reflect the latest conditions. This zoning provides a scientific basis for more adaptive and hazard-based spatial policies, which are crucial in disaster-prone areas. Additionally, it plays a vital role in supporting environmental conservation by designating conservation areas in high-risk zones (Diva et al., 2018). At the same time, it helps direct development to safer areas, ensuring a balance between development and environmental protection (Muzani et al., 2021). Through this approach, Padang Panjang City can manage landslide zoning more effectively and achieve sustainable, disaster-resilient development. Thus, hazard is not static but evolves with environmental and anthropogenic changes (Berhane et al., 2021). While hazard zoning identifies areas with potential instability, risk can escalate over time if vulnerability factors such as population density, unplanned urbanization, and lack of mitigation infrastructure are not addressed (Zhang et al., 2021).

Researchers acknowledge that this study has limitations in the application of variables and other assessment elements. In terms of information, the insights drawn from this study focus on assessing landslide-prone zones in relation to human activities. This disaster assessment factor is one of the key points in determining high hazard characteristics in Padang Panjang City. This raises challenges in data resolution, socio-economic activities of the community, and the need for spatial data standardization to produce renewable information. It is hoped that future research will consider aspects not included in this study and incorporate environmentally friendly technological solutions to monitor ground movements in real time and with greater accuracy.

CONCLUSION

The conclusion of this study emphasizes the importance of applying a GIS-based landslide hazard zoning model in managing landslide potential in highland areas. This zoning serves as a hazard-based decision-making tool that helps minimize economic and social losses due to disasters. Furthermore, the study also highlights the need for disaster mitigation policies that are not only reactive but also proactive. Landslide hazard zoning should be considered in all spatial planning policies and infrastructure development. Public awareness of landslide zonation is also a crucial part of the mitigation strategy, where educating the community on preventive actions is essential. Through the integration of technology and data-driven policies, it is expected that landslide hazard potential can be managed more efficiently, creating a safer environment, and ensuring the welfare of the community in the future.

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