Improving Disaster Resilience in ASEAN: A Practical Statistical Framework to Modeling Natural Catastrophe Risk

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Improving Disaster Resilience in ASEAN

A Practical Statistical Framework to Modeling Natural Catastrophe Risk

AUTHORS Hong Li, PhD, FSA

Haibo Liu, PhD, FSA

Jianxi Su, PhD, FSA

Krittin Tangboriboonrat

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Improving Disaster Resilience in ASEAN

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Executive Summary

Climate change has increased the volatility of natural hazard frequency and severity, particularly for floods and tropical cyclones. These risks are especially acute across the Association of Southeast Asian Nations (ASEAN), where rapid population growth, accelerated urbanization in coastal and riverine areas, and uneven fiscal and insurance capacity amplify disaster impacts and recovery challenges.

To enhance financial resilience, ASEAN countries are increasingly seeking innovative disaster risk financing strategies that enable efficient risk transfer, diversification, and faster post-event support. However, the development and evaluation of these strategies rely on credible natural catastrophe modeling capabilities. Commercial CAT models can be costly, technically demanding, and proprietary, which limits their accessibility, transparency, and adaptability for local needs in emerging markets.

This report presents a practical and accessible statistical framework for catastrophe risk assessment in the region. The proposed model contains two building blocks:

- A State-Space Dynamic Count Mixture Model for forecasting disaster event frequency that captures peril-specific seasonality and regional co-movement.
- A log-linear severity model linking economic losses to population density as a forward-looking exposure proxy.

These models are applied to evaluate a cross-region risk sharing mechanism, which demonstrates how the predictive outcomes of the proposed modeling framework can be used to inform the design of innovative disaster financing solutions tailored to ASEAN markets.

Section 1 Introduction

The effects of climate change are reshaping the landscape of natural catastrophe (NAT CAT) risk worldwide. Rising global temperatures, shifting precipitation patterns, and increasing sea-surface thermal energy have contributed to greater volatility in natural hazard frequency and severity, particularly for weather-related perils such as floods and tropical cyclones. These changes pose heightened challenges for countries in the Association of Southeast Asian Nations (ASEAN), where geographic exposure to monsoons, typhoon basins, and major river systems intersects with rapid urbanization and population concentration in low-lying coastal regions.

Economic vulnerability further amplifies disaster impacts. Several ASEAN countries face constrained fiscal capacity, infrastructure gaps, and uneven insurance penetration, which limit their ability to absorb and recover from large-scale NAT CAT. As climate change interacts with expanding exposure, the financial resilience of the region becomes increasingly strained. These emerging risks underscore a pressing need for innovative disaster financing strategies that enable countries to absorb, transfer, and diversify NAT CAT losses in the era of climate change.

A key component in developing and evaluating these strategies is a reliable NAT CAT modeling framework. While global commercial CAT modeling platforms exist, they often come with high licensing costs and require specialized analytical capabilities. Local agencies and smaller insurers in ASEAN may lack the financial and human resources necessary to adopt these proprietary solutions. In addition, their proprietary "black-box" nature may diminish transparency and stakeholder trust in emerging markets, while also limiting flexibility to incorporate locally relevant knowledge and adaptation measures.

Academic research can help fill this gap by providing openly accessible and transparently validated CAT modeling approaches. However, despite significant global progress in NAT CAT modeling, relatively limited academic work has directly focused on ASEAN hazard landscapes and their unique financial resilience challenges. This report aims to address this vacuum.

In this report, the authors introduce a practical and adaptable NAT CAT risk modeling toolkit tailored to ASEAN member countries. First, a state-space Dynamic Count Mixture Model (DCMM) was developed to forecast country-level disaster frequency. The framework is peril-specific and captures key regional features, including strong seasonal signals driven by monsoons and typhoon regimes, as well as spatial similarity in risk environments. Second, a log-linear severity model is proposed that explains event-level losses using population density as a forward-looking exposure proxy. The authors show that the proposed modeling framework can offer strong predictive performance even where historical data are sparse. Finally, the estimated model is applied to evaluate a cross-region risk sharing strategy in order to demonstrate how the proposed modeling framework can support the design and validation of practical financing solutions that enhance regional resilience.

Collectively, it is hoped that this work can contribute to the establishment of an open, data-driven, and regionally relevant foundation for NAT CAT risk assessment in ASEAN for supporting evidence-based planning while building stakeholder trust in disaster financing innovations.

Section 2 Data

The model will be applied to Emergency Events Database (EM-DAT) data. EM-DAT is an international disaster database maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain. It provides a systematic and harmonized record of major natural and technological disasters worldwide, covering events from 1900 to the present, with particularly comprehensive coverage from the 1980s onward. EM-DAT was established to support humanitarian decision-making and research by offering a consistent cross-country and historical view of disaster occurrence, impacts, and losses. This study will use data from January 1990 to March 2025.

2.1 DATA SECTION

An event is included in EM-DAT if it meets at least one of four inclusion criteria:

- ten or more people reported killed;
- one hundred or more people affected, such as being injured or homeless;
- a declaration of a state of emergency;
- an official call for international assistance.

These criteria ensure that the database captures events of social and economic significance while excluding minor, localized incidents.

Data in EM-DAT are collected from a wide range of reliable sources, including national governments, United Nations agencies, the International Federation of Red Cross and Red Crescent Societies, development banks, non-governmental organizations, academic institutions, and reputable media. CRED continually monitors these information streams and consolidates reports describing the same disaster into a single event entry for each affected country. This means that a multi-country catastrophe, such as a typhoon that strikes several ASEAN nations, will appear once for each country impacted, facilitating country-level statistical modeling.

Each record undergoes extensive validation and harmonization. CRED applies internal consistency checks to verify event dates, locations, and peril classifications, and reconciles conflicting figures across data sources. When multiple estimates of damage or casualties are available, the database retains the most credible figure based on source reliability and corroboration. Recent events are updated regularly as official assessments replace preliminary situation reports. The result is a dataset that balances timeliness with accuracy, suitable for actuarial and risk-management applications.

While EM-DAT's strengths lie in its global scope, long time series, and consistent peril taxonomy, users should be aware of a few limitations. Smaller events, particularly in earlier decades or in regions with limited reporting capacity, may be under-represented. Economic loss estimates can vary in quality and methodology across countries, and insured losses are infrequently reported. Despite these caveats, EM-DAT remains one of the most comprehensive and publicly available sources for analyzing the frequency and severity of natural disasters at the national level.

For the purpose of this study, the authors extract all disaster events classified under the natural disaster group and restrict the "Disaster Type" variable to "Flood" and "Storm," which correspond to the two most frequent disaster types within the ASEAN region. The analysis focuses on the 10 ASEAN member markets: Brunei Darussalam, Cambodia, Indonesia, Lao People's Democratic Republic (PDR), Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Viet Nam. Each EM-DAT record specifies a start date, which is used to assign the event to a calendar quarter: January to March (Q1), April to June (Q2), July to September (Q3), or October to December (Q4). Because the database is organized by country, this allows the data to be aggregated into quarterly event counts at the country level.

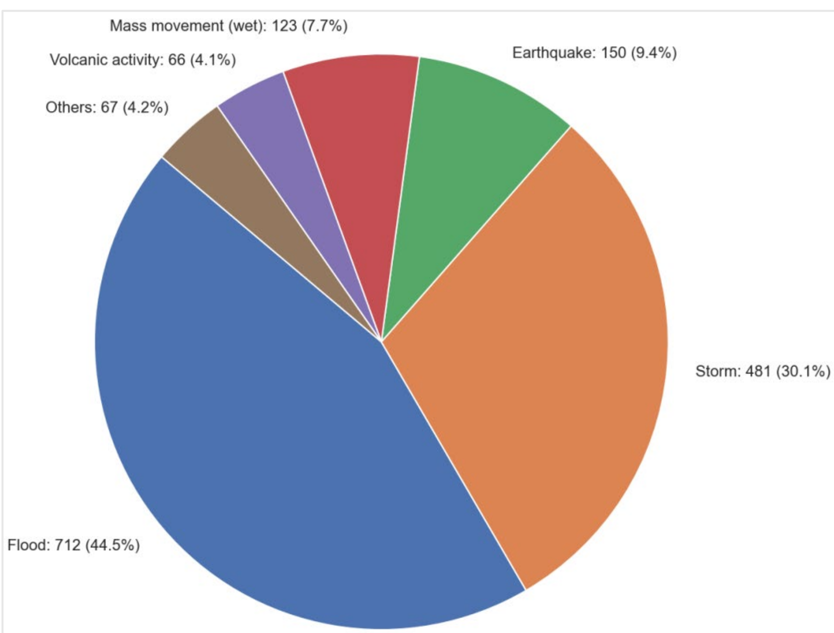
In addition to frequency information, EM-DAT reports the estimated economic damage associated with each event, expressed in nominal U.S. dollars (typically in thousands) at the time of occurrence. For comparability over time, the authors convert these amounts to constant 2025 U.S. dollars using the U.S. GDP deflator. In the rare cases where losses are reported in other currencies, the authors first convert to U.S. dollars using the average exchange rate for the event year before applying inflation adjustments.

Overall, EM-DAT provides a robust foundation for modeling natural catastrophe risk in the ASEAN region. Its event-level granularity enables the construction of quarterly count data suitable for frequency modeling, while its economic loss information allows for subsequent severity analysis or combined frequency-severity modeling. Although some under-reporting and heterogeneity in damage estimates remain inevitable, the database's transparent methodology and consistent structure make it highly valuable for both academic research and practical risk-management applications in insurance and actuarial practice.

2.2 PRELIMINARY DATA ANALYSIS

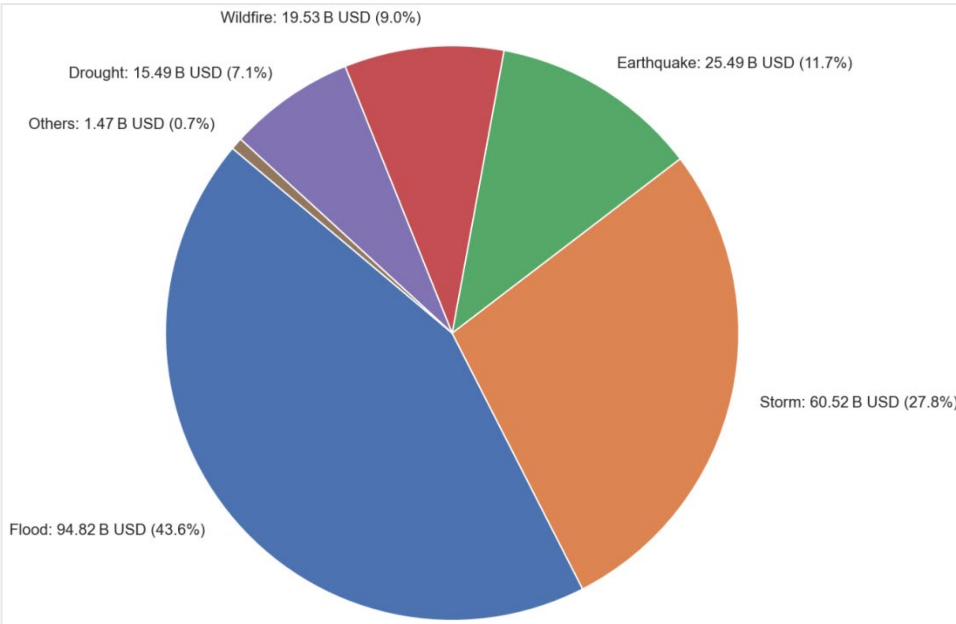
Figure 1 shows the composition of EM-DAT natural disaster events across ASEAN over the study period, counted at the country-event level using the event start date. It is seen that floods account for 712 events (44.5%) and storms for 481 (30.1%), so together they represent roughly three-quarters (74.6%) of all recorded disasters. The remaining events are earthquakes (150; 9.4%), mass movements (wet) (123; 7.7%), volcanic activity (66; 4.1%), and others (67; 4.2%). Because EM-DAT records one entry per affected country, a multi-country catastrophe appears once for each country impacted, which aligns with the country-level modeling. The dominance of floods and storms in event counts motivates focusing on these two perils in the loss modeling.

Figure 1
FREQUENCY OF DISASTER TYPES



Turning from counts to economic impact, Figure 2 shows the distribution of estimated economic damage by disaster type, with each event's loss converted to constant 2025 USD and then summed across ASEAN. Floods contribute about $94.82 billion (43.6%) and storms about $60.52 billion (27.8%) of losses. Earthquakes add $25.49 billion (11.7%), wildfire $19.53 billion (9.0%), drought $15.49 billion (7.1%), and others $1.47 billion (0.7%). The loss shares do not mirror the frequency shares exactly. Namely, storms are less frequent than floods but still produce a sizable portion of total damage, which indicates different severity profiles by peril and reinforcing the need to model both frequency and severity.

Figure 2
TOTAL ESTIMATED ECONOMIC DAMAGES OF DISASTER TYPES (CPI ADJUSTED)



Building on the region-wide totals, Figure 3 shows a two-panel summary of flood risk by country. The left panel ranks ASEAN countries by the number of flood events in the EM-DAT database. Indonesia records the greatest number of events (about 230), followed by the Philippines ($\approx$140), Viet Nam ($\approx$100), Thailand ($\approx$90), and Malaysia ($\approx$70); Myanmar ($\approx$30). Both Cambodia and Lao PDR have less than 25 events. The right panel reports average adjusted flood loss per event in constant 2025 USD expressed in billions. The authors observe that severity does not exactly track frequency. Thailand has by far the highest average loss per event (about $0.7B), while Cambodia, Viet Nam, Malaysia, Indonesia, and the Philippines cluster around $0.03 billion to $0.08 billion, with Myanmar and Lao PDR even lower. This discrepancy between the frequency ranking and severity ranking highlights that exposure concentration and the mix of event severities drive economic impact. A few very large floods (e.g., The 2011 flood event in Thailand) can lift the mean substantially.

Figure 3
COUNTRY-LEVEL BREAKDOWN FOR FLOOD EVENTS

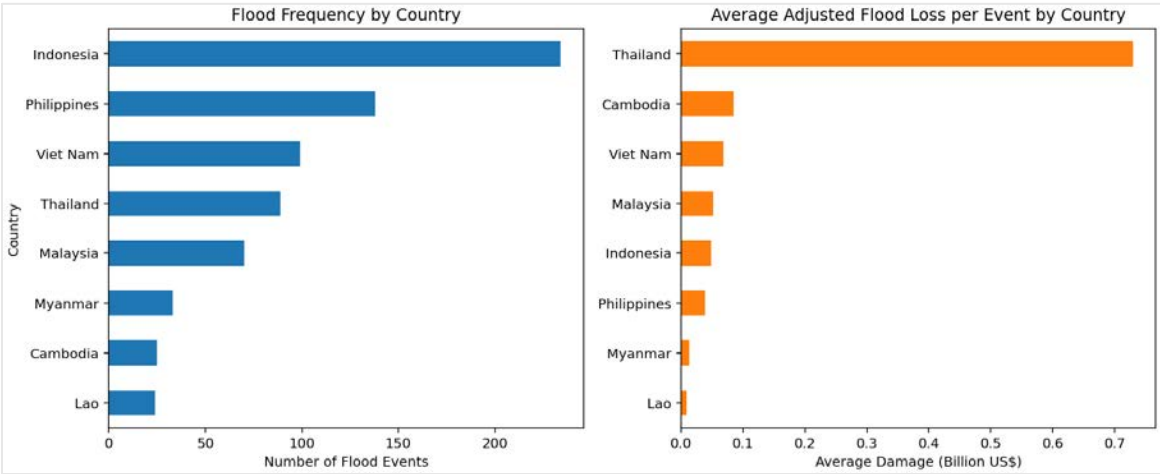
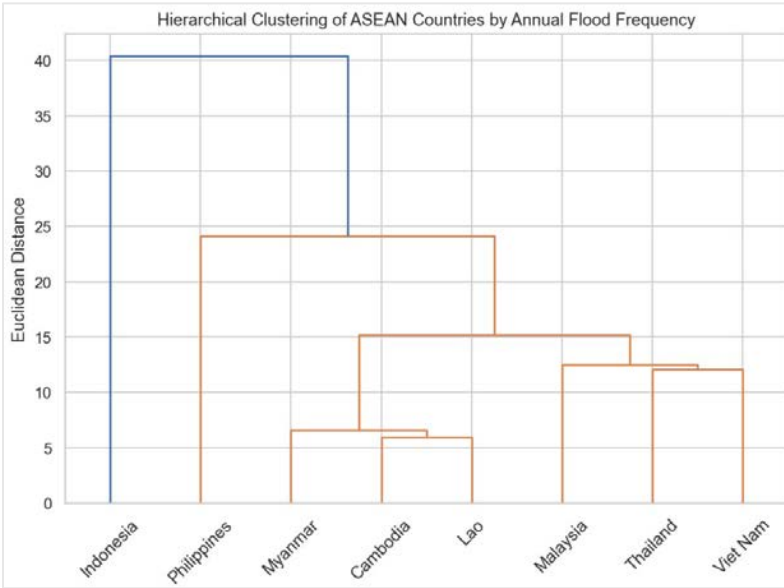


Figure 4 shows a dendrogram from an agglomerative hierarchical clustering of ASEAN countries based on their annual flood event counts from EM-DAT. To implement the clustering, each country starts as its own cluster; at each step, the two most similar clusters measured by Euclidean distance between their annual count histories are merged. Branches that join low on the vertical axis indicate very similar flood-frequency histories, while branches that join high indicate countries that are statistically dissimilar, either because their typical counts are higher/lower, or because their year-to-year patterns differ. To form groups, one can draw a horizontal cut across the tree at a chosen distance; countries connected below that cut are considered a cluster. This is a map of statistical similarity, not geographic proximity.

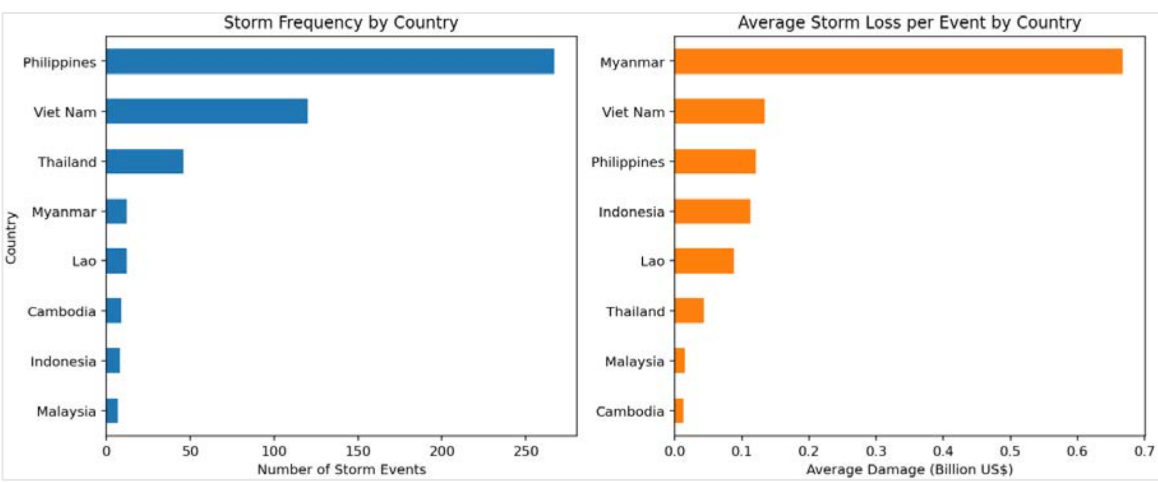
Reading the tree, Myanmar, Cambodia, and Lao PDR merge first at a low distance (≈6 – 7), indicating closely similar annual frequencies. Malaysia joins at a moderate distance (≈12). Thailand and Viet Nam form a tight pair at a similar height and then connect with the preceding group around 15, yielding a broader "mainland" cluster. The Philippines remains separate until a higher distance (≈25), suggesting a distinct frequency profile, and Indonesia merges only at the largest height (≈40), making it the most distinct. Practically, this clustering supports using a shared regional factor for common seasonality while allowing country-specific adjustments for the Philippines and, especially, Indonesia.

Figure 4
COUNTRY-LEVEL BREAKDOWN FOR FLOOD EVENTS



Continuing at the country level, Figure 5 shows the breakdown of storm risk by country. The left panel, which represents the frequency information, shows that the Philippines dominates with roughly 270 recorded storm events, followed by Viet Nam with about 120 and Thailand with nearly 50. Myanmar, Lao PDR, Cambodia, Indonesia, and Malaysia each register far fewer events, generally under 20 over the sample. The right panel, which represents the severity per event, shows that Myanmar has the highest average loss per storm (around \$0.7 billion), despite its lower frequency, while Viet Nam and the Philippines cluster in the \$0.1 billion to\$0.15 billion range; Indonesia and Lao PDR are similar but slightly lower, and Thailand, Malaysia, and Cambodia are lower still (generally <\$0.05 billion). Here, a pattern similar to that of flood events is observed: severity ranking does not mirror frequency ranking.

Figure 5
COUNTRY-LEVEL BREAKDOWN FOR STORM EVENTS

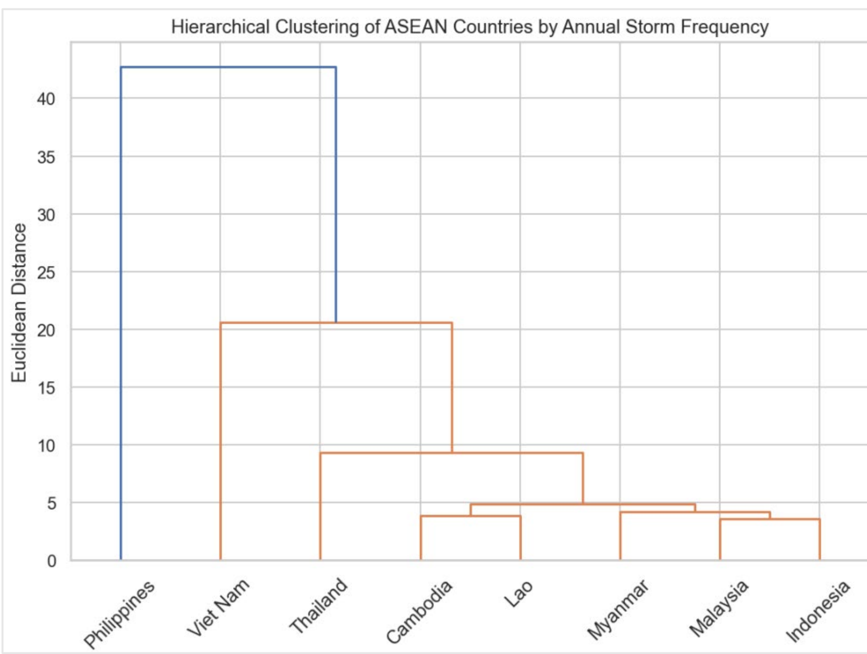


The country-level breakdown of storm frequency reflects well-known patterns in the regional storm climatology of the western North Pacific and northern Indian Ocean. A dense corridor of tropical cyclones forms in the western

North Pacific and the Philippine Sea, moving west–northwest across the Philippines and into the South China Sea. This pattern explains the Philippines' exceptionally high storm frequency relative to its neighbors. In contrast, a separate storm corridor forms over the Bay of Bengal, with landfalls primarily along the coasts of Myanmar, Bangladesh, and northeastern India. This system affects ASEAN countries less frequently than storms originating in the Philippine Sea. Storm-track density is much lower across the equatorial maritime continent, including southern Malaysia, Indonesia, Singapore, and Brunei, where atmospheric conditions are less favorable for cyclone formation, leading to fewer recorded storm events. Countries along the South China Sea rim, such as Viet Nam, Cambodia, and Thailand, are mostly exposed to storms that either form within the South China Sea or traverse it after crossing the Philippines, whereas storms impacting Myanmar are typically associated with the Bay of Bengal system.

Finally, Figure 6 shows the hierarchical clustering of ASEAN countries based on their annual storm counts. At a moderate cut height, the tree yields three interpretable groups: (i) the Philippines as a stand-alone outlier, reflecting its much higher and more variable storm activity; (ii) Viet Nam–Thailand–Cambodia–Lao PDR, whose counts co-move under South China Sea and westward-moving western North Pacific tracks; and (iii) Myanmar–Malaysia–Indonesia, which share lower frequencies consistent with Bay of Bengal influences (for Myanmar) and the relative scarcity of cyclogenesis near the equator (for Malaysia/Indonesia).

Figure 6
SPATIAL CLUSTERS: STORM FREQUENCY



Section 3 Modeling of Catastrophe Losses

3.1 FREQUENCY MODEL

The authors model the number of disaster events at the country–quarter level using a dynamic count model (Berry & West, 2020; Li & Su, 2024), which is particularly suitable for handling two features inherent in the EM-DAT data: (i) zero inflation in the sense that many quarters have no events, and (ii) overdispersion in quarters that do have events. Let $n_{i,q}^{(h)}$denote the number of events of peril $h \in \{\text{Flood}, \text{Storm}\}$ recorded for country i in quarter q. Define the indicator

$$z_{i,q}^{(h)} = \mathbf{1}\{n_{i,q}^{(h)} > 0\}.$$

The Dynamic Count Mixture Model (DCMM) with a Bernoulli-shifted-Poisson specification is adopted, in which the authors first model whether any event occurs, then, conditional on occurrence, model the number of events. To be specific, the model contains two layers:

- **The occurrence layer**:

$$z_{i,q}^{(h)} \sim \text{Bernoulli}(\pi_{i,q}^{(h)}), \qquad \pi_{i,q}^{(h)} = \Pr(z_{i,q}^{(h)} = 1).$$

  Here, $\pi_{i,q}^{(h)}$ is the quarterly probability of at least one event for country i and peril h.

- **The intensity layer**:

$$n_{i,q}^{(h)} \mid z_{i,q}^{(h)} = \begin{cases} 0, & z_{i,q}^{(h)} = 0, \\ 1 + x_{i,q}^{(h)}, x_{i,q}^{(h)} \sim \text{Poisson}(\mu_{i,q}^{(h)}), & z_{i,q}^{(h)} = 1. \end{cases}$$

  Here, the shifted Poisson guarantees that once an event quarter "turns on," the count is at least one. The Poisson mean $\mu_{i,q}^{(h)}$ drives the intensity of additional events in that quarter.

The authors let the Bernoulli probability $\pi_{i,q}^{(h)}$ and Poisson mean $\mu_{i,q}^{(h)}$ evolve over time with dynamic regressions. The key regressor is a systemic latent factor φ_q that captures region-wide seasonality and slow-moving changes common across ASEAN countries (e.g., monsoon timing, basin-scale climate modes, and administrative/reporting rhythms). With design vector $F_q = (1, \varphi_q^\top)$, the authors set

$$\text{logit}\,\pi_{i,q}^{(h)} = F_q^\top \xi_{i,q}^{(h)}, \qquad \xi_{i,q}^{(h)} = \xi_{i,q-1}^{(h)} + \omega_{i,q}^{(h)},$$

$$\log \mu_{i,q}^{(h)} = F_q^\top \theta_{i,q}^{(h)} + r_{i,q}^{(h)}, \qquad \theta_{i,q}^{(h)} = \theta_{i,q-1}^{(h)} + \eta_{i,q}^{(h)}.$$

Here are some justifications of the model's setting:

- The logistic link for $\pi_{i,q}^{(h)}$ maps covariates to an occurrence probability between 0 and 1.
- The log link for $\mu_{i,q}^{(h)}$ ensures a positive Poisson mean and gives multiplicative interpretations.
- The random effect $r_{i,q}^{(h)}$ soaks up residual overdispersion or occasional clustering (e.g., two storms in quick succession), improving forecast calibration without forcing the Poisson mean to chase transient spikes.

- State vectors $\xi_{i,q}^{(h)}$ and $\theta_{i,q}^{(h)}$ follow random-walk evolutions with innovations $\omega_{i,q}^{(h)}$ and $\eta_{i,q}^{(h)}$, which are controlled through discount factors or variance priors. This allows the model to adapt to structural changes (e.g., shifts in reporting or climate regimes) while smoothing out noise.

Because φ_q couples all country models, estimating everything jointly would be challenging. Therefore a two-step (multiscale) approach is used that is standard in many-series Bayesian count forecasting:

1. **Region step (one DCMM).** For each peril h, individual countries' frequencies over a given region are aggregated, and the aggregated frequency is denoted by $N_q^{(h)} = \sum_i n_{i,q}^{(h)}$. Then a Poisson dynamic generalized linear model (DGLM) with harmonic seasonality is fitted to the aggregate quarterly frequency. The filtered seasonal component and local trend provide $\hat{\varphi}_q$, a low-dimensional signal representing region-wide conditions in quarter q.
2. **Country step (independent DCMMs).** Condition on $\hat{\varphi}_q$ as an observed covariate and fit each country–peril DCMM separately using conjugate updating (Beta for π, Gamma for μ) with first/second-moment approximations. This yields closed-form filtering, coherent multi-step predictive distributions, and fast computation country by country.

For horizon $q + 1$, the model produces the predictive probability of any event (via the occurrence layer) and the predictive distribution of the positive count (via the positive count layer). Simulation is straightforward and fully analytic:

1. Draw $z_{i,q+1}^{(h)} \sim \text{Bernoulli}(\hat{\pi}_{i,q+1}^{(h)})$.
2. If $z = 0$, set $n = 0$. If $z = 1$, draw $x_{i,q+1}^{(h)} \sim \text{Poisson}(\hat{\mu}_{i,q+1}^{(h)})$ and set $n = 1 + x$.
3. Repeat the above steps to obtain predictive distributions and quantiles for planning, pricing, and solvency analysis (e.g., one-in-10-year quarterly event counts at country or ASEAN level).

Because $\hat{\varphi}_q$ is shared, the country models co-move appropriately during active seasons (e.g., typhoon quarters), yet each country retains its own baseline occurrence and intensity patterns through α- and slope-states in $\xi_{i,q}^{(h)}$ and $\theta_{i,q}^{(h)}$. The random effect $r_{i,q}^{(h)}$ ensures that occasional bursts do not contaminate long-run intensity, improving out-of-sample calibration.

3.2 SEVERITY MODEL

To complement the frequency analysis, a severity model is developed that explains and projects economic losses associated with individual disaster events. For each country–peril combination (e.g., floods in Viet Nam, storms in the Philippines), the logarithm of event-level total damage is modeled as a function of the contemporaneous population density. The specification is

$$\log\left(\text{Damage}_{i,j}^{(h)}\right) = \alpha_i^{(h)} + \beta_i^{(h)} \log\left(\text{PopulationDensity}_{i,j}\right) + \varepsilon_{i,j}^{(h)},$$

where i indexes the country and j indexes individual disaster events. The dependent variable, $\text{Damage}_{i,j}^{(h)}$, represents the economic loss from event j in country i for peril h, expressed in constant 2025 U.S. dollars as described in the data section. The explanatory variable, $\text{PopulationDensity}_{i,j}$, is the annual population density (persons per square kilometer) for country i in the year of event j, obtained from the World Bank World Development Indicators. In additional unreported analyses, the authors also experimented with other covariates, such as national GDP and various economic indicators. Among these alternatives, population density seemed to yield the most robust predictive performance.

This log-log formulation implies an elasticity interpretation. Namely, the coefficient $\beta_i^{(h)}$ measures the percentage change in disaster losses associated with a 1% increase in population density. Intuitively, higher population density reflects greater asset concentration and exposure to natural hazards, which tends to amplify economic losses when a disaster occurs. Fitting the model separately for each country and peril allows for heterogeneity in both baseline vulnerability (through $\alpha_i^{(h)}$) and exposure elasticity (through $\beta_i^{(h)}$). The residual term $\varepsilon_{i,j}^{(h)}$ captures idiosyncratic event-level variability, including differences in event magnitude, local protection infrastructure, and reporting uncertainty.

To project future population density, the authors estimate a simple quadratic time-trend model for each country:

$$\text{PopulationDensity}_{i,t} = a_i t + b_i t^2,$$

where t denotes calendar year. This specification captures both linear and nonlinear growth patterns observed in many ASEAN economies, accommodating saturation effects in highly urbanized countries and acceleration in rapidly developing ones. The fitted model provides a smooth trajectory of population density over time and serves as a forward-looking exposure proxy in the loss simulation exercise.

Using the estimated parameters $\hat{a}_i$ and $\hat{b}_i$, the expected population density is forecasted in each country for year $t+1$:

$$\widehat{\text{PopulationDensity}}_{i,t+1} = \hat{a}_i(t+1) + \hat{b}_i(t+1)^2.$$

This projected population density is then substituted into the previously estimated log-linear damage model to obtain a predictive distribution of disaster losses. Specifically, for peril h in country i and year $t+1$, simulated losses are generated as

$$\log\left(\text{Damage}_{i,t+1}^{(h,s)}\right) = \hat{\alpha}_i^{(h)} + \hat{\beta}_i^{(h)} \log\left(\widehat{\text{PopulationDensity}}_{i,t+1}\right) + \varepsilon_{i,t+1}^{(h,s)},$$

where $\varepsilon_{i,t+1}^{(h,s)}$ is a random draw from the normal residual distribution estimated from historical data. Exponentiating these simulated values yields the distribution of total damages in level terms.

This structure allows the severity model to evolve endogenously with population exposure while keeping the model transparent and data-driven. By combining it with the frequency model described earlier, scenario-consistent forecasts of catastrophe losses can be produced across ASEAN countries, which can then be aggregated or stress-tested for insurance-linked security valuation, solvency analysis, or risk-transfer design.

Section 4 Empirical Results

This section presents empirical results from the frequency and severity models introduced earlier. Based on the discussions in the previous sections, two perils are considered, namely floods and storms. Within each peril, one high-frequency country where disaster events occur regularly and provide richer disaster data is contrasted with one low-frequency country where events are rare and the data are sparser. This comparison highlights both the flexibility of the modeling approach and the advantages of working with quarterly data when event frequencies are low. Results for the remaining countries are collected in Appendix A of this report.

The examples are structured consistently across countries and perils. For each country-peril pair, four diagnostic figures are presented: (1) a one-year-ahead forecast of peril frequency using the DCMM; (2) fitted event-specific loss estimates with the mean forecast and 95% prediction interval; (3) a Quantile-Quantile (QQ) plot of standardized residuals; and (4) a residual plot against fitted values.

4.1 INDONESIA – FLOOD

The first example examines floods in Indonesia, a country that experiences the highest flood frequency in ASEAN. Figure 7 shows the one-year-ahead forecast of quarterly flood counts derived from the DCMM. The blue fan represents the predictive distribution, which combines uncertainty from both the Bernoulli occurrence and shifted-Poisson count components. Indonesia's quarterly pattern exhibits strong regularity, reflecting the country's well-defined wet and dry seasons. The model captures this seasonal pattern effectively. Predictive intervals widen during monsoon quarters, reflecting higher uncertainty around peak flood periods, but remain well-calibrated around the central tendency. In addition, the observed flood frequency shows a noticeable decline beginning around 2023. The model adapts to this emerging signal, leading to a modest downward shift in the forecasted mean and a tightening of the predictive intervals in more recent quarters. This indicates the DCMM's ability to respond to evolving trends while still preserving seasonal structure.

Figure 7

ONE-YEAR-AHEAD FORECAST OF QUARTERLY FLOOD COUNTS IN INDONESIA

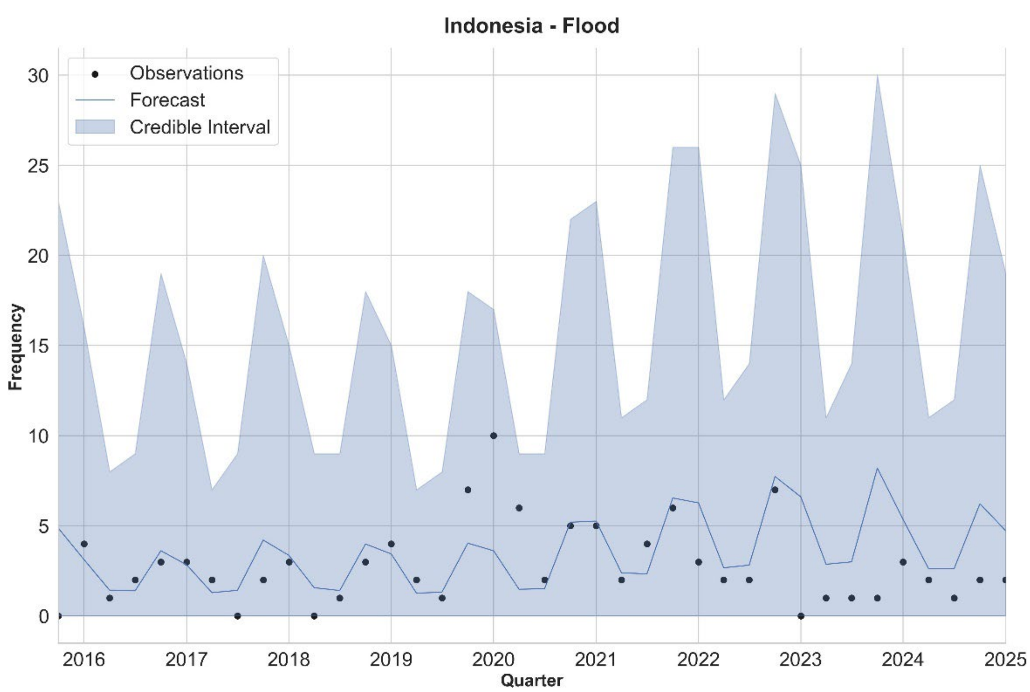
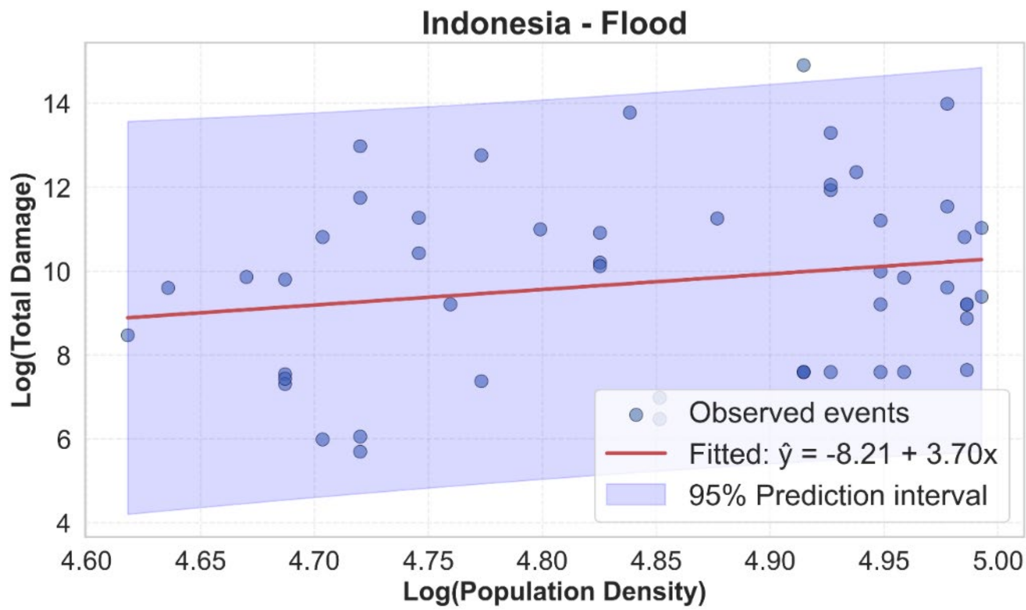


Figure 8 illustrates the fitted severity model, which links event-level log damage to log population density. The positive slope indicates that higher population density is associated with larger expected losses, consistent with greater exposure and asset concentration in more urbanized areas. The 95% prediction interval remains relatively narrow due to Indonesia's large sample of flood events, suggesting robust parameter estimation.

Figure 8

INDONESIA FLOOD LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL



The QQ plot in Figure 9 shows that standardized residuals align closely with the 45-degree line, confirming approximate normality of the residuals on the log scale. Figure 10 displays residuals against fitted values, revealing no systematic bias or heteroskedasticity. Together, these diagnostics confirm that the model fits the Indonesian flood data well and is suitable for forward simulation of future losses.

Figure 9
QQ PLOT OF STANDARDIZED RESIDUALS FOR THE INDONESIA FLOOD SEVERITY MODEL

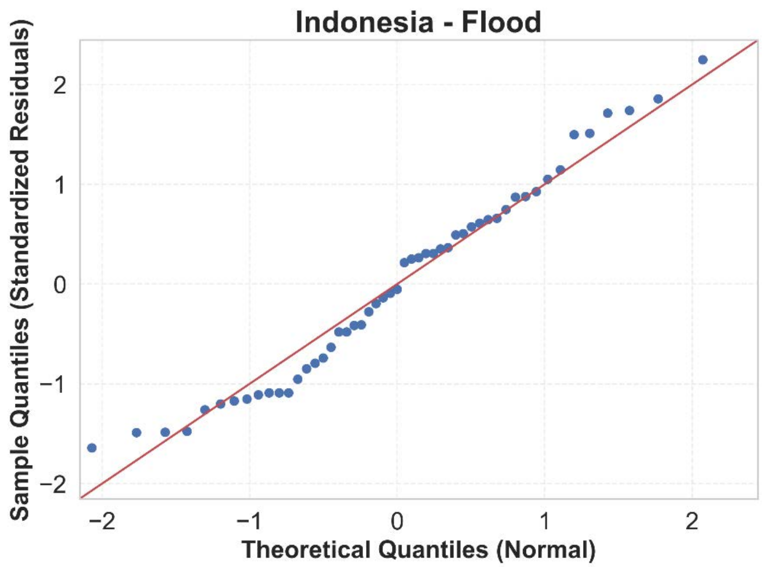
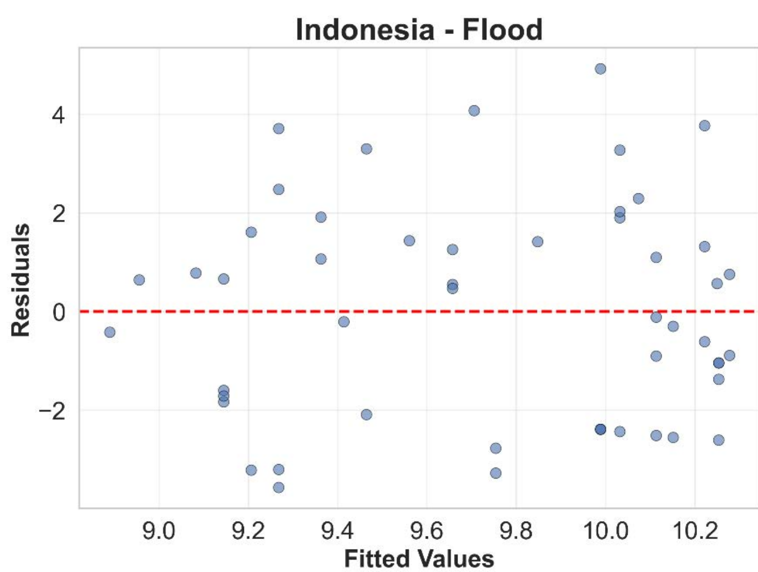


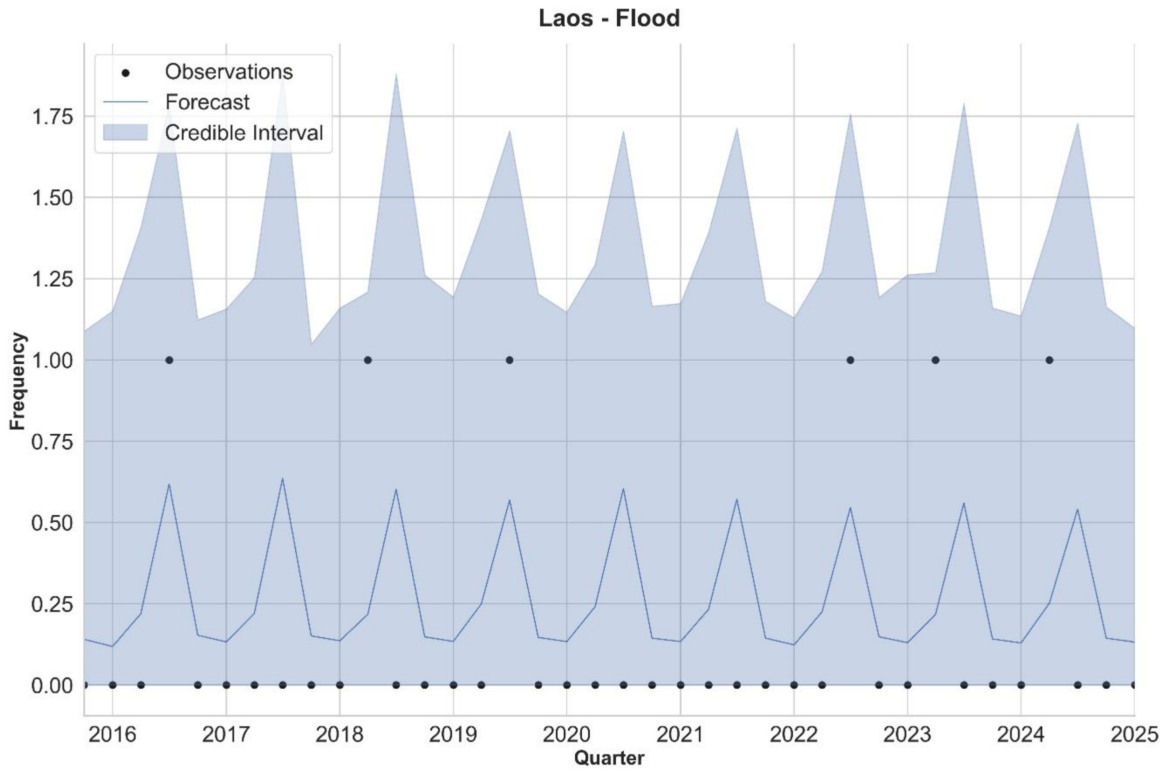
Figure 10
RESIDUALS VERSUS FITTED VALUES FOR THE INDONESIA FLOOD SEVERITY MODEL



4.2 LAO PDR – FLOOD

The discussion next turns to Lao PDR, where floods occur much less frequently. The forecast in Figure 11 exhibits wide predictive intervals and a large probability of zero events in each quarter, reflecting the sparsity of observations. This example highlights the benefit of modeling at a quarterly frequency rather than monthly frequency. With monthly data, almost all periods would be zero, making it difficult to identify any seasonal structure or meaningful trend. By aggregating to the quarterly level, the model retains enough signal to estimate occurrence probabilities and capture broad temporal dynamics.

Figure 11
ONE-YEAR-AHEAD FORECAST OF QUARTERLY FLOOD COUNTS IN LAO PDR



In Figure 12, the relationship between log damage and log population density appears nearly flat, with wide prediction bands due to the limited number of events. Figure 13 and Figure 14 show diagnostic plots that remain within acceptable bounds but display greater variability, which is expected given the small sample size. In low-frequency settings like Lao PDR, parameter uncertainty and event variability dominate, so the frequency component contributes most to the overall loss uncertainty.

Figure 12
LAOS FLOOD LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

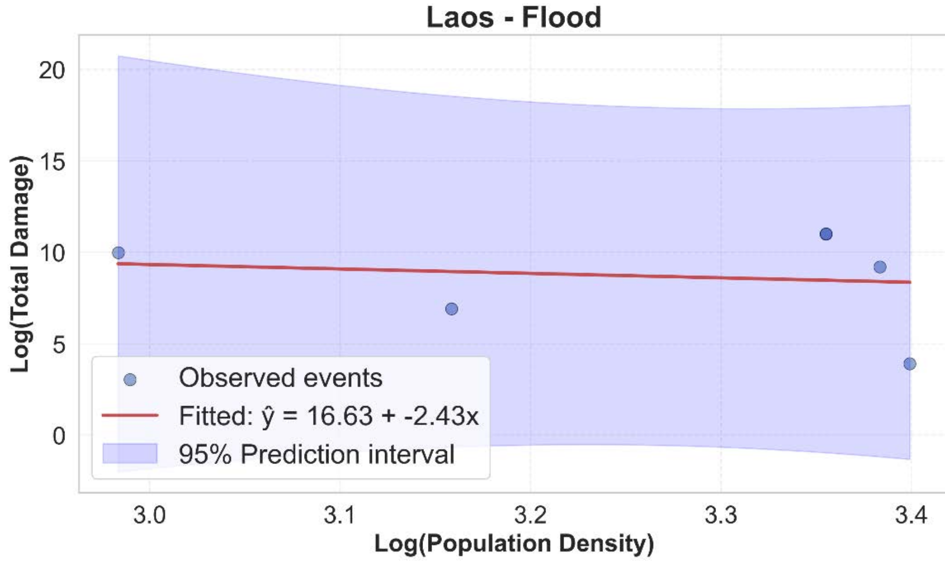


Figure 13
QQ PLOT OF STANDARDIZED RESIDUALS FOR THE LAOS FLOOD SEVERITY MODEL

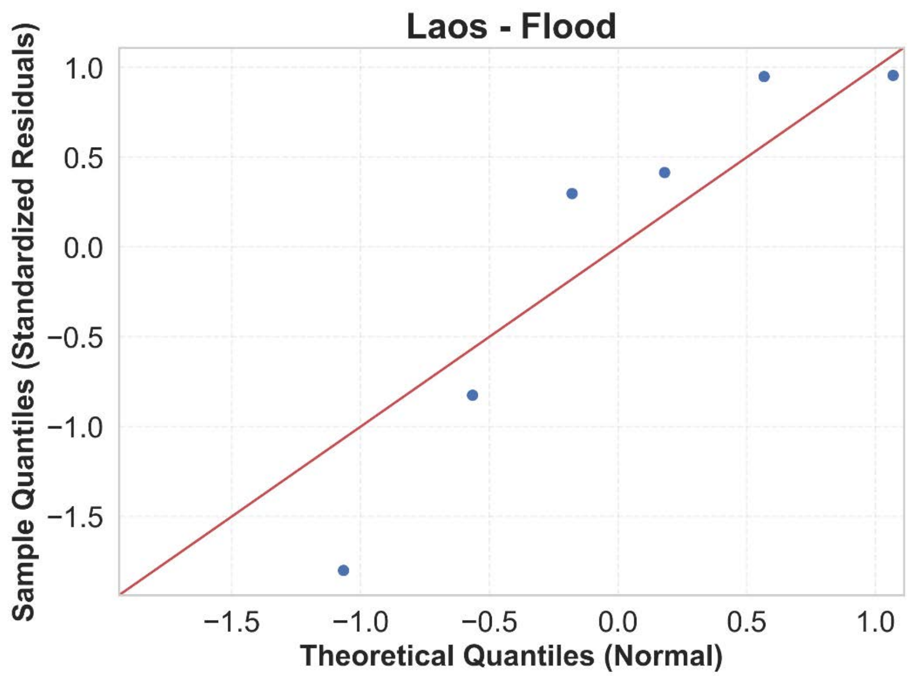
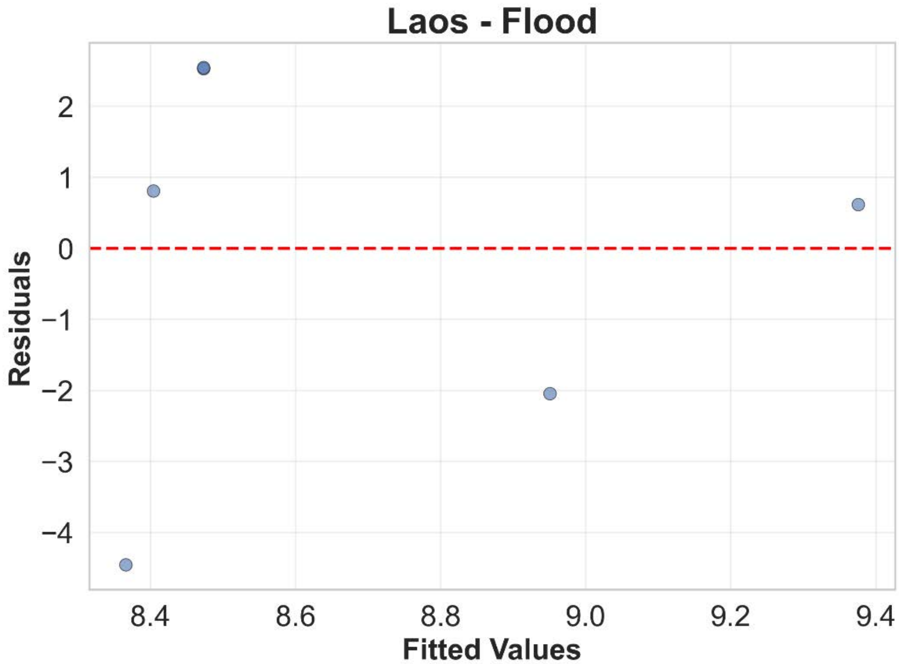


Figure 14
RESIDUALS VERSUS FITTED VALUES FOR THE LAOS FLOOD SEVERITY MODEL



4.3 PHILIPPINES – STORM

The focus now shifts from floods to storms beginning with the Philippines. The Philippines is the ASEAN country most exposed to tropical cyclones. The quarterly forecast in Figure 15 shows a pronounced seasonal pattern, with high predicted activity during the second half of each year, corresponding to the typhoon season. Predictive uncertainty is relatively narrow because the country's long storm history provides ample data for estimation.

Figure 16 presents the severity model results. The slope coefficient is positive and statistically meaningful, implying that denser population correlates with higher storm losses per event. The QQ and residual plots in Figure 17 and Figure 18 confirm that the model residuals are approximately normal and uncorrelated with fitted values, mirroring the behavior observed for Indonesia floods.

Figure 15

ONE-YEAR-AHEAD FORECAST OF QUARTERLY STORM COUNTS IN PHILIPPINES

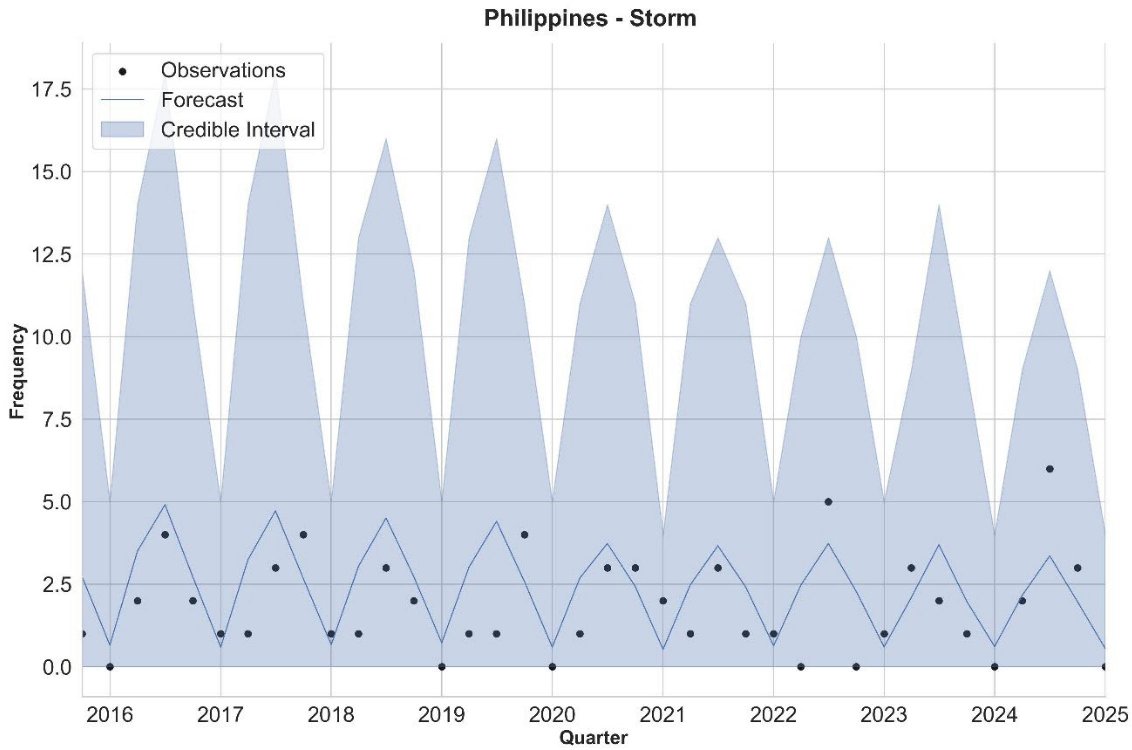


Figure 16

PHILIPPINES STORM LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

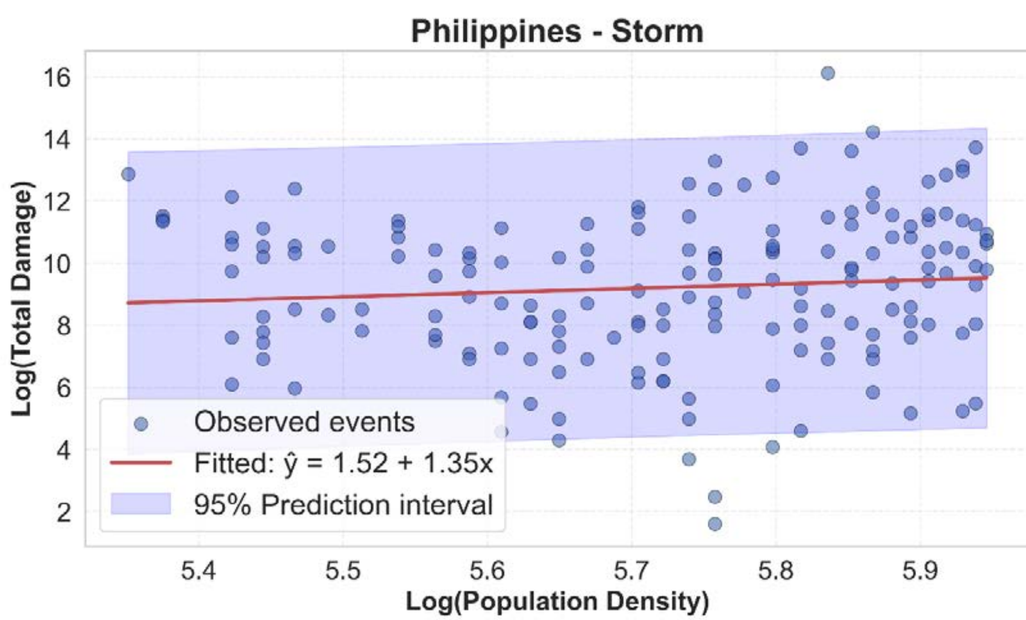


Figure 17
QQ PLOT OF STANDARDIZED RESIDUALS FOR THE PHILIPPINES STORM SEVERITY MODEL

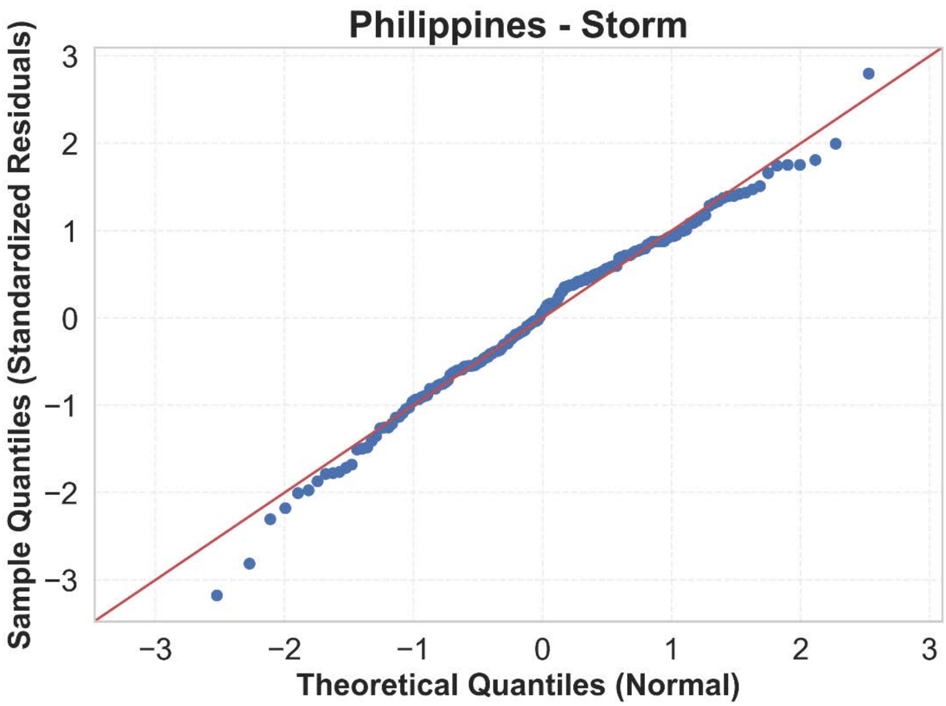
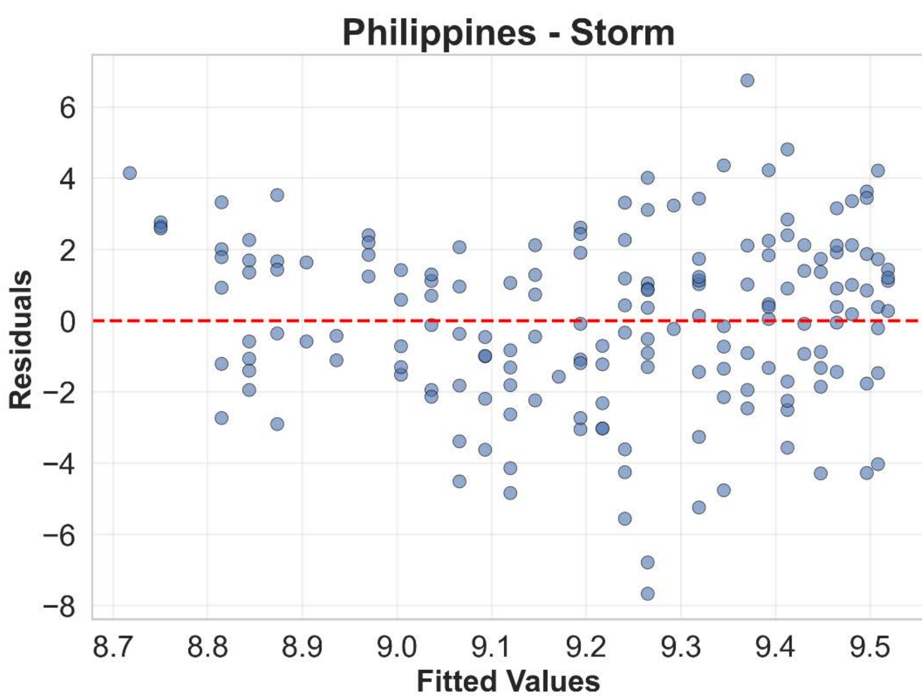


Figure 18
RESIDUALS VERSUS FITTED VALUES FOR THE PHILIPPINES STORM SEVERITY MODEL



4.4 VIET NAM – STORM

Lastly, the discussion investigates the storm losses in Viet Nam. Viet Nam provides an intermediate case between very high-frequency exposure (i.e., the Philippines) and the low-frequency settings observed in some other ASEAN members. Figure 19 shows strong quarter-to-quarter seasonality. The forecasted counts rise into the late-year typhoon season and decline thereafter, while remaining at relatively low integer levels (typically zero to three per quarter). Predictive bands widen appreciably during the seasonal peak, reflecting both higher expected activity and greater dispersion captured by the random-effects term.

Figure 20 reports the severity fit on the log-log scale. The slope is positive (approximately 2.9 in the fitted line shown), indicating that higher population density is associated with larger storm losses, consistent with greater concentration of exposed assets in more urbanized years. The 95% prediction interval is wider than that of the Philippines, owing to fewer events and more heterogeneity in reported losses, but still provides usefully bounded forecasts for simulation.

Diagnostics in Figure 21 and Figure 22 indicate acceptable calibration. The QQ plot tracks the 45° line with mild right-tail deviations, which is common when a few extreme storms dominate the upper loss distribution. Residuals vs. fitted values show no systematic curvature; dispersion is roughly homoscedastic over the fitted range. Overall, the model captures both the seasonal frequency structure and the exposure-loss relationship with sufficient fidelity for use in prospective loss aggregation.

It is noteworthy Viet Nam's storm frequency is not as sparse as Lao PDR floods, so monthly modeling would be feasible but less stable. Quarterly aggregation remains advantageous: it sharpens the seasonal signal, reduces the prevalence of zeros, and improves parameter stability without sacrificing essential dynamics.

Figure 19

ONE-YEAR-AHEAD FORECAST OF QUARTERLY STORM COUNTS IN VIET NAM

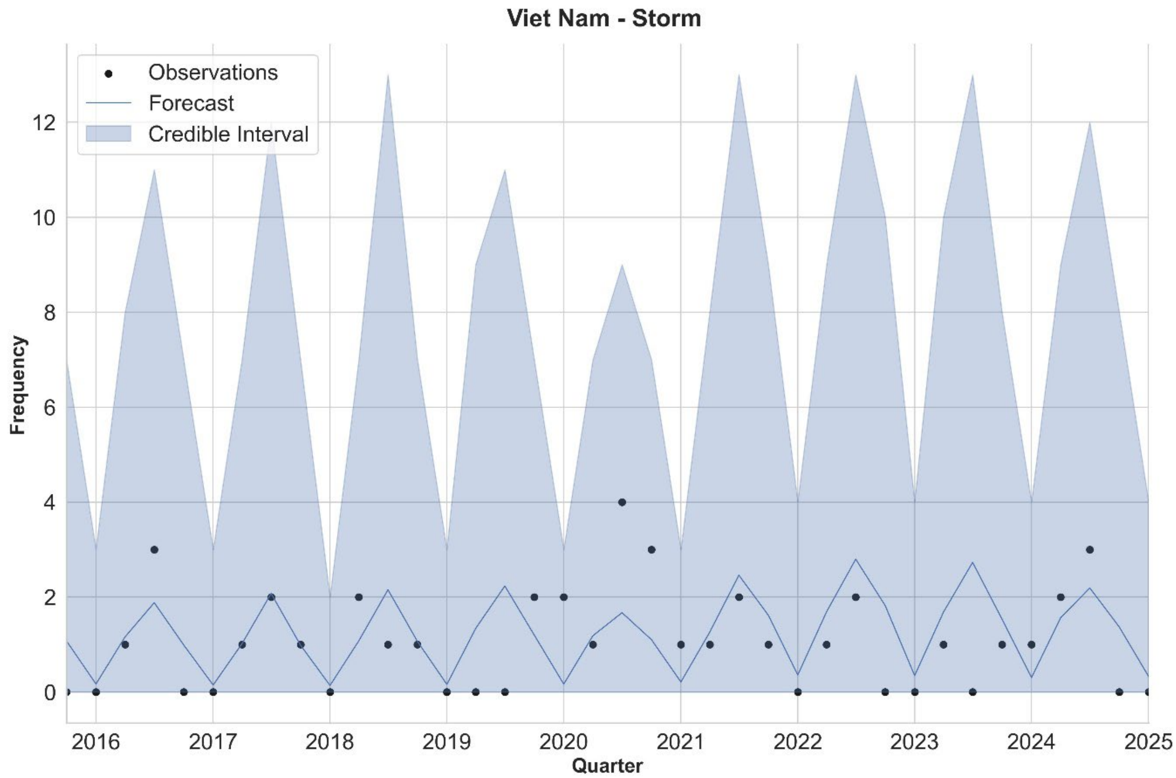


Figure 20

VIET NAM STORM LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

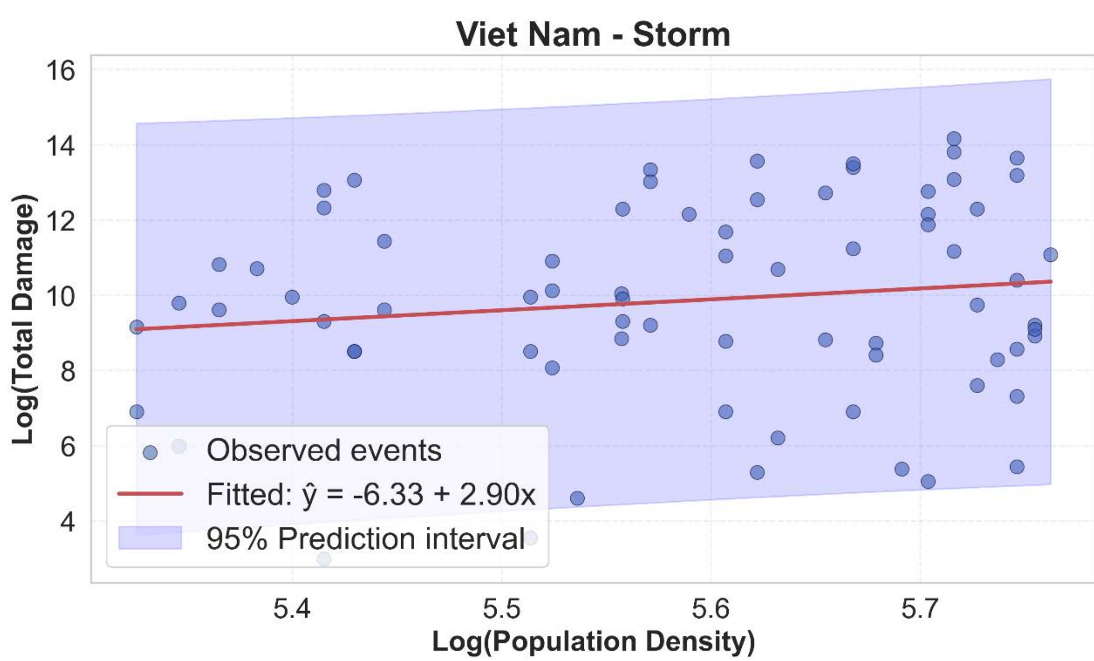


Figure 21
QQ PLOT OF STANDARDIZED RESIDUALS FOR THE VIET NAM STORM SEVERITY MODEL

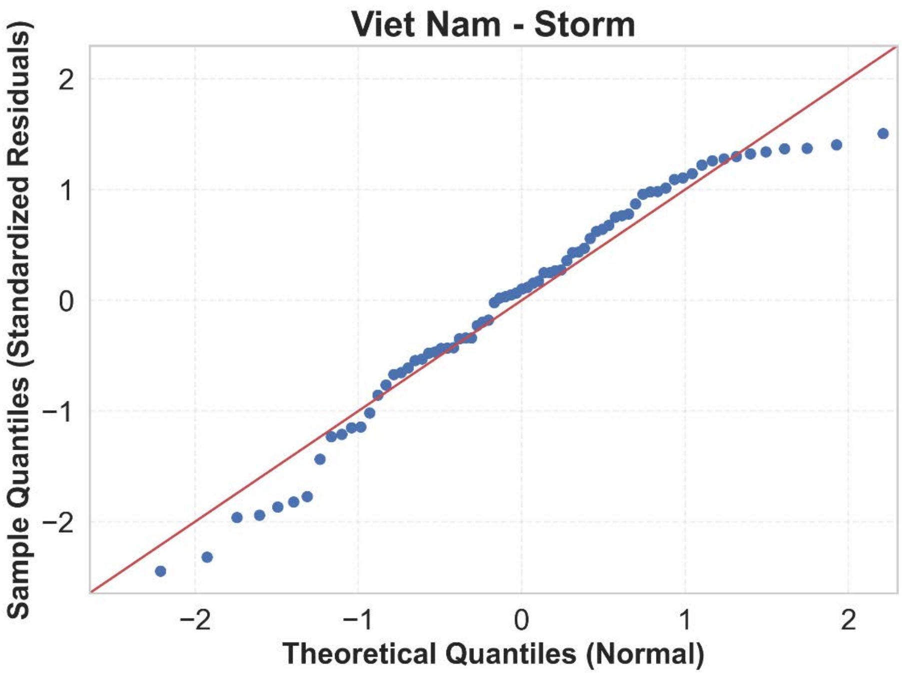
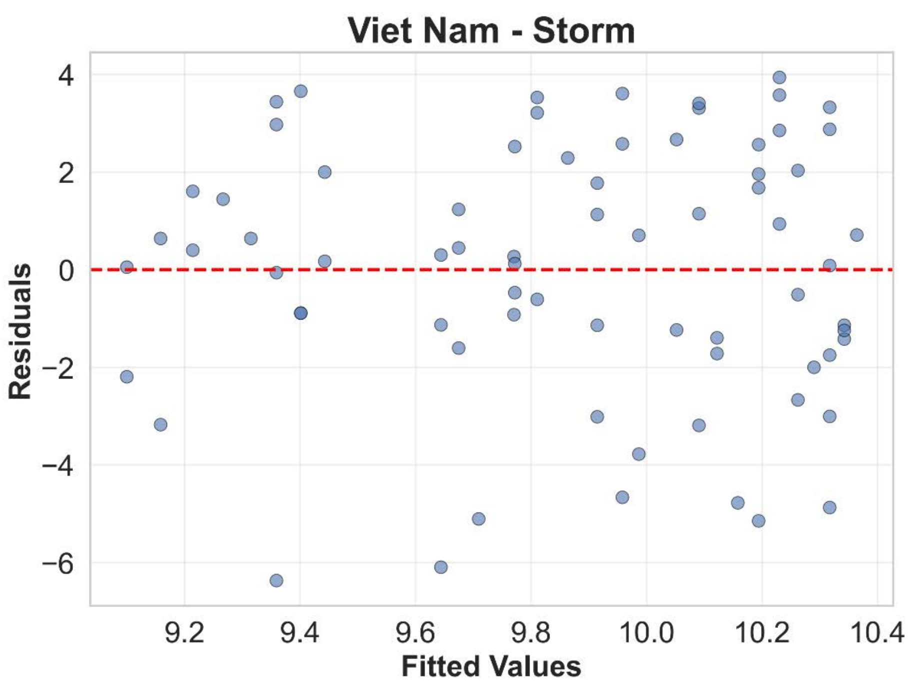


Figure 22
RESIDUALS VS. FITTED VALUES FOR THE VIET NAM STORM SEVERITY MODEL



4.5 DISCUSSIONS

Taken together, these four examples demonstrate that the proposed DCMM model and the proposed severity model perform consistently across countries and perils, adapting to both data-rich and data-scarce environments. The frequency model effectively captures quarter-to-quarter variability and seasonality where sufficient data exist, while still yielding stable forecasts for low-frequency countries when monthly modeling would fail. The severity model provides intuitive, exposure-driven relationships between population density and economic loss, though its precision naturally depends on the number of events available for calibration.

Overall, quarterly aggregation strikes a practical balance between temporal resolution and statistical stability. It preserves key seasonal signals in countries with frequent events while ensuring adequate information content for those with sparse data. The combination of frequency and severity models thus provides a unified framework for simulating future catastrophe losses across ASEAN, forming the foundation for the regional risk sharing analysis presented in the next section.

Section 5 Risk Sharing Application

5.1 OVERVIEW AND OBJECTIVES

In this section, a cross-region risk sharing framework is proposed that diversifies catastrophe risk exposure across the ASEAN region, strengthens the region's financial resilience against extreme catastrophe losses, enables more efficient capital utilization, and promotes equitable and transparent participation. The authors also apply the empirical results in Section 4 to assess the potential of the framework to enhance regional financial resilience and reduce post-disaster funding gaps.

5.2 CROSS-REGION RISK SHARING

The cross-region risk sharing strategy combines key features of catastrophe (CAT) bonds and peer-to-peer (P2P) insurance, in which the risk coverage functions as a CAT bond, while the risk sharing component operates similarly to P2P insurance. The key elements of the framework are illustrated in a one-period setting below, which can be readily extended to a multi-period setting.

5.2.1 AGGREGATE LOSSES

Suppose there are M countries. For country i, the one-period aggregate loss L_i due to certain types of catastrophe events, such as earthquakes, floods, or storms, is given by

$$\mathrm{L_i} = \sum_{\mathrm{j=1}}^{\mathrm{N_i}} \mathrm{X_{i,j}},$$

where N_i is the number of events over the period and $X_{i,j}$ is the loss caused by event j.

5.2.2 RISK COVERAGE

Each country i can choose its own risk coverage, characterized by the notional amount F_i, attachment point $b_{i,1}$, and exhaustion point $b_{i,2}$. Mathematically, the risk coverage is given by

$$f_i(L_i) = F_i \times \frac{\max\{0, \min\{L_i - b_{i,1}, b_{i,2} - b_{i,1}\}\}}{b_{i,2} - b_{i,1}}.$$

With this setup, country i will be reimbursed if its aggregate loss L_i exceeds the attachment point $b_{i,1}$, and the coverage amount is capped at F_i if L_i exceeds the exhaustion point $b_{i,2}$. To ensure fairness, the attachment probability $P(F_i > b_{i,1})$ and the exhaustion probability $\Pr(F_i > b_{i,2})$ should be set at the same levels for all countries. The total risk coverage is given by

$$S = \sum_{i=1}^{M} f_i(L_i).$$

5.2.3 PREMIUMS AND THE SHARED FUND

Each country contributes a risk-based premium proportional to its expected coverage:

$$p_i = (1+\theta)\mathbb{E}[f_i(L_i)].$$

The parameter θ represents a safety loading to ensure the financial sustainability of the risk sharing fund pool. The risk-based contribution provides a built-in incentive for risk reduction, as countries with lower expected losses benefit from lower premiums.

The premiums collected from individual countries will be pooled into a shared fund. It is assumed that the shared fund only invests in low-risk, highly liquid assets. Thus, at the end of the period, the value of the shared fund is approximately

$$v = (1+r)\sum_{i=1}^{M} p_i \, ,$$

where r is the simple risk-free interest rate over the period.

5.2.4 MANAGEMENT OF THE SHARED FUND

At the end of the period, the shared fund will be used to cover losses based on actual losses and risk coverage functions. There are three possible scenarios:

1. If the total risk coverage $S = 0$, then the premiums will be fully refunded. In this case, country i will receive $(1+r)p_i$ from the shared fund.
2. If the total risk coverage $S > 0$ and the shared fund is sufficient with $v \geq S$, country i will receive $f_i(L_i)$ to cover its loss. Moreover, the remaining balance of the shared fund after payouts will be refunded in proportion to premium payments; that is, country i will receive $(v - S)\frac{p_i}{\sum_{j=1}^{M} p_j}$.
3. If the total risk coverage $S > 0$ and the shared fund is insufficient with $v < S$, the shared fund will be distributed in proportion to realized risk exposures; that is, country i will receive $v\frac{f_i(L_i)}{\sum_{i=1}^{M} f_i(L_i)}$.

5.3 EMPIRICAL ANALYSIS

The empirical results in Section 4 are now applied to the proposed risk sharing framework presented in Subsection 5.2. A one-year period from 2025Q2 to 2026Q1 is considered. For country i, the attachment point $b_{i,1}$ and the exhaustion point $b_{i,2}$ are set to the 90% and 95% quantiles of their aggregate loss L_i, respectively. Moreover, the notional amount F_i is set to $b_{i,2} - b_{i,1}$. Then its risk coverage is given by

$$f_i(L_i) = \max\{0, \min\{L_i - b_{i,1}, b_{i,2} - b_{i,1}\}\}.$$

The one-year risk-free interest rate r and the safety loading factor θ are 4% and 0.5, respectively.

In the following subsections, three examples are presented to illustrate the proposed risk sharing framework. To compute the expectations and probabilities, 50,000 simulated scenarios are used over the one-year period from 2025Q2 to 2026Q1.

5.3.1 FLOOD ANALYSIS

In the first illustrative example, it is assumed that eight ASEAN countries—Indonesia, the Philippines, Thailand, Malaysia, Viet Nam, Myanmar, Cambodia, and Laos—participate in the risk sharing program to diversify their flood risk.

Table 1
EXPECTED RISK COVERAGE FOR FLOOD LOSSES (USD ’000)

Country	Indonesia	Philippines	Thailand	Malaysia	Viet Nam	Myanmar	Cambodia	Laos
Expected coverage	69,648	37,588	423,284	38,713	13,474	4,634	32,636	95,845

Table 1 shows the expected risk coverage $\mathbb{E}[f_i(L_i)]$ for each country. Even though the attachment and exhaustion probabilities are the same for all countries, their parts of risk being shared still differ substantially in terms of magnitude. In particular, Thailand's expected coverage is the highest, accounting for roughly 59% of the total across all eight countries. Myanmar's expected coverage is the lowest, accounting for less than 1% of the total. The implications for pooling countries that share different levels of risk are illustrated in Table 3 below.

Table 2
PROBABILITIES OF THREE SCENARIOS

	Probability
No Payout	0.43
Sufficient fund	0.41
Insufficient fund	0.16

One major advantage of the proposed risk sharing framework over CAT bonds and reinsurance is that any remaining premiums after payouts will be returned. Table 2 presents the probabilities of three scenarios: (1) no payout, in which the premiums are fully refunded; (2) the fund is sufficient to cover the ceded losses; and (3) the fund is not sufficient to cover the ceded losses. The table shows that there is a high probability that the premiums will be fully returned. Additionally, the probability that the fund will be insufficient is relatively low.

Table 3
SUMMARY STATISTICS FOR UNHEDGED LOSSES AND NET LOSSES WITH RISK SHARING (USD ’000)

Country	Strategy	Expectation	Standard Deviation	$VaR_{0.92}$	$VaR_{0.95}$	$VaR_{0.98}$
Indonesia	Unhedged	1,689,064	2,008,546	5,056,241	5,738,376	7,465,554
	Risk sharing	1,662,437	1,873,150	4,816,069	5,082,080	6,754,288
Philippines	Unhedged	217,464	449,027	698,133	1,081,672	2,244,077
	Risk sharing	201,788	356,244	564,865	696,504	1,745,519
Thailand	Unhedged	2,284,126	6,307,036	6,611,841	11,203,345	27,305,905
	Risk sharing	2,388,380	6,187,585	6,348,235	10,764,620	26,948,219
Malaysia	Unhedged	736,072	1,127,293	2,406,596	2,847,442	4,331,464
	Risk sharing	719,996	1,046,363	2,298,206	2,441,569	3,843,817
Viet Nam	Unhedged	279,568	339,721	830,289	960,679	1,240,070
	Risk sharing	273,703	310,240	774,719	815,892	1,087,312
Myanmar	Unhedged	19,530	44,901	77,147	125,550	180,098
	Risk sharing	17,483	32,398	59,409	74,753	119,989
Cambodia	Unhedged	100,648	250,572	610,641	781,500	827,525
	Risk sharing	86,726	173,055	405,943	420,789	594,627
Laos	Unhedged	484,893	1,880,459	1,185,506	2,215,248	6,156,466
	Risk sharing	460,851	1,732,142	917,088	1,484,987	5,450,849

Under the risk sharing framework, the net loss of a country is defined as the sum of its hedged loss and the future value of its premium payment, minus the premium refund. Table 3 presents summary statistics—including the expectation, standard deviation, and value at risk—for unhedged losses and net losses under the risk sharing framework. It is observed that the expected net loss is lower than the expected unhedged loss for all countries except Thailand. As mentioned earlier, the portion of risk shared by Thailand is much higher than that of the other countries. This implies that when countries that share different levels of risk are pooled, those with the highest shared risk are penalized in terms of expected net losses.

On the other hand, it is observed that all countries benefit from significantly lower standard deviations and values-at-risk for their net losses, compared to unhedged losses. In particular, the 95% value-at-risk decreases by about 11% for Indonesia, 35% for the Philippines, 14% for Malaysia, 15% for Viet Nam, 40% for Myanmar, 46% for Cambodia, and 33% for Laos. The standard deviations move in the same direction: roughly -7% for Indonesia, -21% for the Philippines, -7% for Malaysia, -8% for Viet Nam, -26% for Myanmar, -31% for Cambodia, and -8% for Laos. These figures highlight the effectiveness of the proposed framework in reducing risk.

5.3.2 STORM ANALYSIS

In this illustrative example, it is assumed that four ASEAN countries—Myanmar, the Philippines, Thailand, and Viet Nam—participate in the risk sharing program to diversify their storm risk. Like Tables 1–3, the expected risk coverage is presented in Table 4, the probabilities of three funding scenarios in Table 5, and summary statistics for unhedged losses and net losses under the risk sharing framework in Table 6.

Table 4

EXPECTED RISK COVERAGE FOR STORM LOSSES (USD ’000)

Country	Myanmar	Philippines	Thailand	Viet Nam
Expected coverage	16,560	203,728	791	41,547

Table 5

PROBABILITIES OF THREE SCENARIOS

	Probability
No payout	0.66
Sufficient fund	0.20
Insufficient fund	0.14

Table 6

SUMMARY STATISTICS FOR UNHEDGED LOSSES AND NET LOSSES WITH RISK SHARING (USD ’000)

Country	Strategy	Expectation	Standard Deviation	$VaR_{0.92}$	$VaR_{0.95}$	$VaR_{0.98}$
Myanmar	Unhedged	130,481	733,534	85,726	293,206	2,090,934
	Risk sharing	120,708	700,857	46,737	111,664	1,876,244
Philippines	Unhedged	1,333,713	2,019,947	4,347,124	6,487,139	8,019,265
	Risk sharing	1,359,547	1,991,829	4,279,764	6,405,713	7,933,664
Thailand	Unhedged	5,984	12,730	18,973	26,878	49,775
	Risk sharing	5,507	10,753	15,733	17,950	40,311
Viet Nam	Unhedged	1,031,032	1,415,175	3,298,913	3,745,937	5,162,044
	Risk sharing	1,015,449	1,356,712	3,178,331	3,452,215	4,853,195

From Table 4, it is observed that the portion of risk being shared differs substantially across the four countries. The Philippines has the highest expected coverage, accounting for approximately 78% of the total, while Thailand has the smallest, at less than 1% of the total. Table 5 shows that there is a high likelihood that the premiums will be fully refunded, and that the likelihood of the fund being insufficient is relatively low.

For Myanmar, risk sharing lowers the expectation, standard deviation, and tail risk. The expectation falls by 7.5%, and the standard deviation falls by 4.5%. The values-at-risk drop even more materially, roughly by 46% for the 92% value-at-risk and by 62% for the 95% value-at-risk.

For the Philippines, which contributes the largest share of risk, the expectation rises by approximately 1.9%, while standard deviation and the values-at-risk decrease by only 1–2%. This again implies that countries that share higher levels of risk do not enjoy as much benefit as other countries under the risk sharing framework.

Thailand shares the lowest level of risk and hence benefits significantly from the risk sharing program across all dimensions. Specifically, the expectation, standard deviation, 92% value-at-risk, 95% value-at-risk, and 98% value-at-risk decrease by 8%, 16%, 17%, 33%, and 19%, respectively.

For Viet Nam, the results are all positive but less pronounced than Thailand. In particular, the expectation decreases by 1.5%, the standard deviation by 4%, and the 92%, 95%, and 98% values-at-risk by roughly 4%, 8%, and 6%, respectively.

In summary, when countries sharing different levels of risk join the risk sharing program, those sharing lower levels of risk enjoy greater benefit across various risk metrics. Moreover, all countries experience reduced standard deviations and tail risk. To ensure fairness, the risk shared by different countries should be set at similar levels in terms of the probabilities of attachment and exhaustion, as well as the expected risk coverage. This is demonstrated in Subsection 5.3.3.

5.3.3 RISK SHARING POOL

In this illustrative example, *it is* assume*d* that only the Philippines and Malaysia participate in the risk sharing program to diversify their flood risk. Table 7 shows that their expected risk coverage is almost the same, implying that the risks being shared are very similar in magnitude.

Table 7

EXPECTED RISK COVERAGE FOR FLOOD LOSSES (USD ’000)

Country	Philippines	Malaysia
Expected coverage	37,588	38,713

Table 8
PROBABILITIES OF THREE SCENARIOS

	Probability
No payout	0.81
Sufficient fund	0.03
Insufficient fund	0.16

Table 9
SUMMARY STATISTICS FOR UNHEDGED LOSSES AND NET LOSSES WITH RISK SHARING (USD ’000)

Country	Strategy	Expectation	Standard Deviation	$VaR_{0.92}$	$VaR_{0.95}$	$VaR_{0.98}$
Philippines	Unhedged	217,464	449,027	698,133	1,081,672	2,326,847
	Risk sharing	217,199	434,717	650,547	1,028,431	2,270,551
Malaysia	Unhedged	736,072	1,127,293	2,406,596	2,847,442	4,605,839
	Risk sharing	736,337	1,115,005	2,359,995	2,792,484	4,553,422

Table 8 shows that the probability of the fund being sufficient is roughly 3%. This low probability arises from the fact that only two countries participate in the program, contributing a relatively low total premium. From Table 9, *it is* observe*d* that the expected unhedged loss and the expected net loss are almost identical for both countries, demonstrating the fairness of the framework when countries with similar levels of shared risks participate. Moreover, the risk sharing program helps both countries reduce their flood risk, resulting in lower standard deviations and values-at-risk.

This two-member example illustrates a model case of best practice in risk sharing: the risks shared by participating members should be set at similar levels. In this case, the expected unhedged loss and the expected net loss are nearly identical for each member, while the standard deviation and tail risk are reduced under the risk sharing framework.

Section 6 Discussion and Industry Implications

Beyond illustrating model fit and forecast performance across both data-rich and data-scarce settings, a key motivation of this report is to provide a practical open modeling toolkit that can be adopted by industry participants with minimal friction. In the supplemental materials, an Excel tool associated with this project has been provided. This Excel tool is not intended to serve as a "standalone implementation" of the statistical modeling component. Instead, it is designed to serve two practical purposes. First, it provides direct access to the disaster scenario outputs produced by the analysis. Therefore, for users who do not have their own dataset and would like to rely on the EM-DAT data source and the implemented analysis, they can directly extract the prediction results and incorporate them into downstream planning, budgeting, and risk financing exercises. Second, the Excel tool is meant to illustrate, in a transparent and user-friendly format, the workflow of the case study. This allows future users to see how the model-generated disaster scenarios can be translated into risk analysis practice, and how the setup can be modified (e.g., by regrouping markets, changing allocation rules, or adjusting financing assumptions) to fit their specific business needs.

In the remainder of this section, two implementation-oriented use cases are discussed: (i) insurers and reinsurers seeking to apply the proposed framework using proprietary underwriting and claims data, including potential multi-party deployment; and (ii) new entrants to a market that lack credible internal loss experience and must begin with industry-level benchmarks before transitioning to experience-based pricing.

6.1 USING THE PROPOSED FRAMEWORK WITH PRIVATE INSURER/REINSURER DATA

A direct industry application is for an insurer or a reinsurer to treat the frequency–severity structure developed in this report as an "off-the-shelf" statistical engine, and then re-estimate (or recalibrate) the model using its own internal portfolio experience. Conceptually, the implementation steps mirror the workflow already laid out in the report: construct quarterly event-count series for the relevant peril(s) and geography, fit the DCMM-style frequency component to obtain an internally consistent predictive distribution for event counts, and then fit a transparent severity model to obtain loss-per-event distributions conditional on an exposure proxy. The key advantage is that the statistical framework is already developed and validated in a way that is computationally light, interpretable, and adaptable across heterogeneous data environments.

In practice, private-data implementation will often involve two adjustments that preserve the model structure while improving business relevance. First, "loss" will typically mean insured loss rather than total economic loss. This can be handled by fitting the same log-linear specification to insured losses (or to losses net of terms and conditions), and by aligning the unit of analysis to the insurer's coverage structure (e.g., by line of business, policy limit band, or ceded layer). Second, while this report uses population density as a forward-looking exposure proxy at the national level, practitioners can naturally substitute portfolio-relevant exposure measures (e.g., sums insured, number of locations, insured values by construction class, or geocoded exposure concentration). The conceptual message is that the framework is not tied to any single proxy. Rather, it is designed so that exposure drivers can be replaced with variables that better reflect the insurer's risk profile, while retaining a transparent "exposure to severity" mapping.

A further application is joint deployment by multiple insurers or reinsurers. The core frequency model includes a shared systemic component intended to capture common seasonality and regional co-movement, which makes the framework well-suited for situations where firms operate in different ASEAN markets but face correlated climate regimes. For example, a reinsurer with exposure in Malaysia could collaborate with a reinsurer operating in Indonesia to apply a common modeling framework and then pool a predefined portion of their liabilities into a structured risk-sharing pool. This is conceptually similar to the mechanism designed in this report. In such a setting, the model outputs provide an analytically consistent way to: (i) quantify each participant's expected ceded loss under common attachment/exhaustion criteria; (ii) stress test tail outcomes under coherent joint simulations; and

(iii) support a transparent premium contribution rule and refund mechanism. Importantly, this type of collaboration does not require public disclosure of granular policyholder information. Operationally, it can be supported by sharing only the model inputs needed for calibration (e.g., aggregated quarterly counts and loss summaries) or by using a trusted third-party computation workflow. The broader point is that the toolkit is designed to support standardization: multiple entities can use the same modeling language, agree on risk metrics, and design pooling arrangements that are easier to communicate to stakeholders (boards, regulators, and counterparties) than proprietary "black-box" outputs.

6.2 USING THE PROPOSED FRAMEWORK AS AN INDUSTRY BENCHMARK FOR NEW MARKET ENTRANTS

A second important use case is for a new entrant (or a rapidly expanding insurer) that does not yet have sufficient internal catastrophe underwriting and claims history to fit an experience-based model reliably. For such entities, the national-loss results in this report can be treated as industry-level benchmarks. This is analogous in spirit to industry tables or market statistics sometimes disseminated by regulators, supervisory bodies, or actuarial associations for pricing and reserving guidance. Because the framework is built on publicly available national disaster-loss information and a transparent modeling structure, it provides an immediately usable baseline for initial pricing assumptions, early-stage reinsurance purchasing, portfolio steering (e.g., exposure limits by region), and preliminary capital or solvency stress testing.

As the entrant accumulates its own experience, a natural transition is to blend the "industry" signal (represented by the national-level model outputs in this report) with the firm's emerging internal signal through a credibility-style approach. Conceptually, the national model can be interpreted as a prior (or an external reference model), and the entrant's private experience can be interpreted as incremental evidence. Early on, when the entrant has limited data, greater weight should be placed on the national benchmark to avoid overreacting to a small number of observations. Over time, as the entrant's exposure and claims history grows, the credibility weight of the entrant's own data increases, and the blended estimate moves progressively toward a portfolio-specific view of risk. In operational terms, this supports both better governance (because assumptions evolve systematically rather than ad hoc) and better comparability across firms (because the benchmark reference is explicit and interpretable).

All in all, these two applications underscore the broader contribution of the report: the proposed models are not only empirically workable, but also structured to be deployable, either as a private-data analytics engine for established insurers and reinsurers, or as a transparent industry benchmark that supports entry, growth, and eventual credibility-based customization as private experience develops.

6.3 IMPLICATIONS FOR CLIMATE CHANGE ADAPTATION IN INSURANCE

The proposed framework naturally gives rise to a practical pathway for insurers and reinsurers to incorporate climate change considerations into risk management and decision-making. On the risk measurement and pricing side, the proposed modeling framework allows companies to monitor evolving hazard regimes. Because the regional latent factor captures slow-moving, basin-scale dynamics and the state vectors evolve via random-walk structures, the model can gradually reflect shifts in seasonal patterns, storm tracks, or flood regimes that may be influenced by climate change. In practice, insurers could use this framework to monitor whether the estimated occurrence probabilities or intensities exhibit systematic upward or downward trends over time, thereby informing adjustments to catastrophe loadings, reinsurance structures, or portfolio limits.

The risk-sharing application demonstrates how quantitative modeling can support collective climate risk adaptation. As climate change increases the potential for correlated extreme events across countries, purely national risk retention becomes less efficient. The cross-region pooling mechanism analyzed in this report illustrates how transparent, model-based estimates of expected coverage and tail risk can underpin cooperative financing arrangements that diversify climate-related losses. From an industry perspective, similar principles could be applied to multi-insurer pools, regional catastrophe facilities, or public–private partnerships designed to spread climate risk more broadly while maintaining clear, rule-based governance.

Finally, the open and replicable nature of the framework supports long-term climate resilience planning. Because the model relies on publicly available data, clear statistical assumptions, and interpretable parameters, it can serve as a common analytical language among insurers, reinsurers, regulators, and governments. This shared baseline can facilitate discussions about how risk is evolving, how adaptation measures affect loss distributions, and how financial protection mechanisms should be redesigned in response to climate change.

Section 7 Summary

This report presented a NAT CAT modeling toolkit tailored to the needs of ASEAN countries. For frequency modeling, the proposed DCMM effectively captures the quarterly frequency of floods and storms by combining occurrence and intensity components, while accommodating strong seasonal patterns and shared regional climate influences. Complementing this, a simple log–linear severity model leverages population density as a forward-looking exposure proxy, which provides stable and interpretable loss projections even in data-limited environments.

The report then demonstrated how the model outputs can inform practical catastrophe risk financing decisions through a cross-region risk sharing design. The case study showed that pooling NAT CAT exposure across countries can meaningfully reduce volatility and tail risk, while also improving overall financial resilience. The results highlight that well-structured risk transfer mechanisms can help alleviate post-disaster funding burdens and promote equitable participation across countries with different risk levels. Overall, the analysis illustrates how the proposed accessible statistical tools grounded in local data and transparent methodology can be useful for supporting evidence-based planning and build trust in disaster finance innovations across the ASEAN region.

Section 8 Acknowledgement

The researchers' deepest gratitude goes to those without whose efforts this project could not have come to fruition: the Project Oversight Group for their diligent work overseeing, reviewing and editing this report for accuracy and relevance.

Project Oversight Group members:

Horng Cherng Lim, FSA

Tony Tan, FIA

Fiona Fuk Yee Tang, FSA

Jing Ling Zhang, LEED BD+C

At the Society of Actuaries Research Institute:

R. Dale Hall, FSA, CERA, CFA, MAAA

Jessie Li, FSA

Rose Northon

Xiao Xu, PhD, FSA, CERA

Wai Ling Yung, PhD

Appendix A: Additional Results

A. MALAYSIA – FLOOD

Figure 23

ONE-YEAR-AHEAD FORECAST OF QUARTERLY FLOOD COUNTS IN MALAYSIA

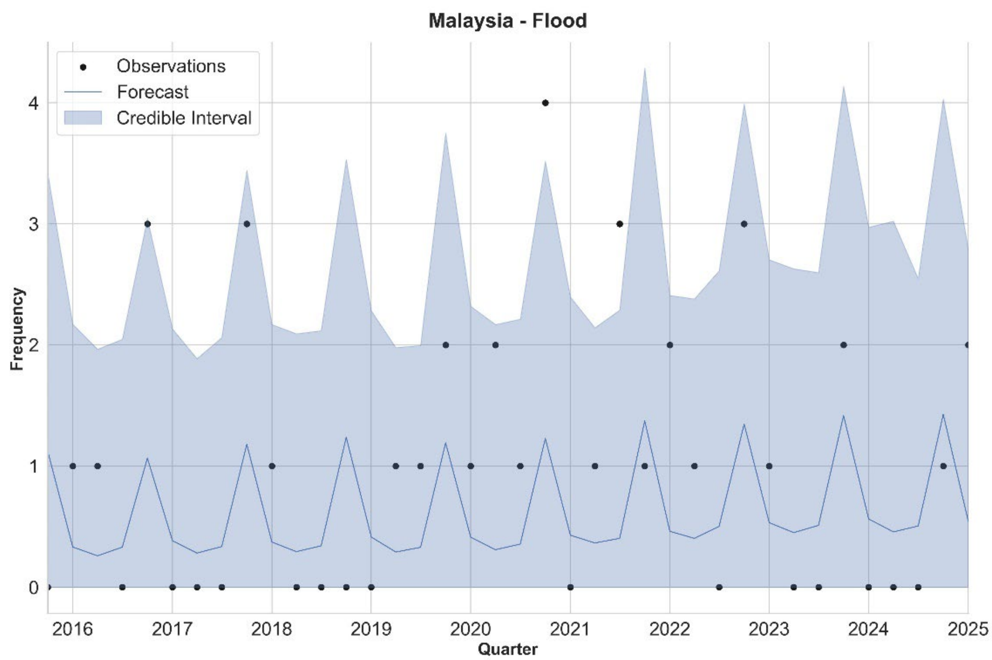


Figure 24

MALAYSIA FLOOD LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

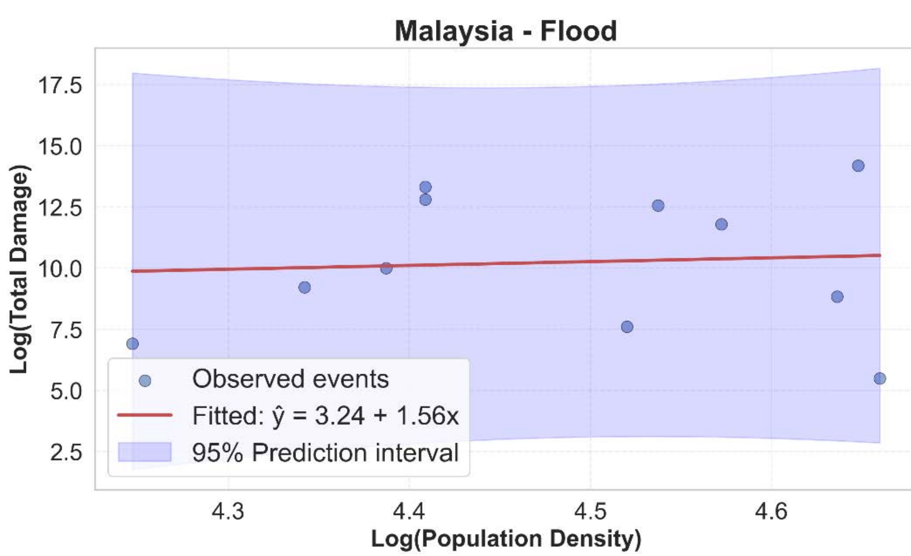


Figure 25

QQ PLOT OF STANDARDIZED RESIDUALS FOR THE MALAYSIA FLOOD SEVERITY MODEL

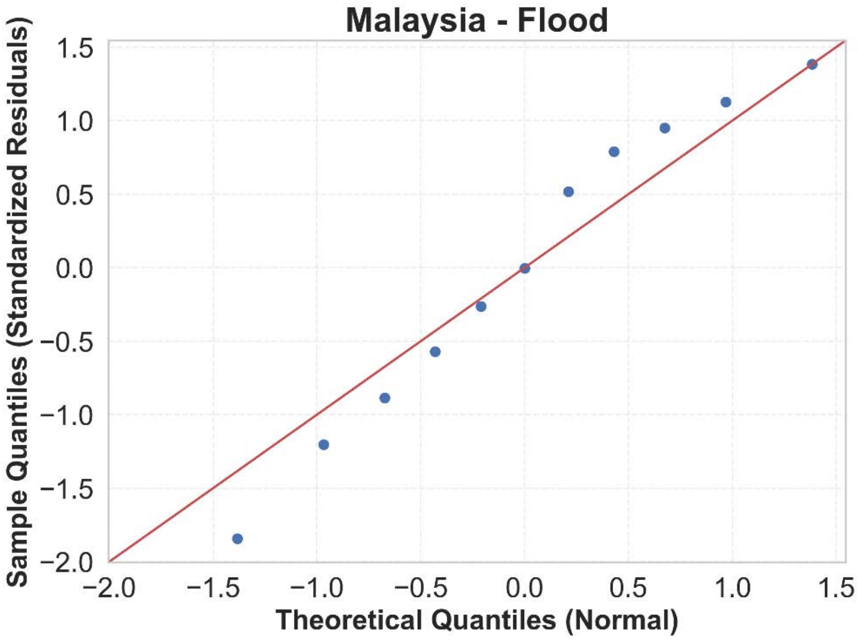
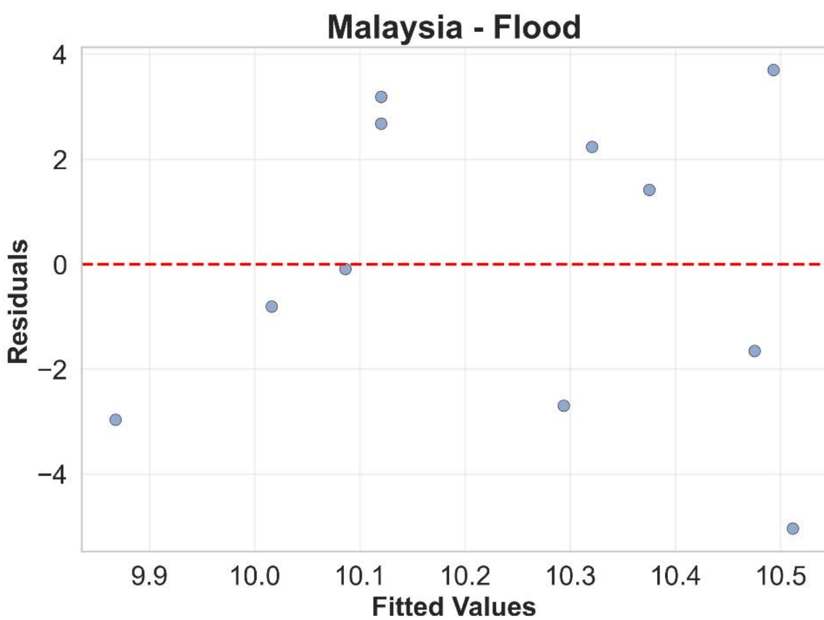


Figure 26

RESIDUALS VERSUS FITTED VALUES FOR THE MALAYSIA FLOOD SEVERITY MODEL



B. VIET NAM – FLOOD

Figure 27

ONE-YEAR-AHEAD FORECAST OF QUARTERLY FLOOD COUNTS IN VIET NAM

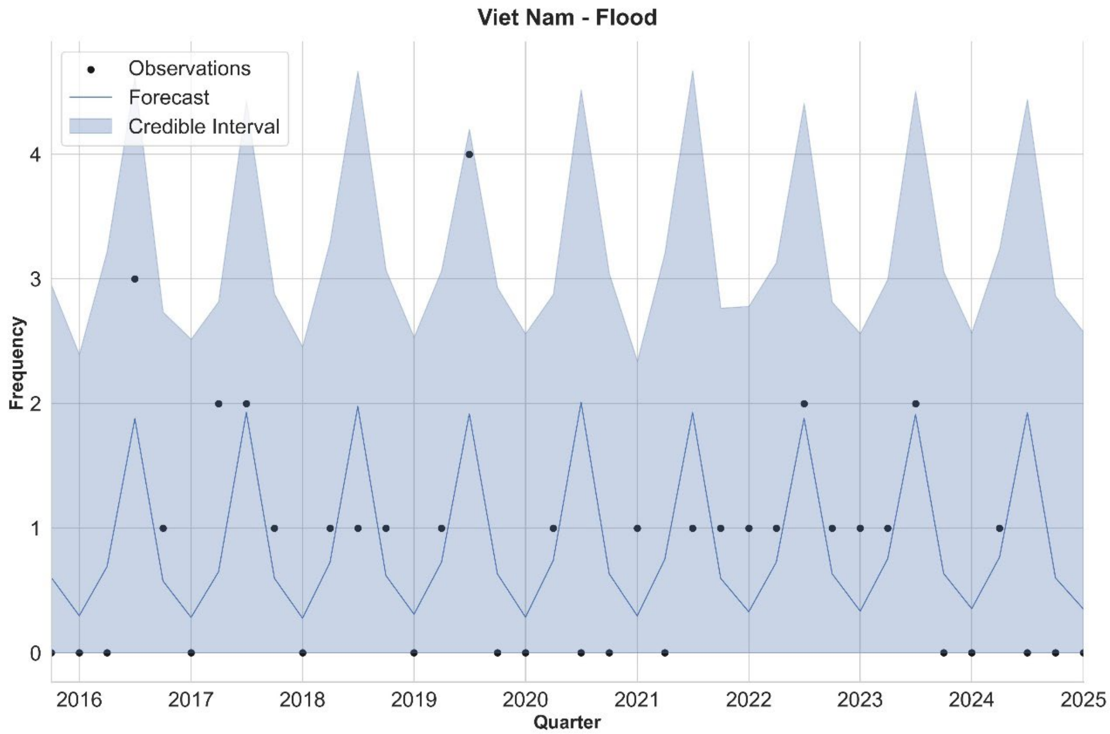


Figure 28

VIET NAM FLOOD LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

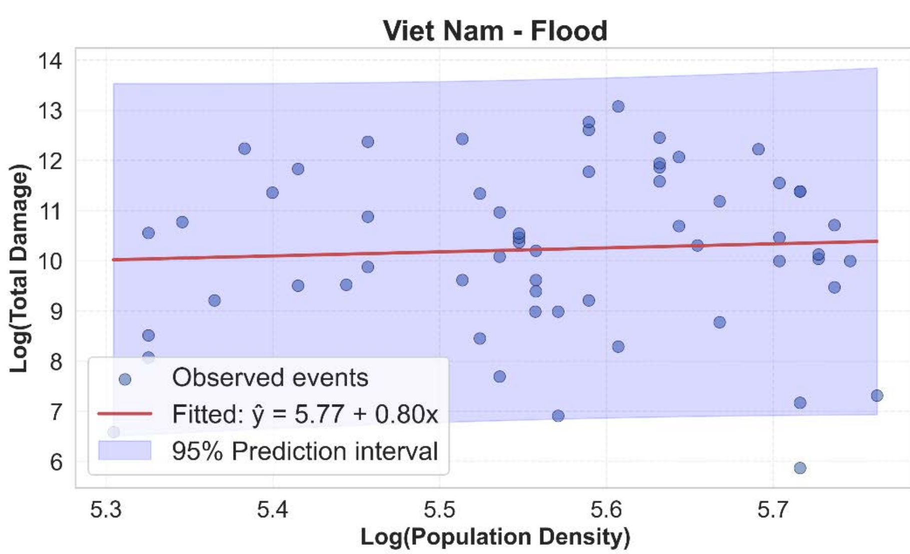


Figure 29
QQ plot of standardized residuals for the Viet Nam flood severity model

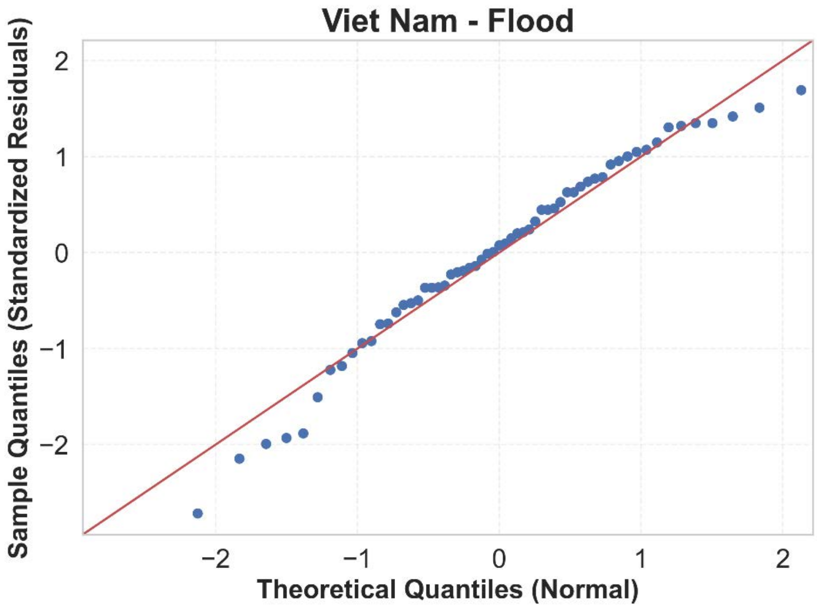
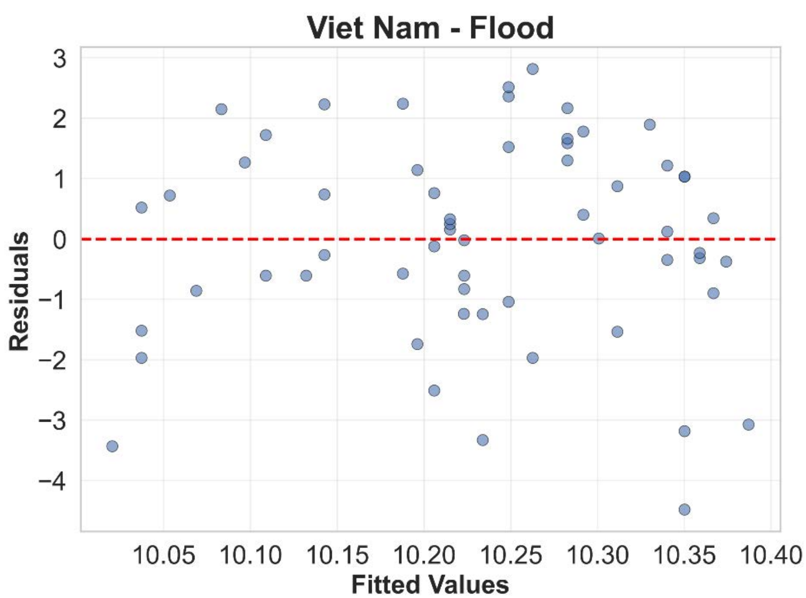


Figure 30
RESIDUALS VS. FITTED VALUES FOR THE VIET NAM FLOOD SEVERITY MODEL



C. CAMBODIA – FLOOD

Figure 31

ONE-YEAR-AHEAD FORECAST OF QUARTERLY FLOOD COUNTS IN CAMBODIA

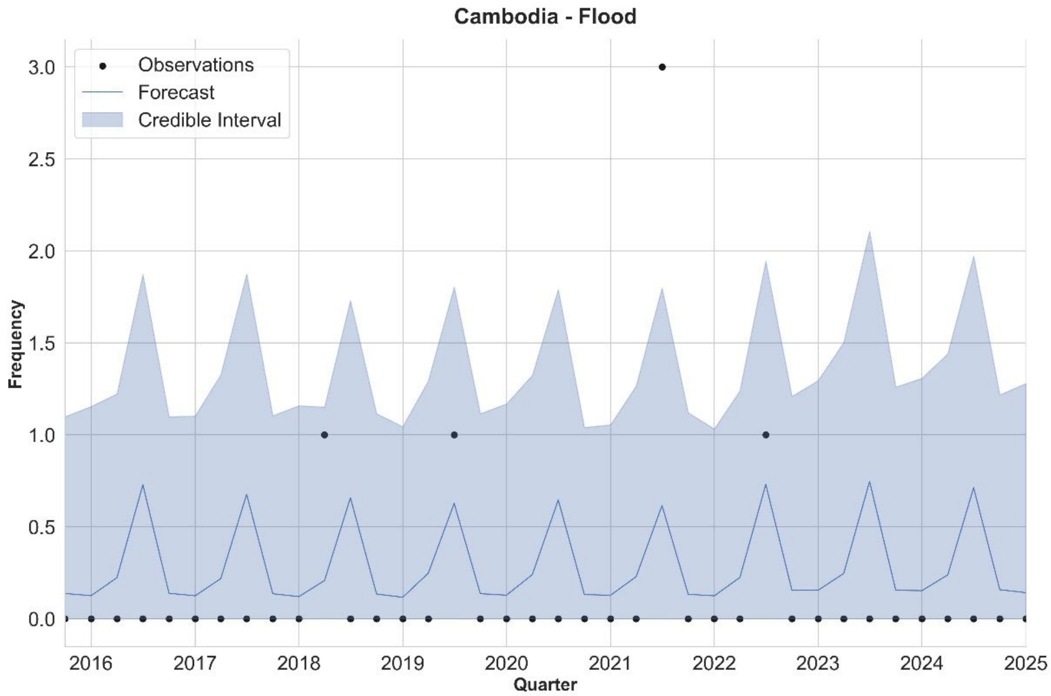


Figure 32

CAMBODIA FLOOD LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

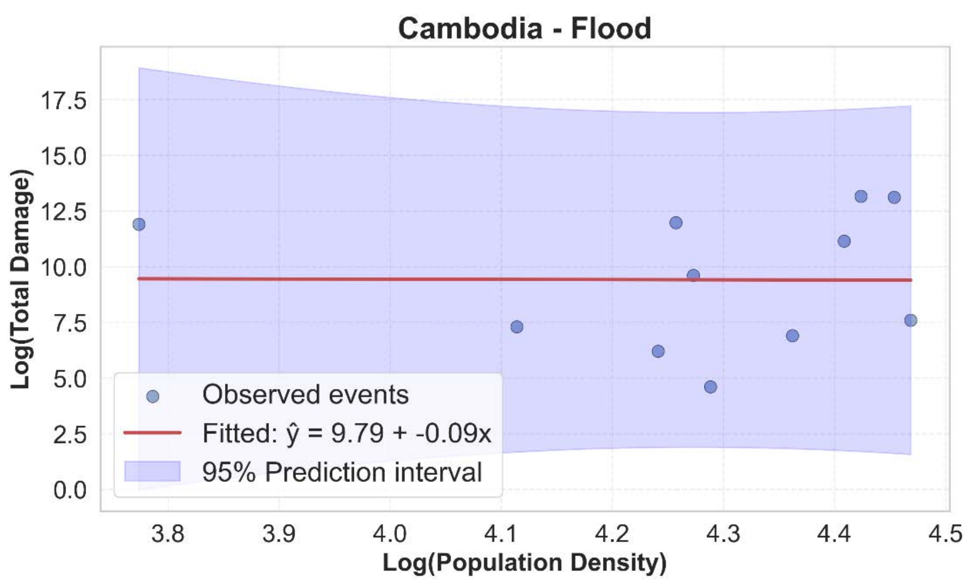


Figure 33
QQ PLOT OF STANDARDIZED RESIDUALS FOR THE CAMBODIA FLOOD SEVERITY MODEL

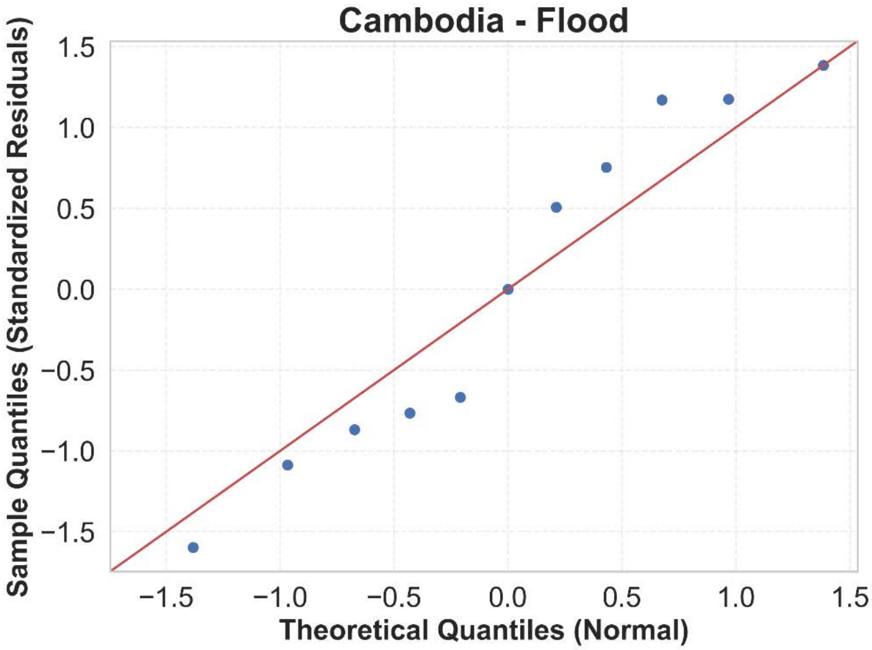
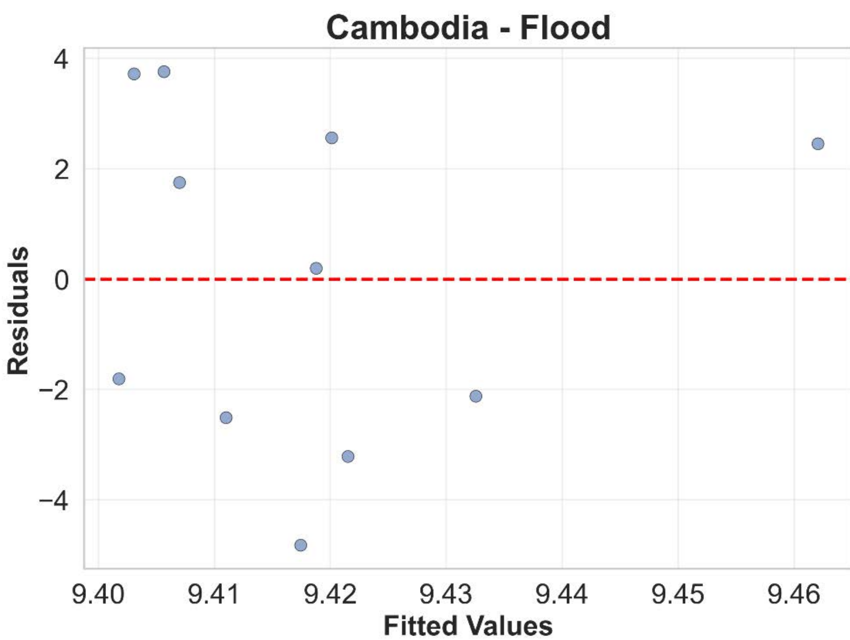


Figure 34
RESIDUALS VS. FITTED VALUES FOR THE CAMBODIA FLOOD SEVERITY MODEL



D. PHILIPPINES – FLOOD

Figure 35

ONE-YEAR-AHEAD FORECAST OF QUARTERLY FLOOD COUNTS IN PHILIPPINES

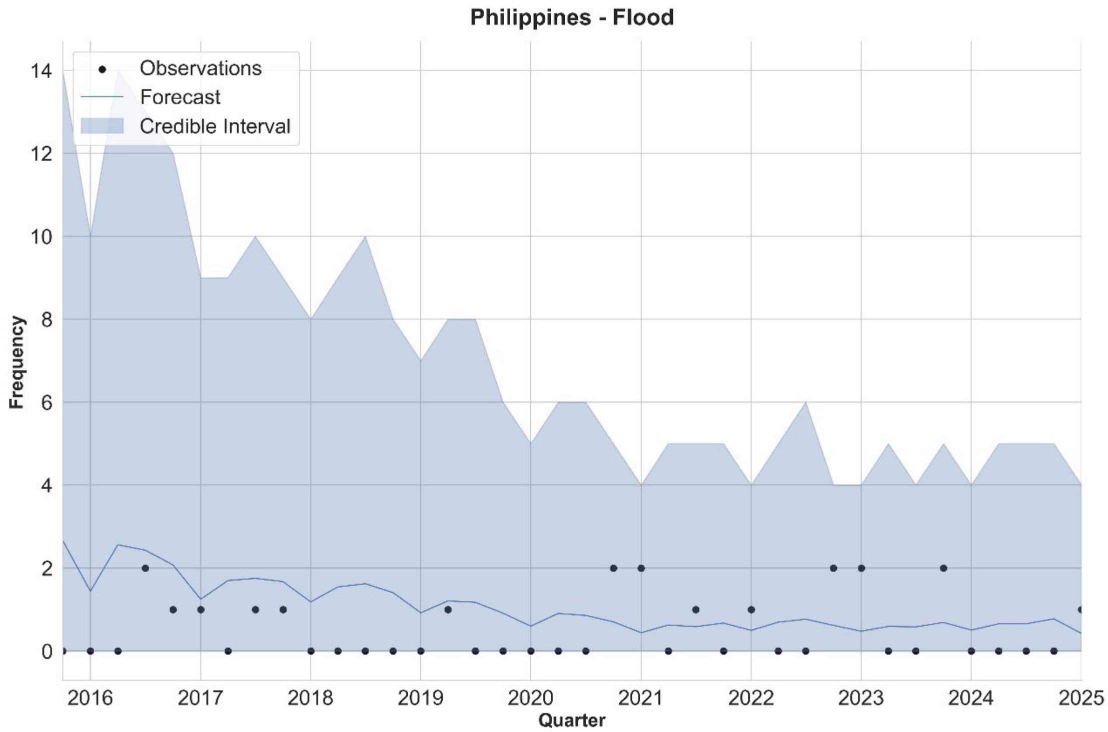


Figure 36

PHILIPPINES FLOOD LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

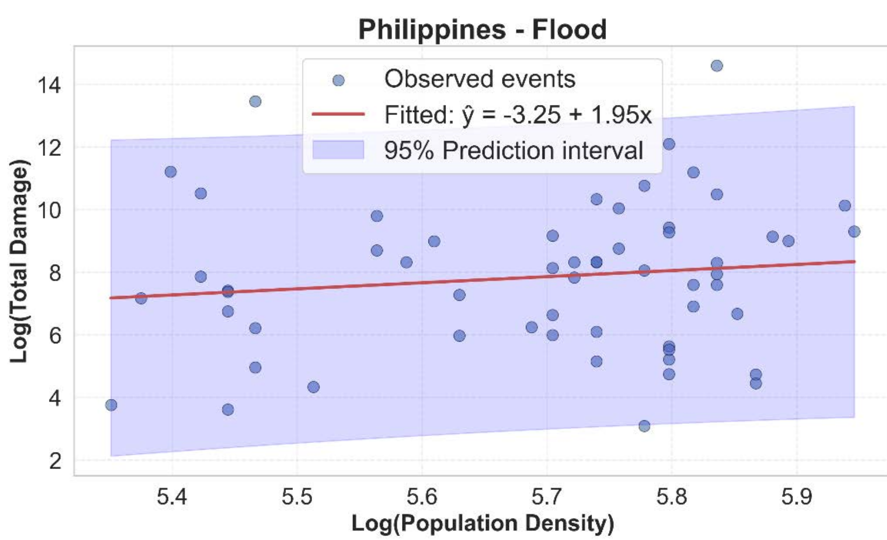


Figure 37
QQ plot of standardized residuals for the Philippines flood severity model

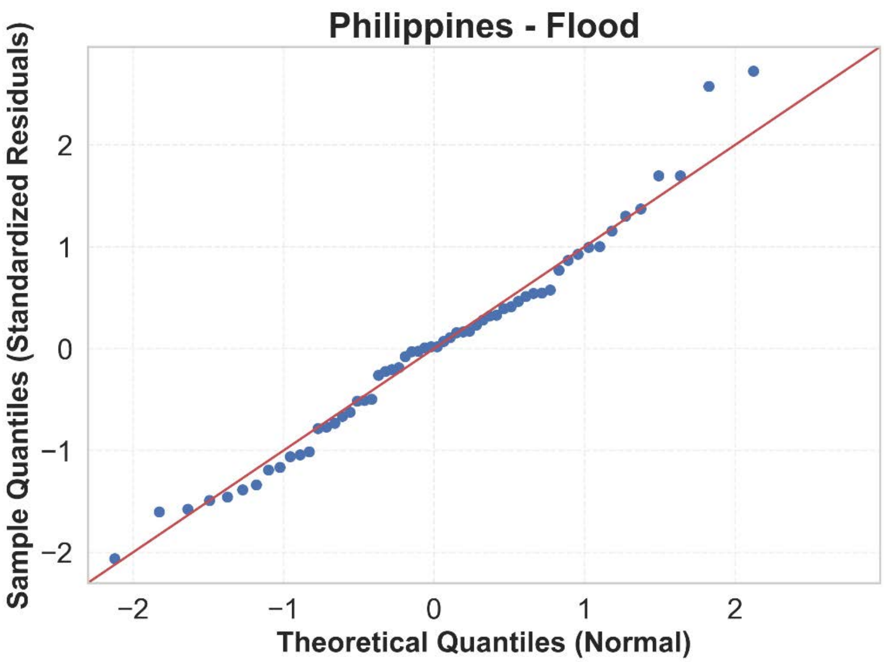
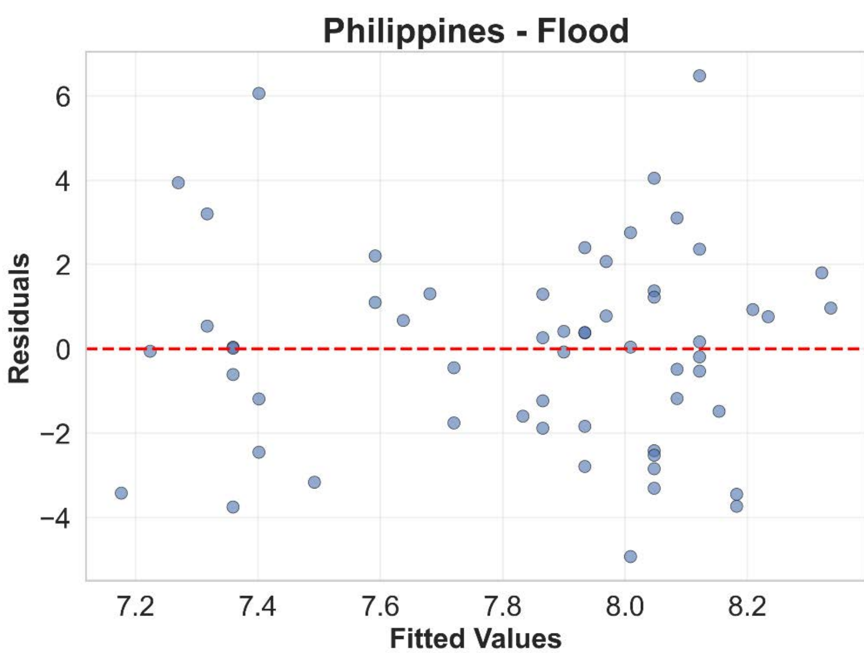


Figure 38
RESIDUALS VS. FITTED VALUES FOR THE PHILIPPINES FLOOD SEVERITY MODEL



E. MYANMAR – FLOOD

Figure 39

ONE-YEAR-AHEAD FORECAST OF QUARTERLY FLOOD COUNTS IN MYANMAR

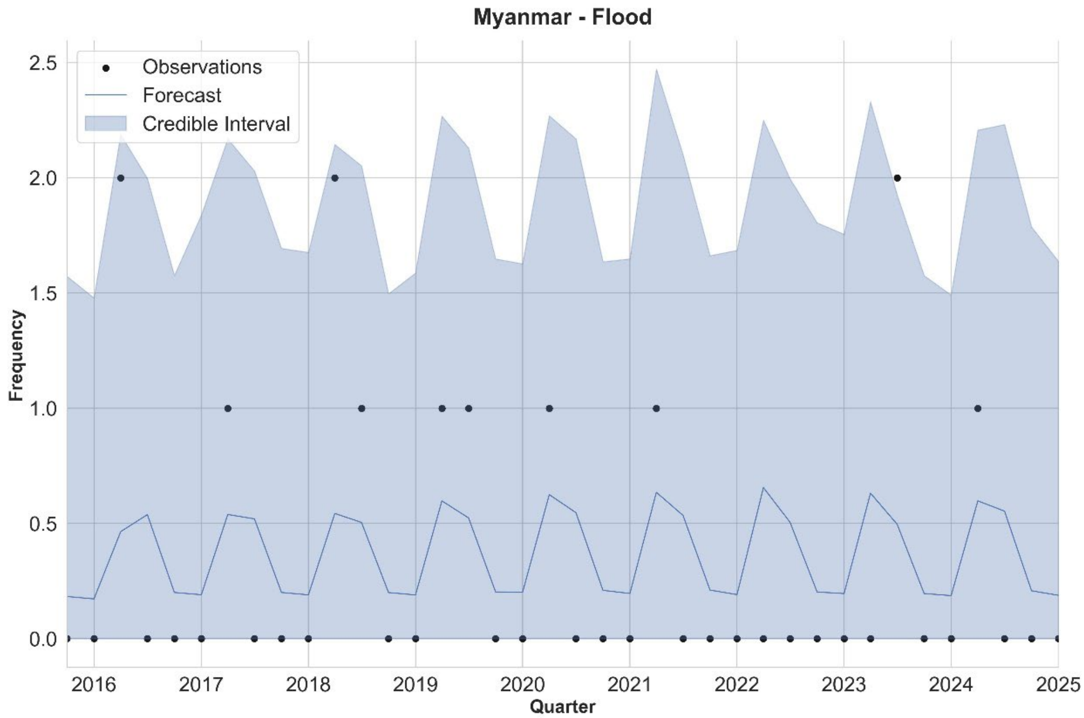


Figure 40

MYANMAR FLOOD LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

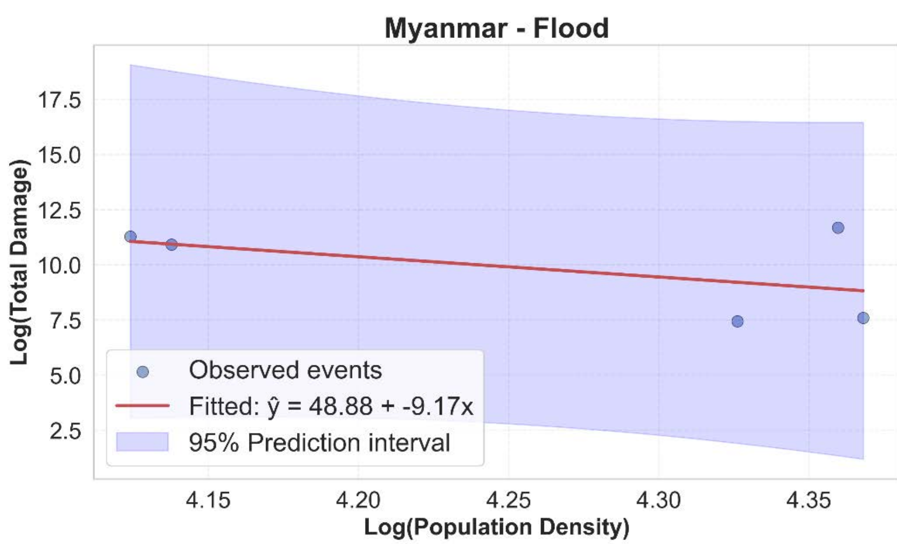


Figure 41

QQ PLOT OF STANDARDIZED RESIDUALS FOR THE MYANMAR SEVERITY MODEL

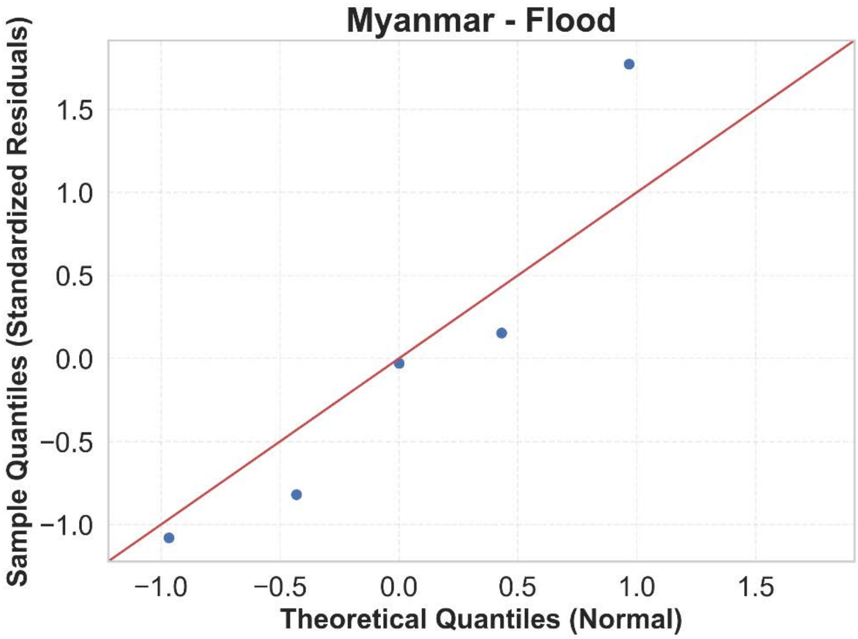
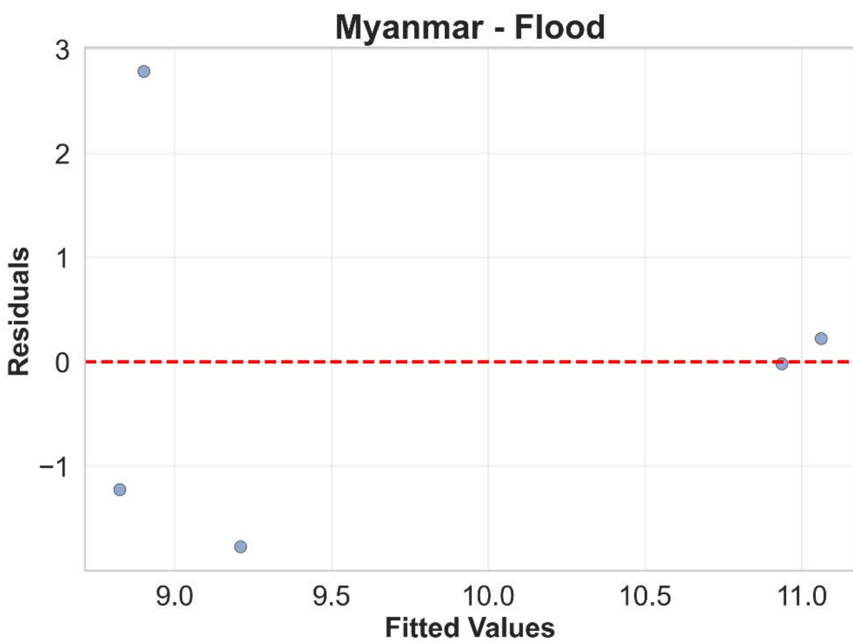


Figure 42

RESIDUALS VS. FITTED VALUES FOR THE MYANMAR FLOOD SEVERITY MODEL



F. THAILAND – FLOOD

Figure 43

ONE-YEAR-AHEAD FORECAST OF QUARTERLY FLOOD COUNTS IN THAILAND

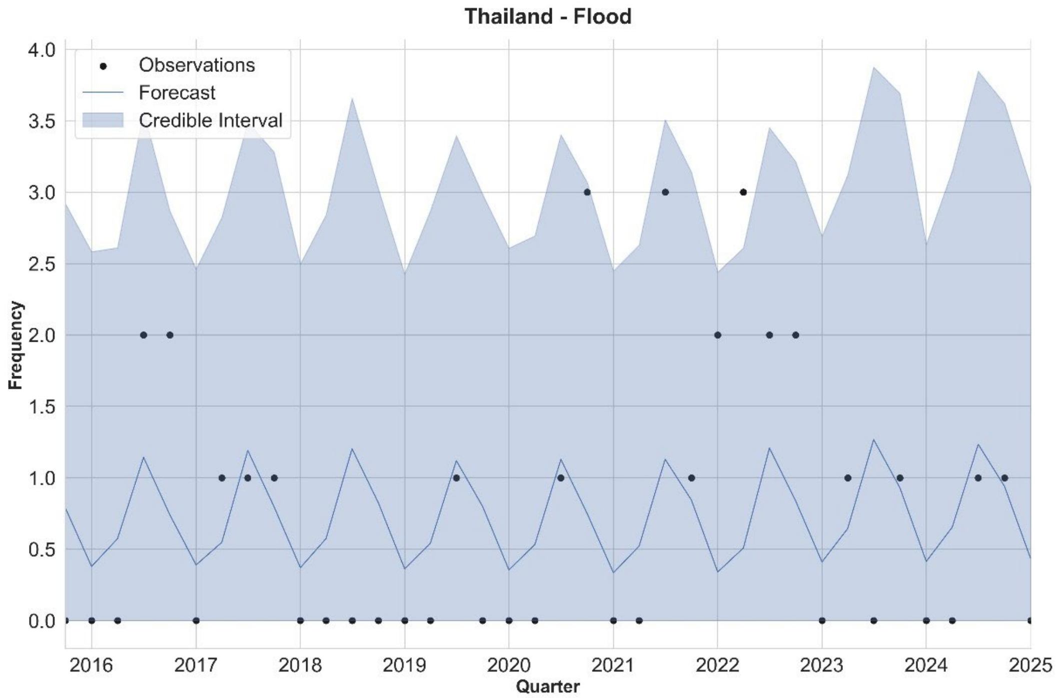


Figure 44

THAILAND FLOOD LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

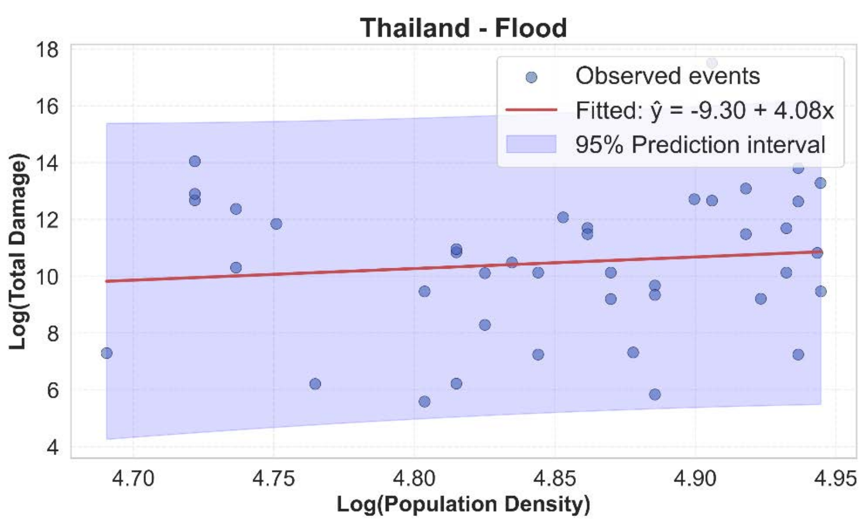


Figure 45

QQ PLOT OF STANDARDIZED RESIDUALS FOR THE THAILAND SEVERITY MODEL

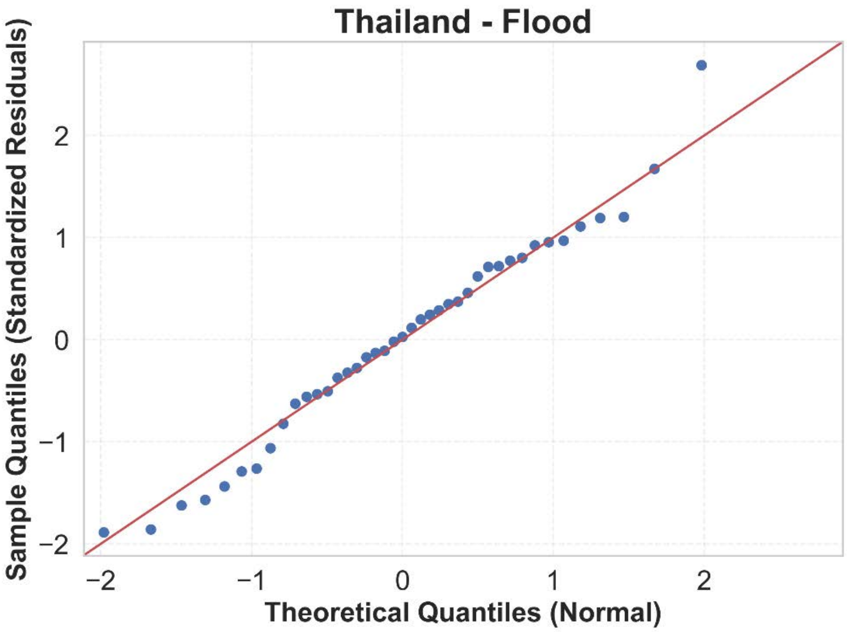
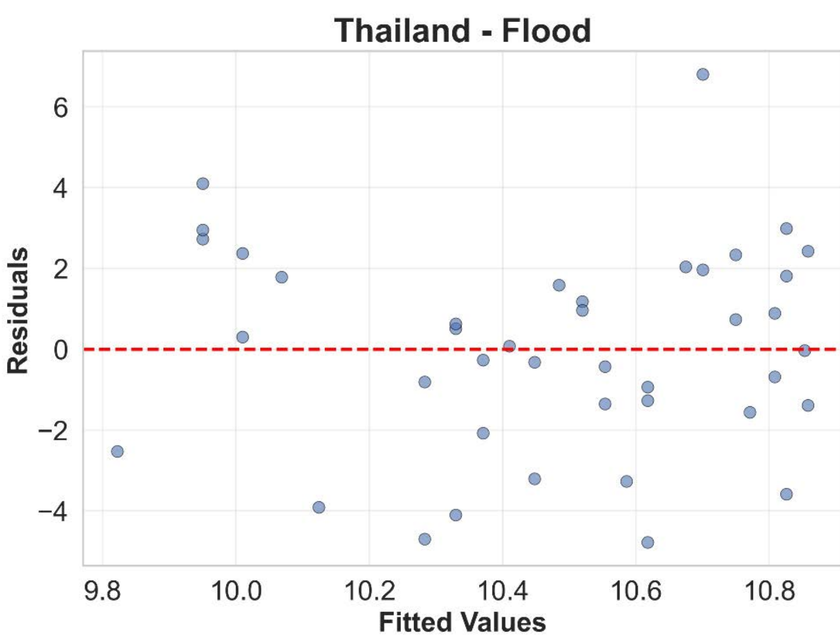


Figure 46

Residuals vs. fitted values for the Thailand flood severity model



G. MYANMAR – STORM

Figure 47

ONE-YEAR-AHEAD FORECAST OF QUARTERLY STORM COUNTS IN MYANMAR

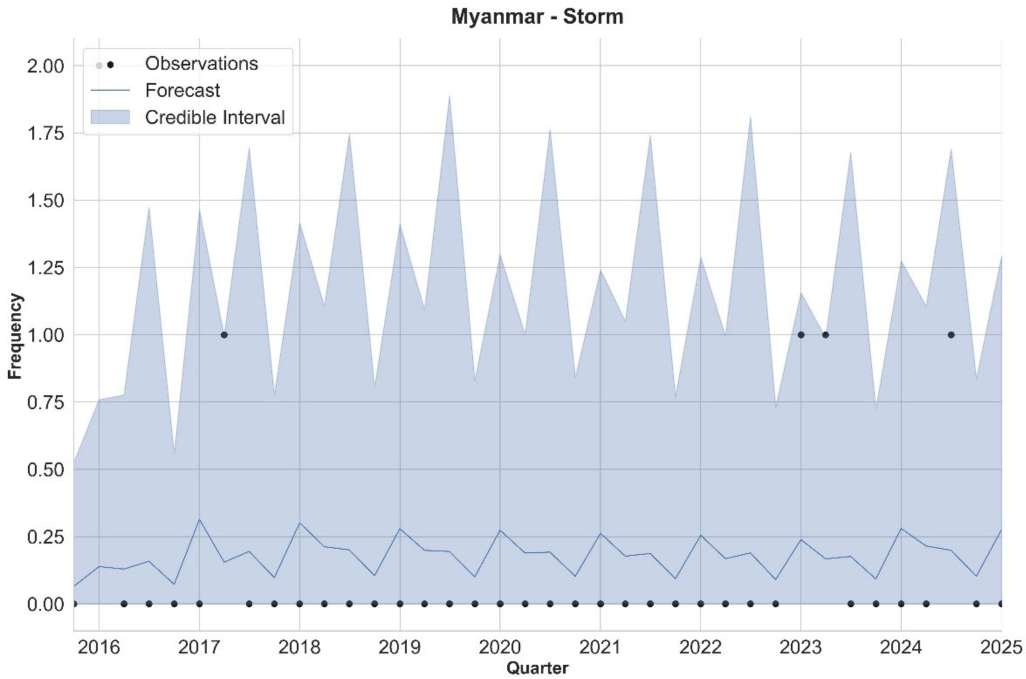


Figure 48

MYANMAR STORM LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

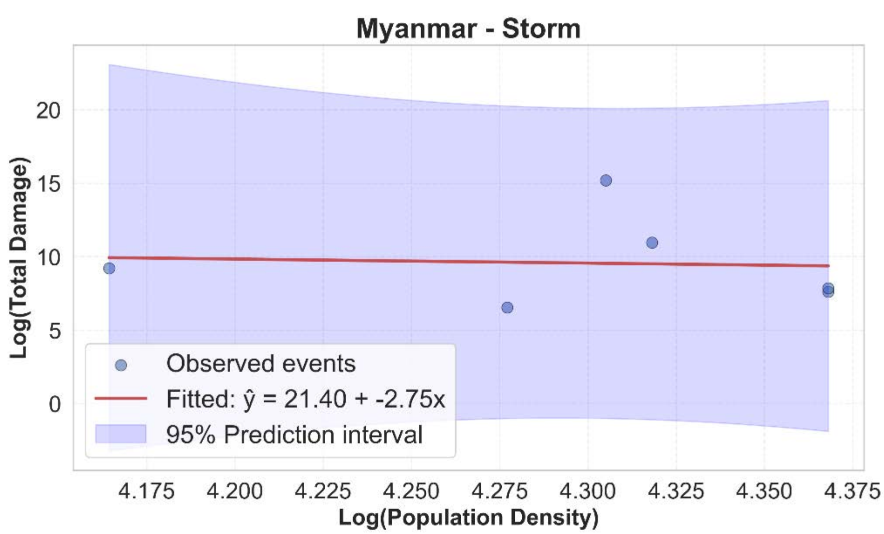


Figure 49

QQ PLOT OF STANDARDIZED RESIDUALS FOR THE MYANMAR STORM SEVERITY MODEL

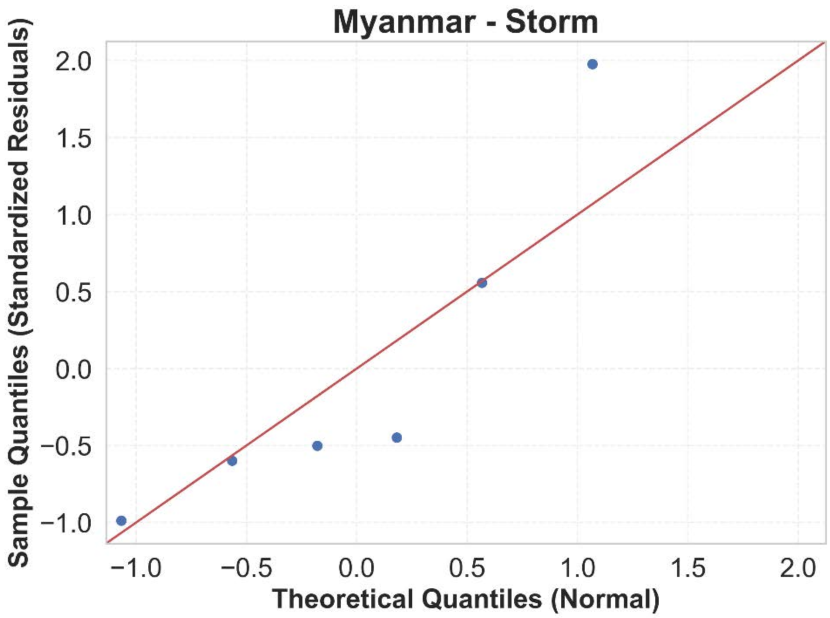
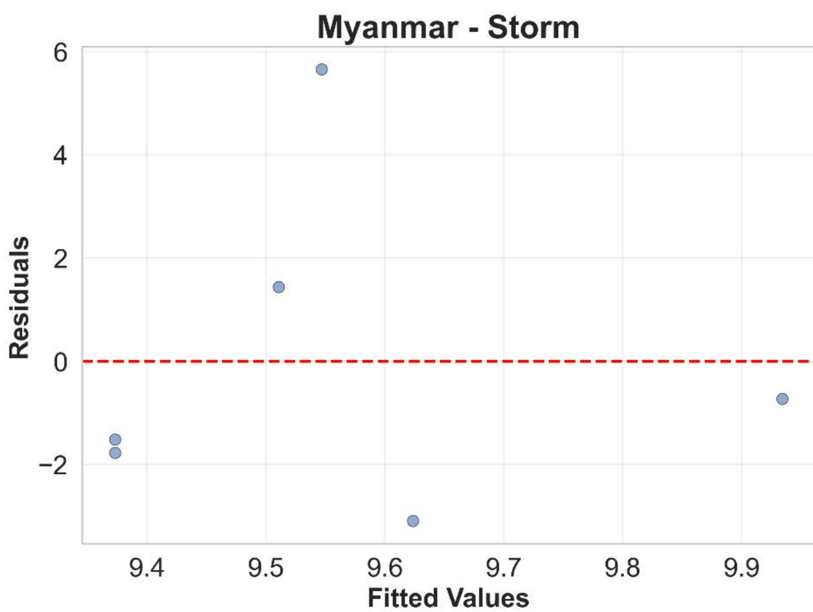


Figure 50

RESIDUALS VS. FITTED VALUES FOR THE MYANMAR STORM SEVERITY MODEL



H. THAILAND – STORM

Figure 51

ONE-YEAR-AHEAD FORECAST OF QUARTERLY STORM COUNTS IN THAILAND

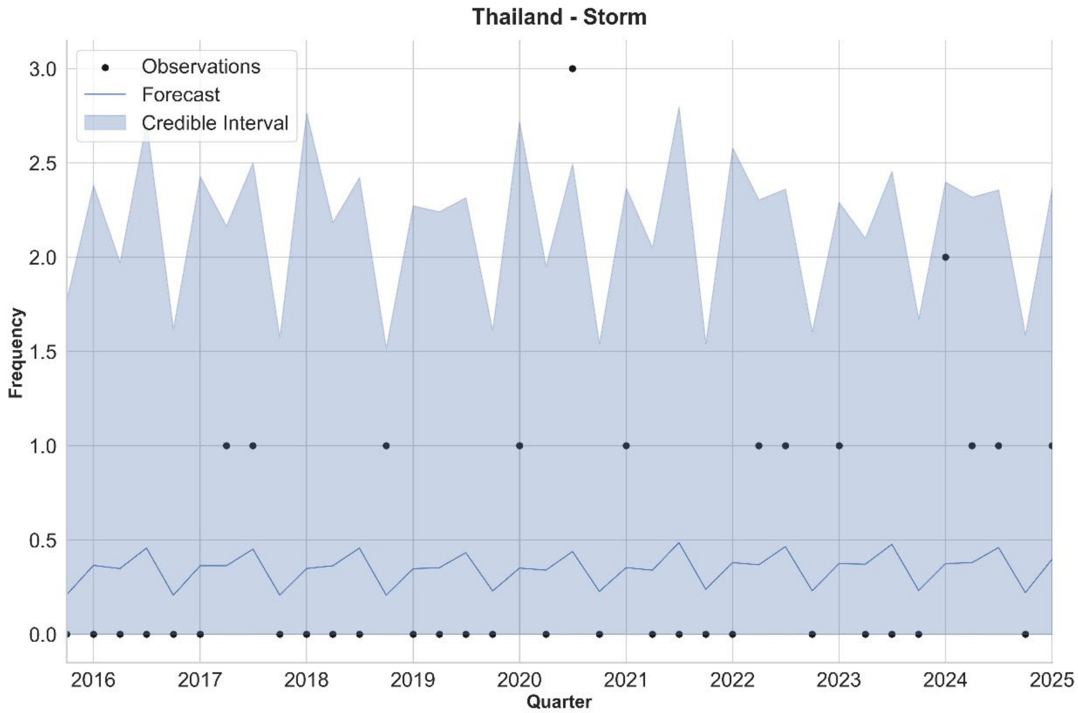


Figure 52

THAILAND STORM LOSS FIT AGAINST LOG POPULATION DENSITY WITH 95% PREDICTION INTERVAL

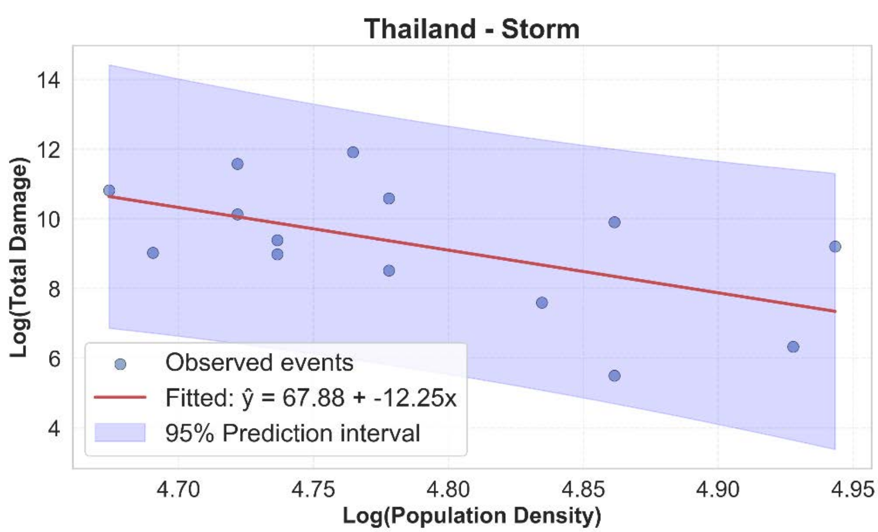


Figure 53
QQ PLOT OF STANDARDIZED RESIDUALS FOR THE THAILAND STORM SEVERITY MODEL

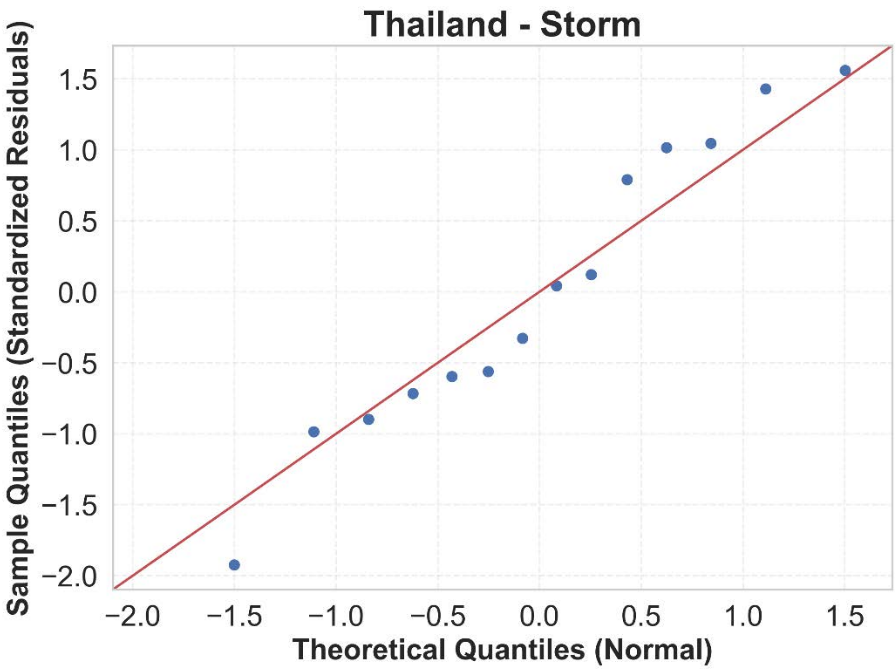
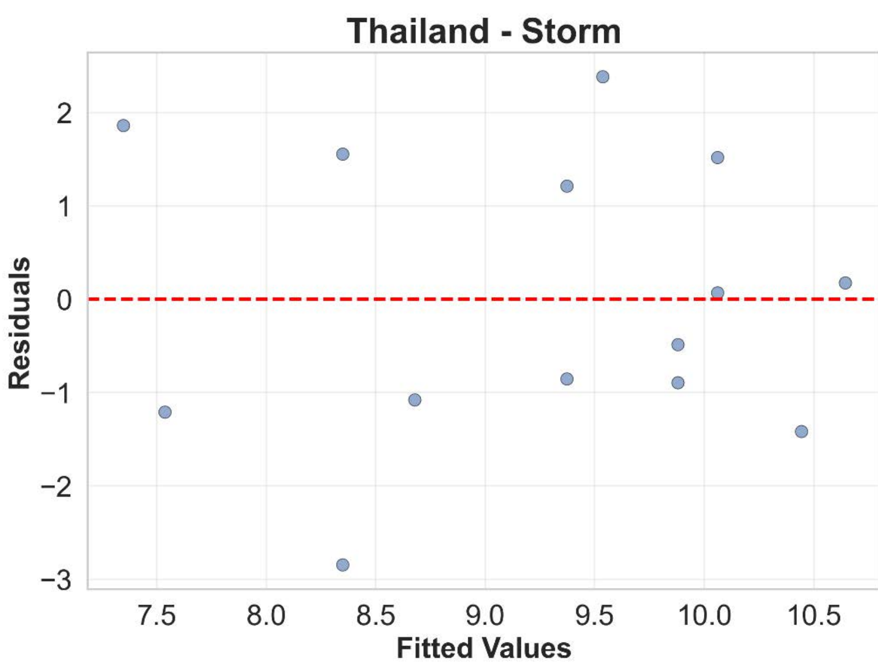


Figure 54
RESIDUALS VS. FITTED VALUES FOR THE THAILAND STORM SEVERITY MODEL



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Society of Actuaries Research Institute
8770 W Bryn Mawr Ave, Suite 1000
Chicago, IL 60631
www.SOA.org