



EVALUATION OF SEISMIC VULNERABILITY FOR NON-ENGINEERED BUILDINGS USING INTEGRATED ANALYTIC HIERARCHY PROCESS AND FUZZY INFERENCE SYSTEM

Catur Singgih¹, *Setya Winarno¹, Sri Kusumadewi², and Albani Musyafa¹

¹Department of Civil Engineering, Universitas Islam Indonesia, Indonesia

²Department of Informatics, Universitas Islam Indonesia, Indonesia

*Corresponding Author, Received: 20 May 2026, Revised: 29 June 2026, Accepted: 01 July 2026

ABSTRACT: Seismic vulnerability evaluation of non-engineered buildings (NEBs) in developing countries is hindered by data uncertainty, building diversity, and impractical conventional tools. This study proposes an integrated Analytic Hierarchy Process–Fuzzy Inference System (AHP–FIS) model to evaluate the seismic vulnerability of NEBs. Fourteen factors covering technical, socio-economic, and environmental dimensions were collected through field-based scoring and then processed using a Mamdani FIS model. A total of 120 observed post-earthquake house damage records were used to demonstrate the predictive accuracy of the model. The results show that AHP weighting indicated that the technical dimension (0.5151) was the dominant driver, followed by the environmental (0.2698) and socio-economic (0.2151) dimensions. The houses assessed fell to 47.5% of the High to Very High vulnerability classes. The model achieved 81.03% sensitivity, 83.87% specificity, 82.46% precision, and an overall accuracy of 82.50%, indicating that the model showed satisfactory classification performance and this is suitable as a preliminary regional screening and prioritization tool for seismic-risk mitigation of NEBs.

Keywords: AHP–FIS model, Mamdani fuzzy inference system, Non-engineered buildings, Vulnerability index

1. INTRODUCTION

Indonesia is located along the Pacific Ring of Fire, which makes Indonesia very vulnerable to the occurrence of strong ground motion and repeating damaging earthquakes [1]. This highlights the importance of strengthening evidence-based disaster risk reduction strategies due to the widespread presence of non-engineered buildings (NEBs) that constitute a major source of seismic vulnerability [2]. Post-earthquake evidence from recent Indonesian events, including Lombok 2018 [3], Palu-Donggala 2018, Cianjur 2022 [4], and Pacitan 2023 [5], indicates that severe and total damage are frequently concentrated in NEBs [6]. These buildings are typically built using conventional building practices and locally available materials, with variable structural quality, sub-standard materials, poor architectural configuration, and construction practices learned from experience rather than from formal seismic design principles, often with little regard to seismic load paths, connection integrity, and detailing requirements [7].

An important methodological challenge identified in literature is the high level of uncertainty regarding field data for NEBs. Information on

material quality, construction techniques, and maintenance history is often qualitative, incomplete, and expressed in linguistic terms, which makes it difficult to be processed by deterministic approaches [8]. At the same time, the relevant factors should be quantified to prioritize urgent and priority actions. The Analytic Hierarchy Process (AHP) is a methodological approach that involves weighting the operationalized indices. This is much easier for the human brain to process accurately because it focuses on relative importance rather than absolute values. Besides AHP, fuzzy logic shows a more robust approach to managing field data with uncertainty and ambiguity. Fuzzy Inference System (FIS)-based models have shown the capability to integrate multi-domain indicators and to offer more adaptive vulnerability classifications [9]. Integrating AHP and FIS could help overcome limitations of conventional vulnerability assessment models in the literature, which are often developed and validated within a single case-study site. This approach would enable more systematic evaluation of their transferability across regions with diverse socio-technical characteristics.

These constraints are particularly critical in countries such as Indonesia, where non-engineered

construction practices, local material quality, housing density, and post-seismic aid procedures vary significantly between regions, as proven by the severe seismic events of the last decades [2]. Consequently, a clear research gap remains in which existing global literature still offers limited solutions that simultaneously satisfy these requirements for non-engineered residential buildings in developing-country contexts. Therefore, there is a need for a practical Vulnerability Index (VI) evaluation framework for NEBs that (i) integrates technical, socio-economic, and environmental determinants; (ii) handles uncertain and linguistic field information without forcing unrealistic precision; and (iii) remains stable and transferable across regions with distinct socio-technical characteristics and seismic contexts [4, 6].

To address these gaps, this study proposes an AHP–FIS model for the evaluation of seismic vulnerability of NEBs, which is transparent, interpretable, and potentially adaptable to different local contexts, by integrating technical, socio-economic, and environmental dimensions at the building and household levels. This research has the objective to: (1) identify and weight the main factors that influence the seismic VI of NEBs based on a detailed literature review and field evidence; (2) develop an AHP–FIS model to generate robust vulnerability indices and classes with quantifiable factor contributions; and (3) validate the proposed model directly using real observed post-earthquake damage data to show its predictive capability. The next sections cover the research significance, the integration of AHP and FIS, methodology, then the findings and discussion, and finally the conclusions.

2. RESEARCH SIGNIFICANCE

The study makes a major contribution to the field of disaster risk management by proposing a transparent, interpretable, and potentially adaptable to different local contexts and analytically robust AHP–FIS model to assess the composite seismic vulnerability of NEBs. The research combines technical, socio-economic, and environmental aspects at the building and household levels and finds and weighs principal factors through literature and field evidence. It is calibrated against actual data on post-earthquake damage and provides both a methodological framework for international research that can be replicated and a practical operational tool. This synthesis allows stakeholders to directly lead evidence-based mitigation planning, prioritize retrofitting, and implement risk-based policies in high-risk seismic areas.

3. INTEGRATION OF AHP AND FIS

Given the inherent lack of standardized engineering documentation for NEBs, vulnerability assessments must integrate heterogeneous field observations and expert judgments. The AHP approach was selected for weighing operationalized variables when dealing with complex, multi-dimensional constructs. This ensures the disproportionate influence of specific technical, socio-economic, and environmental dimensions, thereby avoiding the analytical oversimplification of equal weighting and more accurately reflecting the reality of seismic vulnerability. The cognitive advantage of AHP lies in its ability to deconstruct a problem into a hierarchical structure. By focusing on two elements at a time, it reduced the "cognitive load" and minimized the bias inherent in trying to rank a dozen variables simultaneously.

The AHP then complemented FIS-based models to demonstrate the ability to integrate multi-domain indicators and provide more adaptive vulnerability classifications. The Mamdani FIS model was selected in this study, as this proved to be more suitable than those employing Sugeno and Tsukamoto techniques [9] when it came to seismic vulnerability assessment of NEBs in recent complex and multivariable structural engineering problems. The Mamdani FIS was capable of handling its high interpretability and capacity to leverage qualitative human expertise through human-centric logic. Mamdani employed a fuzzy rule base for input and output, in contrast to Sugeno's system, which was based on constants (or linear functions), and Tsukamoto's monotonicity characteristic, which utilized linear outputs. This Mamdani FIS allowed the analysis to express a wider variety of non-linear membership functions regarding the "grey areas" of technical and non-technical dimensions. Additionally, civil engineers are able to manually audit "IF-THEN" rules using natural language because of the native transparency of regulations in the Mamdani approach. This was crucial for safety in the NEBs sector, where there was no room for error as an accurate risk-mitigation strategy.

4. RESEARCH METHODOLOGY

This study adopted a quantitative, field-based, and expert-informed framework through structured field observation, household-level contextual information, expert interviews, and focus group discussions (FGD) to facilitate indicator weighting, fuzzy rule building, and model validation [10]. This

integration was intended to address uncertainty and nonlinearity in NEBs vulnerability assessment. This was done in MATLAB software to simplify the complex, computationally intensive phases. There are ten detailed proposed stages, as follows.

Stage 1: Identification of operationalized factors

The factors were identified through literature synthesis, contextual screening, and expert consultation. Investigation areas for the identification of fuzzy factors covered earthquake-prone regencies across Java Island, the most densely populated island, in Indonesia, over a three-month investigation. Eleven purposively selected participants, consisting of small-to-medium construction practitioners, local technical personnel, and experienced homeowners familiar with non-engineered housing construction, participated in semi-structured interviews [11]. Then, eleven experts who were part of the interview participated in an FGD to confirm these factors. There were 14 significant factors that controlled the vulnerability of NEBs, defining a practical and conceptual source [12] (Fig. 1).

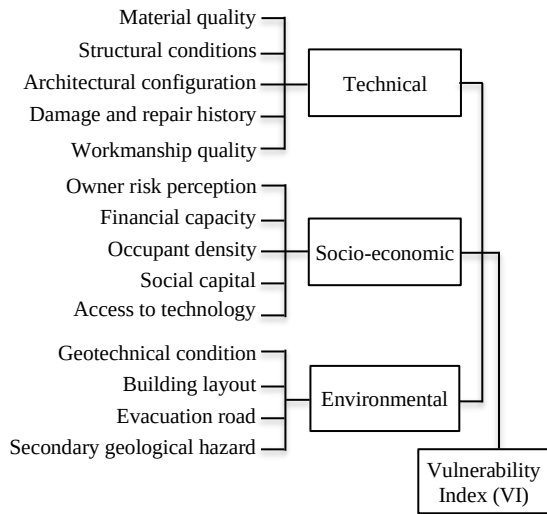


Fig. 1 Vulnerability factors of NEBs

Stage 2: Score standardization

Each factor identified in Stage 1 was assessed using a five-point Likert rubric to quantify the importance of factors: a score of 1 denotes the most significant factor in reducing vulnerability, a score of 5 the least significant factor and scores 2 to 4 represent a linear, incremental decrease in relative significance. This procedure ensured that qualitative and semi-qualitative information could be consistently converted into numerical form before

weighing and fuzzy modeling.

Then each raw factor score s_j was normalized to the interval 0 to 1 for comparability of scale, numerical consistency, and compatibility with the fuzzy inference process. Moreover, this interval provides a homogeneous universe of discourse for the definition of fuzzy membership functions.

Stage 3: AHP-based relative weights of the variables

The first computational step was to use AHP for computing the relative weights of the variables. The AHP turned subjective opinions into measurable numbers by conducting pairwise comparisons where experts compared two variables at a time. This was much more easily interpreted correctly by the human brain, since it used relative importance rather than absolute numbers. There was a scale from 1 to 9 where each a_{ij} is the relative importance of the variable i over the variable j , with $a_{ji} = 1/a_{ij}$ and $a_{ii} = 1$. Because the AHP assessment involved multiple respondents, individual pairwise comparison matrices were aggregated using the geometric mean method before weight calculation. For each pairwise comparison element, the aggregated value was calculated using Eq. (1).

$$\tilde{a}_{ij} = \left(\prod_{r=1}^m a_{ij}^{(r)} \right)^{1/m} \quad (1)$$

Where: $\tilde{a}_{ij}$ is the aggregated comparison value between variables i and j of all respondents, m =number of respondents, $a_{ij}^{(r)}$ is the judgment provided by respondent r , and m is the total number of respondents. The geometric mean was used because AHP judgments are expressed on a ratio scale and this method preserved the reciprocal property of the pairwise comparison matrix.

The next step was to develop a normalized matrix by dividing each individual element by the sum of its respective column ($\tilde{a}_{kj}$), as shown in Eq. (2).

$$c_{ij} = \frac{\tilde{a}_{ij}}{\sum_{k=1}^n \tilde{a}_{kj}} \quad (2)$$

Where: c_{ij} is the normalized value of element $\tilde{a}_{ij}$ and n =number of variables. Finally, the weight of each variable (W_i) was derived by calculating the average of the elements in each row of the normalized matrix, resulting in a priority vector where the sum of all weights equaled to 1.0, as presented in Eq. (3).

$$W_i = \frac{\sum_{j=1}^n c_{ij}}{n} \quad (3)$$

The individual weights for the primary variables and 14 factors are initially derived using Eq. (3), where the parent variable weights serve directly as their global weights; subsequently, the global weight of each factor was determined by multiplying its local weight by the weight of its respective parent variable, as formulated in Eq. (4).

$$GW_{sv} = W_{pv} \cdot W_{sv} \quad (4)$$

Where: W_i = individual weight, GW_{sv} = global weight of factors, W_{pv} = individual parent variable weight, and W_{sv} = individual factor weight. These weights provide the relative importance of each variable in the decision-making hierarchy as the main determinants of the seismic vulnerability, which could be used for the strategic mitigation of engineering hazards under different conditions. This prioritization logic is the primary basis for the later development of the fuzzy inference rule base.

To verify the mathematical validity of the pairwise comparisons, a Consistency Ratio (CR) was computed for each matrix using Eq. (5). A $CR < 0.10$ was categorized as acceptable consistency.

$$CR = \frac{CI}{RI} \quad (5)$$

Where: CI (consistency index) = $\frac{\lambda_{max} - n}{n - 1}$
 λ_{max} (principal eigenvalue) = $\frac{1}{n} \sum_{i=1}^n \frac{(Aw)_i}{W_i}$
 $(Aw)_i$ is the i element of the vector resulting from the multiplication of the original comparison matrix and the weight vector, and RI denotes the random index corresponding to the matrix order n .

Stage 4: Identification of fuzzy variables

The 14 operationalized vulnerability factors were clustered into three main dimensions, namely Technical (T), Socio-Economic (SE), and Environmental (E), computed using Eqs. (6, 7, and 8). These were fed as input variables to the Mamdani FIS model, and the Vulnerability Index (VI) was taken as the output variable.

$$T = \sum_{j=1}^5 w_{Tj} \cdot x_{Tj} \quad (6)$$

$$SE = \sum_{j=1}^5 w_{SEj} \cdot x_{SEj} \quad (7)$$

$$E = \sum_{j=1}^4 w_{Ej} \cdot x_{Ej} \quad (8)$$

Where: x_{Tj} , x_{SEj} , x_{Ej} are the normalized factor scores, and w_{Tj} , w_{SEj} and w_{Ej} are the corresponding local weights derived from AHP within each dimension. This step reduced the

original 14 field-based factors to three standardized and interpretable macro-level indices, thus allowing a more transparent fuzzy inference structure.

Stage 5: Determination of fuzzy sets and membership functions (MF)

After defining the variables, Stage 5 involved assigning fuzzy sets and membership functions to each variable. The three input variables were defined on the normalized universe of discourse. The lower and upper linguistic terms were represented by trapezoidal MF (trapmf), while the intermediate term was represented by a triangular MF (trimf), as in Eqs. (9) and (10) respectively. This choice was made because the extreme categories were better represented as shoulder sets, whereas the middle category was centered around a single modal value.

$$\mu_{tri}(x; a, b, c) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ \frac{c-x}{c-b}, & b < x \leq c \\ 0, & x \geq c \end{cases} \quad (9)$$

$$\mu_{trap}(x; a, b, c, d) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ 1, & b < x \leq c \\ \frac{d-x}{d-c}, & c < x \leq d \\ 0, & x \geq d \end{cases} \quad (10)$$

Stage 6: Fuzzy knowledge base development

Stage 6 focused on the construction of the fuzzy knowledge base by setting "IF-THEN" rules derived from the expert via FGD. A Mamdani FIS model was developed using T, SE, and E as input variables, while VI was defined as the output variable. These rules characterized the logical relationship between three input indices and the resulting VI. Since such rules were based on expert professional experience, they assisted in the reduction of uncertainties found in standard deterministic evaluations.

Stage 7: Application of the implication function

The seventh stage consisted of fuzzy set operations and the implication function to determine membership values through visual inspection, short-structured household interviews, and contextual environmental verification. The "and" operator, which represented the intersection of the sets, was used in this method to determine the "fire strength" (α_r) of each rule. The firing strength of each rule was computed using the minimum operator of Mamdani FIS, as described in Eq. (11) [9].

$$\alpha_r = \min[\mu_{Ti}(T), \mu_{SEj}(SE), \mu_{Ek}(E)] \quad (11)$$

Where: α_r is the firing strength of the rule r , $\mu_{Ti}(T)$ is the value of Ti 's membership in the T (technical) set, $\mu_{SEj}(SE)$ is the value of SEi 's membership in the SE (socio-economic) set, and $\mu_{Ek}(E)$ is the value of Ei 's membership in the E (environmental) set.

In order to assess the membership value of the k -th rule, the "min" function was utilized, employing the Mamdani FIS. The formula is in Eq. (12).

$$\mu_{Bk}(z) = \min(\alpha_r, \mu_B^{(k)}(z)) \quad (12)$$

Where $\mu_{Bk}(z)$ is the membership value of z in the output set B in the k -th rule, and $\mu_B^{(k)}(z)$ is the consequent membership function of the r -th rule.

Stage 8: Aggregation of fuzzy rule

Stage 8 encompassed the aggregation of these fuzzy rules using the maximum function. This process sequentially combined the results of the rules to create a single fuzzy output distribution. The aggregation started with the second rule and continued until the final rule in the set was processed, as in Eq. (13).

$$\mu_B(z) = \max(\mu_{B1}(z_1), \mu_{B2}(z_2), \dots, \mu_{Bn}(z_n)) \quad (13)$$

Where z is the output variable, $\mu_B(z)$ is the fuzzy output's membership value set B at z .

Stage 9: Defuzzification

The defuzzification process was a transformation of the results of the fuzzy inference into crisp numerical values, using the centroid approach. This approach was definitely selected because it was able to capture the complete distribution of the output membership degrees and produce more balanced and stable VI measure values. The crisp VI score (z^*) was obtained using Eq. (14).

$$z^* = \frac{\int z\mu(z)dz}{\int \mu(z)dz} \quad (14)$$

Stage 10: Performance testing

The performance testing of the proposed AHP-FIS model was assessed by comparing its predicted vulnerability classes with independent empirical data. Performance testing was performed on 120 non-engineered buildings (NEBs) evenly distributed with 30 houses per regency as the separate

analytical strata following the 2018 Banjarnegara, 2017 Tasikmalaya, 2020 Cilacap, and 2022 Cianjur earthquakes. These were generally unreinforced or lightly confined masonry houses made from local materials with variable connection quality and were selected using random or systematic selection where feasible, subject to the inclusion criteria of low-rise residential use, non-engineered construction, masonry-based structural system, and availability of observed damage information.

The model outputs were based on field surveys of these structures, while the corresponding "ground truth" data was obtained from official post-disaster reports from the respective Regency Disaster Management Agencies (and field verified), and recorded in five ordinal damage states: very light, light, moderate, severe and collapse. The validation protocol used binary categorical testing to evaluate the model's capability to differentiate between "critical damage" and "non-critical damage", because the reference data comprised discrete damage classifications instead of continuous numerical values. To this end, the five observed ordinal damage states were aggregated into these two broader categories, and the AHP-FIS outputs were transformed into an identical binary structure. This safety-oriented screening approach was chosen explicitly to determine whether the framework could reliably identify structures that require urgent, immediate intervention.

Finally, the model performance was summarized using a confusion matrix which represents the four standard conditions: True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). In this classification structure, a positive condition indicates critical NEB damage that needs immediate attention whereas a negative condition indicates non-critical damage as shown in Table 1.

Table 1. Confusion matrix

	FIS critical damage	FIS non-critical damage
Observed critical damage	True Positive (TP)	False Negative (FN)
Observed non-critical damage	False Positive (FP)	True Negative (TN)

Based on Table 1, five key indicators were calculated to determine the model's reliability: Sensitivity/Recall, Specificity, Precision, F1-score, and overall Accuracy, as shown in Eqs. (15-19). Sensitivity measured the model's ability to correctly

identify critically damaged buildings, while specificity measured its ability to correctly identify non-critically damaged cases. Precision indicated the reliability of critical damage predictions, whereas the F1-score provided a balanced measure between precision and sensitivity. Overall accuracy represented the proportion of correctly classified cases among all evaluated buildings [4].

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \quad (15)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100\% \quad (16)$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\% \quad (17)$$

$$\text{F1 - score} = 2 \left(\frac{(\text{precision})(\text{sensitivity})}{\text{precision}+\text{sensitivity}} \right) \quad (18)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (19)$$

This categorical validation approach allowed the AHP–FIS model to be evaluated using available post-earthquake damage categories without converting them into artificial numerical values. The binary scheme was used to assess whether the model could distinguish critical damage from non-critically damaged buildings, which was important for prioritizing emergency assessment, retrofitting, and risk-reduction actions.

5. RESULTS AND DISCUSSIONS

5.1 Variables and Their Relative Weights

The development of variables was synthesized through extensive literature reviews and field investigations across earthquake-prone regencies on Java Island, further refined by the insights of eleven

purposefully selected professionals. Table 2 presents the variables and factors as the AHP-FIS inputs.

After the variables were determined in Table 2, the application of the AHP framework (Eqs. (3 and 4)) was to calculate their weight. At Level 1, the three major dimensions were compared, and at Level 2, pairwise comparisons were done separately within each factor. The CR was then derived through Eq. (5), and the validity of the weights was verified within the limits of mathematical boundaries. These final figures are summarized in Table 3.

All CRs are less than 0.10, as shown in Table 3, indicating that all respondents have given consistent and coherent results. The technical dimension has the highest weight of 0.5151, followed by the environmental dimension of 0.2698 and the socio-economic dimension of 0.2151, emphasizing structural integrity as the main driver of seismic vulnerability, with socio-economic and environmental dimensions as modifiers, not substitutes, for physical performance.

This weighting scheme is consistent with recent studies on non-engineered and URM buildings [13], which consistently indicate structural condition, connection integrity, material quality, and workmanship as the most direct determinants of seismic damage. However, current literature also underscores that site effects and household constraints further aggravate vulnerability, especially in data-constrained developing-country contexts [14].

Although high technical vulnerability is treated as a sufficient condition for a high VI, favorable non-structural conditions do not artificially attenuate inherent engineering risks. This logic is the required basis for the further development of the fuzzy inference rule base.

Table 2. Operational variables and main data sources

Dimensions	Code	Factors	Main sources
Technical	T1	Use and quality of materials	Visual observation
Technical	T2	Structural condition and connection integrity	Visual observation
Technical	T3	Architectural configuration and irregularity	Visual observation
Technical	T4	Damage history and repair condition	Observation + interview
Technical	T5	Workmanship quality	Visual observation
Socio-economic	SE1	Owner risk perception and disaster knowledge	Interview
Socio-economic	SE2	Financial capacity for repair	Interview
Socio-economic	SE3	Occupant density	Interview + observation
Socio-economic	SE4	Social capital and community networks	Interview
Socio-economic	SE5	Access to technology and information	Interview
Environmental	E1	Geotechnical condition and site amplification	Spatial/field verification
Environmental	E2	Building layout and settlement density	Observation
Environmental	E3	Evacuation and road access	Observation
Environmental	E4	Potential secondary geological hazards	Spatial/field verification

Table 3. Dimension and factor weights

Code	Dimensions and Factors	Local Weight	Dimensions Weight	Global Weight
	Technical (CR = 0.0089)		0.5150	
T1	Use and quality of materials	0.2401		0.1237
T2	Structural condition and connection integrity	0.2805		0.1445
T3	Architectural configuration and irregularity	0.1602		0.0825
T4	Damage history and repair condition	0.1201		0.0619
T5	Workmanship quality	0.1990		0.1025
	Socio-economic (CR = 0.0005)		0.2151	
SE1	Risk perception and disaster knowledge	0.2211		0.0476
SE2	Financial capacity for repair	0.2800		0.0602
SE3	Occupant density	0.1181		0.0254
SE4	Social capital and community networks	0.1794		0.0386
SE5	Access to information and technical support	0.2014		0.0433
	Environmental (CR = 0.0247)		0.2698	
E1	Geotechnical condition and site amplification	0.3428		0.0925
E2	Building layout and settlement density	0.2185		0.0590
E3	Evacuation and road access	0.1799		0.0485
E4	Secondary geological hazards	0.2588		0.0698
	Sum		1.00	1.00

Socio-economic aspects constitute 21.51% of the overall vulnerability rate weight and indirectly influence vulnerability by affecting the quality of maintenance, feasibility of repair, the likelihood of retrofitting, household preparedness, and capacity for post-disaster recovery. In other words, socio-economic conditions are more like modifiers of vulnerability and recovery capacity than direct triggers of structural failure. Theoretically, this is a significant distinction. Financial hardship and a lack of expertise are not the primary reasons for building collapse during seismic activity. Instead, structural collapse is a physical reality caused by a building system that is physically weak. However, the continuation of these physical deficiencies over time, the adequacy of repairs, and the ability of households to recover from damage are all heavily dependent on socio-economic factors. Recent research on preparedness, post-disaster recovery, and developing-country building functionality supports this interpretation only. Household capacity, aid access, and community support are highly relevant, but through pathways of maintenance, preparedness, and resilience, rather than direct structural resistance [4, 15]. The present model provides a methodical contribution to literature by making this distinction explicit and demonstrating how socio-economic factors can be incorporated without distorting the physical logic of building vulnerability.

At the factor level, the global weights reveal an even more explicit hierarchy (Table 3). The highest

weights were given to T2 – Structural condition and connection integrity (0.1445), T1 – Use and quality of materials (0.1237), T5 – Workmanship quality (0.1025), and E1 – Geotechnical condition and site amplification (0.0925). The ranking is not only numerically consistent but also mechanistically pertinent. T2 is dominant because the seismic behavior of NEBs depends heavily on the continuity of load transfer through the structure. If roof diaphragms are weak, wall intersections are poorly tied, or ring beams are missing or discontinuous, seismic forces will not be well redistributed. Local cracking can rapidly result in partial or global instability. T1 and T5 are a natural consequence since even if the structural layout is simple, weak masonry units, low mortar strength, honeycombed concrete, and poor construction practices suffer immensely, reducing the actual capacity of the system. E1, on the other hand, ranks highest among the environmental dimensions because poor site conditions may increase input demand even before structural weaknesses are mobilized. These four factors in combination constitute the main path from hazard to damage in NEBs. Amplified shaking acts on a structurally discontinuous and poorly executed system to accelerate brittle failure. This order has also been found in recent URM and first-level fuzzy assessment studies [14, 16].

Table 3 shows that the model does not overemphasize contextual variables. Instead, it maintains a physically credible structure in which the dominant contributors remain those most strongly

associated with building failure mechanisms. The relatively prominent position of E1 is also methodologically justified because local amplification and soil vulnerability have repeatedly been reported as decisive factors in Indonesia, including in Banjarnegara and Tasikmalaya. By contrast, SE3 – Occupant density-received the smallest global weight, which is also reasonable because it is better understood as a consequence or contextual pressure indicator than as a direct determinant of structural damage [17].

5.2 FIS Modeling

The first stage of Mamdani FIS modeling was to define the fuzzy input and output variables. The fuzzy input variables consisted of the three macro-indices derived from the AHP-weighted aggregation process: T, SE, and E. The Vulnerability Index (VI) was defined as the output variable. Each input variable was represented by three linguistic terms, namely Low, Medium, and High, using triangular membership functions (trimf) and trapezoidal membership functions (trapmf) as shown in Eqs. (9 and 10). The output variable, VI was also partitioned into Very Low, Low, Moderate, High, and Very High. The output partition used trapmf for the two extreme classes and trimf for the intermediate classes. The membership function parameters were strongly calibrated and justified on empirical realities evoked through FGDs. These specific thresholds were directly linked to the standardized legal frameworks and technical thresholds that were necessary for Indonesian field operations. This participatory approach also served as a successful way to empirically calibrate us by linking the fuzzy membership functions to expert consensus instead of arbitrary assignment, as mentioned in Table 4.

After defining the fuzzy sets, the “IF-THEN” rules were generated from an expert-based knowledge base that linked the linguistic states of the three input macro-indices to the final VI class, as in Table 5. These groups managed the determination of T values, (2) SE values, (3) E values, and (4) the final VI levels. This rule-based model ensured a systematic transition from linguistic variables to effective assessments of VI. The rules were designed under a monotonic and interpretable logic, where worsening input conditions could not produce a lower vulnerability class. Technical vulnerability was treated as the dominant driver, whereas socio-economic and environmental vulnerabilities were incorporated as amplifying modifiers that may elevate the final vulnerability class when unfavourable contextual conditions coexist with structural weakness.

Table 4. Fuzzy variables for Input and Output

Var.	Linguistic Term		Parameters			
			a	b	c	d
Input						
T	Low	(trapmf)	0.00	0.00	0.25	0.50
	Medium	(trimf)	0.25	0.50	0.75	-
	High	(trapmf)	0.50	0.75	1.00	1.00
SE	Low	(trapmf)	0.00	0.00	0.25	0.50
	Medium	(trimf)	0.25	0.50	0.75	-
	High	(trapmf)	0.50	0.75	1.00	1.00
E	Low	(trapmf)	0.00	0.00	0.25	0.50
	Medium	(trimf)	0.25	0.50	0.75	-
	High	(trapmf)	0.50	0.75	1.00	1.00
Output						
VI	Very Low	(trapmf)	0.00	0.00	0.10	0.25
	Low	(trimf)	0.10	0.25	0.40	-
	Medium	(trimf)	0.30	0.50	0.70	-
	High	(trimf)	0.60	0.75	0.90	-
	Very High	(trapmf)	0.75	0.90	1.00	1.00

Table 5. Rule basis for VI

Rule	T	SE	E	Output VI
1.	Low	Low	Low	Very Low
2.	Low	Low	Medium	Low
3.	Low	Low	High	Moderate
4.	Low	Medium	Low	Low
5.	Low	Medium	Medium	Moderate
6.	Low	Medium	High	Moderate
7.	Low	High	Low	Moderate
8.	Low	High	Medium	High
9.	Low	High	High	High
10.	Medium	Low	Low	Moderate
11.	Medium	Low	Medium	Moderate
12.	Medium	Low	High	High
13.	Medium	Medium	Low	Moderate
14.	Medium	Medium	Medium	Moderate
15.	Medium	Medium	High	High
16.	Medium	High	Low	High
17.	Medium	High	Medium	High
18.	Medium	High	High	Very High
19.	High	Low	Low	Very High
20.	High	Low	Medium	Very High
21.	High	Low	High	Very High
22.	High	Medium	Low	Very High
23.	High	Medium	Medium	Very High
24.	High	Medium	High	Very High
25.	High	High	Low	Very High
26.	High	High	Medium	Very High
27.	High	High	High	Very High

Corresponding to variable weighting results in Table 3, “High” technical vulnerability alone was sufficient to produce a “Very High” vulnerability class.

Also, “Very High” vulnerability was assigned when severe technical weakness coincided with either severe environmental exposure, severe socio-economic constraints, or both. This conservative rule reflects the safety-oriented purpose of the model. In screening applications, severe technical deficiencies should not be compensated by favourable socio-economic or environmental conditions because structural collapse risk is governed primarily by the physical capacity of the building system.

5.3 Performance Testing

The performance of the AHP-FIS model was tested on the data of 120 investigated houses using Eqs. (11-14). The model performance was evaluated categorically by comparing the “True Condition” with the “FIS Model Outputs” as presented in Table 6. The “true condition” data were expressed by their damage. The observed damage condition was expressed in five ordinal categories, namely very light, light, moderate, severe, and collapse. For binary validation, the observed categories of very light, light, and moderate were grouped as non-critical damage, whereas severe and collapse were grouped as critical damage because both conditions require urgent intervention and are associated with unacceptable seismic safety. Similarly, to make possible the categorical classification, the numerical outputs of the FIS model were first transformed into five vulnerability classes, according to predefined VI intervals, namely very low (0.00–0.20), low (0.21–0.40), moderate (0.41–0.60), high (0.61–0.80), and very high (0.81–1.00). These five classes were subsequently reclassified into two binary categories: “critical damage” or “non-critical damage”. The very low, low, and moderate classes were grouped as noncritical damage, while the high and very high classes were categorized as critical damage, giving a direct comparison between predicted vulnerability and the actual appearance of the structure.

There were 39 units (32.5%) classified as moderate, 37 units (30.8%) as high, and 20 units (16.7%) as very high. The rest were in the very low

and low classes of vulnerability. Almost 50% of the evaluated buildings are in high-very high vulnerability, requiring priority intervention. The model clearly shows the spatial gradient of seismic vulnerability in the four regencies studied. This is not spatially homogeneous and cannot be summarized in one structural indicator but is a consequence of the joint action of the building conditions, household capacity, and local site context.

Cianjur has the highest average vulnerability index ($VI = 0.69$) and the highest concentration of buildings in the high and very high classes, which are 66.7% of the regency sample. Followed by Tasikmalaya with an average VI of 0.62. Half of the buildings in Tasikmalaya are also in the two highest classes. Meanwhile, Banjarnegara and Cilacap are still in the moderate class, but both still have a significant percentage of severe cases. The regency contrast is not merely statistical but also mechanistic. The higher VI in Cianjur and Tasikmalaya can be interpreted as the practical manifestation of the simultaneous concentration of four dominant vulnerability components, namely T2, T1, T5, and E1.

Hence, the higher VI in Cianjur and Tasikmalaya signals a more adverse failure environment where structural systems and site conditions compound damage. This aligns with recent research on non-engineered URM and masonry buildings emphasizing that weak connections, poor material quality, and local site effects synergistically worsen seismic damage [14, 18]. Consequently, intervention planning must look beyond regency averages to address localized concentrations of severe classes.

Table 7 presents the AHP-FIS model performance to correctly classify cases among all evaluated houses. The model correctly identified 47 true positives and 52 true negatives, while 11 houses were classified as false negatives and 10 houses as false positives. A binary validation threshold with the true positive class (39.2%) being critical damage and the true negative class (43.3%) being non-critical damage was used to evaluate the model classification performance.

Table 6. AHP-FIS modeling results based on 120 evaluation houses

Regencies	Dimensions			VI	Number of Investigated Houses					Percentage of High and Very High
	T	SE	E		Very Low	Low	Moderate	High	Very High	
Banjarnegara	0.60	0.51	0.59	0.57	2	5	11	8	4	40.00%
Cilacap	0.49	0.50	0.61	0.53	2	7	11	7	3	33.33%
Tasikmalaya	0.63	0.55	0.60	0.62	1	4	10	10	5	50.00%
Cianjur	0.70	0.58	0.66	0.69	0	3	7	12	8	66.67%
Total/Mean	0.60	0.53	0.61	0.60	5	19	39	37	20	47.50%

Table 7. Regency-level Confusion matrix summary

Regencies	Number of evaluated houses			
	TP	TN	FP	FN
Banjarnegara	10	17	2	1
Cilacap	8	16	2	4
Tasikmalaya	12	11	3	4
Cianjur	17	8	3	2
Total	47	52	10	11
Percentage	39.2%	43.3%	8.3%	9.2%
Classification	82.5% Correct Classification		17.5% Mis-classification	

Multiple categorical evaluations using Eqs. (15-19) were performed, and the results are a sensitivity of 81.03%, a specificity of 83.87%, a precision of 82.46%, an F1-score 81.74%, and an overall accuracy of 82.50%. The high sensitivity and F1-scores show the capability to measure VI. The current balance indicates that the proposed framework is precise enough to help prioritize fields. This finding compares favorably with fuzzy-based rapid visual screening studies such as Bektaş et al. [13], where the use of fuzzy inference improved the responsiveness of classification to building features and recent hierarchical fuzzy methods for post-earthquake building functionality in developing-country settings where interpretability was prioritized alongside predictive performance [18].

When the three macro-indices are considered, the differences at the regency level become more evident. As shown in Table 6, Cianjur has the highest Technical VI of 0.70, the highest Environmental VI of 0.66, and the highest Socio-Economic VI of 0.58, which leads to the highest VI of 0.69. Tasikmalaya and Banjarnegara have the second and third places.

This pattern confirms: Technical (T) sets the baseline severity, whereas Environmental (E) and Socio-Economic (SE) modulate the final class through contextual interaction. In other words, regencies with a high environmental burden do not necessarily show the highest total vulnerability if their building stock is technically more robust, whereas regencies with weak buildings are much more critical if there are adverse site conditions. Such an interaction is difficult to model using rigid linear models, but it is exactly the kind of non-linear reasoning that Mamdani FIS is designed to model. Similar logic has been reported in recent fuzzy-based seismic assessment studies and hierarchical fuzzy models for building risk in developing-country settings [18].

Finally, the research results demonstrate that the proposed AHP-FIS model can determine complex NEBs VI profiles with high reliability. The model is a useful tool for early critical evaluation to provide

much safer structures. The true value of the proposed framework is not only the final index but also the ability to create a transparent and differentiated prioritization logic for the local governments, retrofit programs, and disaster-risk reduction planning.

6. CONCLUSIONS

The proposed AHP–FIS model for the evaluation of seismic vulnerability for NEBs was successfully developed with high reliability. The technical dimension has a more significant impact on the vulnerability structure of NEBs than the environmental and socio-economic dimensions. The proposed model demonstrated satisfactory agreement with the observed damage categories and can be used as a tool to assist preliminary screening and prioritization of NEBs. The model validation showed satisfactory performance with an accuracy of 82.50%, sensitivity of 81.03%, specificity of 83.87%, precision of 82.46%, and F1-score of 81.74%. The results indicate that the proposed framework is robust and interpretable enough for practical vulnerability screening in contexts comparable to the investigated regions, subject to further external validation. In future work, the model should be calibrated on larger empirical post-earthquake classified datasets for ordinal validation and its transferability to other regions should be evaluated.

7. ACKNOWLEDGEMENTS

The authors would like to thank the experts, practitioners, suppliers, and local builders from Banjarnegara, Tasikmalaya, Cilacap, and Cianjur regencies for their contribution of insight during the performance assessment phases of this study.

8. REFERENCES

1. Irsyam M., Cummins P.R., Asrurifak M.; Faizal L., Natawidjaja D.H., Widiyantoro S.; Irwan Meilano I., TriyosoW., Ariska Rudiyanto A., Sri Hidayati S., Ridwan M., Hanifa N.R., Syahbana A.J., Development of the 2017 National Seismic Hazard Maps of Indonesia, Earthquake Spectra, vol. 36, no. 1, 2020, pp. 112–136.
<https://doi.org/10.1177/8755293020951206>
2. Kristiawan, S. A., Safarizki, H. A., Purwanto, E., Sangadji, S., Trisnawan, A. D., Nugroho, T. S., Damage State of Non-Engineered Residential Buildings Owing to Earthquakes, Civil and Environmental Engineering, vol. 20, no. 1, 2024, pp. 426–439.

- <https://doi.org/10.2478/cee-2024-0033>

3. Sunarti, E., Gunawan, E., Widiyantoro, S., Marliyani, G. I., Critical Point on Housing Construction, Resilience and Family Subjective Welfare after Disaster, *Geomatics, Natural Hazards and Risk*, vol. 12, no. 1, 2021, pp. 922–938.
<https://doi.org/10.1080/19475705.2021.1910576>
4. Tampubolon, S. P., Mulyani, A. S., Setyadi, S., Simanjuntak, R. M., Building Assessment Post Earthquake 21 November 2022 in Cianjur District, *Asian Journal of Community Services*, vol. 3, no. 8, 2024, pp. 801–814.
<https://doi.org/10.55927/ajcs.v3i8.10819>
5. Purwanto, E., Kristiawan, S. A., Sangadji, S., Saifullah, H. A., Influence of Joint Strengthening on the Seismic Performance of Non-Engineered Buildings, *Buildings*, vol. 14, 2024, p. 488.
<https://doi.org/10.3390/buildings14020488>
6. Rildova, Kusumastuti, D., Suarjana, M., Mulyadi, S. S., Lessons Learned from Recent Earthquakes in Indonesia, in *The 18th World Conference on Earthquake Engineering*, Milan, Italy, 2024, pp. 1–9.
7. Adamy, A., Meillyta, Maharani, L., Aidina, F., Aini, Q., Disaster Vulnerability Assessment of Low-Cost Houses in Java Island, *Journal of Contemporary Urban Affairs*, vol. 7, no. 2, 2023, pp. 20–37.
<https://doi.org/10.25034/ijcua.2023.v7n2-2>
8. Pratama, G. A., Latief, Y., Sihombing, L. B., A Novel Rough Fuzzy Based Delphi Method for Highway Projects Risk Analysis: The Soe Assignment Scheme Case Study, *International Journal of GEOMATE*, vol. 23, no. 100, 2025, pp. 110–117.
<https://doi.org/10.21660/2022.100.g12137>
9. Azeem, M. F., Fuzzy Inference System-Theory and Applications. Rijeka, Croatia: InTech, 2012, pp.1-169.
10. Nisah, K. et al., Fabrication and Characterization of SiO₂-Embedded Castor Oil-based Membrane (*Ricinus communis* L) for Aqueous Fe Adsorption, *Narra X*, vol. 2, no. 2, 2024, p. 158.
<https://doi.org/10.52225/narrax.v2i2.158>
11. Chaipetch, P., Ratanavaraha, C. A. P., Vatanavongs, P., Analitical of Multi-criteria Approach for Identifying the Weight and Factor of Rural Road Maintenance Prioritization, *International Journal of GEOMATE*, vol. 22, no. 91, 2022, pp. 70–79.
<https://doi.org/10.21660/2022.91.gxi334>
12. Tarigan, T. A., Ahmad, A. L., Suciana, Fauzi, M. A. R., Fatkhurrozi, M., Assessment of Coastal Vulnerability Index (CVI) and Its Application along the Sragi Coast, South Lampung, Indonesia, *International Journal of GEOMATE*, vol. 26, no. 116, 2024, pp. 134–141.
<https://doi.org/10.21660/2024.116.4233>
13. Bektaş, N., Lilik, F., Kegyes-Brassai, O., “Development of a Fuzzy Inference System Based Rapid Visual Screening Method for Seismic Assessment of Buildings Presented on a Case Study of URM Buildings, Sustainability (Switzerland), vol. 14, no. 23, 2022. p. 142316318.
<https://doi.org/10.3390/su142316318>
14. Syamsidik, B., Umar, M., Margaglio, G., Fitrayansyah, A., Post-Tsunami Survey of the 28 September 2018 Tsunami Near Palu Bay in Central Sulawesi, Indonesia,” *International Journal of Disaster Risk Reduction*, vol. 38, 2019. p. 101229.
<https://doi.org/10.1016/j.ijdrr.2019.101229>
15. Kassem, M. M., Mohamed Nazri, F., Noroozinejad Farsangi, E., The Seismic Vulnerability Assessment Methodologies: A Atate-of-the-art Review, *Ain Shams Engineering Journal*, vol. 11, no. 4, 2020, pp. 849–864.
<https://doi.org/10.1016/j.asej.2020.04.001>
16. Joshi, G. C., Ghildiyal, S., Rautela, P., Seismic Vulnerability of Lifeline Buildings in Himalayan Province of Uttarakhand in India, *International Journal of Disaster Risk Reduction*, vol. 37, 2019, p. 101168.
<https://doi.org/10.1016/j.ijdrr.2019.101168>
17. Ortega, J., Vasconcelos, G., Rodrigues, H., Correia, M., “A Vulnerability Index Formulation for the Seismic Vulnerability Assessment of Vernacular Architecture, *Engineering Structures*, vol. 197, 2019, p. 109381.
<https://doi.org/10.1016/j.engstruct.2019.109381>
18. Janpila, A., Foytong, P., Tirapat, S., Thanasisathit, N., Ruangrassamee, A., The Optimal Method for Building Damage Fragility Curve Development, *International Journal of GEOMATE*, vol. 18, no. 69, 2020, pp. 74–80.
<https://doi.org/10.21660/2020.69.9192>

Copyright © Int. J. of GEOMATE All rights reserved, including making copies, unless permission is obtained from the copyright proprietors.
