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Flood Risk Financing Gap in Malaysia: A Monte Carlo Simulation Analysis across Regional Archetypes

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ABSTRACT

Flooding in Malaysia presents a growing financial challenge, with a substantial proportion of losses remaining uninsured and largely dependent on post-disaster government assistance. This study aims to assess the flood risk profile and quantify the financing gap across regional rainfall archetypes using a probabilistic modeling approach. A Monte Carlo simulation with 10,000 iterations was employed to generate potential annual flood loss scenarios, incorporating projected urbanization growth and stochastic variability. Key risk metrics, namely Expected Annual Loss (EAL) and Probable Maximum Loss (PML) at the 99.5th percentile, were estimated to evaluate financial exposure. The results indicate significant variation in loss distributions across six regional groups, reflecting differences in rainfall intensity, exposure levels, and elasticity characteristics. At the national level, the EAL is estimated at RM2.63 billion, while the PML reaches RM8.07 billion, resulting in a financing gap of RM5.43 billion. The findings further reveal a right-skewed loss distribution with substantial tail risk concentrated in high-exposure regions. Additionally, diversification effects reduce overall national risk compared to aggregated regional extremes. The study highlights the limitations of deterministic approaches and demonstrates the importance of probabilistic modeling in disaster risk financing. It also emphasizes the need for risk-based premium structures, strengthened reinsurance arrangements, and integrated public–private financing mechanisms to enhance national financial resilience against flood events.

Keywords: Flood Risk; Financing Gap; Monte Carlo Simulation; Expected Annual Loss (EAL); Probable Maximum Loss (PML)

INTRODUCTION

The motivation behind conducting this study emanates from the large flood risk financing gap within Malaysia. According to the World Bank & Bank Negara Malaysia (2024) report, the majority of flood-related losses in the country remain uninsured. While the government has historically provided "Ex-Post" assistance, which refers to financial aid distributed after a disaster occurs, this model is becoming increasingly unsustainable as losses move into the billions of Ringgit (World Bank & Bank Negara Malaysia, 2024). Data indicate that a large percentage of flood losses remains outside formal risk-financing mechanisms (World Bank & Bank Negara Malaysia, 2024). Such conditions highlight the structural limitations in current risk financing arrangements, especially when addressing extreme catastrophic losses (Ahmad et al, 2025).

In order to overcome these shortcomings, therefore, the objective of this study is to simulate the flood risk profile and the resulting financing gap across regional archetypes. Using a Monte Carlo simulation framework, we model flood losses across thousands of potential future scenarios. This allows for the estimation of loss distributions by region and the calculation of Expected Annual Loss (EAL) and Probable Maximum Loss (PML) to measure the financing gap.

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This data-driven framework connects rainfall patterns and urban development with financial risk assessment to help policymakers and insurers establish necessary capital requirements (Mabahwi et al, 2020). Without such modeling, financial resources may be misallocated, leaving vulnerable communities underinsured and at risk of economic failure during extreme events (Shafiai & Khalid, 2023).

LITERATURE REVIEW

The Malaysian insurance industry has traditionally used deterministic modeling for premium calculation because this approach requires only fixed parameters and average historical data. The implementation of deterministic frameworks cannot effectively assess "fat-tail" risks, which stem from climate change, because these frameworks only depend on regular distribution patterns to predict extreme events (Yoshida 2018). The Monte Carlo method provides an approach that generates multiple possible results through the use of Log-Normal and Pareto distribution probability patterns instead of examining individual data points (Probabilistic Urban Flood Risk Assessment 2023). The method uses a thousand test runs to discover extreme tail events that occur at 99th percentile loss levels. The actuarial field uses this method to determine Value-at-Risk (VaR) and Tail Value-at-Risk (TVaR), which creates a more reliable prediction of how the general insurance industry will maintain its financial stability (World Bank & Bank Negara Malaysia 2024).

Capital adequacy assessment needs Probable Maximum Loss (PML) and Expected Annual Loss (EAL) measurements to determine solvency requirements. The Risk-Based Capital (RBC) framework established by Bank Negara Malaysia (BNM, 2024) requires insurers to retain a capital buffer that must match their potential losses at a defined confidence level. The PML creates a limit that determines the reinsurance needs of an insurer who wants to maintain financial stability during severe flooding events (World Bank, 2022). The EAL measures expected annual damage costs, which directly affect the calculation of pure premium costs (Romali & Yusop, 2018). This study examines how these frameworks interact to determine whether existing capital requirements in the industry can handle the anticipated loss patterns found in regional archetypes.

METHODOLOGY

This quantitative research applied the Monte Carlo Simulation as a statistical technique used to understand the impact of risk involved. This simulation measured the Expected Annual Loss (EAL), Probable Maximum Loss (PML), and the financing gap of each archetype and at the national scale. The simulation follows the following process:

1. Baseline Projection

A 2% annual urbanization growth rate is applied to the household exposure (living quarters) data, consistent with Malaysia's historical urban population growth trends (Department of Statistics Malaysia, 2023). The projected exposure is calculated as:

$$LQ_{\text{proj,i}} = LQ_{2024,\text{i}} \times 1.02 \quad (1)$$

where i represents each district.

2. Expected Loss Prediction

The previously estimated log-log regression model is used to predict the expected log-loss for each state under the projected living quarters scenario:

$$\log(\widehat{Loss}_i) = \hat{\beta}_0 + \hat{\beta}_1 \log(LQ_{\text{proj},i}) + \sum_{j=2}^{6} \hat{\gamma}_j Group_{ij} + \sum_{j=2}^{6} \hat{\delta}_j [\log(LQ_{\text{proj},i}) \times Group_{ij}] \quad (2)$$

where:

$\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\gamma}_j$, $\hat{\delta}_j$ are the estimated coefficients from the regression model

$LQ_{proj,i} = LQ_{2024,i} \times 1.02$, projected number of living quarters for district i

$Group_{ij}$ are the dummy variables indicating membership of district i in Tukey HSD group j

3. Add random volatility

Flood losses are uncertain due to factors like monsoon intensity and drainage performance. This uncertainty is captured by the residual standard error ($\hat{\sigma}$) from the regression model. For each of 10,000 iterations, a random shock is drawn:

$$s_{i,k} \sim N(0, \hat{\sigma}^2)$$

The simulated loss for each district is:

$$Loss_{sim,i,k} = \exp\left(\log\left(\widehat{Loss_i}\right) + s_{i,k}\right) \quad (3)$$

4. Aggregation by group and nationwide

For each iteration, district-level simulated losses are aggregated by group:

$$Group\ Loss_{g,k} = \Sigma\, Loss_{sim,i,k} \quad (4)$$

where g represents one of the six Tukey HSD group, and the summation is over all districts whose states belong to that group. National losses are then:

This produces 10,000 possible annual loss scenarios for each group and for Malaysia overall.

$$National\ Loss_{g,k} = \sum_{i=1}^{N} Loss_{sim,i,k} \quad (5)$$

where N is the total number of districts nationwide

5. Calculate Risk Metrics

Three key metrics are derived:

• Expected Annual Loss (EAL): The average loss across all 10,000 iterations. This is the average annual cost of flood risk.

• Probable Maximum Loss (PML) at 99.5th percentile: The loss value exceeded in only 0.5% of iterations, representing a 1-in-200-year extreme event (European Commission, 2009).

• Financing gap,

$Financing\ Gap = PML99.5 - EAL$

This gap represents the additional funds needed during catastrophic years that cannot be covered by standard premiums alone.

RESULTS

Monte Carlo simulation was used to project future flood losses and quantify the resultant financing gap in the six rainfall archetypes. The simulation aims to simulate the flood risk profile and the resulting financing gap across regional archetypes. The simulation uses a 2 percent urbanization growth rate and produces 10,000

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iterations, and the financing gap is the difference between the Probable Maximum Loss (PML) at the 99.5th percentile and the Expected Annual Loss (EAL).

Simulation Results by Tukey HSD Group:

The simulation produced distinct loss distributions for each of the six rainfall groups, reflecting their underlying elasticity characteristics, exposure bases, and volatility profiles.

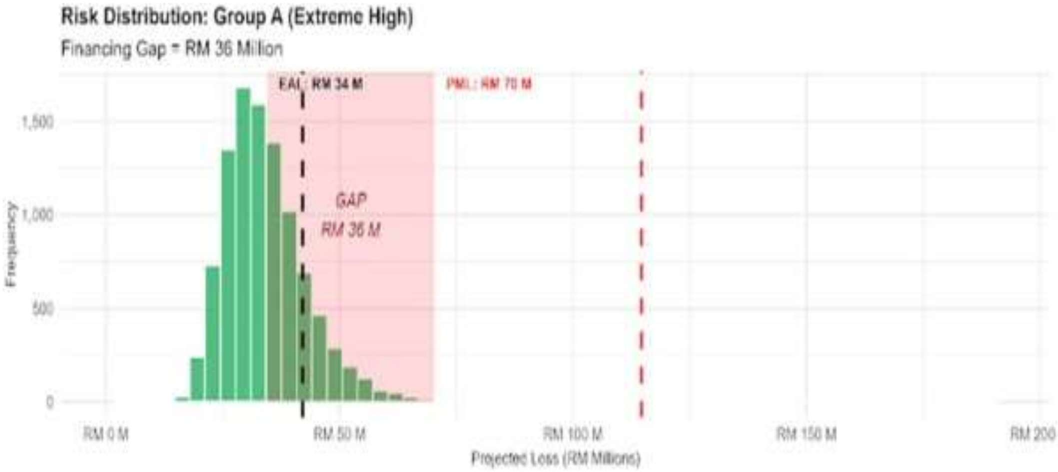

Figure 1: Monte Carlo Results (Group A)

Group A, as in the case of Sarawak, has an EAL of RM34 million and a PML of RM70 million, which translates to a financing gap of RM36 million. The distribution is skewed, with most of the simulated years being below the EAL and very few years stretching into the gap between the EAL and PML. The PML is about two times the EAL, indicating the inelastic profile of this group (B = 0.378) -losses in Sarawak do not increase or compound dramatically with exposure, and even extreme events result in losses only slightly above the mean. The riverine trap dynamic, in which exposure is concentrated in a few corridors, narrows the geographic area of risk and avoids catastrophic losses on a large scale. The histogram indicates that the overwhelming majority of the simulated years are below the PML, and the red-colored gap indicates the comparatively rare years that need extra financing.

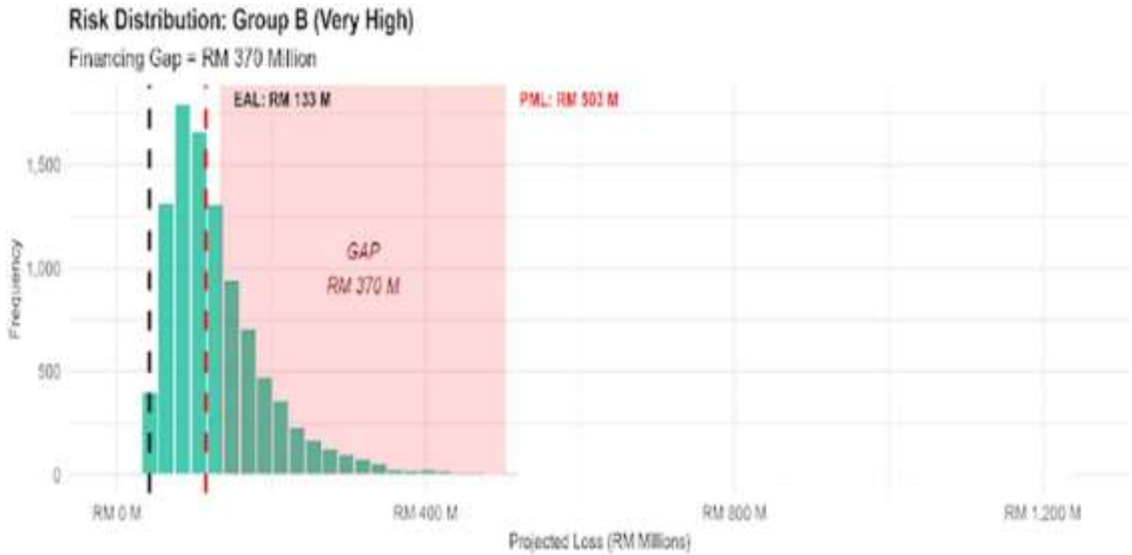

Figure 2: Monte Carlo Results (Group B)

Group B, as in the case of Terengganu, shows an EAL of RM133 million and a PML of RM503 million, which results in a financing gap of RM370 million. The PML is about 3.8 times the EAL, which is a hyper-elastic profile of this group (B=1.561). The distribution is significantly broader than that of Group A, and the tail is longer and extends to greater values of loss. This shows that Terengganu has a very few districts but the compounding effect of its coastal urbanization under direct exposure to the monsoon generates a lot of volatility. The histogram indicates that the majority of the simulated years are below RM200 million, with the tail having events above RM500 million, which would need to be financed by more than the average years of premiums would cover.

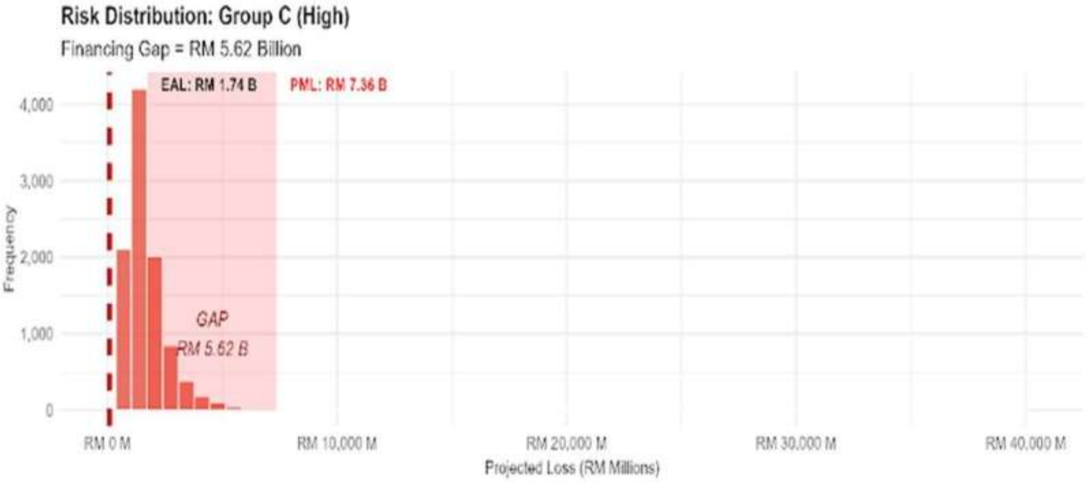

Figure 3: Monte Carlo Results (Group C)

Group C includes Sabah, Pahang, Selangor, and Kelantan, states that have high rainfall characteristics, and Selangor and Kelantan also show transitional characteristics to Group D. This group has the highest absolute values of all groups, as it has an EAL of RM1.74 billion and a PML of RM7.36 billion, which gives it a financing gap of RM5.62 billion. The PML is about 4.2 times the EAL, which is in line with the very elastic profile of this group (B=1.423). Group C has 40 districts (the highest exposure base of any group) and includes both East Malaysian (Sabah) and Peninsular (Pahang, Selangor, Kelantan) states with high rainfall regimes. The high elasticity and high exposure base results in a distribution with a strong right tail, with extreme events causing losses that are many times the average. The histogram indicates that the modal results are concentrated in the RM1-2 billion range, but the tail stretches to almost RM8 billion, and the red-colored financing gap is a significant financing need.

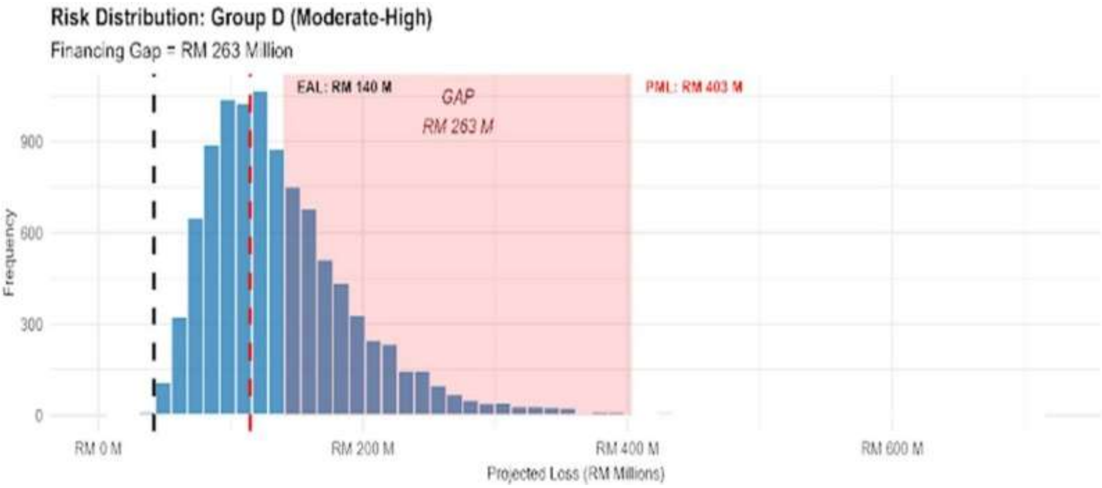

Figure 4: Monte Carlo Results (Group D)

Group D includes Selangor, Kelantan, Johor, and Perlis, which have moderate- high rainfall patterns, with Selangor and Kelantan also having high rainfall patterns of Group C, and Johor and Perlis shifting to Group E. The group has an EAL of RM140 million and a PML of RM403 million, which results in a financing gap of RM263 million. The PML is about 2.9 times the EAL, which indicates the inelastic profile of this group (B = 0.648). The histogram shows that a large percentage of the simulated years are above the EAL. This means that the group is inelastic (losses increase at a slower rate than exposure) but above-average loss years are not infrequent occurrences, but they happen with significant frequency. The upper tail of these frequent above-average events is the tail, which is about RM400 million instead of a thin extreme tail. The combination of Selangor with its infrastructure resilience, Kelantan with its severity of hazards, and Johor and Perlis as transitional states creates an interesting dynamic in which states with very different mechanisms of floods come together to form a risk profile of frequent above-average losses instead of rare catastrophic spikes.

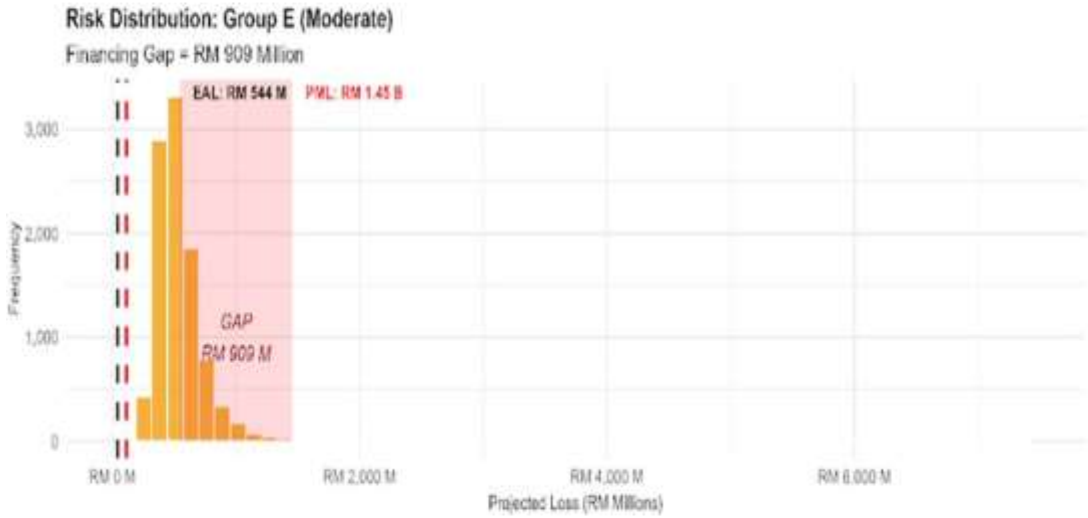

Figure 5: Monte Carlo Results (Group E)

Group E includes Johor, Perlis, Perak, Negeri Sembilan, and Melaka, which have moderate rainfall patterns, with Johor and Perlis also showing transitional patterns of Group D, and Perak, Negeri Sembilan, and Melaka showing transitional patterns to Group F. The group has an EAL of RM544 million with a PML of RM1.45 billion, which gives it a financing gap of RM909 million. The PML is about 2.7 times the EAL, which indicates the slightly elastic profile of this group (Β = 1.118). Group E has a very large exposure base (35 districts), and therefore, even with a slightly elastic coefficient, the absolute values are large. Most of the simulated years are below the EAL, with average years making losses in the RM500 million bracket. Nevertheless, there is a reasonable percentage of years between EAL and PML, which means that events of above-average losses are not uncommon. The tail is up to RM1.45 billion, and the PML is the maximum of these, less frequent but possibly catastrophic events. The financing gap of RM909 million is therefore a substantial amount of risk that occurs at a moderate frequency, not only in extreme cases.

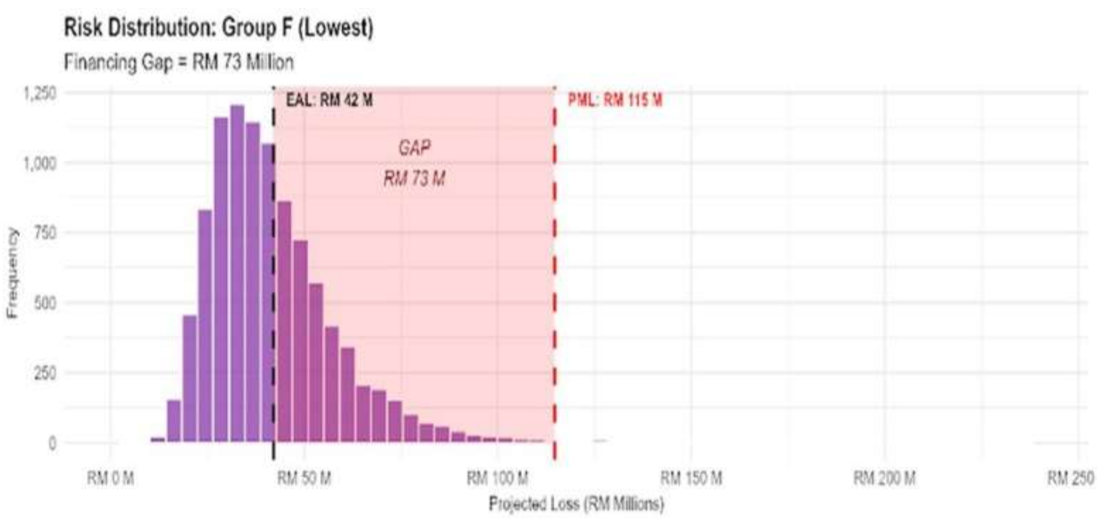

Figure 6: Monte Carlo Results (Group F)

Group F includes Kedah, Perak, Negeri Sembilan and Melaka, states that have the least rainfall features and Perak, Negeri Sembilan, and Melaka also show transitional features of Group E. This group has an EAL of RM42 million and a PML of RM115 million, resulting in a financing gap of RM73 million. The PML is about

2.7 times the EAL, which is an inelastic agricultural profile of this group (B = 0.634). The distribution is skewed, and the tail is short, which is in line with the lower rainfall regime and agricultural economy of these states, where household density is less important than crop cycles and planting seasons in determining flood losses. The histogram indicates that the majority of the simulated years are concentrated around the EAL, and the tail is not very long.

National Aggregation:

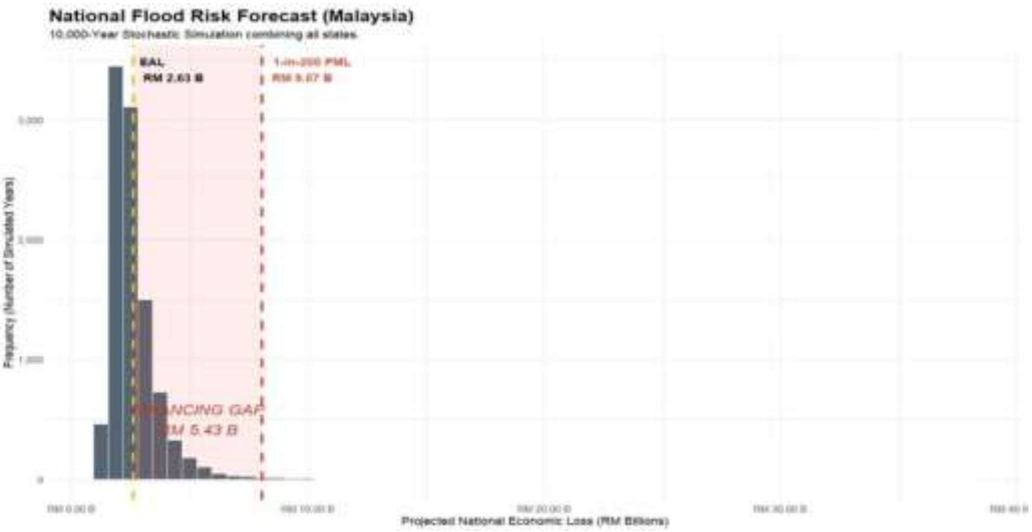

Figure 7: Monte Carlo Results (National)

Summing up all six groups, the Monte Carlo simulation estimates the overall financial needs of a national flood insurance program. The national Expected Annual Loss (EAL) is approximated to be RM2.63 billion, which is the pure risk premium, the average cost of flood risk over the long term. The national Probable Maximum Loss (PML) at the 99.5th percentile is estimated at RM8.07 billion, which represents events that have 0.5% annual exceedance probability. The national financing gap, which is PML-EAL, is thus RM5.43 billion.

The form of the national loss distribution is also in line with the right-skewed nature of flood risk, with most of the simulated years below the EAL and a significant fraction between the EAL and PML, which are above-average but not catastrophic events. It is interesting to note that no simulated year is above the PML, which proves that the 99.5th percentile bound was not violated in this simulation.

A significant observation is made when the national PML is compared to the aggregate of the individual group PMLs. The sum of the group PMLs amounts to RM9.90 billion, and this is higher than the national PML of RM8.07 billion by about RM1.83 billion. This difference is a diversification advantage: not every group has its 1-in-200-year events at the same time. The simulation takes into consideration the fact that extreme monsoon years can have a devastating impact on certain areas and leave others relatively unaffected, which is an important factor to risk pooling because it lowers the overall financing needs compared to a naive summation of individual group tails.

The national tail is dominated by group C. Group C has 40 districts, high elasticity (B=1.423), and the largest average loss of all groups, which explains 66% of national EAL and 91% of national PML. The concentration of tail risk in one group has significant consequences: financing mechanisms must be tailored to the properties of Sabah, Pahang, Selangor, and Kelantan, since the overall financing need is driven by events in these states.

The tail of Group B is more extreme than that of Group E, even though it has a smaller exposure base. The hyper-elastic profile of Group B (b=1.561) generates a PML multiple (3.8x EAL) that is greater than that of Group E (2.7x EAL), even though Group B has only 8 districts versus 35 in Group E. Nevertheless, the absolute exposure base of Group E is greater, which leads to a greater absolute PML (RM1.45B vs RM503M).

This is how the relative volatility (number of times the mean) and the absolute risk (monetary value at risk) differ.

The inelastic profile of Group A is indicated by the narrow distribution. Although Sarawak is a hydrological outlier with regard to rainfall volume, the pattern of riverine settlement and the inelastic exposure-loss relationship result in a fairly predictable risk profile in which even extreme events do not significantly exceed average expectations.

The overlapping group structure is duly represented. States that are represented in more than one group, e.g., Selangor and Kelantan in Groups C and D, Johor and Perlis in Groups D and E, and Perak, Negeri Sembilan, and Melaka in Groups E and F, have their transitional properties captured in the regression coefficients and, by implication, in the simulation results.

The simulation results reveal several important characteristics of Malaysia's flood risk profile.

First, the Expected Annual Loss (EAL) differs significantly among rainfall groups, as they have different risk dynamics. This difference suggests that premium structures must be regionalized to the risk characteristics of the region instead of being applied uniformly across the country. The national EAL of RM2.63 billion is the average of the regions, which is very heterogeneous.

Second, the Probable Maximum Loss of RM8.07 billion at the 99.5 th percentile is the extreme tail of the distribution- events that have a 0.5 percent probability of annual exceedance. By definition, such extreme events are rare. This is confirmed by the simulation: in most of the simulated years, the losses are less than the EAL, not to mention that they are nowhere near the PML. As such, standard premiums would not be efficient or even necessary to fund this tail risk. Rather, the PML is the risk layer that needs special financing tools like reinsurance, catastrophe bonds, or government- sponsored contingency funds.

Third, the size of this tail risk layer is measured by the financing gap of RM5.43 billion (PML-EAL). This is not a deficit in the sense of lacking funds, but the sum that would have to be available in the infrequent years when disastrous events happen in terms of risk transfer arrangements. The 2014 Kelantan floods and the 2021 floods in Segamat (Johor) show that such tail events are not frequent, but they do occur and have to be planned.

The tail risk concentration of Group C implies that the financing mechanisms are to be tailored to the specifics of Sabah, Pahang, Selangor, and Kelantan. The diversification advantage that is present also brings out the importance of risk pooling at the national level, since not every region has catastrophic years at the same time.

Through the Monte Carlo simulation, the objective of the study, which is to simulate the flood risk profile and the resulting financing gap across regional archetypes, has been successfully achieved. The analysis estimates the national EAL to be RM2.63 billion, the PML to be RM8.07 billion, and the financing gap to be RM5.43 billion. At the group level, the findings indicate that Group C is the largest contributor to national tail risk, Group B is the hyper-elastic but smaller-scale risk, and Groups A and F have contained and predictable profiles. These metrics offer an empirical basis for how the functions of the private insurance, reinsurance markets, and the public sector backstops can be designed**.**

CONCLUSION AND RECOMMENDATION

The Monte Carlo simulation, which was done using 10,000 projected annual loss scenarios, estimated a national Expected Annual Loss (EAL) of RM2.63 billion and a Probable Maximum Loss (PML) of RM8.07 billion at the 99.5th percentile. The resulting financing gap of RM5.43 billion is the extra funds that would have to be available in the years of catastrophic floods (the standard premiums would not be sufficient to cover such tail events). The tail risk concentration in particular rainfall archetypes, and the diversification benefits observed in the case of national aggregation, highlight the importance of structured and differentiated risk financing approaches. For future studies, the definition of flood losses should encompass indirect economic and social effects. This may involve supply chain interruptions, business interruption of small and medium enterprises, and flood-related long-term health expenses. These factors should be included to give a more accurate picture of the actual economic cost of floods, and would probably show a bigger financing gap that needs more national efforts. This study advances flood risk assessment in Malaysia by transitioning from traditional deterministic modeling, which relies on fixed parameters and average historical data, to a probabilistic Monte Carlo simulation framework. By incorporating projected urbanization growth and stochastic variability over 10,000 iterations, the research effectively captures "fat-tail" risks and extreme events at the 99.5th percentile, providing a more robust quantification of financial exposure than previously available.

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