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Bayesian Spatial Quantile Regression for Earthquake Risk Assessment and Insurance Pricing in Indonesia

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ABSTRACT

Indonesia's geographical location along the Pacific Ring of Fire makes it one of the most seismically active countries in the world, with earthquakes causing recurrent and significant economic losses. To address the need for more accurate and regionally sensitive insurance pricing, this study develops a Bayesian spatial quantile regression model that estimates the 90th percentile of earthquake-induced economic losses. Unlike conventional models that focus on mean losses, this approach captures the upper tail of the loss distribution, which is essential for designing risk financing instruments that can withstand catastrophic events. The model incorporates two main predictors: earthquake magnitude (on the Richter scale) and a provincial risk exposure index constructed from population and GDP per capita. Spatial effects are modelled using a Gaussian kernel with multiple bandwidths. Based on Leave-One-Out Cross-Validation, a bandwidth of 500 kilometers yields the best model performance, effectively capturing regional dependence in earthquake loss data. Historical data from 1930 to 2024 are used to estimate parameters via Markov Chain Monte Carlo sampling with the No-U-Turn Sampler. Results indicate that both earthquake magnitude and socioeconomic exposure are significant drivers of high-end losses. For instance, the model estimates that West Sumatra and Yogyakarta could experience annual benefit payouts exceeding USD 300,000 in high-severity scenarios. Earthquake insurance premiums are then derived using the expected payout values and a 10% premium loading factor. Premium estimates range from USD 0 to over USD 50,000 across provinces, with 20 out of 34 provinces requiring positive premiums. This study contributes a novel modelling framework that integrates quantile regression, spatial weighting, and exposure-based risk assessment. The results provide a data-driven basis for setting premiums and allocating disaster risk financing more equitably across regions. Limitations include reliance on proxy variables for exposure and the exclusion of building-level vulnerability data, which may affect precision in highly localized assessments.

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A. INTRODUCTION

This Indonesia's location on the Pacific Ring of Fire places it among the most earthquake-prone nations globally, with seismic event regularly resulting in loss of life and substantial economic disruption (Djalante, 2018; Zanoletti & Bontempi, 2024). In such a high-risk environment, insurance plays a critical role in disaster risk management by helping communities recover and maintain resilience. However, conventional indemnity-based insurance often struggles to deliver timely financial support, as payouts depend on post-disaster damage assessments that time consuming and resource intensive. To overcome this limitations, index-based insurance has been proposed as a more efficient alternative. In this model, payouts are triggered by predefined indicators such as earthquake magnitude rather than verified losses, allowing for faster and more transparent compensation (Shin et al., 2022; Belissa, 2024).

Regression methods are commonly used for this purpose due to their ability to capture relationships between predictors or covariates and loss outcomes, even when data is limited (Jarantow et al., 2023; Aissaoui et al., 2020). In earthquake contexts, the extent of loss heavily depends on both the earthquake's magnitude and the exposure level of the affected area. Traditional regression focuses on modeling the mean of the response variable and thus fails to capture the full distribution, especially in the presence of heteroskedasticity and extreme events (Hsiao et al., 2021). Quantile regression addresses this gap by allowing the modeling of different points along the loss distribution, including the upper tail where severe damage occurs (Cooray & Özmen, 2024). At the same time, earthquake impacts often display spatial dependence, as damage may spread across multiple provinces beyond the epicenter. Ignoring this spatial structure can lead to biased or incomplete risk estimates (Burnett & Mothorpe, 2021). Therefore, spatial quantile regression is employed to incorporate the geographical impact of earthquakes and improve model accuracy. Earthquake losses are influenced by many latent factors not directly observed in the data. A Bayesian approach is chosen due to its strength in incorporating prior knowledge and belief updating, enabling the resulting posterior model to serve as a prior in future studies if new data becomes available (Iacopini et al., 2022).

This approach integrates prior information with observational data (Jiang et al., 2020; Li et al., 2016; Fuzi et al., 2016). In the context of earthquake insurance, Bayesian methods can accommodate prior information such as historical loss patterns or seismic characteristics of surrounding areas. Bayesian quantile regression can be implemented using the Asymmetric Laplace Distribution (ALD) as a likelihood function, embedding the quantile loss function into the model (Fuzi et al., 2016; Hu & Zhang, 2024). The prior information and likelihood function are combined to obtain the posterior distribution of earthquake losses. As more predictors and data are used, model complexity increases, requiring numerical estimation of posterior parameters. This is done using the Markov Chain Monte Carlo (MCMC) method with the No-U-Turn Sampler (NUTS) algorithm (Nishio & Arakawa, 2019; Alawamy et al., 2024). MCMC leverages the posterior distribution to generate numerous samples, assessing convergence across iterations. NUTS improve sampling efficiency using Hamiltonian dynamics to focus sampling in high-probability regions of the parameter space, making it suitable for complex, high-dimensional models (Marwala et al., 2023).

Motivated by the approach proposed by Pai et al. (2022), this study develops a Bayesian spatial quantile regression model specifically tailored for analyzing Indonesian earthquake data. The methodological foundation of this model which combines spatial modeling, quantile estimation, and Bayesian inference to capture regional disparities in earthquake impacts. Unlike conventional regression methods that typically focus on the conditional mean, the quantile regression framework allows this study to explore how covariates influence the entire distribution of earthquake losses, particularly in the upper tail where catastrophic damages are more likely to occur. The model is applied at the provincial level, where loss estimates are derived based on a set of carefully selected risk factors, including but not limited to seismic exposure (e.g., fault line proximity and historical magnitude data), population density, building infrastructure quality, and economic vulnerability. By incorporating spatial dependence among provinces through hierarchical Bayesian priors, the model captures regional clustering of risk while improving estimates in data-scarce areas through spatial smoothing (Tu et al., 2025). The estimated quantiles of earthquake loss are then used to design an index-based parametric insurance product, where benefit payouts are directly tied to measurable earthquake characteristics, specifically, earthquake magnitude as reported on the Richter scale. Following the principles outlined by Wenjun & Zhang (2025), this parametric design eliminates the need for lengthy claims assessments, enabling rapid disbursement of funds. Such an approach is not only more efficient but also reduces administrative costs and minimizes the risk of moral hazard and fraud. This payout mechanism plays a critical role in disaster recovery, providing timely financial support to affected communities. In disaster prone like Indonesia, rapid access to financial support is essential for recovery, particularly for rebuilding homes, restoring livelihoods, and restarting local economies (Ogie et al., 2022) . By aligning insurance benefits with objective, verifiable indices like earthquake magnitude, the model ensures transparency and predictability in the delivery of financial relief (Katsuichiro & Wenzel, 2021).

This study aims to develops a novel insurance pricing framework that combines spatial modeling, quantile estimation, and Bayesian inference to reflect Indonesia's unique seismic and socioeconomic landscape. Its key contribution lies in advancing a tail sensitive, spatially aware model that enables actuarially fair and regionally differentiated insurance premiums. By aligning model outputs with the design of index-based insurance products, the study offers both methodological innovation and practical value for disaster risk financing in earthquake vulnerable contexts.

B. RESEARCH METHODS

1. Overview of Earthquake Loss Modeling Approaches

Earthquake-induced economic losses have been extensively studied to support disaster preparedness and financial planning. Traditional approaches include macroeconomic index-based models, empirical loss functions, and extreme value theory (EVT). For example, Gross Domestic Product (GDP)-based models assess regional vulnerability by integrating seismic hazard probabilities with economic exposure and vulnerability functions (Jaiswal & Wald, 2013). While these models provide broad regional loss estimates, they often oversimplify geological and socioeconomic heterogeneity. EVT-based methods, such as the Generalized Pareto Distribution (GPD) and Generalized Extreme Value (GEV), are commonly used to model the tails of the loss distribution and extrapolate rare, high-impact events (Pisarenko et al., 2014; Kruschke & Liddell, 2018). However, their estimates tend to be highly sensitive to threshold selection and distributional assumptions, potentially reducing their reliability in disaster-prone contexts. In response to these challenges, recent studies propose quantile regression as a robust alternative for modelling extreme losses, especially in cases where upper-tail behavior is critical for decision-making (Zhang et al., 2021).

This study focuses on earthquake-induced economic losses at the provincial level in Indonesia as the unit of analysis. The dependent variable economic loss per event is derived from the EM-DAT disaster database, reported in constant 2020 USD to ensure comparability. The main predictors include earthquake magnitude (measured on the Richter scale), obtained from EM-DAT and cross-validated with USGS data, and a risk exposure index**,** constructed from population and GDP per capita figures at the provincial level. These socioeconomic indicators are sourced from *Badan Pusat Statistik* (BPS) Indonesia and averaged annually to align with the disaster records. The exposure index approximates regional vulnerability by capturing both the concentration of people and economic activity in hazard-prone areas. The model does not use physical vulnerability functions in the engineering sense, but rather employs statistical proxies to represent aggregate risk sensitivity across provinces.

Bayesian inference is a statistical approach that incorporates uncertainty in the estimation of parameters, unlike the frequentist approach, which treats parameters as fixed. In Bayesian statistics, conclusions are drawn in terms of probability statements that reflect uncertainty about quantities of interest. A key distinction between Bayesian and frequentist approaches lies in their treatment of observed data. Bayesian inference treats data as a means of updating prior beliefs into posterior distributions, whereas frequentist inference relies solely on data as the primary source of information. Bayesian methods account for sampling uncertainty in defining credible intervals, whereas frequentist methods assume that samples are ideally representative of the entire (Kennedy et al., 2017). In the Bayesian framework, parameters are estimated in the form of posterior distributions to explicitly express uncertainty in the final estimates. The posterior distribution is derived by combining the prior distribution with the likelihood, making it a balance between prior knowledge and information provided by the observed data (Gelman et al., 2013). Posterior distributions can serve as prior distributions in subsequent studies, allowing for "belief updating" as new data becomes available. This iterative process enables Bayesian models to evolve over time in response to additional information (Li et al., 2016; Reich et al., 2011; Yu & Moyeed, 2001). This study adopts a Bayesian Spatial Quantile Regression (BSQR) framework, which offers three key advantages: (1) Quantile regression models different parts of the loss distributions, particularly the upper tail to capture catastrophic risk; (2) Bayesian inference allows the integration of prior knowledge with observed data and provides full posteriors distributions for parameters; and (3) Spatial modelling accounts for geographical dependencies, improving prediction accuracy across region with uneven data availability, as shown in Figure 1.

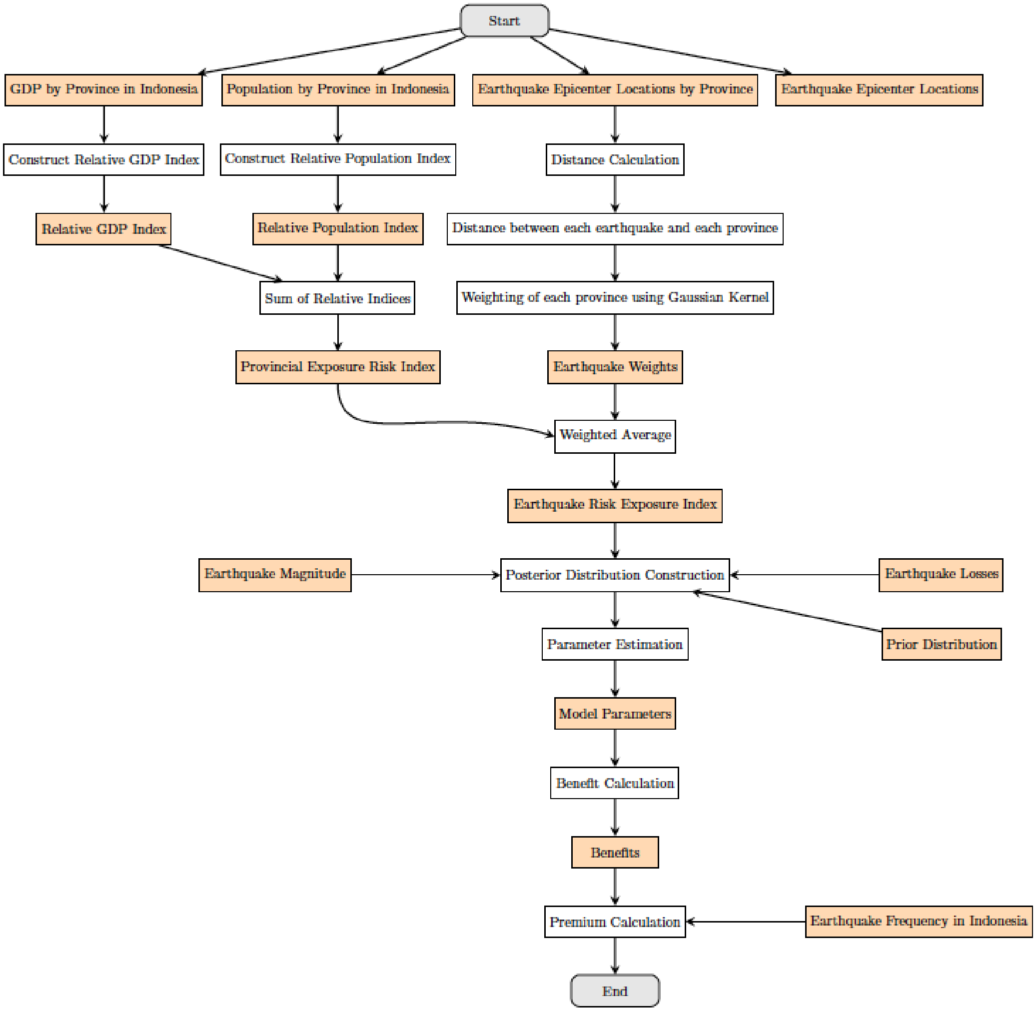

Figure 1. Research Flow Chart

2. Bayesian Spatial Quantile Regression

The Bayesian approach can be used to model quantile regression to provide more comprehensive statistical inference. This approach was introduced by Yu & Moyeed (2001), Reich et al. (2011) for analyzing complex models. The likelihood function in Bayesian quantile regression is based on the Asymmetric Laplace Distribution (ALD), which can be written as follows:

$$f(y|\mu,\sigma,\tau) = \frac{\tau(1-\tau)}{\sigma}\exp\left\{-\rho_\tau\left(\frac{y-\mu}{\sigma}\right)\right\} \tag{1}$$

$$\rho_\tau(u) = u\big(\tau - I(u<0)\big) = \begin{cases} u(\tau-1), & u<0 \\ u\cdot\tau, & u\geq 0 \end{cases} \tag{2}$$

where y is the response variable, τ is the quantile and skewness parameter, σ is the scale parameter, and $\rho_\tau(u)$ is the quantile loss function. The posterior distribution of the model parameters is proportional to the product of the likelihood and the prior distribution:

$$f(\boldsymbol{\beta},\sigma|y) \propto f(\boldsymbol{\beta})f(\sigma)\cdot L(\boldsymbol{\beta},\sigma|\,y) \tag{3}$$

where $\boldsymbol{\beta}$ is the vector of regression coefficients, $L(\boldsymbol{\beta}, \sigma| y)$ is the likelihood function, $f(\boldsymbol{\beta})$ and $f(\sigma)$ are the prior distributions of the regression coefficients $\boldsymbol{\beta}$ and scale parameter σ, respectively. Since deriving the posterior distribution analytically is too complex, parameter estimation is performed using MCMC (Markov Chain Monte Carlo) simulation with the No-U-Turn Sampler (NUTS) algorithm (Marwala et al., 2023). Subsequently, all models are evaluated and compared based on their predictive performance using the Leave-One-Out Cross-Validation (LOOCV) method. The selected model is the one with the highest Expected Log Predictive Density (ELPD) which demonstrates the best predictive capability among all models considered (Magzumov & Kumral, 2025). The Bayesian spatial quantile regression model is represented by the following equation (Marwala et al., 2023).

$$y_i^* = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \varepsilon_i,\ i = 1, \dots, 44 \tag{4}$$

where y_i^* is natural logarithm of the loss caused by the *i-th* earthquake (USD); $x_{1,i}$ is Magnitude of the *i*-th earthquake (M); $x_{2,i}$ is Risk exposure index of the *i*-th earthquake; ε_i is Error term associated with the *i*-th earthquake; and $\beta_0, \beta_1, \beta_2$ is Parameters of the Bayesian spatial quantile regression model.

3. Spatial Analysis

Spatial analysis, as defined by (Fischer et al., 2009) refers to a set of methods and models involving spatial mapping of data points in a study. It consists of three core elements: cartographic modeling, mathematical modeling, and spatial data analysis. Cartographic modeling involves visualizing data points on a map and identifying spatial objects (Závadský et al., 2019). Mathematical modeling describes spatial interactions between those objects. Spatial data analysis involves drawing statistical conclusions based on spatial data (Ślusarski & Jurkiewicz, 2020). Distance plays a critical role in spatial analysis as it characterizes the spatial relationship between objects. One method to account for this is inverse distance weighting (IDW), represented as:

$$\hat{Z}(s_0) = \frac{\sum_{i=1}^{n} \omega(s_i) Z(s_i)}{\sum_{i=1}^{n} \omega(s_i)} \tag{5}$$

where ω represents the weight of each observation at location s_i, calculated using a kernel function based on distance (Andruszkiewicz & Korycka-Skorupa, 2021). A commonly used kernel is the Gaussian kernel, defined as:

$$\omega(s_i) = \exp\left(-\frac{d_{ij}^2}{2\sigma^2}\right) \tag{6}$$

where $\omega(s_i)$ is the weight for location i, d_{ij}^2 is the Haversine distance between points i and j, and σ is the bandwidth of the Gaussian kernel (Cao et al., 2023; Babaud et al., 1986; Weglarczyk, 2018).

4. Benefit Calculation

In index-based earthquake insurance, benefits are determined based on an earthquake severity index commonly the earthquake magnitude. Not all earthquakes cause damage; hence, benefits are only paid if the earthquake exceeds a certain threshold. Let mmm denote the earthquake magnitude index, then the benefit schedule is defined as:

$$C = \begin{cases} C_1, & b_1 \leq m < b_2 \\ C_2, & b_2 \leq m < b_3 \\ & \vdots \\ C_t, & b_t \leq m \end{cases} \tag{7}$$

where C_k is the payout when the earthquake magnitude falls within the interval $[b_k, b_{k+1}]$ for $= 1,2, \dots, t-1$ and interval $[b_k, +\infty)$ for $j = t$. The amount of benefit payment is defined as the τ-th quantile of earthquake-induced losses, given the earthquake magnitude $x_1(s_i)$ and covariates $x_2(s_i), x_3(s_i), \dots, x_p(s_i)$ as expressed in the following equation:

For $k = 1,2, \dots, t-1$

$$\begin{aligned} C_k(s_i) &= Q_{y(s_i)}\left(\tau | b_k \leq x_1(s_i) < b_{k+1}, x_2(s_i), \dots, x_p(s_i)\right) \\ &= \hat{\beta}_0 + \hat{\beta}_1 x_1(s_i) + \hat{\beta}_2 x_2(s_i) + \cdots + \hat{\beta}_p x_p \end{aligned} \tag{8}$$

and for $k = t$

$$\begin{aligned} C_t(s_i) &= Q_{y(s_i)}\left(\tau | b_t \leq x_1(s_i), x_2(s_i), \dots, x_p(s_i)\right) \\ &= \hat{\beta}_0 + \hat{\beta}_1 x_1(s_i) + \hat{\beta}_2 x_2(s_i) + \cdots + \hat{\beta}_p x_p(s_i) \end{aligned}$$

Since the benefit amount is based on the level of earthquake magnitude, the expected value in equation (8) is calculated for each earthquake category, resulting in the modified equation (8) becoming equation (9) as follows:

$$\begin{aligned} C_k(s_i) &= Q_{y(s_i)}\left(\tau | x_1(s_i) = E[x_1(s_i) | b_k \leq x_1(s_i) < b_{k+1}], x_2(s_i), \dots, x_p(s_i)\right) \\ &= \hat{\beta}_0 + \hat{\beta}_1 E[x_1(s_i) | b_k \leq x_1(s_i) < b_{k+1}] + \hat{\beta}_2 x_2(s_i) + \cdots + \hat{\beta}_p x_p(s_i) \\ &= \hat{\beta}_0 + \hat{\beta}_1 \left(\int_{b_k}^{b_{k+1}} u \Pr\left(x_1(s_i) = u\right) du \right) + \hat{\beta}_2 x_2(s_i) + \cdots + \hat{\beta}_p x_p(s_i) \\ &= \hat{\beta}_0 + \hat{\beta}_1 \frac{\sum_{i=1}^{m} x_1(s_i)}{m} + \hat{\beta}_2 x_2(s_i) + \cdots + \hat{\beta}_p x_p(s_i) \\ &= \hat{\beta}_0 + \hat{\beta}_1 \bar{x}_1(s_i) + \hat{\beta}_2 x_2(s_i) + \cdots + \hat{\beta}_p x_p(s_i). \end{aligned} \tag{9}$$

where m is the number of earthquakes that occurred in the past at epicentre with magnitudes in the range $b_k \leq x_1(s_i) < b_{k+1}$. The expected value of earthquake magnitude $x_1(s_i)$ is calculated empirically, using the average magnitude of historical earthquake events in the corresponding region.

5. Premium Calculation

In an insurance contract, the premium is the amount paid by the policyholder to the insurer in exchange for coverage. The premium is calculated based on the equivalence principle, ensuring that the expected value of premiums equals the expected value of benefits. This yields the net premium. However, in practice, a gross premium is charged, which includes additional costs such as administrative expenses and risk margins. These are accounted for using **a** premium loading factor, as shown below:

$$G = (1 + \alpha)P = (1 + \alpha)E[PV(\text{Benefit})] \quad (10)$$

where G is the gross premium, α is the loading factor, and P is the net premium (expected present value of benefit payments).

C. RESULT AND DISCUSSION

The dataset consists of eight variables, including 45 historical records of earthquake-induced economic losses in Indonesia (1930-2024), data from 34 provinces, and 203 earthquake events recorded between 1975 and 2023. A provincial risk exposure index was developed as the sum population and GDP indices, normalized relative to the smallest observed across provinces. This index reflects the economic value potentially exposed to earthquake damage in Figures 2 as follows.

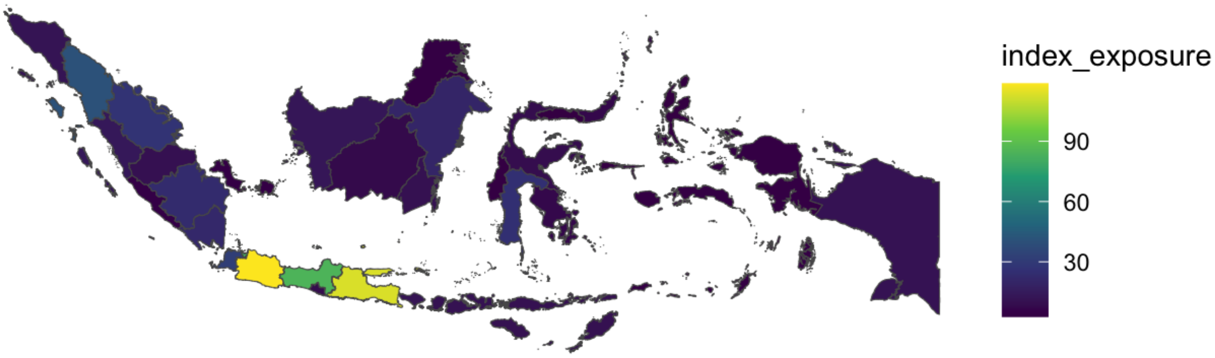

Figure 2. Map of Provincial Exposure Index in Indonesia

To account for multiple-provincial impacts of earthquakes the exposure index for each event is computed using a distance weighted average of the affected provinces within a 350 km radius of epicenter. Weight are calculated using Inverse Distance Weighting (IDW) with a Gaussian kernel. Five bandwidth parameters settings were exploded and compared to determine the best performing model during estimation. Parameter estimation was conducted using a Bayesian spatial quantile regression framework, focusing on 0.9 quantile, which captures extreme economic losses rather than average losses which is crucial for disaster risk financing. Estimation employed the No-U-Turn Sampler (NUTS) algorithm in a Markov Chain Monte Carlo (MCMC) framework. The Table 1 below shows the posterior estimates:

Table 1. Parameter Estimation of Bayesian Spatial Quantile Regression

Parameter	Mean	St Dev	Lower CI 0.025	Upper CI 0.975
β_0	1.78	3.11	-4.733	7.532
β_1	1.62	0.44	0.084	2.553
β_2	0.03	0.01	0.001	0.063
σ	0,40	0.06	0.30	0.540

The intercept (β_0) was not significant, but this is not problematic as the model is intended for moderate to high magnitudes (≥ 5) and non-zero exposure values. Model outputs are in log-scale and require back-transformation for interpretation. Based on this model, benefit payments (insurance payouts) are calculated per province and categorized by earthquake severity (magnitude). For each province, the expected loss at the 0.9 quantile is calculated within each magnitude band. These expected losses serve as proxy payouts to be covered by index-based insurance. Each category corresponds to earthquake magnitude ranges, with average or midpoint values used where data are missing. The expected loss in each category informs the benefit payment needed to cushion the province's economic impact.

$$C = \begin{cases} C_1, & 5 \leq x_1(s_i) < 5.5 \\ C_2, & 5.5 \leq x_1(s_i) < 6 \\ C_3, & 6 \leq x_1(s_i) < 6.5 \\ C_4, & 6.5 \leq x_1(s_i) < 7 \\ C_5, & 7 \leq x_1(s_i) < 7.5 \\ C_6, & 7.5 \leq x_1(s_i) < 8 \\ C_7, & 8 \leq x_1(s_i) < 8.5 \\ C_8, & 8.5 \leq x_1(s_i) \end{cases}$$

The amount of benefit payment is obtained using the previously developed Bayesian spatial quantile regression model by inputting the values of x_1 and x_2 based on the data from the respective region, as shown in equations (8). For earthquake magnitude x_1 , the average of historical data in the region is used if available. For regions without recorded historical data, the midpoint of the respective earthquake category is used as the average magnitude. To determine whether an earthquake is considered to have occurred in a specific region, a distance threshold of 350 km is applied from the earthquake epicenter to the provincial capital. For each province, the average earthquake magnitude is calculated within each category. Then, the 0.9 quantile expectation of earthquake-induced loss is estimated for each category.

This expected value represents the amount of benefit required by each province to mitigate the economic impact of an earthquake disaster. Annual insurance premiums are computed as the expected value of benefit payouts, adjusted with a 10% premium loading. Earthquake frequencies per category and per province are used to determine expected payouts. As shown in Figure 4, some provinces (e.g., Kalimantan, Riau Islands, Bangka Belitung) have no recorded major earthquakes and thus have zero premiums under this model. This modelling approach enables a clear and practical translation of statistical results into insurance decisions, providing differentiated premiums and payouts based on regional risk. For policymakers and insurers, this support data-informed premium setting that is sensitive to both seismic hazard and socioeconomic vulnerability, as shown in Figure 3 and Figure 4.

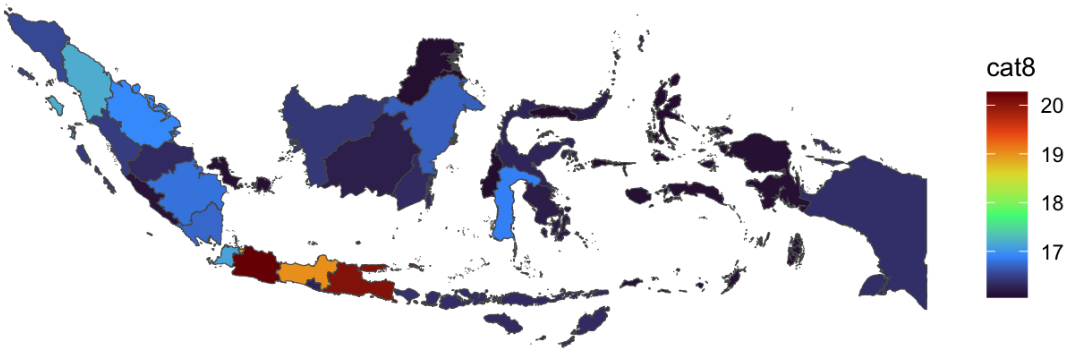

Figure 3. Map of Earthquake Benefit Payments for C_8

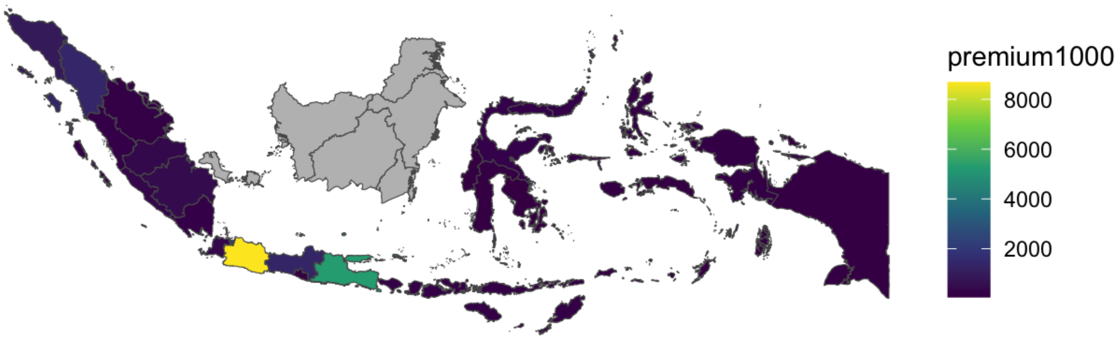

Figure 4. Map of Annual Earthquake Insurance Premiums for Provinces in Indonesia (in thousands of USD)

This study extends prior research in disaster insurance modeling. Burton et al. (2016) introduced risk indexing in developing country contexts; here, we advance that framework by incorporating Bayesian spatial quantile regression, which better captures tail risks and spatial dependencies. Pai et al. (2022) used similar methods in China but relied on latent vulnerability variables; this study takes a more transparent, data-driven approach. Kreibich et al. (2017) and Ghorbani et al. (2023) validate the use of population and GDP in flood and discharge modeling, supporting this study's exposure design. While the proposed framework effectively links spatial risk exposure and extreme-loss quantiles, several limitations warrant discussion. First, the economic loss data is sparse, especially before 1975, which may introduce historical bias. Second, the use of provincial-level GDP and population may obscure within-province heterogeneity. Third, the model assumes stationarity in earthquake frequency and magnitude distributions, which may not hold under evolving geophysical or urban conditions. Finally, despite the robustness of Bayesian inference, prior specification and MCMC convergence may affect parameter stability in smaller datasets. These limitations should be considered when generalizing the model to other contexts or timeframes, or when integrating the results into national-scale insurance policy.

D. CONCLUSION AND SUGGESTIONS

This study develops a Bayesian spatial quantile regression model to analyze and estimate economic losses from earthquakes in Indonesia, with a focus on informing fair and region-specific insurance premium structures. By integrating earthquake magnitude and a risk exposure index constructed from provincial GDP and population into a spatial quantile framework, the model captures both the severity and geographic disparity of earthquake impacts. The use of the Asymmetric Laplace Distribution and Markov Chain Monte Carlo (MCMC) estimation enables robust modeling of the upper quantiles of the loss distribution, which are crucial for disaster risk financing. A key contribution of this study is its demonstration of how quantile-based modeling, when spatially adapted, can improve the pricing of earthquake insurance by focusing on the extreme tails of potential losses. This addresses a critical gap in traditional models that often rely on average loss estimates, potentially underestimating high-impact, low-probability events. By applying the model to historical earthquake data and evaluating its performance using Leave-One-Out Cross Validation (LOOCV**)**, the research provides a replicable framework for risk-based premium calculation. The resulting insurance payouts and premiums can serve as **a** practical tool for policymakers and insurers to allocate resources more efficiently and equitably across regions. However, several limitations should be acknowledged. The study relies on historical loss records that may be incomplete or inconsistent, particularly for older events. The exposure index is based on aggregated provincial-level data, which may not fully capture intra-provincial heterogeneity. Additionally, the assumption of a fixed 350 km impact radius and the use of static socioeconomic indicators may limit the model's responsiveness to evolving risk conditions. Future research should aim to address these limitations by incorporating higher-resolution data**,** dynamic exposure indicators**,** and event-specific vulnerability assessments. Furthermore, applying expert-informed prior distributions and expanding the model to account for other disaster types (e.g., tsunamis or floods) could enhance its generalizability. Scenario-based simulations and validation with observed insurance claims data would also strengthen the practical applicability of this approach in real-world insurance design and disaster risk management.

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