

Multi-Hazard Risk Typology and Temporal Trends of Disaster Events in East Nusa Tenggara Province (2008–2025)

Firman Almaliky Gapi Amra¹

¹Undergraduate Program in Applied Instrumentation of Meteorology, Climatology and Geophysics, STMKG, Tangerang, Indonesia

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ABSTRACT

East Nusa Tenggara (NTT) Province faces complex multi-hazard threats from hydrometeorological and geological disasters. This study developed a multi-hazard risk typology for 22 regencies/cities in NTT and examined temporal trends in disaster frequency over 2008–2025 (complete years; partial 2026 data excluded). The dataset comprised 1,158 records, adjusted to 1,128.5 real events using fractional weights across eight disaster types. Clustering was evaluated across three feature schemes and two algorithms (K-Means and Agglomerative Ward), with the number of clusters validated through a consensus of Silhouette, Davies-Bouldin, and Calinski-Harabasz indices while avoiding degenerate solutions. Temporal trends and change points were evaluated using the Mann-Kendall and Pettitt tests, preceded by lag-1 autocorrelation (ACF) screening. The selected hazard-only Agglomerative Ward model ($k = 6$; Silhouette = 0.2105, DBI = 1.205, CHI = 5.28) categorized regions into six distinct typologies, from low-risk to high-frequency flood/extreme-weather clusters, with Sabu Raijua identified as an impact-severity outlier. Auto correlation checks confirmed the validity of test assumptions. The Mann-Kendall and Pettitt tests consistently revealed no statistically significant monotonic trend or change point ($p > 0.05$) across the province, dominant disaster types, and all clusters. This meaningful null result demonstrates that disaster occurrences in NTT are driven by sharp inter-annual fluctuations rather than long-term trends, emphasizing the necessity of continuous preparedness and differentiated, typology-based mitigation strategies.

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Corresponding Author:

Firman Almaliky Gapi Amra

Undergraduate Program in Applied Instrumentation of Meteorology, Climatology and Geophysics, STMKG

Tangerang, Indonesia

Email: firman.amra14@gmail.com

1. INTRODUCTION

East Nusa Tenggara (NTT) Province is located at the junction of tectonic plates and an active volcanic arc, and its climate is influenced by strong seasonal rainfall variability; consequently, the region faces complex multi-hazard threats, ranging from hydrometeorological disasters such as floods, landslides, and extreme weather, to geological disasters such as earthquakes and volcanic eruptions [1], [2].

Most disaster studies conducted in Indonesia, including in NTT, tend to be single-hazard, focusing on one particular disaster type in one study area. Such an approach has rarely accommodated the simultaneous multi-hazard character of a region or linked it to long-term temporal trend patterns, even though combining a multi-hazard profile with temporal trend analysis is highly relevant for differentiated mitigation planning across regions [3].

This study aimed to (1) build a multi-hazard risk typology for the 22 regencies/cities in NTT Province based on hazard profiles (real frequency) and impact severity from eight disaster types, using a clustering method selected systematically among several feature schemes and algorithms and validated across three cluster indices, and (2) test the significance of the temporal trend and possible change points in disaster

event frequency over the 2008–2025 period using the Mann-Kendall test and the Pettitt test, both preceded by an autocorrelation-assumption check, including a comparison of trend patterns among the resulting risk-typology clusters. The contribution/novelty of this study lies in integrating multi-hazard typology analysis with temporal trend and change-point analysis for the context of NTT Province, accompanied by a number of data- and method-validity assurance steps rarely found together in similar studies: (a) correction of the event-frequency definition for data containing fractional weights arising from cross-regency events, (b) exclusion of the current, not-yet-complete year from the trend test, (c) validation of the number of clusters across three indices rather than a single index, and (d) an autocorrelation check prior to the non-parametric trend test.

2. LITERATURE REVIEW

A comprehensive disaster risk science perspective emphasizes the importance of characterizing multiple hazard types and their interactions within a region simultaneously, rather than treating each hazard in isolation [4].

2.1. Disaster Characteristics of East Nusa Tenggara

The geographical and geological characteristics of NTT, which lies along the Pacific Ring of Fire and experiences a long dry season, make the region vulnerable to a wide range of disasters, both hydrometeorological and geological [2], [5].

2.2. Clustering and Cluster-Number Validation for Disaster-Prone Area Typology

Non-hierarchical clustering methods such as K-Means and hierarchical methods such as Agglomerative Clustering are commonly used to group regions based on the similarity of their disaster-risk characteristics. Selecting the optimal number of clusters should not rely on a single validity index; the Silhouette Score, Davies-Bouldin Index, and Calinski-Harabasz Index each capture slightly different aspects of cluster compactness and separation, so using more than one index simultaneously strengthens the reliability of the choice of k . The data-mining literature also emphasizes the importance of avoiding degenerate or trivial cluster solutions (clusters consisting of a single observation unit caused by an extreme outlier) [6], [7].

2.3. Mann-Kendall Trend Test, Autocorrelation, and Change-Point Test

The Mann-Kendall test is a widely used non-parametric statistical test for detecting monotonic trends in climate and disaster time series, with Sen's slope used as an estimate of the rate of change. The test theoretically assumes the data are independent and identically distributed (free of serial autocorrelation); if a series has strong positive autocorrelation, the Mann-Kendall p -value can become overly optimistic (prone to detecting spurious trends), so checking the autocorrelation function (ACF) and, where necessary, using an autocorrelation-corrected test (e.g., the Hamed & Rao modification) is recommended as a screening step before interpreting the results. As a complement to the monotonic trend test, the Pettitt test is commonly used to detect a single change point in a time series [8], [9].

3. RESEARCH METHOD

3.1. Data

The data used in this study consisted of disaster event records for East Nusa Tenggara Province, comprising 1,158 recorded rows over 2008–2026, covering 22 regencies/cities and 8 disaster types. Initial screening found no duplicate rows or missing values in the columns used in the analysis.

Important data note: the 'Number of Events' column in the source data was not uniformly valued at 1, but rather carried a FRACTIONAL WEIGHT (e.g., 0.5; 0.333; 0.25; 0.0909) for events recorded across multiple regencies or split into several impact sub-rows, such that the sum of the weights for one physical event equaled 1. Calculating event FREQUENCY from the ROW COUNT would double-count these multi-regency/multi-row events. Therefore, every frequency calculation in this study (Table 1, hazard features for clustering, and annual series for the trend test) used SUM('Number of Events') rather than row count, so the actual total number of events in this dataset was approximately 1,128.5 events from 1,158 recorded rows. In contrast, the IMPACT variables (deaths, injuries/illness, displaced/affected persons, damaged houses) did not suffer from the same issue because their values were already specific and real per row/regency (not the result of a proportional split of a total impact figure), and were therefore summed as recorded.

Second data note: 2026 data were recorded only through the eighth month (36 event rows) and thus did not represent a complete year. Including an incomplete year at the end of the series risks biasing the Mann-Kendall test, Sen's slope, and the Pettitt test (an apparently 'low' event count in 2026 would simply reflect a shorter time coverage, not an actual decline). Accordingly, all TEMPORAL TREND ANALYSIS (Sections 3.4 and 4.2–4.3) in this study was restricted to the COMPLETE years 2008–2025; the 2026 data are still reported descriptively but

were excluded from the statistical trend tests. The typology clustering (Sections 3.2–3.3, 4.1) was not affected by the same issue because it is cross-sectional (an accumulation over the entire period) rather than a time series.

A summary of the real number of events per disaster type together with the total impact (entire data period, including partial 2026) is presented in Table 1.

Table 1. Summary of Real Number of Events and Total Impact per Disaster Type in NTT, 2008–2026

Disaster Type	Number of Events (real)	Total Deaths (persons)	Total Damaged Houses (units)	Total Displaced/Affected (persons)
Extreme weather	429.0	62	16,185	58,397
Flood	365.0	297	77,138	868,081
Landslide	150.0	44	1,299	9,043
Drought	60.0	2	0	2,999,936
Tidal wave / Abrasion	53.0	9	1,735	11,370
Forest and land fire	40.0	0	15	111
Earthquake	18.5	70	14,700	142,625
Volcanic eruption	13.0	20	2,384	121,877

As shown in Table 1, extreme weather was the disaster type with the highest number of real events (429.0 events), followed by flood (365.0 events), which recorded the highest number of deaths and displaced/affected persons among all disaster types, at 297 persons and 868,081 persons, respectively.

3.2. Data Preprocessing and Feature Engineering

Event data were aggregated to the regency $\times$ disaster-type level by summing the 'Number of Events' weights (not row counts, see the data note in Section 3.1) to compute the REAL frequency of events for each combination, producing 8 HAZARD feature columns.

For impact features, this study formed 4 SEVERITY feature columns as average-impact-PER-REAL-EVENT indices — namely the number of deaths, the number of displaced/affected persons, total damaged houses, and the number of injured/ill persons — each summed as recorded and then divided by the real event frequency (SUM 'Number of Events') for that regency, rather than a raw total that would be dominated by a single extreme event.

Three feature schemes were formed and compared at the clustering stage: (a) Hazard-only (8 real-frequency features), (b) Severity-only (4 per-event impact-index features), and (c) Combined Hazard+Severity (12 features). All features were standardized using a StandardScaler prior to clustering.

3.3. Feature Scheme, Method, and Cluster-Number Selection

This study compared 2 clustering algorithms — K-Means (k-means++, n_init=20) and Agglomerative/Hierarchical Clustering (Ward linkage) — across the three feature schemes above, each for k=2 to k=6 (3 schemes $\times$ 2 methods $\times$ 5 values of k = 30 combinations), evaluated with 3 indices: Silhouette Score (higher is better), Davies-Bouldin Index/DBI (lower is better), and Calinski-Harabasz Index/CHI (higher is better).

Methodological note (degenerate solution): the highest raw silhouette score was found in the Severity-only scheme with the K-Means method at k=2 (silhouette=0.6137), but this was degenerate (smallest cluster size=1) due to Sabu Raijua Regency separating out as an extreme outlier on the severity indices (see Table 4 and the robustness discussion in Section 4.1). Model selection was therefore restricted to non-degenerate solutions (smallest cluster size ≥ 2).

Among the non-degenerate solutions, the highest silhouette score was obtained with the Hazard-only scheme using the Agglomerative (Ward) method (see Table 2a). For this scheme-method combination, the number of clusters was further validated across the 3 indices for k=2 to k=6 (Table 2b, Fig. 1).

Table 2a. Ten Non-Degenerate Feature-Scheme $\times$ Clustering-Method Combinations with the Highest Silhouette Score

Feature Scheme	Method	k	Silhouette	DBI	CHI	Min. Cluster Size
Hazard-only	Agglomerative (Ward)	5	0.2340	1.227	5.24	2

Feature Scheme	Method	k	Silhouette	DBI	CHI	Min. Cluster Size
Hazard-only	K-Means	5	0.2235	1.267	5.12	2
Hazard-only	K-Means	4	0.2219	1.334	4.97	2
Hazard-only	Agglomerative (Ward)	4	0.2142	1.357	5.00	2
Hazard-only	Agglomerative (Ward)	6	0.2105	1.205	5.28	2
Hazard-only	Agglomerative (Ward)	3	0.1996	1.482	4.86	2
Hazard-only	K-Means	3	0.1993	1.499	4.99	3
Hazard-only	K-Means	2	0.1829	1.783	5.51	11
Hazard-only	Agglomerative (Ward)	2	0.1688	1.880	4.97	11
Combined Hazard+Severity	K-Means	3	0.1471	1.661	4.02	4

Methodological note (k selection via 3-index consensus): for the Hazard-only + Agglomerative (Ward) combination, the highest Silhouette Score was at $k=5$ (0.2340), whereas the Davies-Bouldin Index and Calinski-Harabasz Index BOTH showed (marginally) better performance at $k=6$ (DBI=1.2048; CHI=5.278) than at $k=5$ (DBI=1.2265; CHI=5.244). Because the majority of indices (2 of 3) favored $k=6$ and that solution remained non-degenerate, $k=6$ was selected as the final decision through a majority-consensus/voting principle across indices, rather than relying on the Silhouette Score alone — following the methodological recommendation to validate the number of clusters with more than one index.

Table 2b. Cluster-Number Validation with 3 Indices for the Selected Scheme (Hazard-only, Agglomerative (Ward))

k	Silhouette (higher better)	Davies-Bouldin (lower better)	Calinski-Harabasz (higher better)
2	0.1688	1.8796	4.966
3	0.1996	1.4820	4.861
4	0.2142	1.3568	4.999
5	0.2340	1.2265	5.244
6	0.2105	1.2048	5.278

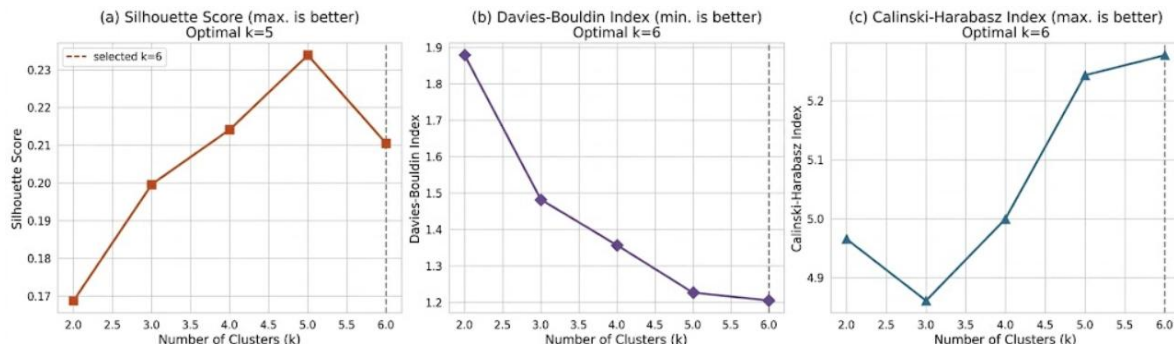


Fig. 1. Cluster-Number Validation with 3 Indices (Hazard-only Scheme, Agglomerative (Ward))

A comparison of the silhouette curves for all 30 feature-scheme and method combinations is shown in Fig. 2, clarifying the position of the degenerate solution (Severity-only scheme) relative to the selected non-degenerate solution.

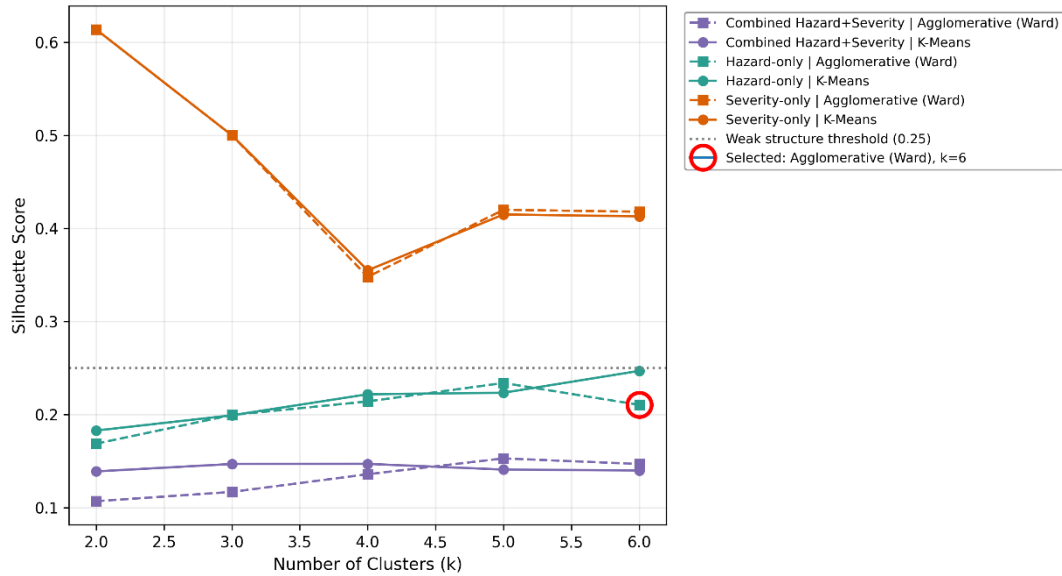


Fig. 2. Comparison of Silhouette Scores across Feature Schemes and Clustering Methods

The final clustering result (Hazard-only scheme, Agglomerative (Ward) method, $k=6$) was then projected into two-dimensional space using Principal Component Analysis (PCA) for visualization purposes.

3.4. Trend and Temporal Change-Point Analysis

Trend analysis was performed on the annual REAL disaster-event series (SUM 'Number of Events') at the provincial level and for the three most frequent disaster types, restricted to the COMPLETE years 2008–2025 (see the note in Section 3.1 regarding the exclusion of the partial 2026 data). Before applying the Mann-Kendall test, the lag-1 autocorrelation (ACF) of each series was checked against the significance threshold of $\pm 1.96/\sqrt{n}$; where autocorrelation was significant, the Hamed-Rao modified Mann-Kendall test (robust to autocorrelation) was to be reported as a sensitivity check. The (original) Mann-Kendall test was used to detect monotonic trends at the 5% significance level, with Sen's slope as the rate-of-change estimate, and the Pettitt test was used to detect a possible single change point. The same analysis was also applied to the annual series of each risk-typology cluster.

4. RESULT AND DISCUSSION

4.1. Regency Typology Based on Multi-Hazard Profile

The final clustering result (Hazard-only scheme, Agglomerative (Ward), $k=6$) produced clusters of varying size with no single-member cluster (silhouette=0.2105; DBI=1.205; CHI=5.28). The two-dimensional PCA projection (Fig. 3) explained 27.5% of variance on PC1 and 18.5% on PC2 (46.0% total).

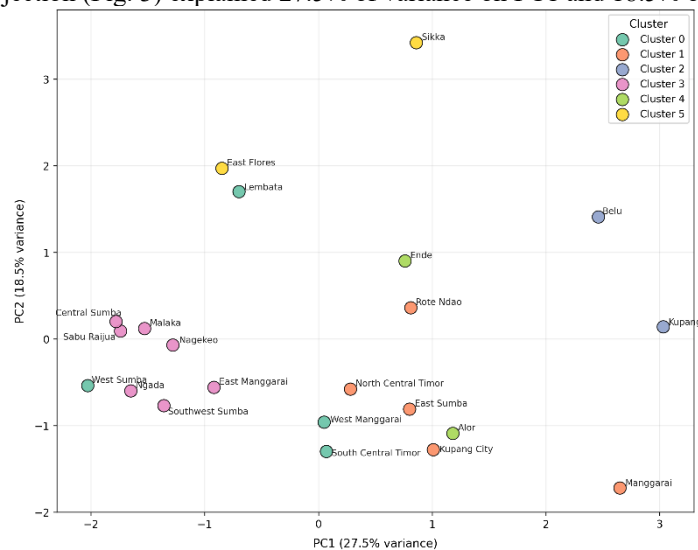


Fig. 3. Agglomerative (Ward) Clustering Result ($k=6$) for NTT Regencies/Cities Based on Multi-Hazard

Profile (2D PCA Projection)

The average real-frequency profile of each disaster type per cluster is shown in Table 3 and Fig. 4.

Table 3. Membership Profile and Dominant Disasters of Each Risk-Typology Cluster

Cluster	Descriptive Name	No. of Reg./City	Member Regencies/Cities	Dominant Disaster (avg. freq.)
K0	Moderate Extreme Weather–Flood Cluster with Forest/Land Fire	4	Lembata, Manggarai Barat, Sumba Barat, Timor Tengah Selatan	Extreme weather (11.0); Flood (9.8)
K1	Extreme Weather and Landslide–Prone Cluster	5	Kota Kupang, Manggarai, Rote Ndao, Sumba Timur, Timor Tengah Utara	Extreme weather (35.0); Flood (19.3)
K2	Highest-Frequency Flood and Extreme Weather–Prone Cluster	2	Belu, Kupang	Flood (40.7); Extreme weather (28.0)
K3	Low Multi-Hazard Risk Cluster	7	Malaka, Manggarai Timur, Nagekeo, Ngada, Sabu Raijua, Sumba Barat Daya, Sumba Tengah	Flood (7.7); Extreme weather (7.1)
K4	Extreme Weather and Coastal Abrasion–Prone Cluster	2	Alor, Ende	Extreme weather (37.0); Flood (23.5)
K5	Volcanic and Coastal Abrasion–Prone Cluster	2	Flores Timur, Sikka	Flood (23.5); Extreme weather (15.0)

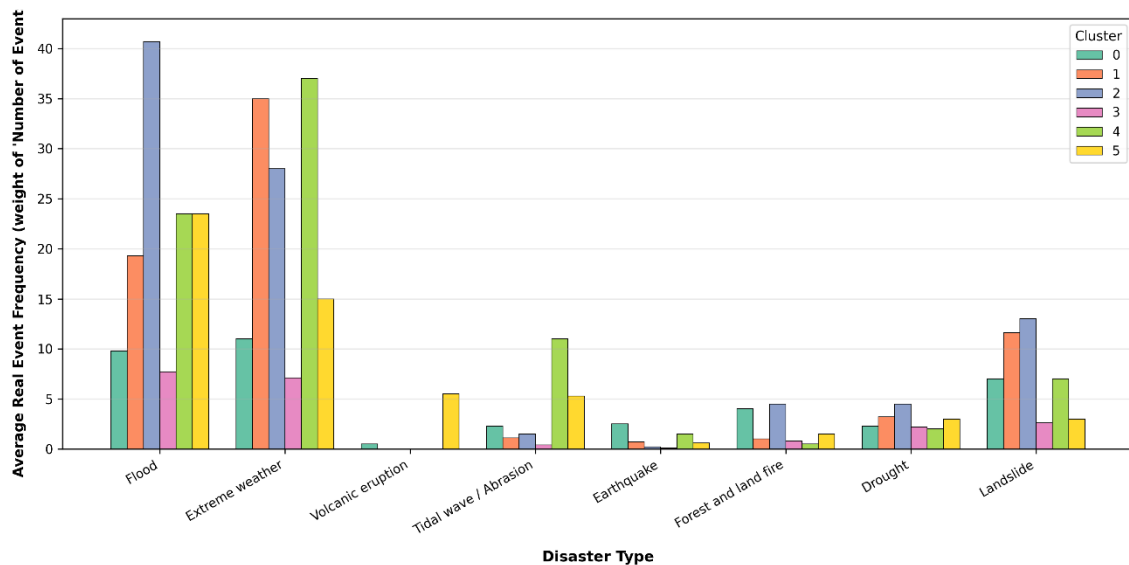


Fig. 4. Average Real-Event-Frequency Profile per Cluster

Based on Table 3 and Fig. 4, the six clusters show distinct hazard profiles. Cluster 0 (Lembata, Manggarai Barat, Sumba Barat, Timor Tengah Selatan) shows the highest forest and land fire frequency among all clusters (4.0 events) alongside moderate extreme weather and flood, hence named the “Moderate Extreme Weather–Flood Cluster with Forest/Land Fire.” Cluster 1 (Kota Kupang, Manggarai, Rote Ndao, Sumba Timur, Timor Tengah Utara) has a high extreme-weather frequency (35.0 events) together with the second-highest landslide frequency (11.6 events), named the “Extreme Weather and Landslide–Prone Cluster.” Cluster 2 (Belu, Kupang) records the highest flood frequency among all clusters (40.7 events) together with high extreme weather (28.0 events) and the highest landslide frequency (13.0 events), named the “Highest-Frequency Flood and Extreme Weather–Prone Cluster.” Cluster 3 (Malaka, Manggarai Timur, Nagekeo, Ngada, Sabu Raijua, Sumba Barat Daya, Sumba Tengah), with 7 members — the largest cluster — shows the lowest frequency across almost all disaster types, named the “Low Multi-Hazard Risk Cluster.” Cluster 4 (Alor, Ende) stands out with the highest extreme-weather frequency (37.0 events) and the highest tidal-wave/abrasion frequency (11.0 events) among all clusters, named the “Extreme Weather and Coastal

Abrasion-Prone Cluster.” Cluster 5 (Flores Timur, Sikka) stands out with the highest volcanic-eruption frequency (5.5 events), named the “Volcanic and Coastal Abrasion-Prone Cluster.”

Robustness Analysis: Additional Findings from the Severity-Only Scheme

As a robustness check, the Severity-only scheme ($k=2$), which had briefly produced the highest silhouette score (though degenerate, Section 3.3), still provided substantive information: this scheme consistently separated Sabu Raijua Regency as the sole outlier in impact severity. The average number of displaced/affected persons per event in Sabu Raijua reached 20,067 persons/event and the average damaged houses per event reached 1,037.5 units/event, far exceeding the average of the other 21 regencies/cities (4,648 persons/event and 86.4 units/event). Sabu Raijua Regency did not stand out in terms of hazard frequency (it was grouped in Cluster 3, the low-risk cluster) but showed a very high per-event impact vulnerability and deserves separate attention in mitigation planning.

Table 4. Per-Event Impact-Severity Index: Sabu Raijua (Outlier) vs. the Average of Other Regencies/Cities

Regency	Sev. Deaths (persons/event)	Sev. Displaced (persons/event)	Sev. Damaged Houses (units/event)	Sev. Injured (persons/event)
Sabu Raijua (outlier)	0.80	20,067	1,037.5	0.90
Average of other 21 regencies/cities	0.49	4,648	86.4	3.11

4.2. Temporal Trend and Change-Point of Disaster Events 2008–2025 (Complete Years)

Trend analysis was performed on the annual real disaster-event series at the provincial level and for the three most frequent disaster types, restricted to the complete years 2008–2025 (2026 data, recorded only through month 8, were excluded; see Section 3.1). The annual fluctuation pattern, Sen's slope trend line, Pettitt change-point indication, and lag-1 ACF value for each series are shown in Fig. 5.

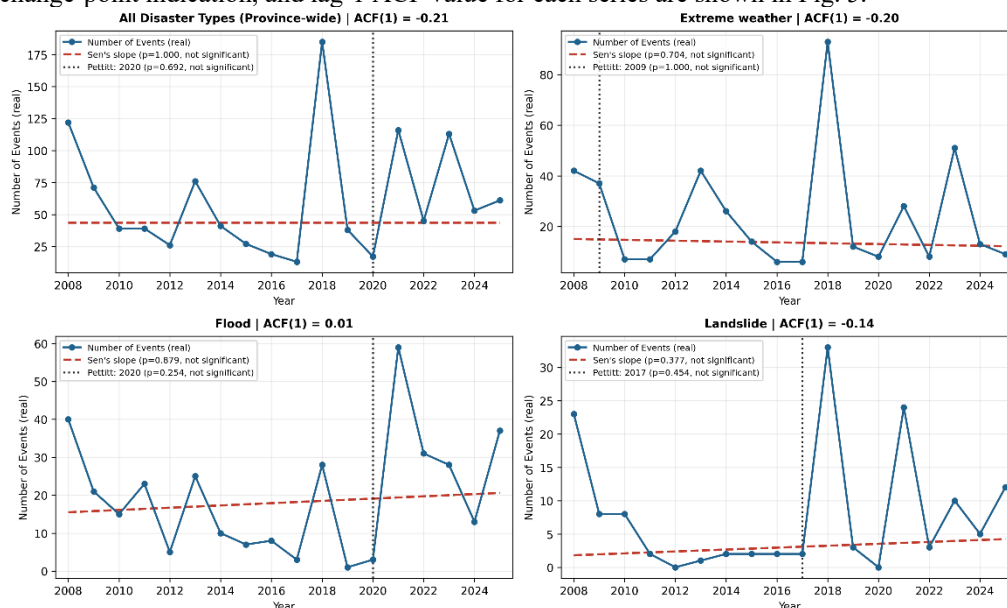


Fig. 5. Temporal Trend and Change-Point Indication for Disaster Events in NTT, Complete Years 2008–2025

Table 5a. Mann-Kendall Test, Sen's Slope, and Lag-1 Autocorrelation (ACF) Check Results

Data Series	Trend Direction	Significant ($p < 0.05$)	p-value	Sen's Slope	ACF Lag-1	Autocorr. Sig.?
Province (all disasters)	No trend	No	1.0000	0.0000	-0.206	No
Extreme weather	No trend	No	0.7040	-0.1667	-0.202	No
Flood	No trend	No	0.8794	0.3000	0.007	No
Landslide	No trend	No	0.3768	0.1429	-0.144	No

As shown in Table 5a, the lag-1 autocorrelation (ACF) check found NO significant autocorrelation in any tested series (all $|ACF(1)|$ values were below the $\pm 1.96/\sqrt{n}$ threshold), so the independence assumption of the original Mann-Kendall test was satisfied and the Hamed-Rao correction was not required for these series (the Hamed-Rao sensitivity-check results were therefore empty across all series). The Mann-Kendall test on the province-wide series found no statistically significant monotonic trend ($p=1.0000$; Sen's slope=0.0000 events/year). Similar results were found for extreme weather ($p=0.7040$), flood ($p=0.8794$), and landslide ($p=0.3768$).

Table 5b. Pettitt Test Results (Change-Point Detection)

Data Series	Indicated Change Year	K Statistic	p-value	Significant ($p<0.05$)
Province (all disasters)	2020	33.0	0.6919	No
Extreme weather	2009	21.0	1.0000	No
Flood	2020	46.0	0.2543	No
Landslide	2017	39.0	0.4542	No

The Pettitt test in Table 5b likewise found no statistically significant change point at the 5% level in any tested series. The peak Pettitt statistic for the province-wide and flood series both occurred in 2020 (though not significant), while the landslide series peaked in 2017 and extreme weather in 2009.

Overall, the absence of a significant monotonic trend, change point, or serial autocorrelation in the series above is a meaningful finding in itself (a meaningful null result): disaster-event frequency in NTT over 2008–2025 appears to be dominated by sharp year-to-year fluctuation that is relatively uncorrelated between consecutive years, rather than by a consistent long-term trend (see the spikes in 2018 and 2021–2023 in Fig. 5) [3]. This pattern is consistent with a disaster character strongly influenced by inter-annual climate variability (e.g., El Niño/La Niña) and sporadic large-scale extreme events such as tropical cyclones, rather than a gradually unidirectional climate/environmental shift from one year to the next [10].

4.3. Relationship between Risk Typology and Temporal Trend

The Mann-Kendall test was also applied to the annual (complete-year) real disaster-event series of each cluster, to examine whether regencies of a particular risk type showed trend patterns different from the provincial aggregate pattern. The per-cluster temporal patterns are shown in Fig. 6, and a summary of the test results (including lag-1 ACF) is shown in Table 6.

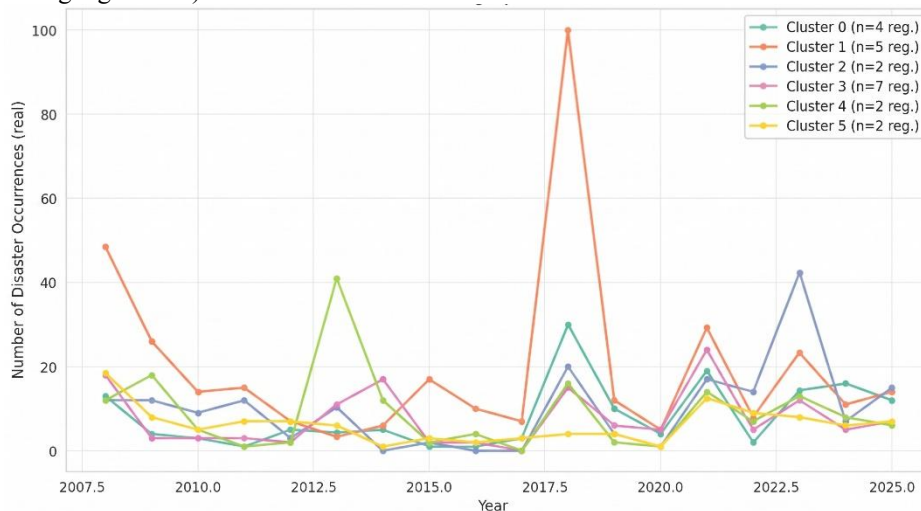


Fig. 6. Temporal Trend of Real Disaster-Event Frequency per Risk-Typology Cluster, Complete Years 2008–2025

Table 6. Mann-Kendall Test Results per Risk-Typology Cluster

Cluster	No. of Reg.	Trend Direction	Significant ($p<0.05$)	p-value	Sen's Slope	ACF Lag-1
K0	4	No trend	No	0.1956	0.4615	0.043
K1	5	No trend	No	0.7615	-0.2000	-0.107
K2	2	No trend	No	0.5424	0.1818	0.065

Cluster	No. of Reg.	Trend Direction	Significant ($p<0.05$)	p-value	Sen's Slope	ACF Lag-1
K3	7	No trend	No	0.5668	0.1538	-0.146
K4	2	No trend	No	0.8492	-0.1250	-0.065
K5	2	No trend	No	0.7604	-0.0625	0.248

As shown in Table 6, NONE of the 6 clusters showed a statistically significant trend at the 5% level, consistent with the province-wide and per-disaster-type results (Section 4.2). Lag-1 autocorrelation was also non-significant across all clusters, so the original Mann-Kendall test remained valid without requiring the Hamed-Rao correction. Descriptively (not statistically significant), Cluster 0 (the “Moderate Extreme Weather–Flood Cluster with Forest/Land Fire,” comprising Lembata, Manggarai Barat, Sumba Barat, and Timor Tengah Selatan) showed the largest positive Sen's slope among all clusters (0.4615 events/year; $p=0.1956$); however, this p-value remained far from the 5% significance threshold, so it cannot be concluded as a genuinely increasing trend — this pattern warrants further monitoring as the data series lengthens in future years, but CANNOT be claimed as a significant finding based on current data. This finding differs from an earlier exploratory stage of the study which, before the frequency-definition correction (Section 3.1) and before the exclusion of the partial-year data (Section 3.1), had briefly shown one cluster with a significant trend — after both methodological corrections were applied, no cluster showed a statistically significant trend, underscoring the importance of both data corrections to the study's final conclusions [7].

4.4. Implications for Disaster Mitigation

The absence of a statistically significant long-term trend, change point, or per-cluster trend does not mean that disaster risk in NTT can be ignored; on the contrary, the sharp and unpredictable year-to-year fluctuation (low lag-1 autocorrelation, Fig. 5) indicates that preparedness needs to be CONSISTENT over time, rather than reactive to trends perceived as “declining” in certain years. The risk typology produced by this study can serve as a basis for Regional Disaster Management Agencies (BPBD) and local governments to design differentiated mitigation strategies: regions in the “Extreme Weather and Landslide–Prone Cluster” and the “Highest-Frequency Flood and Extreme Weather–Prone Cluster” require strengthened extreme-weather early-warning systems and flood/landslide preparedness given their high event frequency; regions in the “Extreme Weather and Coastal Abrasion–Prone Cluster” and the “Volcanic and Coastal Abrasion–Prone Cluster” require coastal-abrasion mitigation, with additional volcanic-specific mitigation for the latter; regions in the “Moderate Extreme Weather–Flood Cluster with Forest/Land Fire” require strengthened forest- and land-fire prevention alongside extreme-weather/flood preparedness; while Cluster 3, as the relatively low-risk group, still requires basic preparedness. Special attention should also be given to Sabu Raijua Regency, given its per-event impact-severity index far exceeding that of other regencies/cities (Section 4.1), despite its relatively low hazard frequency [1], [5].

5. CONCLUSION

This study produced two main findings, both obtained after applying a number of important methodological corrections to the event-frequency definition and the data's temporal coverage. First, through a model-selection procedure comparing 3 feature schemes, 2 clustering algorithms, and a consensus of 3 cluster-validity indices (Silhouette, Davies-Bouldin, Calinski-Harabasz), clustering of the REAL frequency profile of 8 disaster types across 22 regencies/cities in NTT produced 6 risk-typology clusters (silhouette=0.2105; DBI=1.205; CHI=5.28), ranging from a low-risk cluster, an extreme-weather/landslide-prone cluster, a highest-frequency flood/extreme-weather-prone cluster, an extreme-weather/coastal-abrasion-prone cluster, and a volcanic/coastal-abrasion-prone cluster, to a cluster distinguished by forest/land fire. Robustness analysis further identified Sabu Raijua Regency as an outlier in impact severity. Second, after correcting the event-frequency definition (using the 'Number of Events' weight rather than row count) and excluding the not-yet-complete 2026 data from the trend test, the Mann-Kendall and Pettitt tests on the annual province-wide series, the three most frequent disaster types, AND all risk-typology clusters CONSISTENTLY found no statistically significant trend or change point ($p>0.05$) over 2008–2025, with lag-1 autocorrelation also non-significant across all series (confirming the validity of the original Mann-Kendall assumption). The contribution/novelty of this study lies in the integrated analysis of multi-hazard typology and temporal trend/change-point analysis for the context of NTT Province, accompanied by a series of data- and method-validity assurance steps (correction of fractional event weights, exclusion of partial-year data, multi-index validation of k, and an autocorrelation check) rarely applied together in similar disaster studies, while also illustrating how methodological correction can change a study's substantive conclusions (from one cluster briefly showing a significant trend in an early exploratory stage, to no significant trend in the final,

corrected analysis). Further research is recommended to extend the historical data coverage to increase the statistical power of trend detection, to consider socio-economic exposure and vulnerability variables as additional clustering features, and to explore the relationship between NTT's annual disaster fluctuations and large-scale climate indicators (e.g., El Niño/La Niña indices).

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