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Modelling the costs of natural disasters in indonesia: A Monte Carlo simulations

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Abstarct

This research investigates the economic impact of natural disasters on a national scale and explores how this impact can be reduced through various mitigation and adaptation strategies.

Utilizing Indonesia as a case study, probabilistic models and Monte Carlo simulations were employed to predict future losses from earthquakes, floods and wildfires. This methodological approach mirrored risk assessment practices leveraging historical disaster data to accurately reproduce past loss patterns in specific regions. JMP statistical software facilitated the comprehensive analysis, generating robust estimates designed to empower policymakers in implementing effective measures for minimizing economic disruption. The findings and subsequent discussions analyse these strategies to identify various approaches that can be employed to reduce the financial burden imposed by natural disasters.

Key words: Monte Carlo simulations, Probabilistic Models, Risk Assessment

Code Jel : C02, C15, E17, F47, G22

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INTRODUCTION

Background

The perception of disasters has evolved from a supernatural paradigm to one rooted in natural physical realities, notably influenced by the 1755 Lisbon earthquake. As Dynes (Dynes, 1993)noted, this event marked a shift from viewing disasters as divine communication to a more secular, proto-scientific understanding. By the early 20th century, this theory led to engineering solutions to "tame" natural forces, such as ancient dams and earthquake-resistant dwellings.

However, increasing losses in the 20th century revealed that natural phenomena alone weren't the sole cause. This led to a third theory: disasters result from the interaction between natural phenomena and societal systems. (Carr, 1932) first proposed this human-nature interplay. (White G. , 1936), observing the limits of flood protection, introduced the societal dimension, advocating for judicious land use planning based on (Barrows, 1923) "human ecology" concept. (McHarg I. , 1969) championed a similar ecological design for urban planning, arguing it could significantly reduce disaster impact. This study aims to understand and mitigate disaster impact through modelling economic consequences, providing invaluable information for effective risk management strategies

Literature review

Research on the macroeconomic costs of natural disasters, particularly the cost-effectiveness of mitigation and adaptation strategies, has grown. Empirical studies, including those by Benson (Benson C. , The Economic Impact of Natural Disasters in Viet Nam., 1997b) (Benson C. , The Economic Impact of Natural Disasters in Fiji, 1997a) (Benson C. , The Economic Impact of Natural Disasters in the Philippines, 1997c) (Benson C. a., The Impact of Drought on Sub-Saharan African Economies, 1998) (Benson C. a., Developing Countries and the Economic Impacts of Catastrophes, 2000) (Benson C. a., Dominica: Natural Disasters and Economic Development in a Small Island State, 2001) ECLAC (1982, 1985, 1988, 1999, 2000, 2002) (ECLAC, Nicaragua: Las inundaciones de mayo de 1982 y sus repercusiones sobre el desarrollo economico y social del pais, 1982), (ECLAC, Damage caused by the Mexican Earthquake and its repercussions upon the country's economy. Santiago de Chile, 1985) (ECLAC, Damage caused by Hurricane Joan in Nicaragua. , 1988) (ECLAC, Manual for estimating the socio-economic effects of natural disasters, 1999), (ECLAC, A matter of development: how to reduce vulnerability in the face of natural disasters, 2000), (ECLAC, Handbook for estimating socio-economic and environment effects of disasters, 2002); Otero and Marti (Otero, 1995)], (Albala-Bertrand, 1993), (Murlidharan, 2001), (Crowards, 2000), (Charveriat, 2000), generally find significant short- to medium-term macroeconomic effects, often considering disasters a barrier to long-term development. The only dissenting view is presented by (Albala-Bertrand, 1993)

(Dacy & H. Kunreuther, 1969) examined industrialized countries, noting decreased tax revenue and stable demand/prices, advocating for comprehensive disaster insurance, a concept further explored in works like Kunreuther et al. (1978), Kunreuther (1996), and Kunreuther and Roth (1998). Benson (1997a, b, c) and Clay (1998, 2000, 2001) conducted short-term case studies on Fiji, Vietnam, the Philippines, and Dominica, revealing severe negative economic impacts, particularly in agriculture, and exacerbated inequalities.

ECLAC, through numerous case studies since 1972, developed a manual for assessing disaster impacts, with Otero and Marti (1995) summarizing findings of serious shorter-term impacts (decreased national income, increased fiscal and trade deficits) and substantial longer-term development challenges, as also noted by ECLAC and IDB (2000). Murlidharan and Shah (2001) found catastrophes significantly affect short-term growth, with effects subsiding over time, and associations with external debt, budget deficit, and inflation. Crowards (1999) observed a GDP growth slowdown post-hurricane in Caribbean nations, followed by a rebound due to investment. Charveriat (2000) identified a typical GDP decrease in the event year with subsequent recuperation, influenced by loss-to-GDP ratio, event scope, and economic vulnerability.

In contrast, Albala-Bertrand (1993) argued that natural disasters do not negatively affect GDP, public deficit, or inflation in the short to medium term, and might even improve GDP due to capital inflows. He concluded that long-term effects fade after two years in developing countries, though income distribution issues persist, viewing disasters as "a problem of development, but essentially not a problem for development." However, ECLAC (2002) challenged Albala-Bertrand's assumptions, presenting contradicting examples on GDP and inflation impacts, arguing against the underestimation of damages, and asserting that disaster events occur more frequently, ultimately considering disasters "a problem for development."

Problem

Most researchers rely on input output models to estimate the effect of disasters on economies. On the basis of a theoretical discussion, it is argued by (Yasuhide Okuyama.; Adam Rose, 2019) that the traditional demand-driven IO model and the IIM models may be suitable for modelling man-made disasters, such as a terrorist attack, which will mainly result in spatial and product shifts in final demand (i.e., effect on tourism and consumer demand). For the modelling of natural disasters such as earthquakes or floods, which primarily affect the supply-side of economy, they argued that the IO models are unsuitable as they suffer from shortcomings in representing supply-side shocks.

Objective

Therefore, in this thesis I decided to use probabilistic methods and risk assessment techniques to help predict the potential damage natural hazards might to hurt the economy hence leading to a pivotal question guiding this whole research which is:

What is are the various mitigation and adaptation strategies in reducing the economic impact of natural disasters on a country?

Research hypotheses;

H1: Insurance and Risk transfer strategies have a positive impact on the economic recovery and reduce on the general costs of natural disasters.

H2: Economic growth tends to have a positive relationship with the increase of costs of natural disasters

METHODOLOGY

A straight forward approach in estimating future disaster costs was used where l determined these costs by using probabilistic distribution methods and Monte Carlo simulations. The Monte Carlo is a powerful technique which involves random generation of statistical data that allows numerical solutions to problems that may be difficult to solve analytically. The method is named after the Monte Carlo Casino in Monaco where games of chance exhibit random behaviour similar to the random variables used in these methods. This methodology is adapted to model complex systems where there is significant uncertainty to understand potential outcomes and their likelihoods.

Probabilistic models to forecast costs of disasters in the future. Simulating the extreme events with a mathematical model might provide a better understanding of the stochastic nature of these events. This thesis models each type of disaster separately and fits a probability distribution for the frequency and the cost for each type of disaster. The costs of disasters are unevenly spread for each type of disaster and split. I therefore simulated each type of disaster to generate an annual cost of these disasters in Indonesia. Just fitting probability distributions to all the losses/costs[†] of the disaster in the respective years they were record (1970 to 2022) assumes that there is no economic growth and inflation. Since this is a very highly unlikely assumption, I therefore also incorporated real GDP (Gross Domestic Product) to account for the inflation and

[†] The terms costs and losses are used interchangeably throughout this thesis

economic growth factor into a model and evaluate its effect on the costs of these disasters. It is important to note that this type of modelling assumes that the relationship between the costs of disasters and GDP remains constant over the time.

This research presents the simulated results to give a broader picture of the risk that Indonesia can face from natural disasters. A probabilistic forecast of disasters' costs provides better insights than a deterministic model into the risks. Policymakers can use these types of models to develop strategies and allocate resources to prepare for disasters in order to minimise damage costs

Data Review

A survey of literature on economic loss data due to disasters shows that disaster economic loss data for floods and earthquakes hazards are available from the late 1960s but insufficient for wildfires in the case of Indonesia. Thus, the report will present analyses and estimates of natural disasters based on the historical events that have affected the country over the last 53 years (1970 to 2022).

Data sources

Since 1970, significant efforts have been made by various academic and multilateral development agencies to compile historical disaster data and generate standardized data across the globe for disaster risk mitigation activities. As a result, numerous databases are available in print and on the Internet. This section describes the most relevant data sources that have been identified for this study;

1. The Centre for Research on the Epidemiology of Disasters (CRED) maintains the EM-DAT global emergency events database on disasters (natural and technological hazards), which is one of the most exhaustive sources of data available in the public domain. While EM-DAT data date back to the 1900s, data on economic losses caused by disasters in most countries have become generally available since the 1980s.
2. The Asian Disaster Reduction Centre (ADRC) has compiled data from various sources, including: UNOCHA, DesInventar, the Government of the United States, the Government of Japan, OFDA, IFRC, WMO and the reinsurance industry and private agencies.
3. Asia Disaster Preparedness Centre (ADPC) has compiled data from various sources. The data are available for Indonesia in the form of country and regional reports The World Bank's East Asia and Pacific (EAP) unit has prepared brief country disaster risk profiles for Indonesia
4. The World Bank

APPLICATION OF THE METHODOLOGY

We initially attempted to fit a probability distribution to this entire data set, but no distribution fits well to the observed data or provided good forecasts hence the better approach was fitting the models separately for each disaster type. Analysing each type of disaster also provided a better understanding of these disasters. Modelling each type of disaster separately made the model more robust to changes in the data. Using probabilistic models rather than deterministic models reflects the uncertainty that is inherent in forecasting future economic costs from natural disasters.
We modelled the distributions of each type of natural disaster separately: Earthquake, flood and Wildfires
First, we fitted a discrete distribution to the annual frequency of each type of disaster.

Then we fitted a continuous probability distribution to the cost of each type of disaster. We assumed that the cost for each type of disaster was identically and independently distributed. used the Akaike information criterion (AIC) and the log-likelihood as the criteria of best model selection and also used the goodness of fit test to validate that the selected distribution.

JMP Statistical Software was used to fit a continuous random variable for the costs of each type of disaster. We fitted the costs for each type of disaster to the following continuous distributions: Johnson with a lower bound, sinh-arcsinh (SHASH), lognormal, generalized log, gamma, normal mixtures (2 and 3), Weibull, extreme value, exponential, and normal. Two distinct models are created, and each model uses a different dataset to analyse the economic impact of these natural disasters.

We started by using all of the data to fit the discrete distribution to the annual frequency. This frequency was analysed and incorporated into a model to generate the number of disasters that occur in a year for each of the three types of disasters separately.

Then we used two different types of models for the costs associated with the natural disasters separately.

Model 1 – This model uses the actual costs recorded in their respective years without adjusting for economic growth or inflation. It uses all the historical data from 1970 to 2022 to model the costs of natural disasters where a probability distribution is fit to the cost of each type of disaster separately. Then the AIC and log-likelihood values are evaluated and the best fit of the probability distribution is selected for each type of disaster. Monte Carlo simulations are used to generate the estimated costs for all three disasters.

Model 2 – This model adopts the same methodology as model 1 but in this case, we incorporated the real GDP factor to adjust for economic growth and inflation over the years. In order to do this, we divided the natural disaster costs by the corresponding real GDP of every year since 1970 to 2022 in order to obtain the cost to real GDP ratio. We chose the real GDP of the year 2022 as reference (Base year) (because it was a relatively stable year without sudden economic booms and recessions) and thenwe multiplied each cost to real GDP ratio by the real GDP of the reference year (2022) where we obtained the costs of each year.

$$\textbf{GDP adjusted economic cost} = \frac{\textbf{Costs of disasters recorded for each year}}{\textbf{Real GDP of the corresponding year}} \times \textbf{Real GDP of 2022}$$

The new disaster costs are used in a Monte Carlo simulation and to generate a probabilistic estimate of the cost of natural disasters of each simulated year.

Then trials in the Monte Carlo simulations begin to randomly generate the number of disasters that occur every year for each of the three disasters as well as their costs from the probability distribution that best fits each type of disaster. We excluded the white noise from the analysis because it makes the estimates highly volatile and give un realistic probabilities and significant inaccurate estimates. The Indonesian GDP in 2022 was $1,32 trillion. As mentioned previously, for Model 2, to convert the ratio of data to the GDP to the costs of disasters, we multiply the costs generated by the model for each type of disaster and the GDP in 2022. We calculate the total annual disaster costs in a single trial by summing the costs of individual disasters. This process is repeated 100,000 times to generate a simulated probability distribution of the annual costs of these disasters. The annual costs for each of the three types of disasters and the total annual costs from all the disasters are analysed and presented.

RESULTS

Natural disaster Frequency Analysis

The annual frequency of these disaster was analysed and found out wild fires tend to be more frequent followed by floods and earthquakes respectively.

Table below depicts the distribution for the annual frequency for each disaster. The Poisson distribution is used to model the number of events for Wildfires, earthquakes and flood. The parameter λ (average number of annual events) for the Poisson distribution is given in Table 3 for these disasters. The average annual number of floods, earthquakes and wildfires was 5,54, 2.81 and 27.5 respectively from 1970 to 2022. The annual frequency of all the disasters increases.

Table 1:Distribution of annual frequency of Earthquakes, Floods and Wildfires in Indonesia

DISASTERS	DISTRIBUTION TYPE	MODEL PARAMETER
EARTHQUAKES	POISSON	λ=2.81
FLOODS	POISSON	λ=5.54
WILDFIRES	POISOON	λ=27.5

Source; Table made by authors

Validation of the selected distributions

Sensitivity tests were carried out to make sure the selected distributions vividly fit the data well hence all the three distributions were validated using a goodness fit test where the probability of the calculated Pearson Chi-Square was largely inferior to the 5 % threshold rendering the distributions significantly viable. The predicted frequency was also compared to the actual observed frequency to further validate the model. Further illustrations are provided in the appendices.

Application of the monte Carlo simulation to the distribution

A 100 thousand monte Carlo simulation was applied on the distributions where the summary statistics such as the mean and standard deviation are closely similar to those observed in the actual data. I analysed the frequency risk of these disasters in different return periods from a 10 to 100 year return periods and the number of wildfires is expected to be as high as 2850 in a 100 year return period followed by floods and earthquakes respectively. The table below shows the total number of disasters expected in different returns periods categorically .

Table 2: Annual frequency of Earthquakes, Floods and Wildfires expected in different return periods

RETURN PERIODS	EARTHQUAKES	FLOODS	WILDFIRES
10 YEARS	32	54	277
20 YEARS	58	102	605
50 YEARS	135	291	1543
100 YEARS	257	574	2850
AA FREQUENCY	2.83	5.74	28.5

Source; Table made by authors

The CDF plots at a 100 year return period of the three disasters were analysed where the annual frequency of earthquakes is expected to range between 0 to 6, floods is expected to range between 0 to 8 and wildfires is expected to range between 0 and 40 at a 90% confidence level.

Natural Disaster Cost/Loss Analysis

The costs/losses were also analysed using the two models described in the methodology. The statistical summary was analysed for each of the disasters and therefore fitted a continuous distribution to each of the disasters to determine the best distribution for each of the disasters based on the AIC and loglikelihoods statistics. All cases lognormal distribution was found to be the most suitable distribution for all the three disasters.

Table 3: Distribution types of costs/losses of Earthquakes, Floods and wildfires in Indonesia

NATURAL DISASTERS	MODEL 1	MODEL 2
EARTHQUAKES	Lognormal distribution	Lognormal distribution
FLOODS	Lognormal distribution	Lognormal distribution
WILDFIRES	Lognormal distribution	Lognormal distribution

Source; Table made by authors

Validation of the selected distributions in Model 1 and 2

Sensitivity tests were carried out to see how well the selected distributions fit the observed data hence the goodness fit test was applied to all distributions and the probability of the calculated Anderson-Darling coefficient was found to be significantly inferior to a 5% threshold and PP plot was also applied to provide a visual context where most of the points followed the reference line which suggested that the fitted distribution was a reasonable representation of the data. Hence it indicated that the empirical cumulative distribution function (CDF) of the data was identical or similar to Fitted CDF of the historical data observed. Therefore, the model was deemed to be good and validated for all the three natural disasters

Application of the monte Carlo simulation to the distributions

100 thousand Monte Carlo Simulations were carried out using the selected distributions

MODEL 1

- Earthquakes
  The Average Annual Losses of Earthquakes calculated was approximately 757.9 million US Dollars with a standard deviation of about 761,5 million US Dollars.

The results also suggested that annual losses can be extreme and reach a maximum of approximately 114,5 billion US Dollars and minimum of around 3167.1 US Dollars.

- Floods

The annual average losses of floods are expected to be approximately 506.33 million US Dollars with a standard deviation of about 253 million US Dollars. In a 100 thousand year return period Indonesia is expected to incur flood costs between 20 thousand US dollars and 25 billion US dollars annually.

- Wildfires

The average annual losses in a 100,000 year return period are expected to be approximately to 125.9 million US Dollars with a standard deviation of approximately a billion US Dollars. And the costs/losses are expected to range between 2937 US Dollars to 124.8 billion USD dollars annually.

MODEL 2

- Earthquakes

The Average Annual Losses of Earthquakes is expected to be approximately 396.7 million US Dollars with a standard deviation of about 2.54 billion US Dollars according the Monte Carlo Simulation of 100 thousand year return period. The results also suggest that annual losses can be extreme and reach a maximum of approximately 241 billion US Dollars and minimum of around 78088.4 US Dollars in the same return period.

- Floods

The average annual costs of floods are expected to be approximately 159.2 million US Dollars with a standard deviation of about 517.1 million US Dollars. In a 100,000 year scenario, the costs of floods are expected to range between 362.7 thousand US Dollars and 37.54 billion US Dollars annually.

- Wildfires

The average annual losses in a 100,000 year return period are expected to be approximately to 527.25 million US Dollars with a standard deviation of 6.82 billion US Dollars. The costs of wildfires are expected to range between 12907 US Dollars to 1.178 trillion USD dollars annually.

MODEL COMPARISONS

Table 4: Summary of Model comparisons between Model 1 and Model 2

	MODEL 1	MODEL 2
EARTHQUAKES	• **Model 1** estimates the Average Annual Losses (AAL) at approximately **$757.9 million** with a standard deviation (SD) of about **$761.5 million**. The potential annual losses range from a minimum of **$3,167.1** to a maximum of **$114.5 billion**.	• **Model 2** estimates the AAL at approximately **$396.7 million** with a higher SD of about **$2.54 billion**. The annual losses can range from **$78,088.4** to an extreme maximum of **$241 billion**.
FLOODS	• **Model 1** predicts AAL of floods at about **$506.33 million** with an SD of **$253 million**. The costs can vary between **$20 thousand** and **$25 billion** annually.	• **Model 2** has a lower AAL prediction at **$159.2 million** but with a higher SD of **$517.1 million**. The annual flood costs are expected to be between **$362.7 thousand** and **$37.54 billion**.
WILDFIRES	• **Model 1** estimates the AAL to be around **$125.9 million** with an SD of **$1 billion**. The annual costs may range from **$2,937** to **$124.8 billion**.	• **Model 2** predicts a significantly higher AAL at **$527.25 million** with a much larger SD of **$6.82 billion**. The costs can vary from **$12,907** to a staggering **$1.178 trillion** annually.

Source; Table made by authors

Model 1 generally predicts higher average annual losses for earthquakes and floods but lower for wildfires compared to **Model 2**. However, **Model 2** shows a greater variability in the potential losses across all three disaster types as indicated by the higher standard deviations. This suggests that while **Model 1** might estimate a higher average loss, **Model 2** predicts a wider range of potential outcomes including extreme events, which are crucial for risk assessment and management strategies. The choice between models would depend on whether the focus is on average expected losses or the full range of potential outcomes.

Different return periods are analysed between the two models

Table 5: Annual losses/ costs estimated by Model 1 and Model 2 in different return periods

Source: Table made by authors (these results were obtained by manual calculations using the

RETURN PERIODS	EARTHQUAKES		FLOODS		WILDFIRES	
	MODEL 1 (IN MILLIONS)	MODEL 2 (IN MILLIONS)	MODEL 1 (IN MILLIONS)	MODEL 2 (IN MILLIONS)	MODEL 1 (IN MILLIONS)	MODEL 2 (IN MILLIONS)
10 YEARS	$1.960	$22.127	$456.182	$23,250.014	$2,611.108	$288,003.932
20 YEARS	$8.469	$33.210	$1,862.763	$33,691.754	$7,997.499	$295,536.056
50 YEARS	$23.307	$438.004	$14,481.904	$103,230.000	$33,784.278	$341,133.671
100 YEARS	$46.986	$558.196	$30,387.953	$185,997.459	$114,733.059	$491,146.959

Monte Carlo output of the first 100 years[‡]*)*

The comparative analysis presented in the table clearly demonstrates that **Model 2** forecasts a more pronounced financial impact from natural disasters across various return periods in comparison to **Model 1**.

In specific context, **Model 2** projects a substantial financial burden in the **short run** which is significant but decreases as time advances while Model 1 on the other hand projects the same behaviour as Model 2 in the case of floods and wildfire but with a significantly lower financial constrain compared to Model 1. Earthquakes in Model 1 however show a very low financial burden in the short run but significantly increase in the long run.

The Cumulative Distribution Function analysis (CDF)

Furthermore, CDF plot graphs of a 100 year return period for all the three disasters were analysed and the range of annual losses were determined at a 90% confidence interval both in Model 1 and Model 2

[‡] results of the first 100 year return period each model of the were cumulated in order to find the losses incurred in the different return periods

Table 6: Summary of expected annual range of losses/ costs caused by Earthquakes, Floods and Wildfires in a 100 year return period in Indonesia

NATURAL DISASTERS	MODEL 1(IN MILLIONS)	MODEL 2(IN MILLIONS)
EARTHQUAKES	1.8 – 150	2.5 – 500
FLOODS	0.9 – 100	15.3 – 400
WILDFIRES	0.9 - 150	0.2 – 1000

Source; Table made by authors (see appendix 06)

DISSCUSSIONS

A national disaster risk financing strategy should be designed to improve the capacity of

the Government of Indonesia to access immediate financial resources in case of natural disaster while maintaining its fiscal balance. Building on the country disaster risk financing framework promoted by the World Bank, six options for a comprehensive disaster risk financing in Indonesia are discussed below.

1. **Crafting Tools for Financial Disaster Risk Evaluation**

   Initiating a national strategy for disaster risk finance hinges on a comprehensive risk evaluation. Techniques in catastrophe risk modelling can enhance actuarial studies of historical loss data, providing insights into the economic and budgetary risks posed by natural calamities.

   It's essential to create hazard modules for significant threats. PT Maipark has pioneered an earthquake hazard module, drawing from an exclusive historical earthquake catalog. Similarly, a flood hazard module tailored for major metropolitan regions, such as Greater Jakarta, is also viable.

   Constructing a national, geo-referenced exposure database is imperative. This repository would encompass details of both public and private structures and infrastructure vulnerable to natural disasters, including educational institutions, medical facilities, government buildings, thoroughfares, and viaducts. Additionally, it could catalog private holdings like residential properties. When integrated with the catastrophe risk model, this database would facilitate, among other functions, the evaluation of the economic and budgetary repercussions of natural disasters. Moreover, this data is crucial for the insurance sector to provide property catastrophe insurance solutions that are both viable and economically accessible.

The Ministry of Finance should adopt a financial catastrophe risk model. The existing earthquake risk model could serve as a foundation for a financial catastrophe risk model employed by the Ministry. This model would amalgamate an actuarial/financial framework that capitalizes on the projected losses from the catastrophe risk model and historical loss records. This instrument would be instrumental for the Ministry in formulating a national disaster risk finance strategy, which includes determining the annual budgetary allocation for the Rehabilitation and Reconstruction Fund and any strategies for disaster risk transfer, like insurance. The Ministry of Finance in Mexico is currently utilizing a similar financial model.

2. **Formulating a Strategic Framework for National Disaster Risk Finance**

A national disaster risk finance strategy should be anchored in a risk layering methodology. This strategy provides a balanced combination of risk retention mechanisms, such as reserves or contingency budgets and contingent credit, alongside risk transfer mechanisms like insurance.

Adopting a "bottom-up" approach to disaster risk finance is advisable. Initially, the Indonesian Government should ensure financial provisions for frequent, lower-magnitude events (the bottom risk layer) through risk retention strategies. Subsequently, it can enhance its financial robustness by incorporating disaster risk transfer tools.

Presently, the national budget does not forbid insurance procurement, yet there is no designated budget line item for insurance premium payments. As per the prevailing budget legislation, the BNPB is barred from utilizing its annual budget for insurance acquisition. The budget law should permit the allocation of a portion of its funds for insurance procurement. For instance, in Mexico, the budget legislation empowers FONDEN's Trust Fund to allocate a part of its yearly budget for acquiring financial risk transfer instruments, such as insurance and catastrophe bonds, facilitated by the public reinsurance entity Agroasemex.

To bolster financial capacity, the Indonesian Government could integrate parametric insurance with its reserves or contingent credit. Parametric insurance policies disburse funds based on the severity of an event, like wind velocity or earthquake magnitude, rather than actual damages incurred. These policies employ a pre-established formula for loss estimation, relying on external variables that correlate strongly with individual losses, yet are independent of the policyholder and insurer. This enables swift claim settlements, typically within two to four weeks, and reduces susceptibility to moral hazard and adverse selection. Nonetheless, parametric insurance is subject to basis risk that payouts may not align precisely with individual damages. Therefore, meticulous calibration of index insurance parameters is crucial to mitigate basis risk.

The Government of Indonesia can also bolster its financial disaster risk transfer approach by issuing **catastrophe bonds**. These index-linked securities tap into capital markets, providing funds in the event of predefined natural disasters. Typically, catastrophe bonds cover the most severe risks and are tailored to specific perils with an annual occurrence probability of 2 percent or less (equivalent to a return period of 50 years or more). Notably, Mexico issued catastrophe bonds in 2006 and 2009.

To fortify resilience, Indonesia could allocate **0.5 percent** of its annual government budget expenditures (approximately **US$500 million**) for disaster recovery costs related to recurrent events within a return period of up to **4 years**. Already, Indonesia increased its annual budget allocation to approximately **IDR 4 trillion** (around **US$450 million**) in 2011.

Additionally, securing a **contingent credit line** of **US$500 million** would enhance Indonesia's retention capacity. This credit line, akin to the World Bank's DPL with Cat DDO, would activate approximately every **4 years** when the annual budget allocation is depleted. While Indonesia could raise the annual budget allocation to **US$1 billion**, opting for a contingent credit line may be politically more sustainable. It allows pre-funding of losses expected every **4 years**, while larger losses (anticipated every **4 to 20 years**) can be post-funded by repaying any drawn-down debt. The contingent credit serves as a bridging facility, offering flexibility for post-disaster rapid recovery, especially during budget revision cycles, and repayment once the new fiscal year begins.

3. **Creating an Agile National Disaster Reserve Fund (NDRF)**

The current post-disaster budget allocation process faces delays, leading to liquidity constraints. The Rehabilitation and Reconstruction Fund, with an annual allocation of IDR 4 trillion in 2011, serves as a primary source for post-disaster recovery and early reconstruction. However, disbursements from this fund require parliamentary approval, resulting in operational delays. To address this, the national disaster risk financing strategy should establish a **National Disaster Reserve Fund (NDRF).** This financial trust, akin to Mexico's successful FONDEN, would swiftly disburse funds after disasters, enabling rapid recovery operations.

Key features of the NDRF would be:

i. To ensure transparent allocation and efficient use of post-disaster funds. Immediate disbursement would be available for BNPB and implementing agencies, bypassing parliamentary bottlenecks.
ii. To integrate existing disaster funding mechanisms, including the On-Call budget. Restrictions on disaster contingency funds should be lifted to maximize its effectiveness.
iii. To build up reserves over time from unspent portions of its annual budget allocations. This gradual accumulation would enhance its retention capacity.
iv. To purchase disaster risk transfer instruments to bolster its financial capacity during disasters. Government regulation would permit the NDRF to pay insurance premiums from its annual budget allocation.
v. To design and implement a comprehensive risk financing strategy. This could include contingent debt agreements, indemnity and parametric insurance, and the issuance of catastrophe bonds or alternative risk transfer mechanisms.
vi. To finance emergency assistance and post-disaster recovery, prioritized by BNPB and local agencies. It would cover critical infrastructure damages (e.g., roads, bridges) and public buildings (e.g., schools, hospitals).

4. **Initiating a Public Asset Disaster Risk Insurance Initiative**

In Indonesia, vital public assets and infrastructure like schools, hospitals, roads, and bridges are susceptible to natural disasters and lack insurance coverage. While developed nations often self-insure such assets due to their ready access to capital markets, Indonesia's public assets typically remain unprotected, despite a few regions recently opting to insure select properties.

In nations with constrained fiscal resources and limited capital market access, legal mandates sometimes require property insurance for public assets to safeguard against natural calamities. This practice is observed in Latin American countries, including Costa Rica, Mexico, and Colombia. Yet, the reality is that many public assets are either uninsured or under-insured, as public administrators are hesitant to allocate scarce budgetary funds for insurance premiums and often lack the necessary information to choose cost-effective insurance options.

To enhance the protection of public assets against disasters, Indonesia could launch a **Disaster Risk Insurance Program for Public Assets**. This initiative would work in tandem with the private insurance sector to provide technical support to public entities in crafting their disaster insurance plans. The program would aim to establish uniform policy terms and conditions in partnership with private insurers, aiding public managers in assessing their risk profiles and insurance requirements. Furthermore, the program could organize a collective insurance portfolio for public assets, which would then be offered to the private (re)insurance market. Adopting a national stance on insuring public assets could yield scale economies and diversification advantages, potentially reducing reinsurance costs.

5. **Promoting Catastrophe Insurance for Private Dwellings in Indonesia**

Despite efforts by specialized reinsurer PT Maipark, the penetration of catastrophe property insurance in Indonesia remains low. Currently, less than 5 percent of properties are insured against natural disasters, primarily commercial and industrial properties. This limited adoption is a consequence of the underdeveloped non-life insurance market in the country. Therefore, to mitigate Indonesia's implicit contingent exposure to major disasters, the government should encourage property catastrophe insurance for private residential dwellings. Establishing a robust domestic property catastrophe insurance market would be crucial. Here are some strategies:

i. **Technical Support and Models**: The government could finance and provide exposure and loss models to private insurers. These tools would assist insurers in assessing risk exposure and designing effective insurance coverage.
ii. **Awareness Campaigns**: Information and awareness campaigns can educate homeowners about the benefits of catastrophe insurance. Turkey's example provides insights.
iii. **Turkish Catastrophe Insurance Pool (TCIP):** Turkey's TCIP, established in 2000, addressed market failure related to earthquake coverage. The World Bank supported its design, including earthquake exposure modelling and affordable, compulsory earthquake-only policies for registered urban houses.

iv. **Microinsurance for Livelihood Protection**: Indonesia could develop microinsurance products to safeguard households affected by recurrent natural disasters. These products, linked to savings or credit mechanisms, would offer comprehensive coverage. Leveraging existing community empowerment programs, such as PNPM, could enhance distribution.

v. **Enhanced Insurance Supervision**: Strengthening insurance supervision is essential. A risk-based assessment of insurers' retention capacity and reinsurance strategies, informed by catastrophe risk modelling and actuarial tools, would improve oversight. Developing an actuarial model to refine commercial earthquake premium rates and assess disaster impact on insurers' portfolios is crucial. Additionally, a scoring tool for evaluating insurers' reinsurance strategies could enhance quality and adequacy.

6. **Forming a Collective Disaster Reserve Fund for Indonesian Localities**

Over the past decade, it has become evident that local Indonesian authorities, such as municipalities and provinces, often face financial shortfalls when responding to natural disasters. Their limited economic scale often precludes them from amassing the necessary reserves to cover disaster-related losses not addressed by the Central Government.

A proposed Collective Disaster Reserve Fund would significantly enhance the disaster response capabilities of these local governments at minimal cost. Local authorities bear a substantial portion of disaster-related expenses and frequently struggle to gather the financial means for emergency response and recovery efforts. This Fund would serve as a communal reserve, ready to be deployed in the event of a disaster granting immediate access to substantial resources without the individual burden of reserve accumulation. Moreover, by consolidating their risks, local governments could more efficiently engage with the reinsurance market thereby reducing the costs associated with securing additional coverage.

The Fund would operate as a communal reserve for local governments with contributions tailored to each locality's risk profile and coverage needs. These contributions would maintain a reserve level adequate to cover annual disbursements to localities impacted by natural events. To address the variability of financial demands, the Fund would procure additional capacity from international reinsurance and capital markets.

The Fund would enable local governments in Indonesia to swiftly access unrestricted resources following a disaster. For transparency and expedience, disbursements would be based on parametric triggers, which, unlike traditional indemnity insurance, do not require on-site loss verification. This immediate liquidity would alleviate reliance on Central Government allocations for post-disaster emergency and recovery operations.

By participating in the Fund, local governments gain access to catastrophe risk insurance at the most economical cost. A preliminary analysis indicates that a joint reserve Fund would consolidate the natural disaster risks of local governments into a diversified portfolio, substantially lowering reserve costs. The expense of financial protection correlates with risk variability since local government disaster risks are not perfectly synchronized, a pooled portfolio's coverage cost is less than the cumulative individual coverage costs.

CONCLUSION

Natural disasters exert significant economic pressure on countries worldwide. As we grapple with the repercussions of climate change, understanding the cost-effectiveness of mitigation and adaptation strategies becomes paramount. Our research specifically delved into assessing the effectiveness of various strategies in reducing the economic impact of natural disasters on a country.

For this study, we chose Indonesia as a case study due to its substantial exposure to the selected natural disasters (earthquakes, floods, and wildfires). Leveraging probability distributions and Monte Carlo simulations, we quantified the losses incurred by these calamities. Notably, the size of a country's economy emerged as a critical factor influencing disaster costs. This relationship was evident in the cost estimates, particularly as Indonesia's GDP increased in the second model.

Furthermore, our findings underscored the effectiveness of insurance and risk transfer options in managing the extreme costs associated with natural disasters. Drawing from recovery strategies advocated by the World Bank, these mechanisms provide essential funds for both short-term and long-term for post-disaster recovery.

Recommendations

Carrying out careful planning and preparedness which includes expansion of early warning systems that provide timely alerts for impending disasters. It is important to also conduct a thorough risk assessment and create hazard maps to identify vulnerable areas and prioritize interventions.

Promoting investment in resilient Infrastructure that is designed to withstand natural hazards (such as, earthquake-resistant buildings, flood-resistant bridges).

Encouraging community engagement by raising awareness among communities about disaster risks, evacuation routes and emergency procedures. Also, integration of disaster risk reduction education into school curricula and community programs helps to raise awareness

Improving land-use practices and building codes such as enforcing more strict building codes and land-use regulations to ensure safer construction practices. This also includes properly zoning areas to prevent construction in high-risk zones (e.g., floodplains, earthquake and wildfire prone areas).

The government should carry out reforms in order to reduce the bureaucratic tendencies and provide the much needed funds for economic recovery. The government should be able to swiftly respond and implement disaster mitigation strategies which are instrumental in the cost reduction of natural disasters.

In summary, our research underscores the critical role of cost-effective adaptation measures in mitigating the economic impact of natural disasters. As policymakers and practitioners navigate these challenges, a holistic approach that considers both economic and non-economic dimensions is essential for building resilience and safeguarding communities.

Challenges and limitations

In our research, we encountered several challenges. First, selecting the most suitable methodology was crucial. While IO (Input-Output) and CGE (Computable General Equilibrium) models are commonly used, their data requirements often exceed what is readily available. Second, data shortages especially for pre-2000s wildfire records which limited the accuracy of my models. Finally, choosing a relevant geographical area posed difficulties, as many countries were not significantly affected by all three natural disasters. Despite these obstacles, our research contributes valuable insights to disaster risk assessment and mitigation.

APPENDICES

Appendix 01: Graphs showing frequency distribution of Floods, Earthquakes and Wildfires in Indonesia

Figure 1; Earthquakes frequency Graph

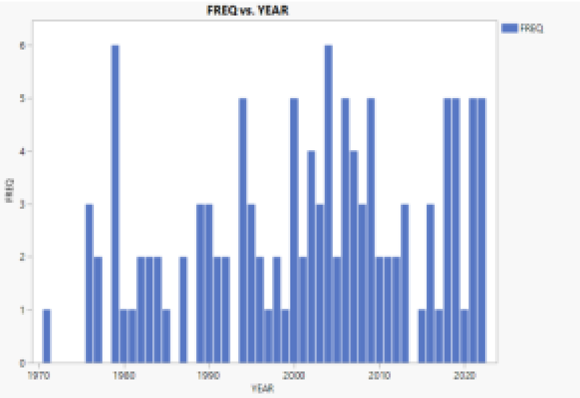


Figure 2: Floods frequency graph

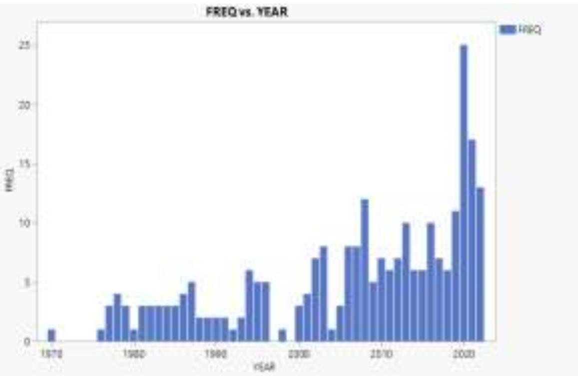
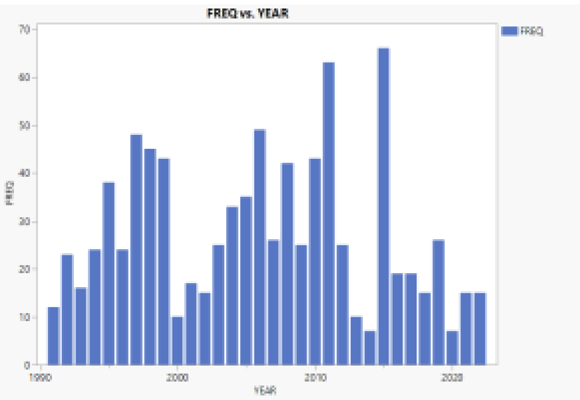


Figure 3;Wildfires frequency graph



Appendix 02: Comparison of the best fit distribution of Losses of Natural disasters

Table 7; Continuous fit of losses by Earthquakes (Model 1)

Compare Distributions

Show	Distribution	AICc	AICc Weight	BIC	-2*LogLikelihood
☑	Lognormal	1097.5514	0.8346	1099.6431	1093.0514
☐	Johnson Sb	1101.4767	0.1173	1104.8419	1091.6585
☐	Weibull	1103.2617	0.048	1105.3534	1098.7617
☐	Gamma	1116.0162	0.0001	1118.1079	1111.5162
☐	Exponential	1150.06	0	1151.1958	1147.9
☐	Normal 3 Mixture	1160.6402	0	1163.0069	1136.6402
☐	Normal 2 Mixture	1204.6238	0	1208.2458	1191.7666
☐	Student's t	1219.9574	0	1222.8014	1212.9139
☐	SHASH	1220.6637	0	1224.0288	1210.8455
☐	Normal	1223.977	0	1226.0686	1219.477
☐	Cauchy	2351.986	0	2354.0777	2347.486

Table 8; Continuous fit of losses by earthquakes (Model 2)

Compare Distributions

Show	Distribution	AICc	AICc Weight	BIC	-2*LogLikelihood
☑	Lognormal	1196.5341	0.8913	1198.6258	1192.0341
☐	Weibull	1202.0281	0.0572	1204.1198	1197.5281
☐	Johnson Sb	1202.2356	0.0515	1205.6008	1192.4174
☐	Exponential	1246.7494	0	1247.8852	1244.5894
☐	Normal 2 Mixture	1263.4772	0	1267.0993	1250.6201
☐	Gamma	1263.7119	0	1265.8036	1259.2119
☐	Student's t	1323.0199	0	1325.8639	1315.9764
☐	SHASH	1326.1359	0	1329.5011	1316.3177
☐	Normal	1331.6879	0	1333.7796	1327.1879
☐	Normal 3 Mixture	1337.5446	0	1340.9098	1327.7264
☐	Cauchy	2567.4078	0	2569.4995	2562.9078

Table 9; Continuous fit of losses by floods (Model 1)

Show	Distribution	AICc	AICc Weight	BIC	-2*Loglikelihood
[x]	Lognormal	1181.7993	0.7481	1184.0723	1177.3378
[ ]	Johnson Sb	1184.9166	0.1574	1188.7191	1175.2499
[ ]	Weibull	1186.0615	0.0888	1188.3346	1181.6
[ ]	Gamma	1191.5498	0.0057	1193.8228	1187.0882
[ ]	Exponential	1210.9112	0	1212.1304	1208.7631
[ ]	Normal 2 Mixture	1257.0538	0	1261.2816	1244.4451
[ ]	Normal 3 Mixture	1259.9922	0	1264.3777	1244.174
[ ]	Student's t	1273.5451	0	1276.6869	1266.5851
[ ]	SHASH	1275.1777	0	1278.9803	1265.5111
[ ]	Normal	1277.5734	0	1279.8465	1273.1119
[ ]	Cauchy	2452.4475	0	2454.7205	2447.9859

Table 10; Continuous fit of losses by floods (Model 2)

Show	Distribution		AICc	AICc Weight		BIC	-2*Loglikelihood
[x]	Lognormal		1266.8093	0.6266		1269.0824	1262.3478
[ ]	Weibull		1268.0862	0.3309		1270.3593	1263.6247
[ ]	Johnson Su		1273.3114	0.0243		1277.1139	1263.6447
[ ]	Exponential		1274.5523	0.013		1275.7715	1272.4042
[ ]	Normal 2 Mixture		1277.2614	0.0034		1281.4892	1264.6527
[ ]	Gamma		1278.4301	0.0019		1280.7032	1273.9686
[ ]	Normal 3 Mixture		1302.5501	0		1306.2884	1279.3501
[ ]	Normal		1321.2262	0		1323.4993	1316.7647
[ ]	SHASH		1321.6693	0		1325.4718	1312.0026
[ ]	Student's t		1322.9741	0		1326.116	1316.0141
[ ]	Cauchy		2539.7531	0		2542.0262	2535.2916

Table 11; Continuous fit of losses by wildfires (Model 1)

Show	Distribution		AICc	AICc Weight		BIC	-2*LogLikelihood
[x]	Lognormal		1328.486	0.9988		1331.0036	1324.0722
[ ]	Weibull		1342.2014	0.0011		1344.7191	1337.7876
[ ]	Johnson Su		1346.6976	0.0001		1351.079	1337.2161
[ ]	Gamma		1387.0544	0		1389.5721	1382.6406
[ ]	Exponential		1413.9258	0		1415.2582	1411.7925
[ ]	Normal 2 Mixture		1445.065	0		1450.086	1432.7573
[ ]	Normal 3 Mixture		1447.7704	0		1453.2048	1432.4104
[ ]	SHASH		1501.2757	0		1505.6571	1491.7942
[ ]	Student's t		1501.5198	0		1505.0599	1494.6627
[ ]	Normal		1507.2077	0		1509.7253	1502.7939
[ ]	Cauchy		2901.6082	0		2904.1259	2897.1944

Table 12; Continuous fit of losses by wildfires (Model 2)

Show	Distribution		AICc	AICc Weight		BIC	-2*LogLikelihood
[x]	Lognormal		1409.0254	1		1411.5431	1404.6116
[ ]	Weibull		1429.4533	3.7e-5		1431.9709	1425.0395
[ ]	Johnson Su		1455.6636	0		1460.0451	1446.1822

Show	Distribution		AICc	AICc Weight		BIC	-2*LogLikelihood
[ ]	Exponential		1529.1108	0		1530.4432	1526.9775
[ ]	Normal 2 Mixture		1548.1364	0		1553.1574	1535.8287
[ ]	Normal 3 Mixture		1551.697	0		1557.1314	1536.337
[ ]	Gamma		1582.4321	0		1584.9498	1578.0183
[ ]	Student's t		1624.6939	0		1628.234	1617.8368
[ ]	SHASH		1624.741	0		1629.1225	1615.2595
[ ]	Normal		1631.6735	0		1634.1912	1627.2597
[ ]	Cauchy		3150.5399	0		3153.0576	3146.1261

Appendix 03: Estimated distribution parameters of natural disasters in Indonesia

Table 13; Discrete fitted Poisson distribution of frequency of earthquakes

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Mean	λ	2.8139535	0.255814	2.3418933	3.3455502

Table 14; Discrete fitted Poisson of frequency of floods

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Mean	λ	5.5434783	0.3471461	4.8906317	6.2519888

Table 15; Discrete fitted Poisson of frequency of wildfires

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Mean	λ	27.5	0.9270248	25.722858	29.357169

Table 16; Continuous lognormal fit of losses by earthquakes (Model 1)

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Scale	μ	18.036583	0.4224234	17.178307	18.894858
Shape	σ	2.1949766	0.2986985	1.7180725	2.9413354

Table 17; Continuous lognormal fit of losses by earthquakes (Model 2)

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Scale	μ	19.911885	0.4049321	19.089148	20.734622
Shape	σ	2.1040887	0.2863302	1.6469318	2.8195428

Table 18; Continuous lognormal fit of losses by floods (Model 1)

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Scale	μ	18.232206	0.3549191	17.512892	18.951519
Shape	σ	1.9112977	0.2509657	1.5079263	2.5325915

Table 19; Continuous lognormal fit of losses by floods (Model 2)

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Scale	μ	19.860076	0.3017834	19.248452	20.471699
Shape	σ	1.6251536	0.2133931	1.2821716	2.1534322

Table 20; Continuous lognormal fit of losses by wildfires (Model 1)

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Scale	μ	18.454406	0.3994826	17.647339	19.261474
Shape	σ	2.2598146	0.2824768	1.8017602	2.9506613

Table 21; Continuous lognormal fit of losses by wildfires (Model 2)

Parameter		Estimate	Std Error	Lower 95%	Upper 95%
Scale	μ	19.685766	0.4104439	18.856553	20.514979
Shape	σ	2.3218214	0.2902277	1.8511985	3.0316242

Appendix 04: Validation of the selected distributions

Table 22; Sensitivity test of frequency distribution of earthquakes

	X2	DF	Prob>X2
Pearson Chi-Square	8.5929257	3	0.0352*

Table 23; Sensitivity test of frequency distribution of floods

	X2	DF	Prob>X2
Pearson Chi-Square	31.426311	5	<.0001*

Table 24; Sensitivity test of frequency distribution of wildfires

	X2	DF	Prob>X2
Pearson Chi-Square	26.8344	2	<.0001*

Table 25; Sensitivity test of losses by earthquakes (Model 1)

	A^2	Simulated p-Value
Anderson-Darling	1.66436	0.0249*

Table 26; Sensitivity test of losses by earthquakes (Model 2)

	A^2	Simulated p-Value
Anderson-Darling	2.01336	0.0015*

Table 27; Sensitivity test of losses by floods (Model 1)

	A^2	Simulated p-Value
Anderson-Darling	0.72648	0.0435*

Table 28;; Sensitivity test of losses by floods (Model 2)

	A^2	Simulated p-Value
Anderson-Darling	1.77231	0.0386*

Table 29;; Sensitivity test of losses by wildfires (Model 1)

	A^2	Simulated p-Value

	A^2	Simulated p-Value
Anderson-Darling	0.864306	0.0236*

Table 30;; Sensitivity test of losses by wildfires (Model 2)

	A^2	Simulated p-Value
Anderson-Darling	1.2037197	0.0044*

Appendix 05: PP plots of natural disaster

Figure 4;PP plot of losses by Earthquakes (Model 1)

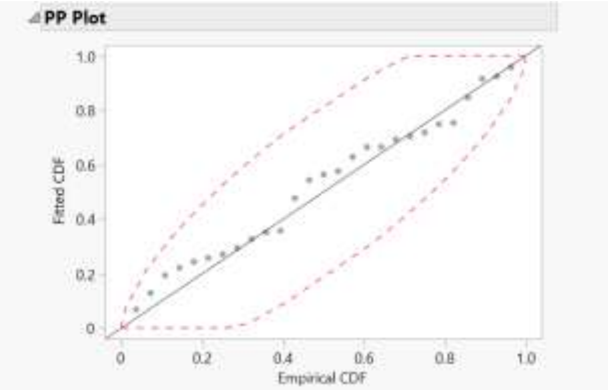


Figure 5; PP plot of losses by Earthquakes (Model 2)

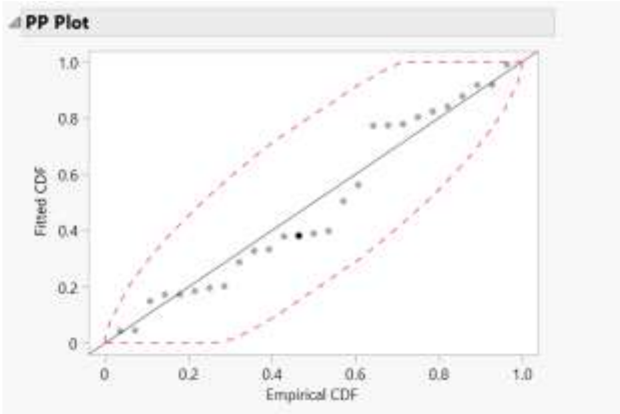


Figure 6; PP plot of losses by Floods (Model 1)

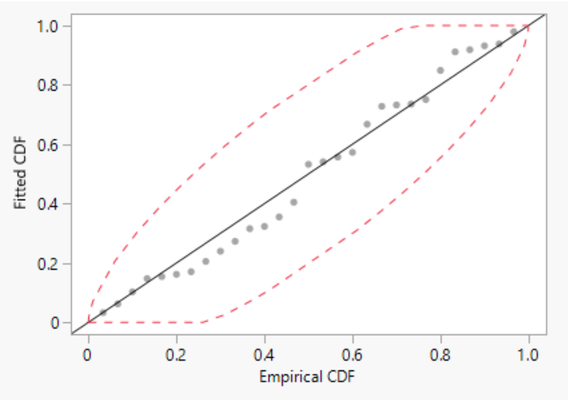


Figure 7; PP plot of losses by Floods (Model 2)

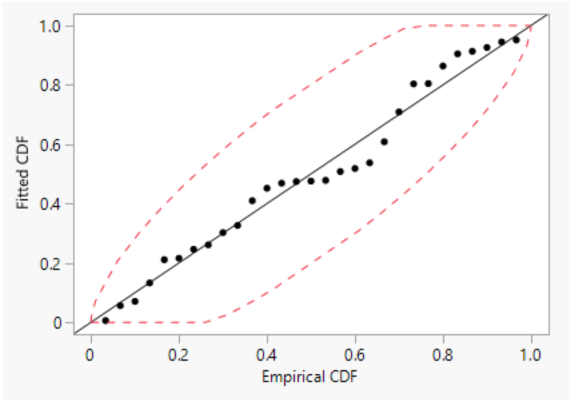


Figure 8; PP plot of losses by wildfires (Model 1)

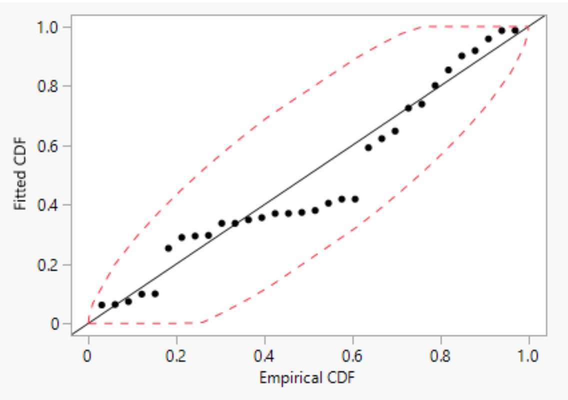
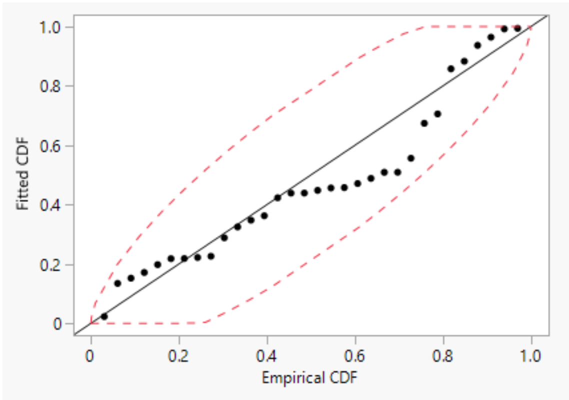


Figure 9;PP plot of losses by wildfires (Model 2)



Appendix 06: Statistics summary of the Monte Carlo simulations of the natural disasters

Mean	**5.53245**
Std Dev	2.3547192
Std Err Mean	0.0074463
Upper 95% Mean	5.5470446
Lower 95% Mean	5.5178554
N	100000
N Missing	0

Table 31; Frequency statistics of earthquakes

Mean	**2.81456**
Std Dev	1.6747955
Std Err Mean	0.0052962
Upper 95% Mean	2.8249404
Lower 95% Mean	2.8041796
N	100000
N Missing	0

Table 32; Frequency statistics of floods

Mean	**27.48268**
Std Dev	5.2441143
Std Err Mean	0.0165833
Upper 95% Mean	27.515183
Lower 95% Mean	27.450177
N	100000
N Missing	0

Table 33; Frequency statistics of wildfires

Mean	**757919251**
Std Dev	7.615e+9
Std Err Mean	24080741
Upper 95% Mean	805117207
Lower 95% Mean	710721296
N	100000
N Missing	0

Table 34; Statistics of earthquake losses (Model 1)

Mean	**3.9673e+9**
Std Dev	2.541e+10
Std Err Mean	80357316
Upper 95% Mean	4.1248e+9
Lower 95% Mean	3.8098e+9
N	100000
N Missing	0

Table 35; Statistics of earthquake losses (Model 2)

Mean	**506334274**
Std Dev	2.5309e+9
Std Err Mean	8003369.9
Upper 95% Mean	522020781
Lower 95% Mean	490647767
N	100000
N Missing	0

Table 36; Statistics of flood losses (Model 1)

Mean	**1.5919e+9**
Std Dev	5.1708e+9
Std Err Mean	16351566
Upper 95% Mean	1.624e+9
Lower 95% Mean	1.5599e+9
N	100000
N Missing	0

Table 37; Statistics of flood losses (Model 2)

Mean	**1.2596e+9**
Std Dev	1.009e+10
Std Err Mean	31918700
Upper 95% Mean	1.3222e+9
Lower 95% Mean	1.197e+9
N	100000
N Missing	0

Table 38; Statistics of wildfire losses (Model 1)

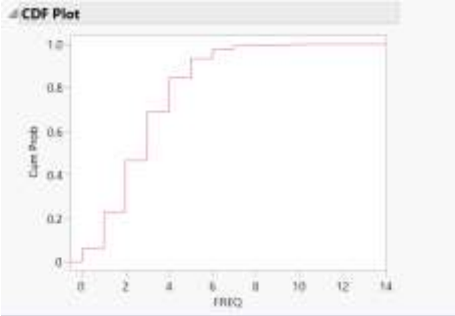
Mean	**5.2725e+9**
Std Dev	6.82e+10
Std Err Mean	215652321
Upper 95% Mean	5.6951e+9
Lower 95% Mean	4.8498e+9
N	100000
N Missing	0

Table 39; Statistics of wildfire losses (Model 2)

Appendix 07: CDF plots in a 100 year return period

Figure 10; Earthquakes frequency CDF

Figure 11; Floods frequency CDF



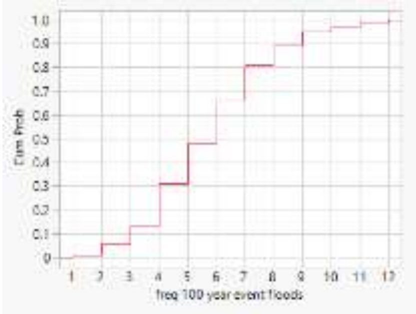
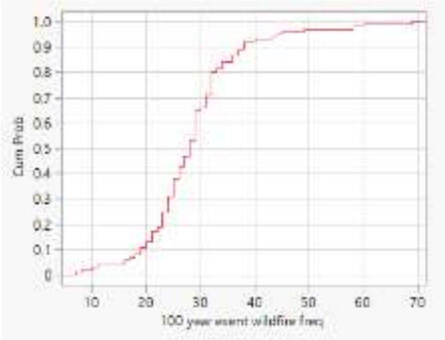


Figure 12; Wildfires frequency CDF

Figure 13; Earthquake losses CDF (Model 1)



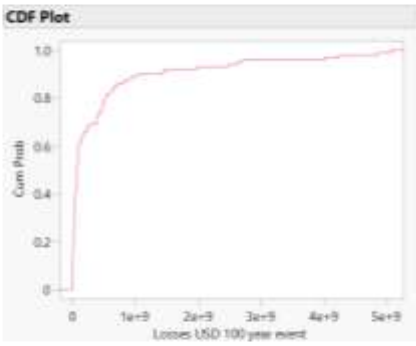


Figure 14; Earthquake losses CDF (Model 2)

Figure 15; Flood losses CDF (Model 1)

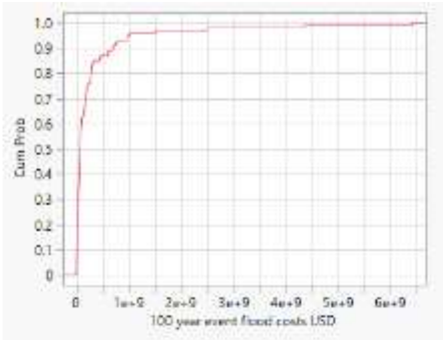
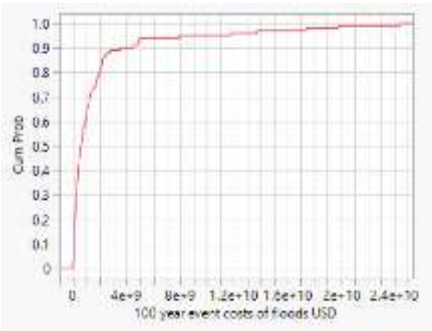


Figure 16; Flood losses CDF (Model 2)

Figure 17; Wildfire losses CDF (Model 1)



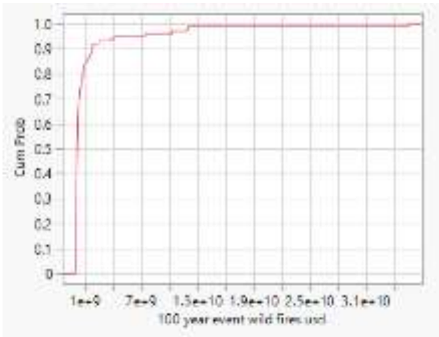
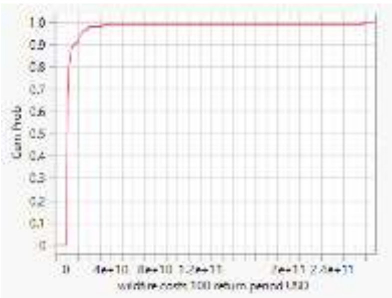


Figure 18; Wildfire losses CDF (Model 2)



References

- Albala-Bertrand, J. M. (1993). *Political Economy of Large Natural Disasters With Special Reference to Developing Countries.* Oxford: Clarendon Press.
- Barrows, H. (1923). Geography as Human Ecology. 13, 1–14.
- Benson, C. (1997a). The Economic Impact of Natural Disasters in Fiji.
- Benson, C. (1997b). The Economic Impact of Natural Disasters in Viet Nam.
- Benson, C. (1997c). The Economic Impact of Natural Disasters in the Philippines.
- Benson, C. a. (1998). The Impact of Drought on Sub-Saharan African Economies.
- Benson, C. a. (2000). Developing Countries and the Economic Impacts of Catastrophes. *In A. Kreimer and M. Arnold. Managing Disaster Risk in Emerging Economies*, 11-21.
- Benson, C. a. (2001). Dominica: Natural Disasters and Economic Development in a Small Island State.
- Burby, R. (1998). Natural hazards and land use. *An introduction. In Cooperating with Nature: Confronting Natural Hazards with Land-Use Planning for Sustainable Communities*, 1–26.
- Carr, L. (1932). Disaster and the Sequence-Pattern Concept of Social Change. Am. J. Social. 38, 207–218.
- Charveriat, C. (2000). Natural Disasters in Latin America and the Caribbean. *An Overview of Risk*, 434.
- Crowards, T. (2000). Comparative Vulnerability to Natural Disasters in the Caribean.
- Dacy & H. Kunreuther, D. C. (1969). *The Economics of Natural Disasters: Implications for Federal Policy.* New York: Free Press.
- Dynes, R. (1993). Disaster Reduction. *The Importance of Adequate Assumptions about Social Organization. Social. Spectr.* , 13,175–192.
- ECLAC. (1982). Nicaragua: Las inundaciones de mayo de 1982 y sus repercusiones sobre el desarrollo economico y social del pais.
- ECLAC. (1985). Damage caused by the Mexican Earthquake and its repercussions upon the country's economy. Santiago de Chile.
- ECLAC. (1988). Damage caused by Hurricane Joan in Nicaragua. . *Its effects on economic development and living conditions, and requirements for rehabilitation and reconstruction*.
- ECLAC. (1999). Manual for estimating the socio-economic effects of natural disasters.
- ECLAC. (2000). A matter of development: how to reduce vulnerability in the face of natural disasters. *Seminar "Confronting Natural Disasters: A Matter of Development"*, 25-26.
- ECLAC. (2002). Handbook for estimating socio-economic and environment effects of disasters.
- McHarg, I. (1969). Design with Nature. 198.
- Murlidharan, T. L. (2001). Catastrophes and Macro-economic Risk Factors. *An Empirical Study. Proceedings of First Annual IIASA-DPRI Meeting on Integrated Disaster Risk Management: Reducing Socio-Economic vulnerability*, 1-50.

- Otero, R. C. (1995). The impacts of natural diasters on developing economies . *Implications for the international development and disaster community*, 11-40.
- White, G. (1936). The limit of economic justification for flood protection. J. Land Public Util. Econ. 12, 133–148.
- Yasuhide Okuyama.; Adam Rose. (2019). Advances in Spatial Science. In Y. Okuyama, *Advances in Spatial and Economic Modelling of Disaster Impacts* (p. 422). Springer.