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PRICING RESIDENTIAL EARTHQUAKE INSURANCE IN INDONESIA

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Abstract: Adaptive Social Protection (ASP) is a framework that integrates social protection, disaster risk reduction, and climate change adaptation to enhance resilience against shocks and hazards. As a country vulnerable to earthquakes, Indonesia faces threats of losses due to seismic disasters. The national budget available to cover these losses can only address 13.6% of the total disaster-related losses. This study proposes an earthquake insurance scheme to protect all residences in Indonesia as part of the ASP framework, followed by the calculation of premium rates for this insurance scheme. This study utilizes the built-in OpenQuake calculator known as the probabilistic event-based risk calculator to simulate annual earthquake losses over a period of 10,000 years. The negative binomial distribution and the Pareto IV distribution are assessed as the most optimal models in modeling frequency and severity through distribution fitting. The application of collective risk models and the principle of pure premium results in a pure premium rate of 0.3994073 ‰. This pure premium rate can serve as a starting point in the establishment of comprehensive residential earthquake insurance in Indonesia.

1. INTRODUCTION

The concept of adaptive social protection (ASP) is a response to the multidimensional risks encountered by the poor and vulnerable population (Arnall et al., 2010). ASP integrates elements of social protection (SP), disaster risk reduction (DRR), and climate change adaptation (CCA) (Davies et al., 2008). As part of ASP, DRR aims to prepare communities for hazards before events occur (Davies et al., 2008). Disaster risk financing strategies represent a shift in perspective by viewing natural disasters not as unpredictable crises but as events with impacts that can be mitigated. (Bowen et al., 2020).

The Sendai Framework for Disaster Risk Reduction (SFDRR) 2015-2030 assesses disaster risk transfer and insurance as important instruments for reducing financial impacts on governments and communities (UNISDR, 2015). Insurance integrated into social protection is considered capable of protecting vulnerable households from falling into the poverty trap due to significant shocks (Jensen et al., 2017), as impacts such as asset loss during natural disasters can push the poor into a downward spiral of deepening poverty (Davies et al., 2008).

Indonesia's position above and as a meeting point of several tectonic plates makes it highly vulnerable to earthquakes (Hutchings & Mooney, 2021; Verstappen, 2010). This is evident from recent seismic events that have resulted in substantial economic losses, such as the 2004 Sumatra-Andaman earthquake, which caused economic losses of 41.4 trillion IDR, the 2006 Yogyakarta earthquake (29.15 trillion IDR in losses), the 2018 Lombok earthquake (7.45 trillion IDR in losses), and the 2018 Palu-Donggala earthquake (10 trillion IDR in losses) (Sagala et al., 2020).

In facing disasters, the Indonesian government allocates an average disaster reserve fund of Rp 3.1 trillion per year in the state budget (BKF, 2018). With an average annual loss due to natural disasters amounting to Rp 22.8 trillion during the period of 2000–2016, it indicates that only about 13.6% of the losses from natural disasters can be covered by the state budget (BKF, 2018). This demonstrates the limitations of fiscal capacity in addressing disaster risks in Indonesia, thus necessitating other instruments such as risk transfer mechanisms and insurance in efforts to finance disaster risks.

In this paper, we propose the establishment of comprehensive residential earthquake insurance in Indonesia as part of adaptive social protection by addressing the pure premium rates of this insurance. The seismic risk and hazard assessment software named OpenQuake is utilized as a tool in this research. The built-in calculator inside the OpenQuake Engine, named the probabilistic event-based (PEB) risk calculator, is specifically used to produce scenarios of earthquake disasters for 10,000 years. With the collective risk model method, the output of the PEB risk calculator is then modeled by performing a fitting distribution for frequency and severity. Using the pure premium principle, the premium of this insurance is then calculated by multiplying the expected frequency and severity of earthquake losses.

2. LITERATURE REVIEW

In several countries with high earthquake disaster risk, residential earthquake insurance is implemented as a form of risk transfer through the collection of funds by government-owned entities to finance post-disaster losses, as practiced by the Earthquake Commission (EQC) in New Zealand, the Taiwan Residential Earthquake Insurance Fund (TREIF), and the Turkish Catastrophe Insurance Pool (TCIP) (GFDRR, 2011; New Zealand Government, 2015; TREIF, 2024). The Government of Japan takes a different approach by providing government-owned reinsurance through the Japanese Earthquake Reinsurance (JER) Company, while the insurance is written by private companies (GIROJ, 2022). In contrast, Mexico established FONDEN, a disaster fund used to finance recovery and reconstruction of public infrastructure through Mexico’s Federal Budget allocations and catastrophe bonds (Cat MEX) (World Bank, 2012).

A catastrophe model is developed to produce unbiased estimates of financial risk across the risk spectrum (Guin, 2018). The four basic modules of a catastrophe model are hazard, inventory, vulnerability, and loss (Grossi et al., 2005). All these components are illustrated in Figure 1.

In the context of catastrophe modeling for earthquake disasters, hazard is defined through seismic hazard. Seismic hazard refers to the probability of damaging earthquakes occurring within a specified time frame and geographic location (Bommer, 2002). Seismic hazard involves two main components, namely the seismic source model and ground motion prediction equations. The seismic source model describes the location, geometry, and activity of seismic sources represented through a magnitude-frequency distribution (Silva et al., 2014). Meanwhile, the ground motion prediction equations relate the intensity measure of ground motion to variables associated with seismic hazard (Stewart et al., 2015).

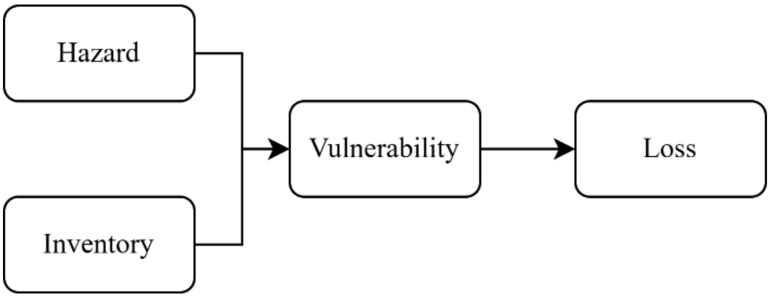

Figure 1. Modules in The Catastrophe Models

The vulnerability module provides a relationship between the expected level of damage to buildings and the external forces generated by earthquakes. These external forces are expressed as measures of ground motion intensity, such as Peak Ground Acceleration (PGA) or Spectral Acceleration (SA) (Grossi et al., 2005).

The inventory module contains detailed information related to the insured exposure such as location, building value, occupancy, construction type, and other relevant details (Grossi et al., 2005). This information is important as the damage caused by disasters is highly dependent on the location and the strength of the construction of the exposure.

The loss module is then modeled by the Collective Risk Model, as described by Klugman et al. (2019). This model represents aggregate losses as a sum, denoted as *S*, of a random discrete number, *N*, from individual payment amounts $(X_1, X_2, \dots, X_N)$ as expressed by the following equation.

$$S = X_1 + X_2 + \cdots + X_N, \qquad N = 0, 1, 2, \dots$$

where $S = 0$ when $N = 0$. The expected aggregate loss is calculated using:

$$E(S) = E(N)E(X)$$

Using the Pure Premium Principle proposed by Dickson (2005), the pure premium (Π) is determined by the insurer’s expected claims under the risk, defined as:

$$\Pi = E(S)$$

Through this modeling process, the calculation of pure premium can be systematically conducted, providing a consistent approach to determine earthquake insurance premiums based on the expected aggregate losses.

3. MATERIAL AND METHOD

3.1. Data Sources

In this study, we use a seismic hazard model and ground motion prediction equation referenced from Irsyam et al. (2020) and Irsyam et al. (2023), respectively. The vulnerability model used is a model from Martins & Silva (2023). Exposure data from Yepes-Estrada et al. (2023) is utilized for the inventory module, with an additional step of disaggregating the originally aggregated exposure at the provincial level into the regency/city level based on the population percentage in each regency/city, obtained from the BPS-Statistics Indonesia. This results in aggregated residential exposure data for each regency/city, as shown in Figure 2. Furthermore, the coordinates of the Regent/Mayor's office are used as reference points representing each regency/city.

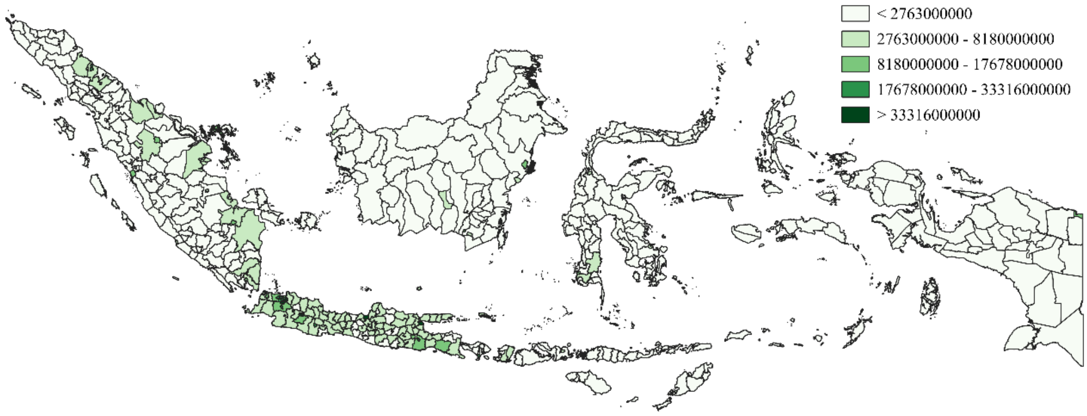

Figure 2. Residential Exposure in Indonesia Aggregated at The City/Regency Level

3.2. OpenQuake and Probabilistic Event–Based (PEB) Risk Calculator

OpenQuake is an open-source software developed by the Global Earthquake Model (GEM) Foundation for seismic hazard and risk assessment, providing tools to model, calculate, and visualize earthquake risk at various scales (Silva et al., 2014). One of the OpenQuake calculators called the Probabilistic Event-Based (PEB) calculator is widely used to produce various outputs related to hazards and losses (Hosseinpour et al., 2021). Monte Carlo simulations, along with a logic tree calculator, are used in PEB to process Seismic Source Models (SSM). Each source model is utilized to generate a list of all possible future events, known as the Stochastic Event Set (SES). Ground motion fields are then produced for each event within the SES. These ground motion fields, together with the vulnerability model and exposure, are combined to calculate the loss values for each asset in each ground motion field. (Hosseinpour et al., 2021; Silva et al., 2014).

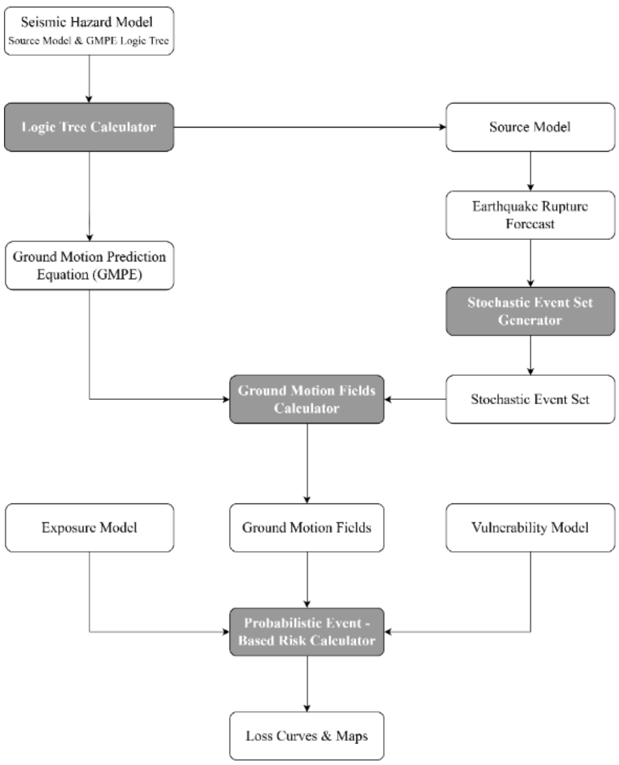

Figure 3. Procedure of The Probabilistic Event-Based Risk Calculator (adapted from (Silva et al., 2014))

The PEB calculator produces a series of outputs that describe the risks and potential losses associated with a given exposure. Pagani et al. (2022) mentioned that one of the outputs generated by the PEB calculator is the stochastic event loss table, which contains event id, rupture id, year, and the resulting losses.

4. RESULTS AND DISCUSSION

The PEB calculator produces loss module outputs using input data related to hazards, vulnerabilities, and inventories, as described in the previous section. The output is then transformed into a frequency and severity table that includes annual frequency, annual severity, and average annual severity. Table 1 summarizes the descriptive statistics for annual frequency and average annual severity. Figure 4 and Figure 5 illustrate the annual frequency and severity, respectively.

Table 1. Descriptive Statistics of Frequency and Severity

	Annual Frequency	Average Annual Severity
n	10000	10000
Mean	22.3519	12089545.17
Standard deviation	7.541256755	45878147.43
Median	21	2448107.865
Min	2	2.613305
Max	55	1534340249
Skewness	0.862277119	15.9308925
Kurtosis	0.91009821	369.0641848

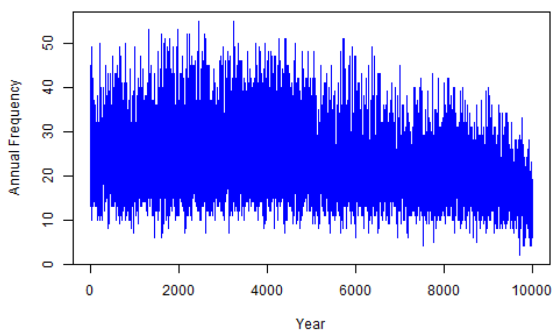

Figure 4. Annual Frequency Plot

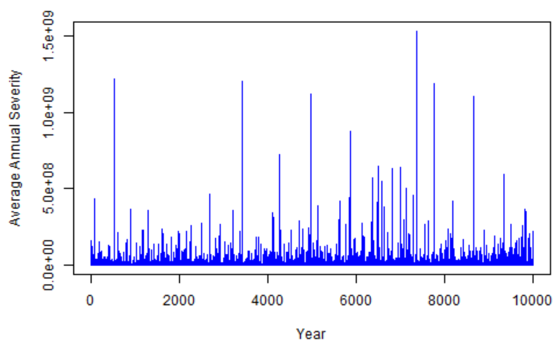

Figure 5. Annual Average Severity Plot

Frequency modeling is conducted by estimating parameters for each candidate distribution using the maximum likelihood estimation method. Discrete distributions should be chosen due to the natural counting distribution of frequency. The estimated parameters for each distribution can be found in Table 2.

Table 2. The Estimated Parameter Value Using MLE for Frequency

No	Distribution	Parameter(s)
1	Uniform	$a = 2, b = 55$
2	Geometric	$p = 0.04282307$
3	Poisson	$\lambda = 22.3519$
4	Negative Binomial	$n = 15.53945, \mu = 22.35257$

After the parameter estimation has been conducted, a chi-squared test is performed to assess the goodness-of-fit of the distribution. Additionally, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are also considered in determining the most suitable distribution of the data. A summary of the chi-squared statistics, AIC, and BIC values for each candidate distribution can be found in Table 3.

Table 3. Chi-squared statistic, AIC, and BIC for the frequency distribution candidates

No	Distribution	Chi-squared Statistic	Goodness-of-fit Criteria	
			AIC	BIC
1	Uniform	11978.68	79409.84	79424.26
2	Geometric	14514.43	82581.09	82588.30
3	Poisson	43675.1	73436.70	73443.91
4	Negative Binomial	308.3991	67754.64	67769.06

As shown in Table 3, it is obtained that the negative binomial distribution has the smallest chi-squared statistic, AIC, and BIC values compared to the uniform, geometric, and Poisson distributions. This finding suggests that the negative binomial distribution is the most suitable model for modeling annual frequency compared to other distributions.

Similar to frequency modeling, severity modeling begins with estimating parameters using the maximum likelihood estimation method. Candidate distributions are selected from continuous and non-negative distributions. The result of the parameter estimates for each distribution can be found in Table 4.

Table 4. The Estimated Parameter Value Using MLE For Severity

No	Distribution	Parameter(s)	
1	Lognormal	$\mu = 14.566614$	$\sigma = 1.9944808$
2	Gamma	$\alpha = 134852056$	$\lambda = 11.435729$
3	Log-gamma	$\alpha = 49.176614$	$\lambda = 3.375875$
4	Weibull	$\alpha = 0.5455472$	$\sigma = 6032236.1$
5	Log-logistic	$\gamma = 0.8857917$	$\theta = 2263969.4$
6	Fatigue Life	$\alpha = 373.13822$	$\beta = 70.11781$
7	Generalized Extreme Value	$\mu = 1726915$	$\sigma = 9277407$
8	Generalized Pareto	$\mu = -54339.09$	$\sigma = 11527695$
9	Pareto	$\alpha = 0.8931397$	$\theta = 1893957.4$
10	Pareto III	$\mu = 2.4380314$	$\gamma = 0.8851209$
		$\theta = 2265013.5$	
11	Pareto IV	$\mu = 2.48264$	$\alpha = 2.09745$
		$\gamma = 0.73175$	$\theta = 8924963$
12	Rayleigh	$\sigma = 12400786$	

After parameter estimation, the Kolmogorov-Smirnov (KS) test and the Cramér-von Mises (CvM) test were conducted to evaluate the goodness of fit for each candidate distribution. Additionally, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were calculated to identify the most appropriate distribution for the data. A summary of the KS statistics, CvM statistics, AIC, and BIC values for each candidate distribution is provided in Table 5.

Table 5. KS Statistic, CvM Statistic, AIC, and BIC Values for The Severity Distribution Candidates

No	Distribution	KS Statistic	CvM Statistic	Goodness-of-fit Criteria	
				AIC	BIC
1	Lognormal	0.032269	62.4722	7454781	7454802
2	Gamma	0.808817	39943.15	1.01162E+14	1.01162E+14
3	Log-gamma	0.051140	189.2154	7469962	7469983
4	Weibull	0.054173	267.4754	7466728	7466749
5	Log-logistic	0.023398	52.9332	7455641	7455662
6	Fatigue Life	0.505375	15756.5	7833092	7833112

7	Generalized Extreme Value	0.299814	3634.7322	7984909	7984929
8	Generalized Pareto	0.308725	10012.49	7710871	7710891
9	Pareto	0.041563	163.5812	7460073	7460094
10	Pareto III	0.023192	52.3394	7455637	7455668
11	Pareto IV	0.018677	16.1662	7450851	7450892
12	Rayleigh	0.573525	30687.76	10912214	10912224

As shown in Table 5, the Pareto IV distribution exhibits the smallest values for the KS statistic, CvM statistic, AIC, and BIC compared to the other candidate distributions. This suggests that the Pareto IV distribution is the most suitable model for representing the annual average severity.

Modeling frequency and severity as separate components facilitates the application of the collective risk model for premium calculation. By assuming $E(S)$ in the collective risk model as pure premium, $E(N)$ as the expected value of frequency, and $E(X)$ as the expected value of severity, the following results are obtained:

$$E(N) = 22.35257$$

$$E(X) = 12994053$$

$$E(S) = E(N)E(X) = (22.35257)(12994053) = 290450487$$

This indicates that the annual pure premium for the structural residential exposure in Indonesia amounts to 290,450,487 USD, based on the total structural residential value of 727,203,792,016.315 USD. Consequently, the rate per unit of exposure (R) can be calculated as follows:

$$R = \frac{290450487}{727203792016.315} = 0.0003994073 = 0.3994073‰$$

To evaluate the variance of aggregate loss (S), the variances of frequency and severity distributions are required. The variance of the frequency distribution can be calculated analytically using the equation:

$$Var(N) = \mu + \frac{\mu^2}{n} = 22.35257 + \frac{22.35257^2}{15.53945} = 54.5054$$

Unlike the frequency variance for which an analytical solution can be obtained, the variance of the severity distribution requires a numerical approach such as Monte Carlo simulation to achieve the results. Using this approach, the variance of severity is calculated as:

$$Var(X) = 1.115971 \times 10^{17}.$$

Since both the frequency variance and severity values have been obtained, the aggregate loss variance can be derived using the following equation:

$$Var(S) = E(N)Var(X) + Var(N)[E(X)]^2 = 2.503686 \times 10^{18}$$

In addition, the Value at Risk (VaR) can also be obtained through a numerical approach in the form of Monte Carlo simulation. The VaR value for aggregate loss can be seen in Figure 6. Table 6 shows the VaR values at selected quantile points.

Research related to earthquake insurance premium prices within the scope of social insurance as part of social protection is still lacking. However, there is a standard earthquake insurance policy in Indonesia that has been a reference for commercial insurance companies. By assuming a loading factor of 40% proportional to the premium rate, the total rate for this social insurance scheme is 0.5591702. Then, we can compare this value with premium rates of the Indonesian Earthquake Insurance Standard Policy (Polis Standar Asuransi Gempa Bumi Indonesia-PSAGBI), as referenced in Otoritas Jasa Keuangan (2017), and shown in Table 7.

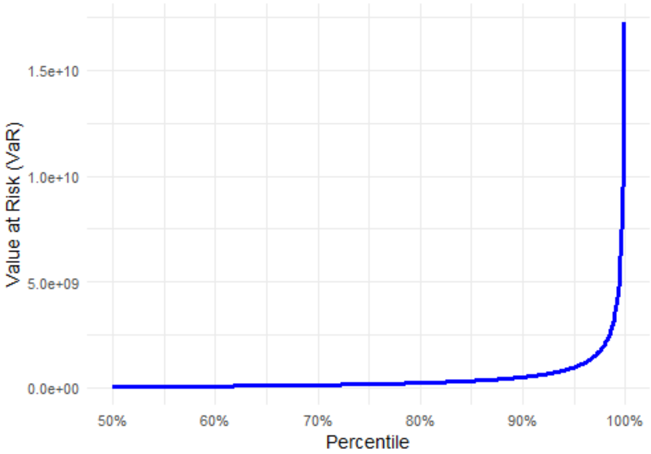

Figure 6. Value at Risk of Aggregate Loss

Table 6. VaR Values at Specific Quantile Points

Percentiles	VaR (in USD)
75.0	176,200,988.8
80.0	235,888,193.9
90.0	507,331,662.6
95.0	964,984,447.4
97.5	1,715,298,421.0
99.0	3,458,119,460.0
99.6	6,690,593,315.0
99.8	10,816,458,879.0
99.9	17,245,451,619.0

Table 7. PSAGBI Premium Rates

PSAGBI		Construction Type	
		Steel, Wood, RC	Others
Rate per Mille	Zone I	0.76	0.80
	Zone II	0.79	1.00
	Zone III	1.04	1.55
	Zone IV	1.35	2.24
	Zone V	1.60	4.50
	Average	1.108	2.018

Based on the comparison between this insurance premium rates and the values in Table 7, these are evidence that the premium rates generated by this model are consistently lower than the average premium rates established in PSAGBI across all zones. Notably, even in Zone I (a region with the lowest seismic risk), the proposed model still yields more affordable rates. This notable pricing advantage underscores the model's potential to offer a more accessible and comprehensive residential earthquake insurance solution. Such affordability serves as an effort to enhance inclusivity, aligning with the spirit of adaptive social protection.

This insurance scheme does not consider risk differentiation based on construction class or seismic risk zones to promote inclusivity and prevent the exclusion of vulnerable populations. Recognizing that vulnerable groups often live in lower-quality buildings, applying risk-based pricing would result in higher premiums for them.

5. CONCLUSION

This study emphasizes the integration of Social Protection (SP), Disaster Risk Reduction (DRR), and Climate Change Adaptation (CCA) within the Adaptive Social Protection (ASP) framework to enhance resilience and decrease vulnerability, particularly in earthquake-prone areas such as Indonesia. The country's high earthquake risk and limited fiscal capacity to address substantial losses underscore the pressing need for more effective disaster risk financing solutions.

This research proposes a residential earthquake insurance scheme as part of ASP to address gaps in disaster risk financing and strengthen resilience against seismic events. Using the probabilistic event-based risk calculator from OpenQuake, this study simulates earthquake losses over a 10,000-year period to estimate the frequency and severity of potential future losses. The fitting distribution identifies the negative binomial distribution for frequency and the Pareto IV distribution for severity. Applying the Collective Risk Model and Pure Premium Principle, the derived premium rate is 0.3994073‰.

In addition, this research found the potential magnitude of losses caused by earthquakes, with the variance of aggregate losses estimated at 2.5×10^{18} USD. The Value at Risk (VaR) analysis highlights the significant financial risks associated with extreme seismic events: 176.2 million USD at the 75th percentile (PML 176.2 million USD for a 4-year return period), 235.9 million USD at the 80th percentile (PML 235.9 million USD for a 5-year return period), 507.3 million USD at the 90th percentile (PML 507.3 million USD for a 10-year return period), 965 million USD at the 95th percentile (PML 965 million USD for a 20-year return period), 1.715 billion USD at the 97.5th percentile (PML 1.715 billion USD for a 40-year return period), 3.458 billion USD at the 99th percentile (PML 3.458 billion USD for a 100-year return period), 6.691 billion USD at the 99.6th percentile (PML 6.691 billion USD for a 250-year return period), 10.816 billion USD at the 99.8th percentile (PML 10.816 billion USD for a 500-year return period), and 17.245 billion USD at the 99.9th percentile (PML 17.245 billion USD for a 1,000-year return period). These results emphasize the potentially catastrophic impact of rare but severe earthquakes, reinforcing the necessity of establishing a robust financial mechanism, such as the proposed insurance scheme, to mitigate large-scale economic losses.

By embedding this insurance model within the broader context of ASP, the study highlights how this approach can bridge the gap in Indonesia's disaster risk financing and provide a sustainable solution to earthquake-related financial risks. This research contributes not only to the development of an effective earthquake insurance model but also to the broader discourse on ASP, offering valuable insights for other seismically vulnerable regions. The proposed scheme not only offers a practical and affordable way to mitigate the economic impact of earthquakes but also strengthens the adaptive capacity of communities to face future disaster risks, aligning with the goals of ASP to reduce vulnerability and enhance resilience.

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