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Urban Flood Susceptibility Analysis Using Multi Criteria Decision Analytical Hierarchy Process (AHP) Method: Case Study of Bandung City

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Abstract

Flood is one of the natural disasters and is supported by bad human habits, of course, this disaster can cause enormous losses, which can take lives. Flood handling certainly requires proper analysis before handling is carried out. Various methods for mapping flood susceptibility can be done, one of which is using the AHP Multi-Criteria Decision method which is considered the most up-to-date and very accurate method in terms of accuracy. This study aims to map the susceptibility of flood hazard in urban areas, especially in the city of Bandung with the help of satellite imagery. The method in this study uses the AHP Multi-Criteria Decision method, where five experts are needed to carry out an assessment in determining the variable weight value, with the variable in question namely; (1) TWI; (2) Elevations; (3) Slopes; (4) Precipitation; (5) Land Cover; (6) NDVI; (7) Distance from Rivers; and (8) Distance from Roads. In addition, this study validates the results of the mapping by comparing the real events of flooding in the city of Bandung in 2002-2022 with the map of the susceptibility of flood hazard in the city of Bandung. The results obtained in this study are flood hazard susceptibility maps created well with validation of 80.20%. In addition, areas that are very at hazard of being affected by flooding are the East Bandung area (Mandalajati, Ujungberung, Cibiru, Gedebage, and Panyileukan) with a high hazard of over 75%, and an extreme hazard of above 0.1%.

1. Introduction

Floods are one of the natural disasters caused by nature and supported by bad human behavior, such as the neglect of rivers, sewers, and gutters (Liu et al., 2020; Sejati et al., 2024). Bad human behavior is stated to be the biggest factor besides heavy and frequent rains (Berndtsson et al., 2019). Especially in dense urban areas where some drains are sometimes clogged or provided but cannot hold much water, or in other words, the ditches are made too small. As a result, urban areas often experience severe flooding even though the rainfall that occurs is quite light (Singh et al., 2018). The consequences of flooding in urban areas can be detrimental to many parties, such as many social or educational activities that are disrupted. In addition, floods in urban areas sometimes always release their floodwater towards residential areas which submerges the residential areas so that many material losses occur, not even a few urban area floods claim lives (Bertilsson et al., 2019).

As the preliminary study conducted in this research shows that during the 2018-2020 period, the Bandung city area experienced frequent flooding in various regions. Even though the Bandung area has high slopes in the northern area, this does not prevent the central to southern areas from being flooded. According to Hosseiny et al. (2020), floods can be classified into three main classifications, but there can also be four to five classifications depending on the strongest variable used, the three main classifications are; (1) Light flooding (0.1 – 0.8 meters); (2) Moderate flood (0.9 – 1.5 meters); and (3) High Flood (>1.3 meters). The city of Bandung according to data from the "Central Bureau of Statistics for the City of Bandung" (BPS Kota Bandung) (BPS, 2021) noted that there were around 54 flood events in 2018, including 35 mild floods, 14 moderate floods, and 7 high floods, in 2019 there were around 50 flood events including 32 mild floods, 12 moderate floods, and 6 high floods, in 2020 around 38 flood events occurred including 21 light floods, 10 moderate floods, and 7 high floods.

Based on preliminary studies conducted by researchers, it appears that the city of Bandung has many problems regarding flood disasters, where floods often occur even though rainfall is small. Floods in urban areas often occur due to the small number of waterways and small ditches, so water spills more easily onto the streets and is difficult for the soil to absorb (O'Donnell & Thorne, 2020). In addition, the dense factor of adjacent buildings makes it very easy to trap rainwater that overflows from the ditches, so due to the lack of soil that can absorb rainwater it can cause the overflow to be absorbed for a long time (Nkwunonwo et al., 2020). Other researchers also stated that urban areas often easier to trap water overflow due to a less vegetation index, even in the worst conditions when there is no bio pores between buildings (Mignot et al., 2019).

In terms of handling, flooding in urban areas is a little difficult to do, because it requires very complex regional planning, plus many clashes of political needs in urban areas, so the processing time needed to deal with flooding in urban areas is relatively long (Zhou et al., 2019). Therefore, planning to handle flooding in urban areas must be based on complex analysis, so that accuracy can be trusted. With an analysis of the probability of flooding in urban areas, researchers, communities, and the government will know the main overview of regional priorities that must be addressed, in order to reduce the probability of flooding in the area (Abebe et al., 2019). One possible effort to obtain the probability of flooding in urban areas is by using satellite imagery based on the Geographic Information System (GIS). GIS is able to present data widely and fairly accurately if the treatment of the data is used correctly (Quattrochi et al., 2023). It is felt that the use of GIS in disaster hazard analysis will shorten time because the entire process is carried out by computing and assisted by satellite imagery which can record very large areas (Dikau, 2020). In addition, in terms of accuracy, GIS is fairly accurate because according to Supriadi & Oswari (2020) in his research stated that GIS accuracy is 98% accurate, and it all depends on the dataset used, if all datasets used have the same timeframe, and there are no clouds blocking, will be very accurate results. Including flood hazard probability analysis, which can be carried out using satellite imagery and assisted by GIS.

Flood hazard probability analysis using satellite imagery and the assistance of GIS can be done by looking at the various variables used. According to Motta et al. (2021), states that an analysis of the probability of flooding in urban areas can pay attention to the main variables, namely; (1) Topographic Wetness Index (TWI); (2) Land Slope (LS); and (3) Distance from road (Dro). However, Feng et al. (2020) revealed that other variables in the probability analysis of flood hazard in urban areas can pay attention to variables such as; (1) Elevation (EL); (2) Precipitation (Pc); (3) Land Use/Land Cover (LULC); and (4) Distance from the river (Drv). In addition, NDVI is felt to be very necessary for the analysis of flood hazard probabilities, because NDVI will play an important role in urban water absorption (Putra et al., 2022). Of course, all the variables used by various researchers need to be re-analyzed according to the characteristics of the urban area to be studied, as was done by previous researchers, using the seven variables mentioned by previous researchers, but not using NDVI, because the area is in the barren dominated by dry land (Nsangou et al., 2022).

Based on the variables, of course, the data needs to be analyzed using a method in disaster hazard probability analysis, for example by using the LSTM Neural Network model, where the LSTM Neural Network prioritizes connections between variable weight reliability, without regard to data validation, so that the accuracy for flood disaster hazard probabilities uses LSTM Neural Network needs to be questioned again. What is possible to do for flood hazard probability analysis is to use the Multi-Criteria Decision Analysis (MCDA) model because the MCDA model is one of the most recent disaster hazard models (Boulomytis et al., 2022). In addition, MCDA

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is in the process, it requires joint analysis with several experts, where the expert must come from the area to be analyzed and the number of experts must be at least five experts so that accuracy is maintained (Morales-Ruano et al., 2022). However, the MCDA model will not be completely perfect if there is no weighting to be done, MCDA must therefore be integrated with the Analytical Hierarchy Process (AHP), which utilizes pairwise comparisons to determine the relative importance of each variable by evaluating them against predefined criteria. (Msabi & Makonyo, 2021).

The AHP technique offers a key advantage over other methods by allowing researchers the flexibility to select variables, provided they carefully consider essential aspects when assigning weights in flood susceptibility analysis (Abdullah et al., 2021). In contrast, other approaches are often viewed as less effective and adaptable. For instance, methods based on the geomorphological characteristics of basins cannot fully substitute traditional hydraulic modeling and usually require detailed field studies, making them more time-consuming and labor-intensive. Moreover, such methods are only applicable in areas with multiple basins, and their accuracy becomes questionable in regions with generally flat terrain (Adnan et al., 2019). Statistical methods like frequency ratio and logistic regression also present limitations, as their effectiveness heavily relies on the relevance of input variables and the size of the dataset used (Rahmati et al., 2016; Tehrany et al., 2015).

Each method and model used to analyze flood probability in urban areas comes with its own strengths and weaknesses. Therefore, selecting an appropriate method for flood susceptibility mapping must consider the clarity of cumulative effects and the spatial continuity influenced by flood-triggering parameters. Moreover, a critical factor in mapping flood susceptibility is the spatial scale, whether it is conducted at a local or national level. This study focuses on identifying and analyzing the probability of urban flooding in Bandung City at a regional scale using the AHP-MCDA model, supported by satellite imagery and GIS tools. For validation purposes, a GIS-based point database will be included, documenting flood events that occurred between 2002 and 2022, with at least one recorded event in each of those years.

2. Data and Methods

2.1. Study Area

The study area used in this study uses the city of Bandung, where the city of Bandung has an area of 167.64 km2, and consists of thirty districts and one hundred and fifty-one sub-districts. Based on the population as of 2023, there were 2,469,589 people consisting of 1,242,674 male residents and 1,226,915 female residents (BPS, 2023). The city of Bandung is an area surrounded by quite high mountains, and the city of Bandung is often referred to as a sunken area like a bowl.

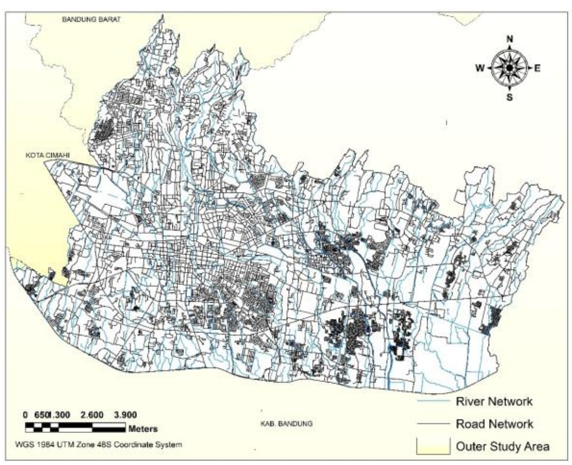

Figure 1. Study Area of Bandung City

In terms of climate, it was recorded from the Bandung City geophysical station that in 2021 the average temperature for the City of Bandung has an average temperature of 23.5°C, with the lowest temperature reaching

15.6°C, and the highest reaching 32.2°C. In addition, it was also recorded from the Bandung City geophysical station that in 2021 the rainfall for Bandung City was 180.89 mm/year, with the lowest rainfall occurring in July which reached 33.2 mm/month, and the highest rainfall occurring in November with rainfall reaches 454.3 mm/month. In full, geographic information about the city of Bandung as a study area can be seen in Figure 1.

2.2. Data and Process

This study utilizes a diverse range of data obtained from creditable and reliable sources, which are subsequently processed using GIS. As outlined in the literature review presented in the introduction, the data used for analyzing flood conditioning factors is summarized in Table 1.

Table 1. Types of Data used and their Sources to Process Flood Conditioning Criteria

No	Data Type	GIS Data Type		Scale or Resolution	Source of Data
		Spatial Database	Derived Map	Spatial Database	
1	TWI	GRID	Slope Gradient (°)	30 m	ASTER GDEM Version 3
2	Elevation		Elevation (m)		
3	Slope		Topographic wetness index		
4	Rainfall	GRID	Precipitation map (mm/yr)	1:50.000	(Harris et al., 2020)
5	LULC	ARC/INFO GRID	Land Use	10 m	ESRI Land Cover (2020)
6	NDVI	ARC/INFO GRID	NDVI	30 m	Landsat 8 OLI/TIRS + Images
7	Distance from River	ARC/INFO GRID Line Coverage	Distance from River	30 m	Indonesian Geospatial Information Agency (BIG)
8	Distance from Road	ARC/INFO GRID Line Coverage	Distance from Road	30 m	Indonesian Geospatial Information Agency (BIG)
9	Flood Inventory	Point and Polygon	-	-	Indonesian National Disaster Management Agency (BNPB)

Eight datasets are used as flood conditioning factors in this study, chosen specifically to minimize the complexity of data processing at a regional scale encompassing City of Bandung. These factors include: (1) TWI, (2) Elevation, (3) Slope, (4) Rainfall (Annual Precipitation), (5) Land Use, (6) NDVI, (7) Distance from River, and (8) Distance from Road. A ninth dataset is used for validating the resulting flood susceptibility map of the City of Bandung, consisting of recorded flood events from 2002 to 2022, with at least one event documented each year. The overall research flow is illustrated in Figure 2.

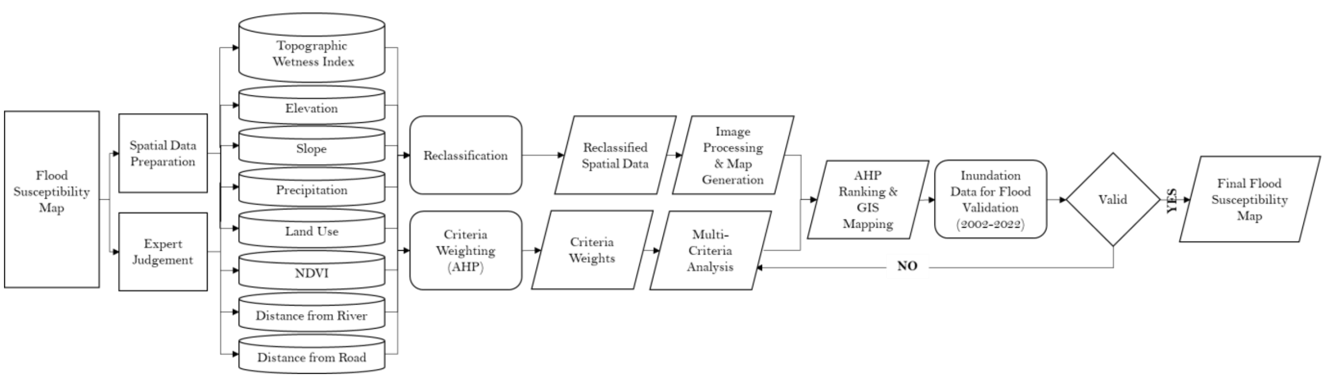

Figure 2. Research Flowchart

This study employed ArcGIS 10.8 software to compile and analyze all flood conditioning factors within a local GIS database. The processing steps, including the reclassification of conditioning factor maps, application of the weighted linear combination (WLC) method, and the validation of the flood susceptibility map for the City of Bandung area were entirely conducted using ArcGIS 10.8. All GIS-based analyses were performed in a two-dimensional spatial format, without incorporating 3D analysis. Meanwhile, the AHP was executed using Microsoft Excel, applying a quantitative approach to determine preferences among various decision alternatives

(Chourabi et al., 2019). A pair-wise comparison matrix (PCM) was utilized in the AHP method to rank the parameters, enabling the construction of weighting factors for each criterion based on individual judgments using a standardized ranking scale (Lin & Kou, 2015).

The weighting scale ranges from 1 to 9, where a score of 1 indicates equal importance between two factors, and a score of 9 signifies an extreme preference for one factor over another. The resulting Consistency Index (CI) values derived from PCM calculations vary depending on the number of conditioning factors, with corresponding matrix sizes. The Consistency Ratio (CR) is then used to quantitatively validate the input data through mathematical equations, as outlined in Equations 1 and 2.

$$CR = \frac{CI}{RI} \ldots\ldots\ldots\ldots \textit{(Equation 1)}$$

$$CI = \frac{(\lambda_{max-n})}{n-1} \ldots\ldots\ldots\ldots \textit{(Equation 2)}$$

where CR is the consistency ratio, CI is consistency index, λ is average value of consistency vector, n is the number of criteria, and RI is random CI randomly generated by PCM.

The Random Index (RI) values were derived from pairwise comparison matrices (PCMs) generated through random, inconsistent pairwise selections (Althuwaynee et al., 2016). To validate the assigned weights of the conditioning factors, the Consistency Ratio (CR) must be less than 0.1. If the CR exceeds 0.1, the weighting matrix developed by experts must be revised. Weight normalization within the PCM is conducted through various techniques, based on expert judgment and methodological preferences (Bozorgi-Amiri & Asvadi, 2015). Once the final weights are determined from expert evaluations, an aggregation method is applied by multiplying each conditioning factor map in ArcGIS 10.8 with the corresponding weight, following the procedure outlined in Equation 3.

$$FS = \sum w_i x_i \ldots\ldots\ldots\ldots \textit{(Equation 3)}$$

where, FS is flood susceptibility, w_i is weight of factor *i*, and x_i is classes of flood susceptibility for each factor *i*.

2.3. Flood Validation by Flood Inventory Database

For accuracy validation of the flood susceptibility map generated through various data processing and analytical stages, a GIS-based flood event database was utilized, encompassing flood occurrences from 2002 to 2022. During this period, data were collected for one or more flood events per year. The information on these events was sourced from the Disaster Information Data provided by the Indonesian National Disaster Management Agency (BNPB). However, the dataset for City of Bandung does not cover all flood incidents, only those classified within levels one to three. According to BNPB classifications, level one refers to a critical condition where flooding persists for more than six hours without receding; level two indicates a situation where floodwaters have begun to spread; and level three refers to non-critical inundation events, often identified as flash floods.

3. Result and Discussion

This study focuses on the probability analysis of flood hazard in urban areas, especially the area of Bandung City, West Java, Indonesia. Before displaying the flood hazard probability map for the city of Bandung, this study will display eight data that are used as conditioning factors that will affect the probability of flooding hazard for the city of Bandung, with a list of data and their sources which can be seen in Table 1. The conditioning factor data that has been obtained is then checked. reconsidering the values in the raster data, and readjusting the units used, so that when weighting is carried out it is relevant to the conditions that occur in the study area. Sometimes the data obtained has units that are different from what the researcher believes and what has been determined according to the law in force in the research area, for example, most areas use the temperature unit as Celsius, but some data will provide temperature data in Fahrenheit units. because the data manager is in an area that applies temperature in Fahrenheit units, conversions must be carried out so that they are aligned and there is no confusion in units later when a disaster hazard probability map has been made (Cabrera & Lee, 2019). The results of the data obtained in this study can be seen in Figure 3.

After all the data is obtained properly, the units are in accordance with the applicable provisions, and the resolution used is quite good or in accordance with what is desired, even if all the resolutions used are more or less similar to other data, then the data classification is carried out according to the values that have been determined. previously defined. Classifying raster data aims to produce equivalent values that are used when doing weighting so that no data weight has more or less value between one data and another (Shahiri Tabarestani & Afzalimehr, 2021). In addition, the classification aims to provide specific values which later these values will appear as a new classification, but sometimes the classification that is set does not match the final results obtained so the classification must be considered properly according to the data presented in the raster (Wijaya & Buchori, 2022). The following is the result of reclassification based on the class or value of each map data which can be seen in Table 2.

Table 2. Classes of Conditioning Factors, and Estimated Ratings for Reclassify

No.	Factor	Abbreviation	Class	Rating
1.	TWI (Level)	TW	<5	1
			6 – 10	2
			11 – 15	3
			16 – 20	4
			20>	5
2.	Elevation (m)	EL	<650	5
			651 – 700	4
			701 – 750	3
			751 – 800	2
			800>	1
3.	Slope (°)	SL	0 – 10	5
			11 – 30	4
			31 – 50	3
			51 – 70	2
			70>	1
4.	Precipitation (mm/yr)	PC	<195	1
			196 – 197	2
			198 – 199	3
			200 – 201	4
			201>	5
5.	Land Use	LU	Water	1
			Agriculture Land	2
			Building	3
			Bare Land	4
			Vegetation	5
6.	NDVI	ND	-0.00649 – -0.012	1
			-0.012 – 0.125	2
			0.126 – 0.200	3
			0.201 – 0.300	4
			0.301 – 0.476	5
7.	Distance from Rivers (m)	DRv	<85	5
			85 – 184	4
			185 – 296	3
			297 – 431	2
			431>	1
8.	Distance from Roads (m)	DRo	<160	5
			161 – 316	4
			317 – 474	3
			475 – 632	2
			633>	1

Source: Analysis, 2023

The classification presented in Table 2 was conducted utilizing the Jenks Natural Breaks Optimization (NBO) method, a technique that groups data based on inherent distribution patterns to minimize intra-class variance and maximize inter-class differences. This approach ensures alignment with the dataset's empirical distribution curve, thereby mitigating risks of data fragmentation or voids during classification (Hadipour et al., 2020). Following this, a weighted assessment was performed by a panel of five regional experts from Bandung City to contextualize the classification outcomes according to local geographical and socio-environmental conditions. Each expert's input was subjected to a consistency validation process, with a predetermined threshold for the Consistency Ratio (CR) set at ≤0.1 to ensure analytical reliability. The individual expert weightings were subsequently aggregated using a composite scoring framework, and the synthesized results are comprehensively detailed in Table 3.

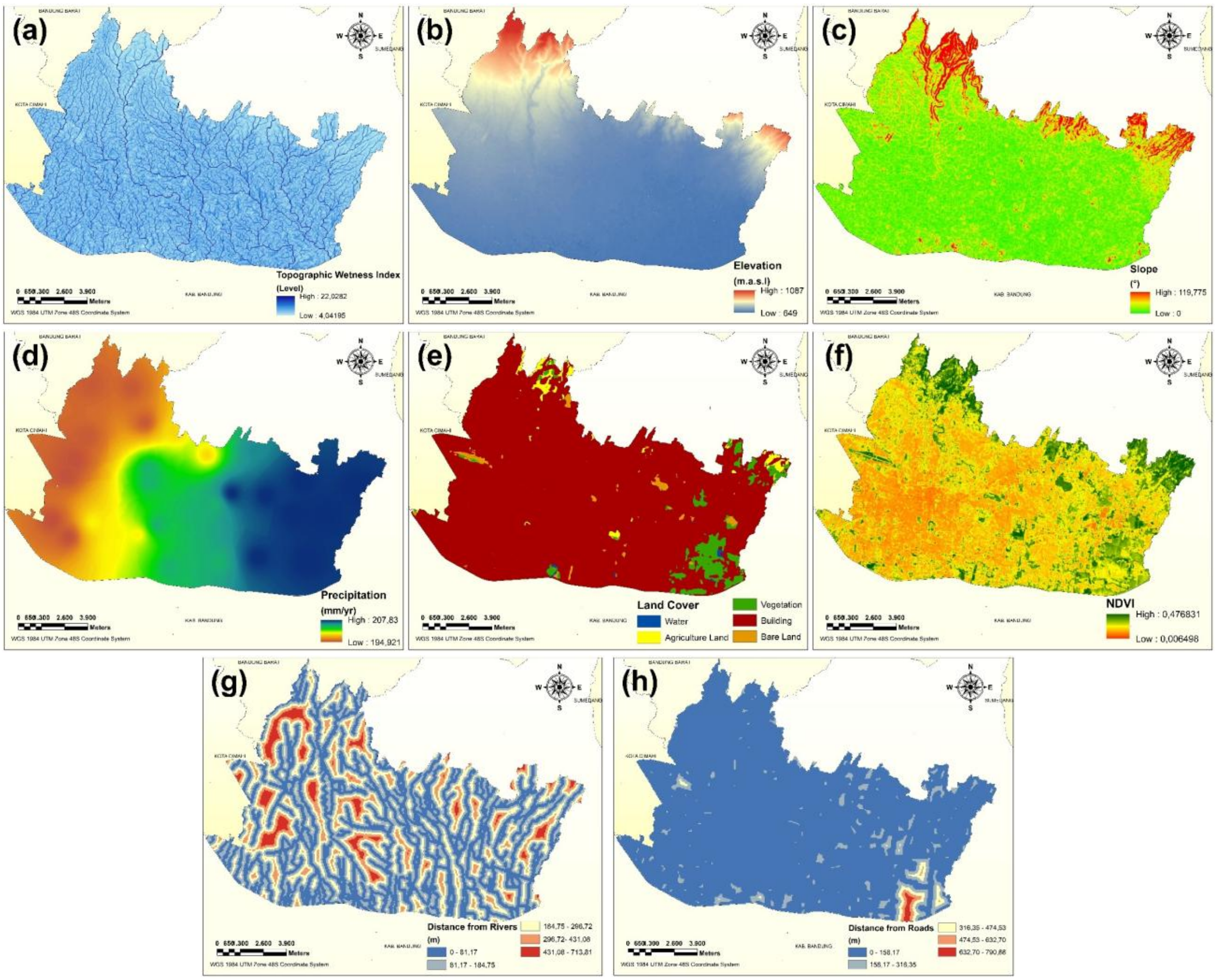

Figure 3. The Map of (a) TWI; (b) Elevation; (c) Slope; (d) Precipitation; (e) Land Cover; (f) NDVI; (g) Distance from Rivers; and (h) Distance from Roads in City of Bandung

Table 3. The Results of the Weighting Matrix along with the Normalized Principal Eigenvector Values

	TW	EL	SL	PC	LU	ND	DRv	DRo	Normalized Principal Eigenvector
TW	1	1.51	1	1.27	1.32	1.55	2.11	1.24	16.29%
EL	0.66	1	0.51	1.12	0.85	1	1.24	1.24	11.22%
SL	1	1.93	1	1.38	1.14	1.64	1.71	1.14	16.31%
PC	0.78	0.89	0.72	1	1.11	0.92	1.14	1.24	11.82%
LU	0.75	1.17	0.87	0.89	1	1.32	2.22	1.55	14.18%
ND	0.64	1	0.60	1.08	0.75	1	1.38	0.87	10.79%
DRv	0.47	0.80	0.58	0.87	0.45	0.72	1	0.92	8.57%
DRo	0.80	0.80	0.87	0.80	0.64	1.15	1.08	1.00	10.82%

Source: Analysis, 2023

By applying AHP, the weighting criteria were determined through the normalized principal eigenvector, which was derived by comparing the values in each row to calculate the total weight for all flood conditioning factors in the City of Bandung. The analysis produced a maximum eigenvalue (λmax) of 8.08 and a Consistency Ratio (CR) of 0.08, indicating that the weighting results are valid, as the CR value (0.08) is less than the acceptable threshold of 0.1. The resulting weights for each conditioning factor are as follows: TWI in 16.29%, Elevation in 11.22%, Slope in 16.31%, Precipitation in 11.32%, Land Use in 14.18%, NDVI in 10.79%, Distance from Rivers in 8.57%, and Distance from Roads in 10.82%. These weights were then applied in ArcGIS 10.8 using the weighted overlay method to produce the flood susceptibility map (see Figure 4) for the City of Bandung.

In order to analyze more deeply regarding the percentage and area of the area affected, an analysis per sub-district was carried out (see Table 4). This per-sub-district analysis was carried out by pasting the sub-district boundary shapefiles, which were then cut using the overlay method, so the researchers would find out how many areas were affected along with their flood hazard classification.

Table 4. Area Coverage of Flood Susceptibility by its Classes

Subdistrict	Low Hazard (sq km)	%	Quite Hazard (sq km)	%	High Hazard (sq km)	%	Extreme Hazard (sq km)	%	Total area (sq km)	Total %
Andir	0	0	4.09	97.10	0.12	2.89	0	0	4.21	100
Astana Anyar	0	0	2.44	99.31	0.01	0.69	0	0	2.46	100
Antapani	0	0	3.47	71.82	1.36	28.17	0	0	4.83	100
Arcamanik	0	0	3.31	48.38	3.51	51.26	0.02	0.35	6.85	100
Babakan Ciparay	0.08	1.18	6.55	96.49	0.15	2.32	0	0	6.79	100
Bandung Kidul	0	0	3.76	71.92	1.46	28.07	0	0	5.21	100
Bandung Kulon	0.11	2.04	5.33	96.26	0.09	1.69	0	0	5.53	100
Bandung Wetan	0	0	2.49	60.48	1.62	39.51	0	0	4.11	100
Batununggal	0	0	4.18	86.61	0.64	13.38	0	0	4.82	100
Bojongloa Kaler	0.00	0.23	3.01	98.40	0.04	1.37	0	0	3.06	100
Bojongloa Kidul	0	0	4.57	93.74	0.30	6.25	0	0	4.87	100
Buahbatu	0	0	5.20	75.25	1.71	24.75	0	0	6.90	100
Cibeunying Kaler	0	0	2.90	63.70	1.64	35.92	0.01	0.37	4.56	100
Cibeunying Kidul	0	0	3.46	85.52	0.58	14.47	0	0	4.04	100
Cibiru	0	0	0.78	10.01	6.43	82.30	0.60	7.67	7.81	100
Cicendo	0	0	6.77	89.55	0.79	10.44	0	0	7.56	100
Cidadap	0	0	5.45	73.49	1.96	26.50	0	0	7.42	100
Cinambo	0	0	1.61	41.29	2.29	58.62	0	0.07	3.91	100
Coblong	0	0	5.39	74.34	1.86	25.65	0	0	7.25	100
Gedebage	0	0	2.51	26.22	7.05	73.67	0.01	0.10	9.57	100
Kiaracondong	0	0	4.58	80.56	1.10	19.43	0	0	5.69	100
Lengkong	0	0	4.41	84.54	0.80	15.45	0	0	5.22	100
Mandalajati	0	0	0.95	20.27	3.70	78.91	0.03	0.80	4.69	100
Panyileukan	0	0	2.53	43.17	3.34	56.82	0	0	5.88	100
Rancasari	0	0	3.85	45.74	4.57	54.25	0	0	8.42	100
Regol	0	0	4.54	95.04	0.23	4.95	0	0	4.78	100
Sukajadi	0	0	4.64	90.32	0.49	9.67	0	0	5.14	100
Sukasari	0	0	3.60	61.18	2.29	38.81	0	0	5.89	100
Sumur Bandung	0	0	2.32	73.31	0.84	26.68	0	0	3.17	100
Ujungberung	0	0	1.41	20.61	5.16	75.05	0.29	4.33	6.87	100
TOTAL	0.19	0.11	110.20	69.15	56.25	30.27	0.99	0.45	167.64	100

Source: Analysis, 2023

According to the percentages presented in Table 4, Bandung Kulon has the highest proportion of areas classified as low flood hazard, accounting for 2.04% of its total area. The highest percentage of areas under moderate (quite) flood hazard is found in Astana Anyar, with 99.31%. For high flood hazard zones, Cibiru exhibits the greatest extent, comprising 82.30% of its area. Additionally, Cibiru also records the largest proportion of areas under extreme flood hazard, at 7.67%. Generally, administrative regions with larger land areas tend to exhibit higher absolute values of flood hazard zones compared to smaller regions (Rincón et al., 2018).

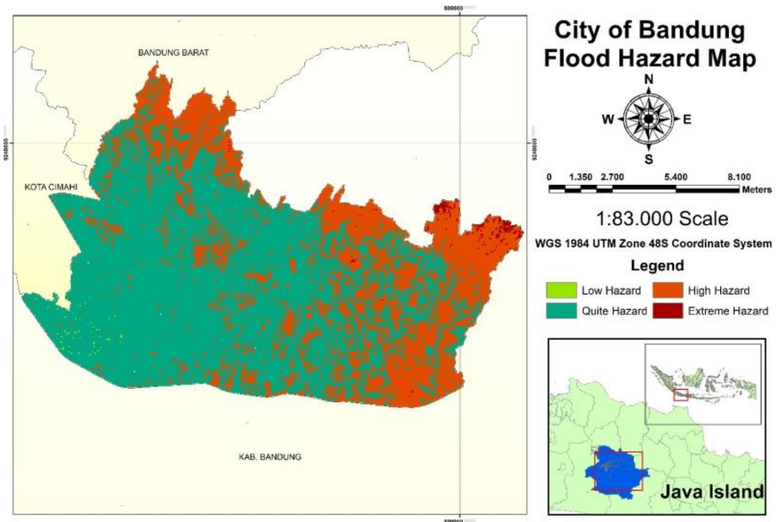

Figure 4. Susceptibility Flood Hazard Map in City of Bandung

Then, the results of the flood hazard susceptibility mapping in Bandung City were validated to determine the validity percentage of the flood hazard susceptibility that was carried out. Validation was carried out by comparing the real events of flooding in the city of Bandung in the 2002-2022 timeframe with the results of the flood hazard susceptibility map for the city of Bandung. Previously, the criteria for real flood event data in the city of Bandung were classified according to the laws in force in Indonesia, such as "Siaga 1" will be classified as low flood hazard, up to "Siaga 4" will be classified as extreme flood hazard. validation criteria that data can be said to be valid if the average validation of all flood classification levels reaches > 50% (de Moel et al., 2015). The validation results can be seen in Table 5.

Table 5. Flood Validation in City of Bandung based on BNPB Data and Flood Susceptibility Map

Flood Susceptibility Level	Number of Flood Validation Points	% of Total Number of Flood Validation Points	% Average and it's Validation
Low Hazard	12	76.60	80.20% (Valid)
Quite Hazard	117	84.20	
High Hazard	304	82.70	
Extreme Hazard	54	77.30	

Source: Analysis, 2023

Careful selection of flood conditioning factors and appropriate spatial scale is essential for valid flood susceptibility analysis (Al-Juaidi et al., 2018; Wing et al., 2017). In particular, finer spatial resolution typically yields more accurate and valid data, whereas coarse or mismatched data scales can compromise model validity. In this study, a primary issue is that the input data are at a relatively coarse scale compared to the broad regional extent of the analysis, which likely undermines validation accuracy.

Hasanloo et al. (2019) similarly observed that excessively large study areas relative to the data resolution result in low validation and coarse-detail outputs. Furthermore, employing MCDA with the AHP introduces significant subjectivity, since expert judgments are required to weight the conditioning factors. In large, multi-city analyses, differing expert opinions can lead to one or two factors receiving disproportionately large weights. Consistent with this, Doorga et al. (2022), Ha-Mim et al. (2022), and Vignesh et al. (2021) reported that researchers often rebalance or adjust their data to equalize the influence of all conditioning factors, thereby avoiding one-sided bias.

The analysis performed in Table 4 shows information that the high to extreme flood probability is centered on East Bandung which includes the Mandalajati, Ujung Berung, Cibiru, Gedebage, and Panyileukan areas. Globally, similar patterns emerge in diverse contexts. For instance, Anelli et al. (2022) in Rome, Italy, found that proximity to rivers and impervious surfaces drove flood susceptibility, aligning with Bandung's high-risk zones near rivers and roads. However, Rome's historical drainage infrastructure mitigated central-area risks, unlike Bandung's limited drainage capacity. In Lagos, Nigeria, Nkwunonwo et al. (2016) highlighted elevation and vegetation loss as key factors, mirroring Bandung's challenges, though coastal tides added complexity. Contrastingly, New Orleans' reliance on levees (Abbott, 2024) and São Paulo's impervious surfaces (Young & Papini, 2020) underscore the variability in mitigation strategies and risk drivers across continents. These comparisons emphasize that while Bandung's flood susceptibility aligns with global urban patterns, localized infrastructure and planning critically shape outcomes.

Flood hazard with a high and extreme level of probability in East Bandung has a high percentage of coverage, which is above 75% for high-hazard probability, and above 0.1% for extreme-hazard probability. Of course, this is because, in the East Bandung area, the roads are close together, with the rivers also close together. The proximity of roads and rivers can increase the probability of flood hazard, because the distance between the roads that are close together will make it difficult for water to be absorbed by the ground, besides that the distance between rivers that are close to urban areas will make the accumulated water easily overflow onto the roads so that the absorption capacity of the soil will increase. fills up quickly when roads and rivers are close together, let alone coincide (Khosravi et al., 2020; Rafiei-Sardooi et al., 2021).

From a review of land cover, which is shown in Figure 3e, it can be seen that the East Bandung area is filled with buildings, and little vegetation, and also that the vegetation is relatively far from settlements, so water absorption when it rains only applies to areas that have vegetation. Less or far distances between vegetation and settlements will certainly make flood handling inappropriate, so it is essential to notice the distance between vegetation and settlements (Ferrini et al., 2020). Machado et al. (2019) in his research revealed that the role of vegetation is of course very large in absorbing water when it rains so as to avoid flooding in urban areas, however, the layout of the vegetation must be considered again. to be more effective.

O'Donnell & Thorne (2020) suggests building a vegetation area at the headwaters of a river, or the corner of a road to make it easier for water to infiltrate when rain occurs in urban areas, besides that, Maragno et al. (2018) provides the best design for developing urban vegetation, namely by building the vegetation area encircles several parts of the residential area, the circular shape is expected to be able to hold water coming from other directions towards the residential area with the aim that the water can be absorbed first. In addition, the construction of floating buildings is considered very possible to deal with flooding, because floating buildings will create new paths for river flow so that water will move quickly and reduce overflows in other parts of the river (Piątek & Wojnowska-Heciak, 2020).

In terms of environmental review and regional planning for the East Bandung area, it is indeed deemed inadequate to withstand flooding. This can be seen by the very small width of the ditch in residential areas, and the absence of qualified bio pores. Schools and bio pores in urban areas are indeed the most important thing in overcoming flooding because the provision of sufficient wide ditches and an adequate number of bio pores and strategic locations will make water infiltration and flow faster so that water that falls when it rains will not quickly accumulate and causing flash floods to occur (Hamel & Tan, 2022; Karunia et al., 2021). In addition, the Gedebage area has a market on the border between Gedebage and Panyileukan, where the market produces and accumulates quite a lot of waste, around ten tons a year (Idris, 2022), where this waste is one of the supporting factors. in the occurrence of floods in the city of Bandung, especially the East Bandung area which is vulnerable to being affected. The accumulation of garbage in urban areas will certainly result in clogged river flows or drainage so that the water will quickly overflow due to obstacles from the garbage (Mensah & Ahadzie, 2020). Moreover, solid waste will seriously interfere with river flow and drainage, because its accumulation will block the flow of water in rivers and drainage and become a dead end for water flow (Zambrano et al., 2018).

This study provides critical insights into flood susceptibility in Bandung City, Indonesia, through a multi-criteria decision framework. The most significant finding is the identification of East Bandung, which encompasses Mandalajati, Ujungberung, Cibiru, Gedebage, and Panyileukan, as the region with the highest flood risk. Over 75% of this area falls under "high" to "extreme" susceptibility categories, driven by its dense road networks, proximity to rivers, and limited vegetation cover (NDVI < 0.3). These factors collectively hinder natural water infiltration, exacerbating surface runoff during rainfall events. Such spatial clustering of risk aligns with patterns observed in other flood-prone urban regions globally, such as São Paulo, Brazil, where impervious surfaces and informal settlements amplify flood hazards (Young & Papini, 2020).

The AHP weighting revealed that topographic and hydrological factors, specifically the Topographic Wetness Index (TWI, 16.29%) and Slope (16.31%), were the most influential criteria. This underscores the role of Bandung's "bowl-like" topography, where lower elevations and gentle slopes in central-southern zones trap floodwaters. Conversely, anthropogenic factors like Distance from Roads (10.82%) and Land Cover (14.18%) highlighted human contributions to vulnerability, such as inadequate drainage systems and urban sprawl. This dual emphasis on natural and human-driven factors mirrors methodologies applied in Rome, Italy, where AHP-GIS frameworks similarly prioritized river proximity and impervious surfaces (Anelli et al., 2022).

The validation accuracy of 80.20%, achieved by cross-referencing predicted susceptibility zones with 20 years of historical flood data (2002–2022), underscores the model's reliability. This high accuracy stems from two pillars of robustness; (1) Methodological Rigor; and (2) Data Diversity and Resolution. The integration of five expert assessments ensured localized relevance while minimizing subjectivity. The Consistency Ratio (CR = 0.08) confirmed logical coherence in pairwise comparisons, adhering to Saaty's threshold (CR < 0.1). This approach contrasts with single-expert studies, such as Maskrey et al. (2022), stated that limited expert input reduced decision transparency. Combining high-resolution satellite imagery (30 m) with multi-source datasets (e.g., ASTER DEM, Landsat NDVI, and BNPB flood inventories) enabled granular analysis. For instance, the 30 m resolution of Distance from Rivers and Roads allowed precise identification of at-risk settlements, a refinement absent in broader-scale studies like Lagos, Nigeria (Nkwunonwo et al., 2016), which relied on coarser administrative boundaries.

The AHP-MCDA framework's adaptability further demonstrates robustness. Unlike machine learning models (e.g., LSTM) that require vast datasets, this method delivered accuracy despite Bandung's moderate data availability. This flexibility is critical for cities in developing regions, where data scarcity often impedes flood modeling. For example, in New Orleans, USA, advanced hydraulic models depend on extensive levee and rainfall data (Abbott, 2024). Globally, these findings resonate with flood susceptibility drivers identified across continents. In Rome, historical drainage infrastructure reduced central-zone risks despite river proximity (Anelli et al., 2022), whereas Bandung's infrastructural gaps amplified vulnerabilities. Similarly, Lagos shares Bandung's challenges with elevation and vegetation loss but faces compounded risks from coastal tides (Nkwunonwo et al., 2016). These parallels highlight the universality of topographic and anthropogenic factors in flood risk, while contextual differences emphasize the need for tailored mitigation strategies.

4. Conclusion

The study, which aimed to map flood susceptibility in the City of Bandung using the AHP-MCDA approach integrated with ArcGIS 10.8, revealed that, following the reclassification of each conditioning factor and the weighting assessment provided by five expert evaluators, four distinct flood susceptibility classes were identified within the City of Bandung; (1) Low hazard; (2) Quite hazard; (3) high hazard; and (4) Extreme hazard. The East Bandung area which includes Mandalajati, Ujungberung, Cibiru, Gedebage, and Panyileukan is an area that is very at hazardof flooding with a high-hazard percentage of above 75% and extreme hazard above 0.1%, where this needs to be considered again for Bandung City policymakers and the community must take part in dealing with floods in the city of Bandung, especially East Bandung. Based on the results of the validation carried out by comparing the real events of flooding in the city of Bandung in 2002-2022, a validation result of 80.20% showed that the map of susceptibility to flood hazard in the city of Bandung is valid. This research is expected to make the Bandung City flood susceptibility map the main basis for local government to deal with flooding in the Bandung City area so that the determination of development plans for urban areas is more organized and can cope with Bandung City flooding more efficiently.

This study successfully mapped flood susceptibility in Bandung City using the AHP-MCDA-GIS framework, identifying East Bandung as the highest-risk zone due to its dense infrastructure, proximity to rivers, and limited green spaces. The model's 80.20% validation accuracy against historical flood events underscores its reliability for urban planning and disaster mitigation. However, future research should address several avenues to enhance practical applicability like expanding criteria to include socio-economic factors e.g., population density, poverty levels, infrastructure resilience to assess human vulnerability and prioritize equitable mitigation strategies. Also, pilot and quantify the effectiveness of proposed solutions (e.g., bio-pores, decentralized drainage systems, or urban greening) in high-risk zones like Gedebage and Cibiru, using pre- and post-intervention flood data.

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