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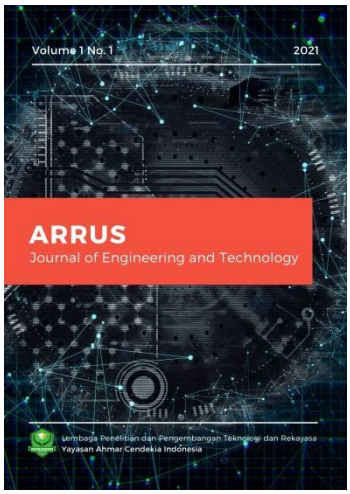

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RESEARCH ARTICLE

Optimizing Disaster Risk Clustering in Indonesia with Bisecting K-Means, Fuzzy C-Means, and Gaussian Mixtures

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Abstract: This study optimizes the clustering of Indonesia's 38 provinces by natural disaster risk using Bisecting K-Means (BKM) and Fuzzy C-Means (FCM), with a Gaussian Mixture Model (GMM) as a model-based benchmark. Data were taken from the Indonesian Disaster Information Data (DIBI) of the National Disaster Management Agency for 2024–2025, covering 8,549 natural disaster events, 2,559 dead and missing, 20.9 million people affected, and 366,870 damaged houses. Eleven log-transformed, standardized indicators were clustered while jointly optimizing the number of clusters, the BKM bisecting strategy, the FCM fuzzifier, and the GMM covariance structure, using the silhouette, Davies–Bouldin, Calinski–Harabasz, Xie–Beni, and modified partition coefficient indices, the Bayesian information criterion (BIC), and bootstrap stability (200 replicates, adjusted Rand index). The results show that BKM and FCM both select two clusters (BKM silhouette 0.327; FCM m = 1.5, Xie–Beni 0.394), whereas the BIC selects a three-component diagonal GMM that is less well separated and less stable (silhouette 0.177; ARI 0.411). Nine provinces form a high-risk core that accounts for 52% of events, 81% of fatalities, and 89% of damaged houses, and the GMM isolates six of them as a very-high-risk group. FCM initialized with BKM centroids is the most stable method (ARI 0.691) and identifies eight transitional provinces with memberships between 0.25 and 0.75. The findings of this study suggest that combining the BKM hierarchy with FCM memberships yields robust three-tier priorities.

Keywords: Bisecting K-Means, Fuzzy C-Means, Gaussian Mixture Model, Disaster Risk, Bootstrap Stability

1. Introduction

Indonesia is among the countries most exposed to natural disasters. The WorldRiskReport 2024 ranks Indonesia second worldwide, after the Philippines, with a WorldRiskIndex of 41.13 (Bündnis Entwicklung Hilft & IFHV, 2024). Nationally, the 2024 Indonesian Disaster Risk Index (*Indeks Risiko Bencana Indonesia*, IRBI) places eight provinces in the high-risk class and the remaining 30 in the medium class (BNPB, 2025). The Sendai Framework for Disaster Risk Reduction 2015–2030 makes understanding disaster risk its first priority for action (UNDRR, 2015). Such understanding requires an objective way of grouping regions by the disasters and losses they actually experience.

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Cluster analysis is widely used for this purpose. Annas and Rais (2020) mapped disaster-prone areas in Indonesia with k-means and a geographic information system, and Firdaus and Sofro (2022) compared K-Means and Fuzzy C-Means (FCM) for provincial disaster intensity in 2017–2021, reporting a higher silhouette value for FCM. FCM has also been applied to disaster-prone districts in West Java (Audy et al., 2023) and East Java (Setiawan & Oktafianto, 2025). Our group has applied k-prototypes to earthquakes in Sulawesi (Annas et al., 2022a), k-means and self-organising maps to air pollution (Annas et al., 2022b), FCM and Gath–Geva clustering to human development data (Annas et al., 2019), and hybrid hierarchical clustering for landslide-prone districts in South Sulawesi (Azzahrah et al., 2022) and Bisecting K-Means (BKM) to group Indonesian earthquakes in 2023 (Rais et al., 2025a). Provinces of Indonesia have also been grouped with K-Medoids and K-Affinity Propagation for environmental pollution (Muttaqim et al., 2023; Annas & Rais, 2025) and with a hybrid SOM–LVQ network for crime patterns (Rais et al., 2025b). Shara (2026) subsequently compared BKM and FCM for grouping natural disasters in Indonesia.

These studies leave four gaps. First, the number of clusters is usually fixed in advance or chosen with a single index, for example the Davies–Bouldin index alone (Rais et al., 2025a), although different validity indices can disagree, and distance-based partitions are rarely checked against a probabilistic, model-based alternative whose number of clusters can be chosen by a likelihood criterion (Fraley & Raftery, 2002). Second, the FCM fuzzifier is almost always set to $m = 2$ without testing, even though a sensible value depends on the size and dimension of the data (Schwämmle & Jensen, 2010). Third, the stability of the clusters under resampling is rarely examined, so it is unclear whether reported clusters are real or accidental (Hennig, 2007). Fourth, most studies use only event frequencies, whereas risk is also reflected in casualties and damage.

This study addresses these gaps with three objectives: (1) to optimise the number of clusters, the BKM bisecting strategy and the FCM fuzzifier jointly, using several validity indices and a bootstrap stability test; (2) to compare BKM, randomly initialised FCM, FCM initialised with BKM centroids (hybrid FCM) and a Gaussian mixture model (GMM) as a model-based benchmark; and (3) to derive provincial risk-priority tiers that combine the BKM hierarchy with FCM membership degrees. The analysis uses the 2024–2025 records of BNPB's Indonesian Disaster Information Data (DIBI), which cover all 38 provinces and follow BNPB's new event-recording mechanism (BNPB, 2026).

2. Literature Review

2.1. Clustering in Disaster Risk Studies

Clustering methods used in regional disaster studies fall into three families. Partitional methods such as K-Means divide the regions into a fixed number of groups by minimising within-group dispersion; they are fast and easy to interpret but need k in advance and depend on their starting centroids (Savaresi & Boley, 2004). Hierarchical methods build nested groups, either by merging (agglomerative) or by splitting (divisive), so that a single run gives partitions at several levels of detail (Azzahrah et al., 2022; Steinbach et al., 2000). Fuzzy methods such as FCM let a region belong partly to several groups, which suits regions whose hazard and impact profiles lie between clear types (Bezdek et al., 1984; Firdaus & Sofro, 2022). BKM combines the first two families: each split is a K-Means step, but the sequence of splits forms a hierarchy (Rais et al., 2025a). Studies of Indonesian provinces have applied these families to disasters (Annas & Rais, 2020; Firdaus & Sofro, 2022; Shara, 2026), environmental pollution (Muttaqim et al., 2023; Annas & Rais, 2025) and crime (Rais et al., 2025b), but they rarely combine a crisp hierarchical method with a fuzzy one, and they usually judge the result with a single internal index. Because internal indices reward different properties, compactness for DBI and separation for the silhouette, and because small samples such as 38 provinces make partitions sensitive to individual observations, Hennig (2007) recommends complementing them with resampling-based stability checks. The present study follows that recommendation.

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2.2. *Bisecting K-Means*

BKM is a divisive algorithm that starts with one cluster containing all objects and repeatedly splits one cluster into two with K-Means (k = 2) until k clusters are obtained (Steinbach et al., 2000). The cluster to be split can be the one with the largest sum of squared errors (SSE) or the one with the most members (Savaresi et al., 2002). Because each step splits only one cluster, the solution for k clusters is nested in the solution for k − 1 clusters, which yields a hierarchy that can be read directly as an order of priority. Savaresi and Boley (2004) showed that K-Means-based bisection tends to produce good partitions but remains sensitive to initialisation, so each split should be repeated from several starting points. At each step, cluster C is divided into C_1 and C_2 so as to minimise

$$\mathrm{SSE}(C_1, C_2) = \sum_{j=1}^{2} \sum_{\mathbf{x}_i \in C_j} \| \mathbf{x}_i - \boldsymbol{\mu}_j \|^2$$

where μ_j is the centroid of C_j.

2.3. *Fuzzy C-Means*

FCM assigns each object a membership degree $u_{ij} \in [0, 1]$ in every cluster, with $\Sigma_j u_{ij} = 1$ (Bezdek, 1981; Bezdek et al., 1984). It minimises the objective function

$$J_m(U, V) = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^{m} \| \mathbf{x}_i - \mathbf{v}_j \|^2, \qquad m > 1$$

through the alternating updates

$$u_{ij} = \left[\sum_{l=1}^{c} \left(\frac{\| \mathbf{x}_i - \mathbf{v}_j \|}{\| \mathbf{x}_i - \mathbf{v}_l \|} \right)^{2/(m-1)} \right]^{-1}, \qquad \mathbf{v}_j = \frac{\sum_i u_{ij}^{m} \mathbf{x}_i}{\sum_i u_{ij}^{m}}$$

In practice, FCM starts from an initial membership matrix or initial centroids, alternates the two updates until the objective function stops decreasing, and assigns each object to the cluster with its largest membership when a crisp partition is required. The fuzzifier m controls the degree of fuzziness. Values of m close to 1 make FCM behave like K-Means, whereas an overly large m pulls every centroid towards the data mean so that the clusters collapse. Schwämmle and Jensen (2010) derived an empirical rule for a reasonable m as a function of the number of objects N and the dimension D:

$$f(D, N) = 1 + \left(\frac{1418}{N} + 22.05 \right) D^{-2} + \left(\frac{12.33}{N} + 0.243 \right) D^{-0.0406 \ln N - 0.1134}$$

2.4. *Gaussian Mixture Models*

A Gaussian mixture model treats the data as a sample from k multivariate normal components with mixing proportions π_j, mean vectors μ_j and covariance matrices Σ_j (Fraley & Raftery, 2002):

$$f(\mathbf{x}) = \sum_{j=1}^{k} \pi_j \, \phi(\mathbf{x}; \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j), \qquad \tau_{ij} = \frac{\pi_j \, \phi(\mathbf{x}_i; \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}{\sum_{l=1}^{k} \pi_l \, \phi(\mathbf{x}_i; \boldsymbol{\mu}_l, \boldsymbol{\Sigma}_l)}$$

The parameters are estimated by the expectation–maximisation (EM) algorithm (Dempster et al., 1977), and the posterior probabilities τ_{ij} play the role that membership degrees play in FCM, but they follow from a probability model rather than from a fuzzifier chosen by the analyst. Constraining Σ_j gives a family of models: spherical (a single variance per component), diagonal (a separate variance for each indicator and component), tied (one full covariance matrix shared by all components) and full (an unrestricted matrix per component). The

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number of components and the covariance structure are chosen with the Bayesian information criterion (Schwarz, 1978),

$$\mathrm{BIC} = -2\ln\hat{L} + q\ln n$$

where $\hat{L}$ is the maximised likelihood and q the number of free parameters; a smaller BIC indicates a better balance between fit and complexity.

2.5. *Validity and Stability Indices*

Crisp partitions are assessed with three indices. The silhouette coefficient compares each object's mean distance to its own cluster with its distance to the nearest other cluster; higher is better (Rousseeuw, 1987). The Davies–Bouldin index (DBI) is the ratio of within-cluster scatter to between-centroid distance; lower is better (Davies & Bouldin, 1979). The Calinski–Harabasz index (CHI) is the ratio of between- to within-cluster dispersion; higher is better (Caliński & Harabasz, 1974). Fuzzy partitions are assessed with the partition coefficient (PC), the modified partition coefficient $\mathrm{MPC} = 1 - c/(c-1)\cdot(1-\mathrm{PC})$, which removes the bias of PC towards small c (Dave, 1996), the partition entropy (PE), and the Xie–Beni index (Xie & Beni, 1991):

$$\mathrm{XB} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^{m} \parallel \mathbf{x}_i - \mathbf{v}_j \parallel^2}{n \cdot \min\limits_{j \neq l} \parallel \mathbf{v}_j - \mathbf{v}_l \parallel^2}$$

A small XB indicates compact and well-separated clusters; XB rises sharply when two centroids coincide. Internal indices do not guarantee that clusters can be reproduced. Hennig (2007) therefore recommends assessing stability by bootstrap: the data are resampled, re-clustered and compared with the original partition. This study measures that agreement with the adjusted Rand index (ARI; Hubert & Arabie, 1985), which equals 1 for perfect agreement and is close to 0 for chance agreement.

3. Research Method and Materials

3.1. *Data*

The units of analysis are the 38 provinces of Indonesia. Data were taken from BNPB's DIBI dashboard on 13 November 2026, filtered to the years 2024 and 2025, to records flagged as disasters, and to nine types of natural disaster (BNPB, 2026). Event counts by province and disaster type, the number of dead and missing, the number of people affected and displaced, and the numbers of heavily, moderately and lightly damaged houses were read from the dashboard's aggregate tables for the selected period. This period was chosen because BNPB introduced a new event-recording mechanism in 2024, making earlier and later records incomparable. DIBI apportions events that span several provinces, so some event counts are fractional. Earthquakes, volcanic eruptions and tsunamis were merged into a single geological indicator because they are rare (55 events in total). The eleven indicators are listed in Table 1.

Table 1. Clustering indicators (totals for 2024–2025 per province; source: BNPB, 2026)

Code	Indicator	Unit	National total
X1	Floods	events	3,738
X2	Landslides	events	539
X3	Extreme weather	events	1,752
X4	Forest and land fires	events	2,275
X5	Droughts	events	130
X6	Tidal waves and abrasion	events	60
X7	Geological (earthquakes, eruptions, tsunamis)	events	55
X8	Dead and missing	persons	2,559
X9	Affected and displaced	persons	20,929,242
X10	Heavily damaged houses	units	83,495
X11	Damaged houses (heavy, moderate, light)	units	366,870

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3.2. *Pre-processing*

All indicators are strongly right-skewed (skewness 1.1–5.9) and differ in scale by up to seven orders of magnitude. Each indicator was therefore transformed with log(1 + x) and standardised to z-scores. The log transformation prevents a single extreme province, such as Aceh with 3.8 million people affected, from dominating the Euclidean distances. After transformation, the correlations between indicators range from −0.01 to 0.85, the highest being between heavily damaged houses and all damaged houses.

3.3. *Optimisation Procedure*

The analysis followed eight steps. (1) *BKM optimisation*: for k = 2, …, 8 and two bisecting strategies (largest SSE and largest cluster), BKM was run with 10 initialisations per split and 20 random seeds, keeping the solution with the smallest SSE, and silhouette, DBI and CHI were computed. (2) *FCM optimisation*: for k = 2, …, 8 and m ∈ {1.5, 1.75, 2.0, 2.25, 2.5, 3.0}, FCM was run 30 times from random membership matrices, keeping the solution with the smallest J_m; iterations stopped when the relative change in J_m fell below 10^{-6}. Besides the crisp indices (computed from maximum membership), PC, MPC, PE and XB were computed, and configurations that left an empty cluster were discarded. (3) *GMM benchmark*: GMMs with spherical, diagonal, tied and full covariance structures were fitted for k = 1, …, 8 by EM with 20 initialisations and a covariance regularisation of 10^{-3}; models with as many free parameters as data values were excluded, and the structure and k with the smallest BIC were selected. (4) *Configuration selection*: each configuration was ranked on every index and the configuration with the smallest rank sum was chosen, using silhouette, DBI and CHI for BKM and adding MPC and XB for FCM; solutions containing a single-member cluster were excluded. (5) *Hybrid initialisation*: FCM with the selected configuration was started from the BKM centroids and compared with 100 randomly initialised FCM runs in terms of J_m, number of iterations and partition agreement. (6) *Bootstrap stability*: 200 bootstrap samples of provinces were drawn; each method, including the GMM, was re-run on every sample and the ARI was computed between the bootstrap labels and the full-data labels of the provinces drawn, for k = 2, …, 6 and for standard K-Means as a benchmark. (7) *Priority tiers*: clusters were ordered by a risk score, the mean z-score over all indicators, and the FCM membership in the high-risk cluster $u_{i,high}$ was used to assign provinces to a high tier ($u \geq 0.75$), a transitional tier ($0.25 < u < 0.75$) or a low tier ($u \leq 0.25$); sensitivity to the threshold was checked at 0.70 and 0.80. (8) *Interpretation*: each tier was profiled by the medians of the original indicators, and the data structure was summarised by principal component analysis (PCA; Jolliffe & Cadima, 2016).

The analysis was carried out in Python 3. BKM, K-Means and the GMM used scikit-learn 1.9 (Pedregosa et al., 2011), and FCM and all fuzzy indices were implemented in NumPy. Random seeds were fixed so that the results can be reproduced, because the performance of machine-learning algorithms can vary with the choice of random seed (Utomo et al., 2026); for the same reason, BKM and FCM were run from many seeds and the best solution was kept.

4. Results and Discussion

4.1. *Data Overview*

In 2024–2025, DIBI recorded 8,549 natural-disaster events across the 38 provinces. Floods dominated (43.7%), followed by forest and land fires (26.6%), extreme weather (20.5%) and landslides (6.3%); geological disasters accounted for only 0.6% of events. West Java recorded the most floods, landslides and extreme-weather events (343, 177 and 396), while North Sumatra recorded the most forest and land fires (399). Impacts were concentrated in northern Sumatra: Aceh recorded 605 dead and missing, 3.82 million people affected and 54,010 heavily damaged houses, mostly from floods. Central Papua, South Papua and Southwest Papua recorded the fewest events and the least damage.

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4.2. *Optimal Number of Clusters and Fuzzifier*

Figure 1 shows that, for BKM and FCM, k = 2 performs best on all three criteria. BKM with k = 2 reaches a silhouette of 0.327, a DBI of 1.104 and a CHI of 19.47, the best values among k = 2–8. The silhouette drops to 0.252 at k = 3 and stays between 0.21 and 0.23 for k ≥ 4, and the CHI declines monotonically to 11.91 at k = 8. The two bisecting strategies give identical partitions for k ≤ 5 and k = 7; at k = 6 and k = 8 the largest-SSE strategy gives a smaller SSE and was therefore selected. Bootstrap stability confirms the choice: the mean ARI at k = 2 is 0.671 for BKM and 0.691 for FCM, against 0.48–0.59 for k = 3–6. For FCM, the highest MPC (0.611) and the lowest PE (0.322) are also obtained at k = 2.

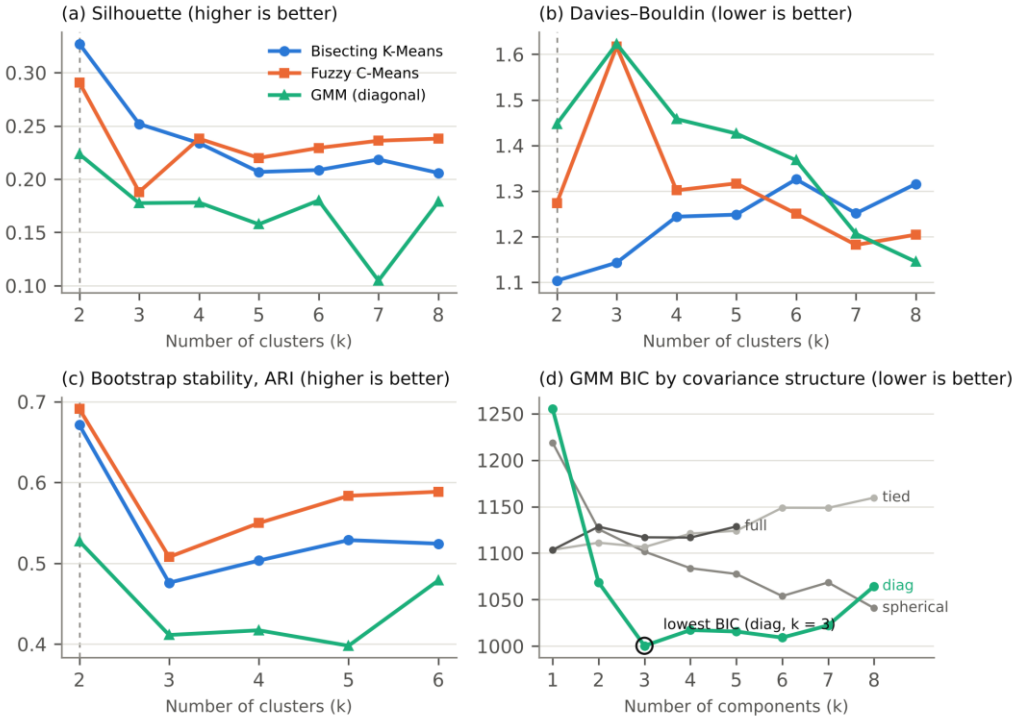

Figure 1. Selection of the number of clusters: (a) silhouette coefficient, (b) Davies–Bouldin index, (c) bootstrap stability (mean ARI, 200 replicates), and (d) BIC of the GMM by covariance structure. For FCM, each k uses the m with the smallest Xie–Beni index; the GMM curves in (a)–(c) use the diagonal covariance structure selected by BIC. The dashed line marks k = 2.

Across the whole k × m grid, the smallest XB for every k is reached at m ≤ 2.0. For k ≥ 3, raising m to 2.25 or more increases XB from below 2 to between 2.65 and well above 10, and for m ≥ 2.5 with k ≥ 5 empty clusters appear, meaning that centroids coincide. This agrees with the rule of Schwämmle and Jensen (2010), which gives m ≈ 1.79 for N = 38 and D = 11, so the customary m = 2 already lies at the upper end of the sensible range. The selected configuration is k = 2 and m = 1.5 (XB = 0.394; MPC = 0.611).

4.3. *Comparison of Methods, Initialisation and Stability*

At k = 2, BKM and standard K-Means produce exactly the same partition (ARI = 1), with nine provinces in the high-risk cluster and 29 in the other cluster. By maximum membership, FCM places 13 provinces in the high-risk cluster; the four additional provinces, Bali, Central Sulawesi, East Kalimantan and North Maluku, have memberships of only 0.52–0.65. The agreement between BKM and FCM is ARI = 0.605. Table 2 compares the methods.

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Table 2. Comparison of methods at their selected configurations (bootstrap: 200 replicates, adjusted Rand index)

Method	k	Silhouette	DBI	CHI	Mean ARI	ARI 5% quantile
Bisecting K-Means	2	0.327	1.104	19.47	0.671	0.081
Standard K-Means	2	0.327	1.104	19.47	0.671	0.068
FCM, random initialization (m = 1.5)	2	0.291	1.273	19.42	0.689	0.203
FCM, BKM initialization (m = 1.5)	2	0.291	1.273	19.42	0.691	0.224
GMM, diagonal covariance (BIC)	3	0.177	1.623	13.92	0.411	0.141

BKM is better on the internal indices, but FCM is more stable under resampling. The difference is clearest in the lower tail: the worst 5% of BKM replicates barely agree with the original partition (ARI ≤ 0.081), whereas hybrid FCM stays above 0.224. Initialising FCM with BKM centroids does not change its final solution, because all 100 random FCM runs also reached the same minimum J_m (244.30). Its benefit is efficiency: hybrid FCM converges in 13 iterations against a mean of 16.6 for random initialisation, about 22% faster, and its partition is deterministic. This is consistent with Savaresi and Boley (2004), who recommend using the output of divisive bisection to initialise iterative K-Means.

4.4. *Model-Based Clustering with Gaussian Mixtures*

The BIC selects a different answer (Figure 1d). The lowest BIC is obtained by a diagonal GMM with three components (BIC = 1,000.3); the next best diagonal models have six (1,009.1), five (1,015.7) and four components (1,017.2), while the two-component diagonal model is far behind (1,068.6). Every multi-component diagonal model beats the best one-component model (1,103.5), so the data do contain cluster structure. With k = 2, the spherical, tied and full GMMs reproduce the BKM partition exactly, which shows that the two-cluster solution is also a valid mixture solution when the components share a simple covariance form. The selected three-component model separates a very-high-risk group of six provinces, namely Aceh, North Sumatra, West Sumatra, West Java, Central Java and East Java, with median values of 249 floods, 306 dead and missing, 2.09 million people affected and 25,548 damaged houses. It places South Sulawesi, West Nusa Tenggara and East Nusa Tenggara in a 17-province middle group together with seven transitional and seven low-tier provinces, and it assigns the remaining 15 provinces, including South Sumatra, to a low group. The partition is unchanged when the regularisation is increased to 10^{-2}.

The GMM is, however, weaker on the other criteria (Table 2). Its silhouette (0.177) and CHI (13.92) are the lowest and its DBI (1.623) the highest of the methods compared, its bootstrap stability is lower (mean ARI 0.411; 5% quantile 0.141), and its agreement with BKM and FCM is modest (ARI 0.282 and 0.270). Its posterior probabilities are also almost crisp: every province has a posterior above 0.99 for its own component and the mean posterior entropy is below 0.001. With 38 provinces and eleven indicators, each diagonal component estimates its own variances from few observations, which makes the likelihood sharply peaked. The GMM therefore confirms the high-risk core and singles out its six most affected provinces, but it does not reproduce the graded transitional band that FCM reveals.

4.5. *Provincial Risk-Priority Tiers*

Figure 2 shows each province's membership in the high-risk cluster. Nine provinces have u ≥ 0.89 and coincide exactly with the BKM high-risk cluster: North Sumatra, West Sumatra, Central Java, East Java, West Java, South Sulawesi, West Nusa Tenggara, Aceh and East Nusa Tenggara. Eight provinces fall in the transitional band (0.25 < u < 0.75): East Kalimantan and Bali (0.65), Central Sulawesi (0.57), North Maluku (0.52), South Sumatra (0.38), Lampung (0.35), Banten (0.32) and Maluku (0.29). All of them belong to the "not high" cluster of BKM, so FCM adds information that the crisp partition hides. The transitional provinces reach this position for different reasons. Bali recorded 112 dead and missing, mainly from floods and extreme weather; East Kalimantan combined 134 forest and land fires with 115 floods; Central Sulawesi and North Maluku recorded 197 and 126 floods together with geological events; and South Sumatra, Lampung and Banten recorded between 136 and 165 floods each, with South Sumatra also recording 209 forest and land fires. Except for Bali and Maluku,

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their flood frequency is comparable to that of the high tier, but casualties and housing damage are much lower. The other 21 provinces form the low tier. The tiers are robust to the threshold: at 0.70, 0.75 and 0.80 the high tier always contains the same nine provinces, and only the transitional–low boundary moves, giving 7, 8 and 9 transitional provinces respectively.

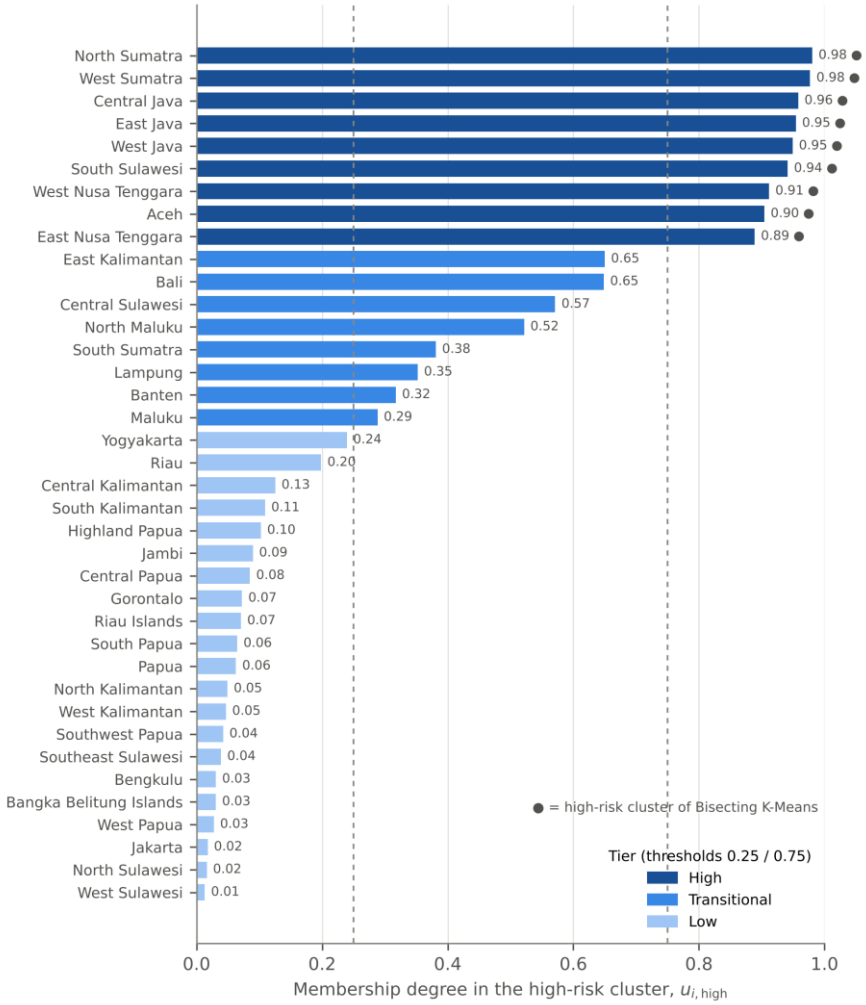

Figure 2. FCM membership degree (k = 2, m = 1.5) in the high-risk cluster. Dashed lines are the 0.25 and 0.75 thresholds; ● marks members of the BKM high-risk cluster.

The high tier is distinguished mainly by the size of its impacts (Table 3). Its nine provinces account for 52.3% of events but 80.7% of the dead and missing, 68.5% of people affected, 88.8% of damaged houses and 92.0% of heavily damaged houses nationally. The median number of damaged houses in the high tier is about 8 times that of the transitional tier and 20 times that of the low tier. The transitional tier already experiences frequent floods (median 131 events), but with much smaller losses.

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Table 3. Profile of the priority tiers (median per province, 2024–2025)

Indicator	High (n = 9)	Transitional (n = 8)	Low (n = 21)
Floods (events)	188	131	32
Landslides (events)	24	11	3
Extreme weather (events)	107	21	5
Forest and land fires (events)	44.5	5.5	0
Droughts (events)	12	0	0
Tidal waves/abrasion (events)	2	3	0
Geological (events)	2.5	0.9	0
Dead and missing (persons)	128	21.5	8
Affected and displaced (persons)	1,048,561	256,021	58,102
Heavily damaged houses (units)	2,570	356	81
Damaged houses, total (units)	16,794	1,996	849

A PCA of the standardised indicators supports this structure. The first principal component (54.1% of the variance) loads on all indicators with similar weights and can be read as overall intensity of events and impacts. The second component (13.4%) separates provinces with geological and coastal hazards (loadings +0.53 and +0.52), such as North Maluku, Maluku, Central Sulawesi, Bali and East Nusa Tenggara, from provinces dominated by forest and land fires and large numbers of people affected (loadings −0.48 and −0.35), such as South Sumatra, Central Kalimantan, Jambi and Lampung.

The BKM hierarchy (Figure 3) offers a complementary view. The first split separates the nine high-risk provinces. The second split does not divide the intermediate group but isolates four Papuan provinces with the fewest events and losses (West Papua, Southwest Papua, South Papua and Central Papua). Only the third split divides the remaining 25 provinces, and it does so by hazard profile rather than by level of risk. Seventeen mostly western provinces dominated by floods and forest and land fires, including Riau, Jambi, South Sumatra, Lampung, Banten and the Kalimantan provinces, separate from eight mostly eastern provinces with geological and coastal hazards: Bali, Bengkulu, Maluku, North Maluku, Papua, Central Sulawesi, Southeast Sulawesi and North Sulawesi. The mean risk scores of the two groups are close (−0.24 and −0.04 in standardized units), which mirrors the second principal component. This order of splits explains why the silhouette and stability deteriorate for k ≥ 3: outside the high-risk cluster, the provinces differ more in the type of hazard than in the overall level of risk, and that difference is graded rather than separated into distinct groups.

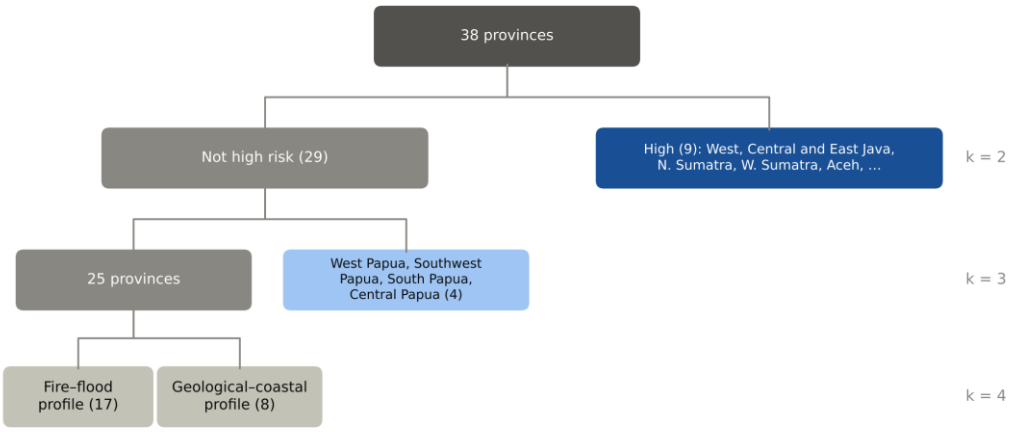

Figure 3. Bisecting K-Means splitting hierarchy from k = 2 to k = 4 (largest-SSE strategy).

4.6. Why Two Clusters

The preference for k = 2 is not an artefact of one index. Silhouette, DBI, CHI, MPC, XB and bootstrap stability all point to k = 2, and BKM and FCM reach the same conclusion from different directions. The BIC of the GMM prefers three components, but this is because a likelihood criterion rewards components with their own variances, and here it splits the

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high-risk core into its six most affected provinces and a remainder; the three-component solution is less stable and less well separated than the two-cluster one. The two answers are therefore complementary rather than contradictory: the high-risk core is robust across all methods, and its six most affected provinces are the most robust part of it. Forcing three or four crisp clusters onto such graded data produces boundaries that shift easily, as the drop in ARI to 0.48–0.59 shows; an intermediate tier is therefore better derived from FCM memberships than from extra crisp clusters. The finding also shows why several indices should be checked together: an earlier application of BKM to Indonesian earthquakes fixed three clusters on the DBI alone (Rais et al., 2025a), whereas here the choice of k is supported by six indices and a stability test. The silhouette obtained here (0.33) is lower than the 0.84 reported by Firdaus and Sofro (2022), but the two are not directly comparable because the period, indicators and pre-processing differ. With untransformed counts, a few provinces with very large values can dominate the Euclidean distances and sit far from the rest, inflating the silhouette even when the other provinces are not distinguished; the log transformation and standardisation used here let every indicator contribute evenly, at the cost of a more moderate silhouette.

4.7. Comparison with the Indonesian Disaster Risk Index

The tiers are not meant to replace the IRBI. The IRBI assesses potential risk from hazard, vulnerability and capacity, whereas this study groups risk that has already materialised as events and losses, and the difference is visible. West Sulawesi, Maluku and the Bangka Belitung Islands had the highest IRBI scores in 2023 (BNPB, 2024), yet in 2024–2025 they fall in the low or transitional tier ($u = 0.01$, 0.29 and 0.03). Conversely, West, Central and East Java recorded the highest events and impacts. Both perspectives are needed: the IRBI for long-term planning, and event-based clustering to evaluate where losses actually occur.

4.8. Policy Implications and Limitations

The three tiers call for different responses. For the high tier, the priority is reducing impacts through flood- and landslide-resilient housing, flash-flood early warning, evacuation routes and logistics preparedness, because losses there far exceed what event frequency alone would suggest. The transitional tier already floods often but has not yet suffered losses on the scale of the high tier; Bali, East Kalimantan, Central Sulawesi and North Maluku ($u > 0.5$) should be monitored because a single large event could move them into the high tier, and the second principal component shows two profiles within this tier, geological and coastal hazards in the east and forest and land fires in southern Sumatra. For the low tier, the focus is maintaining capacity and improving recording, since the low figures for the new Papuan provinces may reflect genuinely low hazard but may also reflect incomplete records.

The study has four limitations. First, the two-year window is influenced by one extreme event: the flash floods and landslides in Aceh, North Sumatra and West Sumatra at the end of November 2025 had killed 1,006 people, with 217 still missing, by 13 December 2025 (Investortrust, 2025), so much of the impact recorded for these three provinces comes from a single event. Second, the indicators are absolute counts not normalised by population or area, so populous and large provinces are more likely to fall in the high tier. Third, DIBI data are continuously updated, so the figures may change if downloaded at another time. Fourth, provincial aggregation hides differences between districts. Future work could normalise the indicators per capita, extend the window as more records under the new mechanism accumulate, and apply the same procedure at the district level.

5. Conclusion

Jointly optimising the number of clusters, the bisecting strategy and the fuzzifier shows that the 2024–2025 disaster event and impact data are best grouped into two clusters. This conclusion is supported consistently by six validity indices and by bootstrap stability for both Bisecting K-Means and Fuzzy C-Means; the best configurations are BKM with the largest-SSE strategy and FCM with $m = 1.5$. A Gaussian mixture model selected by BIC prefers

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three components and isolates Aceh, North Sumatra, West Sumatra, West Java, Central Java and East Java as a very-high-risk group, but it is less stable and gives almost crisp memberships. Nine provinces form a stable high-risk core: West Java, Central Java, East Java, North Sumatra, West Sumatra, Aceh, South Sulawesi, West Nusa Tenggara and East Nusa Tenggara. They account for about half of the events but more than 80% of the fatalities and nearly 90% of the damaged houses. FCM initialised with BKM centroids is the most stable of the methods compared, converges faster than randomly initialised FCM, and reveals eight transitional provinces that the crisp partition does not show. Combining the BKM hierarchy with FCM memberships yields three priority tiers (high, transitional and low) that can be used directly to set mitigation priorities. Future studies should normalise the indicators by population and area, lengthen the data period, apply the procedure at the district level, and combine these event-based results with the hazard and vulnerability components of the IRBI.

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