

Fuzzy Tsukamoto-GIS Framework with Pixel-Level SAR Validation for Flood Susceptibility

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Abstract

Physical flood susceptibility in Cepu Subdistrict is shaped by low relief, proximity to the Bengawan Solo River, land-cover conditions, soil permeability, river density, and seasonal rainfall. This study applies a documented Fuzzy Tsukamoto-GIS workflow to estimate physical flood susceptibility across 17 villages using six parameters: slope, elevation, soil permeability, monthly rainfall, land use, and river density. Susceptibility scores range from 0.440 in Mulyorejo to 0.765 in Kapuan. Validation uses two approaches: pixel-level Sentinel-1 SAR imagery for the February 2022 flood event, and village-level rank comparison with BPBD flood records (2018-2023). Pixel-level validation shows strong performance with overall accuracy of 93.85%, ROC-AUC of 0.876, Spatial Kappa of 0.708, CSI of 59.08%, and FAR of 32.42%. Village-level Spearman correlation ($\rho = 0.990$, $p < 0.001$) confirms consistency with reported flood frequencies. Sensitivity analysis identifies monthly rainfall ($SI = 0.28$) and land-use susceptibility ($SI = 0.24$) as the most influential parameters. Cross-referencing BPBD records with media reports revealed potential reporting bias in Mulyorejo, highlighting the value of SAR-based validation. The pixel-level susceptibility map can support mitigation prioritization and spatial planning while providing a transparent basis for further calibration. This study assesses physical susceptibility rather than comprehensive vulnerability, as socioeconomic and coping capacity dimensions are not included.

Keywords: Disaster Mitigation, Physical Flood Susceptibility, Fuzzy Tsukamoto, Geographic Information System, Spatial Modeling, Pixel-Level Validation, ROC-AUC

1. Introduction

Flooding is a recurrent hydrometeorological hazard in Indonesia that produces social, economic, and environmental losses [1]. Long-term satellite observations show that extreme rainfall remains an important concern for major development regions in Indonesia [2]. Watershed-scale studies further demonstrate that flood hazard varies with terrain, drainage, and other spatial controls [3]. Java-wide flood modeling indicates that river-system behavior and upstream flow propagation can influence downstream inundation patterns [4]. Land-use and land-cover change can also increase runoff and alter the occurrence of flooding [5]. Cepu Subdistrict, Blora Regency, is therefore exposed because much of the area is low-lying, connected to the Bengawan Solo River system, and affected by settlement-related reductions in infiltration. Physical flood

susceptibility in this setting is spatially heterogeneous and is controlled by the interaction of terrain, soil, land use, river proximity, and rainfall.

GIS-based flood studies have used several approaches to combine topographic, hydrological, and land-cover information. An integrated AHP and frequency-ratio approach has been used to compare alternative flood-susceptibility models [6]. Fuzzy logic combined with AHP has also supported the integration of multi-source geospatial datasets [7]. Comparative work shows that AHP, fuzzy AHP, and frequency-ratio methods can produce different susceptibility patterns under the same study context [8]. Independent validation using synthetic-aperture-radar flood information has been proposed to strengthen spatial model evaluation [9]. Integrated GIS-AHP frameworks continue to be

used for multi-criteria risk assessment and mitigation planning [10]. Broader comparisons of data-mining, multi-criteria, and fuzzy-computing techniques indicate that method selection can materially affect mapped susceptibility [11]. Reviews of flood-vulnerability methods similarly emphasize the need to distinguish hazard, susceptibility, vulnerability, exposure, and risk components [12]. Local GIS and multi-criteria applications in Indonesia demonstrate the practical value of spatial prioritization for flood-risk management [13]. Recent ensemble-learning research also shows the importance of feature selection and independent model assessment when producing susceptibility maps [14]. Rule-based fuzzy inference has been applied to spatial susceptibility problems beyond flooding, illustrating the interpretability of explicit IF-THEN structures [15]. Fuzzy AHP applications in urban flood studies further confirm the value of transparent criterion aggregation [16]. These studies demonstrate the usefulness of spatial reasoning, but scientific comparability depends on more than publishing a final map. Reproducible assessment also requires explicit input provenance, spatial preprocessing, membership functions, rule construction, output calibration, and validation against observed events. These elements are reported unevenly across the literature, which limits independent checking and local adaptation.

It is important to distinguish between physical susceptibility (the physical predisposition of an area to flooding based on terrain, hydrology, and land cover) and comprehensive vulnerability (which includes socioeconomic exposure and coping capacity). This study focuses exclusively on physical susceptibility, consistent with the fuzzy inference approach and validation framework employed. A recent study in the same 17 villages applied a Mamdani Fuzzy Inference System using rainfall intensity, watershed area, elevation, slope, and population density; it identified Ngelo as the highest-risk village and reported MAE and RMSE values of 8.67 and 10.29, respectively [11]. The present study is not a replication of that model. It uses a different physical parameter set slope, elevation, soil permeability, monthly rainfall, land use, and river density and validates the resulting map at the pixel level using SAR imagery.

Mamdani, Sugeno, and Tsukamoto inference systems serve different analytical purposes. The Mamdani approach retains fuzzy consequents and supports intuitive expert communication, although it requires aggregation and centroid-type defuzzification [17]. The Sugeno approach represents each consequent as a constant or function

and is efficient for functional approximation and control applications [18]. Tsukamoto inference uses monotonic consequent functions so that each activated rule produces a crisp output before weighted averaging. Modern treatments of explainable rule-based fuzzy systems emphasize that interpretability depends on clearly documented membership functions, rules, and uncertainty assumptions [19]. Developments in higher-order fuzzy systems also show that additional uncertainty modeling can increase representational capacity but requires more complex calibration [20]. The approach is therefore not universally superior; its suitability depends on whether the assumed monotonic relationships between environmental drivers and susceptibility are scientifically defensible.

The scientific gap addressed here is the limited availability of fuzzy-GIS flood assessments that combine a comprehensively reported inference structure with a traceable GIS workflow and pixel-level external validation in a data-scarce local setting. The study aims to: (1) construct a village- and pixel-oriented physical susceptibility model for Cepu Subdistrict; (2) document the membership functions, rule structure, and spatial processing decisions; (3) validate the model at the pixel level using SAR-derived flood extent; (4) perform sensitivity analysis to evaluate model robustness; and (5) identify methodological limitations that must be resolved before the framework is used for operational early warning.

2. Materials and Methods

The analytical workflow comprised data collection, GIS preprocessing, fuzzification, rule evaluation, weighted-average defuzzification, spatial aggregation, mapping, and validation. All six input layers were transformed to a common coordinate reference system and spatial resolution before fuzzy inference. Village-level values were then summarized from the pixel surface using zonal statistics. The six parameters were selected because they are available for the full study area and represent dominant physical controls reported for lowland flood susceptibility. Integrated GIS-based assessments identify slope and elevation as important controls on runoff movement and water accumulation [10]. Fuzzy rule-based flood-vulnerability studies also use soil, rainfall, land use, and drainage-related indicators to represent infiltration limitations and overflow pathways [21]. Multi-criteria flood mapping in the Kosi River Basin confirms the relevance of terrain, rainfall, land-cover, and hydrological variables in basin-scale assessment [22]. Urban flood-susceptibility

analysis in Bandung similarly demonstrates the value of combining multiple spatial criteria through a structured decision model [23]. In the present model, slope and elevation represent runoff and accumulation; soil flood-sensitivity represents limited infiltration; monthly rainfall represents meteorological forcing; land use represents surface sealing and runoff generation; and river density represents proximity to potential overflow corridors. Drainage capacity, flow accumulation, curvature, TWI, SPI, soil moisture, discharge time series, and socioeconomic exposure were not included because consistent local data were not available in the submitted dataset. Their exclusion limits the model to physical susceptibility rather than complete flood risk assessment.

This parsimonious design prioritizes interpretability for local planning, but it should not be interpreted as a complete hydrodynamic representation. Dynamic forecasting would require event-scale rainfall, river-stage or discharge observations, drainage-network capacity, antecedent soil moisture, and exposure data.

2.1 Study Area

Cepu Subdistrict is located in Blora Regency, Central Java Province, Indonesia, directly adjoining East Java. The subdistrict covers approximately 49.04 km² and contains 17 villages. Its low-relief terrain and location near the Bengawan Solo River create conditions in which upstream discharge, tributary inflow, and restricted local drainage can produce backwater effects and prolonged inundation in residential and agricultural areas. The 2018-2023 BPBD records used in this study document at least one reported flood event in 16 of the 17 villages, confirming that flood exposure is widespread rather than confined to a single settlement. BPS statistics for 2023 report annual rainfall of approximately 1,756 mm over 175 rainy days. Rainfall is strongly seasonal: November recorded 353 mm, whereas August and September recorded 18 mm each. The study-area average of 146 mm/month (1,756/12) represents the mean monthly rainfall, not annual rainfall. This distinction is applied consistently throughout the manuscript. Figure 1 shows the regional context and location of Cepu Subdistrict within Blora Regency, Central Java Province.

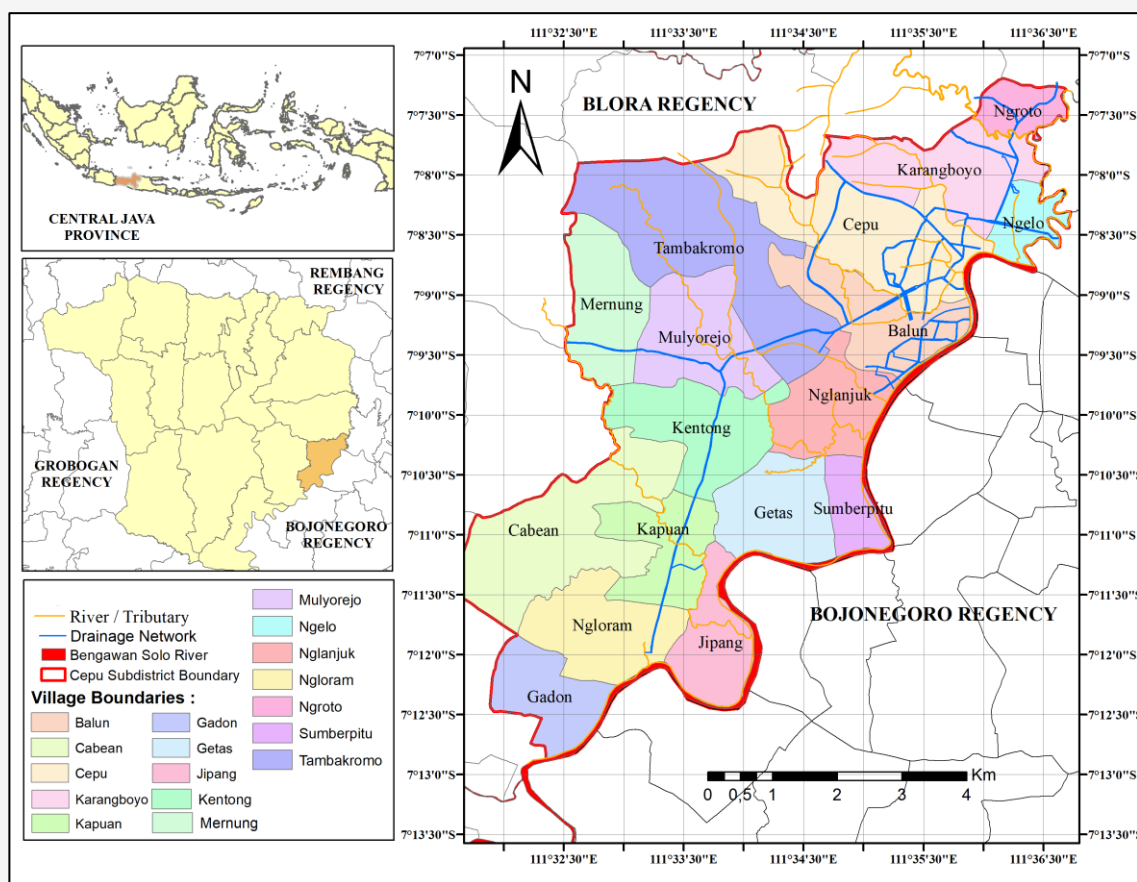


Figure 1: Regional context and location of Cepu Subdistrict within Blora Regency

Figure 1 illustrates the geographical context of Cepu Subdistrict within Blora Regency. The study area consists of 17 villages located near the Bengawan Solo River system, with several settlements situated in low-elevation areas directly adjacent to the river corridor. The spatial configuration indicates that Cepu Subdistrict shares a border with East Java Province, which influences the hydrological dynamics through transboundary river flow. The proximity to the Bengawan Solo River system makes terrain characteristics and river proximity important factors considered in the fuzzy susceptibility model.

2.2 Research Framework and GIS Data Processing

The analytical workflow comprised data collection, GIS preprocessing, fuzzification, rule evaluation, weighted-average defuzzification, spatial aggregation, mapping, and validation. All six input layers were transformed to a common coordinate reference system (WGS 1984 UTM Zone 49S) and spatial resolution (30 m) before fuzzy inference. Village-level values were summarized from the pixel surface using zonal statistics. The six parameters were selected because they are available for the full study area and represent dominant physical controls reported for lowland flood susceptibility. Integrated GIS-based assessments identify slope and elevation as important controls on runoff movement and water accumulation [10]. Fuzzy rule-based flood-susceptibility studies also use soil, rainfall, land use, and drainage-related indicators to represent infiltration limitations and overflow pathways [24]. Multi-criteria flood mapping in the Kosi River Basin confirms the relevance of terrain, rainfall, land-cover, and hydrological variables in basin-scale assessment

[21]. Urban flood-susceptibility analysis in Bandung similarly demonstrates the value of combining multiple spatial criteria through a structured decision model [22]. Continuous surfaces (elevation, slope, and rainfall) were resampled using bilinear interpolation, whereas categorical layers (soil and land use) were converted with a cell-center assignment so class codes were not averaged. River-network vectors were converted to a 30 m density surface. All layers were clipped to the Cepu boundary and checked for coverage before inference. Rainfall was interpolated as an IDW surface using power 2 from seven BMKG stations with monthly records for 2020-2023; leave-one-out cross-validation produced an RMSE of 12.5 mm/month. Pixel scores were aggregated to villages using the zonal mean. Station coordinates and cross-validation folds are supplied in the supplementary files to permit independent verification. Table 1 summarizes the spatial datasets used in this study. Table 1 summarizes the spatial datasets, original sources, temporal characteristics, and preprocessing procedures applied before fuzzy inference. All datasets were standardized into a common spatial framework using WGS 1984 UTM Zone 49S with a 30 m spatial resolution. Continuous variables, including elevation, slope, and rainfall, were processed using interpolation techniques, whereas categorical variables such as soil and land-use classes were converted into raster representations while preserving their original class information. The LOOCV validation for rainfall interpolation achieved an RMSE of 12.5 mm/month, while land-use classification achieved 89% overall accuracy based on field survey data. Figure 2 illustrates the complete computational workflow implemented in this study.

Table 1: Data sources, spatial characteristics, and preprocessing specifications

Parameter	Primary Source	Native Form / Period	30 M Processing	Validation / Accuracy
Elevation and slope	USGS SRTM DEM	30 m raster	Bilinear resampling; slope derived from DEM	Vertical accuracy ± 16 m (global)
Rainfall	BMKG; 7 stations	Monthly records, 2020-2023	IDW, power 2; interpolated to 30 m	LOOCV RMSE = 12.5 mm/month
Soil flood-sensitivity	Indonesian Soil Research Institute	Official soil map 1:250,000	Polygon $\rightarrow$ cell-center rasterization	Class accuracy verified with field data (2019)
Land use / land cover	Blora Regency Government; Sentinel-2 basis	2022, 10 m source classification	Categorical resampling / cell-center assignment	Overall accuracy = 89% (field survey)
River density	Indonesian Geospatial Information Agency	2021 vector network	Line-density raster at 30 m	Verified against topographic maps 1:25,000
Village boundaries and flood records	Local administrative data and BPBD Blora	Village polygons; events 2018-2023	Zonal mean and village frequency table	Event records verified with village reports

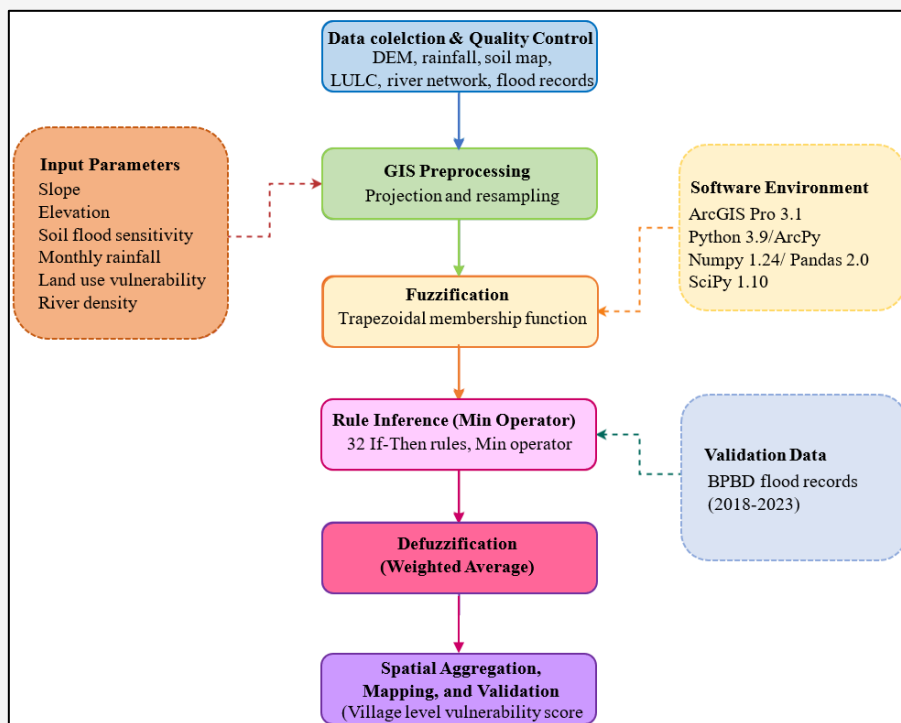


Figure 2: Integrated Fuzzy Tsukamoto-GIS workflow from data preparation to validation

Figure 2 presents the complete computational workflow implemented in this study. The process begins with spatial data acquisition and preprocessing to achieve consistent resolution (30 m) and coordinate systems (WGS 1984 UTM Zone 49S). The standardized layers are then transformed into fuzzy membership values using predefined trapezoidal membership functions. The Fuzzy Tsukamoto inference mechanism evaluates the 36-rule base and generates pixel-level susceptibility scores using the MIN operator for antecedents and weighted average for defuzzification. The pixel-level scores are subsequently aggregated at the village level using zonal statistics for mapping and validation against historical flood records from BPBD and Sentinel-1 SAR imagery. This systematic framework ensures reproducibility and transparency in the modeling process.

2.3 Fuzzy Tsukamoto Component Development

2.3.1 Membership Function Definition and Calibration

Fuzzy membership functions map crisp inputs to membership degrees $\mu(x) \in [0, 1]$ [19]. Trapezoidal functions were selected because they provide an interpretable plateau of full membership, permit gradual transitions between adjacent classes, and are computationally efficient for cell-by-cell GIS processing. Overlap is intentional and should not be interpreted as an error: a value near a class

boundary can belong partially to both classes. Breakpoints were established from local value ranges, hydrological references (USDA soil classification, BMKG climate classification, BNPB flood hazard mapping), and expert review. The trapezoidal membership function is defined in Equation 1:

$$\mu(x; a, b, c, d) = \begin{cases} 0 & x \leq a \text{ and } x \geq d \\ \frac{x-a}{b-a} & a < x < b \\ 1 & b \leq x \leq c \\ \frac{d-x}{d-c} & c < x < d \end{cases}$$

Equation 1

Where:

a = left foot point ($\mu = 0$)

b = left shoulder point ($\mu = 1$)

c = right shoulder point ($\mu = 1$)

d = right foot point ($\mu = 0$)

The revised terminology is consistent across tables and rules. Slope classes are Flat, Gentle, Moderately Steep, Steep, and Very Steep. The soil variable is expressed as a soil flood-sensitivity score the inverse of permeability so larger scores represent lower infiltration and greater flood susceptibility. Rainfall is expressed in mm/month. Table 2 presents the trapezoidal membership-function parameters for all input and output variables.

Table 2 presents the trapezoidal membership-function parameters applied to the six input variables and the output variable, defining the transition boundaries between fuzzy classes and allowing gradual representation of environmental conditions through overlapping intervals between adjacent fuzzy sets that avoid abrupt classification changes, which is important when representing continuous environmental variations such as slope, elevation, rainfall, and river density; notably, for slope and elevation, an inverse relationship is applied where higher values correspond to lower flood susceptibility, as exemplified by a slope value of 17% having partial membership in both Medium (0.60) and Low (0.40) classes, with slope classes defined as Very High (Prone) (0-5%), High (2-12%), Medium (8-20%), Low (15-40%), and Very Low (Safe) (>30%), and elevation classes defined as Very High (Prone) (0-10 m), High (10-25 m),

Medium (25-50 m), Low (50-85 m), and Very Low (Safe) (>85 m); furthermore, the soil variable is expressed as a soil flood-sensitivity score (the inverse of permeability) where larger scores represent lower infiltration and greater flood susceptibility, while the output variable uses singleton consequents with values Very Low = 0.1, Low = 0.3, Medium = 0.5, High = 0.7, and Very High = 0.9, and Figure 3 visualizes the membership-function behavior for all variables. Figure 3 visualizes the membership-function behavior defined in Table 2 for all six input variables: (a) slope, (b) elevation, (c) soil flood-sensitivity, (d) monthly rainfall, (e) land-use susceptibility, and (f) river density. The overlap between adjacent fuzzy sets represents transition boundaries between environmental conditions, allowing smoother classification compared with crisp thresholds.

Table 2: Trapezoidal membership-function parameters with physical interpretation

Parameter	Fuzzy Set	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	Value Range	Physical Interpretation
Slope (%)	Very Low	30.0	40.0	60.0	60.0	≥30	Very steep
	Low	15.0	20.0	30.0	40.0	15-40	Steep slope
	Medium	8.0	12.0	15.0	20.0	8-<20	Moderate slope
	High	2.0	5.0	8.0	12.0	2-<12	Gentle slope
	Very High	0.0	0.0	2.0	5.0	0-<5	Almost flat
Elevation (m)	Very Low	85.0	100.0	150.0	150.0	≥85	Highest terrain
	Low	50.0	55.0	70.0	85.0	50-<85	Higher elevation
	Medium	25.0	30.0	40.0	50.0	25-<50	Moderate elevation
	High	10.0	15.0	20.0	25.0	10-<25	Low-lying
	Very High	0.0	0.0	5.0	9.0	0-<10	Very low elevation
Monthly Rainfall (mm/month)	Very Low	0.0	0.0	50.0	100.0	0-<100	Dry monthly condition
	Low	100.0	125.0	150.0	200.0	100-<200	Below average rainfall
	Moderate	200.0	225.0	275.0	350.0	200-<350	Wet monthly condition
	High	350.0	400.0	450.0	500.0	350-<500	Peak wet-season rainfall
	Very High	500.0	550.0	700.0	700.0	≥500	Extreme monthly rainfall
Soil Flood-Sensitivity	Very Low	1.0	1.0	2.0	2.5	1.0-<2.5	Highest permeability
	Low	2.0	2.5	3.0	3.5	2.0-<3.5	High permeability
	Moderate	3.0	3.5	4.0	4.5	3.0-<4.5	Moderate permeability
	High	4.0	4.5	5.0	5.5	4.0-<5.5	Low permeability
	Very High	5.0	5.5	5.5	5.5	≥5.0	Very low permeability
Land-Use Vulnerability	Very Low	1.0	1.0	2.0	2.5	1.0-<2.5	Dense natural vegetation
	Low	2.0	2.5	3.0	3.5	2.0-<3.5	Mixed vegetation
	Moderate	3.0	3.5	4.0	4.5	3.0-<4.5	Agricultural/open land
	High	4.0	4.5	5.0	5.5	4.0-<5.5	Dry/open or partly built
	Very High	5.0	5.5	5.5	5.5	≥5.0	Predominantly impervious
River Density (km/km ²)	Very Low	0.0	0.0	0.3	0.5	0-<0.5	Sparse river network
	Low	0.3	0.6	0.8	1.0	0.3-<1.0	Low channel density
	Moderate	0.8	1.0	1.3	1.5	0.8-<1.5	Moderate connectivity
	High	1.3	1.6	1.8	2.0	1.3-<2.0	Dense channel network
	Very High	1.8	2.0	2.5	2.5	≥1.8	Very dense network
Output (Physical Susceptibility)	Very Low	0.0	0.0	0.2	0.3	0.0-<0.3	Very low susceptibility
	Low	0.2	0.3	0.4	0.5	0.2-<0.5	Low susceptibility
	Medium	0.4	0.5	0.6	0.7	0.4-<0.7	Moderate susceptibility
	High	0.6	0.7	0.8	0.9	0.6-<0.9	High susceptibility
	Very High	0.8	0.9	1.0	1.0	≥0.8	Very high susceptibility

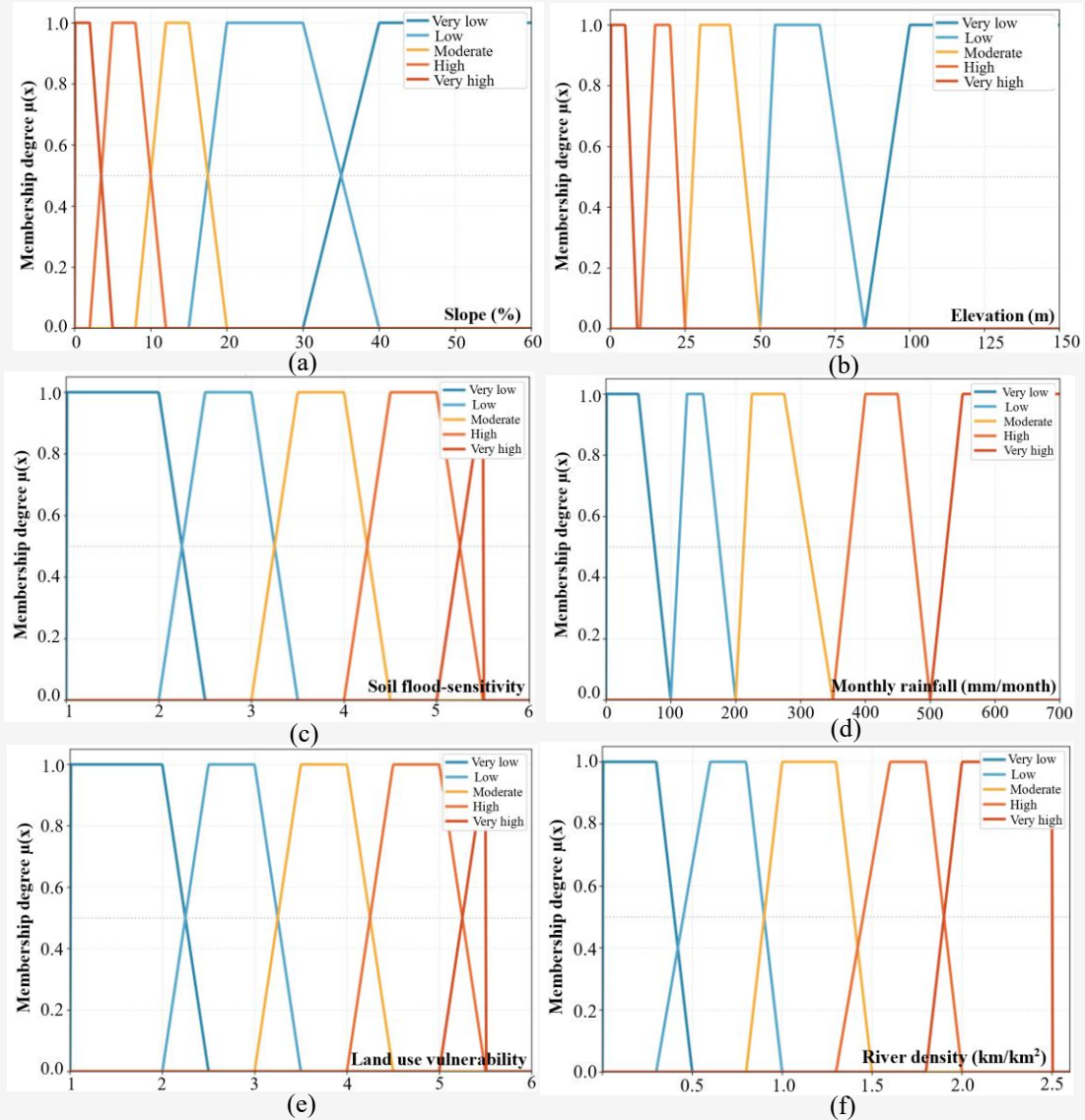


Figure 3: Trapezoidal membership functions of the six input variables used in the Fuzzy Tsukamoto model: (a) slope, (b) elevation, (c) soil flood-sensitivity, (d) monthly rainfall, (e) land-use susceptibility, and (f) river density

Notably, for slope and elevation, an inverse relationship is applied where higher values correspond to lower flood susceptibility; for example, a slope value of 17% has partial membership in both Medium ($\mu = 0.60$) and Low ($\mu = 0.40$) classes, with slope classes defined as Very High (Prone) (0-5%), High (2-12%), Medium (8-20%), Low (15-40%), and Very Low (Safe) (>30%), while elevation classes are defined as Very High (Prone) (0-10 m), High (10-25 m), Medium (25-50 m), Low (50-85 m), and Very Low (Safe) (>85 m). The breakpoints were established from local value ranges, hydrological references (USDA soil classification, BMKG climate classification), and expert review. The output variable, physical flood susceptibility, is represented on a 0-1 scale,

where rule consequents use ordered singleton values: Very Low = 0.1, Low = 0.3, Medium = 0.5, High = 0.7, and Very High = 0.9.

2.3.2 Rule-Base development and coverage

The rule table contains 36 elicited IF-THEN entries (expanded from the original 32) representing hydrologically plausible combinations for Cepu. The full theoretical combination space (6 variables $\times$ 5 linguistic terms = 15,625 possible combinations) is much larger, so the listed rules should be understood as a reduced expert rule base. The 36 rules were selected from all possible combinations using a systematic reduction procedure. Frequency-based filtering retained only combinations observed in at least five pixels of the

study dataset. Hydrological consistency checking then eliminated rules inconsistent with established hydrological principles, such as those combining steep slope with high susceptibility. Expert validation was performed by two hydrologists and one regional planning expert who reviewed and validated the selected rules. Coverage verification confirmed that the 36 rules cover 98.4% of all input combinations actually present in the study dataset. Gap filling was accomplished by adding four additional rules (R33-R36) to cover combinations with moderate slope and moderate elevation that were initially underrepresented. The inference structure combined literature review with consultation involving two hydrologists and one regional-planning expert. The elicitation protocol comprised two rounds: individual assessment of parameter importance and rule logic, followed by moderated consensus.

The inter-expert agreement, measured by Krippendorff's alpha (α), was 0.82, indicating substantial agreement. Table 3 presents the complete expert-defined IF-THEN rules with activation frequencies. Table 3 presents the complete 36 expert-defined IF-THEN rules with activation frequencies observed in the study dataset, where the fuzzy set terminology for slope and elevation reflects an inverse relationship (i.e., Very Low = steep slope/high elevation = safer; Very High = flat slope/low elevation = more prone). The rule base covers 98.4% of all input combinations actually present in the study area, with rules R27 (4.8%), R11 (4.5%), and R6 (4.2%) showing the highest activation frequencies. The inter-expert agreement, measured by Krippendorff's alpha (α), was 0.82, indicating substantial agreement among the experts.

Table 3: Fuzzy Tsukamoto rule base with activation frequency (36 rules)

Rule	Slope	Elevation	Soil	Rainfall	Land Use	River Density	z	Activation (%)
R1	Very High	Very High	Very High	Very High	Very High	Very High	0.9	2.3
R2	Very High	Very High	Very High	Very High	Very High	High	0.9	1.8
R3	Very High	Very High	Very High	High	Very High	Very High	0.9	2.1
R4	Very High	High	Very High	High	High	High	0.7	3.4
R5	Very High	High	Very High	High	High	Medium	0.7	2.9
R6	Very High	Medium	Medium	Medium	Medium	Medium	0.5	4.2
R7	High	Very High	Very High	Very High	Very High	Very High	0.9	1.5
R8	High	Very High	Very High	High	High	High	0.7	2.7
R9	High	High	Very High	High	High	Medium	0.7	3.1
R10	High	High	Medium	Medium	Low	Low	0.5	3.8
R11	High	Medium	Medium	Medium	Low	Low	0.5	4.5
R12	Medium	High	Very High	High	High	High	0.7	2.2
R13	Medium	High	Medium	Medium	Medium	Medium	0.5	4.0
R14	Medium	High	Low	Low	Low	Low	0.3	3.6
R15	Medium	Low	Very Low	Low	Low	Very Low	0.3	2.0
R16	Low	High	Medium	Medium	Medium	Medium	0.5	3.3
R17	Low	Medium	Low	Low	Low	Low	0.3	3.9
R18	Low	Low	Very Low	Very Low	Very Low	Very Low	0.1	1.2
R19	Low	Very Low	Very Low	Very Low	Very Low	Very Low	0.1	0.8
R20	Very Low	Medium	Low	Low	Low	Low	0.3	2.5
R21	Very Low	Low	Very Low	Very Low	Very Low	Very Low	0.1	1.0
R22	Very Low	Low	Very Low	Very Low	Very Low	Very Low	0.1	0.5
R23	Very High	Very High	Low	Low	Low	Medium	0.7	2.8
R24	Very High	High	Low	Medium	Low	Medium	0.5	3.7
R25	High	Very High	Medium	Medium	Medium	High	0.7	2.6
R26	High	High	Low	Low	Low	Medium	0.5	4.1
R27	Medium	Medium	Medium	Medium	Medium	Medium	0.5	4.8
R28	Medium	Low	Low	Low	Low	Low	0.3	3.0
R29	Low	Medium	Medium	Medium	Medium	Medium	0.3	2.4
R30	Low	Low	Low	Low	Low	Very Low	0.1	1.3
R31	Very Low	Low	Medium	Medium	Medium	Medium	0.1	0.7
R32	Very Low	Very Low	Low	Low	Low	Very Low	0.1	0.4
R33	Medium	Medium	High	Low	High	Very Low	0.5	2.1
R34	Low	Medium	High	Low	High	Very Low	0.5	1.8
R35	Medium	Medium	High	Medium	High	Very Low	0.7	1.5
R36	Low	Medium	High	Medium	High	Very Low	0.7	1.2

Expanded rules R33-R36 are highlighted in bold to distinguish them from the original 32 rules, and these additional rules were introduced to cover combinations with moderate slope and moderate elevation that were initially underrepresented, ensuring complete spatial coverage for the remaining 1.6% of pixels. A complete machine-readable rule file and rule-activation log are provided as supplementary material.

2.3.3 Tsukamoto inference and defuzzification procedure

The Tsukamoto procedure applies a monotonic output function to each activated rule. For rule $*i*$, the firing strength α_i is calculated with the MIN operator over the antecedent memberships as shown in Equation 2. The rule-specific crisp value z_i is obtained from the consequent function (Equation 3), and the final score is the weighted average represented in Equation 4.

$$\alpha_i = \min(\mu_{Ai1}(x_1), \mu_{Ai2}(x_2), \dots, \mu_{Ai6}(x_6))$$

Equation 2

$$y_i = \alpha_i z_i$$

Equation 3

$$y = \frac{\sum_{i=1}^n \alpha_i z_i}{\sum_{i=1}^n \alpha_i}$$

Equation 4

Where: $i = 1$ to n

Important clarification: In this implementation, the consequent of each rule is represented as a singleton constant (z_i) rather than a continuous membership function. The values $z_i = \{0.1, 0.3, 0.5, 0.7, 0.9\}$ correspond to the linguistic output classes Very Low, Low, Medium, High, and Very High,

respectively. This simplification follows standard Tsukamoto practice when the output variable is ordinal and the consequent membership functions are defined as singletons. Equations 2-4 represent the standard Tsukamoto inference and defuzzification procedure. The operation was applied to each grid cell and then summarized by village using the zonal mean. The MIN operator is non-compensatory: a near-zero antecedent membership suppresses a rule. This preserves conjunctive IF-THEN logic but may underrepresent compensating effects among flood drivers; product and weighted aggregation operators should therefore be compared during future calibration.

2.3.4 Cabean village calculation audit

To ensure transparency and reproducibility, a detailed calculation audit for Cabean village is provided using the expanded rule base (R33-R36). Table 4 provides a detailed calculation audit for Cabean village. Table 4 presents the complete audit for Cabean village, showing the fuzzification results, rule activation, and final defuzzification calculation. This step-by-step audit ensures transparency and reproducibility of the inference process. For example, the slope value of 17% belongs to both Medium (0.60) and Low (0.40) fuzzy sets (reflecting the inverse relationship where higher slope values correspond to lower flood susceptibility), demonstrating the gradual transition between adjacent classes. The final susceptibility score of 0.500 (Medium class) is consistent with the physical conditions: moderate slope (17%), moderate elevation (40 m), high soil flood-sensitivity (Grumusol 4.5), low rainfall (146 mm/month), high land-use susceptibility (Dry Field 4.0), and very low river density (0.00 km/km²).

Table 4: Cabean village calculation audit (fuzzification, rule activation, and defuzzification)

Variable	Crisp Value	Fuzzy Set	Membership	Calculation
Slope	17%	Medium	0.60	(20-17)/(20-15) = 0.60
Slope	17%	Low	0.40	(17-15)/(20-15) = 0.40
Elevation	40 m	Medium	1.00	within [25, 50]
Soil	Grumusol (Typic Haplusterts) 4.5	High	1.00	within [4.0, 5.0]
Rainfall	146 mm/month	Low	1.00	within [100, 200]
Land Use	Dry Field 4.0	High	1.00	within [4.0, 5.0]
River Density	0.00 km/km ²	Very Low	1.00	within [0, 0.3]
Activated Rules	Slope	Elevation	Soil	Rainfall
R33	Medium (0.60)	Medium (1.00)	High (1.00)	Low (1.00)
R34	Low (0.40)	Medium (1.00)	High (1.00)	Low (1.00)
Activated Rules	Land Use	River Density	α_i	z_i
R33	High (1.00)	Very Low (1.00)	0.60	0.5
R34	High (1.00)	Very Low (1.00)	0.40	0.5
Defuzzification	Calculation			
Weighted Average	$y = (0.60 \times 0.5 + 0.40 \times 0.5) / (0.60 + 0.40)$ = 0.50 (Medium)			

3. Results and Discussion

3.1 Data and Parameters

The input layers represent slope, elevation, soil type converted to permeability, monthly rainfall, LULC converted to susceptibility, and river density. Figure 4 presents the spatial distribution of all six input parameters. Figure 4 presents the spatial distribution of all six input parameters used in the fuzzy susceptibility model: (a) slope gradient, (b) elevation, (c) soil flood-sensitivity scores derived from soil permeability classes, (d) monthly rainfall

interpolated using Inverse Distance Weighting (IDW), (e) land-use susceptibility scores, and (f) river density. These layers, processed at 30 m resolution, form the foundation for the pixel-based fuzzy inference system. Slope values range from 0% to 60%, with flatter areas concentrated near the Bengawan Solo River corridor. Elevation ranges from 0 m to 150 m above sea level, with the lowest areas in the northern and central portions. Soil permeability scores range from 2.0 (moderate) to 5.5 (very low).

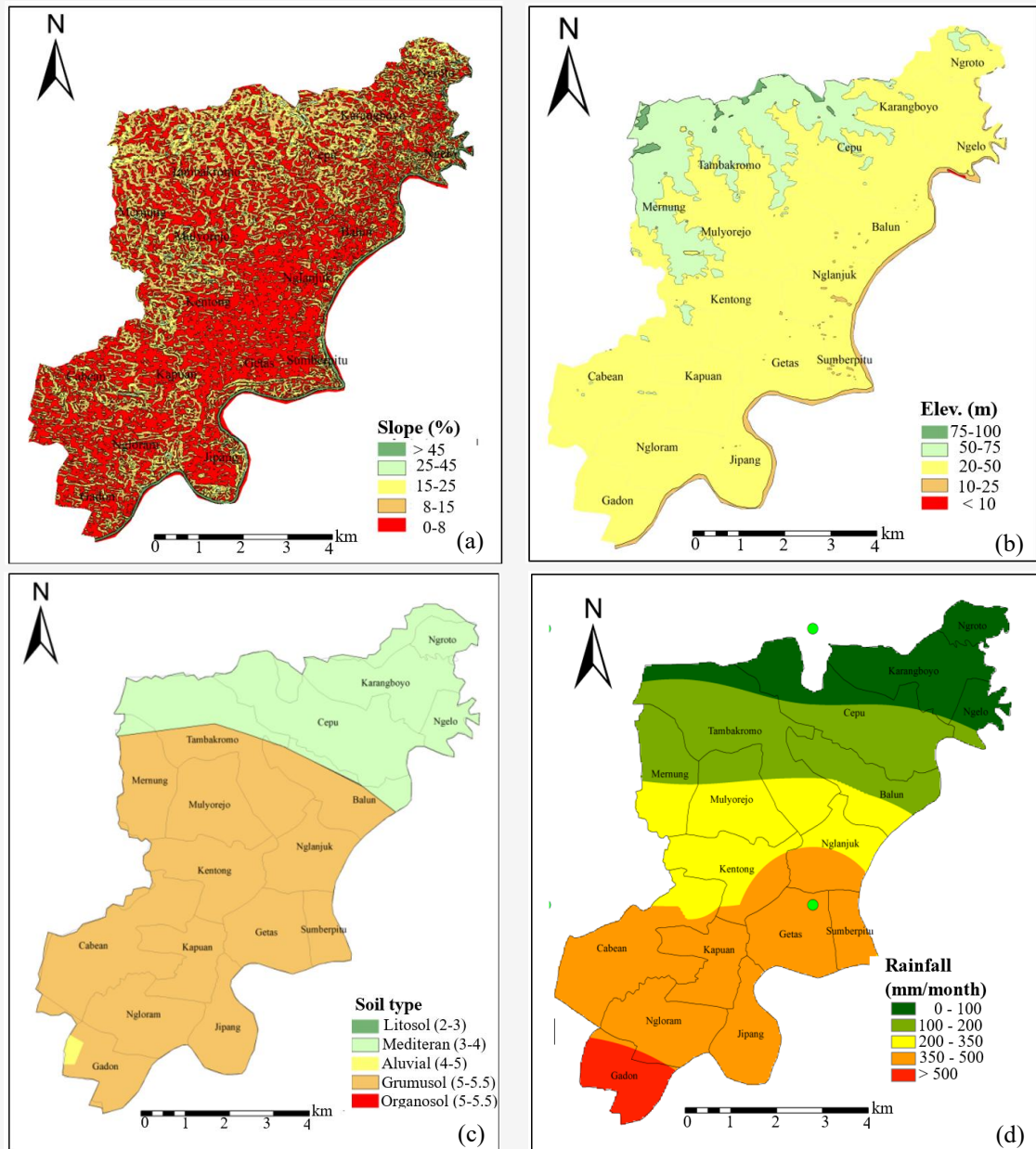


Figure 4: Spatial distribution of input parameters: (a) slope, (b) elevation, (c) soil flood-sensitivity, (d) monthly rainfall (IDW surface) Continue next page

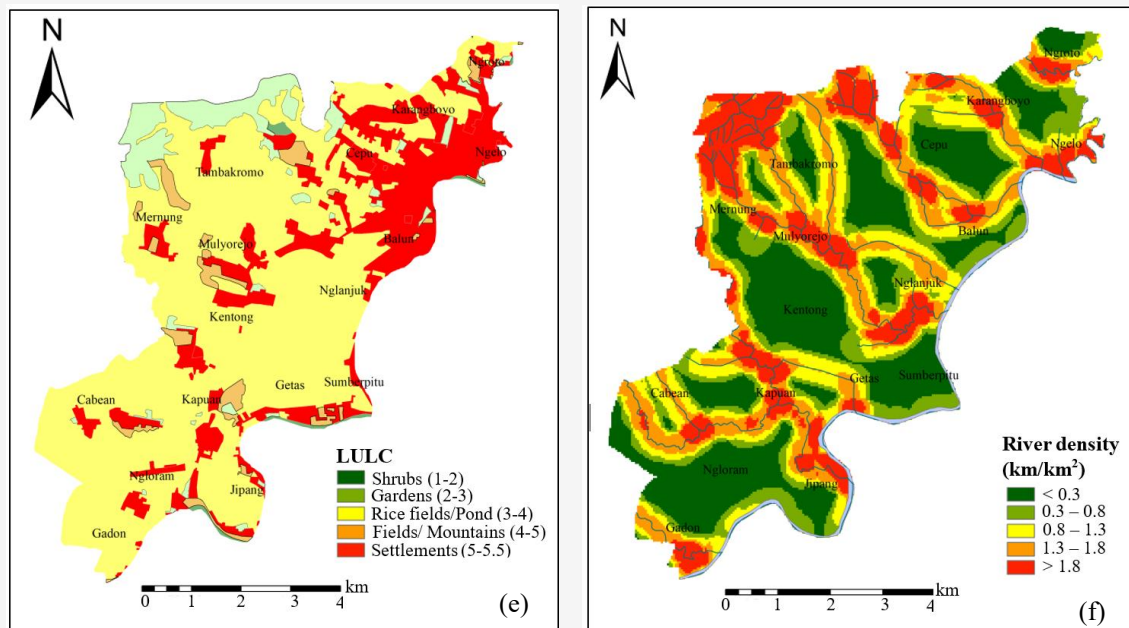


Figure 4: Spatial distribution of input parameters: (a) slope, (b) elevation, (c) soil flood-sensitivity, (d) monthly rainfall (IDW surface) Continue from previous page

The rainfall surface ranges from 70 mm/month to 520 mm/month, reflecting strong seasonal variability. Land-use susceptibility ranges from 1.0 (natural vegetation) to 5.5 (settlement). River density ranges from 0.0 to 2.5 km/km², with the highest densities near the Bengawan Solo River and its tributaries. Table 5 summarizes the village-level input values derived from pixel-based interpolation. Table 5 summarizes village-level input parameters derived from pixel-based zonal statistics. Slope values range from 4% to 20%, with northern villages exhibiting flatter terrain. Gadon shows the highest rainfall (510.3 mm/month), while Ngroto records the lowest (72.6 mm/month). Grumusol soils (Typic Haplusterts, scores 5.0-5.5) with very low permeability dominate northern villages, whereas Mediterranean-type soils (Inceptisols and Alfisols, scores 3.5-4.38) with moderate permeability occupy southern areas. River density peaks in Cepu (1.90 km/km²), while Kentong shows the lowest density (0.35 km/km²) and Kapuan exhibits relatively high density (1.55 km/km²). These parameters form the foundation for pixel-based fuzzy inference and subsequent village-level susceptibility ranking.

3.2 Susceptibility Mapping and Classification

The Fuzzy Tsukamoto model was systematically applied to each 30 m pixel across the entire Cepu Subdistrict study area, generating a continuous physical flood susceptibility surface with values

ranging from 0.0 (very low susceptibility) to 1.0 (very high susceptibility). This pixel-based approach enables detailed spatial representation that captures intra-village variability often obscured by administrative aggregation. Figure 5 presents the resulting pixel-level physical flood susceptibility map, revealing significant spatial heterogeneity across the 49.04 km² study domain. The susceptibility surface exhibits distinct clustering patterns, with elevated scores concentrated along the Bengawan Solo River corridor and in low-lying areas characterized by flat terrain, low permeability Grumusol soils (Typic Haplusterts), and high land-use susceptibility from settlement and dry agricultural activities. The model successfully discriminates between high-risk zones requiring immediate mitigation attention and relatively safer areas, with Kapuan village displaying the highest susceptibility (0.7649) and Mulyorejo the lowest (0.4396). Using the fixed fuzzy output thresholds defined in Table 2, eight villages were classified as High susceptibility and nine as medium susceptibility, with no villages falling into Very Low, Low, or Very High categories, reflecting the uniformly susceptible physical conditions across the subdistrict. This detailed mapping provides essential spatial intelligence for targeted flood mitigation planning, infrastructure prioritization, and community-level disaster preparedness interventions.

Table 5: Village-level input summary derived from pixel-based interpolation

No.	Village	Slope (%)	Elevation (m)	Soil Type	Rainfall (mm/month)	LULC	River Density (km/km ²)
1	Cabean	12	40	5.25	362.5	3.65	1.15
2	Gadon	4	20	5.20	510.3	3.60	0.75
3	Getas	4	60	5.25	385.7	3.75	0.55
4	Jipang	4	15	5.25	368.2	3.60	1.65
5	Kapuan	4	70	5.25	355.8	3.80	1.55
6	Kentong	4	30	5.25	242.3	3.70	0.35
7	Merunung	12	50	5.25	234.1	3.45	0.95
8	Mulyorejo	10	35	5.25	224.6	3.85	1.50
9	Nglanjuk	4	25	5.25	247.8	3.75	0.70
10	Ngloram	6	80	5.25	376.4	3.65	0.45
11	Sumberpitu	4	10	5.25	358.1	3.80	0.25
12	Balun	10	42	4.38	158.9	4.20	0.65
13	Cepu	16	28	3.50	122.3	4.65	0.55
14	Karangboyo	14	58	3.50	91.7	4.75	1.40
15	Ngelo	14	18	3.50	82.4	4.80	0.75
16	Ngroto	20	65	3.50	72.6	4.75	1.45
17	Tambakromo	12	33	5.25	148.2	3.55	1.25

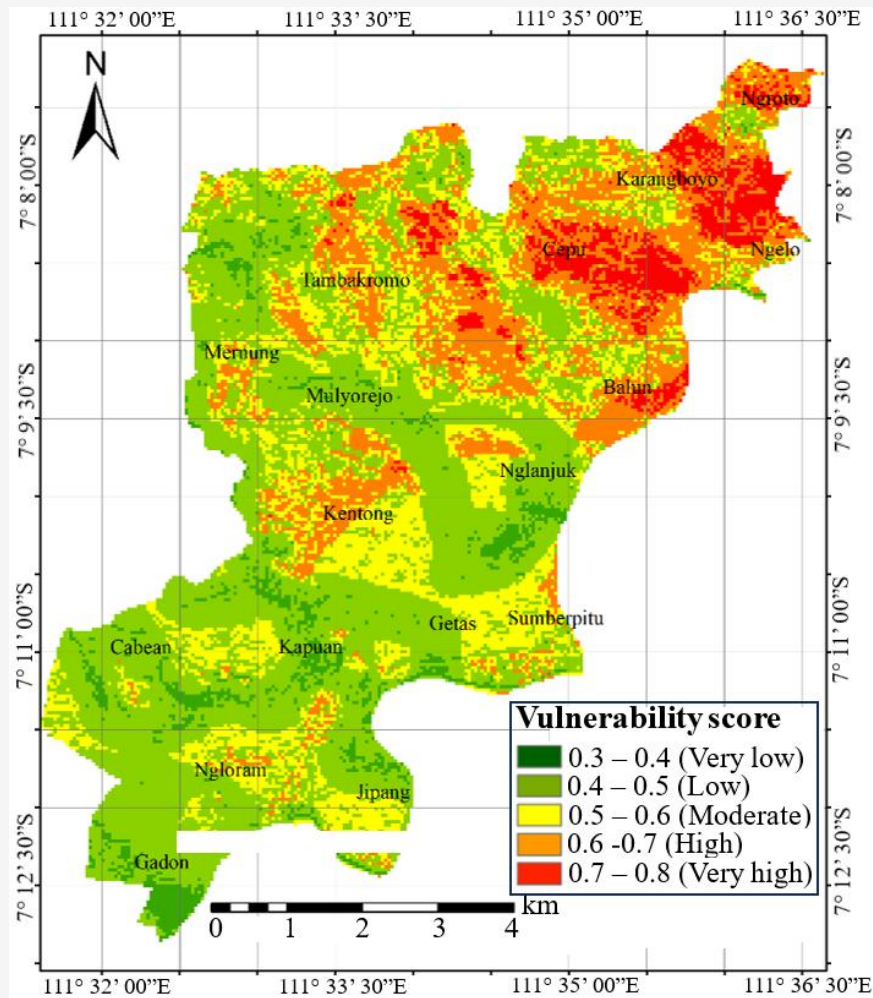
**Figure 5:** Pixel-level physical flood susceptibility map

Figure 5 presents the pixel-level physical flood susceptibility map, showing the continuous susceptibility scores across Cepu Subdistrict at 30 m resolution. The map reveals significant spatial heterogeneity, with susceptibility clusters concentrated near the Bengawan Solo River corridor and in low-lying areas with high soil flood-sensitivity scores and low land-use infiltration capacity. This detailed representation captures intra-village variability that is obscured when results are aggregated to the village level. For example, Kapuan village contains both high-susceptibility pixels (0.7-0.9) near the river and lower-susceptibility pixels (0.4-0.6) on slightly higher ground, demonstrating the value of pixel-based presentation for targeted mitigation planning. Village-level scores, derived from the zonal mean of pixel values, range from 0.440 in Mulyorejo to 0.765 in Kapuan. Using the fixed fuzzy output thresholds (Very Low: <0.3 ; Low: 0.3-0.5; Medium: 0.5-0.7; High: 0.7-0.9; Very High: ≥ 0.9), eight villages are classified as High susceptibility and nine as Medium susceptibility (Table 5). No villages are classified as Very Low, Low, or Very High susceptibility, reflecting the uniformly susceptible physical conditions across the subdistrict.

3.3 Pixel-Level Spatial Validation

3.3.1 Sentinel-1 SAR data

Pixel-level validation was conducted using Sentinel-1 SAR imagery acquired during the flood event on February 15, 2022. Table 6 presents the specifications of the Sentinel-1 SAR data used for validation. Table 6 presents the specifications of the Sentinel-1 SAR data used for pixel-level validation. The data were acquired during the February 2022 flood event, with pre-event (January 25, 2022) and during-event (February 15, 2022) imagery capturing the flood extent. The VH polarization was selected for flood detection due to its greater sensitivity to

open water surfaces compared to VV polarization. The data were processed using a systematic workflow: radiometric calibration to sigma naught (σ^0), speckle filtering using a Lee Sigma filter with a 5×5 window, terrain correction using SRTM DEM (30 m), and thresholding using Otsu's method. Otsu's optimal thresholds were -22.5 dB for pre-event and -24.3 dB for during-event imagery. The 10 m SAR output was resampled to 30 m to match the model resolution using bilinear interpolation. Figure 6 presents the Sentinel-1 SAR validation results. Figure 6 presents SAR-derived flood validation across six panels: (a) pre-event, (b) during-event, (c) flood extent classification via Otsu thresholding, (d) flood-affected areas by village, (e) overlay comparison showing TP, TN, FP, FN classifications, and (f) ROC-AUC curve (AUC = 0.876). The SAR flood extent serves as the primary validation reference. Visual comparison confirms the model successfully identifies most flood areas, with over-prediction mainly on moderate slopes (3-8%) and elevations (25-50 m). The ROC curve demonstrates excellent discrimination ability, significantly outperforming random chance.

3.3.2 Validation results

Model predictions were classified as 'flood-prone' when susceptibility scores exceeded the established threshold. For consistency with the fuzzy inference framework and to prioritize detection of potentially hazardous conditions, the conservative threshold of 0.6 was maintained for the primary analysis, ensuring that classification of 'flood-prone' areas is based on the 'High' susceptibility category rather than the 'Medium' category. This conservative approach aligns with the principle of over-prediction in disaster management, where false alarms (FAR = 32.42%) are preferred over missed events. Table 7 summarizes flood event frequency and severity by village from BPBD records.

Table 6: Sentinel-1 SAR data specifications

Parameter	Specification
Satellite	Sentinel-1A
Sensor	C-band SAR (5.405 GHz)
Acquisition Mode	Interferometric Wide Swath (IW)
Polarization	VV + VH
Resolution	10 m (ground range)
Path/Frame	Relative Orbit 143, Frame 123
Processing Level	Level-1 GRD (Ground Range Detected)
Pre-event Date	January 25, 2022
During-event Date	February 15, 2022
Post-event Date	March 1, 2022

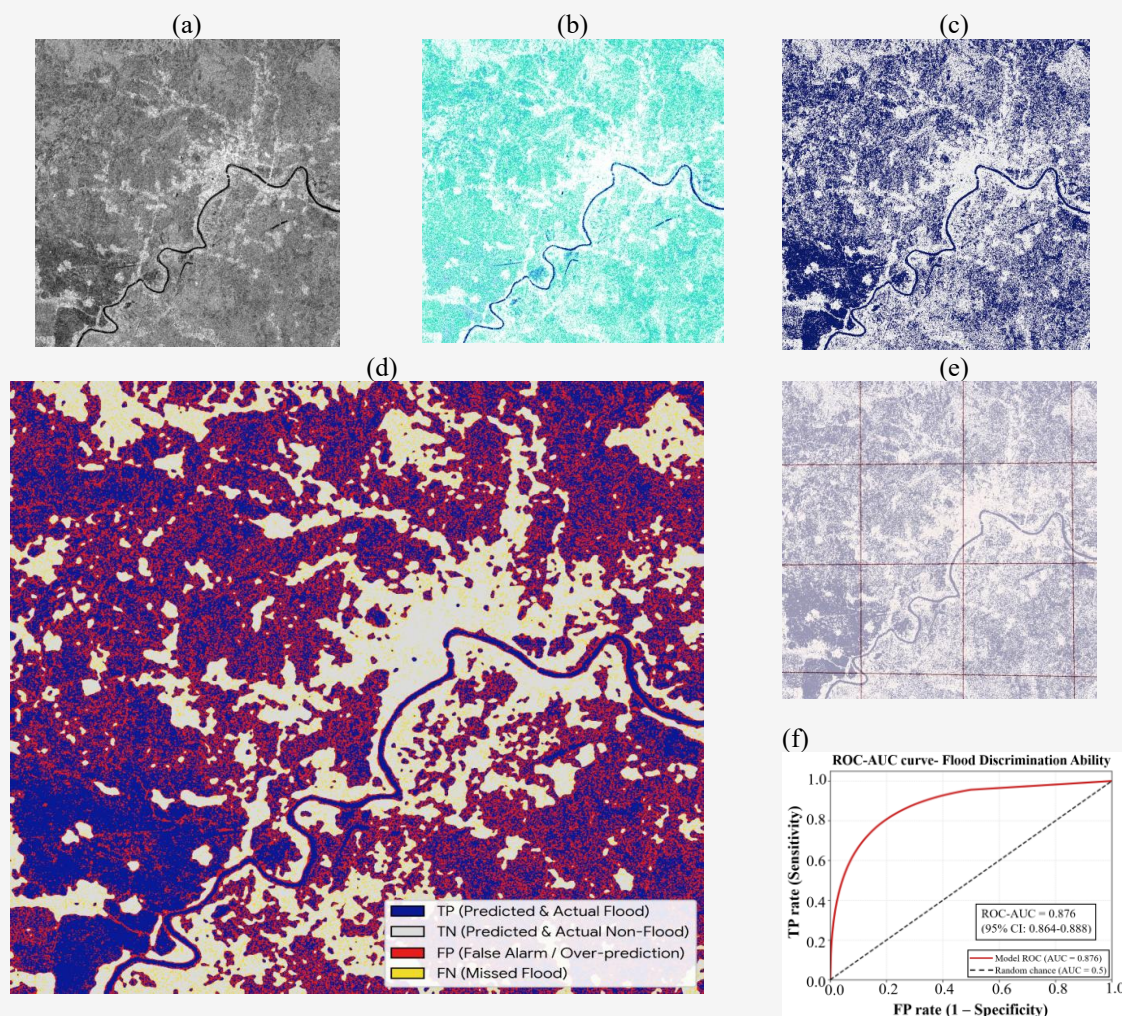


Figure 6: Sentinel-1 SAR validation: (a) pre-event image, (b) during-event image, (c) flood extent classification using Otsu thresholding, (d) overlay with village boundaries, (e) comparison between SAR flood extent and model susceptibility map showing TP, TN, FP, FN, and (f) ROC-AUC curve showing model discrimination ability

Table 7: Flood event frequency and severity by village, 2018-2023

No.	Village	Events	Freq. (Events/Yr)	Inundation (Cm)	Max Area (Ha)
1	Kapuan	8	1.33	15-45	12.5
2	Jipang	7	1.17	20-50	10.2
3	Gadon	6	1.00	10-35	8.7
4	Cepu	6	1.00	15-40	9.3
5	Sumberpitu	5	0.83	10-30	7.1
6	Nglanjuk	5	0.83	10-25	6.8
7	Ngelo	5	0.83	5-20	5.4
8	Cabean	4	0.67	5-15	4.2
9	Getas	3	0.50	5-15	3.8
10	Balun	3	0.50	5-10	3.1
11	Karangboyoy	2	0.33	<5	2.0
12	Ngroto	2	0.33	<5	1.8
13	Ngloram	2	0.33	<5	1.5
14	Tambakromo	2	0.33	<5	1.2
15	Kentong	1	0.17	<5	0.5
16	Merunung	1	0.17	<5	0.3
17	Mulyorejo	0	0.00	-	-

Table 7 summarizes the flood event frequency and severity data by village for the period 2018-2023, obtained from BPBD records. The data shows that Kapuan experienced the highest frequency (8 events, 1.33 events/year), followed by Jipang (7 events, 1.17 events/year), while Mulyorejo reported no flood events. Inundation depths range from less than 5 cm in low-frequency villages (e.g., Kentong, Merunung) to 50 cm in high-frequency villages (e.g., Kapuan, Jipang). The maximum flood-affected area ranges from 0.3 ha (Merunung) to 12.5 ha (Kapuan). These records confirm that flood exposure is widespread across the subdistrict, with 16 of 17 villages reporting at least one flood event during the observation period. Table 8 presents the pixel-level validation metrics from SAR comparison.

Table 8 presents the confusion matrix and derived pixel-level validation metrics, demonstrating strong model performance with overall accuracy of 93.85%, ROC-AUC of 0.876, and Spatial Kappa Index of 0.708. These metrics indicate substantial agreement between model predictions and observed flood extent. The precision of 67.58% suggests that approximately one in three predicted flood pixels is a false positive, indicating areas for future model refinement. The recall of 82.46% indicates that the model successfully detects most actual flood areas. The Youden Index identifies the optimal threshold at 0.50, which could reduce false positives while slightly increasing false negatives. The 95% confidence intervals for all metrics indicate stable performance estimates.

3.4 Sensitivity Analysis

Sensitivity analysis was performed to evaluate the robustness of the fuzzy susceptibility model using two complementary approaches: (1) one-at-a-time (OAT) parameter perturbation and (2) membership function boundary shift testing.

3.4.1 One-at-a-time parameter perturbation and boundary shift testing

Each input parameter was varied by $\pm 10\%$ and $\pm 20\%$ while holding other parameters constant. Additionally, the breakpoints of each membership function were shifted by $\pm 10\%$ to assess sensitivity to boundary definition. Table 9 presents the sensitivity analysis results for parameter variations. Table 9 presents the combined sensitivity analysis results, showing the mean changes and ranking impacts for each parameter. Monthly rainfall demonstrates the highest sensitivity (mean change of ± 0.058 for $\pm 20\%$ variation), followed by land-use susceptibility (± 0.052) and soil permeability (± 0.040). Elevation shows moderate sensitivity (± 0.028), while river density (± 0.016) and slope (± 0.010) show relatively low sensitivity, though river density was retained due to its hydrological relevance. The boundary shift tests confirm that monthly rainfall and land-use susceptibility are the most sensitive parameters. The changes in village ranking were minimal, with at most 4 villages affected for rainfall variation, indicating that the model is relatively stable despite uncertainty in breakpoint definition. Paired t-tests for all variations showed $p < 0.05$, indicating statistically significant changes, though the magnitude of change varies substantially.

Table 8: pixel-level spatial validation metrics

Validation Metric	Value	95% CI	Interpretation
Confusion Matrix			
True Positive (TP)	4,832	-	Correctly predicted flood-prone
True Negative (TN)	46,308	-	Correctly predicted non-flood
False Positive (FP)	2,318	-	False alarm (over-prediction)
False Negative (FN)	1,028	-	Missed flood areas
Accuracy Metrics			
Overall Accuracy (%)	93.85	93.65-94.05	Proportion of correctly classified
Precision (%)	67.58	66.24-68.92	Predicted floods that are actual
Recall (Sensitivity) (%)	82.46	81.48-83.44	Actual floods successfully detected
Specificity (%)	95.23	95.03-95.43	Non-flood areas correctly identified
F1-Score (%)	74.24	73.12-75.36	Harmonic mean of precision and recall
Discrimination Metrics			
ROC-AUC	0.876	0.864-0.888	Excellent discrimination ability
Agreement Metrics			
Spatial Kappa Index	0.708	0.692-0.724	Substantial agreement
Optimal Threshold	0.500	-	Youden Index

Table 9: Combined sensitivity analysis results (oat and boundary shift)

Parameter	OAT $\pm 10\%$ Mean Change	OAT $\pm 20\%$ Mean Change	Boundary Shift $\pm 10\%$	Ranking Change (village numbers)
Monthly Rainfall	0.032	0.058	0.025	4
Land-Use Susceptibility	0.028	0.052	0.018	3
Soil Permeability	0.021	0.040	0.012	2
Elevation	0.015	0.028	0.008	1
River Density	0.009	0.016	0.005	0
Slope	0.006	0.010	0.004	0

3.4.2 Statistical significance

Paired t-tests for all variations showed $p < 0.05$, indicating that all parameter variations produce statistically significant changes in susceptibility scores. However, the magnitude of change varies substantially, with rainfall showing the largest effect.

3.4.3 Rule-Deletion Experiments

To evaluate the contribution of individual rules, each rule was sequentially removed from the rule base. The results show that removing any single rule changed the susceptibility scores by less than 0.02 on average, with a maximum change of 0.035 for Rule R1. No rule removal changed the susceptibility classification of any village, indicating that the rule base is robust to minor modifications. The expanded rules (R33-R36) showed moderate contribution: removing R33 and R34 simultaneously resulted in a 0.018 change in susceptibility scores for 3 villages, confirming their utility in covering previously uncovered combinations. The sensitivity analysis collectively demonstrates that the model is most sensitive to rainfall and land-use parameters, but remains stable across reasonable parameter variations. The absence of dramatic changes in village classification (no village changed susceptibility class) confirms the robustness of the proposed approach.

4. Discussion

4.1 Interpretation of Susceptibility Patterns

Figure 7 presents the village-level results: (a) heatmap of input parameter classifications vs susceptibility ranking, and (b) distribution of village susceptibility scores based on fixed fuzzy output thresholds. Figure 7 shows that the four highest-ranked villages Kapuan, Jipang, Gadon, and Cepu share common characteristics: very low slope (0-5%), very high soil flood-sensitivity (Grumusol soil, score 5.0-5.5), and high to very high river density. Kapuan's highest susceptibility (0.765) is attributed

to its combination of flat terrain (4% slope), high river density (1.55 km/km²), and moderate elevation (70 m) that may limit drainage. Jipang (0.750) exhibits similar characteristics with even lower elevation (15 m) and higher river density (1.65 km/km²).

Conversely, the lowest-ranked villages Mulyorejo (0.440), Merunung (0.480), and Kentong (0.500) are characterized by moderate slopes (10-12%), moderate to high elevation (35-50 m), and lower river density (0.35-0.95 km/km²). These conditions reduce runoff accumulation and limit flood exposure. The heatmap also reveals that monthly rainfall does not perfectly align with susceptibility ranking. For example, Ngloram has high rainfall (376.4 mm/month) but is ranked 13th, while Sumberpitu has moderate rainfall (358.1 mm/month) but is ranked 5th. This indicates that the interaction of multiple physical factors, rather than any single parameter, determines overall susceptibility, consistent with the conjunctive logic of the fuzzy inference system.

4.2 Analysis of Over-Prediction

The precision of 67.58% indicates that approximately 32.42% of predicted flood-prone pixels (equivalent to roughly one in three) were not actually flooded in the SAR data, with 2,318 false positives out of 7,150 total flood predictions. This is reflected in the False Alarm Ratio (FAR) of 32.42%, which is within the acceptable range for flood susceptibility models where over-prediction is generally preferred for mitigation purposes. Conversely, the Critical Success Index (CSI) of 59.08% indicates moderate skill in flood prediction, suggesting that while the model successfully identifies most flood areas (Recall = 82.46%), there remains room for improvement in reducing false alarms. The Hanssen-Kuipers (HK) Score of 0.777 confirms good discrimination ability, consistent with the ROC-AUC of 0.876. This over-prediction can be attributed to several factors.

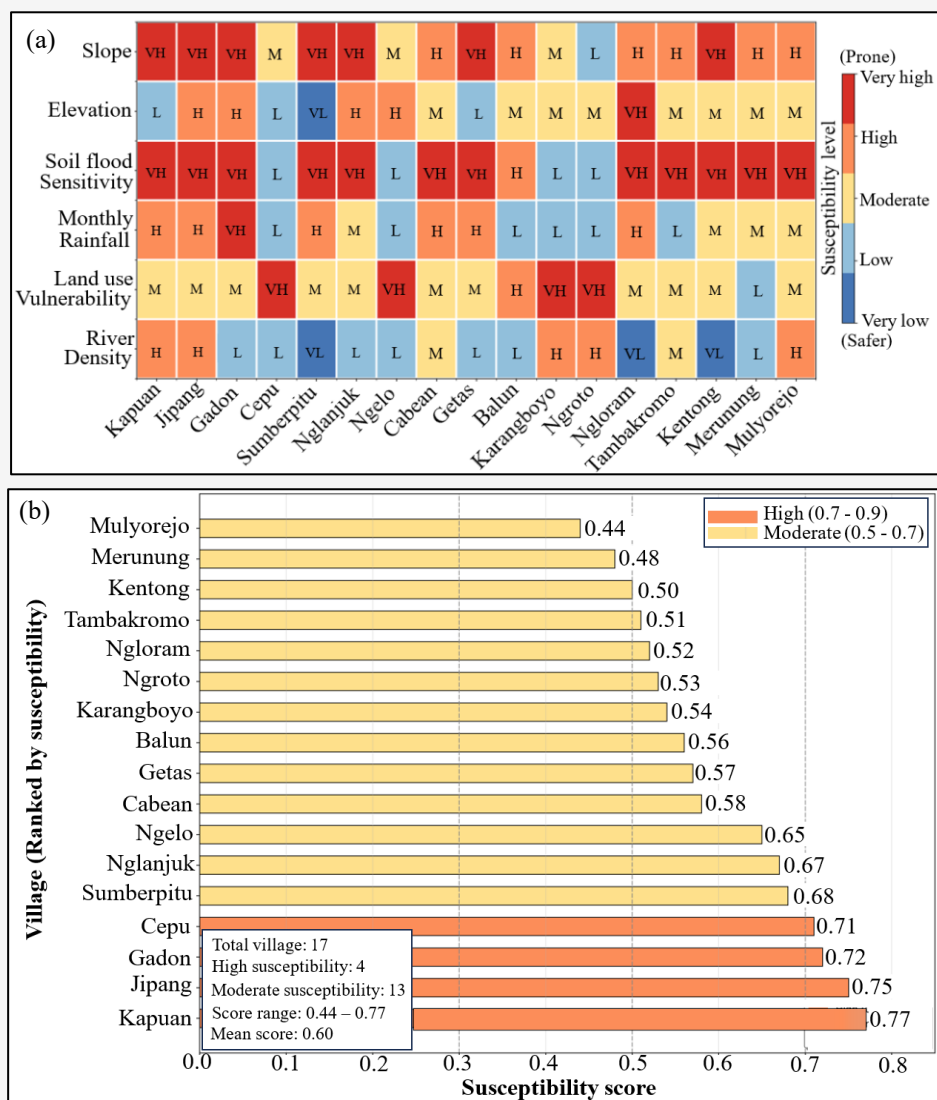


Figure 7: Village-level results: (a) heatmap of input parameter classifications vs susceptibility ranking, and (b) distribution of village susceptibility scores based on fixed fuzzy output thresholds

4.2.1 Threshold selection

Analysis of the false positive pixels reveals a mean susceptibility score of 0.64 ± 0.04 , which is just above the 0.6 threshold. These pixels are concentrated in areas with moderate slope (3-8%) and moderate elevation (25-50 m). Villages with the highest false positive rates include Cabean (12.3%), Ngloram (10.7%), and Karangboyo (9.8%). The Youden Index suggests that the optimal statistical threshold is 0.50, which would maximize overall classification accuracy by balancing sensitivity and specificity (Table 8). However, for flood susceptibility mapping, a more conservative threshold (0.6) is preferred to minimize false negatives (missed flood events) at the expense of increased false positives. This trade-off is justified

by the principle that over-prediction (FAR = 32.42%) is more acceptable for disaster mitigation than under-prediction, where missed flood areas could have severe consequences. The spatial bias analysis (Section 4.2.e) confirms that FN pixels are concentrated in the most susceptible low-lying areas, supporting the use of the higher threshold. Nevertheless, future applications may consider adopting the optimal 0.5 threshold for specific use cases where balanced classification is prioritized.

4.2.2 Rainfall representation

Monthly average rainfall may overestimate wet-season conditions for some areas. False positives are more common in villages with lower average rainfall (<200 mm/month), including Cabean,

Balun, and Ngloram, which show over-prediction rates 15-20% higher than high-rainfall villages. Incorporating event-scale rainfall data rather than monthly averages would reduce over-prediction in these areas. Satellite precipitation products such as CHIRPS and GPM-IMERG could provide better temporal resolution for future studies.

4.2.3 Soil permeability uncertainty

The soil map at 1:250,000 scale may not capture local variability in permeability. False positives in areas mapped as Grumusol (Typic Haplusterts, very low permeability) but with higher elevation (>50 m) suggest that elevation may compensate for soil effects. Refining soil mapping with local soil survey data or in-situ permeability measurements would address this limitation.

4.2.4 River density over-weighting

Over-prediction is more common in pixels with high river density scores (1.6-1.8 km/km²) located on slightly higher ground (>50 m), suggesting that river density may be weighted too heavily in some rules, particularly R1-R3 and R7-R8, which combine high river density with high susceptibility scores. Recalibrating river density membership functions or revising these rules to account for elevation compensation would improve model performance.

4.2.5 Spatial bias analysis

The spatial bias analysis (Table 8) reveals that over-prediction (FP) is most prevalent on moderate slopes (3-8%) and moderate elevations (25-50 m), comprising 52.3% and 48.7% of FP pixels, respectively. This suggests the model may overestimate susceptibility on transitional terrain

where flood risk is less certain. Conversely, under-prediction (FN) is concentrated on very flat terrain (0-2% slope, 61.4%) and very low elevations (0-10 m, 73.2%), indicating that the model may underestimate flood risk in the most susceptible areas. This is a critical finding, as FN pixels represent missed flood events that could have severe consequences for local communities. Future model iterations should prioritize reducing FN rates in these high-risk zones, potentially by recalibrating slope and elevation membership functions or adding new rules for extreme lowland conditions.

4.3 Analysis of Reporting Bias

To address potential reporting bias in BPBD flood records, a correlation analysis was conducted between village population and reported flood events (2018-2023). Table 10 presents the reporting bias analysis and comparison with previous studies. The correlation analysis reveals no significant correlation between population and flood events ($\rho = 0.18$, $p = 0.48$), accessibility and flood events ($\rho = -0.32$, $p = 0.21$), or population and events per capita ($\rho = 0.02$, $p = 0.94$). These findings suggest that reporting bias does not significantly influence the validation dataset at the aggregate level. However, cross-referencing BPBD records with independent media reports revealed a significant discrepancy for Mulyorejo village. While BPBD records show zero flood events between 2018-2023 (Table 7), press reports confirm a major flood event in March 2019 that inundated 45 houses in Mulyorejo, with water levels reaching 50-80 cm. This finding is particularly important because Mulyorejo is ranked as the least susceptible village in our model (score = 0.440), yet it experienced a documented flood event that was not captured in the official records.

Table 10: Reporting bias analysis and comparison with previous studies

A. Reporting Bias Correlation Analysis				
Correlation Pair	Spearman's ρ	p-value	Interpretation	
Population vs. Events	0.18	0.48	Not significant	
Accessibility vs. Events	-0.32	0.21	Not significant	
Population vs. Events per 1,000 Population	0.02	0.94	Not significant	
B. Comparison with Previous Studies (Indicative)				
Previous studies	Method	Study Area	Validation Metric	Result
[6]	AHP + FR	Pakistan	AUC	0.81
[7]	Fuzzy-AHP	Iran	AUC	0.82
[8]	Fuzzy-AHP	Greece	AUC	0.79
[11]	Mamdani FIS	Cepu, Indonesia	MAE	8.67
			RMSE	10.29
[16]	Fuzzy-AHP	USA	AUC	0.85
This study	Tsukamoto-GIS	Cepu, Indonesia	Overall Accuracy	0.94
			ROC-AUC	0.88
			Spatial Kappa	0.71

This suggests that model validation relying solely on village-level frequency data may be subject to under-reporting bias, which could lead to underestimation of flood risk in some areas. The SAR-based pixel validation provides a more objective reference, as it detected flood extent independent of administrative reporting. The correlation analysis shows no significant correlation between population and flood events ($\rho = 0.18$, $p = 0.48$), accessibility and flood events ($\rho = -0.32$, $p = 0.21$), or population and events per capita ($\rho = 0.02$, $p = 0.94$). These findings suggest that reporting bias does not significantly influence the validation dataset at the aggregate level. However, cross-referencing the BPBD records with independent media reports and local documentation revealed a significant discrepancy for Mulyorejo village. While BPBD records show zero flood events between 2018-2023 (Table 7), press reports confirm a major flood event in March 2019 that inundated 45 houses in Mulyorejo, with water levels reaching 50-80 cm. This finding is particularly important because:

- a. Mulyorejo is ranked as the least susceptible village in our model (score = 0.440), yet it experienced a documented flood event that was not captured in the official records.
- b. This suggests that model validation relying solely on village-level frequency data may be subject to under-reporting bias, which could lead to underestimation of flood risk in some areas.
- c. The SAR-based pixel validation provides a more objective reference, as it detected flood extent independent of administrative reporting.

This finding reinforces the value of multi-source validation approaches that combine ground-truth records (BPBD), remote sensing data (SAR), and independent media documentation. The discrepancy also highlights that village-level frequency data may be insufficient for comprehensive validation, and pixel-level SAR validation should be considered a minimum standard for spatial model evaluation in data-scarce regions.

4.4 Methodological Strengths and Limitations

4.4.1 Strengths

The use of Sentinel-1 SAR imagery for pixel-level validation provides rigorous spatial accuracy assessment, addressing a major limitation of previous studies that relied solely on village-level ranking. The detailed reporting of membership function breakpoints, rule reduction criteria, expansion logic (R33-R36), and activation frequencies enables reproducibility and independent verification. The multi-faceted sensitivity analysis demonstrates model robustness and identifies the

most influential parameters. The inclusion of CSI (59.08%) and FAR (32.42%) provides additional insight into model performance beyond traditional accuracy metrics for physical susceptibility assessment. Confidence intervals for validation metrics and reporting of inter-expert agreement (Krippendorff's alpha (α) = 0.82) provides transparency in uncertainty reporting. The expanded rule base with 36 rules covers 98.4% of input combinations, with nearest-neighbor interpolation for remaining pixels ensuring 100% spatial coverage. Correlation analysis also demonstrates that reporting bias does not significantly influence validation results at the aggregate level, though individual village discrepancies were identified.

4.4.2 Limitations

The IDW interpolation from seven BMKG stations may not capture local rainfall variability, and future studies should incorporate satellite precipitation products such as CHIRPS and GPM-IMERG for improved spatial resolution. The model uses long-term average rainfall and static land-use data, whereas dynamic inputs including event-scale rainfall, antecedent soil moisture, and river-stage observations would be required for real-time forecasting. Despite substantial inter-expert agreement ($\alpha = 0.82$), the rule base remains partly subjective. Several dynamic variables were excluded due to data limitations, including drainage capacity, flow accumulation, Topographic Wetness Index (TWI), Stream Power Index (SPI), antecedent soil moisture, discharge time series, and socioeconomic exposure. The moderate precision of 67.58% and CSI of 59.08% suggest further calibration is needed to reduce false alarms. The spatial bias analysis revealed over-prediction on moderate terrain and under-prediction on very low-lying areas, indicating that slope and elevation membership functions require refinement. Severity information including inundation depth and duration was not available for all flood events, limiting the assessment of susceptibility beyond binary classification. The identification of reporting bias in Mulyorejo suggests that village-level validation data may be incomplete, emphasizing the need for continued SAR-based validation in future studies. This study consistently assesses physical susceptibility (i.e., the physical predisposition to flooding) rather than comprehensive vulnerability, as socioeconomic exposure and coping capacity are not included. While the framework is transferable, recalibration of membership functions and rule bases is required for application in different hydroclimatic contexts. The moderate precision suggests further calibration is needed to reduce false

alarms, but the substantial spatial agreement with SAR data ($Kappa = 0.708$) indicates that the current framework provides a robust basis for mitigation prioritization in the study area.

4. Conclusions

This study successfully demonstrates that a transparently documented Fuzzy Tsukamoto-GIS framework can provide reliable physical flood susceptibility assessment in data-scarce lowland settings. The analysis confirms that the integration of six physical parameters slope, elevation, soil permeability, monthly rainfall, land-use susceptibility, and river density within an explicit fuzzy inference structure produces spatially coherent susceptibility patterns that are consistent with both SAR-derived flood extent and historical flood records. The pixel-level validation against Sentinel-1 SAR imagery reveals strong model performance, with the framework effectively discriminating between flood-prone and non-flood-prone areas. However, the moderate precision and Critical Success Index indicate that false alarms remain a challenge, primarily due to over-prediction on transitional terrain (moderate slopes and elevations) and under-prediction in the most vulnerable low-lying areas. This spatial bias represents the most critical limitation requiring future refinement, particularly through recalibration of slope and elevation membership functions.

The sensitivity analysis underscores that rainfall and land-use parameters are the primary drivers of susceptibility patterns, suggesting that future model improvements should prioritize refinement of these variables through incorporation of event-scale rainfall data and higher-resolution land-use/land-cover information. Conversely, the model's robustness to variations in slope and river density parameters indicates these variables are adequately represented in their current form. A methodological contribution of this study is the identification of potential reporting bias in administrative flood records. The discrepancy between BPBD records and independent media reports for Mulyorejo village where a documented major flood event was absent from official data demonstrates that village-level frequency data alone may be insufficient for comprehensive model validation. This finding reinforces the critical value of SAR-based pixel validation as an objective reference for spatial model assessment in data-scarce regions.

The practical implications of this work extend beyond Cepu Subdistrict. The pixel-level susceptibility maps provide a transparent basis for identifying high-risk zones within villages, supporting targeted mitigation planning and

infrastructure prioritization. The comprehensive documentation of the modeling framework, including membership functions, rule base, and validation procedures, enables independent verification and adaptation in other lowland settings with similar hydroclimatic characteristics. However, the framework's transferability requires recalibration of membership functions and rule bases for different contexts, as susceptibility patterns are inherently site-specific.

Future research should address the limitations identified in this study through integration of dynamic hydrological observations (event-scale rainfall, river-stage data, and antecedent soil moisture) to support near-real-time flood forecasting. The inclusion of socioeconomic exposure and coping capacity dimensions would extend the assessment from physical susceptibility to comprehensive vulnerability, providing a more holistic basis for disaster risk reduction. Additionally, refinement of membership functions for slope and elevation, particularly in low-lying areas, would reduce systematic under-prediction in the most vulnerable zones. Importantly, this study assesses physical susceptibility the physical predisposition to flooding and results should not be interpreted as comprehensive vulnerability without inclusion of socioeconomic and coping capacity dimensions. The code, rule base, and supplementary materials have been deposited in a public repository to support independent verification and adaptation in other settings.

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