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Landslide Susceptibility and Vulnerability Identification of the Greater Bogor Area in 2020

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Landslide events are among Indonesia's most devastating disasters. From 2014–2023, 7,235 landslide events occurred in Indonesia, hence, recorded as the third most frequent disaster after tornadoes and floods (BNPB, 2023). West Java Province is the second most frequent place for landslide events on a national scale. With 1,775 events happening from 2014–2023, landslide disasters caused the loss of 293 people and the destruction of 8,978 houses (BNPB, 2023). During the same period, the economic damage was estimated at around 17 trillion rupiahs in West Java province alone (BNPB, 2023). Silalahi et al. (2019) mentioned that the Greater Bogor Area, which includes Bogor City and Bogor Regency, suffers from an increasing trend of landslide events, from around 20 events in 2014 to 60 events in 2018, causing 39 deaths and 48 injuries since 2014. Those historical data reveal the severity of the damage from landslide events and, more importantly, the significance of efforts to mitigate the potential damage.

Due to the numerous factors that could induce landslide events, stakeholders must identify the likelihood of landslides in any given area to mitigate the risk of landslide events. Such identification requires landslide susceptibility mapping or zonation (Shano et al., 2020). According to Raghuvanshi et al. (2014) and Anbalagan (1992) in Shano et al. (2020), this method evaluates landslide susceptibility through factors related to geology, geomorphology, land use and land cover, rainfall, seismicity, and human activities, among others. Since the influencing factors significantly vary from place to place, landslide susceptibility zonation is required for proper landslide mitigation and management (Shano et al., 2020).

Landslide events negatively and dramatically alter the lives of people around the location. According to Lewis (1999) in Glade (2003), vulnerability relates to the consequences or results of the impact of a natural force, not the natural process or force itself. Vulnerability to landslides is usually considered equivalent to the destruction of the elements at risk. Those elements could be identified as buildings and population data (Galli & Guzzetti, 2007). In other words, the vulnerability aspect was commonly simplified to make the problem tractable due to the scarcity of vulnerability data (Galli & Guzzetti, 2007).

The landslide susceptibility zonation in the Greater Bogor Area uses the weighted overlay method, a widely used GIS-based semi-quantitative model for landslide susceptibility zonation (Shano et al., 2020). For each considered causative factor layer, the weighted overlay method requires every raster cell to be reclassified based on the preferred scale as per the significance of the contribution that particular factor class can have on landslide occurrence (Shano et al., 2020). The publication mentioned five different parameters to calculate the landslide susceptibility, namely precipitation, land use (LU), slope, rock type, and soil type, each with its significance or weight in the calculation. The weight used is based on the publication by the Center of Soil and Agroclimate Research (Pusat Penelitian Tanah & Agroklimat/Puslittanak) in 2014, as mentioned in Rahmad et al. (2018). Every piece of data for this calculation could be accessed freely on the internet, specifically on Google Earth Engine and government platforms such as the Ministry of Energy and Mineral Resources (EDM) GeoMap platform.

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According to the spatial model of the landslide susceptibility map in Figure 1 below, the southern part of the Greater Bogor Area is more prone to landslides. This phenomenon is due to the existing mountainous area in the south, which provides a steeper geographical profile that is naturally prone to landslide events (Ali et al., 2018). According to the LU classification, the northern part also contains many barren areas, crop fields, and shrublands. Those LU classes lack vegetation cover, which triggers and aggravates landslide occurrence (Singh et al., 2020; Sur et al., 2020; Altin & Gökkaya, 2018).

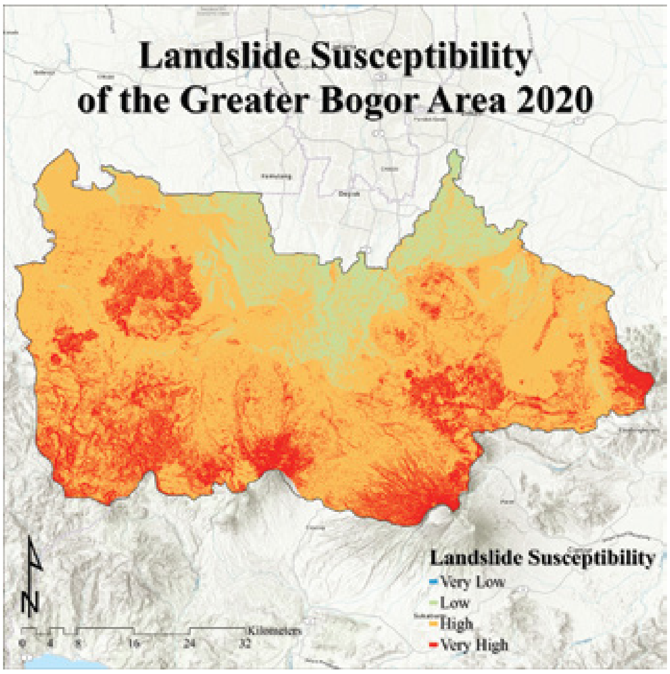

Figure 1 Landslide susceptibility map of the Greater Bogor Area

Table 2 Landslide susceptibility classes

	Very Low		Low		High		Very High	
Year	Ha	%	Ha	%	Ha	%	Ha	%
2020	0.46	0.00	34.342	11.06	206.425	66.46	69.835	22.48

In contrast, the central-to-northern part of the Greater Bogor Area appears less susceptible to landslide events. The stark difference is due to its relatively flat topography, making it less prone to landslide events (Ali et al., 2018). Urban build-up areas, water bodies, forests, and plantations dominate the LU classes.

Those classes have a small contribution to the probability of landslide events (Abedin et al., 2018; Singh et al., 2020). The precipitation aspect of the Greater Bogor Area contributes less to landslide susceptibility in general since the value is well-distributed throughout the region with Puslittanak's weighting schemes.

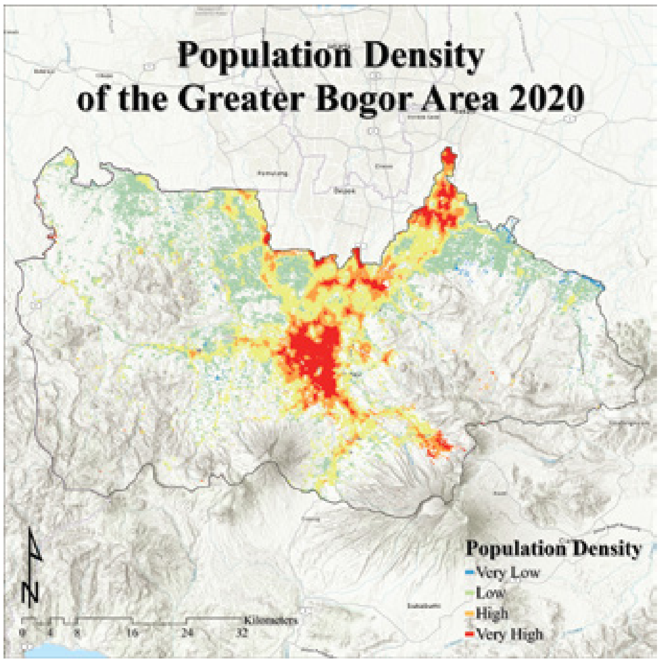

Figure 2 Population density in the Greater Bogor Area

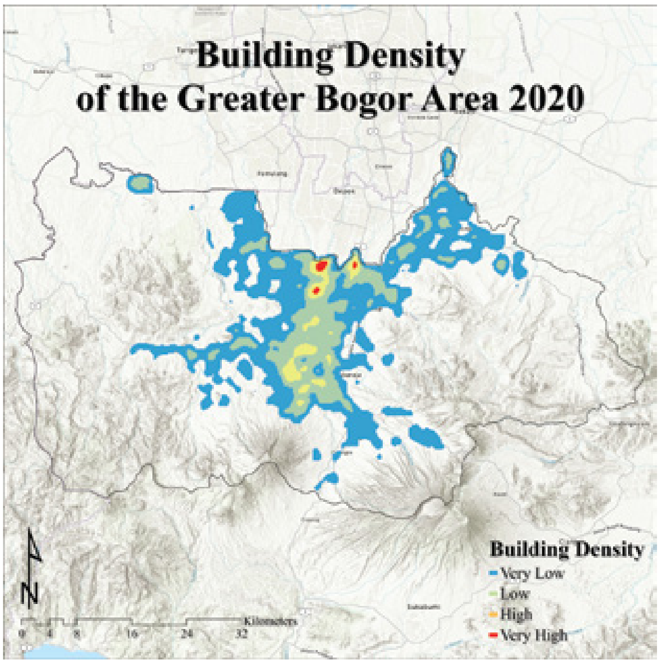

Figure 3 Building density in the Greater Bogor Area

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Table 2 Vulnerability identification in the Greater Bogor Area

Landslide Susceptibility	Population	Buildings
Very High	348,643	71,675
High	4,585,874	1,066,848
Low	2,521,115	712,568
Very Low	112	2

Vulnerability identification was carried out by investigating two elements at risk: population density and building footprint, as seen from the figures above. The analysis exposes that most of the population lives in an area with "High" landslide susceptibility, followed by areas with "Low" and "Very High" landslide susceptibility. The same goes for vulnerable buildings, where most of the building is within the "High", "Low", and "Very High" landslide susceptibility classes, respectively. Those findings were confirmed by Nurwanda & Honjo (2020) since both population and buildings are within the densely populated urban area due to the urbanization phenomenon in the central-to-northern area. On the other hand, the "Very High" susceptible area is located in a sparsely populated mountainous region with a lesser population and building in the south (Nurwanda & Honjo, 2020).

Every analysis for this article was collected from secondary data. For instance, the precipitation data were interpolated using Kriging interpolation from several precipitation stations to get a raster layer that covers the entire Greater Bogor Area (Prasad & Sushma, 2018; Wardah et al., 2011). Land use data were derived from Landsat 8 imagery, utilizing supervised classification with the Random Forest algorithm (Ge et al., 2020; Na et al., 2009; Tian et al., 2016). The population density data provided by WorldPop was derived using semi-automatic dasymetric modeling through a novel random forest regression tree-based mapping approach at ~100 m spatial resolution (Stevens et al., 2015).

Building footprints were identified using the U-Net model, a widely used model in satellite image analysis (Sirko et al., 2021). Soil type, rock type, and DEM were collected from government platforms. Therefore, further validation is needed to confirm the accuracy of this analysis.

The landslide susceptibility zonation and vulnerability identification are paramount for supporting relevant stakeholders and mitigating the potential damage. Multiple studies have also suggested that the southern part of the Greater Bogor Area is prone to landslides (Elfriede et al., 2019; Permadi et al., 2018; Wicaksono et al., 2020). It reflects the need to strengthen the population's resiliency in the southern part of the region. Such goals can be met by, for instance, offering vulnerable populations opportunities to develop their capacity (Sumantri et al., 2021). With close coordination with the Local Disaster Agency (BPBD), local government, and local communities from the Greater Bogor Area, a capacity-building program could empower society by improving disaster management-related activities, including prevention, mitigation, preparedness, and emergency response (Sumantri et al., 2021). City planning agencies could also benefit from this analysis by avoiding susceptible areas for infrastructure development to minimize the number of vulnerable communities. Additionally, this analysis can aid government organizations in better preparing post-disaster initiatives, including rehabilitation, reconstruction, reforestation, and conservation, to build a more resilient society (Sumantri et al., 2021).

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