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Bayesian Inference and Logistic Regression Based Modeling for Earthquake Probability Estimation in East Java

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Abstract:
East Java is one of the most seismically active regions in Indonesia, making earthquake-related disaster mitigation research essential for a deeper understanding of seismic risk. However, existing earthquake modeling studies often focus solely on predictive modeling without fully integrating probabilistic risk assessment and earthquake parameter analysis, thus limiting the comprehensiveness of seismic risk interpretation for disaster mitigation planning. To address this gap, this study proposes a two-stage statistical framework that integrates probabilistic modeling with earthquake parameters. The first stage applies Bayesian inference to estimate the daily probability of an earthquake occurring from 2014 to 2024, yielding an average probability of 13.5% with a 95% credible interval of 12−14%. The second stage employs a logistic regression model which achieved the lowest AIC = 6, indicating a reliable model for estimating the likelihood of moderate to large earthquakes. Magnitude and depth were identified as statistically significant predictors confirming their strong influence on earthquake likelihood ($p = 2 \times 10^{-16}$, $\alpha = 0.05$; 95% $confidence\ level$). Based on the model, high-risk earthquake events are predominantly concentrated in the southern part of East Java. By integrating probabilistic modeling with parameter-based prediction, this framework provides a quantitative and operational foundation for enhancing early warning systems. The practical contribution of this study lies in its ready-to-implement statistical framework, which can directly support disaster mitigation strategies and policy decision-making in vulnerable regions.

Keywords: Bayesian Inference; Logistic Regression; Earthquake Probability; Seismic Risk Assessment; East Java.

Introduction

Indonesia's position in the Pacific Ring of Fire places it among the most seismically active regions in the world, making the country prone to natural disasters such as volcanic eruptions, floods, and earthquakes [1]. Earthquakes pose a particularly significant threat due to their sudden occurrence and potential for widespread damage. According to the Richter Scale, earthquakes with a magnitude of ≥ 5.0 can cause damage locally, while those with a magnitude of ≥ 6.0 can affect areas up to 100 kilometers [2]. The Bawean earthquake on March 22, 2024, served as a critical reminder of this threat, occurring in a region previously considered to have low seismic activity. This event highlights the possibly underestimated seismic vulnerability of East Java.

East Java is intersected by several active fault lines, including the Baribis-Kendeng Fault, the Pasuruan Fault, the Bawean Fault, and the Probolinggo Fault [3, 4, 5]. These faults are associated with the subduction of the Indo-Australian Plate beneath the Eurasian Plate south of Java, emphasizing the urgent need for robust, data-driven seismic risk assessments in the region [6]. A probabilistic framework is essential for modeling seismic uncertainty and supporting effective disaster mitigation strategies. Bayesian inference is a powerful approach for this purpose, as it combines prior knowledge with observational data to generate updated posterior probabilities [7]. Although widely applied in other scientific fields, such as materials science and geotechnical engineering, its application to daily earthquake probability modeling in Indonesia remains limited [8, 9]. Bayesian inference is particularly suitable for quantifying the inherent uncertainty of earthquake events and has been successfully used in probabilistic hazard assessments, including tsunami hazard analysis in Italy [10]. Recent studies in Indonesia have also employed Bayesian simulation integrated with the

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Gutenberg–Richter model and the Copula method to estimate earthquake probabilities and recurrence periods, demonstrating the suitability of probabilistic approaches for local seismic risk assessment [11]. However, these studies primarily focus on geophysical relationships, such as magnitude–frequency interactions, and do not yet extend toward daily probabilistic forecasting or event classification frameworks.

In contrast, earthquake prediction research in East Java has largely adopted deterministic modeling approaches. For example, a study applied Random Forest with feature selection to predict earthquake occurrences, achieving high predictive accuracy but producing only deterministic classifications without quantifying uncertainty [12]. Similarly, an ARIMA time-series model was used to forecast earthquake counts in East Java [13]. While these methods provide valuable frequency-based insights, they lack the capacity to incorporate probabilistic uncertainty or identify statistically influential parameters that directly support mitigation planning.

Building upon these gaps, logistic regression offers a more interpretable and statistically grounded alternative for binary event prediction and parameter influence analysis. It has been successfully integrated with advanced computational methods methods—such as kernel-based approaches—for enhanced prediction performance in fields like biomedical compound classification, demonstrating its adaptability within hybrid probabilistic frameworks [14].

Hence, this study employs logistic regression alongside Bayesian inference to develop an integrated two-stage statistical framework that quantifies earthquake probability while identifying the key seismic parameters driving event likelihood. This integration enables a more comprehensive, data-driven assessment of seismic risk, offering a practical foundation for early warning systems and mitigation strategies in East Java.

Materials and Methods

Materials

The dataset used in this study consists of 544 seismic events recorded over 4018 days (2014–2024) in East Java Province. Data were obtained from the official BMKG account (@infoBMKG) on the X platform. Each record includes five core seismic parameters commonly used in regional seismic modeling [15, 16]:

1. Magnitude : earthquake strength on the Richter scale.
2. Depth : focal depth (km), indicating rupture origin depth.
3. Latitude : epicentral coordinates.
4. Longitude : epicentral coordinates.
5. Location : a categorical variable derived from BMKG location fields.

All data handling, modeling, and visualization were primarily conducted in R version 4.2.2, using the following packages: stats, ggplot2, car, and dplyr. Additionally, for visualization of the predicted logistic regression probabilities in the form of bubble plots, Python (Google Colab) was employed using the pandas, matplotlib, seaborn, and numpy libraries.

Method

A two-stage modeling approach was employed to estimate and predict the probability of earthquake occurrences in East Java Province. In the first stage, Bayesian inference was used to estimate the daily probability of earthquake occurrence. The data were treated as a continuous time series in which all events contributed to constructing the prior and likelihood functions. The posterior probability of the parameter given the data is defined as [17]:

$$P\ (\theta|D) \propto P(\theta) \times\ P\ (D|\theta) \qquad (1)$$

where $P\ (\theta|D)$ is the posterior probability of parameter (θ) given data (D), $P(\theta)$ is the prior distribution, and $P\ (D|\theta)$ is the likelihood of data given (θ).

The prior distribution was chosen as a Beta distribution to encode prior beliefs about earthquake occurrence probabilities, justified by its conjugacy with the Bernoulli likelihood function, which models the binary nature of earthquake occurrence (occurred or not). Previous studies have demonstrated the application of Beta–Bernoulli models in settings with binary or proportion data, including spatial environmental and ecological studies [18]. In addition, the statistical rationale for using a Beta prior with a Bernoulli likelihood is well-established: the Bernoulli likelihood belongs to the exponential family, and the Beta distribution serves as its conjugate prior, providing analytical tractability and interpretable posterior estimates [19]. The posterior distribution therefore follows a Beta distribution as well [20]:

$$(\theta|D) \sim Beta(\alpha + k, \beta + N - k) \qquad (2)$$

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where α and β are prior parameters, k is the number of earthquake occurrences, and N is the total observation days. The prior parameters α and β were selected based on historical regional seismicity to reflect realistic prior beliefs. From the posterior distribution, the mean was used as a point estimate, and the 95% credible interval provided an uncertainty measure.

The second stage involves logistic regression, the dependent variable (Y) was defined as a binary classification of earthquake magnitude, defined as follows:

$$Y = \begin{cases} 0, & if\ 2.0 \le Magnitude \le 3.9 \\ 1, & if\ Magnitude\ > 3.9 \end{cases}$$

The independent variables (X_i) used in the model are:

$X_1 = Magnitude$
$X_2 = Depth$
$X_3 = Latitude$
$X_4 = Longitude$
$X_5 = Location$

The logistic regression model used to estimate the probability (P) of a moderate-to-major earthquake occurrence is formulated as [21]:

$$logit(P) = \ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i \qquad (3)$$

The significance of each predictor coefficient (β_i) on the dependent variable was evaluated using the *Wald test*, with a significance level of $p - value < 0.05$ and a 95% confidence interval [22]. Model selection was based on the *Akaike Information Criterion (AIC)*, where the smallest *AIC* value indicates the most parsimonious model that balances goodness of fit and model complexity [23]. Predictor stability and the absence of multicollinearity were verified using the *Variance Inflation Factor (VIF)*, where $(VIF < 10)$ meaning that all predictor variables were sufficiently independent and contributed unique information to the model [24].

The two-stage framework is designed to provide a comprehensive risk assessment. The Bayesian stage estimates the daily probability of any earthquake occurring, while the logistic regression stage predicts the probability of significant events based on specific parameters. This creates an analytical pipeline from general frequency estimation to specific event characterization

Result and Discussion

Result of Bayesian Inference Model

Using the Bayesian inference framework defined in Equation (1) and the Beta–Bernoulli posterior distribution (Equation 2), the model estimated the posterior probability of daily earthquake occurrence in East Java. The posterior simulation results are shown in **Figure 1**.

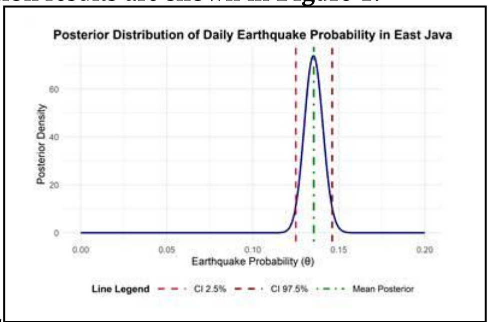

Figure 1. Posterior distribution of daily earthquake probability in East Java with 95% credible interval and posterior mean

The posterior mean probability for East Java was 13.5% (95% credible interval: 12–14%), meaning that the likelihood of at least one earthquake occurring on any given day is approximately one in seven days. This demonstrates the Bayesian model's capacity to integrate prior information and observed data, producing a realistic and updatable assessment of seismic risk.To capture spatial variation, the model was extended across three regional zones based on BMKG Karangkates seismic classification, defined as follows:

1. Region 1 (High Risk): Pacitan, Trenggalek, Tulungagung, Blitar, Malang, Lumajang, Jember, Banyuwangi.

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2. Region 2 (Moderate Risk): Ngawi, Madiun, Ponorogo, Nganjuk, Jombang, Mojokerto, Gresik, Sidoarjo, Surabaya, Pasuruan, Probolinggo, Situbondo, Bondowoso.
3. Region 3 (Low Risk): Tuban, Bojonegoro, Lamongan, and Madura Island.

The Bayesian model was then applied to each regional zone to estimate localized earthquake probabilities based on the same inferential framework. The regional posterior outcomes, illustrated in **Figure 2**, demonstrate clear spatial variations across East Java.

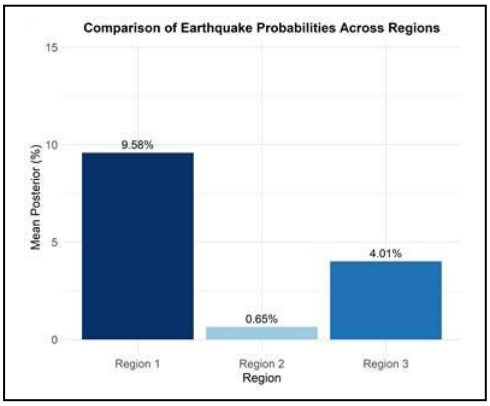

Figure 2. Regional Distribution of Posterior Earthquake Probabilities in East Java

The posterior probability outputs presented in **Figure 2** revealed distinct regional patterns:
1. Region 1: 9.03% (95% credible interval: 8.76–9.29%) → approximately one earthquake every 11 days.
2. Region 2: 0.68% (95% credible interval: 0.52–0.83%) → approximately one earthquake every 147 days.
3. Region 3: 4.01% (95% credible interval: 3.85–4.15%) → approximately one earthquake every 25 days.

These results confirm a clear gradient of seismic activity, with the southern coastal belt (Region 1) experiences the most frequent earthquakes due to its proximity to the Indo-Australian subduction zone, while the central and northern areas (Regions 2 and 3) show lower but non-negligible risks linked to local fault systems such as Baribis–Kendeng, Waru, and Probolinggo. The moderate activity detected in Region 3 indicates possible under-monitored seismic sources, demonstrating the Bayesian model's advantage in revealing hidden seismic potential beyond static tectonic classifications.

From a practical standpoint, these findings support data-driven disaster planning: the southern zone warrants structural reinforcement and intensive monitoring; the central zone requires preparedness for sporadic but potentially strong events; and the northern zone needs improved fault mapping and sensor coverage. Overall, Bayesian inference provides a probabilistic foundation for understanding earthquake risk in East Java—bridging quantitative modeling with actionable regional mitigation insight.

Result of Logistic Regression Model

The second stage of analysis employed the logistic regression model defined in Equation (3). Details of the dependent and independent variables are described in section Materials and Methodology. Model selection was performed progressively by reducing variable complexity and evaluating the *AIC* at each stage. The model evaluation results are summarized in **Table 1**

Table 1. *AIC* Value for Tested Combination of Independent Variables

Regression Logistic Model	Combination of Independent Variables	*AIC* Value
First Model	Magnitude, depth, latitude, longitude, and location	17.208
Second Model	Magnitude, depth, longitude, and location	14.311
Third Model	Magnitude, depth, and longitude	11.416
Fourth Model	Magnitude and depth	6

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As shown in **Table 1**, variable combinations were tested hierarchically until the model with the lowest *AIC* was identified. The fourth model combination of magnitude and depth yielded the minimum *AIC* value of 6, indicating that these two parameters are the most influential predictors of earthquake probability in East Java. Thus, the final logistic regression model can be expressed as:

$$logit(P) = (-3{,}62 \times 10^{15}) + (9{,}187 \times 10^{14} Magnitude) - (1{,}03 \times 10^{10} Depth)$$

The significance tests revealed that both predictors are statistically meaningful. Magnitude with ($p = 2 \times 10^{-16} < \alpha = 0.05$), which mean higher magnitudes significantly increase the probability of moderate-to-major earthquakes, confirming that energy release is a primary determinant of event intensity. Depth ($p = 2 \times 10^{-16} < \alpha = 0.05$), which mean shallower focal depths correspond to a greater likelihood of surface shaking, suggesting stronger felt impacts. Both predictors demonstrated *VIF* = 1.03, indicating no multicollinearity (no strong correlation between predictors) and confirming model stability.

Using this validated model, probability predictions were generated for each of the 544 observed earthquake events. It is important to emphasize that these predictions were derived strictly from the available data—each of the 544 instances was evaluated for its estimated probability of being a moderate-to-major earthquake, based on the regression logistic function. The distribution of these prediction probabilities is visualized in **Figure 3**

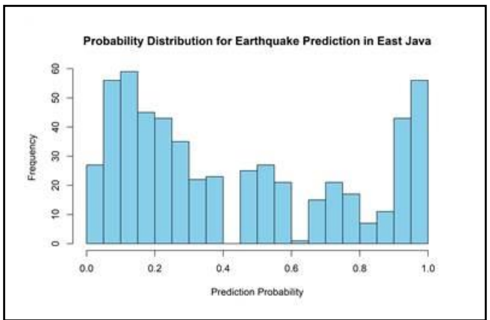

Figure 3. Distribution of Predicted Earthquake Probabilities in East Java Based on The Logistic Regression Model

As shown in the histogram, the predicted probabilities range between 0 and 1. A large number of events fall within the 0.1–0.3 interval, suggesting lower but non-negligible risk levels. Conversely, a notable cluster appears within the 0.9–1.0 range, indicating a subset of events with very high predicted probability of being moderate-to-major earthquakes. The remainder of the predictions are distributed across mid-range intervals, reflecting the model's sensitivity to varying magnitudes and depths. To further refine the insights from this probabilistic output, the study isolates high-probability events—defined as those with predicted probabilities between 80% and 99%—and visualizes them through a bubble plot, shown in **Figure 4**

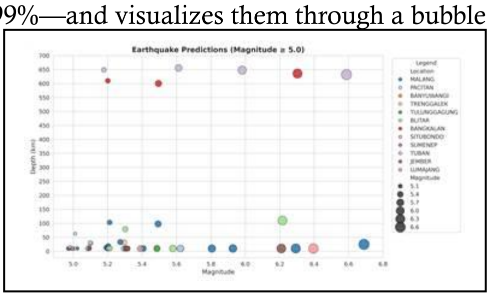

Figure 4. Bubble plot of predicted earthquake events (M ≥ 5.0) by depth and location, filtered by probability ≥ 80%.

Most high-probability events (80–90%) were concentrated in Region 1—specifically Pacitan, Blitar, Malang, Lumajang, and Jember—areas that coincide with the highest posterior probabilities obtained from the Bayesian model. This reinforces the consistency and complementarity between both inferential approaches. A smaller cluster of deep, high-magnitude earthquakes was detected in Region 3, particularly in Tuban and Madura Island, reflecting complex subduction dynamics beneath northern East Java. Meanwhile, Situbondo in Region 2 emerged as the only area with moderate probability, emphasizing that even low-risk zones require continuous seismic monitoring.

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Overall, these findings demonstrate that depth and magnitude are key determinants of earthquake severity. While the Bayesian model quantified the frequency-based likelihood of events, the logistic regression model elucidated the conditional probability of significant occurrences, together providing a comprehensive probabilistic framework for regional earthquake risk interpretation in East Java.

Discussion and Practical Implications

The integration of Bayesian inference and logistic regression introduces a dual analytical framework for earthquake risk analysis in East Java. Bayesian inference estimates the probability of earthquake occurrence, while logistic regression complements this by identifying the types of earthquake events with high likelihood of occurrence in East Java. The combination of both methods provides a comprehensive assessment of event frequency and potential impact, resulting in a more adaptive approach to regional seismic characteristics. In practical terms, this framework contributes to several aspects of risk mitigation, including:

1. **Early Warning Systems and Pre-Earthquake Mitigation Planning**
   The daily posterior probabilities generated by the Bayesian model represent the probabilistic likelihood of earthquake occurrence in East Java. These probabilities can be used as a basis for establishing early warning thresholds and planning mitigation measures before earthquakes occur. This finding complements previous earthquake impact modeling approaches, which focused on post-earthquake mitigation [25]. Such that the combination of both strengthens the overall risk management strategy, from prediction to emergency response.
2. **Regional Prioritization for Structural Mitigation**
   High-risk areas (Zone 1: Pacitan, Trenggalek, Tulungagung, Blitar, Malang, Lumajang, Jember, and Banyuwangi) demonstrate higher daily posterior probabilities of earthquake occurrence. This finding aligns with seismicity studies of southern East Java, where high rock stress due to seismo-tectonic activity in the subduction zone near the Java Trench increases regional vulnerability to earthquake disasters [26]. Based on these probabilities, mitigation priorities can be specifically directed toward strengthening public buildings and dense settlements, securing evacuation routes, and positioning emergency response facilities at strategic points. Thus, pre-earthquake preparedness strategies can be strengthened while complementing post-earthquake emergency response plans more effectively.
3. **Mitigation Based on Geophysical Characteristics**
   Logistic regression analysis indicates that the combination of high magnitude and shallow depth significantly influences damage potential. This finding is consistent with Geographically Weighted Regression (GWR) studies in southern Java, which confirm that shallow offshore earthquakes can cause substantial impact on coastal infrastructure, such as ports and airports [27]. This information enables more focused pre-earthquake mitigation, such as planning the location of critical buildings and evacuation scenarios based on local seismic characteristics, thereby optimizing pre-earthquake preparedness based on specific geophysical factors.
4. **Community-Based Preparedness**
   Beyond statistical modeling, the application of daily earthquake probabilities derived from Bayesian inference can enhance community-based preparedness. These probabilities can be used to design more targeted education programs, evacuation simulations, and risk communication, enabling communities to better prepare for potential earthquakes. This finding aligns with studies in West Java that revealed low public awareness of earthquake-resistant building construction and emergency plans [28]. By understanding risk quantitatively, communities can more effectively organize residential locations, plan evacuation routes, and prepare protection for important assets, making pre-earthquake mitigation more tangible and applicable.

Overall, the integration of Bayesian inference and logistic regression in this study produces a comprehensive earthquake risk assessment for East Java. Bayesian inference identifies patterns of event frequency with measurable uncertainty, while logistic regression confirms magnitude and depth as significant predictors of earthquake severity. The combination of these two methods provides a dual probabilistic framework that is more adaptive and robust compared to single-method approaches, making it a novel methodological contribution to earthquake risk analysis in seismically active regions. This framework fills a gap in East Java-specific probabilistic earthquake assessment, complementing existing deterministic or regionally generalized models

Conclusion

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This study demonstrates that the integrated two-stage approach—combining Bayesian inference with logistic regression—provides a comprehensive framework for earthquake risk assessment in East Java. The Bayesian model successfully estimated daily earthquake probabilities 13.5% (95% credible interval) and spatially identified Region 1 as the highest-risk zone, followed by Region 3 and Region 2. Complementing this, logistic regression analysis highlighted magnitude and depth as statistically significant predictors for moderate-to-major earthquakes ($M \geq 5.0$), revealing a concentration of high-risk events at shallow depths in Regions 1 and 3, while Region 2, though historically less active, remains hazardous due to active fault systems and vulnerable soil conditions. The convergence of these methodologies underscores the value of integrating probabilistic modeling with parameter-based classification, enabling more nuanced risk assessment and targeted mitigation strategies, including enhanced enforcement of building codes in high-probability areas, development of real-time early warning systems, and community-based disaster preparedness programs that prioritize dense settlements and critical infrastructure.

Looking forward, future research could explore machine learning enhancements, such as deep learning architectures like Long Short-Term Memory (LSTM) networks for temporal pattern recognition, ensemble methods like Gradient Boosting Machine (GBM) and eXtreme Gradient Boosting (XGBoost) for improved predictive accuracy, or hybrid models combining physical simulations with data-driven approaches. While this study provides a robust foundation, the dynamic nature of seismic systems necessitates further refinement through expanded datasets and advanced computational techniques, ensuring more adaptive and resilient earthquake risk management in East Java.

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