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Flood susceptibility mapping using GIS-based composite mapping analysis: a multi-district assessment in Lampung Province, Indonesia

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ABSTRACT

Flooding is a recurring hydrometeorological disaster in Lampung Province, Indonesia, particularly affecting Pesawaran Regency, South Lampung Regency, and Bandar Lampung City. This study mapped flood susceptibility using Geographic Information Systems (GIS) with Composite Mapping Analysis (CMA) and scoring methods to support disaster risk reduction planning. Six parameters were analyzed: rainfall, land cover, slope, elevation, soil type, and river buffer distance. Parameter weights were derived objectively through CMA based on spatial analysis of 258 historical flood events (2018-2024). Rainfall data (2015-2024) were interpolated using Inverse Distance Weighting, and spatial analysis was conducted in ArcGIS 10.8. Results show that 90.66% of the study area falls within moderate to high susceptibility classes. Rainfall received the highest weight (20%), followed by elevation (19%), soil type (18%), land cover (16%), river buffer (14%), and slope (13%). Model validation achieved 77.78% accuracy when compared with historical flood locations across 45 sub-districts. High susceptibility areas are characterized by annual rainfall exceeding 2,500 mm, elevations below 50 masl, poor soil infiltration capacity, and dense settlement. The CMA method provides objective parameter weighting while maintaining computational simplicity suitable for resource-constrained settings, offering a practical framework for flood susceptibility assessment in similar tropical regions.

Keywords: Composite mapping analysis, flood susceptibility, Geographic Information System, Lampung Province, multi-criteria analysis

PLAIN LANGUAGE SUMMARY

This study created flood risk maps for three districts in Lampung Province, Indonesia, using geographic information systems. We analyzed six factors including rainfall, elevation, soil type, land use, slope, and river proximity based on 258 flood events (2018-2024). Results show that over 90% of the study area has moderate to high flood risk, with rainfall, elevation, and soil type as the most important factors. Low-lying coastal areas with heavy rainfall and dense urban development face the highest risk. The mapping approach achieved 78% accuracy and provides a practical tool for local governments to plan flood mitigation strategies with limited resources.

Introduction

Flooding is one of the most common hydrometeorological disasters globally, causing economic losses and impacting human settlements. In Lampung Province, Indonesia, flood events occur regularly in Pesawaran Regency, South Lampung Regency, and Bandar Lampung City [1–3]. According to BPBD (Regional Disaster Management Agency) of Lampung Province, the February 2025 floods affected 30,935 people and inundated 9,425 houses in Bandar Lampung City [4]. In South Lampung Regency, flooding occurred across three sub-districts [5], while Way Punduh River overflow caused flooding in Pesawaran Regency's Marga Punduh and Padang Cermin sub-districts [6]. These events result from multiple factors including high-intensity rainfall, poor soil infiltration capacity, inadequate drainage systems, and land-use changes that increase impervious surfaces [7]. Flood susceptibility mapping can support disaster risk reduction planning by enabling authorities to identify high-risk areas, inform spatial planning decisions, and improve community preparedness [8].

Geographic Information Systems (GIS) have been utilized for flood susceptibility assessment through the integration of multiple spatial datasets and overlay analysis techniques [9]. Current GIS-based approaches include multi-criteria decision analysis (MCDA) methods, statistical approaches, and machine learning algorithms [10]. Among MCDA methods, the Analytical Hierarchy Process (AHP) has been applied in various contexts due to its ability to incorporate multiple flood conditioning factors [11–13]. However, AHP relies on expert judgment for weight assignment, which can introduce subjectivity and inconsistency [14,15]. The Composite Mapping Analysis (CMA) method addresses this limitation by deriving parameter weights through quantitative spatial analysis, calculating the relationship between flood conditioning factors and historical flood occurrence [9,16]. While CMA offers potential advantages in objectivity, it has received limited application in flood susceptibility studies, particularly in Southeast Asian contexts. Scoring techniques integrated with spatial overlay methods provide a framework for classifying flood susceptibility zones based on multiple parameters [17,18].

Several gaps exist in flood susceptibility mapping for Indonesian regions. First, while research has been conducted in major urban centers, smaller cities and peri-urban regions remain less studied. Lampung Province experiences recurring floods [19,20], yet lacks comprehensive flood susceptibility maps at the multi-district scale. Second, most existing studies in Indonesia focus on single administrative units or employ conventional AHP without exploring alternative MCDA approaches like CMA [1,2]. Third, validation using historical flood data varies across studies, with some relying on limited temporal coverage [18,21]. Fourth, methodological approaches requiring extensive computational resources may not be readily implementable by local disaster management agencies with limited technical capacity [22]. Fifth, integrated multi-district assessments are uncommon, despite river systems that cross administrative boundaries requiring hydrologically coherent analytical frameworks [23].

This study develops a flood susceptibility map for Pesawaran Regency, South Lampung Regency, and Bandar Lampung City using GIS-based Composite Mapping Analysis (CMA) with scoring and spatial overlay techniques. The CMA approach derives parameter weights from spatial analysis of six flood conditioning factors (rainfall, land cover, slope, elevation, soil type, and river buffer distance) and 258 historical flood events recorded by BPBD Lampung Province from 2018 to 2024. Rainfall data from BBWS Mesuji-Sekampung (2015-2024) [24], topographic data from FABDEM, and land cover information from Badan Informasi Geospasial (BIG) were utilized [25]. The Inverse Distance Weighting (IDW) method was applied for rainfall interpolation [26], and spatial analysis was conducted using ArcGIS 10.8. The methodology uses publicly accessible datasets and standard GIS software, facilitating potential replication by local government agencies. By analyzing three administratively distinct but hydrologically connected jurisdictions, this research provides an assessment of flood dynamics across political boundaries.

Methods

Study area

The study was conducted in Pesawaran Regency, South Lampung Regency, and Bandar Lampung City, located in Lampung Province, Indonesia (Figure 1). Geographically, Pesawaran Regency is situated in the southern part of Sumatra Island with diverse topography ranging from lowlands to hills. This regency experiences flood risk influenced by intense rainfall, river flow patterns, topography, and land cover variations [27]. South Lampung Regency also experiences considerable flood risk. According to the Regional Medium-Term Development Plan (RPJMD) of Lampung Province 2019-2024, South Lampung Regency has a high flood risk category with a flood hazard area of 70,032 hectares [19]. Bandar Lampung City, as the provincial capital, contains dense settlement areas in low-elevation zones near rivers and coastal areas, contributing to flood vulnerability [3]. The study area encompasses approximately 373,644 hectares across the three jurisdictions, with elevations ranging from 0 to over 300 meters above sea level.

Data sources

Data used in this study were secondary data consisting of spatial and non-spatial types. Spatial data included administrative boundaries, slope, land cover, elevation, river buffer, and soil type. Non-spatial data consisted of rainfall records from Pesawaran Regency, South Lampung Regency, and Bandar Lampung City. Administrative boundary data were obtained from Badan Informasi Geospasial (BIG) for 2023 [25]. Rainfall data covering the period 2015-2024 were obtained from BBWS Mesuji-Sekampung [24]. Land cover data (2019) were sourced from BIG, while soil type data (2022) were obtained from FAO (Food

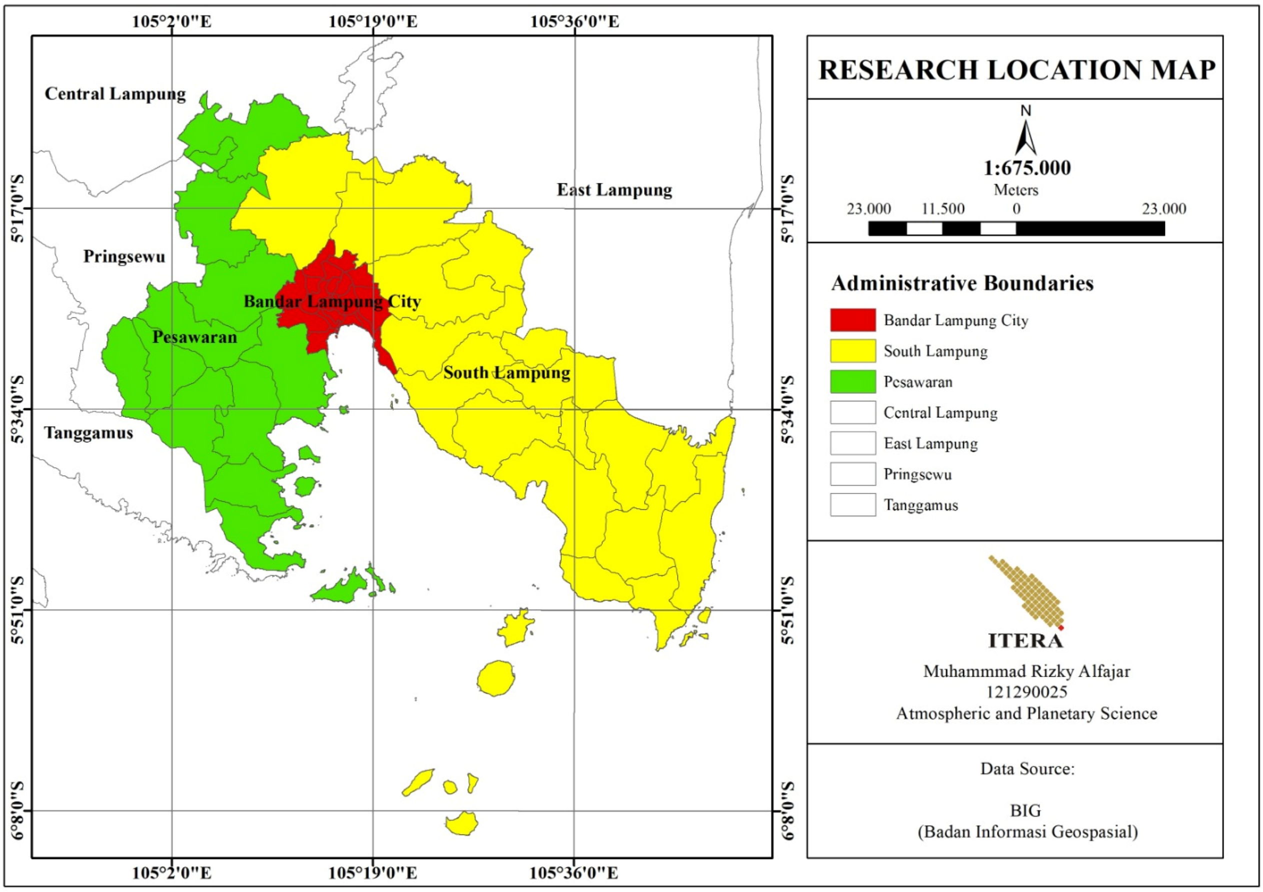


Figure 1. Location map of the study area showing Pesawaran Regency, South Lampung Regency, and Bandar Lampung City in Lampung Province, Indonesia, with administrative boundaries and major geographical features

and Agriculture Organization) [28]. Slope and elevation data (2023) were derived from FABDEM (Forest And Buildings Removed Copernicus DEM). River network data (2023) were obtained from BIG. Historical flood occurrence data from 2018-2024 were provided by BPBD Lampung Province, consisting of 258 flood event locations used for validation (Table 1).

Data processing tools

Data processing was conducted using ArcGIS 10.8 for spatial analysis, mapping, and parameter overlay operations. Microsoft Excel 2021 was used for processing numerical data, including rainfall calculations and statistical analysis for parameter weighting. Microsoft Word 2021 was used for report preparation. The hardware consisted of a laptop with AMD Ryzen™ 7 5800H Processor 3.2GHz, 8 GB memory, and 512 GB SSD storage.

Rainfall interpolation using IDW

Rainfall distribution was calculated using the Inverse Distance Weighting (IDW) method, which estimates values at unmeasured locations based on nearby measured points [26]. In the IDW model, points closer to the estimation location have greater influence than more distant points. The IDW equation is expressed as:

$$Z(x_0) = \frac{\sum_{i=1}^{n} \omega_i . Z(x_i)}{\sum_{i=1}^{n} \omega_i} \quad (1)$$

where the weight is calculated as:

$$\omega_i = \frac{1}{d(x_0, x_i)^p} \quad (2)$$

where:

$Z(x_0)$: estimated value at location x_0

$Z(x_i)$: observed rainfall value at location x_i

$d(x_0, x_i)$: distance between x_0 and x_i

p : distance power parameter (higher p increases the influence of nearby points)

n : number of neighboring data points used

Annual rainfall data from multiple stations within and around the study area were interpolated using the IDW tool in ArcGIS 10.8 to produce a continuous rainfall surface. The power parameter (p) was set to 2, following standard practice in rainfall interpolation studies [26]. This value of p=2 represents a balance between local variation and spatial smoothing: lower values (p=1) produce smoother surfaces but may overestimate values between stations, while higher values (p>3) create more localized estimates but can produce bull's-eye patterns around data points [26]. The IDW method assumes spatial autocorrelation, where nearby locations have similar rainfall values, which is generally valid for regional-scale rainfall patterns in tropical monsoon climates. However, this method has limitations in areas with complex topography or sparse station networks, where it may not adequately capture orographic effects or localized convective rainfall patterns. The accuracy of IDW interpolation depends on station density and spatial distribution; areas distant from measurement stations have higher uncertainty in estimated values.

Composite mapping analysis (CMA) for parameter weighting

The CMA method was applied to determine parameter weights based on the empirical spatial relationship between conditioning factors and historical flood occurrence [9]. Unlike conventional AHP which relies on expert judgment, CMA derives weights through quantitative analysis of flood density distribution across parameter classes [16]. The procedure consisted of five sequential steps:

First, all six parameter layers (rainfall, land cover, slope, soil type, river buffer, and elevation) were spatially overlaid with the 258 flood occurrence points from the 2018-2024 inventory. This overlay operation identified which parameter classes contained flood events and calculated the area of flood occurrence within each class.

Second, the flood density for each parameter class was calculated as the ratio of flood-affected area to total class area:

$$P_i = \frac{A_{\text{flood}.i}}{A_{\text{total}.i}} \quad (3)$$

where

P_i : the flood proportion in class i

$A_{\text{flood},i}$: the area containing flood points within class i

$A_{total,i}$: the total area of class i

Higher P_i values indicate stronger association between that class and flood occurrence.

Third, the spatial mean M for each parameter was computed by averaging the flood proportions across all classes within that parameter:

$$M = \frac{\sum X_i}{n} \quad (4)$$

where:

X_i : the area containing flood points within class i.

n : the number of classes in the parameter.

This spatial mean quantifies the overall contribution of each parameter to flood occurrence, with higher values indicating greater importance.

Table 1. Data sources and types used in the study

No.	Data type	Source	Year
1.	Administrative boundaries	Badan Informasi Geospasial	2023
2.	Rainfall data	BBWS Mesuji - Sekampung	2015-2024
3.	Land cover	Badan Informasi Geospasial	2019
4.	Soil type	FAO (Food and Agriculture Organization)	2022
5.	Slope	FABDEM (Forest and Buildings Removed Copernicus DEM)	2023
6.	River buffer	Badan Informasi Geospasial	2023
7.	Elevation	FABDEM (Forest and Buildings Removed Copernicus DEM)	2023
8.	Flood occurrence points	BPBD Lampung Province	2018 - 2024

Fourth, parameter weights were normalized to sum to unity:

$$B_i = \frac{M_i}{\sum M} \quad (5)$$

where:

B_i : weight for parameter i

M_i : spatial mean (from equation 4)

$\sum M$: total sum of spatial mean values of all parameters

Fifth, the final flood susceptibility score for each spatial unit was calculated as:

$$L_{\text{potency}} = L_{\text{moderately susceptible}} + L_{\text{highly susceptible}} \quad (6)$$

Scoring method

The scoring method assigns scores to each class of flood-related parameters based on their influence on flood likelihood. Classes with greater influence on flooding receive lower scores, following a scale of 1-5, where 1 indicates the highest susceptibility and 5 indicates the lowest susceptibility [8]. This scoring approach has been applied in various Indonesian flood studies (Ambon City [18], Padang City [29], Pacitan Regency [23]), providing a standardized framework for parameter classification (Table 2).

Flood susceptibility classification

Flood susceptibility classes were determined using interval classification based on the range of total scores [17]. Three susceptibility classes were established based on several considerations. First, three classes provide sufficient differentiation for practical disaster management decisions while avoiding the pseudo-precision of five or more classes given the inherent uncertainties in input data and modeling assumptions. Second, this classification scheme aligns with risk communication practices in Indonesia, where BPBD typically categorizes hazards into three levels (low-moderate-high) for public advisories and emergency response planning. Third, the validation dataset of 258 flood points provides adequate sample size for assessing model performance across three classes, whereas finer subdivisions would result in insufficient flood events per class for robust validation. The class interval was calculated using:

$$I = (C - B)/K \quad (7)$$

where:

I : the class interval

C : the highest possible total score (29, when all parameters receive a score of 1 plus maximum weights)

B : the lowest possible total score (approximately 1, with scores of 5 and minimum weights)

K : the number of desired classes (3).

The interval calculation yielded:

$$I = (29 - 1)/3 = 9.33$$

Based on this interval, the flood susceptibility classification was defined as:

- Not susceptible: 1.0-10.3 (areas where cumulative parameter conditions are least favorable for flooding)
- Moderately susceptible: 10.4-19.6 (areas with intermediate conditions)
- Highly susceptible: 19.7-29.0 (areas where cumulative parameter conditions are most favorable for flooding)

The boundaries between classes represent natural breaks in the score distribution rather than abrupt transitions in actual flood susceptibility. Areas near class boundaries should be interpreted with caution, as small changes in input data or classification schemes could shift their categorization.

Spatial overlay analysis

Spatial overlay analysis was conducted using the Union tool in ArcGIS 10.8, which combines all parameter layers while preserving the attributes of each layer [16]. This process integrated the six parameter layers (rainfall, land cover, slope, soil type, river buffer, and elevation) after each had been reclassified according to the scoring scheme and weighted using CMA-derived values. The overlay operation produced a composite map showing cumulative flood susceptibility based on all parameters. Areas with lower total scores indicated higher flood susceptibility, while higher scores indicated lower susceptibility [9].

Table 2. Scoring scheme for flood conditioning parameters

No.	Parameter	Class	Score	Weight
1.	Rainfall [30]	<1,500 mm	5	Spatial mean
		1,501 – 2,000 mm	4	
		2,001 – 2,500 mm	3	
		2,501 - 3,000 mm	2	
		>3,001 mm	1	
2.	Land cover [9]	Forest	5	Spatial mean
		Shrubland	4	
		Dryland agriculture	3	
		Paddy field	2	
		Settlement	1	
3.	Slope [9]	>45%	5	Spatial mean
		30 - 45%	4	
		15 - 30%	3	
		8 - 15%	2	
		<8%	1	
4.	Soil type [9]	Regosol, lilthosol, acrisol	5	Spatial mean
		Andosol, laterite, grumosol	4	
		Nitosol	3	
		Alluvial, planosol	2	
		Lithosol	1	
5.	River buffer [18]	>100	5	Spatial mean
		75 - 100	4	
		50 - 75	3	
		25 - 50	2	
		0 - 25	1	
6.	Elevation [30]	>300 masl	5	Spatial mean
		101 – 300 masl	4	
		51 – 100 masl	3	
		21 – 50 masl	2	
		0 – 20 masl	1	

Validation

Model validation was performed using 258 historical flood occurrence points from BPBD Lampung Province covering the period 2018-2024. These flood points were overlaid with the flood susceptibility map to assess the correspondence between predicted susceptibility classes and actual flood locations. Validation was conducted at the sub-district level, comparing whether flood events occurred in areas predicted to have moderate or high susceptibility. The accuracy was calculated as:

$$\text{Accuracy} = \frac{N_{\text{matching sub-districts}}}{N_{\text{sub-districts with floods}}} \times 100\% \quad (8)$$

A sub-district was considered a match if the flood susceptibility classification (moderately or highly susceptible) corresponded with the occurrence of historical flood events in that location. This validation approach has been used in previous flood susceptibility studies to assess model performance.

Results

Parameter weight determination using CMA

The spatial mean values calculated for each parameter through CMA analysis were: river buffer (0.6279), elevation (0.8747), slope (0.5933), land cover (0.7569), soil type (0.8480), and rainfall (0.9483). These spatial mean values were normalized to obtain parameter weights (Table 3). Rainfall received the highest weight (20%), followed by elevation (19%), soil type (18%), land cover (16%), river buffer (14%), and slope (13%). The sum of all weights equals 100%, ensuring proper normalization for the weighted overlay analysis.

Table 3. Parameter weights derived from CMA based on spatial mean values and historical flood occurrence data (2018-2024)

No.	Parameter	Spatial Mean	Weight (%)
1	Rainfall	0.9483	20
2	Elevation	0.8747	19
3	Soil type	0.8480	18
4	Land cover	0.7569	16
5	River buffer	0.6279	14
6	Slope	0.5933	13
Total	**4.6491**	**100**	

Spatial distribution of individual parameters

Rainfall distribution

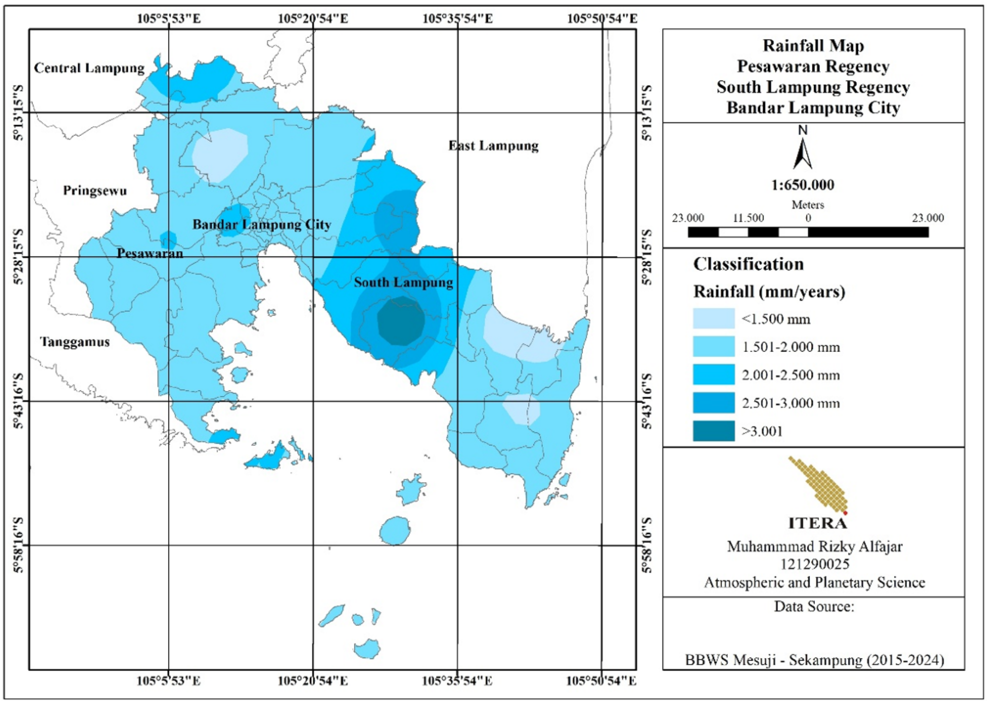
Annual rainfall across the study area ranges from less than 1,500 mm/year to greater than 3,000 mm/year (Figure 2). Bandar Lampung City experiences rainfall predominantly in the 1,501-2,500 mm/year range, with higher values (2,001-2,500 mm/year) in elevated areas such as Kemiling sub-district. In South Lampung Regency, several sub-districts including Tanjung Sari, Candipuro, Way Sulan, Katibung, and Sidomulyo receive annual rainfall exceeding 2,500 mm/year. Pesawaran Regency shows rainfall mainly in the 1,501-2,000 mm/year range, with higher values (2,001-2,500 mm/year) in Tegineneng, Way Lima, and Punduh Pidada sub-districts.

Land cover distribution

The land cover map (Figure 3) shows the distribution of five classes across the study area. Paddy fields and dryland agriculture dominate in Pesawaran Regency and South Lampung Regency. Settlement areas are concentrated in Bandar Lampung City, particularly in the central and coastal zones. Forest and shrubland are distributed primarily in the southern portions of South Lampung Regency and Pesawaran Regency, including small islands in the coastal areas.

Soil type distribution

Five soil types were identified in the study area: Acrisol, Andosol, Cambisol, Fluvisol, and Luvisol (Figure 4). Bandar Lampung City is characterized by Andosol in the western portion, and Cambisol and Luvisol in the central and eastern portions. Pesawaran Regency is dominated by Cambisol and Luvisol in the central and southern regions. South Lampung Regency shows Fluvisol distribution in Candipuro, Way Panji, and Way Sulan sub-districts, while Andosol and



Gambar 2. Spatial distribution of annual rainfall (mm/year) across Pesawaran Regency, South Lampung Regency, and Bandar Lampung City, interpolated using Inverse Distance Weighting method based on data from 2015-2024

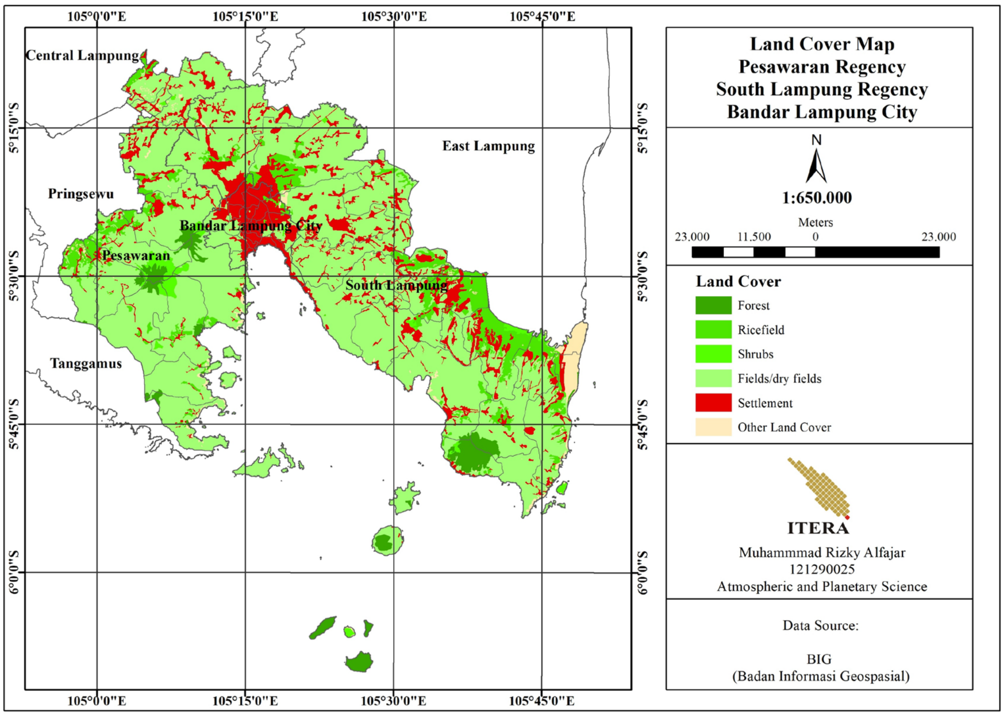


Figure 3. Land cover classification map showing the distribution of settlement, paddy field, dryland agriculture, shrubland, and forest across the study area (data source: BIG 2019)

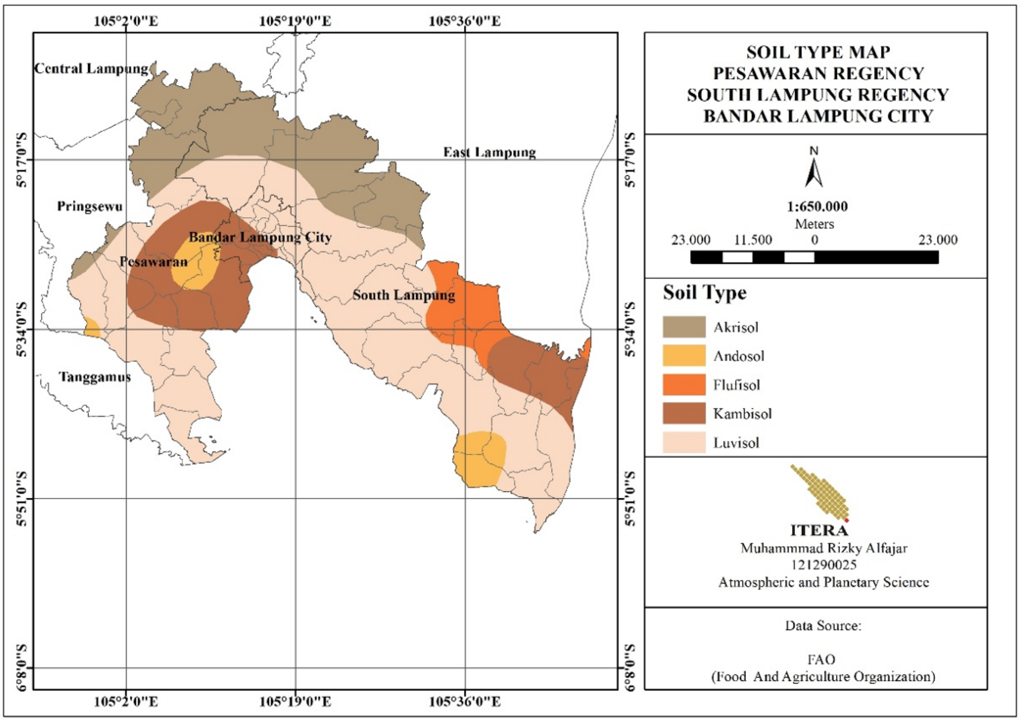


Figure 4. Soil type distribution map showing Acrisol, Andosol, Cambisol, Fluvisol, and Luvisol classifications based on FAO soil taxonomy (data source: FAO 2022)

Luvisol are found in coastal areas including Kalianda, Raja Basa, Bakauheni, Sidomulyo, and Katibung.

River buffer distribution

River buffer zones were classified into five distance classes: 0-25 m, 25-50 m, 50-75 m, 75-100 m, and >100 m from river channels (Figure 5). Major rivers in Bandar Lampung City include Way Garuntang, Way Simpur, Way Balau, and Way Tapuas, which flow through densely populated areas. In South Lampung Regency, Way Katibung, Way Gelam, and Way Panji traverse Way Panji, Sidomulyo, and Candipuro sub-districts. Pesawaran Regency contains Way Ratai, Way Piabung, and Way Cempaka rivers.

Elevation distribution

Elevation across the study area ranges from 0 to over 300 meters above sea level (masl) (Figure 6). Bandar Lampung City is dominated by elevations of 101-300 masl in the western portion, while sub-districts such as Teluk Betung Selatan, Teluk Betung Timur, Panjang, and Bumi Waras have elevations below 50 masl. South Lampung Regency contains extensive lowland areas (0-50 masl) in Palas, Sragi, Way Panji, Sidomulyo, and Ketapang sub-districts, while Penengahan, Bakauheni, and Raja Basa are located at elevations exceeding 300 masl. Pesawaran Regency shows elevations from 101 masl to over 301 masl in the central and southern portions, with lowland coastal areas in Teluk Pandan, Padang Cermin, Marga Punduh, and Punduh Pidada.

Slope distribution

Slope classes across the study area range from 0-8% (flat) to greater than 45% (very steep) (Figure 7). Coastal and urban center areas are characterized by flat slopes (0-8%). Areas with steep to very steep slopes include Teluk Betung Timur, Punduh Pidada, Padang Cermin, and the Mount Raja Basa area. Settlement centers are predominantly located in flat to gently sloping areas.

Flood susceptibility classification

The overlay analysis of six weighted parameters produced three flood susceptibility classes based on the interval calculation (I = 9.33): not susceptible (score 1-10), moderately susceptible (score 10.1-19), and highly susceptible (score 19.1-29). The areal extent of each class is presented in Table 4 and shown spatially in Figure 8.

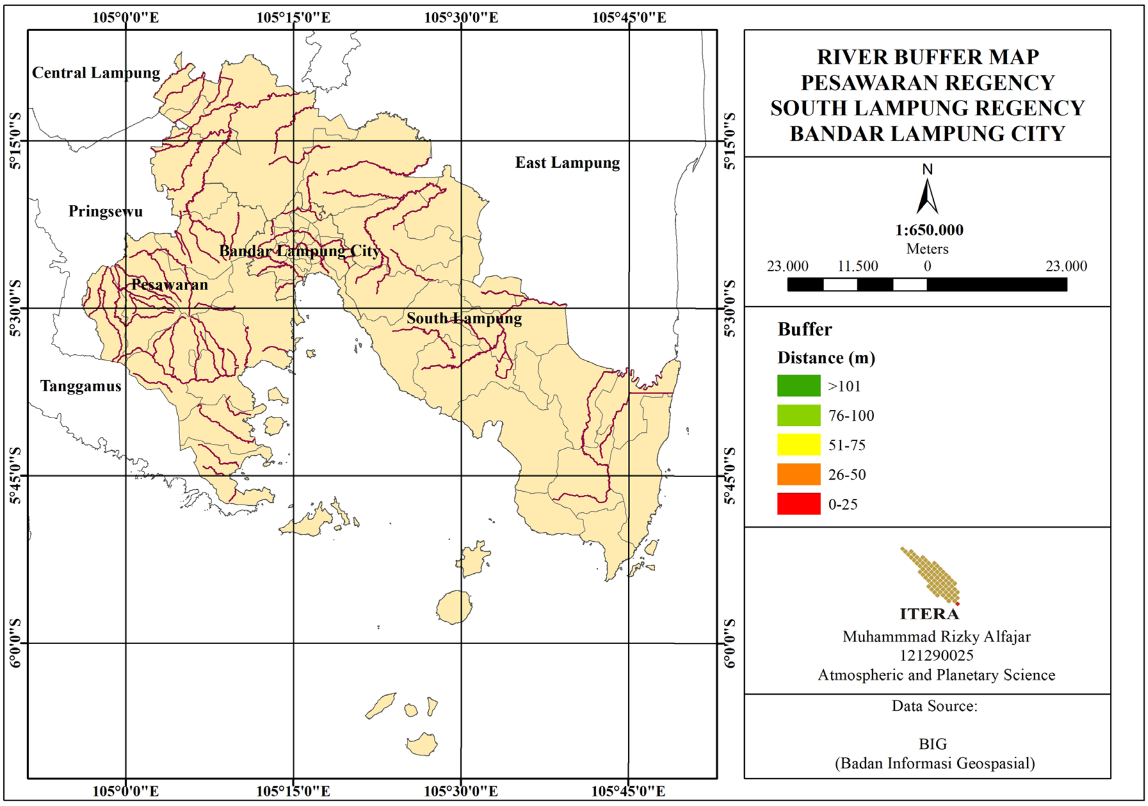
The majority of the study area (53.28%) falls within the moderately susceptible class, followed by highly susceptible (37.39%) and not susceptible (9.34%). Combined, the moderately and highly susceptible classes cover 338,763.58 Ha, representing 90.66% of the total study area.

Spatial distribution of flood susceptibility

The flood susceptibility map (Figure 8) shows distinct spatial patterns across the three administrative units. Bandar Lampung City is dominated by the moderately susceptible class, with coastal sub-districts including Panjang, Teluk Betung Utara, Teluk Betung Selatan, and Bumi Waras classified as highly susceptible. Western elevated portions contain areas classified as not susceptible. South Lampung Regency is dominated by moderately and highly susceptible classes, with sub-districts including Sidomulyo, Way Sulan, Tanjung Sari, Candipuro, Kalianda, Jati Agung, and Natar classified as moderately to highly susceptible. Highland areas in the southern portion show lower susceptibility classifications. Pesawaran Regency shows a distribution with moderately susceptible as the dominant class, while lowland areas near Way Ratai, Way Piabung, and Way Campang rivers are classified as highly susceptible. Highland and hilly areas in the central and southern portions are predominantly classified as not susceptible to moderately susceptible.

Table 4. Areal extent and percentage distribution of flood susceptibility classes in Pesawaran Regency, South Lampung Regency, and Bandar Lampung City

No.	Susceptibility Class	Score Interval	Area (Ha)	Percentage (%)
1	Not Susceptible	1.0-10.0	34,880.70	9.34
2	Moderately Susceptible	10.1-19.0	199,069.85	53.28
3	Highly Susceptible	19.1-29.0	139,693.73	37.39
Total			**373,644.28**	**100.00**



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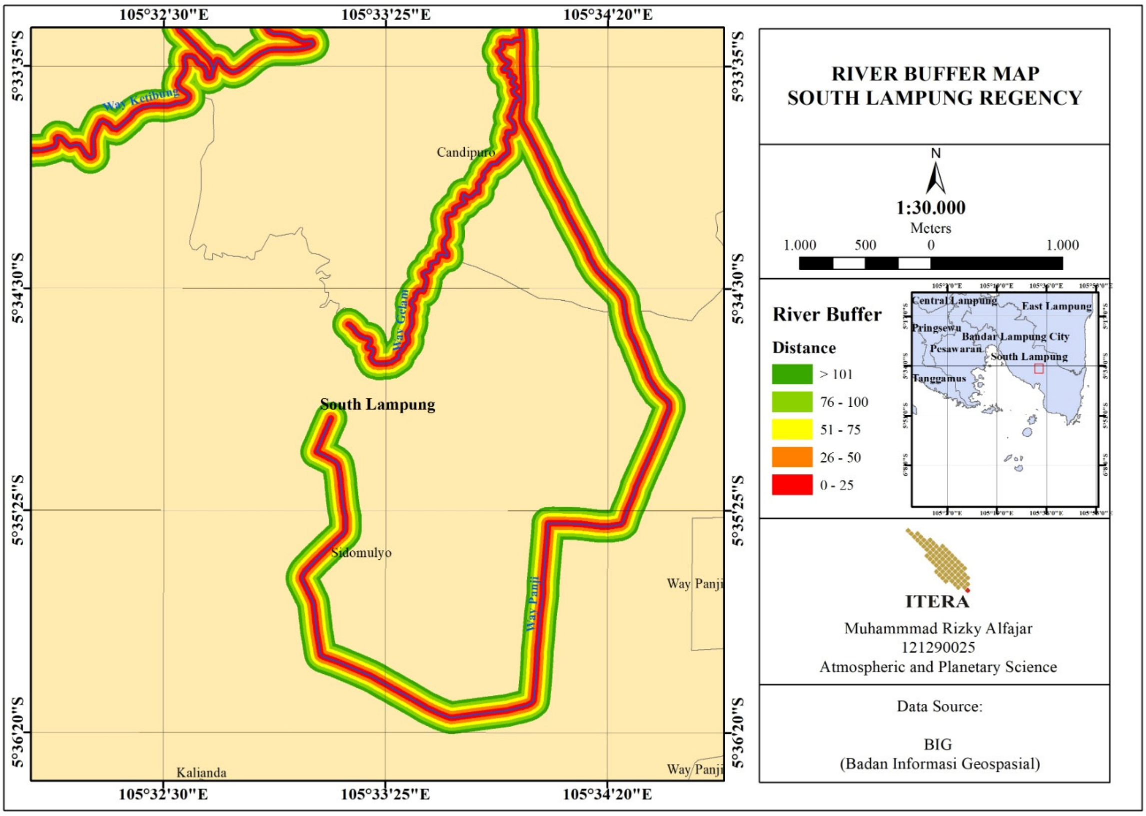

B

Figure 5. River buffer distance map showing proximity zones to major river networks across the study area, with 25-meter interval classifications (A), River buffer distance map showing proximity zones to major river networks across the study area, with 25-meter interval classifications (B). (data source: BIG 2023)

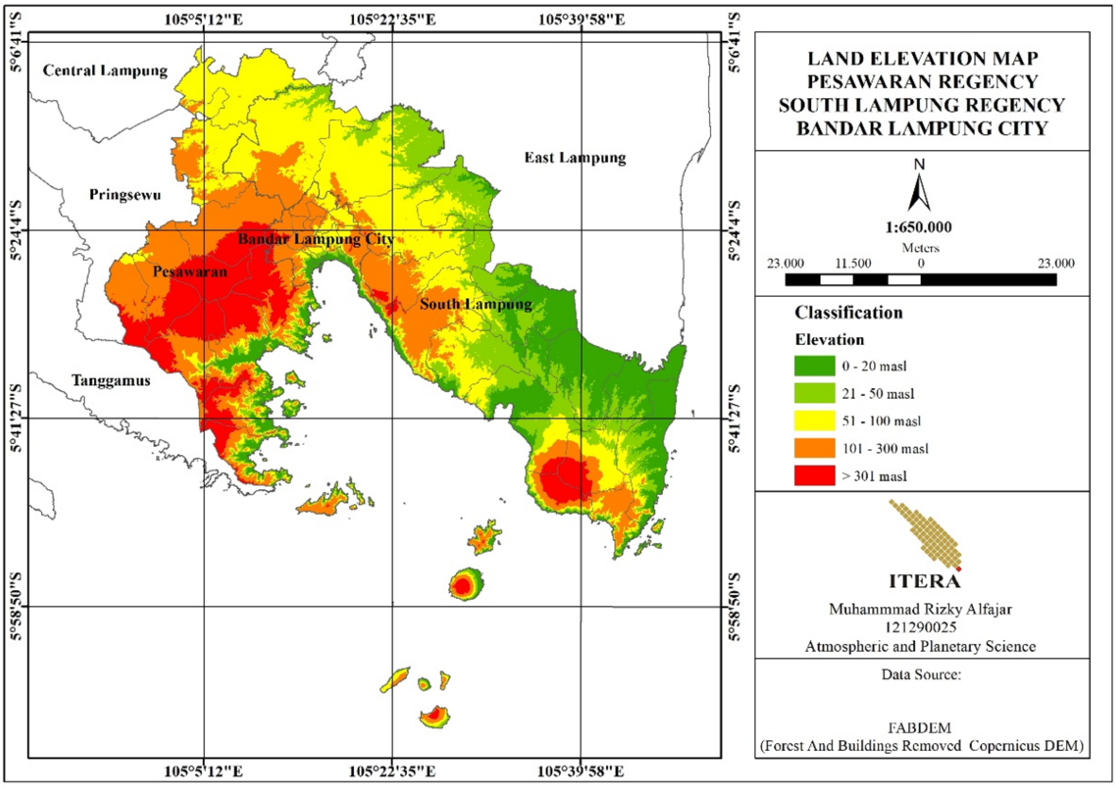

Figure 6. Digital elevation model showing topographic variation across the study area, ranging from sea level to over 300 meters above sea level (data source: FABDEM 2023)

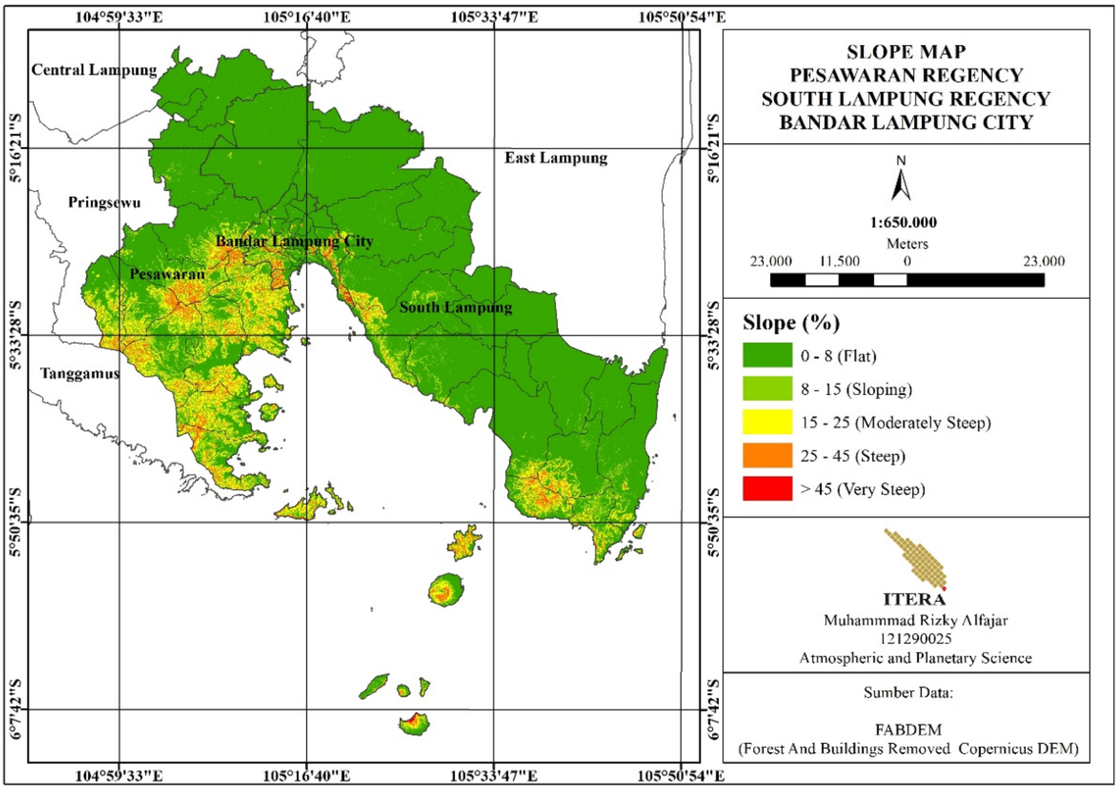

Figure 7. Slope gradient map derived from digital elevation model, classified into five classes based on terrain steepness percentage (data source: FABDEM 2023)

Model validation

The flood susceptibility map was validated using 258 historical flood occurrence points from 2018-2024 spanning 45 sub-districts (Figure 9). Validation was conducted by overlaying flood points with the susceptibility classification and comparing whether flood events occurred in areas predicted to have moderate or high susceptibility. Of the 45 sub-districts with recorded flood events, 35 were correctly classified as moderately or highly susceptible, while 10 sub-districts had floods in areas classified as not susceptible. This yielded an overall validation accuracy of 77.78% (Table 5).

Table 5. Model validation results comparing predicted flood susceptibility classes with observed flood occurrences across 45 sub-districts

Validation Metric	Value
Total sub-districts with floods	45
Correctly classified sub-districts (moderate/high)	35
Incorrectly classified sub-districts (not susceptible)	10
Validation Accuracy	**77.78%**

The validation demonstrates that the majority of historical flood locations correspond with areas predicted as moderately or highly susceptible by the model. The 10 sub-districts that did not match represent cases where floods occurred in areas classified as not susceptible, potentially indicating localized factors not captured by the six parameters used in this analysis or limitations in spatial resolution of input data.

Discussion

This study developed a flood susceptibility map for Pesawaran Regency, South Lampung Regency, and Bandar Lampung City using GIS-based Composite Mapping Analysis integrated with scoring and spatial overlay techniques. The key findings reveal that 90.66% of the study area (338,763.58 Ha) falls within moderate to high flood susceptibility classes, with rainfall (20%), elevation (19%), and soil type (18%) emerging as the dominant controlling parameters. The CMA-derived weights reflect empirical spatial relationships

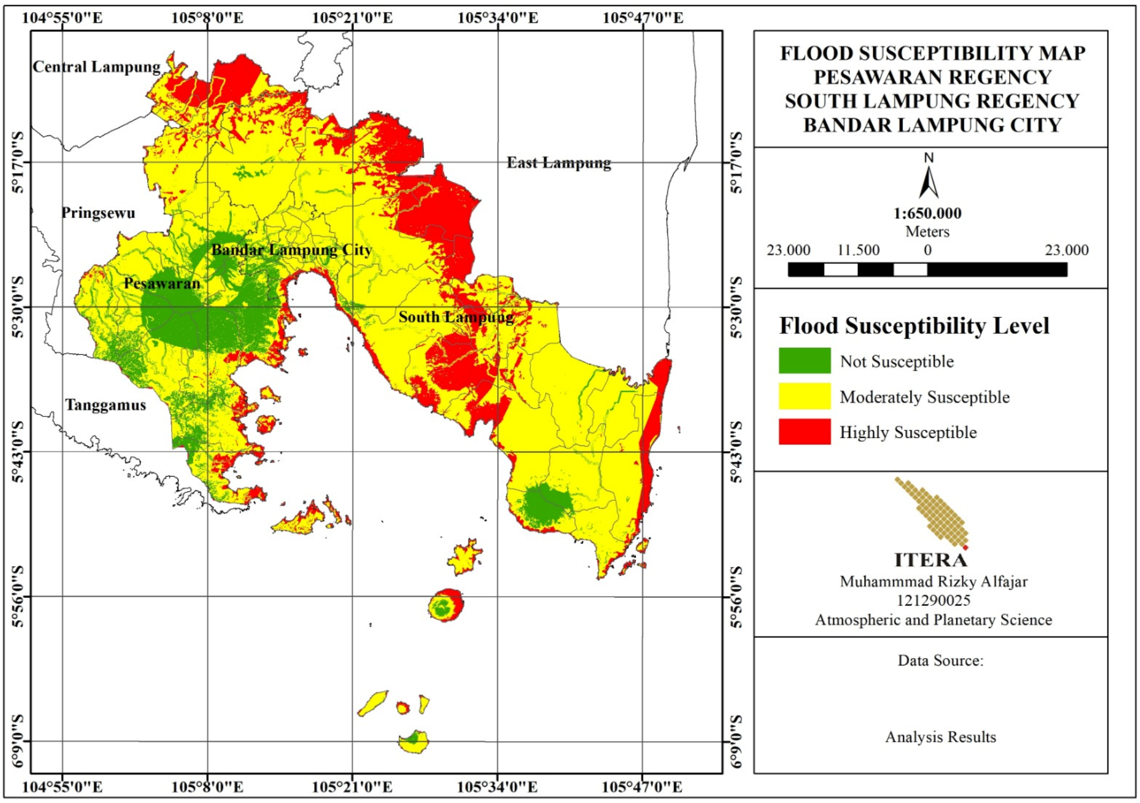

Figure 8. Flood susceptibility map showing the spatial distribution of three susceptibility classes (not susceptible, moderately susceptible, and highly susceptible) across the study area, derived from weighted overlay analysis of six parameters

between parameters and 258 historical flood events recorded from 2018-2024, providing an objective basis for parameter importance assessment. Model validation yielded an accuracy of 77.78%, with 35 of 45 flood-affected sub-districts correctly classified as moderately or highly susceptible. These findings demonstrate that the CMA approach provides reliable flood susceptibility assessment while maintaining methodological simplicity suitable for implementation by local disaster management agencies with limited computational resources.

The dominance of rainfall as the highest-weighted parameter (20%) aligns with findings from multiple flood susceptibility studies globally. Research in Ethiopia found rainfall to be the primary factor influencing flood susceptibility through exploratory regression analysis [31], while studies in Iraq and Pakistan similarly identified rainfall as a critical conditioning factor in arid and semi-arid regions [32][33]. In tropical monsoon climates like Lampung Province, high-intensity rainfall events exceeding 2,500 mm/year generate substantial runoff that overwhelms drainage capacity, particularly when combined with other susceptibility factors. The February 2025 floods that affected over 30,000 people in Bandar Lampung occurred during a period of intense rainfall, confirming the critical role of precipitation in triggering flood events in this region. The spatial distribution analysis shows that sub-districts receiving annual rainfall above 2,500 mm/year, including Tanjung Sari, Candipuro, Way Sulan, Katibung, and Sidomulyo in South Lampung Regency, consistently fall within high susceptibility zones, indicating strong correspondence between rainfall intensity and flood occurrence patterns.

Elevation emerged as the second most important parameter (19%), reflecting the fundamental role of topography in controlling water accumulation and drainage patterns. Low-lying areas below 50 masl, particularly in coastal sub-districts such as Teluk Betung Selatan, Teluk Betung Timur, Panjang, and Bumi Waras in Bandar Lampung City, exhibited high susceptibility due to their position as natural collection points for upstream runoff and their limited capacity for gravitational drainage. Similar findings have been reported in studies

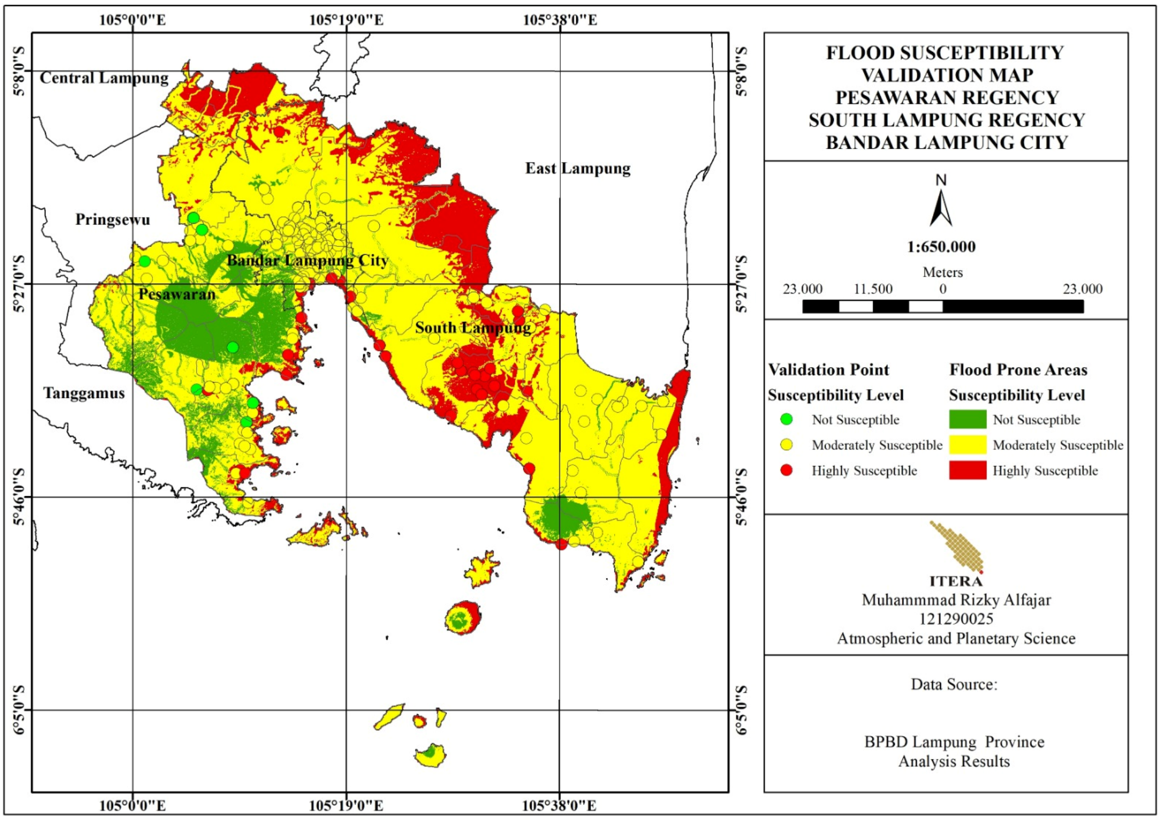

Figure 9. Validation map showing the overlay of 258 historical flood occurrence points (2018-2024) with the flood susceptibility classification, demonstrating spatial correspondence between predicted susceptibility and observed flood locations

from Ontario, Canada, and Duhok, Iraq, where elevation was identified as a dominant predictor of flood susceptibility, with low-elevation areas consistently showing higher flood ris [32,34]. The interaction between elevation and slope (13% weight) further influences flood dynamics, as flat terrain below 8% slope in low-elevation areas experiences reduced flow velocity and prolonged inundation duration. Conversely, highland areas in Pesawaran Regency and southern South Lampung Regency at elevations exceeding 300 masl demonstrated lower susceptibility, benefiting from topographic protection against flood accumulation despite receiving substantial rainfall.

Soil type contributed 18% to the overall flood susceptibility model, reflecting its control over infiltration capacity and runoff generation. Fluvisol and Alluvial soils, distributed in lowland areas of South Lampung Regency including Candipuro, Way Panji, and Way Sulan sub-districts, exhibit low infiltration capacity due to fine-grained texture and high clay content, leading to rapid saturation during rainfall events and consequently higher surface runoff. These findings are consistent with studies in Sub-Saharan regions and Indonesia, where soil permeability has been identified as a critical factor influencing flood susceptibility, with impermeable lithological and soil structures facilitating runoff and increasing flood likelihood ([35,36]). In contrast, Andosol soils found in western Bandar Lampung City and highland areas of South Lampung Regency possess better infiltration characteristics due to volcanic origin and porous structure, contributing to reduced flood susceptibility in these zones. The interaction between soil type and land cover becomes particularly important, as areas with low-infiltration soils combined with impervious land cover experience compounded effects that significantly elevate flood risk.

Land cover received a 16% weight in the susceptibility model, highlighting the impact of surface characteristics on runoff generation. Settlement areas in Bandar Lampung City, characterized by high proportions of impervious surfaces including roads, buildings, and paved parking areas, generate substantially greater runoff compared to vegetated areas. Recent research has demonstrated that impervious land cover can increase flooding intensity by up to 240% compared to rainfall changes alone, with an 18% increase in imperviousness percentage proving more impactful than a 25% increase in rainfall intensity for low-frequency flooding events [37]. In urban areas of China, impervious surface expansion from 8.8% to 65.4% over three decades coincided with dramatic reductions in flood regulation capacity [38]. The concentration of settlement areas in low-elevation coastal zones of Bandar Lampung creates a compounding effect where impervious surfaces prevent infiltration while topographic position facilitates water accumulation. Studies from Kuala Lumpur showed that urban expansion increased impervious surfaces by 2.77% while vegetation declined by 4.26%, directly contributing to spatial expansion of high-risk flood zones in urbanized areas [39]. In contrast, forested areas in southern Pesawaran Regency and South Lampung Regency provide multiple flood mitigation benefits including canopy interception, enhanced soil infiltration through root systems, and increased surface roughness that slows overland flow, thereby reducing flood susceptibility in these vegetated zones.

River buffer distance (14% weight) reflects proximity to overflow sources, with areas within 0-25 meters of river channels facing direct inundation risk during high-flow events. Major rivers including Way Garuntang, Way Simpur, and Way Balau in Bandar Lampung City flow through densely populated areas where riparian zones have been extensively modified or eliminated through urban development. Similar patterns have been documented globally, where encroachment on riparian zones and narrowing of river channels through urbanization increase flood hazard in near-river areas [40]. The interaction between river proximity and land cover change is particularly important, as conversion of riparian vegetation to settlement areas eliminates natural buffer zones that would otherwise provide flood storage and flow attenuation functions. In Pesawaran Regency, rivers such as Way Ratai, Way Piabung, and Way Cempaka traverse areas with relatively intact riparian vegetation, contributing to lower flood susceptibility in these zones despite moderate rainfall and low elevation. However, lowland areas near river confluences in Way Panji, Sidomulyo, and Candipuro sub-districts of South Lampung Regency experienced high susceptibility due to back-thrust effects and reduced drainage capacity at river junctions, consistent with findings from studies in India where river confluence zones showed elevated flood risk [35].

The validation accuracy of 77.78% demonstrates reasonable model performance, though ten sub-districts with flood occurrences were classified as not susceptible, indicating potential model limitations. Several factors may contribute to these misclassifications. First, the six parameters used in this study, while representing major flood controls, do not capture all flood-triggering mechanisms. Localized factors such as drainage infrastructure capacity, storm sewer network conditions, and micro-topographic features at sub-district scales may influence actual flood occurrence but are not represented in the regional-scale parameter layers [32]. Second, the spatial resolution of input data may not adequately capture fine-scale variations in parameters, particularly in heterogeneous urban landscapes where flood susceptibility can vary significantly over short distances. Studies using high-resolution LiDAR data have shown that micro-topographic features such as road crowns, curbs, and small depressions significantly affect urban flood patterns [41]. Third, the historical flood inventory from BPBD, while spanning seven years, may be subject to reporting bias where floods in urban areas are more likely to be documented than those in rural or remote locations, potentially affecting weight calculations in the CMA approach. Fourth, temporal dynamics of land cover change between 2019 (land cover data year) and flood occurrence years (2018-2024) may introduce uncertainty, as rapid urban development in Lampung Province could have altered surface conditions in some areas after land cover data collection.

The finding that 90.66% of the study area exhibits moderate to high flood susceptibility has significant implications for disaster risk reduction planning and spatial development strategies in Lampung Province. This extensive spatial coverage indicates that flood risk management cannot rely solely on structural interventions in limited high-risk zones but requires integrated approaches across the entire landscape. For Bandar Lampung City, where coastal low-elevation areas face combined pressures from high rainfall, impervious surfaces, and poor drainage, nature-based solutions including restoration of urban green spaces, permeable pavement implementation, and riparian buffer restoration could provide flood mitigation benefits while supporting other urban ecosystem services [41]. The World Bank's framework for flood risk management emphasizes that successful land use planning requires both educating decision-makers about flood risks and building technical capacity for implementation [42]. In South Lampung Regency, the large proportion of agricultural land (paddy fields and dryland agriculture) currently classified as moderately susceptible presents an opportunity for preventive measures through agricultural water management practices, retention pond development in strategic locations, and preservation of natural drainage corridors to prevent future susceptibility escalation as development pressures increase. For Pesawaran Regency, maintaining vegetated highland areas and protecting riparian zones along major rivers represents a critical strategy for sustaining the natural flood regulation capacity that currently provides relative protection to downstream communities.

The CMA method employed in this study offers several advantages over conventional AHP approaches commonly used in Indonesian flood studies. By deriving parameter weights from empirical spatial analysis of historical flood occurrence rather than relying on expert judgment, CMA reduces subjectivity and provides weights that reflect actual flood patterns in the study area. However, the method has limitations that warrant consideration. The CMA approach assumes that historical flood distribution patterns are representative of future flood risk, which may not hold if climate change, land use transformation, or drainage infrastructure development substantially alter flood-triggering mechanisms. Studies projecting land use change impacts on flooding have shown that urbanization trends can dramatically shift flood patterns over time, with urban expansion potentially increasing flood volumes by over 750% in some watersheds [43]. Additionally, CMA-derived weights reflect correlations rather than causal relationships; high weights indicate spatial association but do not necessarily imply direct causation. The method also depends critically on the completeness and spatial representativeness of the historical flood inventory. Systematic underreporting of floods in certain areas, such as rural zones with limited disaster response infrastructure, could bias weight calculations toward parameters associated with urban flood patterns. Future studies could address these limitations through integration of CMA with sensitivity analysis approaches that test model stability under different weighting scenarios, incorporation of climate change projections for future flood risk assessment, and augmentation of historical flood inventories through analysis of satellite imagery from flood events to identify unreported occurrences.

Comparison with machine learning approaches reported in recent literature provides context for evaluating the CMA method's performance. Random Forest models applied to flood susceptibility mapping in similar tropical contexts achieved accuracies ranging from 94-96% [39], while Deep Learning Neural Network approaches reached accuracies up to 98.4% [44]. The 77.78% accuracy obtained in this study falls below these benchmarks, suggesting potential for improvement through alternative methodologies or refinement of the current approach. However, these machine learning methods require substantially larger training datasets (typically several hundred to thousands of flood points), extensive computational resources, and technical expertise that may not be available to local disaster management agencies in developing regions. Studies comparing MCDA methods with machine learning approaches have shown that while ML models generally achieve higher predictive accuracy, MCDA methods like AHP and CMA provide advantages in interpretability, transparency, and lower data requirements [45]. For the context of Lampung Province, where BPBD operates with limited technical staff and computational infrastructure, the CMA approach represents a practical compromise between methodological sophistication and operational feasibility. The model's 77.78% accuracy, while moderate, provides sufficient reliability for preliminary flood risk assessment and can inform spatial planning decisions when interpreted with appropriate caution regarding uncertainty.

The multi-jurisdictional assessment approach employed in this study, analyzing three administratively distinct regions (Pesawaran Regency, South Lampung Regency, and Bandar Lampung City) as an integrated hydrological system, addresses a common limitation in Indonesian disaster risk studies that typically focus on single administrative units. River systems including Way Punduh, Way Ratai, and other major watersheds traverse multiple jurisdictions, creating hydrological connectivity that transcends political boundaries. Flood events in downstream areas of Bandar Lampung are influenced by land use decisions, water management practices, and natural conditions in upstream portions of Pesawaran and South Lampung Regencies. This interconnected nature of flood risk necessitates coordinated planning and management approaches across jurisdictions, as actions taken in one area can substantially affect flood vulnerability in adjacent regions. The integrated assessment provides a framework for regional cooperation in flood risk management, enabling identification of upstream-downstream relationships and supporting collaborative decision-making for watershed-scale interventions. Similar multi-jurisdictional approaches have been successfully implemented in other regions facing transboundary flood challenges, demonstrating improved effectiveness of mitigation measures compared to fragmented single-jurisdiction approaches [42].

Conclusion

This study successfully mapped flood susceptibility in Pesawaran Regency, South Lampung Regency, and Bandar Lampung City using GIS-based Composite Mapping Analysis. Results show that 90.66% of the study area falls within moderate to high susceptibility classes, with rainfall (20%), elevation (19%), and soil type (18%) as the dominant controlling factors. The CMA method provided objective parameter weighting based on 258 historical flood events, achieving 77.78% validation accuracy. This demonstrates reasonable model performance while maintaining methodological simplicity suitable for local disaster management agencies with limited computational resources.

The findings provide actionable information for spatial planning and disaster risk reduction in Lampung Province. Priority interventions include nature-based solutions for low-elevation coastal areas in Bandar Lampung City, preventive measures in agricultural zones of South Lampung Regency, and protection of vegetated highland areas in Pesawaran Regency. The multi-jurisdictional assessment framework addresses hydrological connectivity across administrative boundaries, supporting collaborative watershed-scale flood management. Future research should incorporate drainage infrastructure data, climate change projections, and satellite-based validation to improve model accuracy while exploring hybrid CMA-machine learning approaches that maintain operational feasibility for local implementation.

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Conflicts of interest

The authors declare no conflicts of interest.

Author contributions

Conceptualization: MRA, LM, AUSS. Methodology: MRA, LM, AUSS. Formal analysis: MRA Investigation: MRA Data curation: MRA. Software: MRA. Visualization: MRA. Supervision: LM, AUSS. Validation: MRA, LM, AUSS. Writing—original draft: MRA. Writing—review and editing: LM, AUSS. All authors have read and agreed to the published version of the manuscript.

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