

Spatiotemporal Dynamics of Flood Susceptibility in Rapidly Urbanizing Areas: A Multi-Criteria Analysis of Tangerang City (2017–2025)

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Abstrak

Banjir merupakan bencana meteorologis yang merugikan baik material maupun non-material. Kejadian banjir tidak hanya dapat dilihat dalam ruang yang sempit, tetapi juga dari kejadian sebelumnya, sehingga diketahui tren naik atau turun. Penelitian ini menganalisis persebaran dan perubahan kerawanan dari 2017 sampai 2025. Sistem informasi geografis digunakan sebagai metode dengan pendekatan *Multi Criteria Decision Analysis* (MCDA) dengan algoritma Weight Sum dan pembobotan menggunakan SMARTER, serta parameter *land use/land cover*, elevasi, kemiringan, curah hujan, tipe tanah, jarak ke sungai, dan *normalized difference vegetation index*. Penelitian ini menghasilkan wilayah klasifikasi rendah atau aman yang mengalami penurunan, dari 5.065,32 hektar di tahun 2017 menjadi 3.519,68 hektar di tahun 2025, sementara klasifikasi kerawanan tinggi dan sangat tinggi naik sekitar 300 hektar dan 1200 hektar. Kecamatan Pinang merupakan wilayah yang mengalami perubahan, dari klasifikasi tinggi menjadi sangat tinggi sekitar 456,83 hektar. Bersama Tangerang dan Pinang, wilayah ini mengalami perubahan klasifikasi dari rendah atau aman menjadi tinggi, kurang lebih 1,5 hektar. Distribusi spasial kerawanan banjir memiliki pola yang sama, di utara Tangerang sangat rendah, mengalami degradasi, dan ke selatan menjadi sangat tinggi, termasuk wilayah kecamatan Pinang dan Ciledug. Hal tersebut menjadi masukan untuk pengambilan tindakan mitigasi dan tata guna lahan yang ramah terhadap lingkungan.

Kata kunci: Sistem Informasi Geografis, Kerentanan Banjir, MCDA

Abstract

Flooding, a meteorological disaster, causes material and non-material losses in society. Flood events can be observed not only in confined spaces but also from previous incidents, allowing the identification of upward or downward trends. This study analyses the distribution and changes in susceptibility from 2017 to 2025. Geographic Information System (GIS) is used as the method, with a Multi-Criteria Decision Analysis (MCDA) approach, employing the Weight Sum algorithm and weighting with SMARTER, using parameters such as land use/land cover, elevation, slope, rainfall, soil types, distance to rivers, and the normalized difference vegetation index. The study results show that the low or safe classification area decreased from 5,065.32 hectares in 2017 to 3,519.68 hectares in 2025, while high and very high susceptibility classifications increased by approximately 300 hectares and 1,200 hectares, respectively. Pinang District experienced a change from high to very high classification, covering about 456.83 hectares. Along with Tangerang and Pinang, this area also saw a shift from low or safe classification to high, covering approximately 1.5 hectares. The spatial distribution of flood susceptibility exhibits a pattern where the northern part of Tangerang is very low and degrades southward to very high, including the Pinang and Ciledug districts. These findings serve as input for implementing mitigation measures and environmentally friendly land use planning.

Keywords: Geographic Information System, Flood Susceptibility, MCDA

Introduction

Floods have become one of the most destructive hydrometeorological disasters worldwide, resulting in economic damage (Yu et al., 2022), hunger (Atanga & Tankpa, 2021), and infrastructure damage (Allaire, 2018). Total losses due to flooding with an average annual loss of USD 388.4 billion in 2025 and it is the most frequent disaster, accounting for 50% of all disasters worldwide. (UNDRR, 2025). The frequency and severity of floods are rising due to climate change and unchecked urban growth, especially in developing nations (Seemuangngam & Lin, 2024). In Indonesia, floods annually worsen economic conditions, disrupt crops, and damage ecosystems. (Farid et al., 2025). Jabodetabek as the most important economic region in Indonesia faces a high risk of flooding (Suni et al., 2024). Tangerang City, part of Jabodetabek, is a city with high economic growth and well-developed infrastructure, underscoring the urgent need to develop a flood susceptibility map as a future mitigation measure (Pribadi et al., 2022). This condition highlights the urgent need to develop a flood susceptibility map to support future mitigation planning.

Tangerang City is an area vulnerable to flooding. According to BPBD data, there have been 79 incidents in 2017 and 2025 (BPBD, 2025). This is caused by the

region's low-lying terrain, high rainfall, and division by the Cisadane River. Additionally, rapid urbanization has led to changes in land use and a reduction in water absorption areas, increasing surface runoff (Zhou et al., 2018). Furthermore, the high population density in Tangerang City contributes to the flood risk (Tang et al., 2025). Therefore, variables such as rainfall, topography, land use, river networks, and population density are important factors in flood risk analysis in Tangerang City (Suni et al., 2024).

Flood Susceptibility refers to the likelihood of an area experiencing flooding (Atanga & Tankpa, 2021; Fauzi & Handayani, 2024). Although many studies have examined flood susceptibility, there are still few that look at changes in flood susceptibility in relation to land use and rainfall (I. Ahmad et al., 2025; Donoso et al., 2026). This research aims to fill this research gap by comparing two different time periods, between 2017 and 2025 (Prasadjaja & Singgalen, 2025; Zhou et al., 2018). Time differences can reveal changes, whether the place is becoming safer or the opposite. The selected parameters are distance to rivers, land use/land cover, proximity to roads, rainfall, soil type, elevation, normalized difference vegetation index (NDVI) and slope (Kollias et al., 2025). Distance from rivers indicates

potential for direct runoff (S. Ahmad et al., 2024), land use shows land absorption ability (Mansida et al., 2025), rainfall gauges hazard severity (Ding et al., 2024), soil type affects infiltration rates; NDVI explains vegetation density, and elevation and slope govern surface water movement (S. Ahmad et al., 2024).

Spatial approaches for assessing flood susceptibility include qualitative like expert judgment, semi – qualitative like multi criteria decision analysis (MCDA), and quantitative methods like the Frequency Ratio (FR) (Mahdizadeh Gharakhanlou & Perez, 2023), Logistic Regression (LR) (Mansour et al., 2024), and Machine Learning (ML) models such as Random Forest (RF) (Rahimi et al., 2026). Statistical techniques like FR and LR are effective for identifying relationships between environmental factors and flood events (Mahdizadeh Gharakhanlou & Perez, 2023), while machine learning models are capable of capturing nonlinear patterns with high accuracy, though they require complete and reliable historical data (Rahimi et al., 2026). In this study, the semi qualitative, multi-criteria decision analysis based on weight sum overlay was chosen because it combines various parameters with importance weights derived from empirical studies and literature (Sukri et al., 2025). Meanwhile, the weighting uses the

Simple Multi-Attribute Rating Technique Exploiting Ranks (SMARTER), which has proven to be effective and efficient (Zhu, 2024). The two approaches provide advantages such as simplicity, interpretability, and high compatibility, especially in the context of limited data, in addition to the absence of historical flood event data (S. Ahmad et al., 2024).

This research aims to analyse the spatiotemporal distribution of flood susceptibility in Tangerang City between 2017 and 2025. The resulting spatial maps are intended to support decision-making for spatial planning and disaster risk reduction. Theoretically, it presents an integrative model combining biophysical and social infrastructure parameters. Practically, it provides a basis for local governments to develop mitigation strategies in the face of flood disasters.

Research Method

Tangerang City is located between 6°05'–6°15' S and 106°33'–106°44' E, encompassing 13 sub-districts. Over the past decade, its population has grown rapidly to over 1.8 million residents, increasing demand for educational facilities. The city experiences a tropical monsoon climate with high annual rainfall, averaging 2,000–2,500 mm, peaking from December to February. It lies in lowland areas at 0–18 meters above sea level (BPS,

2024). Land-use changes, especially the conversion of green and infiltration zones into built-up areas, have increased flood risk (Mansida et al., 2025). Furthermore, the expansion of built-up zones has increased the likelihood of flooding. Therefore, considering land use land cover (LULC) and rainfall as controlling factors is important to observe flood susceptibility.

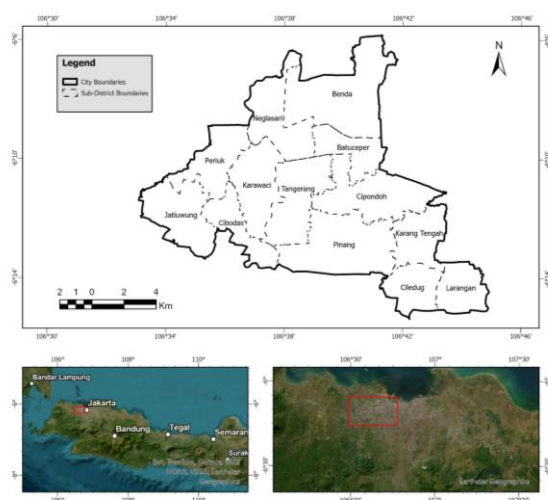


Figure 1 Location Study

This study utilised various spatial datasets to assess flood susceptibility in Tangerang City. Based on Table 1, explain that the parameters used are Land Use Land Cover (LULC), Elevation, Slope, Rainfall, Soil Types, Distance to River, and NDVI. Land-use information was obtained from Sentinel-1 imagery to classify different land cover types (<https://livingatlas.arcgis.com>).

The distances from rivers, elevation, and slope were derived from the Rupa Bumi Indonesia (RBI) maps provided by the

Geospatial Information Agency (BIG) (<https://tanahair.indonesia.go.id/>). Rainfall data were collected from the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS), which offers high spatial resolution and extensive temporal coverage (<https://www.chc.ucsb.edu/>). NDVI is acquired from Landsat 8 for 2017 and Landsat 9 for 2025 (<https://earthexplorer.usgs.gov/>). All these datasets were combined to develop explanatory variables for flood susceptibility in the context of 2017 and 2025.

SMARTER (Simple Multi-Attribute Rating Technique Exploiting Ranks) is one of the methods from Multi-Criteria Decision Analysis (MCDA) used to determine criterion weights based on the order of importance (ranking) provided by experts or decision-makers (Sukri et al., 2025). This method is designed to address difficulties in directly assigning numerical weights, so respondents only need to prioritize criteria from the most important to the least important. SMARTER has an equation (Zhu, 2024) :

$$Wi = \frac{1}{2} \sum_{j=1}^n \left(\frac{1}{j} \right) \dots \dots \dots (1)$$

Where :

W_i = criterion weight i

n = number of criteria

i = ranking order of criteria

SMARTER uses the Rank Order Centroid (ROC) approach to convert rankings into proportional numerical weights (Zhu, 2024). This method is widely used in Geographic Information System (GIS) research because it is simple, consistent, and easy to implement (Feizizadeh & Blaschke, 2013). In addition, the

SMARTER method has ease and simplicity in determining rankings and criteria, making the calculations faster and more transparent. However, it has a weakness when faced with complex data compared to the AHP method (Isgenderzade et al., 2026).

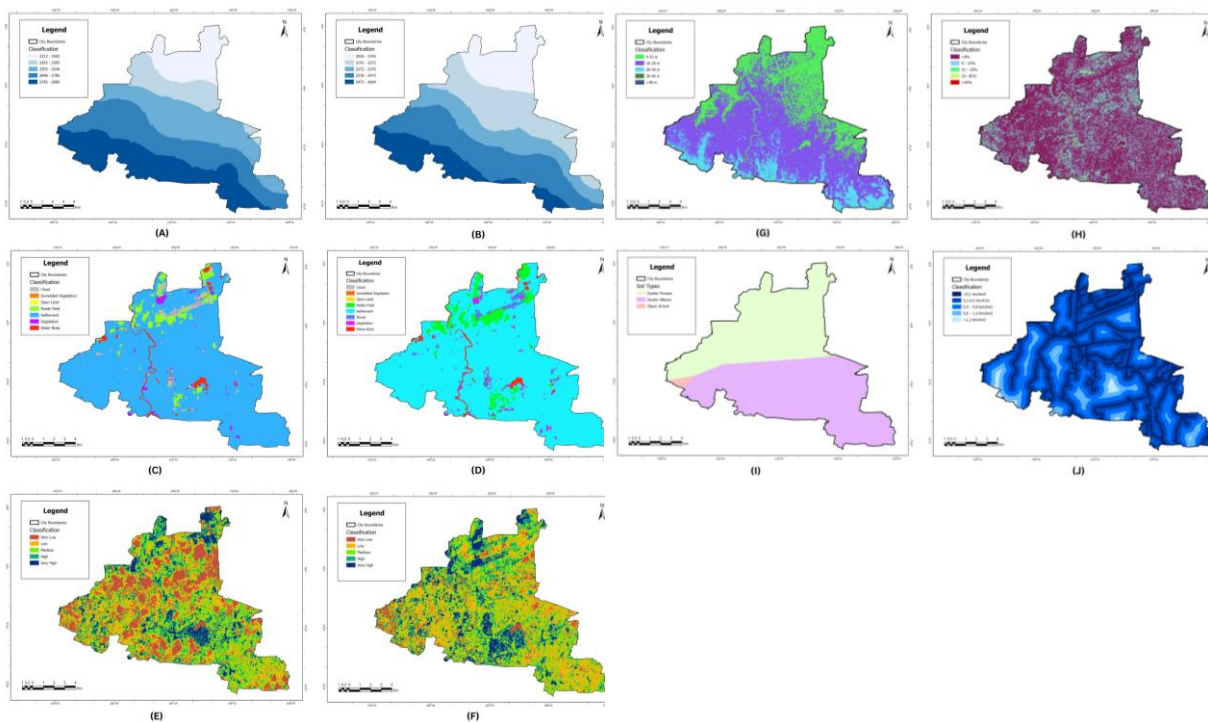


Figure 2 (A) Rainfall of 2017, (B) Rainfall of 2025, (C) LULC of 2017, (D) LULC of 2025, (E) NDVI of 2017, (F) NDVI of 2025, (G) Elevation, (H) Slope, (I) Soil Types, (J) Distance to River.

The Weighted Sum method (also referred to as Weighted Linear Combination or Simple Additive Weighting) is a criterion aggregation method in multi-criteria analysis that assigns scores and weights to each parameter by summing the product of each parameter's score and its

corresponding weight (Malczewski, 1999). This method is part of the Spatial Multi-Criteria Analysis (SMCA) framework. In this study, scoring was performed on a scale of 1 to 5 (Sukri et al., 2025).

The formula for the Weighted Sum method is as follows (Malczewski, 1999):

$$S_i = \sum (W_j \times X_{ij}) \dots\dots\dots (2)$$

relative weight of the j-th criterion, and X_{ij}

where S_i represents the aggregate score
for the i-th spatial location, W_j denotes the

is the normalized value of the j-th criterion
at the i-th location (Zhu, 2024).

Table 1 Parameter of Flood Susceptibility				
Parameter	Classification	Weight (%)	Scoring	Reference
Land Use Land Cover (LULC)	Built Up Area, Flood Vegetation, Water Body	22,76	5	(Fauzi & Handayani, 2024)
	Bare Land		4	
	Crop Land		3	
	Grassland		2	
	Trees		1	
Elevation	0-10 m	7,28	5	(Putra et al., 2023)
	10-20 m		4	
	20-30 m		3	
	30-40 m		2	
	>40 m		1	
Slope	<8%	10,85	5	(Prasetyo & Wulandari, 2023)
	8-15%		4	
	15-25%		3	
	25-40%		2	
	>40%		1	
Rainfall	>2168	37,04	5	(Wibowo et al., 2022)
	1751 - 2167		4	
	1251 - 1750		3	
	751 - 1250		2	
	<750		1	
Soil Types	Gleyic Acrisol	2,04	5	(Dewi & Nurlela, 2023)
	Dystric Fluvisol		3	
	Dystric Nitosol		1	
Distance to River	<0,1 km/km2	15,61	5	(Setiawan et al., 2023)
	0,1 - 0,4 km/km2		4	
	0,4 - 0,8 km/km2		3	
	0,8 - ,2 km/km2		2	
	>1,2 km/km2		1	
NDVI	Very High	4,42	5	
	High		4	
	Medium		3	
	Low		2	
	Very Low		1	

Results and Discussion

Spatial Distribution of Flood Susceptibility

Changes in flood susceptibility in 2017 and 2025 can be seen in Figure 3, which shows the changes in flood susceptibility

levels between 2017 and 2025. Based on the pattern analysis, the northern area is relatively safe, while moving southward, the classification indicates increasing vulnerability. This demonstrates a uniform pattern, which implies the influence of

physical or socio-environmental factors (Mahdizadeh Gharakhanlou & Perez, 2023).

Figure 4 explains the distribution of each flood susceptibility criterion. In 2017, the study area was dominated by high classification zones, covering approximately 11,209.75 hectares, while low and very high (safe) classifications covered 5,065.32 hectares and 1,248,07 hectares, respectively. The very low class, which is considered safe, had a narrow area of only 211.55 hectares. This condition can be interpreted as land use, where settlements in Tangerang City have limited drainage channels and are accompanied by high rainfall (Mansida et al., 2025).

In 2025, the high danger classification had the largest area, covering 11,634.82 hectares, while the very high and low areas were 2,299.68 hectares and 3,519.68 hectares, respectively. Then, the very low or very safe classification was the smallest, with an area of 279.52 hectares. Compared to previous years, a significant change is observed in the increase of very high areas by around 1,051.61 hectares. Meanwhile, areas with a very low increase, but not as large as very high danger mining, numbered 67.97 hectares, and there is also an increase in the great danger classification, covering 425.07 hectares. This indicates an increase in the level of flood disaster vulnerability in Tangerang City.

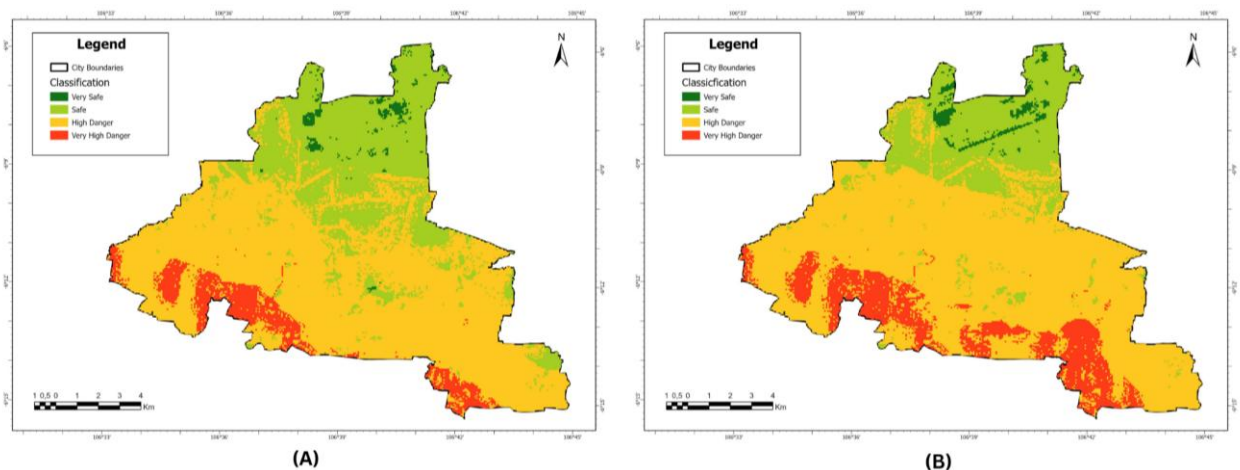


Figure 3 (A) Flood Susceptibility 2017 (B) Flood Susceptibility 2025

A decrease in high classification indicates changes in the area's conditions that may reduce flood hazard levels, whether due to land-use changes, increased precipitation, or other environmental factors (Tang et al., 2025). Conversely, an

increase to the very High danger class indicates areas experiencing an accumulation of flood trigger factors, especially in regions with low absorption capacity, relatively low elevation, and increased impervious surfaces due to

human activity (Sunı et al., 2024).

This finding reinforces the concept that flood susceptibility is a dynamic phenomenon influenced by interactions between natural factors and anthropogenic activities (Sukri et al., 2025). Previous studies have shown that land use changes and urbanization can increase surface runoff and concentrate flow, thereby raising the risk of flooding in specific locations (Mansida et al., 2025). From a regional management perspective, the changes in flood susceptibility patterns between 2017 and 2025 suggest that mitigation strategies need to be spatially targeted and cannot be uniformly applied (Rupngam & Messiga, 2024). Areas that have experienced an increase to the very high danger class should be prioritized for strengthening drainage systems, river revitalization, land use control, and protection of water absorption zones. Meanwhile, regions that have experienced a decrease in susceptibility should be maintained to prevent a return to higher risk levels. The temporal changes in flood susceptibility illustrate that disaster risk is not a static condition but can change in response to environmental dynamics and human activities.

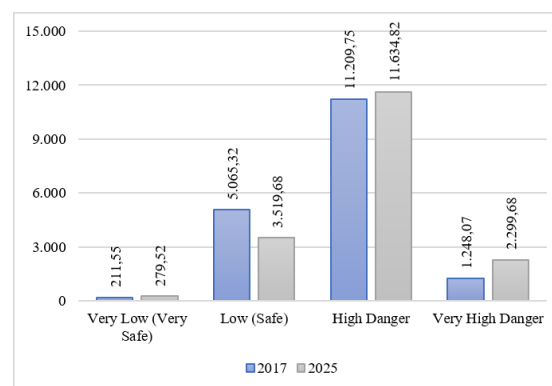


Figure 4 Spatial Distribution of Flood Susceptibility

Change Analysis of Flood Susceptibility

Based on Figures 4 and 5, it shows that the No Change classification is the most extensive, covering 14,767.542 hectares. Meanwhile, the change from low or safe classification to high has an area of 1,498.835 hectares, and is almost the same as the change from high to very high, which covers 1,090.8 hectares. These findings indicate an increase in flood hazard levels in certain locations, suggesting that some areas are experiencing an increase in flood trigger factors (Mansida et al., 2025; Tang et al., 2025). This condition may be related to land cover changes, increased impervious surfaces, reduced infiltration areas, and changes in drainage system capacity (Fauzi & Handayani, 2024).

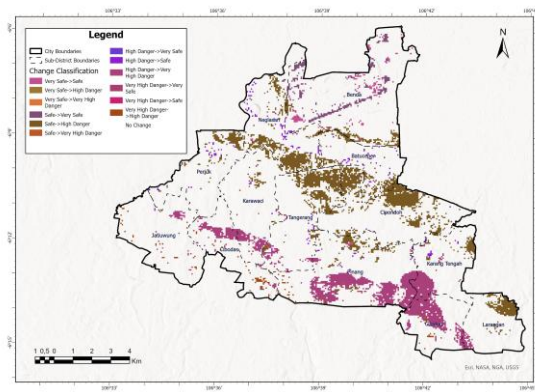


Figure 5 Map of Change Distribution of Flood Susceptibility

Conversely, some areas experienced a decrease in susceptibility levels, such as the reclassification from High to Safe covering an area of 77,079 hectares and from Safe to Very Safe covering an area of 144,679 units. These changes indicate an improvement in the region's ability to reduce the potential for flooding, likely influenced by changes in environmental management or improvements in flood control infrastructure (Mahdizadeh Gharakhanlou & Perez, 2023).

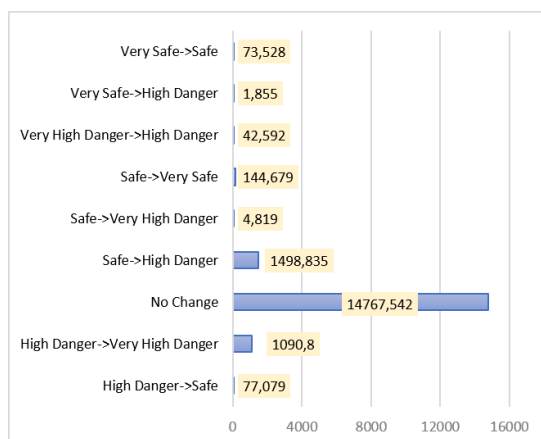


Figure 6 Change Distribution of Flood Susceptibility

The distribution of changes between districts shows that all districts have areas that remain unchanged, such as Benda with an area of 2,182.17 hectares, which has the second-highest very low classification after Pinang, with an area of 2,095.942 hectares. Pinang District has the second-largest area with a constant classification, covering 1,653.73 hectares, but on the other hand, this district experienced a significant change from high to very high classification, covering about 456 hectares. This area is considered to be unaffected by flood risk (Figure 5). This pattern indicates that urban development and the physical characteristics of the area play a role in shaping the spatial variation of flood risk (Atanga & Tankpa, 2021).

These findings reinforce previous research stating that flood risk is a dynamic phenomenon influenced by the interaction between natural factors and human activities (Donoso et al., 2026; Fauzi & Handayani, 2024; Mansida et al., 2025). The change in classification from safe to high danger suggests that land use transformation can increase surface runoff and elevate flood risk, especially in areas with high development density (Tang et al., 2025). Additionally, this can be driven by increased rainfall and poor drainage conditions in the region. This research examines flood susceptibility over time, not

just within a single period. Understanding these changes is important to support risk-based regional management, especially in determining priority mitigation locations through land use control, improving drainage systems, and protecting water absorption areas (I. Ahmad et al., 2025; Zhou et al., 2018).

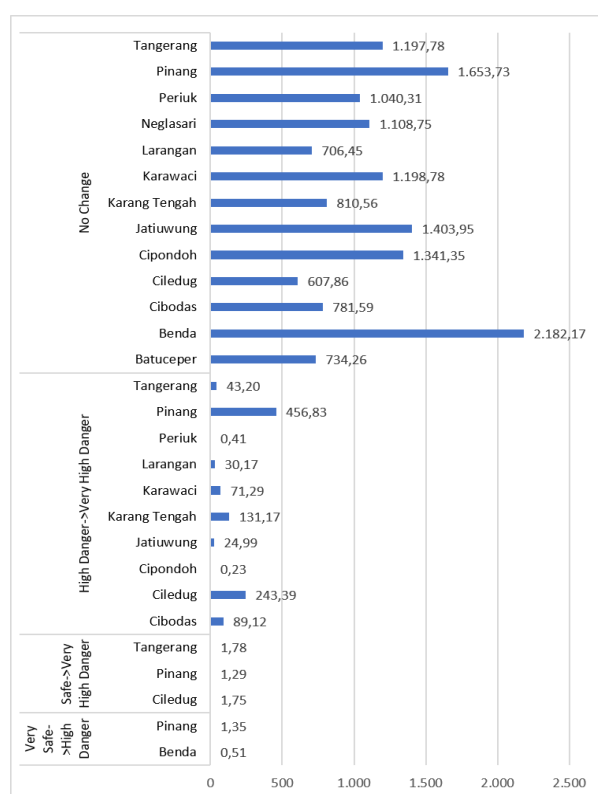


Figure 6 Comparison of Changes Between Districts

Conclusion

Flooding is a disaster that often occurs in Jabodetabek. This study aims to analyze the distribution and changes in flood susceptibility over a nine-year period, from 2017 to 2026. The research approach uses Multi-Criteria Decision Analysis with Weight Sum and weighting with

SMARTER, as well as seven parameters as factors driving flood occurrence.

This study results in changes in spatial distribution between 2017 and 2025. Areas classified as low or safe experienced a decrease, and very low increased, with cover of minus 1,545.64 hectares and 67.97 hectares, while high and very high susceptibility classifications increased by approximately 425.07 hectares and 1.051,61 hectares, respectively. Additionally, an analysis of each district shows that Pinang is an area that experienced a change from high to very high classification, covering about 456.83 hectares. Along with Tangerang and Pinang, this area also saw a shift from low or safe classification to high, covering approximately 1.5 hectares. The study indicates a positive trend in the increase of very high susceptibility, highlighting the importance of regional mitigation, land use adjustments, river cleaning, and revitalization in the future. Furthermore, to make the susceptibility analysis more holistic, it could include drainage networks, population density, and economic conditions, with a comparison to machine learning approaches.

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