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The Impact of Climate Change on the City of Padang, Indonesia

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ABSTRACT

The impact of global warming is climate change which affects elements of society. This condition causes a decrease in the level of community welfare and increases the level of community vulnerability. Some climate change impacts are floods, droughts, landslides, and shoreline changes. In this study, we will focus on landslides. Landslides are among the most dangerous natural disasters that often occur in mountainous areas, especially during the rainy season. Various factors influence events involving landslides. This study aims to utilize GIS to identify landslide-prone areas in Padang. The method used in this study is the Zuidam and Concelado criteria overlay method for the level of landslide hazard and the broken method (jenks). The natural break (jenks) classification method reduces within-class variation and maximizes between-class variation. This study shows that the level of landslide vulnerability in Padang City is low, with a total area of 288854.38173 ha with a percentage of 42.21%. We need to consider more factors and experiment with training and validating data in more detail to gain insight into the physical contributions of the factors to landslide occurrences.

INTRODUCTION

Human activities have led to an increase in Greenhouse Gas (GHG) emissions which has led to the phenomenon of global warming and resulted in climate change. Climate change is happening slowly but surely. In addition, climate change has an impact on all sectors of life. As a country vulnerable to climate change, Indonesia in the Asian region is predicted to see an increase in temperature of 2-6^{o}C and more rainfall. Low <20 mm within 10 days with a 70% chance (Herawaty 2007). This climate change provides opportunities for vulnerability to climatic disasters such as drought and floods caused by changes in temperature and rainfall patterns. These changes provide opportunities for increasing climatic disasters, such as droughts and floods caused by changes in temperature and rainfall patterns. The second is to protect functions such as the danger of erosion and landslides and reduce the danger of fire and pest attack by mixing various plants. The third is the function of utilizing renewable energy with fuelwood-producing plants. The community has not recognized these roles so far, especially in the regions. Along with the increasingly ongoing issue of global warming and climate change, people are gradually starting to understand that they have felt the negative effects of global warming.

Natural disasters can occur anytime, anywhere, bringing tangible and intangible losses to people's lives. Landslides are among the most dangerous natural disasters frequent in mountainous places, particularly during the rainy season. It might lead to a loss of injuries and damage to other facilities and property infrastructures like housing, business, and agricultural property (Rotigliano et al. 2012, Yu & Chen 2020, Yang & Chen 2010, Chen et al. 2019). Additionally, it can significantly impact society, the neighborhood, and the local economy in the affected regions (Abdurrohim & Firman 2018).

Numerous researchers have investigated landslide-prone regions worldwide (Mersha & Meten 2020, Roodposhti et al. 2014, Nurdin & Kubota 2018).

The primary areas of concentration for research studies include the inventory of landslides, the influence of geographic, topographical, hydrological, and environmental elements on the occurrences of landslides, and the participation of triggering factors such as precipitation and earthquake (Gian Quoc et al. 2018, Ya'acob et al. 2019). Events involving landslides are influenced by a variety of causal elements, which can be divided into several categories, including geomorphology, geology, soil, land cover, and hydrological conditions (Huqqani et al. 2021).

Padang is a coastal city with a population of more than 900,000 people, making it the largest city in West Sumatra. Situated in hilly terrain, the city is prone to landslides due to its unique geographical position. The soil is composed of clay, silt, and sand, making it highly susceptible to erosion and landslides. In addition, the city experiences high-intensity rainfall, which can trigger landslides, especially during the rainy season.

To address this issue, there is a need for a comprehensive approach that integrates technology, scientific knowledge, and community participation. One such approach is using Geographic Information Systems (GIS) for landslide hazard analysis (Mukhlisin et al. 2010, Nahayo et al. 2019, Bai et al. 2010, Cao et al. 2016, Lee 2005). GIS technology is a powerful tool that can be used to combine multiple layers of data, such as slope, geology, land use, and precipitation, to identify areas at risk of landslides.

Landslide dangers have been evaluated using remote sensing techniques and GIS. The landslide hazard maps were created using a variety of mathematical techniques, from more traditional advanced intelligence techniques like artificial neural network (ANN) (Shahri et al. 2019, Alkhasawneh et al. 2013, 2014, Lee et al. 2001) to more recent conventional statistic methods like frequency ratio (Regmi et al. 2014, Chen et al. 2020), statistical index and weights-of-evidence.

Most study studies have only used these two data configurations of the landslide data, and many researchers have examined landslide hazard mapping utilizing original data or frequency ratio data (Catani et al. 2013, Liu et al. 2019). We emphasize the major disparities in the generated landslide danger maps and suggest the most effective data configurations.

GIS technology for landslide hazard analysis in Padang has several benefits. First, it provides a cost-effective and efficient approach to identifying areas at risk of landslides (Sukrizal et al. 2019). Traditional approaches, such as field surveys, are time-consuming and expensive and do not provide a comprehensive picture of the area under consideration. Second, GIS-based analysis can be used to inform land use planning decisions, ensuring that vulnerable areas are not developed or that appropriate mitigation measures are taken. Third, the analysis can be used to develop an early warning system that can warn people living in high-risk areas of impending landslides (Miswar et al. 2022). This study aims to utilize GIS to identify landslide-prone areas in Padang. Based on the explanations above, the results of this analysis will provide valuable insights for decision-makers to develop effective disaster prevention and mitigation strategies in urban areas.

MATERIALS AND METHODS

Study Area

This research was conducted in the city of Padang. According to the Central Bureau of National Statistics, On the whole, the area of Padang Municipality was 694,96 Km2. Padang city is geographically located between $0^o44'$ and $01^o08'$ south latitude and between $100^o05'$ and $100^o34'$ East Longitude. Based on data from the National Disaster Mitigation Agency (BNPB), landslides in Padang City occurred due to high rainfall, a very steep slope > 70 (100-150%), and an area classified as prone to ground movement (red zone) (Gemilang et al. 2017).

The data for this study includes 10 landslide failure points obtained from exploratory activities. This study indicates that almost all landslides and most ground failures occur in the loess layer and that rock mass is the rock mass of the entire region and the sliding bed of the loess rock interface landslide (Li et al. 2021).

Methods

To achieve the purpose of this study, we collected and organized data, created a landslide inventory dataset, constructed and applied a database of landslide causative factors, and created and validated a landslide susceptibility map. Data collection and organization: The data required for this study was collected from various sources. This includes gathering relevant literature from published literature, a Data Elevation Model from BIG, a regional geological map from ESDM at a scale of 1:250000, and a soil map from (Badan Penelitian Dan Pengembangan Pertanian Kementerian Pertanian).

During fieldwork, data collection was carried out on different rock types by describing their steepness, soil texture, and landslide inventory mapping on both active landslide and scarp areas by measuring their length, width, accumulation zone, and depth (if possible) (Mersha & Meten 2020). After compiling the actual field investigation, the data was systematically processed and analyzed first in ArcGIS, then in Microsoft Excel, and finally in ArcGIS.

Method of Mapping

To assess the vulnerability of classified landslides to determine the level of landslide hazard (Zuidam & Concelado 1979) with GIS Arc View 10.1. Data scores and maps are needed to obtain data and maps of the potential for avalanche hazard using the method of overlaying the Zuidam and Concelado criteria for the level of landslide hazard (Jumardi & Nurfalaq 2019). The results of landslide vulnerability zoning are further classified into 5 classes: not vulnerable, slightly vulnerable, moderately vulnerable, vulnerable, and very vulnerable. The classification is done using the natural break method (jenks). According to ESRI (2010), the natural break (jenks) classification method tries to reduce within-class variation and maximize between-class variation (Nugroho 2020).

RESULTS AND DISCUSSION

Physical Factors of Landslide

Lithology: Because different lithology units have variable levels of landslide risk, lithology is the most crucial factor in this study of landslides (Cuesta et al. 1999, Dai et al. 2001, Nurdin & Kubota, 2018). According to geology and development centers, the lithological units depicted on the surface geologic maps were reclassified. A broad geology map was the outcome. Lithology shows a great influence on landslide development since different lithological units may be affected by different landslide types (Trisnawati et al. 2022). Moreover, soil cover deposits, mostly exposed to weathering, may influence land permeability and the landslide type, as known from thematic literature (Henriques et al. 2015). In the study area, based on the mapping results, there are 5 lithological units that have different characteristics (Fig. 1).

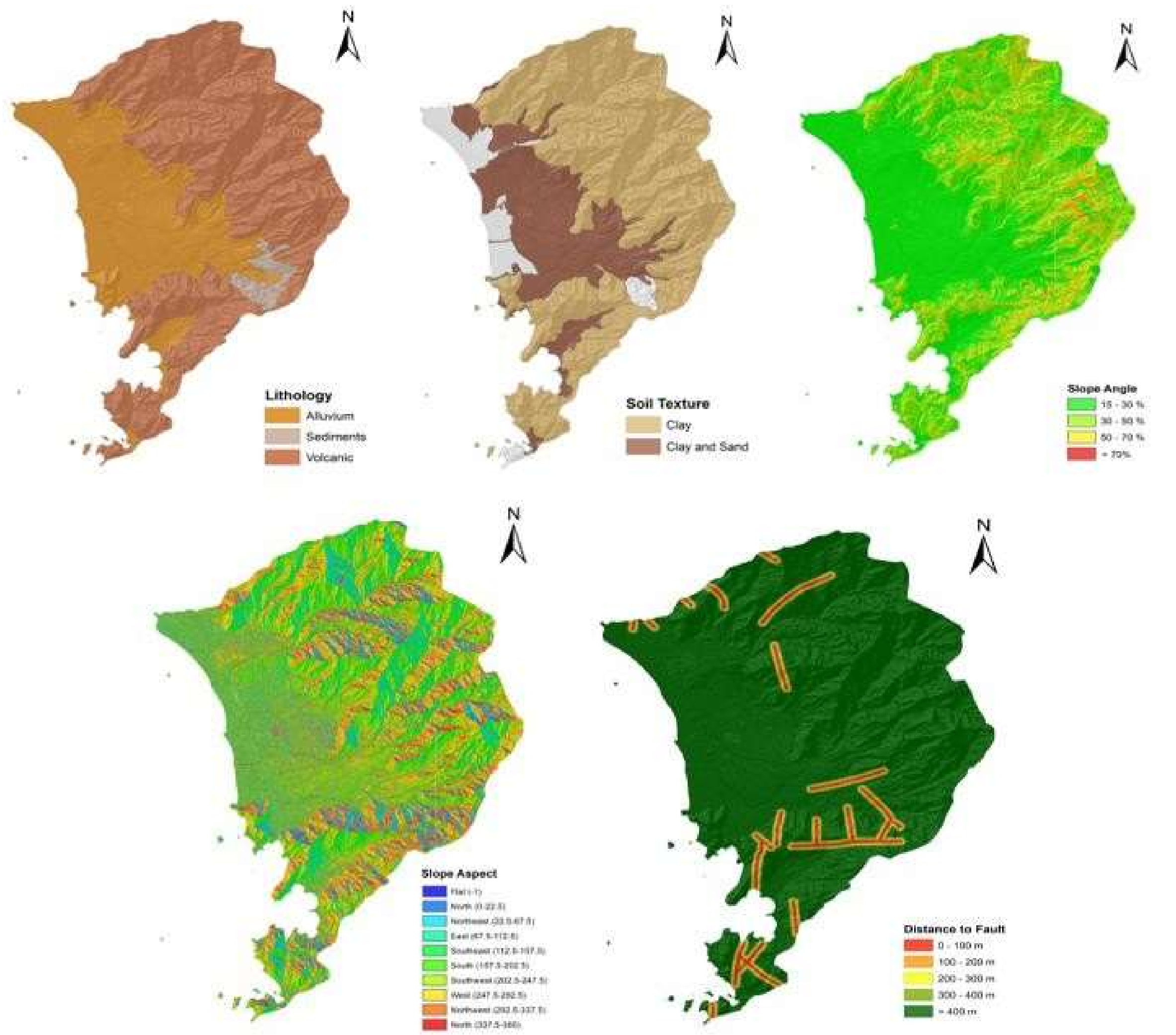

Fig. 1: Thematic maps used in this study, (a) Litologhy; (b) Soil Texture; (c) Slope Angle; (d) Slope Aspect; (e) Distance to Fault.

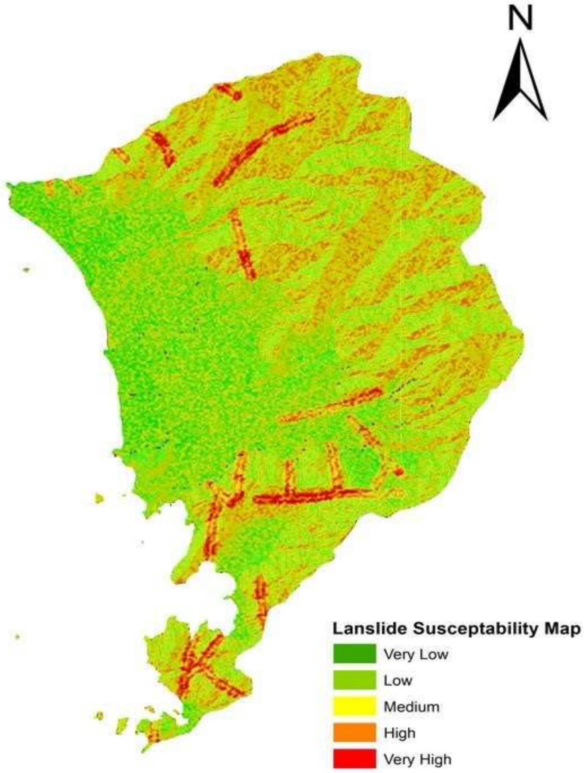

Fig 2: Landslide Susceptibility Map.

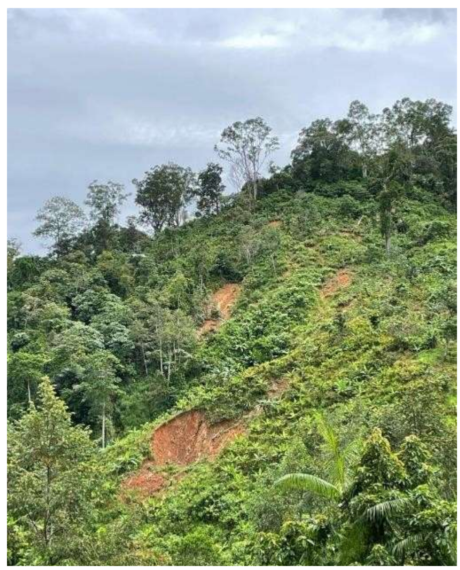

Fig. 3: (a) (A road settled at the slope affected by a landslide; (b) Forest carried by a mass movement.

Slope Angle: Every investigation into the likelihood of landslides takes slope into account because the slope is frequently utilized to study landslide probability (Dai et al. 2001, Lee & Talib 2005, Nurdin & Kubota, 2018). The direct sunshine that strikes heavily sloped slopes and cleared terrain dries the soil and raises the risk of landslides. The slope angle affects the shear pressures operating on hill slopes, so it's generally regarded as one of the most important parameters for landslide modeling (Dai et al. 2001). Landslides increased in the study area as slope steepness increased. 20% of all landslides happened on slopes between 30 and 45 degrees (Fig. 1).

Slope Aspect: The degree of vegetation coverage, surface weathering, and surface evaporation are all impacted by the varying solar radiation that the surface receives depending on the slope's aspect, which also affects the likelihood of landslides. According to the slope aspect, the DEM data can be categorized into 9 types: 0° to 40, 40" to 80", 80-120", 120-160", 200-240", 240-280", and 320- 360". Landslides in the research area typically occur between 160 and 200 of slope aspect (Fig. 1), and those with this slope aspect account for the biggest share (21%), according to the slope aspect backdrop (Li et al. 2021).

Fault: In fault zones, rock and soil structures are prone to collapse and weathering, which has a certain impact on the occurrence of landslide disasters. ArcGIS calculates the Euclidean distance for fault data in your study area. Due to the fault distance, the landslide disasters in the study area are mainly concentrated in the fault distance of 0-2361m, and the landslide disaster in the fault distance of 0-1127m is the most frequent, accounting for 29% (Fig. 1) (Sun et al. 2020, Li et al. 2021).

Soil Texture: With the application of a probabilistic approach to soil texture, the physical characteristics of soil are frequently used for parameter analysis of landslides. Other physical soil characteristics like water infiltration, porosity, water permeability, and groundwater's ability to pass can be impacted by soil texture. The Food and Agricultural Organization (FAO) of the United Nations (, the Centre for Soil and Agroclimatic Research, and the United States Department of Agriculture system are used to classify soil in Indonesia. The three varieties of soil in the study area-Dystrandepth, Dystropepts, and Tropaquepts-all belong to the Andosol family (Fig. 1). The soil type of Dystrandepts is where the majority of landslides occur (77, 25%). This might be related to the location of Dystrandepts deposition, mostly found at higher altitudes. This class accounts for the largest proportion of the areas (Nurdin & Kubota 2018).

Landslide Vulnerability Area

Based on the landslide vulnerability analysis results, five levels of landslide vulnerability were obtained in the Padang City area: very low, low, medium, high, and very high. The distribution of landslide vulnerability levels can be presented in Fig. 2.

Based on Table 1, the area of landslide vulnerability in the city of Padang is obtained as follows:

Table 1: Landslide vulnerability in the city of Padang.

landslide hazard level	Wide (ha)	% ofArea
Very Low	10069.4283	14.73
Low	28854.38173	42.21
Medium	20284.87757	29.67
High	7605.009513	11.12
Very High	1550.376236	2.27
Total	68364.07335	100

The data above shows that the level of landslide vulnerability in Padang City is low, with a total area of 288854.38173 ha with a percentage of 42.21%. However, the government must not be complacent about this, bearing in mind that other areas have very high, high, and medium levels of vulnerability. Fig. 3 shows a road settled at the slope affected by a landslide and a forest carried by a mass movement.

Mitigation measures for landslides can include structural and non-structural approaches. Structural measures include the construction of retaining walls, slope stabilization, and drainage systems. Non-structural measures include land-use planning, zoning, and early warning systems. The effectiveness of these measures depends on the specific characteristics of the landslide and the local conditions (Assilzadeh et al. 2010).

Identifying and mitigating the landslide vulnerability area is critical for reducing slide risks. However, there are challenges associated with this process. One of the significant challenges is the lack of accurate data on landslide occurrences and their causes. In many regions, landslides are not well documented, and the historical data may not be comprehensive or reliable. This makes it difficult to develop accurate landslide susceptibility maps, and identify areas requiring mitigation measures.

Another challenge is the difficulty in predicting landslides. Landslides can occur suddenly and without warning, making developing effective early warning systems challenging. Additionally, the occurrence of landslides is influenced by various factors, including climate, geology, and human activities, making it difficult to predict their occurrence accurately.

Despite these challenges, identifying and mitigating the landslide vulnerability area are essential for reducing landslide risks. In addition to protecting communities and infrastructure, these measures can also have economic benefits. Landslides can cause significant damage to property and infrastructure, leading to economic losses. These losses can be reduced by identifying and mitigating the landslide vulnerability area, and the region's long-term economic viability can be maintained.

CONCLUSION

This study aims to utilize GIS to identify landslide-prone areas in Padang. From this utilization, the result is that the level of landslide vulnerability in Padang City is still low, with a total area of 288854.38173 ha with a percentage of 42.21%. The accuracy of the model might have been affected by the distribution of the random points (factors) used in this study. Therefore, we need to consider more factors and experiment with training and validating data in more detail to gain insight into the physical contributions of the factors to landslide occurrences.

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