



SCENARIO-BASED FLOOD HAZARD AND RISK ASSESSMENT USING MULTI-CRITERIA ANALYSIS IN SEMARANG CITY

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ABSTRACT

This study assessed flood hazard and risk in Semarang City, where increasing hydrometeorological pressures and rapid urban development have heightened flood impacts. An integrated Geographic Information System and multi-criteria spatial modeling approach was applied by combining terrain parameters (slope, height above nearest drainage, distance to stream), hydrological factors (curve number, total precipitation, effective precipitation), and demographic indicators representing social vulnerability. Physical parameters were derived from DEM-based processing and rainfall interpolation, while vulnerability was quantified from population structure, education level, and density. Three hazard scenarios were generated using different weighting schemes, and the resulting hazard layers were multiplied by the social vulnerability index to produce spatially explicit risk maps. Scenario 1 produced hazard patterns more strongly associated with drainage networks and terrain, while Scenario 2 generated more dispersed patterns under the stronger influence of effective precipitation. Scenario 3 formed broader precipitation-driven zones. Flood-risk assessment showed that Scenario 2 had the largest combined High and Very High risk area (13,849.92 ha; 42.00%), followed by Scenario 1 (13,190.40 ha; 40.00%) and Scenario 3 (12,940.01 ha; 39.24%). Validation using 86 ground-referenced points showed the highest model performance for Scenario 1, with an Overall Accuracy of 90.12% and a Kappa coefficient of 0.80, followed by Scenario 3 at 89.53% and 0.79, while Scenario 2 reached 84.88% and 0.70. The results show that changes in parameter weighting alter both spatial risk patterns and predictive performance across Semarang City.

Keywords: flood hazard; flood risk; GIS; multi-kriteria analysis; Semarang

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1. INTRODUCTION

Floods constitute the natural hazard that affects the largest proportion of the global population (Rogers et al., 2025). Between 2000 and 2018, an estimated 250–290 million people were directly impacted by flood events, occurring in regions where population figures simultaneously increased by nearly 24% (Tellman et al., 2021). Although floods are natural processes that cannot be entirely prevented, well-designed flood risk reduction strategies can mitigate their adverse consequences. The success of such strategies depends heavily on the accuracy of flood risk prediction. Therefore, the first step in any mitigation effort is to assess flood risk levels and determine the appropriate structural and non-structural measures needed to reduce potential impacts. In addressing the persistent threat of floods, researchers have increasingly adopted advanced remote sensing technologies and geospatial analytical approaches to support comprehensive flood risk assessment (Basak et al., 2022; Jha & Gundimeda, 2019; Matheswaran et al., 2019; Pandey et al., 2010; Sarkar et al., 2022; Swain et al., 2020; Tripathi et al., 2022).

Rising global temperatures have intensified rainfall extremes and increased global flood frequency (Şen 2018; Couñago et al., 2024) causing economic losses (Slinger et al., 2023), environmental degradation and water quality decline (Challies et al., 2016; Roccati et al., 2018) as well as public health and psychological risks (Spiteri & Gauci, 2022). Climate-related hazards such as floods and droughts pose major global

challenges (Vaheddoost et al., 2023; Yilmaz et al., 2023; Ozcelik et al., 2024), with warming intensifying extreme events, including in Indonesia (Hirabayashi et al., 2013). Meteorological factors such as rainfall, temperature, humidity, and wind influence floods, landslides, and tornadoes, while climate dynamics continue to increase the frequency of hydrometeorological disasters. Indonesia classifies disasters into natural (earthquakes, eruptions, tornadoes, floods), non-natural (land-clearing fires, industrial accidents, pollution), and social categories.

Among various disaster types, floods are among the most frequent, particularly in urban areas, where they stem from both natural factors like high rainfall intensity and anthropogenic factors such as inadequate drainage, land-use changes, and low public awareness of environmental cleanliness. Waste disposal into rivers and drainage channels often causes blockages that worsen inundation during heavy rainfall, while climate change further heightens disaster risks and stresses urban environments. Tidal flooding, intensified by climate change, sea level rise, and severe land subsidence, has become a major threat to coastal cities globally, with pressures being most acute in densely populated and industrial coastal regions (Nicholls et al., 2021; Tay et al., 2022; Catalao et al., 2020). Addressing these complex drivers requires integrated solutions involving technological tools, spatial planning, and sustainable resource management (Herbanu et al., 2024; Murtiaji et al., 2023; Alshaikh et al., 2023).

In Indonesia, the coastal city of Semarang in Central Java exemplifies these challenges, as its environmental vulnerabilities expose it to increasingly severe inundation and significant socio-economic risks (Sunaryo et al., 2018; Syamsurizal et al., 2020; Susilowardhani, 2014). Semarang is a key focus of tidal flood research due to its extreme land subsidence of 2–19 cm per year among the highest in Indonesia (Pramono, 2021; Gumilar et al., 2013; Prasetyo et al., 2017; Abidin et al., 2013) driven largely by intensive groundwater extraction for industrial 30–40 million cubic meters and domestic needs 15–20 million cubic meters, which accelerates ground-level decline and worsens coastal flooding (Lo et al., 2021; Herdiansyah et al., 2022; Gumilar et al., 2013; Abidin et al., 2013; Adnan et al., 2020). Flood vulnerability is intensified by low-lying plains, reduced mangrove cover, and limited green infrastructure (Gumilar et al., 2013; Wijaya, 2016; Yasmin et al., 2022; Hamdani et al., 2022; Rahdriawan et al., 2021), with Northern Semarang lacking sufficient structural and ecological protections (Pramono, 2021; Kurniawan & Suharini, 2021). These combined anthropogenic and environmental pressures make the city central for studying integrated flood management strategies (Abidin et al., 2013; Ikhwanudin, 2017; Susilorini et al., 2019; Yoga et al., 2020) while its low coastal elevation and absence of natural buffers further exacerbate recurrent inundation and environmental impacts (Herbanu et al., 2024; Andreas et al., 2017; Kawata, 2022; Hanif et al., 2023).

This study aims to develop an integrated flood risk assessment for Semarang City by combining terrain-based hydrological indicators with rainfall- and runoff-derived parameters alongside demographic vulnerability metrics within a unified GIS and MCDA environment. The approach builds conceptually on the GIS–MCDM frameworks demonstrated in previous studies, particularly Rincón et al. (2018), who showed that spatially weighted combinations of HAND, distance to streams, slope, Curve Number, and precipitation can yield reliable flood hazard maps even in data-limited settings, and Ariyani et al. (2024), who emphasized the dominant role of rainfall, slope, land cover, and topography in shaping hazard formation across Indonesian watersheds. However, both works concentrate primarily on hazard or parameter weighting and provide limited examination of how alternative hydrometeorological driver combinations generate distinct spatial flood signatures at the city scale. Neither study explicitly integrates total precipitation and effective precipitation simultaneously, nor do they link physical hazard fields with demographic vulnerability patterns at subdistrict resolution. To address these gaps, this research incorporates both total precipitation and effective precipitation as complementary hydrometeorological drivers to capture direct rainfall impacts and runoff efficiency governed by land-surface characteristics. Additionally, this study introduces a multi-scenario hazard modeling structure that systematically varies the weighting of HAND, distance to stream, slope, Curve Number, and precipitation, allowing assessment of how different parameter emphases reshape the resulting hazard surface. A further contribution is integrating high-resolution physical indicators with subdistrict-level vulnerability metrics, enabling a spatially explicit flood risk product for Semarang City that

overcomes limitations in earlier susceptibility-focused studies by explicitly linking hydrological processes with population exposure.

2. DATA AND METHODS

2.1. Study Area

This research is conducted in Semarang City, the capital of Central Java Province, Indonesia. Semarang is one of the largest metropolitan cities on Java Island, with a total area of approximately 373.70 km², and is administratively divided into 16 sub-districts (*kecamatan*). The city lies on the northern coast of Java Island and serves as a major hub for government, trade, industry, and services in Central Java. Geographically, Semarang has highly varied topography, from coastal and lowland zones in the north to hilly, undulating terrain in the south. This elevation differential gives rise to the locally recognized phenomenon of “upper town” and “lower town,” leading to significant spatial variation in flood vulnerability. In the northern coastal zones, Semarang is also exposed to tidal inundation and seawater intrusion (commonly known as “rob”) due to sea-level rise and land subsidence. Semarang City is bordered by Kendal Regency to the west, Demak Regency to the east, and Semarang Regency to the south. To the north, its coastal zone faces the Java Sea. The interplay of physiographic diversity, rapid urban expansion, and suboptimal drainage systems renders Semarang among the urban areas with some of the highest flood risk levels in Indonesia. The combination of varied physical conditions accelerated urban development, and a growing incidence of flooding problems make Semarang City a highly suitable and relevant study area for spatial modelling using Geographic Information Systems (GIS) and Multi-Criteria Decision Analysis (MCDA) in flood risk assessment.

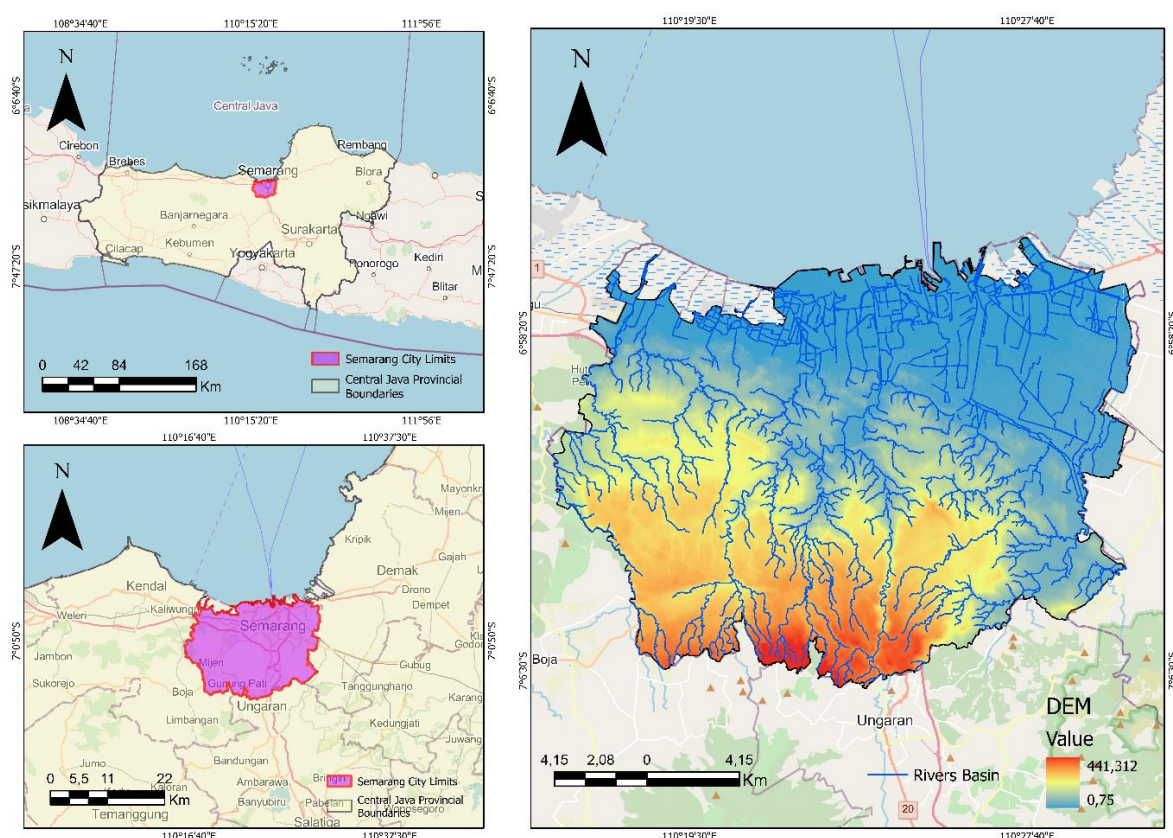


Figure 1. Research Location Map

2.2. Data Collection

This study applies an integrated Geographic Information System (GIS) and Multi-Criteria Spatial Modeling approach to evaluate flood risk in Semarang City. The methodology combines physical flood

hazard indicators with social vulnerability characteristics derived from multiple geospatial and demographic datasets. The physical parameters used in this study include topographic and hydrometeorological elements that significantly influence flood occurrence. Land use data were acquired from the ESA WorldCover dataset and analyzed through the Google Earth Engine (GEE) platform to determine runoff characteristics and associated Curve Number (CN) values (Zanaga et al., 2021). Additional hydrological representation was derived from soil texture-based Hydrological Soil Group (HSG) data sourced from the United States Geological Survey (Wieczorek et al., 2019).

Table 1. Data Sources

Data	Format	Resolution	Year	Source	Extracted Data
SRTM	Raster	30 m	-	Ina-Geoportal	Slope, HAND, Distance to Streams
Rainfall data	csv	-	October 2024 to March 2025	BMKG meteorological stations, including Ahmad Yani, Tanjung Emas, and the Central Java Climatology Station.	Total precipitation, Effective precipitation
Sentinel-1, Sentinel-2	Raster	10 m	2023	ESA WorldCover	Land Use, Curve Number
Hydrological Soil Group	Shapefile	-	-	Soil Texture USGS	Curve Number
Population density	Numerical Table	District	2024	BPS Semarang	Population density map
Population aged +75		District			Population aged +75 map
Population aged <4		District			Population aged <4 map
Elementary School Students or lower		Subdistrict			Population with elementary-level education or lowermap

2.3. Data Processing and Analysis

Data processing and analysis consisted of five sequential stages: (1) preparation and derivation of flood-hazard parameters, (2) standardization and reclassification of the hazard criteria, (3) scenario-based flood-hazard modeling using weighted multi-criteria analysis, (4) construction of the social vulnerability index and integration with flood hazard to derive flood risk, and (5) validation of the model outputs using observed flood and non-flood reference data. All spatial datasets were harmonized within a common spatial framework before raster-based analysis. Figure 2 summarizes the overall methodological workflow.

2.3.1. Flood Hazard Parameter Processing

Six physical and hydrometeorological parameters were processed to represent the major controls of flood occurrence in Semarang City: slope, Height Above Nearest Drainage (HAND), distance to stream, Curve Number (CN), total precipitation (TP), and effective precipitation (EP). Each parameter was derived from the datasets described in Section 2.2 and subsequently standardized into five ordinal hazard classes to enable integration within the MCDA framework.

a. Slope

A 30-meter resolution Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) was processed to generate slope. The slope variable was derived from SRTM data and processed in ArcGIS Pro

using the slope tool. The resulting slope raster was subsequently reclassified into five classes based on the classification scheme presented in Table 2.

b. Height Above Nearest Drainage (HAND)

The Height Above Nearest Drainage (HAND) model was generated from SRTM data using a sequence of hydrological processing tools in ArcGIS Pro, including Fill, Flow Direction, Flow Accumulation, Con, and Flow Distance. The Fill tool removes artificial depressions from the SRTM, producing a hydrologically correct surface. Flow Direction generates a raster indicating the direction of steepest descent for each cell, while Flow Accumulation produces a raster representing the cumulative upstream flow contributing to each cell. The Con tool applies conditional logic to identify drainage cells based on flow thresholds. Flow Distance then calculates the vertical or horizontal distance of each cell relative to the nearest drainage channel, forming the basis of the HAND surface. After completing all processing steps, the resulting HAND raster was reclassified according to the classification scheme presented in Table 2.

c. Distance Streams

The distance to stream was derived from SRTM data using the Distance Accumulation tool, which calculates the accumulated distance of each cell to the nearest drainage feature. The resulting distance raster was then reclassified according to the classification scheme presented in Table 2. The formula for distance stream:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

d. Total Precipitation

Rainfall data were obtained from three BMKG weather stations located within Semarang City. The dataset covers October 2024 to March 2025, which represents Semarang's main rainy season. Total precipitation was spatially interpolated using the Inverse Distance Weighting (IDW) method to generate a continuous rainfall distribution map across the study area. The IDW method was selected because it effectively represents rainfall variability between stations despite the limited number of observation points, and is suitable for urban-scale applications characterized by heterogeneous topography such as Semarang. The resulting interpolated rainfall surface was subsequently reclassified according to the rainfall classification scheme presented in Table 2.

e. Curve Number

The Curve Number (CN) parameter represents the hydrological response of land surfaces by quantifying the balance between infiltration and runoff potential based on land use and soil texture. Higher CN values indicate reduced infiltration capacity and greater susceptibility to rapid runoff generation across impervious surfaces. In this study, CN values were derived by correlating land use and Hydrological Soil Group (HSG) data according to Semarang's physical characteristics. Land use information was extracted from 10 m resolution Sentinel-1 and Sentinel-2 imagery (ESA WorldCover) processed in Google Earth Engine (GEE), while HSG data were obtained from the USGS Soil Texture dataset in shapefile format.

f. Effective Precipitation

Effective precipitation (EP) reflects the portion of total rainfall that becomes direct runoff after accounting for retention capacity influenced by Curve Number values, as shown in the hydrological formula below. EP highlights areas where rainfall converts more efficiently into surface flow, providing a more realistic representation of hydrologic stress than total precipitation alone. The spatial heterogeneity of EP captures interactions between land-surface conditions and rainfall intensity, strengthening the identification of areas with elevated runoff potential.

$$\frac{\left(TP - \frac{5080}{CN} + 60.8 \right)^2}{TP + \frac{20,320}{CN} - 203.2}$$

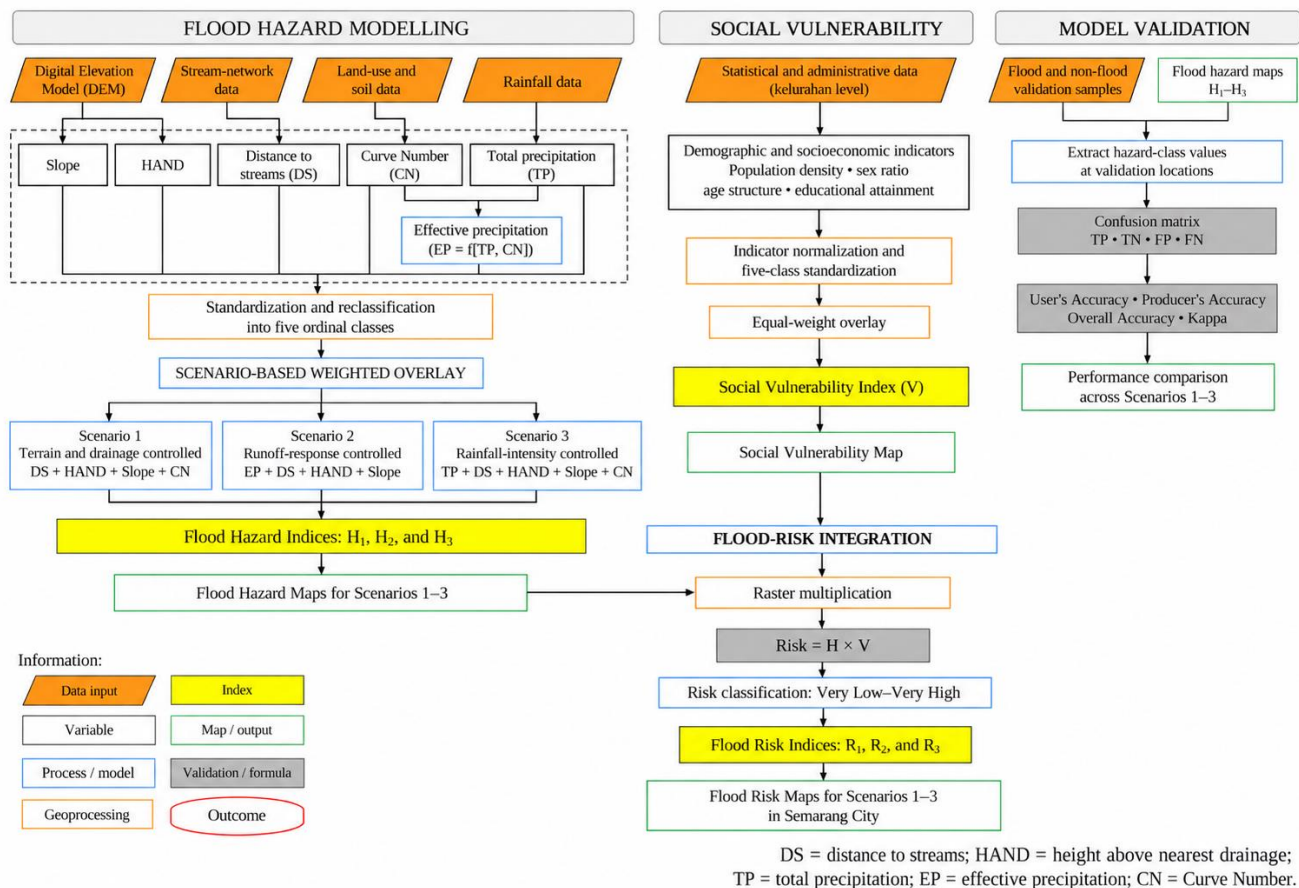


Figure 2. Analytical workflow for GIS-based flood hazard, social vulnerability, flood risk modelling, and model validation in Semarang City.

2.3.2. Standardization of Flood Hazard Criteria

Table 2 presents the classification structure for the physical environmental criteria used to assess flood hazard. The parameters include slope, Height Above Nearest Drainage (HAND), proximity to drainage, Curve Number (CN), total precipitation, and effective precipitation. Each criterion is categorized into five hazard levels ranging from Very Low to Very High. Lower slope, lower HAND values, shorter distances to drainage, and higher CN and precipitation amounts indicate higher susceptibility to flooding, reflecting their physical roles in runoff generation and accumulation. This classification framework transforms various geospatial datasets into a unified scale, ensuring all criteria can be analyzed together in a spatial overlay. The threshold design was adapted and modified from Rincón et al. (2018), enabling a scientifically supported representation of physical flood potential across Semarang City.

Table 2. Classes of criteria that contribute to flood hazard. S: slope, HAND: height above nearest drainage, CN: Curve Number, TP: total precipitation, EP: effective precipitation.

Class	Level	Criteria for Hazard Flood					
		S (Degree)	HAND (m)	DS(m)	CN	TP (mm)	EP (mm)
1	Very low	>50	>8	>1000	74	<79.9	<36.2
2	Low	30.1 - 50	6.1 - 8	501 - 1000	79	80 - 81.2	36.3 - 49.2
3	Medium	20.1 - 30	4.1 - 6	301 - 500	86	81.3 - 82.3	49.3 - 58
4	High	10.1 - 20	2.1 - 4	101 - 300	90.91	82.4 - 83.2	58.1 - 65.1

Class	Level	Criteria for Hazard Flood					
		S (Degree)	HAND (m)	DS(m)	CN	TP (mm)	EP (mm)
5	Very high	<10	<2	<100	94	>83.2	>65

Source: (Rincón et al., 2018)

2.3.3. Scenario-Based Flood Hazard Modeling

Table 3 originally presents alternative weighting schemes for the hazard parameters, with each scenario reflecting different assumptions about dominant flood-generating processes. Scenario 1 assumes that flood hazard is primarily controlled by terrain and drainage proximity. Distance to stream contributes most, followed by HAND and slope, while CN provides a secondary representation of runoff response. This configuration is particularly relevant to Semarang because of its pronounced topographic transition from the southern uplands toward the low-lying northern coastal plain, which promotes downslope runoff concentration and hydrological convergence. Scenario 2 assumes that spatial differences in flood susceptibility are primarily controlled by runoff-generating efficiency. Effective precipitation therefore receives the highest weight because it represents the fraction of rainfall transformed into direct runoff after accounting for land-surface retention. Distance to stream, HAND, and slope remain included to preserve the influence of drainage connectivity and terrain position. Scenario 3 assumes that spatial variation in flood hazard is primarily driven by total rainfall intensity. Total precipitation receives the highest weight, while DS, HAND, slope, and CN retain secondary contributions representing terrain, drainage proximity, and infiltration conditions. The parameter composition follows the alternative weighting schemes adopted from Rincón et al. (2018). In this study, these configurations represent distinct dominant flood-generating processes. Excluding precipitation variables from Scenario 1 preserves its terrain- and drainage-oriented structure, while Scenario 2 relies on effective precipitation as an integrated runoff-response indicator incorporating rainfall and Curve Number effects. Scenario 3 retains total precipitation and Curve Number separately to emphasize direct rainfall forcing and land-surface infiltration characteristics without reproducing the effective-precipitation configuration used in Scenario 2.

Table 3. Flood-hazard criterion weights under the three modeling scenarios.

Scenario 1		Scenario 2		Scenario 3	
Criteria	Weight (%)	Criteria	Weight (%)	Criteria	Weight (%)
DS	42	EP	42	TP	36
HAND	23	DS	27	DS	25
S	23	HAND	16	HAND	16
CN	12	S	15	S	14
-	-	-	-	CN	9
CI	0.003	CI	0.015	CI	0.019

Source: Rincón et al. (2018)

2.3.4. Social Vulnerability Assessment

Social vulnerability was assessed using four demographic and socioeconomic indicators representing population sensitivity, dependency, socioeconomic capacity, and exposure concentration to flooding. The indicators included the proportion of children aged four years and younger, the proportion of residents aged 75 years and older, the proportion of the population with elementary-level education or lower, and population density. Children aged four years and younger and residents aged 75 years and older were included as dependent age groups because of their relatively limited mobility and greater need for assistance during emergency conditions. Low educational attainment served as a proxy for reduced access to disaster information, preparedness capacity, and risk communication, while population density

represented the concentration of potentially exposed residents and the logistical challenges of evacuation and emergency response. Table 4 summarizes the selected indicators and their vulnerability dimensions.

Table 4. Criteria for social vulnerability

Demographic Category	Indicators	Specific Indicators
Demographic characteristics	Age	People under 4 years
		People 75 years and older
Socioeconomic status	Education	Population with elementary education or lower
Neighborhood characteristics	Population density	Population density per km ²

Source: Rincón et al. (2018)

Table 5 presents the classification structure for the social vulnerability indicators, grouping them into five levels from Very Low to Very High using a percentage-based approach. The classification reflects the proportion of the population in each vulnerability category within a given *kelurahan*. Areas with a higher concentration of dependent age groups or low-education populations fall into higher vulnerability classes. This categorization transforms raw statistical data into spatial vulnerability values, ensuring they can be integrated consistently into GIS-based modeling. By applying a standardized scale, this table enables meaningful comparison among neighborhoods to identify groups that may require prioritized flood risk management.

Table 5. Classes of criteria that contribute to social vulnerability

Class	Level	Population for each Criterion %
1 (Very Low)	Very low	<20
2 (Low)	Low	21 - 40
3 (Medium)	Medium	41 -60
4 (High)	High	61 - 80
5 (Very High)	very High	>80

Source: Rincón et al. (2018)

2.3.5. Flood Risk Integration

Flood risk was derived by spatially integrating the scenario-based flood hazard outputs with the composite social vulnerability index. In this framework, flood hazard represents the spatial potential for flood occurrence associated with terrain and hydrometeorological conditions, while social vulnerability represents the population's relative sensitivity to potential flood impacts. The integration therefore identifies locations where elevated physical hazard coincides with socially vulnerable communities. Three flood hazard surfaces generated from the alternative weighting configurations described in Section 2.3.3 were independently combined with the same composite social vulnerability layer developed in Section 2.3.4. Keeping the vulnerability surface constant across the three scenarios ensured that differences in the resulting risk patterns reflected variations in hazard-weighting assumptions rather than changes in demographic conditions.

Flood risk is defined as the interaction between physical flood hazard and social vulnerability. The risk calculation follows a widely used conceptual model in which risk arises when a hazardous event coincides with populations or systems with varying levels of susceptibility. This relationship is expressed mathematically as

$$Risk = Hazard \times Vulnerability$$

Where:

R_s = Flood risk for scenario s ,

H_s = Flood Hazard Index for scenario s , and

V = Social Vulnerability Index.

Three distinct hazard scenarios were generated, each representing different weighting configurations of biophysical factors such as distance to streams, HAND, slope, curve number, and precipitation. The social vulnerability index (V) is derived from demographic variables, including population density, the proportion of residents aged 75 and above, the proportion of children under four years old, and the population with elementary-level education or lower. These indicators reflect population groups highly sensitive to flood impacts. The resulting risk values for each scenario represent the spatial distribution of areas where physical flood hazards intersect with socially vulnerable communities.

2.3.6. Model Accuracy Assessment

Model validation evaluated agreement between the scenario-based flood-hazard outputs and independently observed flood occurrence conditions in Semarang City. The validation was intended to determine whether spatial variations generated under the three weighting scenarios corresponded with documented flooded and non-flooded locations and to quantify differences in predictive performance among the terrain-, runoff-, and rainfall-dominated scenarios.

The confusion matrix is constructed by assigning each of the 172 validation points to either an observed “flood” or “non-flood” category and then intersecting these points with the corresponding raster cells of the modeled hazard or risk output to determine whether the model predicted a flooded or non-flooded condition, producing the four fundamental elements of classification accuracy consisting of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), which subsequently form the basis of the derived accuracy metrics. User Accuracy (UA) is calculated to evaluate the proportion of correctly predicted flood cases relative to all flood predictions using the expression:

$$UA = \frac{TP}{TP + FP}$$

while Producer Accuracy (PA) assesses the proportion of observed flood events that the model correctly identifies, computed as

$$PA = \frac{TP}{TP + FN}$$

Overall Accuracy (OA) is derived by dividing the total number of correctly classified points (TP + TN) by all evaluated points according to

$$OA = \frac{TP + TN}{TP + TN + FP + FN}$$

and the Kappa statistic quantifies agreement beyond chance through the formulation

$$K = \frac{OA - P_e}{1 - P_e}$$

where P_e represents the probability of random agreement based on marginal totals in the matrix. These calculations are applied to each scenario—Scenario 1, Scenario 2, and Scenario 3—by extracting the predicted class value from each respective hazard or risk surface at the location of every validation point, enabling direct examination of how different parameter weightings influence classification performance and producing a consistent comparative framework for quantifying the extent to which predicted flood-prone areas align with empirical flood observations across Semarang.

3. RESULT AND DISCUSSION

3.1. Hazard Parameters Analysis

The spatial distributions of slope, Height Above Nearest Drainage (HAND), and distance to stream in Figures 3a to 3c indicate contrasting topographic and drainage controls between the northern coastal plain and the southern hilly part of Semarang. Lo et al. (2022) describe northern Semarang as an alluvial plain bordered by higher terrain to the south, with Tugu, Semarang Barat, Semarang Utara, Semarang Tengah, Semarang Timur, Gayamsari, Genuk, and northern Pedurungan occupying the city's lower part. Under these conditions, low-gradient surfaces receive higher hazard classes because gravitational drainage is weaker and surface water can remain longer, whereas steeper southern relief routes runoff toward lower terrain. Experimental work by Chen et al. (2024) similarly found that slope gradient alters infiltration and runoff behavior under rainfall. The HAND pattern in Figure 3b adds a vertical measure of drainage position, as low HAND values represent areas situated closer in elevation to channels, while higher values are more common across southern relief. Purwanto and Paiman (2023) used HAND similarly to distinguish inundation-prone areas by their relative elevation above drainage. Distance to stream in Figure 3c forms linear bands along the drainage system across Semarang, assigning higher hazard classes to cells close to channels and progressively lower classes farther away, in line with the relationship between channel proximity and flood susceptibility examined by Akay and Baduna Koçyiğit (2024).

Curve Number, total precipitation, and effective precipitation in Figures 3d to 3f show runoff-generation patterns that differ from the relief-controlled spatial structure. Higher CN classes occur mainly across northern and eastern Semarang, where built-up surfaces occupy a larger share of the urban area, while lower CN classes are more common in the southern sector where vegetation and more permeable surfaces remain more extensive. Welkis et al. (2023) explain that CN links land cover, soil properties, and antecedent moisture conditions to the proportion of rainfall converted into runoff. Total precipitation in Figure 3e forms a higher-precipitation zone from northern to central Semarang, followed by lower classes toward the south. This pattern is relevant to observed rainfall behavior in the city, as Hermawan et al. (2022) documented an extreme precipitation event in February 2021 that flooded ten subdistricts after two mesoscale convective systems developed near the northern coast of Java. Effective precipitation in Figure 3f does not reproduce the TP pattern exactly because direct runoff also depends on CN; Eniyew et al. (2024) showed that the SCS-CN approach links rainfall, land cover, hydrologic soil group, and surface retention when estimating runoff. Wisanggeni et al. (2024) reported a comparable urban response: increasing CN following land-cover change was accompanied by higher peak discharge and runoff volume, so high EP classes in Semarang represent areas where rainfall input coincides with weaker surface retention.

The six parameters in Figure 3 form two principal groups of spatial controls: relief and drainage, represented by slope, HAND, and distance to stream, and rainfall-runoff response, represented by CN, TP, and EP. Ariyani et al. (2024) applied a comparable multicriteria framework in which rainfall, slope, land cover, and topography were assessed together because flood behavior varies according to local physical conditions. Osman and Das (2023) reported similar differences, and their MCDA incorporated elevation, slope, drainage density, distance to river, rainfall, soil, and geology to separate flood-hazard zones. Vojtek et al. (2021) also found that slope, river-network density, distance from river, flow accumulation, and Curve Number contain different hydrological information when used for flood susceptibility mapping. Semarang adds a coastal urban setting to those process controls, as Herbanu et al. (2024) found that urban and tidal flooding in the city is associated with elevation, land cover, river proximity, and coastal position. In Figure 3, the topographic parameters form patterns that follow drainage lines and changes in relief, whereas TP and EP occupy broader zones across northern and central Semarang.

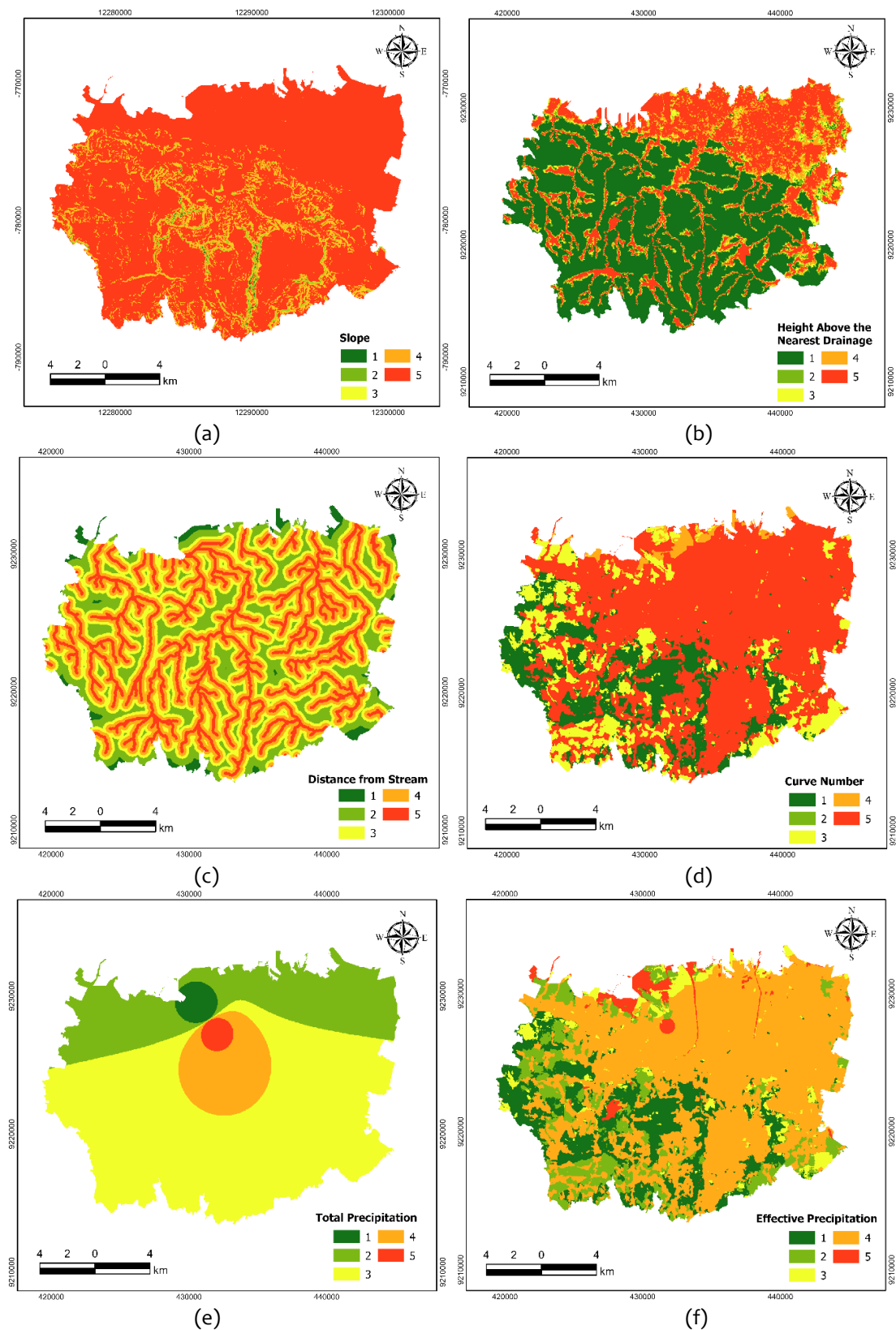


Figure 3. Spatial distribution of the six flood-hazard parameters used in the multi-criteria analysis, illustrating (a) slope-derived terrain steepness, (b) height above the nearest drainage (HAND) as a proxy for local elevation control, (c) distance from stream networks representing flow accumulation pathways,

- (d) curve number indicating land-surface runoff potential (e) total precipitation intensity patterns, and (f) effective precipitation capturing runoff-generating rainfall after accounting for losses.

3.2. Flood Hazard Pattern Analysis Across Scenarios

Figure 4 shows how flood hazard patterns change as parameter emphasis shifts among the three weighting scenarios. Scenario 1 forms a spatial pattern that follows the drainage system more strongly because distance to stream receives the largest weight (42%), while HAND and slope account for 23% each and CN for 12%. High and Very High classes frequently form corridors along the drainage system and expand across parts of the city with lower relief. Romadhon and Aziz (2022) reported a comparable pattern in Semarang, particularly in the northern area where low elevation, relatively flat slopes, extensive settlement land, and short distances from river channels are associated with higher flood susceptibility. Swain et al. (2020) similarly found that a large share of High to Very High susceptibility zones occurred close to river paths, while Sarkar et al. (2022) identified elevation, slope, rainfall, and distance from rivers among the factors associated with flood-prone zones. These conditions are especially relevant to Semarang because its lowland area borders hilly terrain and the sea, exposing the city to pluvial, local, and coastal flooding across different physiographic settings (Kurniawan & Suharini, 2021). Under Scenario 1, the dominant weights assigned to DS, HAND, and slope cause relative elevation and drainage proximity to control hazard-class distribution more strongly than spatial rainfall variation.

Scenario 2 produces a more dispersed pattern after effective precipitation receives a weight of 42%, while distance to stream decreases to 27%, HAND to 16%, and slope to 15%. Figure 4b shows Medium to Very High classes extending beyond drainage corridors and forming patches in areas with stronger runoff response. Effective precipitation in the model represents the portion of precipitation converted into direct runoff after surface retention is accounted for through CN, making this scenario more sensitive to the interaction between rainfall and surface characteristics. Janizadeh et al. (2021) reported that changes in precipitation characteristics and land use can shift the spatial distribution of flood hazard because both modify hydrological response. Xie and Shu (2025), using an SCS-based approach, also demonstrated the importance of rainfall-runoff processes when surface characteristics and precipitation are assessed together. Scenario 3 forms broader, more gradual zones because TP receives the largest weight (36%), while DS, HAND, slope, and CN act as secondary controls. Kefi et al. (2020) reported that increasing extreme rainfall can expand flood impacts in urban catchments, particularly where urban development increases surface response to rainfall, while Tripathi et al. (2022) showed that variations in hydroclimatic conditions produce different spatial distributions of flood hazard at the regional scale. The shift toward runoff response in Scenario 2 and rainfall forcing in Scenario 3 explains why their spatial structures depart from the predominantly drainage-oriented pattern found in Scenario 1.

The patterns shown in Figure 4 also need to be interpreted within Semarang's physical setting, where northern coastal lowlands contrast with higher terrain toward the south. Hazard classes extending toward northern Semarang occur in a coastal area already affected by additional flood pressures not represented in the present model's parameters. Yuwono et al. (2024) reported that flooding in Semarang is associated with hydraulic hazards, land subsidence, and limitations in drainage and water retention systems. In the eastern coastal sector, Ulfani et al. (2024) estimated approximately 174.28 ha of tidal flood inundation in Genuk Subdistrict in May 2022 and reported land subsidence rates of up to 14.4 cm per year in parts of the study area. Ujianti et al. (2023) also identified Semarang position on the northern coast of Java as an important background factor for tidal flood exposure, while Hamdani et al. (2022) reported additional pressure on coastal housing areas from land subsidence and drainage limitations. Land subsidence and tidal flooding are not included as criteria in Scenarios 1 to 3 in the present study, so these processes serve as local context for interpreting northern hazard patterns rather than as direct determinants of the classes shown in Figure 4.

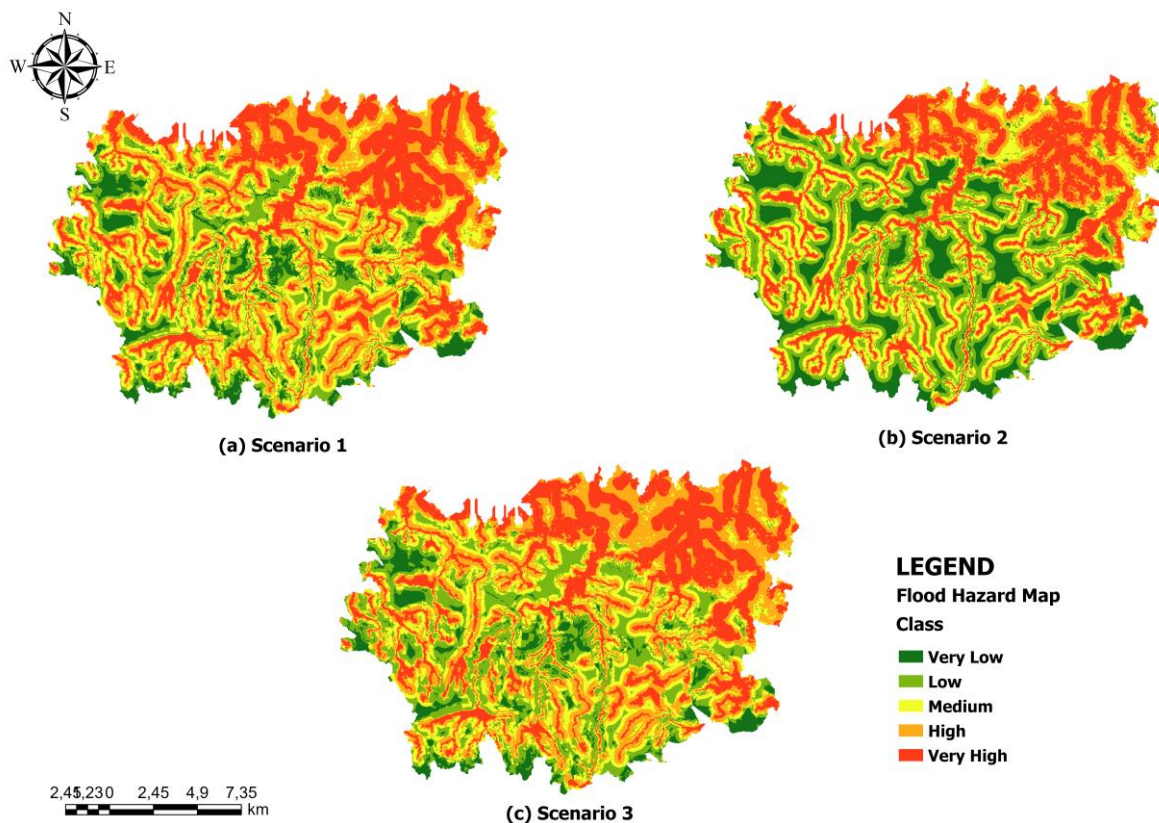


Figure 4. Flood hazard maps generated under three weighting scenarios, illustrating spatial variations in susceptibility derived from the multi-criteria analysis: (a) Scenario 1 emphasizing terrain-controlled factors, (b) Scenario 2 integrating runoff-related components with increased precipitation influence, and (c) Scenario 3 dominated by total rainfall intensity

3.3. Social Vulnerability Analysis

The social vulnerability assessment incorporates four demographic and socioeconomic parameters, each representing a dimension of population sensitivity to flood impacts. These variables are mapped at the subdistrict level and classified into five ordinal categories (1–5), where higher values represent greater vulnerability. The spatial distribution of these parameters reflects demographic concentration patterns across Semarang and highlights areas where population structures intensify potential exposure. Equal weighting of all four indicators (25% each) provides a balanced representation of demographic fragility in constructing the composite vulnerability map. Figure 5 and Table 6 show that the four social vulnerability indicators have different spatial distributions across Semarang's subdistricts. Population density is highest in Semarang Timur at 12,260.54 people/km², followed by Candisari at 11,793.19 people/km² and Gayamsari at 11,316.56 people/km², while Tugu records only 1,212.15 people/km². Pedurungan has the largest population of children aged four years and younger at 13,315 people, followed by Tembalang with 12,717. Semarang Barat has the largest population aged 75 years and older, at 3,316 people, while Genuk has the largest population with elementary-level education or lower, at 6,721 people, followed by Semarang Utara at 6,696. Such variation indicates that social vulnerability does not arise from a single population characteristic. Suherman et al. (2023) also incorporated population density and vulnerable age groups in their assessment of social vulnerability to tidal flooding in Semarang Utara. Clar et al. (2023) reported that demographic structure can affect communities' capacity to deal with floods, while Son et al. (2023) found that densely developed urban areas face additional pressure during urban flooding. Suryanto et al. (2026) similarly included children, elderly residents, low educational attainment, and population density in a social vulnerability assessment in

the Samin watershed, so the patterns in Figure 5 represent different forms of social pressure across administrative areas rather than a single uniform condition

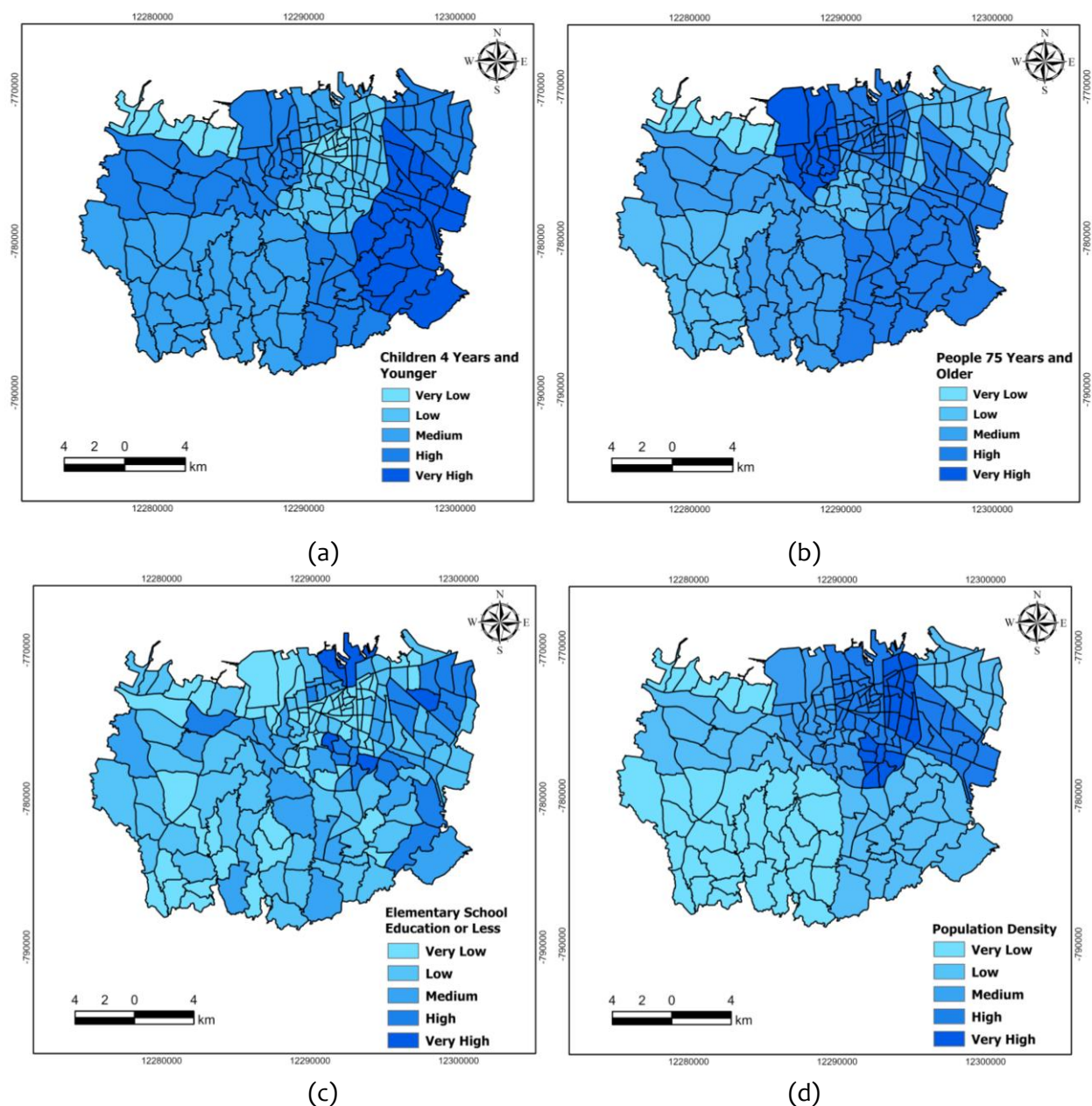


Figure 5. Spatial distribution of the four social vulnerability indicators used in the assessment: (a) proportion of children aged four years and younger, (b) proportion of elderly residents aged 75 years and older, (c) population with elementary-level education or less, and (d) population density across administrative units

Table 6 presents age structure and educational attainment as factors shaping flood response. The large number of children aged four years and younger in Pedurungan and Tembalang indicates greater demand for assistance during evacuation because young children have limited independent mobility and decision-making capacity. Phraknoi et al. (2023) found that older people in urban disasters have specific needs related to health, evacuation, temporary accommodation, information, and social support. Such needs are particularly relevant to Semarang Barat, which records the largest population aged 75 years and

older in Table 6. Atalay et al. (2025) also found that elderly flood experiences are associated with physical limitations, assistance requirements, and different coping capacities among individuals. Educational attainment is another social dimension because Hoffmann and Blecha (2020) identified an association between education and disaster vulnerability in Southeast Asia, while Cerulli et al. (2020) reported links between education, natural-hazard awareness, and reduced disaster impact. Formal education should still be treated as a proxy rather than a direct measure of preparedness; Hildayanto (2020) found that only 37% of respondents in Mangunharjo, Tugu Subdistrict, had good flood-preparedness knowledge and 48% demonstrated a good preparedness attitude.

Table 6. Distribution of Social Vulnerability Indicators Across Subdistricts in Semarang City

Subdistrict	Population Density (people/km ²)	Children Aged 4 Years and Younger (people)	Population Aged 75 Years and Older (people)	Population with Elementary-Level Education or Lower (people)
Banyumanik	4,833.05	8,278	2,822	3,543
Candisari	11,793.19	4,235	1,911	4,729
Gajahmungkur	6,029.02	3,314	1,394	2,483
Gayamsari	11,316.56	4,747	1,159	2,379
Genuk	5,287.18	9,684	1,263	6,721
Gunungpati	1,743.16	6,787	1,892	4,289
Mijen	1,646.90	5,633	1,262	2,590
Ngaliyan	3,410.93	8,673	2,048	3,542
Pedurungan	9,354.39	13,315	2,601	4,839
Semarang Barat	6,888.85	8,215	3,316	3,438
Semarang Selatan	10,429.66	3,204	2,106	1,760
Semarang Tengah	10,671.14	2,436	2,529	1,051
Semarang Timur	12,260.54	3,401	2,365	1,570
Semarang Utara	10,345.67	7,135	2,472	6,696
Tembalang	5,113.34	12,717	2,559	5,100
Tugu	1,212.15	2,132	426	1,162

The composite social vulnerability shown in Figure 6 is derived from four indicators weighted equally at 25%, so subdistricts with elevated values across several indicators receive greater social pressure than areas dominated by only one indicator. Higher vulnerability classes in Figure 6 occur more frequently across northern, central, and eastern Semarang, particularly in areas where several demographic characteristics overlap. Genuk has the largest population with elementary-level education or lower and a relatively large number of young children, while Semarang Utara combines a density of 10,345.67 people/km² with 6,696 residents in the lower-education group. Pedurungan and Tembalang have the two largest child populations and also contain relatively large elderly populations. Semarang Timur differs because its main pressure comes from population density, whereas its child and lower-education populations are smaller than those recorded in several neighboring subdistricts. Ajtai et al. (2023) emphasized that social vulnerability indices should be interpreted through multiple indicators because individual variables represent different social conditions. At the city scale, Findayani et al. (2024) assessed Semarang's climate-disaster preparedness as moderate and identified remaining needs in early-warning coverage and community flood-coping capacity. Permanahadi (2022) reported that Semarang had implemented 52.6% of the flood-mitigation indicators assessed in the study, while Maulana and Maulana (2023) found high flood sensitivity in flat and gently sloping parts of the city where population and building densities were also high. The higher classes in

northern and eastern parts of Figure 6 occur in areas where several demographic and exposure indicators reach elevated values at the same time.

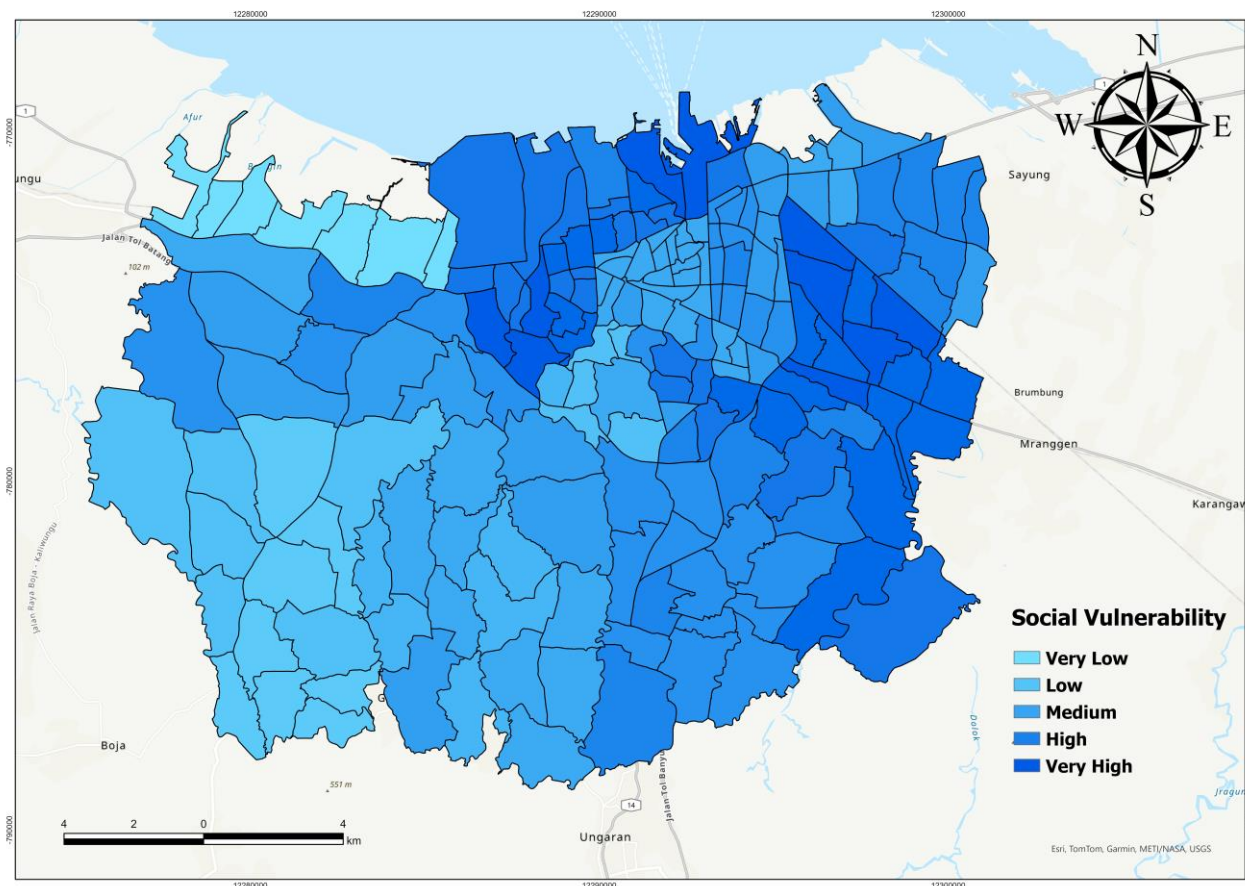


Figure 6. Social Vulnerability Map

3.4. Flood Risk Analysis

Figure 7 shows that integrating hazard and social vulnerability produces different flood risk patterns across the three scenarios even though the same social vulnerability surface is retained. Scenario 1 forms numerous High and Very High corridors along the drainage structure, particularly from the central part of the city toward the northern lowlands, because its hazard component is more strongly influenced by distance to stream, HAND, and slope. Tabasi et al. (2025) define flood risk as the interaction of hazard and vulnerability, meaning changes in one component can shift risk levels even when the other remains fixed. Scenario 2 shows a more dispersed pattern because effective precipitation extends hazard beyond drainage corridors, while Scenario 3 forms broader zones associated with rainfall distribution. Dulawan et al. (2024) found that integrating social vulnerability with flood hazard produces uneven urban risk because hazard levels intersect with different social conditions. In Semarang, elevated risk across the northern sector occurs near densely populated coastal areas such as Tanjung Mas, where Wungo et al. (2025) identified high risk particularly across northern and central residential and industrial areas. Prasetya and Purwantara (2025) also reported spatial differences along the Semarang coast, identifying different risk levels across Semarang Barat, Semarang Utara, Genuk, and Tugu; therefore, interpret the pattern in Figure 7 in light of both physical position and social conditions, not hazard values alone.

The differences become more apparent quantitatively in Table 7 and Figure 8. Scenario 1 contains 9,892.80 ha of Very High risk and 3,297.60 ha of High risk, placing 13,190.40 ha or 40.00% of its classified area within these two categories. Scenario 2 contains 9,892.80 ha of Very High risk and 3,957.12 ha of High risk, producing 13,849.92 ha or 42.00%, while Scenario 3 records 12,940.01 ha or 39.24% in the two upper classes.

La Pietra et al. (2025) showed that spatial risk assessment integrating hazard, population exposure, and social vulnerability can separate critical areas at a local scale, making class area more informative when assessed together with population characteristics and location. Aidinidou et al. (2023) similarly used spatial variation in flood vulnerability and risk to prioritize areas for mitigation planning. At a broader scale, Tellman et al. (2021) documented a growing proportion of the population living within observed flood extents, indicating that flood-affected areas should be assessed alongside population exposure. Hussain et al. (2023) also incorporated spatial hazard and community capacity within an integrated framework because a larger risk area does not necessarily correspond to the same level of social impact. Figure 8 further shows that Scenario 3 has the largest Medium risk area at 12,599.42 ha, or approximately 38.21%, compared with 11,871.36 ha in Scenario 1 and 11,541.60 ha in Scenario 2.

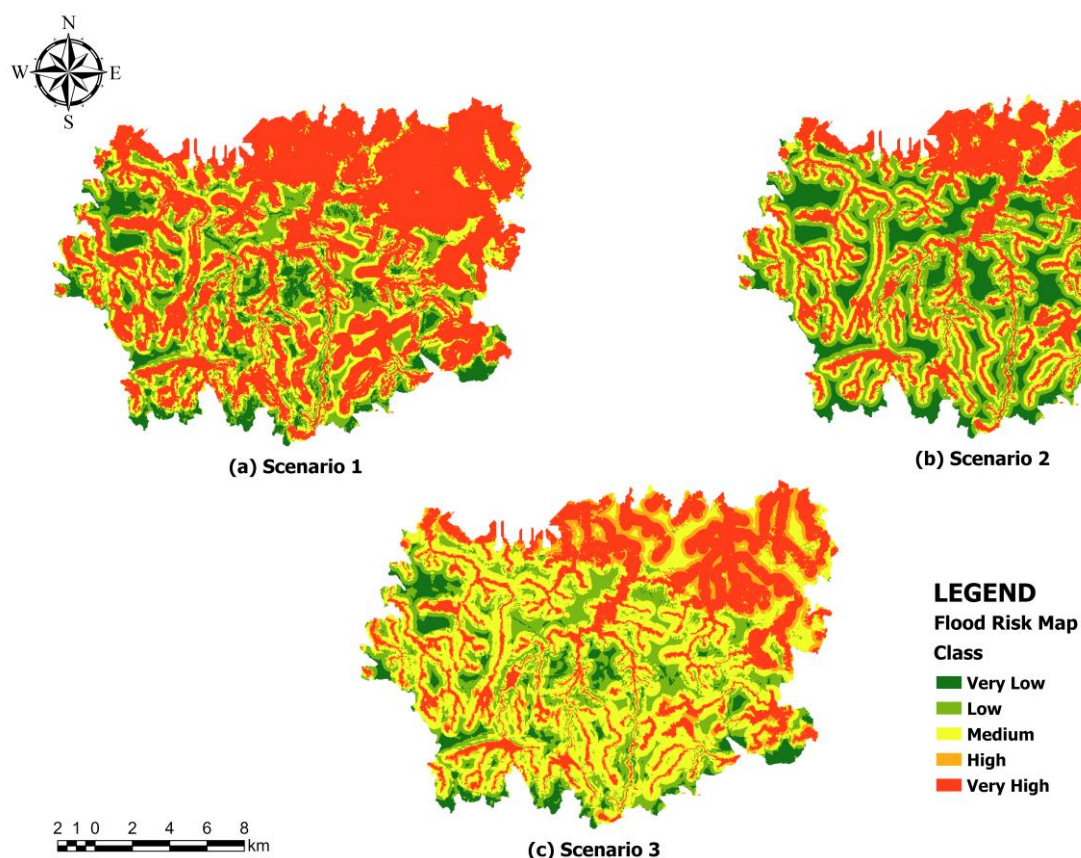


Figure 7. Flood risk maps produced under the three hazard–vulnerability integration scenarios: (a) Scenario 1 driven primarily by terrain-related hazard weighting, (b) Scenario 2 reflecting stronger contributions from effective precipitation and runoff-generating factors, and (c) Scenario 3 dominated by total precipitation intensity.

Table 7. Distribution of Flood Risk Class Areas Across Three Modeling Scenarios in Semarang City (in ha)

Flood Risk Class	Scenario 1	Scenario 2	Scenario 3
Very Low	1,978.56	2,308.32	1,760.44
Low	5,935.68	5,276.16	5,678.46
Medium	11,871.36	11,541.60	12,599.42
High	3,297.60	3,957.12	3,844.38
Very High	9,892.80	9,892.80	9,095.63

The shifts among risk classes in Table 7 occur because all three maps use the same social vulnerability surface, while the hazard pattern changes according to the weighting structure of Scenarios 1 to 3. The increase in High risk under Scenario 2 therefore results from the expansion of runoff response-based hazard into locations that fall into lower classes under other weighting structures, rather than from changes in demographic conditions. Ekmekcioğlu et al. (2022) likewise showed that metropolitan flood risk varies as hazard conditions intersect with urban vulnerability across different administrative units. Semarang adds a specific geographical setting because its northern sector receives runoff from higher terrain while also occupying a coastal environment exposed to marine flooding processes. Rachma et al. (2025) found that coastal flooding affects settlements across several Semarang subdistricts and that its effects vary spatially. Sakina et al. (2025) documented a major coastal flood along northern Semarang in May 2022 associated with enhanced waves and atmospheric conditions over the Java Sea. Such processes are not included as direct parameters in the three scenarios used here, but they remain part of the local setting when interpreting High and Very High risk areas in northern Semarang; Nicholls et al. (2021) found that coastal cities affected by subsidence experience faster relative sea level rise and greater coastal flood exposure.

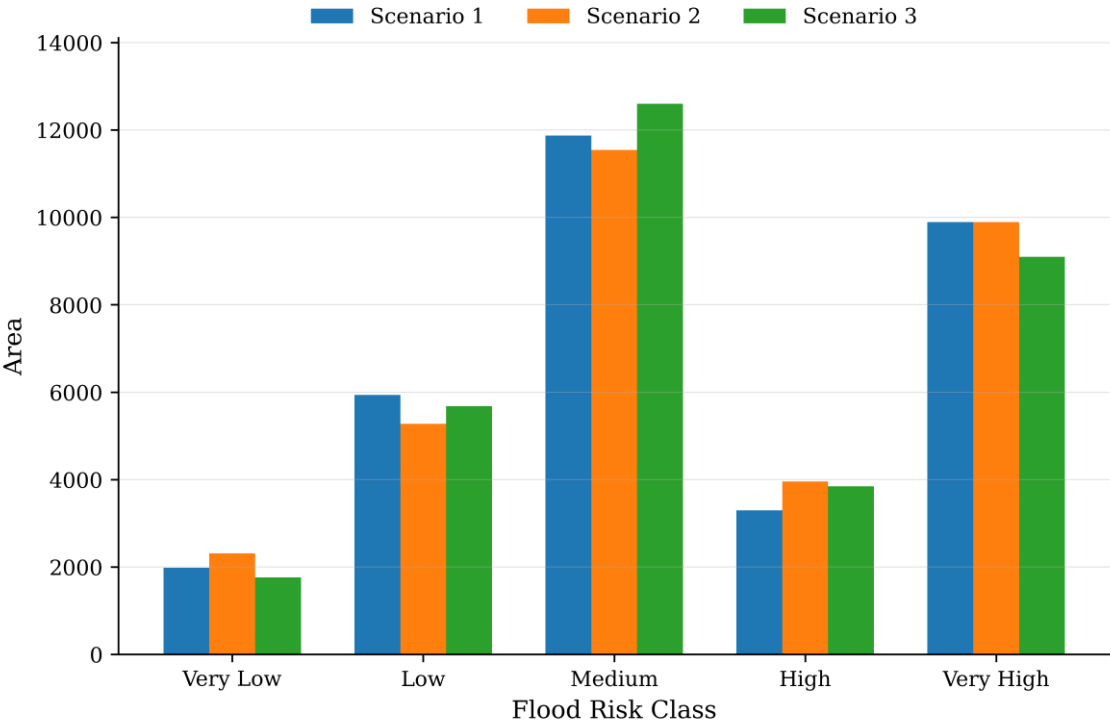


Figure 8. Distribution of Flood Risk Class Areas Across Three Modelling Scenarios in Semarang City

3.5. Model Accuracy and Validation Against Observed Flood Events

Figure 9 and Table 8 show differences in model performance among the three weighting configurations. Scenario 1 records the highest Overall Accuracy at 90.12% with a Kappa coefficient of 0.80, while Scenario 3 performs closely at 89.53% and 0.79, respectively. Scenario 2 records lower values, with an OA of 84.88% and a Kappa coefficient of 0.70. The difference in OA between Scenarios 1 and 3 is only 0.59 percentage points, whereas the difference between Scenarios 1 and 2 reaches 5.24 points. Sahraei et al. (2023) also reported variations in model performance among alternative flood susceptibility weighting approaches, with overall accuracy ranging from 88.89 to 94.15% and Kappa values from approximately 0.78 to 0.88. The Semarang results therefore fall within a comparable performance range, although the modeling structure, study area, and weighting procedures differ.

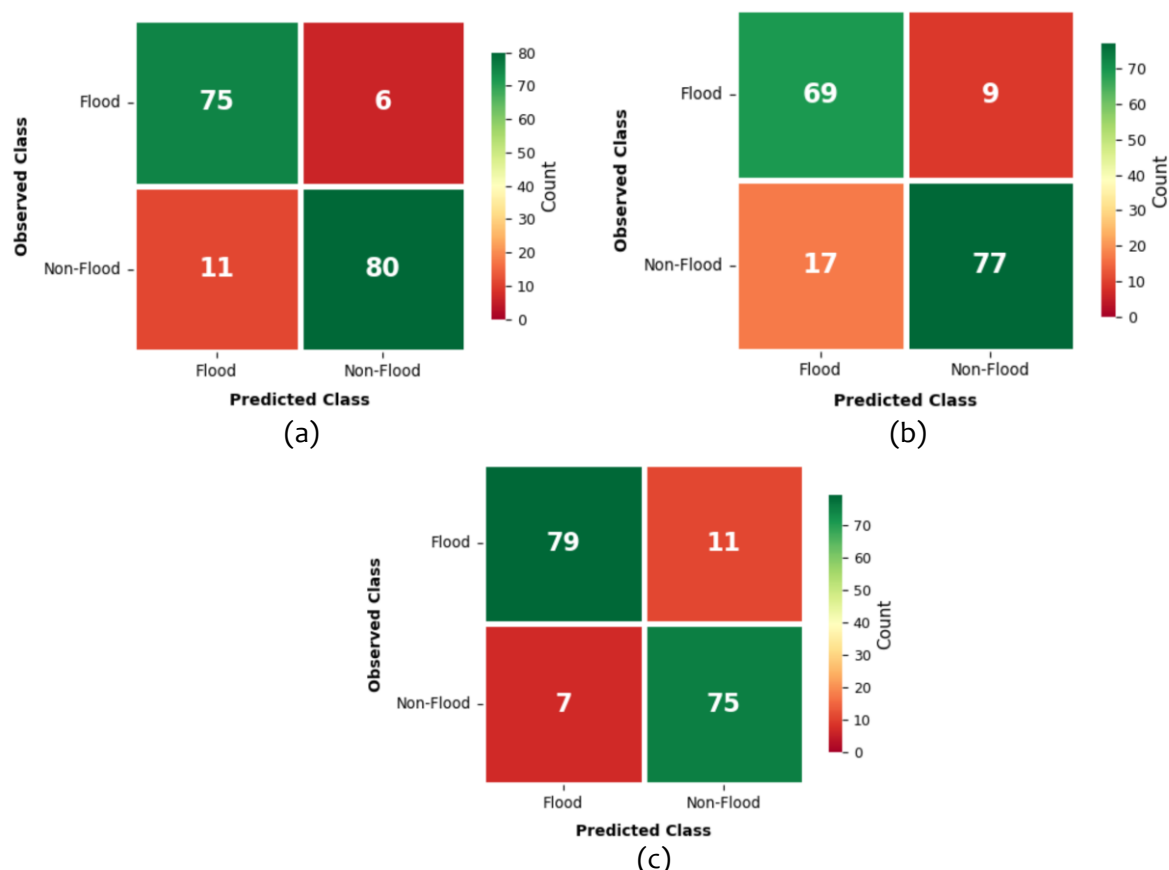


Figure 9. Confusion matrices for model performance evaluation under the three weighting scenarios: (a) Scenario 1, (b) Scenario 2, and (c) Scenario 3. Each matrix displays the distribution of correctly and incorrectly classified flood and non-flood observations, illustrating how changes in parameter weighting influence prediction accuracy and error patterns.

The error structure in Figure 9 provides additional information beyond overall accuracy. Scenario 1 records 75 true positives and 80 true negatives, with 11 false positives and 6 false negatives. A Flood User Accuracy of 87.21% indicates that some locations predicted as high risk correspond to non-flood observations, while its Flood Producer Accuracy of 92.59% indicates that most observed flood cases are captured by the model. Scenario 2 records the most false positives (17), compared with nine false negatives. Such a pattern agrees with the result discussed in Section 3.4, where Scenario 2 contains the largest combined High and Very High risk area because the effective precipitation weighting expands the spatial extent classified at higher risk levels. Scenario 3 shows a different error structure, with seven false positives and 11 false negatives. Its Flood User Accuracy reaches 91.86%, while Flood Producer Accuracy is 87.78%, indicating that high-risk predictions are more frequently associated with observed flood cases, although several flood observations remain outside the predicted high class. Ashhar et al. (2025) similarly used confusion matrices alongside User Accuracy, Producer Accuracy, Overall Accuracy, and Kappa in flood inundation mapping because overall accuracy alone does not distinguish commission from omission errors.

Table 8. Confusion-Matrix-Based Accuracy Assessment of Flood Risk Maps Under Three Modelling Scenarios

Scenario	Observed Flood – Predicted High	Observed Flood – Predicted Low	Observed Non-Flood – Predicted High	Observed Non-Flood – Predicted Low	UA Flood (%)	UA Non-Flood (%)	PA Flood (%)	PA Non-Flood (%)	OA (%)	Kappa
Scenario 1	75	6	11	80	87.21	93.02	92.59	87.91	90.12	0.80

Scenario	Observed Flood – Predicted High	Observed Flood – Predicted Low	Observed Non-Flood – Predicted High	Observed Non-Flood – Predicted Low	UA Flood (%)	UA Non- Flood (%)	PA Flood (%)	PA Non- Flood (%)	OA (%)	Kappa
Scenario 2	69	9	17	77	80.23	89.53	88.46	81.91	84.88	0.70
Scenario 3	79	11	7	75	91.86	87.21	87.78	91.46	89.53	0.79

Note: TP = true positive; FN = false negative; FP = false positive; TN = true negative; UA = User Accuracy; PA = Producer Accuracy; OA = Overall Accuracy.

Performance differences relate to how each scenario represents flood processes in Semarang. Scenario 1 is more sensitive to relative drainage position and terrain, so it identifies a large proportion of observed flood points when flooding follows low-lying areas and drainage pathways. Scenario 2 responds more strongly to runoff generation, expanding the predicted high-risk area and increasing false positives. Scenario 3 is more selective in its high-risk predictions, with only seven false positives, but its 11 false negatives show that a rainfall-dominated structure does not capture every observed flood event that may also depend on local drainage controls. Bagaskara and Hartomo (2024) reported 86% accuracy for flood-prone classification in Semarang using KNN and cross-validation, showing that predictive performance also varies among modeling approaches within the same city. In the present analysis, the contrast among S1, S2, and S3 is expressed not only through different spatial risk patterns but also through different proportions of commission and omission errors at the validation locations.

3. CONCLUSION

This study assessed flood hazard and risk in Semarang City through GIS and multi-criteria analysis by integrating topographic, hydrological, precipitation, and social vulnerability parameters under three weighting scenarios. Scenario 1 produced a hazard pattern more strongly associated with drainage networks and terrain because of the dominant weights assigned to distance to stream, HAND, and slope, while Scenario 2 generated a more dispersed pattern under the stronger influence of effective precipitation. Scenario 3 formed broader zones following the spatial distribution of total precipitation. Hazard and social vulnerability integration showed that Scenario 2 had the largest combined High and Very High risk area at 13,849.92 ha, representing 42.00% of the classified area, followed by Scenario 1 at 13,190.40 ha or 40.00% and Scenario 3 at 12,940.01 ha or 39.24%. Higher-risk areas were concentrated mainly across northern, central, and eastern Semarang, where low-lying terrain, drainage proximity, runoff response, and several social vulnerability indicators overlap. Validation results showed the highest performance for Scenario 1, with an Overall Accuracy of 90.12% and a Kappa coefficient of 0.80, followed by Scenario 3 at 89.53% and 0.79. Scenario 2 recorded an OA of 84.88% and a Kappa coefficient of 0.70 and produced the largest number of false-positive classifications.

Several limitations should be considered when interpreting the model outputs. Precipitation distribution was derived from three BMKG stations covering October 2024 to March 2025, so it did not fully capture local rainfall variability or the characteristics of individual flood events. The hazard model also excluded land subsidence, tidal flooding, urban drainage capacity, and channel conditions as independent parameters, although these factors contribute to flooding in northern Semarang. Social vulnerability was represented by four equally weighted indicators at the subdistrict level, leaving finer-scale social variation and other factors such as income, disability, service accessibility, and household coping capacity outside the index. Future studies could incorporate rainfall data with higher temporal and spatial resolution, land subsidence, tidal conditions, drainage capacity, and a broader set of social indicators, followed by locally calibrated weighting schemes. Further validation could use multiple flood events, inundation depth and extent data, SAR imagery, or hydraulic modeling to examine model performance under different flood conditions.

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