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Probabilistic Earthquake Hazard Assessment in Indonesia Using Poisson Model and Spatial Grid Analysis

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Abstract
Indonesia, located at the convergence of three major tectonic plates in the Pacific Ring of Fire (ROF), is highly susceptible to earthquakes. This study analyzes earthquake hazard in Indonesia using a statistical approach based on the Poisson distribution combined with spatial mapping through a $0.5° \times 0.5°$ grid. Earthquake data from the USGS catalog (1925–2025), including time, location, depth, and magnitude, were analyzed. Annual earthquake frequencies were calculated for each grid cell with magnitude ≥ 5.0, and the probability of at least one event occurring within 10, 25, and 50 years was estimated using the Poisson probability function. Results were visualized as spatial probability risk maps for 10-, 25-, and 50-year horizons, enabling the identification of earthquake-prone areas and classification of risk levels. The findings reveal that subduction zones, particularly along the Sunda Arc, exhibit probabilities exceeding 90% for $M \geq 5$ events within the next 50 years, highlighting their significance for disaster preparedness. These results demonstrate that a Poisson-based statistical and spatial approach is effective for probabilistic earthquake hazard mapping and provides direct support for disaster risk reduction and spatial planning in Indonesia.

Keywords
Earthquake Hazard, Poisson Distribution, Spatial Grid, Seismic Probability, Indonesia, Probabilistic Seismic Hazard Assessment (PSHA)

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1. INTRODUCTION

Indonesia is one of the most seismically active regions in the world because of its location at the triple junction of the Indo-Australian, Eurasian, and Philippine Sea Plates within the Pacific Ring of Fire. This tectonic setting exposes the country to frequent and destructive earthquakes that have caused catastrophic human and economic losses, as illustrated by the 2004 Sumatra–Andaman earthquake and tsunami and the 2018 Sulawesi earthquake and tsunami (Socquet et al., 2019). Globally, probabilistic seismic hazard assessment (PSHA) has become the standard framework for quantifying long-term earthquake risk and supporting disaster preparedness since the pioneering work of Cornell (1968). Recent international efforts have significantly advanced PSHA at global and national scales, such as the Global Earthquake Model (GEM) and regional studies in Europe, North America, and Asia (Gerstenberger et al., 2020; Parsons et al., 2018; Ramalho et al., 2022; Scheingraber and Käser, 2020).

Previous works have contributed to earthquake recurrence modeling and hazard estimation. For example, Parsons et al. (2018) developed characteristic magnitude–frequency models for Californian faults, while Scheingraber and Käser (2020) proposed adaptive sampling approaches to capture spatial uncertainties in global hazard mapping. More recently, machine learning methods have been incorporated into seismic hazard studies to improve ground deformation prediction and spatio-temporal forecasting (Usman et al., 2022). However, many of these studies rely on generalized assumptions, limited temporal coverage, or coarse spatial resolution, which limit their direct applicability for disaster risk reduction in Indonesia.

In the Indonesian context, hazard assessments have often used short-term earthquake catalogs or focused on specific regions, resulting in models that cannot fully capture the spatial heterogeneity of seismicity across the archipelago. Furthermore, most global models adopt grid sizes that are too coarse to identify local variations in seismic activity, which are crucial for infrastructure planning and land-use management in a tectonically complex region like Indonesia. Similar GIS-based susceptibility mapping at the local scale in Indonesia demonstrates how fine spatial units improve planning relevance (e.g., a GIS analysis of landslide potential in Lahat, South Sumatra) (Adiwarman et al., 2018).

This study addresses these gaps by applying a century-long earthquake catalog (1925–2025) from the United States Geological Survey (USGS) to construct a probabilistic hazard model tailored for Indonesia. The novelty of this research lies in three aspects: (i) the use of extended historical data covering 100 years, which strengthens the robustness of long-term hazard estimates; (ii) the application of fine-resolution spatial grids (0.5° × 0.5°) that capture localized seismic variability often missed in global-scale studies; and (iii) the integration of a transparent Poisson probability model to produce reproducible estimates of earthquake occurrence over 10-, 25-, and 50-year horizons. By combining statistical rigor with policy-relevant spatial outputs, this study provides practical tools for disaster risk reduction, seismic building code development, and risk-based financial instruments such as earthquake insurance in Indonesia (Khakim et al., 2023).

2. EXPERIMENTAL SECTION

To achieve the research objective of mapping earthquake hazard probabilistically earthquake risk in Indonesia, a quantitative approach based on statistical and spatial analysis is employed (Pothon et al., 2020). This study integrates the use of long-term historical earthquake data, the construction of high-resolution spatial grids, and the Poisson distribution model to estimate the probability of earthquake occurrence over various time periods (Ogata, 2022).

The methodological steps in this study include data collection, spatial processing, calculation of annual frequency statistics, estimation of earthquake occurrence probabilities, and spatial visualization of risk maps. The earthquake catalog serves only as the raw input. Through data cleaning, grid assignment, frequency calculation, and probabilistic modeling, the authors produced new datasets of annual earthquake frequency per grid, probability of occurrence for different time horizons, and spatially explicit risk maps (Akinci, 2010). This transformation of raw catalog data into structured risk indicators ensures that the outcomes are original and can be considered as primary results derived from our research process (Diantari et al., 2018). These research stages are described in detail as follows:

2.1 Study Area Data

Geographically, Indonesia occupies a strategic position in the Pacific Ring of Fire, where the interaction of the Eurasian, Indo-Australian, and Pacific plates generates frequent seismic events (Kaban et al., 2019; Rajif and Syafriani, 2021). The analysis utilizes historical earthquake data from the United States Geological Survey (USGS) for the period 1925 to 2025 (100 years). The dataset includes parameters such as event time, epicenter location (latitude and longitude), depth, and magnitude. The century-long dataset provides a robust statistical basis for estimating long-term annual earthquake frequencies and probabilistic hazard levels (Hutchings and Mooney, 2021; United States Geological Survey (USGS), 2023).

As shown in Figure 1, earthquake epicenters are concentrated along major tectonic boundaries, particularly the Sunda Arc that extends from Sumatra through Java, Bali, and Nusa Tenggara, as well as in the Banda Sea, Sulawesi, and Papua regions. These areas correspond to subduction zones and active fault systems that dominate the tectonic framework of Indonesia. In contrast, regions such as Kalimantan and parts of central Indonesia exhibit relatively few recorded earthquakes, consistent with their intraplate geological setting (Muthahhari et al., 2025). This spatial pattern reflects the highly active seismotectonic environment of Indonesia and highlights the importance of incorporating spatial heterogeneity into probabilistic seismic hazard assessment (Parsons et al., 2018; Scheingraber and Käser, 2020).

2.2 Datasets

The dataset used in this study was obtained from the United States Geological Survey earthquake catalog covering the period 1925–2025 (United States Geological Survey (USGS), 2023). To ensure analytical consistency, only events with a magnitude of M≥5.0 were selected, as these are considered significant for seismic hazard assessment (Shrestha, 2021). Following data acquisition, the catalog was systematically processed by the authors, including filtering, spatial aggregation into 0.5° × 0.5° grids (Wesseloo et al., 2014), statistical calculation, and probabilistic modeling. This procedure transformed the raw catalog into a structured analytical dataset that provides the basis for all descriptive statistics and probabilistic estimations in this study (Greenhough and Main, 2008).

It should be emphasized that the raw USGS catalog served only as input data. All subsequent stages-including magnitude thresholding, spatial aggregation into 0.5° × 0.5° grids, annual frequency estimation, and Poisson probability modeling—were conducted by the authors. While this study estimates occurrence probabilities via a Poisson model, recent PSHA practice emphasizes updated subduction GMMs and epistemic-uncertainty representations that affect shaking levels and hazard curves (Rezaeian et al., 2024). Therefore, the frequency statistics, probability values, and spatial risk maps presented here represent primary results of this study, not secondary reproductions.

As shown in Table 1, the dataset contains earthquake events with magnitudes ranging from 5.0 to above 7.0, distributed throughout Indonesia during 1925-2025. Most events occurred at shallow to intermediate depths, consistent with the tectonic setting of subduction zones and crustal fault systems in the region. This dataset serves as the primary input for subsequent statistical analyses, including spatial grid aggregation, annual frequency estimation, and Poisson probability calculations.

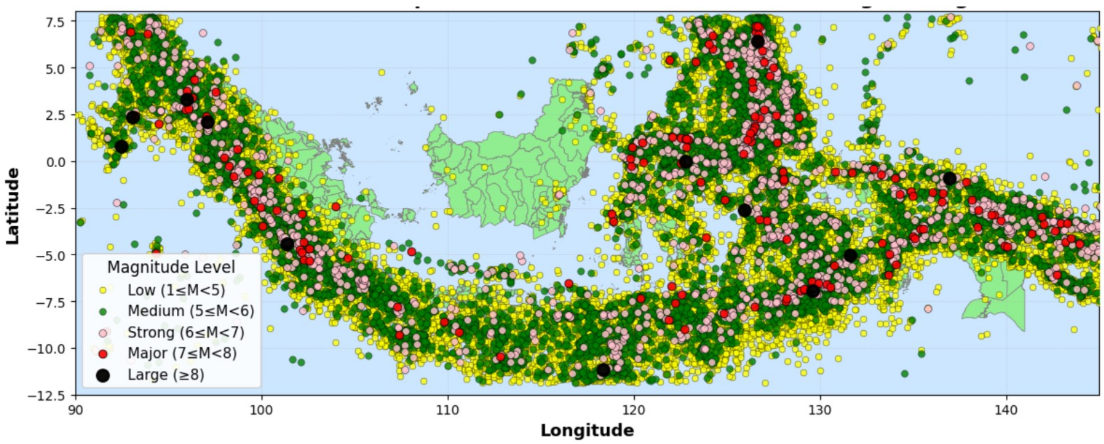

Figure 1. Spatial Distribution of Earthquakes in Indonesia by Magnitude Level, Earthquake Catalog – USGS, 1925–2025

Table 1. Earthquake Events (M ≥ 5.0) in Indonesia, 1925–2025 (Processed from USGS Catalog)

Date	Time	Latitude	Longitude	Depth (km)	Magnitude
1925-06-03	04:42	-3.50	128.00	30.0	6.7
1926-02-21	13:15	-6.20	105.60	40.0	5.5
1927-05-12	21:07	1.80	126.50	30.0	6.1
...	...	...	...	...	...
2023-04-05	08:26	-2.25	140.10	33.0	6.0
2024-09-17	05:33	0.15	122.38	10.0	5.9
2025-05-30	14:09	-7.10	110.25	20.0	5.6

2.3 Method

This study integrates statistical seismology and spatial analysis to transform the earthquake catalog into structured risk indicators. The steps are summarized as follows:

(a) Spatial grid formation. The Indonesian territory was divided into grid cells with a spatial resolution of 0.5° × 0.5°. Each earthquake event with magnitude M≥5.0 was assigned to its corresponding grid cell based on epicenter coordinates.

$$\mathrm{lat}_{b_{in}} = \left\lfloor \frac{\mathrm{lat}}{0.5} \right\rfloor \times 0.5, \quad \mathrm{lon}_{b_{in}} = \left\lfloor \frac{\mathrm{lon}}{0.5} \right\rfloor \times 0.5 \quad (1)$$

The spatial discretization of the study area is defined by Equation (1), which assigns each earthquake event to its corresponding grid cell based on latitude and longitude coordinates. This provides the spatial framework for all subsequent frequency and probability calculations. This discretization provides localized units for statistical computation and hazard estimation (Amaro-Mellado and Bui, 2020). A 0.5° × 0.5° grid was selected as a balance between statistical stability and spatial detail, following previous studies (Wesseloo et al., 2014). Sensitivity tests with 0.25° and 1° grids showed less stable or overly coarse results, respectively.

(b) Statistical aggregation. For each grid cell, descriptive parameters of the recorded events were calculated, including event count, mean, minimum, and maximum magnitude, as well as mean, minimum, and maximum depth. This aggregation yields a structured dataset suitable for frequency and probability analysis.

(c) Annual frequency estimation. For a given grid cell (g_i, g_j), let n_g be the number of recorded earthquake events during the observation period $T = 100$ years (1925–2025). The annual frequency λ_g is given by:

$$\lambda_g = \frac{n_g}{T} \quad (2)$$

The average annual rate of seismic occurrence in each grid cell is calculated using Equation (2), where nnn denotes the total number of earthquake events within the observation period T, and λ represents the expected number of events per year. This parameter represents the average number of earthquake events per year within the grid cell (Baker et al., 2021).

(d) Poisson probability model. The probability of at least one earthquake occurring within a time window t is estimated using the Poisson distribution (Greenhough and Main, 2008):

$$P_{g,t} = 1 - e^{-\lambda_g t} \quad (3)$$

The probability of at least one event occurring within a given time window is determined using Equation (3), where λ is the mean annual rate of occurrence and T

represents the selected time horizon (in years). This equation expresses the cumulative probability of observing one or more events in a Poisson process. The probability was calculated for three planning horizons: 10 years, 25 years, and 50 years, denoted as P_{10yr}, P_{25yr}, and P_{50yr}, respectively (Baker et al., 2021).

(e) Risk classification. Each grid cell was categorized into three risk levels based on the Poisson probability $P_{g,t}$. The classification is defined as:

$$\text{Risk}(g,t) = \begin{cases} \text{High Risk}, & P_{g,t} > 0.9 \\ \text{Moderate Risk}, & 0.5 < P_{g,t} \leq 0.9 \\ \text{Low Risk}, & P_{g,t} \leq 0.5 \end{cases} \quad (4)$$

The probabilistic hazard level for each grid cell is determined according to Equation (4), which categorizes the Poisson probability P into three distinct classes: low ($P \leq 0.5$), moderate ($0.5 < P \leq 0.9$), and high ($P > 0.9$). This classification scheme allows for straightforward interpretation of spatial risk intensity. This classification provides spatially explicit information that can be directly used for disaster mitigation, infrastructure planning, and land-use management. The thresholds of 0.5 and 0.9 were adopted to reflect moderate and high probability levels, respectively, consistent with classifications used in probabilistic hazard studies (Scheingraber and Käser, 2020).

(f) Spatial visualization. The computed probabilities were visualized as spatial risk maps using Python libraries in the Google Colab environment. Separate maps were generated for the 10-, 25-, and 50-year time windows, enabling the identification of earthquake-prone zones (Scheingraber and Käser, 2020).

2.4 Model Validation

Several model validation steps were conducted to ensure the reliability of the results.

(a) Gutenberg–Richter frequency–magnitude relationship. The frequency–magnitude distribution of the processed dataset was compared with the Gutenberg–Richter (G-R) law (Htwe and WenBin, 2009; Letamo et al., 2023):

$$\log_{10} N = a - bM \quad (5)$$

The empirical relationship between earthquake magnitude and cumulative frequency is expressed by Equation (5), which follows the classical Gutenberg-Richter law. This equation quantifies how the logarithm of earthquake frequency ($\log N$) decreases linearly with increasing magnitude (M), reflecting the characteristic distribution of seismic events in active tectonic regions. Where N is the cumulative number of earthquakes with magnitude $\geq M$, a is the seismic activity parameter, and b is the slope describing the relative proportion of small to large events. A linear regression applied to the Indonesian dataset (1925-2025) identified the completeness magnitude at $M_c = 5.0$. The regression yielded $a = 9.235$, $b = 1.01$, and a coefficient of determination $R^2 = 0.998$. These values indicate a balanced proportion of small to large events, consistent with subduction-dominated tectonic environments (Parsons et al., 2018). Figure 2 illustrates the fitted Gutenberg–Richter relationship. The plot shows the characteristic logarithmic decay of earthquake frequency with increasing magnitude, typical of active tectonic regions (Hutchings and Mooney, 2021). The high a-value reflects elevated seismic activity in Indonesia, while the excellent fit (R^2=0.998) confirms the robustness of the Gutenberg–Richter model. Although large earthquakes (M ≥ 7.0) are rare, their catastrophic potential underscores the importance of considering both frequent moderate events and infrequent large events in probabilistic seismic hazard assessments.

(b) Validation of Poisson assumptions. The temporal distribution of earthquake events was analyzed to verify the independence of occurrences and the stationarity of the annual rate λ_g. The century-long dataset (1925–2025) exhibited no significant temporal trend, confirming that the assumptions of independence and stationarity are valid. This supports the use of the Poisson probability model for estimating earthquake likelihood (Greenhough and Main, 2008).

(c) Cross-check of spatial results. Spatial inspection of grid-based outputs was performed to identify cells with unusually high or low frequencies. These outliers were cross-checked against the raw catalog to confirm their tectonic significance rather than artifacts of the gridding process. The results indicate that high-frequency cells align with active subduction zones (e.g., western Sumatra and Java), whereas very low frequencies in regions such as Kalimantan correspond to stable intraplate conditions with minimal seismicity.

(d) Comparison with previous studies Comparison with prior works highlights both similarities and advancements. Parsons et al. (2018) emphasized the value of probabilistic models in capturing fault-specific recurrence, while Scheingraber and Käser (2020) underscored the role of spatial variability in global hazard mapping. More recent approaches, such as Usman et al. (2022) incorporated machine learning into seismic hazard prediction. In contrast, the present study provides two main improvements: (i) the use of a century-long dataset (1925-2025), enabling robust long-term hazard estimates; and (ii) the application of fine-resolution $0.5° \times 0.5°$ grids, which allow localized analysis across Indonesia.

3. RESULTS AND DISCUSSION

The statistical results obtained in this study constitute a primary contribution, as the earthquake catalog was systematically processed by the authors into annual frequency estimates, Poisson probabilities, and spatial risk classifications. To highlight

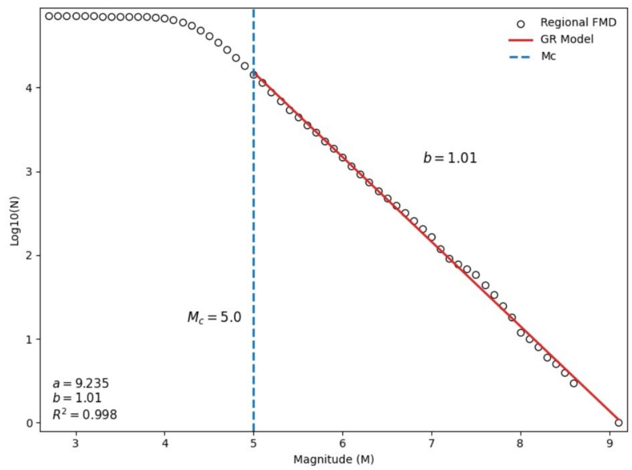

Figure 2. Gutenberg-Richter Frequency-Magnitude Distribution for Indonesia (1925-2025)

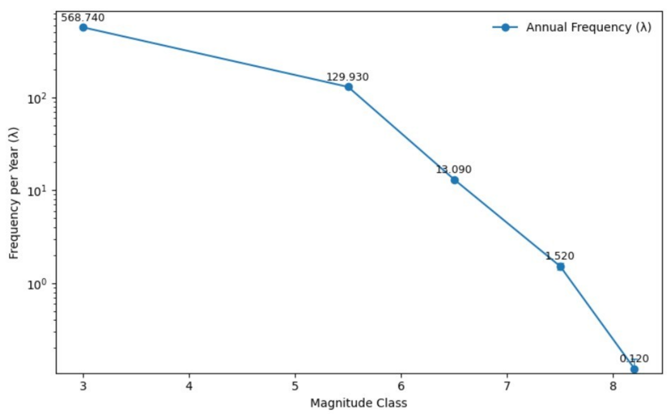

Figure 3. Log-Linear Plot of Annual Earthquake Frequency By Magnitude in Indonesia(1925–2025)

the novelty and advantages of the present work, the following section presents the results in detail and includes a comparison with selected previous studies.

3.1 Earthquake Statistics Per Grid ($0.5° \times 0.5°$)

While our study applies a probabilistic Poisson model with grid-based analysis, recent works highlight the growing role of machine learning for seismic forecasting and eruption prediction (Mandita et al., 2025). Indonesia is situated in the convergence of three tectonic plate boundaries and occupies a geographically unique position referred to as the Ring of Fire, characterized by intense tectonic activity, leading to numerous active volcanoes (Mandita et al., 2025).

Spatial earthquake risk modeling requires the use of a grid-based approach to capture the local distribution of seismic events more representatively. In this study, the Indonesian region was divided into spatial units measuring 0.5° × 0.5° (latitude and longitude) to provide adequate spatial resolution while maintaining statistical stability in the estimations. During the observation period from 1925 to 2025, all earthquake events with magnitude ≥ 5.0 were mapped to grid cells based on the geographic coordinates of their epicenters. For each grid cell, a set of descriptive statistical parameters was calculated, including: event count, average, minimum, and maximum depth, and average, minimum, and maximum magnitude (Amaro-Mellado and Bui, 2020).

This information forms the spatial database required to calculate the average annual frequency of earthquake events per grid cell (λ_g), which serves as the primary input for probability estimation using the Poisson distribution (Greenhough and Main, 2008). The grid-based approach has been widely adopted in seismic hazard studies, as it effectively captures the spatial variation in event frequency and facilitates the integration of spatial analysis into Geographic Information Systems (GIS) for disaster mitigation and spatial planning purposes (Scheingraber and Käser, 2020).

Table 2 presents a summary of statistics from the top observed grid cells. These statistics serve as the basis for identifying areas with high seismic activity that may potentially act as sources of earthquake hazard.

In Table 2, for the grid cell centered at coordinates (-12.0, 116.5), a total of four earthquake events were recorded. The statistics presented are calculated based on the data within this grid cell, as follows: The number of earthquake events (event count) is 4, indicating that four earthquakes occurred within this grid cell during the observation period.

- Mean depth: 33.00 km
- Minimum and maximum depth: 33.0 km and 33.00 km, respectively
- Mean magnitude: 5.03
- Minimum and maximum magnitude: 5.00 and 5.10, respectively

Thus, the grid cell at (-12.0, 116.5) exhibits seismic activity characterized by a depth of 33.00 km and magnitudes ranging from 5.00 to 5.10. From the table above, it can be observed that some grid cells experienced only one earthquake event, while others recorded multiple events. Grid cells with a higher event count indicate areas of more intense and sustained seismic activity. Variations in earthquake depth and magnitude within each grid cell also provide valuable insights into the type and potential impact of the seismic events.

This data serves as the foundation for further analysis, including the calculation of annual earthquake frequency, estimation of the probability of earthquake occurrence over specific time periods, and the mapping of earthquake-prone zones using probabilistic models. The grid-based annual frequencies and probability estimates are newly derived from the authors' systematic processing of the century-long catalog. These values highlight localized seismicity variations across Indonesia that are not visible in the raw catalog. Thus, the tables and maps presented in this section constitute original results generated by our methodological framework.

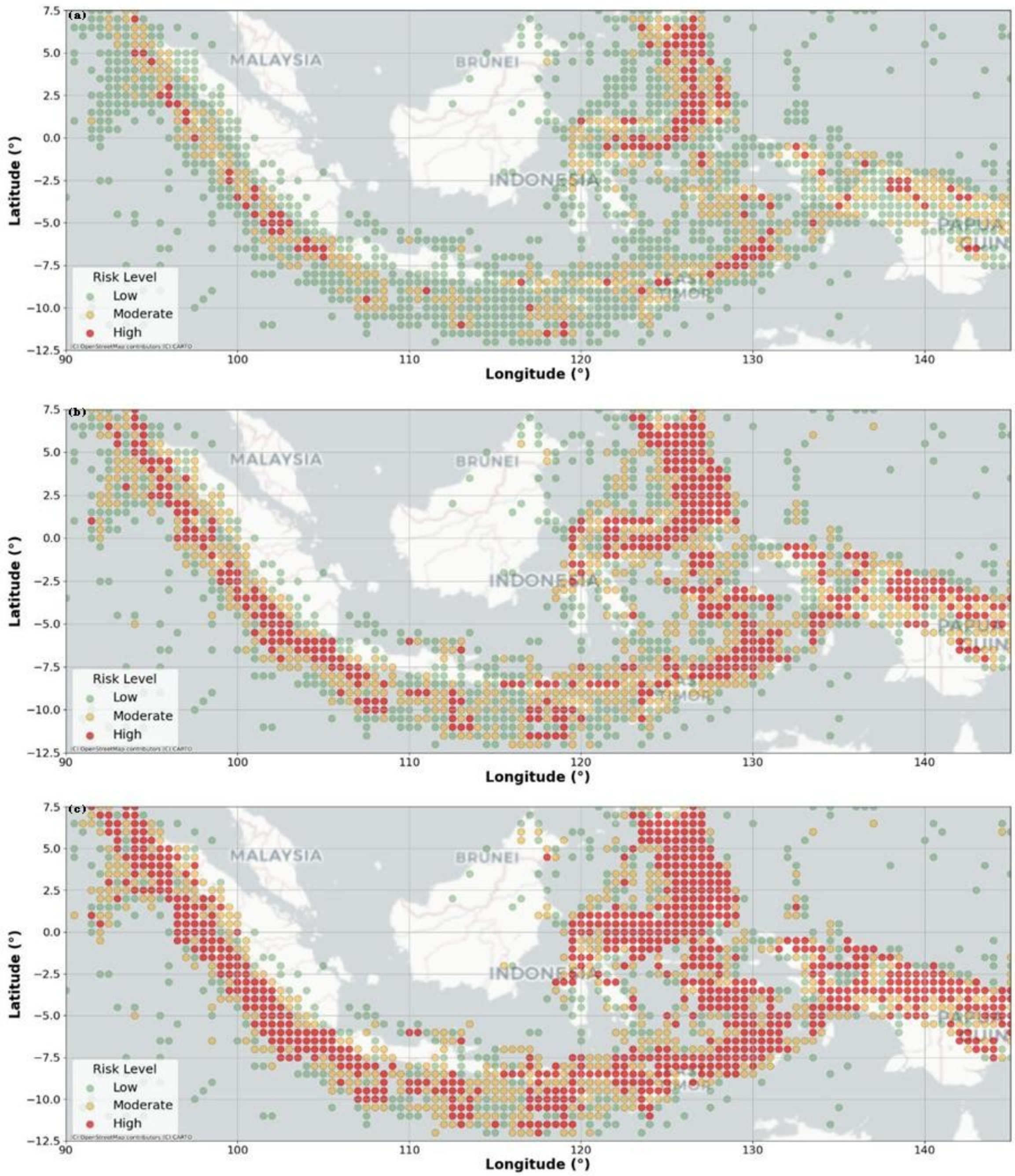

Figure 4. Spatial Probability Maps for Earthquakes with $M \geq 5$ in Indonesia at Different Time Horizons: (a) 10-Year Probability Map, (b) 25-Year Probability Map, and (c) 50-Year Probability Map (Poisson Model, $P = 1 - e^{-\lambda T}$). Probability Classes: Low ($P \leq 0.5$), Moderate ($0.5 < P \leq 0.9$), High ($P > 0.9$). Each dot marks the center of a $0.5° \times 0.5°$ grid cell. Data source: USGS earthquake catalog (1925-2025).

3.2 Magnitude-Frequency Distribution

The frequency–magnitude distribution of earthquake events in Indonesia for the period 1925-2025 is summarized in Table 3. The results show that the majority of earthquakes occur in the magnitude range of 5.0-5.9, while the frequency decreases significantly for higher magnitude classes. This pattern follows the well-established Gutenberg–Richter relationship, which states that earthquake frequency decreases exponentially as magnitude increases (Parsons et al., 2018).

The annual frequency distribution is further illustrated in Figure 3, which depicts the relationship between magnitude class and annual frequency in log-linear scale. The figure con-

Table 2. Earthquake Statistics Per 0.5°×0.5° Spatial Grid in Indonesia (1925-2025)

lat_bin	lon_bin	Event Count	Mag Mean	Mag Min	Mag Max	Depth Mean	Depth Min	Depth Max	Lambda
-12.0	111.5	2	5.05	5.0	5.1	33.0	33.0	33.0	0.02
-12.0	114.5	1	5.20	5.2	5.2	33.0	33.0	33.0	0.01
-12.0	115.0	1	5.40	5.4	5.4	9.1	9.1	9.1	0.01
...	...	...	...	...	...	...	...	...	...
4.0	124.0	1	5.40	5.4	5.4	10.0	10.0	10.0	0.01
4.0	125.0	1	5.50	5.5	5.5	11.0	11.0	11.0	0.01
4.0	125.5	1	5.10	5.1	5.1	33.0	33.0	33.0	0.01

Table 3. Summary of Earthquake Events by Magnitude Classes in Indonesia (1925-2025)

Magnitude Class	Annual Frequency (λ_g)
1.0–4.9	568.74
5.0–5.9	129.93
6.0–6.9	13.09
7.0–7.9	1.52
≥ 8.0	0.12

firms that small to moderate earthquakes (M 5.0–5.9) dominate the catalog, whereas large-magnitude events (M ≥ 7.0) are rare but critical for long-term seismic hazard assessment.

Figure 3 illustrates the relationship between magnitude classes and annual frequency, confirming that the higher the magnitude, the lower the frequency of occurrence. This logarithmic trend, consistent with the Gutenberg–Richter law, forms the basis of probabilistic models in seismic hazard studies. The majority of earthquake events fall within the 5.0–5.9 magnitude class, while higher magnitude events are less frequent but remain critical due to their potential to cause severe damage. This distribution highlights the importance of incorporating both frequent moderate events and rare large events into probabilistic seismic hazard assessment and long-term disaster risk planning.

3.3 Annual Frequency and Poisson Probability

The estimated annual frequencies (λ_g) across grid cells indicate localized variations in seismic activity. For example, some grids along western Sumatra exhibit λ_g >0.1, corresponding to an expected event every 10 years, whereas grids in Kalimantan show $\lambda = 0$. Using the Poisson model, the probability of experiencing at least one event in the next 10, 25, and 50 years was calculated. The results highlight that even regions with moderate λ_g can accumulate substantial long-term probability.

As shown in Table 4, the earthquake statistics vary considerably across the $0.5° \times 0.5°$ grid cells of Indonesia. High event counts and annual frequencies (λ_g) are observed along the Sumatra and Java subduction zones, reflecting their tectonic activity. In contrast, regions such as Kalimantan and parts of southern Papua exhibit very low frequencies, consistent with their intraplate setting. The Poisson probabilities indicate that

Table 4. Annual Frequency and Earthquake Probability Per Grid

lat_bin	lon_bin	count	λ_g	P10yr	P25yr	P50yr
-12.0	111.5	2	0.02	0.181	0.393	0.632
-12.0	114.5	1	0.01	0.095	0.221	0.393
-12.0	115.0	1	0.01	0.095	0.221	0.393
-12.0	116.0	4	0.04	0.330	0.632	0.865
-12.0	116.5	4	0.04	0.330	0.632	0.865
...	...	...	...	...	...	...
7.5	133.5	1	0.01	0.095	0.221	0.393
7.5	134.5	1	0.01	0.095	0.221	0.393
7.5	135.0	1	0.01	0.095	0.221	0.393
7.5	136.5	1	0.01	0.095	0.221	0.393
7.5	137.0	1	0.01	0.095	0.221	0.393

high-risk cells (P >0.9 for 50 years) are concentrated along the Sunda Arc, whereas most of the eastern and central regions remain in the low to moderate risk categories. This spatial variability highlights the importance of grid-based analysis in capturing localized seismic hazard patterns.

3.4 Risk Classification and Spatial Probability Maps

The spatial risk patterns observed in Figure 4 show strong consistency with Indonesia's active tectonic framework. Subduction zones such as the Sunda Megathrust, the Palu–Koro Fault in Sulawesi, and the Papua convergence zone emerge as regions with high probability levels. These patterns are in good agreement with the spatial seismic analyses of Scheingraber and Käser (2020) and Usman et al. (2022), which revealed significant regional variations in seismic hazard across the Indonesian archipelago. High-probability zones align with major plate-boundary systems, whereas intraplate areas such as Kalimantan remain relatively stable with low hazard potential. This spatial consistency confirms the reliability of the Poisson-based probability model in representing long-term seismic potential throughout Indonesia.

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Table 5. Comparison with Previous Studies

Study	Data & Period	Method / Model	Spatial Scale / Resolution & Key Contribution
(Parsons et al., 2018)	California, consensus fault data	Gutenberg-Richter & characteristic models	Fault-specific magnitude-frequency distribution and recurrence estimation
(Scheingraber and Käser, 2020)	Global portfolio sampling	Probabilistic seismic risk analysis with adaptive sampling	Addressed spatial uncertainty in global hazard mapping
(Usman et al., 2022)	Sumatra, 2000–2022	Machine Learning (kNN, RF, NN, GB)	Applied ML to predict earthquake-induced ground deformation
This Study (2025)	Indonesia, 1925–2025 (USGS catalog, processed)	Poisson probability + 0.5°×0.5° grid-based analysis	High-resolution (0.5°×0.5°) probabilistic hazard estimates; long-term (100 years) risk assessment; policy-relevant spatial risk maps

the results of spatial seismic studies by Scheingraber and Käser (2020), which revealed significant regional variations in seismic hazard across the Indonesian archipelago. High-probability zones align with major plate-boundary systems, whereas intraplate areas such as Kalimantan remain relatively stable with low hazard potential. This spatial consistency confirms the reliability of the Poisson-based probability model in representing long-term seismic potential throughout Indonesia.

The probabilistic risk maps developed in this study have direct implications for disaster risk mitigation and policy planning in Indonesia. First, they provide a spatial basis for urban planning and land-use management, by identifying high-probability zones where new settlements or critical facilities should be carefully evaluated. Second, the results inform the development and enforcement of seismic building codes, especially in high-risk regions such as western Sumatra, Java, and Nusa Tenggara, where probabilities exceed 90% within 50 years. Incorporating these probabilistic insights into structural design standards will enhance resilience against future earthquakes. Third, the quantified probabilities offer a transparent foundation for disaster insurance and financial risk transfer mechanisms, such as earthquake insurance premiums and parametric insurance schemes, where risk-based pricing depends on spatially explicit hazard levels. Thus, beyond academic contributions, the findings provide actionable knowledge to support integrated disaster mitigation strategies in Indonesia. In addition to mean values, future versions of this analysis should quantify uncertainty, for example by providing confidence intervals for λ_g and Poisson probabilities. This would help decision-makers understand the range of possible outcomes rather than relying on single-point estimates.

3.5 Comparison with Previous Studies

The statistical results obtained in this study represent a primary contribution, as the earthquake catalog was fully processed into annual frequency vectors, Poisson probabilities, and spatial risk classifications. Previous works have addressed seismic hazard from different perspectives. For instance, Parsons et al. (2018) examined California using Gutenberg–Richter and characteristic models at the fault scale. Scheingraber and Käser (2020) proposed a probabilistic seismic risk framework with adaptive sampling to capture spatial uncertainty at the global level. More recently, Usman et al. (2022) applied machine learning approaches such as kNN, Random Forest, and Neural Networks to analyze earthquake-induced ground deformation in Sumatra, yielding urban-scale insights. In contrast, the present study employs a century-long Indonesian earthquake catalog (1925-2025) to derive robust long-term probabilistic estimates and applies a fine-resolution 0.5° × 0.5° spatial grid. This framework enables the identification of localized seismic hazard variations that are often overlooked in coarser global or regional models. Moreover, by adopting a transparent Poisson probability model, the study produces risk maps that are both statistically rigorous and directly applicable to disaster risk mitigation and spatial planning in Indonesia.

Unlike previous works that relied on secondary compilations or limited catalogs, this study transforms raw seismic records into structured probabilistic indicators. This workflow-from catalog to frequency, probability, and risk maps-ensures originality and establishes the results as primary contributions.

Table 5 summarizes the comparison between this study and previous works. Unlike earlier studies that focused on fault-specific, global, or urban-scale approaches, this research integrates a century-long dataset with fine-resolution grids and a transparent probabilistic model to produce policy-relevant seismic risk maps for Indonesia. This study therefore advances beyond earlier works by producing policy-relevant probabilistic risk maps for Indonesia.

3.6 Limitations

This study assumes temporal stationarity and independence of earthquake occurrences, which are inherent to the Poisson model. In addition, the magnitude threshold was fixed at M ≥ 5.0, and the spatial resolution was constrained to $0.5° \times 0.5°$. These assumptions simplify the modeling process but may overlook clustering effects, smaller magnitude events, and sub-grid heterogeneity. Future work could relax these assumptions by testing alternative thresholds, employing non-Poissonian models, and incorporating multi-scale grid resolutions.

4. CONCLUSIONS

This study converts a century-long USGS catalog (1925-2025) into reproducible, policy-relevant indicators by aggregating events on $0.5° \times 0.5°$ grids, estimating annual rates, and deriving Poisson probabilities of M ≥ 5 over 10, 25, and 50 years. The resulting probability maps delineate persistent high-probability corridors along subduction interfaces and major crustal faults, while interiors generally exhibit lower probabilities-providing a transparent baseline for disaster risk reduction, spatial planning, and risk-transfer applications. Key limitations include potential catalog incompleteness/heterogeneity, the Poisson independence assumption, omission of ground-motion/site effects, and a fixed grid resolution. Future work should incorporate clustered or non-stationary occurrence models (e.g., ETAS/NHPP), link occurrence to hazard via GMPE-based PSHA, quantify epistemic/aleatory uncertainty, test alternative spatial resolutions, and integrate exposure-vulnerability layers to produce loss-based metrics (AAL, PML, TVaR) for decision making.

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