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Forecasting the Unseen: A Stationary Distribution Approach to Earthquake Magnitude Prediction in Bengkulu

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Abstract

Long-term forecasting of earthquake magnitudes plays a vital role in seismic hazard assessment and disaster mitigation, particularly in highly active seismic regions such as Bengkulu, Indonesia. This study introduces a probabilistic framework based on the stationary distribution of discrete-time Markov chains to predict the likelihood of various earthquake magnitudes over an extended period. Historical earthquake records from Bengkulu are categorized into discrete magnitude classes to form the states of the Markov chain. Transition probabilities between these states are estimated from the data, allowing for the construction of a transition matrix that accurately reflects the temporal dynamics of seismic activity. By analyzing the stationary distribution of this Markov chain, we derive the long-term probabilities of occurrence for each magnitude class, revealing inherent patterns in earthquake magnitudes that are otherwise difficult to capture with traditional methods. The stationary distribution serves as a stable, time-independent descriptor of the seismic regime, providing insights into the expected distribution of earthquake magnitudes in the future. The results indicate that this approach not only captures the probabilistic behaviour of seismic magnitudes but also offers a computationally efficient and interpretable model for earthquake forecasting. This modelling technique complements existing seismic hazard assessments and has practical implications for risk management and emergency preparedness in Bengkulu and other seismically active areas. Future research will explore the integration of spatial factors and earthquake depth to further enhance prediction accuracy.

Keywords: earthquake magnitude prediction, stationary distribution, markov chain, seismic hazard assessment, Bengkulu, probabilistic modeling, long-term forecasting

1. Introduction

Bengkulu Province in Indonesia is highly susceptible to seismic activity due to its location along the subduction zone between the Indo-Australian Plate and the Eurasian Plate, a region characterised by frequent and intense earthquakes. This vulnerability is underscored by historical events, such as the significant earthquakes in 2000 and 2007, which highlighted the critical need for effective seismic prediction and hazard assessment in the area (Mase, 2020). The deterministic seismic hazard analysis conducted for Bengkulu City reveals that understanding seismic behaviour through parameters such as peak ground acceleration and spectral acceleration is crucial for developing seismic hazard maps, which can guide structural design and urban planning to mitigate earthquake impacts (Mase, 2020). The broader region of Sumatra, including Bengkulu, is part of the Pacific Ring of Fire, where tectonic interactions have historically led to devastating earthquakes, such as the 2004 Sumatra-Andaman earthquake, which was one of the largest recorded globally and resulted in a catastrophic tsunami (Lay et al., 2005; Sinadinovski, 2006). The earthquake nowcasting framework applied to Sumatra assigns a 34% earthquake potential score to Bengkulu, reflecting the ongoing tectonic stress buildup and the region's seismic progression (Pasari et al., 2021). Despite the high seismicity, Indonesia's social vulnerability to natural hazards remains inadequately assessed, with socioeconomic factors, gender, age, and family structure contributing to the region's vulnerability (Siagian et al., 2014). The development of national seismic hazard maps and the application of models, such as the Cox proportional hazard model, are essential for short- to mid-term earthquake forecasting, which can inform risk reduction strategies and enhance community preparedness (Irsyam et al., 2020; Xu & Burton, 2014). Overall, the integration of seismic hazard analysis, social vulnerability assessment, and predictive modelling is vital for reducing the economic and social impacts of earthquakes in Bengkulu and similar high-risk regions in Indonesia.

Accurate earthquake prediction, especially in terms of magnitude, is crucial for effective disaster risk mitigation, spatial planning, and enhancing the preparedness of communities and government agencies. While numerous studies have focused on forecasting the timing and location of earthquakes, relatively few have addressed the long-term probabilistic forecasting of earthquake magnitudes. Conventional approaches, such as the Gutenberg–Richter law, provide insights into the frequency–magnitude relationship but often fail to capture the stochastic dynamics and transitions between magnitudes over time.

In this context, discrete-time Markov chains offer a promising alternative. By modelling earthquake magnitudes as states within a stochastic process, it becomes possible to estimate transition probabilities between magnitude classes and construct a transition matrix. Analysing the stationary distribution of the Markov chain enables the derivation of long-term probability magnitudes, independent of time, that reflect the stable behaviour of the seismic regime.

This study aims to develop a magnitude prediction model for earthquakes in Bengkulu using the stationary distribution approach of a discrete Markov chain. Through this model, we aim to gain a deeper understanding of the long-term distribution of earthquake magnitudes and contribute to the enhancement of seismic hazard assessments in Indonesia. This study also lays the groundwork for future research that will incorporate spatial factors and earthquake depth to enhance forecasting accuracy further.

2. Literature Review

Earthquake prediction and seismic hazard assessment have been extensively studied, with approaches ranging from deterministic physical models to probabilistic statistical methods. Early studies, such as the Gutenberg-Richter law (Gutenberg & Richter, 1944), established empirical relationships between earthquake magnitude and frequency, laying the foundation for probabilistic seismic hazard analysis (PSHA). Markov chain models have been applied in various geophysical contexts to capture temporal dependencies and stochastic behaviour of seismic events. For instance, Ogata (1988) introduced the use of self-exciting point processes to model earthquake occurrence times, while later studies have incorporated Markovian frameworks to analyze sequences of seismic events and their magnitudes (Vere-Jones, 1995; Zhuang et al., 2002).

The literature on earthquake magnitude prediction, particularly in regions like Bengkulu, highlights a variety of approaches and models that aim to improve forecasting accuracy by incorporating different types of data and methodologies. One significant advancement is the integration of spatiotemporal priors into deep neural networks, as proposed by Liu et al. (2023), which addresses the limitations of historical earthquake samples and the lack of explicit seismic prior Knowledge in machine learning models. This approach utilizes a physics-informed recurrent graph network to extract earthquake precursor data, thereby enhancing the prediction of both magnitude and epicentre by combining event representations with prior Knowledge through activation gates (Liu et al., 2023). Ogata offers another perspective and the importance of using multielement prediction formulas that consider multiple independent precursor anomalies to increase the probability of forecasting large earthquakes despite the historical scarcity of such anomalies (Ogata, 2017). Neely et al. propose the Long-Term Fault Memory (LTFM) model, which accounts for partial strain release and the specific timing of past earthquakes, providing a more realistic probability model that can better forecast earthquake clusters and gaps (Neely et al., 2023). Imoto's work on multidisciplinary observations suggests that considering correlations between different precursory anomalies can significantly enhance earthquake probability estimates, particularly when these anomalies are observed as continuous measurements (Imoto, 2006). The Bayesian approach to earthquake forecasting, as discussed by Petrillo and Zhuang, utilizes the epidemic-type aftershock sequence model to provide probabilistic forecasts, which are more robust than those obtained through maximum likelihood estimation (Petrillo & Zhuang, 2024). Additionally, the ETASI model, applied to the SE Türkiye earthquake sequence, demonstrates its ability to adjust for catalogue incompleteness and accurately predict aftershock sequences, highlighting the importance of local seismicity adjustments (Hainzl et al., 2024). These diverse methodologies underscore the complexity of earthquake prediction and the ongoing efforts to refine models by incorporating various data types and statistical techniques to improve forecast accuracy and reliability.

Despite these advances, relatively few studies have focused explicitly on modelling earthquake magnitude distributions in specific regions using stationary Markov chain methods. Furthermore, many regional studies have concentrated on temporal occurrence patterns rather than magnitude forecasting. This research fills this gap by applying a stationary distribution approach to earthquake magnitude prediction in Bengkulu, integrating local seismic data to derive probabilistic long-term forecasts. This approach aligns with growing interest in stochastic modelling techniques to enhance seismic risk assessment and improve disaster preparedness strategies.

3. Materials and Methods

3.1. Materials

This study utilizes earthquake data and computational tools to analyze seismic activity patterns in the Bengkulu region using a discrete-time Markov chain model. The materials encompass the research object, geographic area, data sources, and analysis tools. The primary object of analysis is the magnitude of earthquakes occurring in Bengkulu Province, Indonesia. The following coordinates define Bengkulu's geographic boundaries:Westernmost longitude: 100.6°, Easternmost longitude: 103.8°, Southernmost latitude: -5.72°, and Northernmost latitude: -2.28°. The earthquake data used in this study covers the period from January 2021 to May 2025.

Earthquake data from the official portal of the Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG). From this dataset, only the magnitude variable was extracted for further analysis, while other variables (e.g., location, depth, time) were used solely for preprocessing. To ensure spatial consistency with the actual administrative region of Bengkulu, OpenStreetMap data, accessed via the OSMnx Python library (Boeing, 2017), is used for the filtering process. This process involved: (i) Retrieving the polygon boundary for the Bengkulu region. (ii) Filtering the earthquake dataset to include only events whose epicentres fall within the official boundary of Bengkulu. (iii) This approach ensures that the dataset accurately reflects seismic activity specific to Bengkulu Province. Administrative region of Bengkulu from OpenStreetMap data can bee seen in Figure 1.

Figure 1: Administrative region of bengkulu province

To prepare the data for Markov chain modelling, earthquake magnitudes were categorized into discrete intervals according to seismic classification standards. These categories serve as the states in the Markov chain model can be seen in Table 1.

Table 1: Earthquake magnitude classification and associated impact categories

Magnitude Range	Earthquake Category	General Description
< 2.0	Micro	Not felt by humans
2.0 – 2.9	Very Small	Rarely felt, usually detected by instruments only
3.0 – 3.9	Small	Occasionally felt, especially near the epicenter
4.0 – 4.9	Light	Felt by many people, minimal damage
5.0 – 5.9	Moderate	Can cause light to moderate damage
6.0 – 6.9	Strong	Can cause moderate to severe damage
7.0 – 7.9	Very Strong	Causes severe damage across wide areas
8.0 – 8.9	Great	Extremely severe and widespread damage
≥ 9.0	Mega	Massive destruction and catastrophic disaster

Each earthquake event was assigned to one of these categories (see Table 1), and transitions between categories over time were analyzed as part of the Markov process. The data processing, filtering, classification, and analysis were carried out using the Python programming language.

3.2. Methods

A discrete-time Markov chain, as described in (Osaki, 2012), is defined as a stochastic process $\{X(n), n = 0,1,2,..\}$ with state space $\{0,1,2,...\}$, which satisfies the Markov property: the probability of transitioning to the next state depends only on the current state and not on the full history of past states. Formally, the transition probabilities satisfy

$$P\{X(n+1) = j | X(0) = i_0, X(1) = i_1, \dots, X(n-1) = i_{n-1}, X(n) = i\}$$

$$= P\{X(n+1) = j | X(n) = i\} = p_{ij}. \tag{1}$$

for all $i_0, i_1, \ldots, i_{n-1}, i, j$, and for every n. Here, p_{ij} is the one-step transition probability from state i to state j. The notation $X(n) = i$ indicates that the process is in state i at time n. This conditional probability encapsulates the memoryless property characteristic of Markov chains, where the future depends solely on the present state.

All these transition probabilities can be organized into a one-step transition probability matrix $\mathbf{P} = [p_{ij}]$, structured as follows:

$$\boldsymbol{P} = [p_{ij}] = \begin{bmatrix} p_{00} & p_{01} & p_{02} & \cdots & p_{0n} \\ p_{10} & p_{11} & p_{12} & \cdots & p_{1n} \\ p_{20} & p_{21} & p_{22} & \cdots & p_{2n} \\ \cdots & \cdots & \cdots & \vdots & \vdots \\ p_{n0} & p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix}. \tag{2}$$

with each element $p_{ij} \geq 0$, and the sum of probabilities in each row equals one:

$$\sum_{j=0}^{n} p_{ij} = 1, (\forall i = 0,1,2,3 \ldots, n). \tag{3}$$

If the transition probabilities do not depend on time (homogeneous Markov chain), meaning the probability of moving from one state to another remains constant over time steps, then the chain may admit a stationary distribution.

To analyze long-term behavior, it is essential that the chain is *irreducible*, meaning all states communicate with each other, that is, it is possible to reach any state from any other state in a finite number of steps with positive probability. This ensures the state space is fully connected and there are no isolated states.

Another important property is *aperiodicity*. The period of a state i is defined as

$$d(i) = gcd\{n \geq 1 | p_{ii}^n > 0\}. \tag{4}$$

where p_{ii}^n is the probability of returning to state i after exactly nnn steps. If $d(i) = 1$, state i is said to be aperiodic, meaning the return times to i do not occur in strictly periodic intervals (Privault, 2013). Since irreducibility guarantees communication between states, if one state is aperiodic, then all states in the chain are aperiodic.

Next, the concepts of recurrence and positive recurrence play a central role. A state i is recurrent if

$$\sum_{n=1}^{\infty} p_{ii}^n = \infty. \tag{5}$$

which means the process returns to state i infinitely often with probability one (Privault, 2013). As described in (Osaki, 2012), if the expected return time (mean recurrence time) μ_i is finite,

$$\mu_i < \infty. \tag{6}$$

then the state i is positive recurrent.

When the chain is irreducible and all states are positive recurrent, the entire chain is said to be positive recurrent. Several important results follow: if a state i is recurrent and communicates with state j, then j is also recurrent; furthermore, the periods of communicating states are equal, meaning $d(i) = d(j)$ if i and j communicate. For chains that are irreducible, positive recurrent, and aperiodic, the long-term behavior of transition probabilities stabilizes. Specifically, the n-step transition probabilities

$$p_{ij}^n = P(X_n = j \mid X_0 = i), \tag{7}$$

converge as $n \to \infty$ to a positive limit independent of the initial state i:

$$lim_{n\to\infty} p_{ij}^n = \pi_j > 0. \tag{8}$$

This vector $\pi = (\pi_0, \pi_1, \pi_2, \ldots)$ is called the stationary distribution, which uniquely satisfies the system of equations

$$\pi_j = \sum_{i=0}^{\infty} \pi_i p_{ij} \text{ with } \sum_{j=0}^{\infty} \pi_j = 1. \tag{9}$$

In other words, π_j represents the long-run proportion of time the process spends in state j, providing a probabilistic equilibrium of the Markov chain that is independent of the starting state. Additionally, for recurrent and aperiodic states, the n-step transition probabilities satisfy

$$lim_{n\to\infty}\, p_{ij}^{n} = \frac{1}{\mu_j}. \quad (10)$$

where μ_j is the mean recurrence time of state j.

4. Results and Discussion

4.1. Data Analysis

The seismic activity in Bengkulu, as shown in a heatmap, is visible in Figure 2. This visualization employs a colour gradient, ranging from green (low density) to red (high density), to represent the spatial distribution of earthquake epicentres.

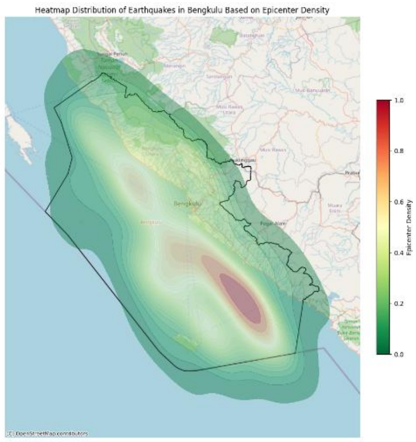

Figure 2: Heatmap distribution of earthquakes in Bengkulu based on epicenter density

The figure shows that the southwestern part of the Bengkulu mainland, especially near the coastline, has the highest epicentre density. The red zone gradually transitions to orange, yellow, and green as we move inland and toward the northern and southern parts of the province. This pattern strongly indicates that the southwestern coastal area is the most seismically active zone in Bengkulu, which is consistent with the tectonic behaviour of the Sunda Megathrust subduction system off the western coast of Sumatra. To further explore spatial and magnitude distributions, a second visualization plots epicentres with colour codes based on earthquake magnitude (see Figure 3).

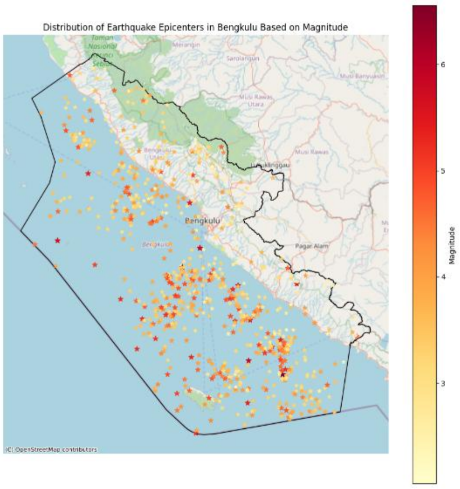

Figure 3: Spatial distribution of earthquake epicentres categorized by the magnitude

The map reveals that most epicentres are located offshore (see Figure 3), particularly to the west and southwest of Bengkulu, forming a linear pattern aligned with the coast. High-magnitude earthquakes (depicted in red and orange) are concentrated in this offshore region, suggesting the presence of an active subduction zone or undersea fault system. Lower-magnitude events (yellow tones) are more widespread, extending inland and to peripheral coastal waters.

The magnitude distribution was also analyzed using a histogram with a kernel density curve, as shown in Figure 4**.**

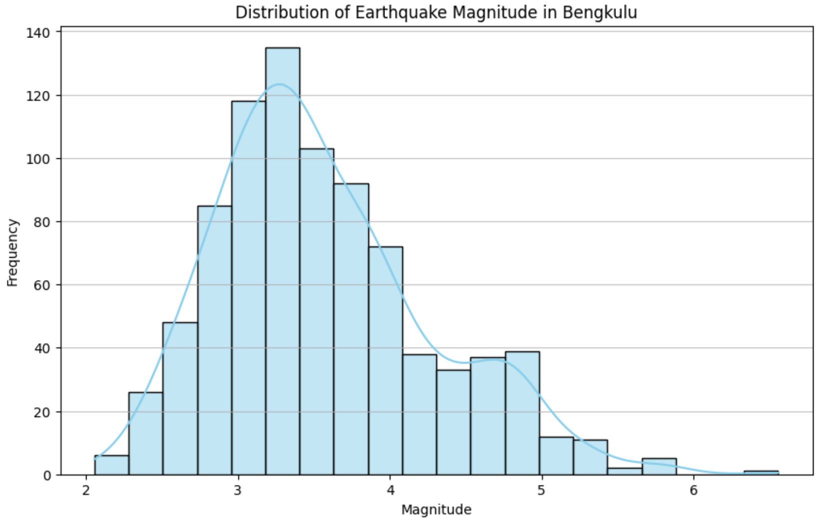

Figure 4: Histogram of earthquake magnitudes with kernel density estimate

Figure 4 indicates that the magnitude distribution follows a slightly right-skewed bell-shaped pattern. Most earthquakes fall within the M3.2–M3.5 range, with a noticeable decline in frequency as magnitude increases. However, the extended right tail signifies that while large-magnitude earthquakes (M6+) are infrequent, they do occur and cannot be ignored when assessing seismic risk in the region. To complement this analysis, Table 2 presents the frequency of earthquake events categorized by magnitude classes. These categories range from Micro to Mega, as shown in Table 2.

Table 2: Frequency of earthquakes by magnitude category

Category	Frequency
Micro	0
Very Small	182
Small	480
Light	170
Moderate	30
Strong	1
Very Strong	0
Great	0
Mega	0

As shown in Table 2, no earthquake occurrences were recorded in the Micro, Very Strong, Great, or Mega categories during the observation period. The highest number of events falls under the Small category, followed by Very Small and Light. Only one event was recorded in the Strong category.

Finally, a categorical bar chart was constructed to visually depict the distribution of earthquake frequencies across the main magnitude categories. Figure 5 presents this chart, highlighting the dominance of low to moderate magnitude events in the Bengkulu region.

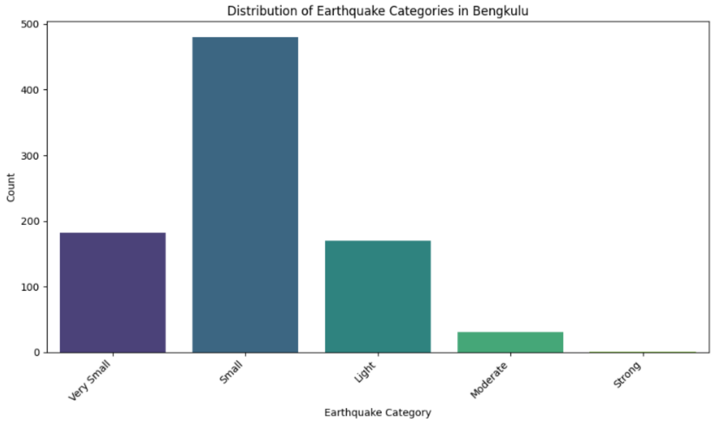

Figure 5: Frequency of earthquake events by category

From Figure 5, it is clear that the “Small” category dominates with nearly 480 recorded events, followed by “Very Small” (~180 events) and “Light” (~160 events). “Moderate” and “Strong” earthquakes are relatively rare, with the latter being almost negligible. This distribution reflects a seismically active region that predominantly experiences low to moderate seismic events, which is typical of tectonic zones where stress is frequently released through frequent, small-magnitude earthquakes.

4.2. Markov Chain Model Construction

In this study, earthquake magnitudes in the Bengkulu region were classified into nine magnitude classes, labeled K0 to K8. However, based on exploratory data analysis and transition patterns, only classes K1 through K4 exhibit significant and meaningful transition probabilities for Markov chain modeling. Additionally, the exclusion of class K5 eliminates deterministic transitions that cause periodicity, thus ensuring the chain is both irreducible and aperiodic.

The transition probability sub-matrix used is as seen in Table 3.

Table 3: The transition probability

From / To	K1	K2	K3	K4
K1	0.3094	0.4972	0.1657	0.0276
K2	0.2000	0.5458	0.2125	0.0396
K3	0.1588	0.6412	0.1824	0.0176
K4	0.1000	0.5667	0.2333	0.1000

This transition matrix represents the probability of moving from one magnitude class to another in the next time step. The diagonal dominance (self-transitions) observed in the matrix implies a tendency for magnitudes to persist within the same class or move to nearby classes. State transition diagram can bee seen in Figure 6.

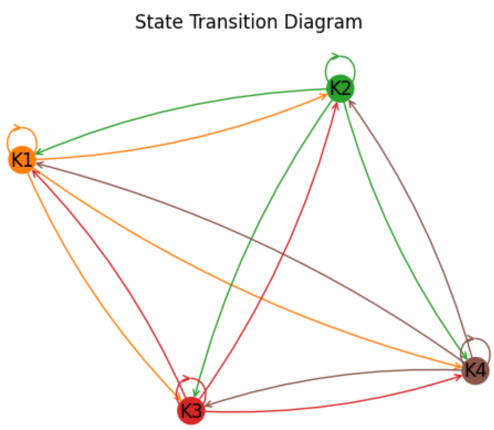

Figure 6: State transition diagram

A Markov chain is irreducible if it is possible to reach any state from any other state in a finite number of steps with positive probability, as seen in Figure 6. In this matrix, since every state K1, K2, K3, and K4 has non-zero transition probabilities leading to at least one other state, and through repeated transitions, it is possible to move between any pair of states. For example, from K1 you can move directly to K2 (0.4972), and from K2 to K3 (0.2125), and from K3 to K4 (0.0176), and vice versa. This interconnectedness means the chain forms a single communicating class, ensuring irreducibility. This property is important because irreducibility guarantees the Markov chain does not decompose into isolated subsets, which ensures a unique stationary distribution exists over the entire state space.

A state in a Markov chain is aperiodic if it can return to itself at irregular time steps, i.e., the greatest common divisor (gcd) of the number of steps in which the state can be revisited is 1. A chain is aperiodic if all states are aperiodic. In this matrix, the diagonal elements (self-transition probabilities) are non-zero for all classes (e.g., 0.3094 for K1, 0.5458 for K2, etc.). This means the chain can remain in the same state in the next step. Because of these self-loops, the gcd of return times for each state is 1, hence the chain is aperiodic. Aperiodicity prevents cyclic or oscillatory behavior in the chain and is essential for the convergence of the Markov chain to a unique stationary distribution regardless of the initial state.

A state is recurrent if, starting from that state, there is a probability of 1 that the process will return to it eventually. Since the chain is finite and irreducible, all states in this Markov chain are recurrent (more specifically, positive recurrent). Positive recurrence means the expected return time to each state is finite. This ensures the system does not "escape" to infinity or get trapped in transient states and stabilizes over time.

The combination of irreducibility, aperiodicity, and positive recurrence means that the Markov chain possesses a unique stationary distribution π, which describes the long-term behavior of earthquake magnitudes.

4.3. Stationary Distribution

The stationary distribution $\pi = [\pi_1, \pi_2, \pi_3, \pi_4]$ represents the long-run probabilities of the Markov chain residing in each magnitude class, assuming the system has reached equilibrium. It satisfies the balance equation (9), where **P** is the transition matrix shown in Table 3. Since this Markov chain is irreducible, every state can be reached from any other state. This ensures that there are no isolated subsets of states and guarantees the existence of a unique stationary distribution. Because the chain is aperiodic (there is a non-zero probability of returning to the same state in one step), the stationary distribution π is also the limiting distribution of the state probabilities after infinitely many iterations. Since the chain is finite and irreducible, all states are positive recurrent. This means the stationary distribution π represents the stable long-term probabilities of the system being in each state.

Solving this system yields the stationary distribution as follows:

Table 4: Stationary probability

Magnitude Class	Stationary Probability
K1	0.1567
K2	0.4392
K3	0.2881
K4	0.1160

This result indicates that in the long term, the earthquake magnitudes in Bengkulu are most likely to fall within class K2 (e.g., magnitude 5.0–5.4), with a probability of approximately 44%. Classes K3 and K1 also show substantial probabilities, while class K4 has a smaller but still notable likelihood.

The stationary distribution confirms the predominance of moderate earthquakes in the region, consistent with the tectonic setting of the Bengkulu area. Earthquake magnitudes are more likely to remain within moderate ranges rather than escalate to higher classes, although those occurrences still exist but with lower probabilities.

4.4. Discussion

The Markov chain model, which uses only magnitude classes K1 through K4, shows that earthquakes in Bengkulu tend to transition probabilistically among these mid-range magnitude classes. This means that earthquakes do not get "stuck" at a single magnitude class but fluctuate within this range over time.

The chain's aperiodicity indicates that these magnitude transitions do not follow a fixed periodic cycle. As a result, the long-term distribution of earthquake magnitudes is stable and does not exhibit cyclic oscillations, which is crucial for making realistic long-term magnitude predictions. The positive recurrence property ensures that each magnitude class will be revisited in a finite expected time, making the stationary distribution a meaningful representation of the long-term probability of earthquakes occurring within each magnitude class.

Practically, this model highlights that moderate-magnitude earthquakes—which often cause moderate damage—are the most common in Bengkulu. While larger magnitude events (class K4) are rare, they still require attention due to their potentially profound impact.

Compared to traditional approaches, such as the Gutenberg-Richter law, which focuses mainly on earthquake frequency, the Markov chain model explicitly captures the dynamics of magnitude transitions over time, offering a more comprehensive view of seismic behaviour. However, this model currently does not incorporate the spatial and depth factors of earthquakes, which are known to influence seismic activity in the region significantly. Future work incorporating these factors is expected to improve prediction accuracy.

5. Conclussion

This study developed a discrete-time Markov chain model based on earthquake magnitude classes K1 to K4 to analyze the long-term seismic behavior in the Bengkulu region. The results demonstrate that the Markov chain is irreducible, aperiodic, and positive recurrent, which guarantees the existence of a unique and stable stationary distribution. This stationary distribution effectively represents the long-term probabilities of earthquake magnitudes occurring within each class.

The findings reveal that moderate-magnitude earthquakes (within classes K2 and K3) are the most frequent in Bengkulu, consistent with the region’s tectonic setting dominated by subduction zone activity. Although large-magnitude earthquakes (class K4) occur less frequently, their presence remains critical due to the potential for significant damage and hazard implications.

Compared to conventional seismic models such as the Gutenberg-Richter law, the Markov chain approach adds an important temporal dimension by explicitly modelling the transitions between different magnitude classes. This dynamic view of magnitude evolution provides deeper insight into earthquake occurrence patterns and better supports probabilistic hazard assessment. However, the current model has limitations, particularly in ignoring spatial heterogeneity and earthquake depth variations that strongly influence seismicity patterns. Integrating these factors in future studies will likely enhance model accuracy and reliability.

Overall, this Markov chain framework offers a valuable tool for seismic risk assessment and long-term earthquake forecasting in Bengkulu. It can support local authorities and disaster management agencies in preparing more effective mitigation strategies, ultimately contributing to improved public safety in this seismically active region.

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