Southeast Asian Journal of Economics Vol.14(3), December 2026: 1-38
Received: April 26, 2025
Revision: May 11, 2025
Accepted: July 28, 2025

Natural Disasters and Financial Institutions: Empirical Insights from a Correlation–Enhanced Bayesian–Optimized XGBoost Framework

Huong Nguyen Quynh Le

School of Banking, University of Economics Ho Chi Minh City (UEH), 59C Nguyen Dinh Chieu Street, Xuan Hoa Ward, Ho Chi Minh City, Vietnam

Corresponding author: quynh_huong@ueh.edu.vn

Abstract

This study examines how Vietnam's financial institutions respond to storms and floods. Using an event study methodology, the research analysed 55 disaster events (2008-2024) to assess cumulative abnormal returns (CAARs) for commercial banks, insurance companies, and brokerage firms. Employing the Extreme Gradient Boosting (XGBoost) algorithm with Bayesian Optimization and lag features, the study enhances return predictions beyond traditional market models. Key findings suggest that financial institutions respond negatively to natural disasters, with sector-specific variations. Insurance firms show the least pronounced negative responses, while brokerage firms and banks demonstrate stronger negative reactions—brokerage firms to floods and banks to storms. Short-term market reactions are volatile, whereas intermediate-term adjustments suggest calculated decision-making. This study broadens the literature by focusing on an emerging market like Vietnam, offering new insights into sector-specific responses compared to developed economies. These insights inform strategies to enhance financial sector resilience, aligning with Sustainable Development Goal 13.

Keywords: Natural disasters, stock market, financial institutions, Vietnam, SDG 13, Event study, XGBoost.

1. Introduction

In 2023, the Emergency Events Database (EM–DAT) [1] recorded 399 natural hazard disasters, up from a 2003–2022 average of 369. Asia, with 163 events (40.8%), was hit hardest, led by floods (164) and storms (139), per Appendix 1. These underscore rising climate risks—both physical threats and transitional risks from policy shifts (Yingtong Chen, Zhang, Wu, & Ji, 2022). As climate risk disrupts financial systems, its integration into risk management is vital, though this study focuses solely on physical impacts, following Yajie Chen, Guo, Ji, and Zhang (2023).

Vietnam, in the tropical monsoon belt, ranks among the most disaster-prone nations[2], battered by floods and storms that damage property and economic stability. This vulnerability echoes in folklore like 'Sơn Tinh, Thủy Tinh'[3]. With climate risk amplifying losses, Vietnam's financial institutions face impaired assets and market shifts. This study focuses on floods and storms, ignoring less impactful disasters such as earthquakes (Appendix 1).

Traditional risk assessment methods, such as linear regression models and conventional event studies, inadequately capture the complex, nonlinear impacts of natural disasters on financial performance (Kousky, 2014). This study addresses these limitations by employing XGBoost, a machine-learning algorithm that enhances predictive accuracy and mitigates overfitting (Ahmetoglu & Das, 2022; T. Chen & Guestrin, 2016). This approach, validated by its effectiveness in classification and regression tasks and its superior performance in global data competitions like Kaggle and DataCastle (Shi, Xu, Li, & Li, 2021), provides a robust foundation for exploring sectoral responses, algorithmic performance, and disaster-specific effects in this study. Using an event study framework with Correlation-Enhanced Bayesian-Optimized XGBoost, this research analyzes the stock market responses of Vietnamese banks,

[1] EM-DAT annual reports: 2023 Disasters in Numbers: A Significant Year of Disaster Impact
[2] Vietnam - Vulnerability | Climate Change Knowledge Portal (worldbank.org)
[3] In Vietnamese folklore, storms and floods are attributed to Thủy Tinh, the water spirit. This capricious god unleashes fierce storms and floods, overflowing rivers and devastating homes, crops, and communities.

insurance, and brokerage firms to natural disasters. The research focuses on three key objectives: (1) sectoral responses across short- and intermediate-term time horizons, (2) the predictive enhancement capabilities of XGBoost compared to traditional and alternative models, and (3) disaster- and sector-specific effects, particularly for floods and storms.

The results show consistently negative yet asymmetric responses to storms and floods across financial institutions. Banks exhibit stronger stock market responses to storms, potentially linked to immediate operational disruptions, whereas insurance and brokerage firms react more strongly to floods, possibly reflecting prolonged financial strain and market uncertainty. Despite sectoral differences, all institutions face adverse impacts, varying in magnitude and timing.

The findings reveal that short-term market reactions are highly volatile, while intermediate-term adjustments show stabilization, indicating a shift from panic to deliberate decision-making. By utilizing the Universal Disaster Severity Classification Scheme (UDSCS) to identify significant storm and flood events, this study enhances climate-related risk assessment in emerging markets, such as Vietnam, through XGBoost, demonstrating the potential of machine learning to strengthen financial sector resilience strategies. This study shows that XGBoost consistently outperforms LightGBM, GARCH, and the market model, confirming its robustness in capturing climate-related financial shocks. The findings enable regulators to design evidence-based, sector-specific stress tests that reflect Vietnam's unique disaster risk profile, including typhoon exposure along the coast and flooding risks in the Mekong Delta. For investors, the study offers quantitative guidance for portfolio adjustments based on demonstrated sector vulnerabilities. At the same time, financial managers can develop targeted resilience strategies informed by actual market responses to historical disasters. As climate change intensifies extreme weather events across Southeast Asia, this research becomes increasingly vital for building adaptive capacity within Vietnam's financial system.

This study contributes to sustainable finance by assessing climate risks in the financial sector and refining market response analysis. First, this study enhances the

event study methodology by integrating XGBoost with Bayesian hyperparameter optimization (BO), which improves predictive accuracy in assessing stock market responses to disasters. Second, it uses the UDSCS to select significant storm and flood events, ensuring a focused disaster analysis. Third, unlike prior studies focused on short-term post-event windows, this research extends the timeframe to an intermediate horizon, offering deeper insights into financial sector responses. Short–window event studies may not fully capture the broader economic implications of disasters, and the inclusion of an intermediate timeframe enhances the understanding of financial sector responses.

The paper comprises five sections: Section 1 introduces the study, Section 2 reviews the literature, Section 3 details the methodology, Section 4 presents the results, and Section 5 concludes.

2. Literature review

2.2. Stock Market Reactions to Natural Disasters

The impact of natural disasters on financial markets varies by region and disaster type, as seen in developed markets like the U.S., Japan, Australia, and China. C. Li, Liu, and Pan (2024) found that climate change affects NASDAQ 100 returns, with biological and hydrological factors reducing them, while climatic factors increase them. Yamori and Kobayashi (2002) noted negative returns for Japanese insurers after the 1995 Hanshin Earthquake. Worthington and Valadkhani (2004) observed mixed effects in Australia, especially in insurance and utilities. In China, Yajie Chen et al. (2023) showed that securities firms are more sensitive to disasters, while banks react mainly to earthquakes; Boungou, Djatche, and Biekpe (2025) confirmed consistent negative impacts across Chinese stock indices. In a broader Asian context, Nguyen, Diaz-Rainey, Roberts, and Le (2024) highlighted banks' role in recovery, and Pagnottoni, Spelta, Flori, and Pammolli (2022) noted stronger stock reactions to climatological events.

In Vietnam, Noy and Vu (2010) and Zhou and Botzen (2017, 2021) studied macroeconomic and firm-level impacts using GMM methods, while Bui, Dungey, Nguyen, and Pham (2014) explored household effects. These studies overlook

immediate market reactions and short-term financial impacts, especially for financial institutions—a gap this study addresses. Using event study methodology, this study examines short-term stock market responses, assuming efficient information processing, to understand natural disasters' immediate effects on Vietnam's financial sector.

2.3.Event Study Methodology

Event study methodology, a key tool in finance and economics since Dolley's (1933) stock split analysis, evaluates stock price reactions to specific, often unforeseen events by measuring abnormal returns (ARs) against expected performance. It has been widely applied to study the impacts of natural disasters on financial markets, as seen in Antoniuk and Leirvik (2024), Yajie Chen et al. (2023), and Pagnottoni et al. (2022). However, the traditional market model, commonly used in event studies, faces criticism for its unreliable estimation of ARs and cumulative ARs (Coutts et al., 1994). Moreover, linear regression models and conventional event study approaches fail to capture the complex, nonlinear impacts of natural disasters on financial performance (Kousky, 2014). To address these limitations, integrating XGBoost, a powerful deep learning algorithm, into the event study framework is essential. This study innovates by employing XGBoost to estimate normal returns, enhancing the accuracy and robustness of the analysis.

2.4. XGBoost (eXtreme Gradient Boosting)

This paper advances the understanding of stock market responses to natural disasters by applying XGBoost, a machine-learning algorithm that enhances model accuracy and mitigates overfitting (Ahmetoglu & Das, 2022). AI applications in economics and finance have gained research attention, with XGBoost, an efficient gradient-boosting implementation, proving effective for classification and regression tasks (T. Chen & Guestrin, 2016). Its superior performance is evident in global data competitions like Kaggle and DataCastle (Shi et al., 2021). The model's regularized

learning objective incorporates key optimizations in gradient-boosting decision trees[4].

XGBoost enhances predictive accuracy by combining multiple decision trees, where each new tree corrects errors from previous ones. Its objective function consists of a regularization term to prevent overfitting and a loss function to measure prediction errors, optimized using Gradient Descent (T. Chen & Guestrin, 2016). This approach improves learning efficiency and model performance.

Bayesian Optimization (BO) has proven superior for tuning XGBoost models, outperforming Grid Search (GS) and Random Search (RS) in accuracy and efficiency, particularly in high-dimensional datasets (Drahokoupil, 2022; Shi et al., 2021). BO not only enhances predictive performance but also optimizes processing time, making it ideal for complex data applications. Drahokoupil (2022) demonstrated BO's advantages in Bitcoin price prediction, showing it achieved the lowest Mean Squared Error (MSE) and faster optimization than GS, though slightly slower than RS (Betrò, 1991; Nour, Cömert, & Polat, 2020). Given its efficiency, this study adopts BO for optimizing XGBoost hyperparameters.

2.5. Natural disasters definition: UDSCS approach

Previous studies have often relied on basic measures of disaster severity, such as the number of fatalities (KIL), the number of people affected (AFF), and the extent of direct damage (DAM) (Yajie Chen et al., 2023; Noy & Vu, 2010; Zhou & Botzen, 2021). This study, however, adopts the Universal Disaster Severity Classification Scheme (UDSCS) proposed by Caldera and Wirasinghe (2022), offering a more comprehensive and standardized approach to assessing disaster severity[5].

---

[4] The mathematical principles underlying XGBoost are detailed in "Introduction to Boosted Trees":
$obj(\varphi) = R(\varphi) + L(\varphi)$ (1)
The logistic loss: $L(\varphi) = \sum_{i=1}^{n} y_i \ln\left(1 + e^{-\hat{y}_t}\right) + (1 - y_i)\ln(1 + e^{\hat{y}_i})$, for the given data set with n examples, $\mathcal{D} = \{(x_i, y_i)\}$ $(|\Delta| = n, x_i \in \mathbb{R}^m, y_i \in \mathbb{R})$.
Where R is the regularization term, and L is a differentiable training loss function. For binary classification, the loss function often takes the form of logistic loss.

[5] The UDSCS integrates quantitative and qualitative methods to assess disaster impacts, aiding decision-making and response planning. It evaluates severity across *human factors* (fatalities, injuries, missing persons, homelessness, evacuees, affected population) and *damage factors* (economic losses, property damage, agricultural impacts, financial repercussions).

Quantifying the true magnitude of a disaster's impact is inherently challenging due to the lack of a universally accepted global framework. The UDSCS addresses this gap by providing a systematic classification that integrates diverse severity metrics to ensure consistency and comparability. This framework enhances communication among various stakeholders, such as policymakers, responders, and the public, by offering clear definitions of disaster severity levels and their potential impacts (Caldera & Wirasinghe, 2022). The framework employs an 11-level scale for human impact (0 to 8.2 billion people – representing the global population as of 2024[6]) and damage impact (0 to 87.698 trillion USD – equivalent to the maximum global GDP in 2019[7]), detailed in Appendix 2. Event selection is critical in event study methodology, as poorly chosen events with ambiguous timing or confounding effects can invalidate results (MacKinlay, 1997; McWilliams & Siegel, 1997). This study addresses these methodological concerns by employing the UDSCS framework, which systematically identifies events with clear timing, unexpected nature, and minimal confounding factors, thereby enhancing the reliability of abnormal return measurements.

3. Data and Methodology

The research identifies disaster events, gathers financial data, and selects features via correlation analysis. It sets event windows with a dual-window approach, trains XGBoost with BO to predict abnormal returns, computes CAAR and AAR, and evaluates sector-specific impacts (Banks, Insurance, Brokerage). Details are in Appendix 3.

3.2. Event study

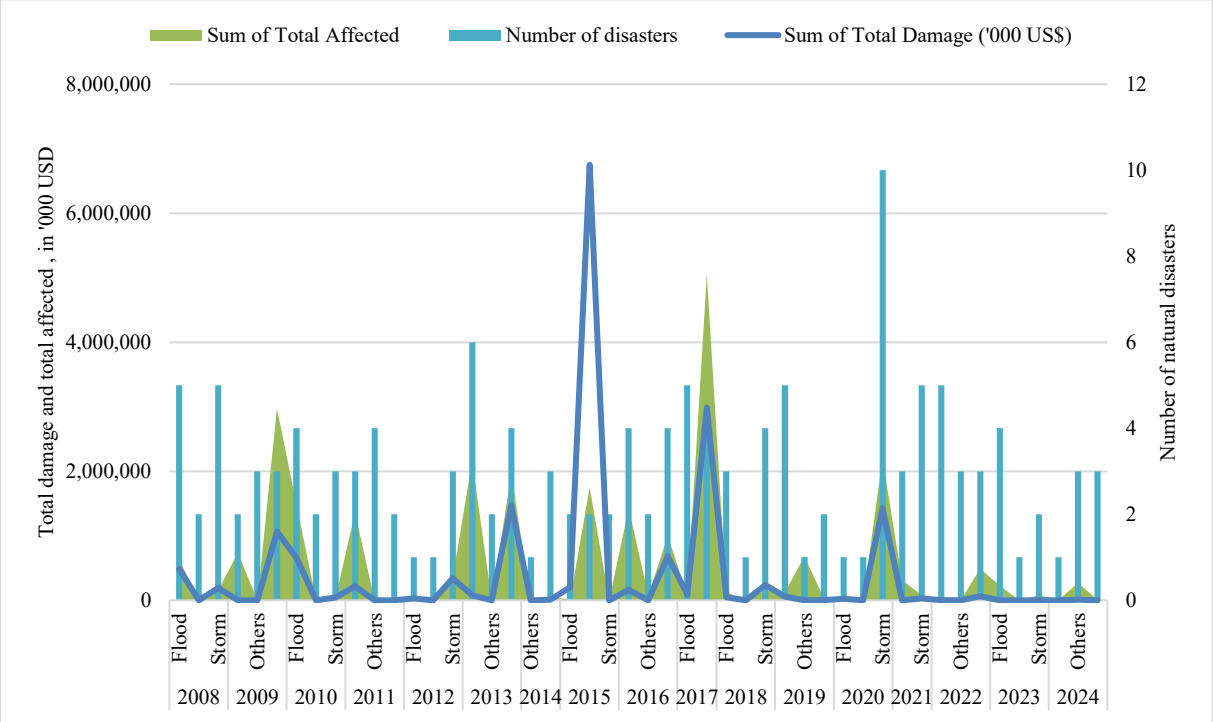
3.2.1. Event Definition

This study selects natural disasters based on two criteria of the UDSCS: an H factor of at least level 2 and a D factor of at least level 3. Disasters above Type 1 ($H \geq 2$) and Type 2 ($D \geq 3$) are included, identifying 55 events in Vietnam from 2008 to

[6] The 2024 Revision of World Population Prospects.
[7] World Bank national accounts data.

2024—33 storms and 22 floods. By applying the UDSCS, this study ensures a systematic disaster classification approach, contributing to improved impact assessment methodologies. Figure 1 illustrates the total damage (in thousands of USD) and the number of disasters in Vietnam from 2008 to 2024, emphasizing that floods and storms are the most frequent and severe physical disasters compared to other types.

Figure 1: Number of disasters and their total damage.



Types of disasters	Sum of Total Affected ('000 US$)	Sum of Total Deaths	% of Total Affected	% of Total Deaths
Storm	14,598,674	1,431	55.83%	46.04%
Flood	8,763,545	1,147	33.52%	36.90%
Others	2,785,705	530	10.65%	17.05%
Grand Total	**26,147,924**	**3,108**	**100.00%**	**100.00%**

Note: The data highlights that storms and floods are the most devastating natural disasters in Vietnam, both in economic terms and loss of life.

Source: Author's figure, data from EM–DAT (www.emdat.be).

3.2.2. Event Window: Selection of estimation, event, and post–event windows

The estimation window, spanning 120 days before the event day (t=0), captures normal stock return behavior relative to a market or industry index. This period, widely used in event studies (Brown & Warner, 1985; MacKinlay, 1997), balances historical depth for accuracy while avoiding structural market shifts (Corrado, 2011).

The event window, designed to capture both immediate and prolonged impacts,

includes a 7-day short-term window (Dewenter, Higgins, & Simin, 2005) for initial market reactions and a 15-day intermediate-term window (Oler, Harrison, & Allen, 2008) for extended economic effects. This dual-window approach balances immediacy and extended impact, avoiding overly short (e.g., 3-day) or excessively long (e.g., 30-day) periods, which may not fully reflect the unpredictable nature and recovery dynamics of natural disasters. Recent studies (Antoniuk & Leirvik, 2024; Yajie Chen et al., 2023; Pagnottoni et al., 2022) reinforce the importance of incorporating longer windows to capture post-event asymmetries. Appendix 4 details the window selection process.

3.2.3. Statistical Analysis: Estimation of Parameters

Following the approaches of Yajie Chen et al. (2023), Pandey and Kumari (2021), and Ullah, Zaefarian, Ahmed, and Kimani (2021), the market model is employed in this study to estimate returns under normal conditions:

$$Ri,t = \alpha i + \beta i Rm,t + \varepsilon i,t \quad (2)$$

Where Ri,t represents daily returns for company i, Rmt is the market portfolio return (e.g., VN-Index), and $\varepsilon i,t$ is the error term. The AAR and CAAR for each event window day are then computed for each sector (banks, brokerage, insurance):

$$AR_{it} = r_{it} - \hat{\alpha}_i + \hat{\beta}_i \times R_{mt} \quad (3)$$

$$AAR_t = {\sum_{i=1}^{N} AR_{it}}/{N} \quad (4)$$

$$CAAR_T = \sum_{t=0}^{10} AAR_t \quad (5)$$

The following formula is used to calculate the cross–sectional error of daily abnormal returns:

$$Steyx_{i,e} = \sqrt{\frac{1}{(n-2)}\left[\sum(r_{it} - \overline{r_{it}})^2 - \frac{\sum[(R_{mt}-\overline{R_{mt}})(r_{it}-\overline{r_{it}})]^2}{\sum(R_{mt}-\overline{R_{mt}})^2}\right]} \quad (6)$$

$$tAAR_t = {AAR_t}\Big/{\sqrt{\frac{\sum Steyx_{i,e}{}^2}{N^2}}} \quad (7)$$

$$tCAAR_t = {CAAR_t} \Big/ \sqrt{\frac{\sum Steyx_{i,e}{}^2}{N^2} \times N_{t+1}} \quad (8)$$

Where $\overline{r_{it}}$ and $\overline{R_{mt}}$ represent the average returns of financial institution i's stock and the VN-Index, respectively, over the 120-day pre-event period. N denotes the number of natural disasters (multiple-event dates). $Steyx_{i,e}$ is the standard error of daily returns for financial institution i during the estimation period. $tAAR_t$ and $tCAAR_t$ are the t-statistics for AAR and CAAR on day t.

3.3. Data collection

The study spans 2007 to 2024, with data collection starting in 2007 to align with key milestones in Vietnam's financial market, including the 2007 Securities Law and the transformation of the Ho Chi Minh City Stock Exchange. Daily stock and market returns (2007–2022) were sourced from FiinPro-X[8]**.** Natural disaster data from EM–DAT (www.emdat.be) focused on storms and floods, excluding rarer events like droughts and wildfires. Disaster data collection began in 2008, ensuring one year of complete stock return data for accurate normal return estimation.

Institutions with incomplete data, banks under special control[9], and unlisted (OTC) firms were excluded. The final dataset includes 30/49 commercial banks, 37/85 brokerage firms, and 13/41 insurance companies. Descriptive statistics are in Appendix 5.

3.4. XGBoost method

This section outlines the process of XGBoost to predict "normal" returns for an event study. The detailed workflow is depicted in Appendix 6. First, feature selection identifies key lag features to capture historical stock behavior and reduce noise. Second, the model is trained with cross-validation and Bayesian Optimization to handle non-

[8] Financial Information, Business Information, Market Research, Credit Rating (fiingroup.vn)
[9] For example, DongA Bank, OceanBank, and CBBank, which were often acquired at a "0" dong price.

linear relationships and optimize performance over a 16-day event window (days 0 to 15).

3.4.1. Feature selection and Feature importance

This study uses lag features to enhance XGBoost's time series forecasting for short-term stock market data, capturing trends and autocorrelation (Hameed & Kusnadi, 2006). Selected features include past returns, lagged market index returns, volatility, and trading volume, reflecting temporal patterns critical for financial analysis (Andersen, Bollerslev, Diebold, & Ebens, 2001; Hyndman & Athanasopoulos, 2018). Lagged market returns account for historical influences, average returns reflect market performance, and volatility enhances predictive accuracy, aligning with financial modeling practices (French, Schwert, & Stambaugh, 1987; Q. Li, Yang, Hsiao, & Chang, 2005). Four lag features were chosen, defined in Appendix 7.

To address multicollinearity, a correlation-based feature selection was employed. Features with an absolute correlation above 0.1 with the target variable were retained—for instance, for `Return_Insu`, `average_return` (0.60) and `lag_return_market_1` (0.13) were selected. Among highly correlated features (|correlation| > 0.8), only the one with the strongest association with the target variable was kept. The final feature set is summarized in Appendix 7.

3.4.2. XGBoost Training with Cross–Validation and Bayesian Optimization approach

Building on feature selection, this section outlines the training and optimization of the XGBoost model using lag features to predict stock returns.

To enhance predictive performance, a 5-fold cross-validation (CV) was employed, testing various hyperparameter combinations, including learning rate (`eta`), maximum tree depth (`max_depth`), subsampling ratio (`subsample`), and number of decision trees (`nround`). Model performance was evaluated using Root Mean Square Error (RMSE) for each combination. RMSE, or Root Mean Square Error, measures the average 'deviation' of predictions from actual stock returns, with lower values indicating higher precision (Kouzehgar & Eslamian, 2023). RMSE is formulated as:

$$RMSE = \sqrt{1/n \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (9)$$

$$Best\ RMSE_k = min(test_rmse_mean) \quad (10)$$

Where y_i and $\hat{y}_i$ are the actual and predicted returns, respectively.

To identify the best hyperparameters, a Bayesian Optimization approach was employed, where the target function is defined as:

$$f(\eta, d, s, nr) = -min_k RMSE_k \quad (11)$$

Where η (eta, learning rate) ∈ [0.001, 0.3], d (`max_depth`) ∈ [3,4, …,15], s (`subsample ratio`) ∈ [0.5,1], and nr (nround, the number of boosting iterations) ∈ [100, …, 2000] are the hyperparameters.

Bayesian Optimization refined hyperparameters using the Upper Confidence Bound (UCB) acquisition function, starting with 10 initial points, followed by 10 optimization iterations. The process continued until reaching a stopping criterion, such as minimal improvement or the maximum iteration limit.

$$Acquisition\ Function: UCB(\mu, \sigma; \kappa) = \mu + \kappa \cdot \sigma \quad (12)$$

Where μ and σ are the predicted mean and standard deviation, and **κ**=2.576 controls the balance between exploration and exploitation.

After training with optimized parameters ($\eta *, d *, s *, nr *$), the study calculates abnormal returns (ARs), average abnormal returns (AARs), and cumulative average abnormal returns (CAARs). The optimized parameters for different financial institutions across all disaster events are summarized in Table 1.

Table 1: The optimized parameters ($\eta *, d *, s *, nr *$).

		Insurance firms	**Brokerage firms**	**Banks**
All events	eta $\eta *$	0.212	0.3	0.178
	max_depth $d *$	15	8	10
	subsample $s *$	0.933	0.576	0.716
	nrounds $nr *$	635	100	211
Storms	eta $\eta *$	0.3	0.286	0.192
	max_depth $d *$	6	15	12
	subsample $s *$	0.523	0.839	0.768

	nrounds $nr*$	100	438	1311
Floods	eta $\eta*$	0.05	0.3	0.052
	max_depth $d*$	15	3	14
	subsample $s*$	0.963	0.603	0.983
	nrounds $nr*$	1963	2000	566

Source: Author's table.

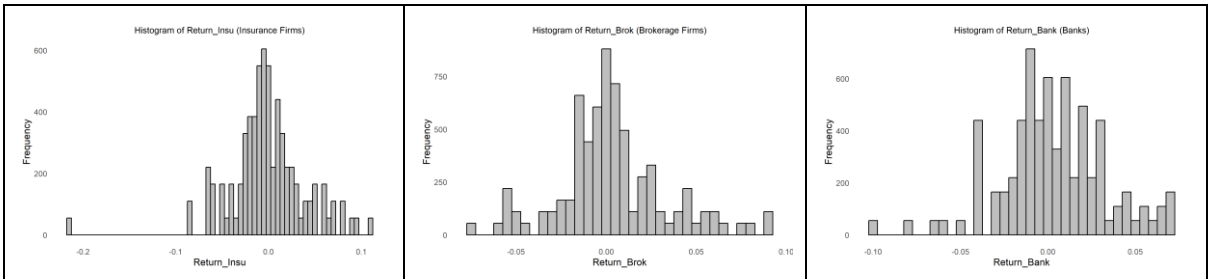
To validate XGBoost's superiority over traditional market models, besides RMSE, the study compares error metrics: Mean Absolute Error (MAE), Symmetric Mean Absolute Percentage Error (SMAPE). In simple terms, RMSE tells us how far off our predicted stock returns are from the actual returns, on average, with bigger errors counting more heavily because it squares the differences. MAE, meanwhile, measures the average size of these mistakes without squaring them, giving a straightforward average error. For example, an MAE of 0.008 means your predictions are off by about 0.8% on average, making it easier to understand the typical error in plain terms. Lastly, SMAPE shows the percentage difference between predicted and actual returns in a fair way, treating overestimates and underestimates equally—like checking how close your guess is to the true stock value as a percentage; a SMAPE of 5% means your predictions are off by 5% on average, which is useful when returns are small or near zero (Dhas & and Singh, 2023).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (13)$$

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{2|y_i-\hat{y}_i|}{|y_i|+|\hat{y}_i|} \times 100 \quad (14)$$

Mean Absolute Percentage Error (MAPE) was initially considered for model evaluation; however, it was discarded due to near-zero values in Return_Bank, Return_Brok, and Return_Insu, which made the metric unreliable. As shown in Figure 2, most daily returns cluster near zero with notable outliers. Therefore, MAPE is unreliable in such contexts because division by near-zero actuals inflates the error. SMAPE, by contrast, normalizes the absolute error by the average of actual and forecasted values, providing a more stable and interpretable measure (Kim & Kim, 2016).

Figure 2. An analysis of the return distribution



a. Histogram of Insurance_return | b. Histogram of Brokerage_return | c. Histogram of Bank_return

Source: Author's figure.

4. EMPIRICAL RESULTS

4.1. Short- vs. Intermediate-Term Windows in Event Study

Table 2 presents short- and intermediate-term AAR volatility for banks, insurance firms, and brokerage firms, measured by standard deviation (S.D.), and range-based volatility (range). The market model yielded statistically insignificant CAARs across all financial institution types. In contrast, the XGBoost model detected significant negative effects across all institutions, with insurance firms at –0.326% (7-day) and –0.241% (15-day), brokerage firms at –0.287% (7-day) and –0.309% (15-day), and banks at –0.388% (7-day) and -0.368% (15-day), all significant. These results, consistent with the work of Boungou et al. (2025), evidence the adverse effect of natural disasters on the financial sector.

Table 2: CAAR by the end of the intermediate–window and short–window

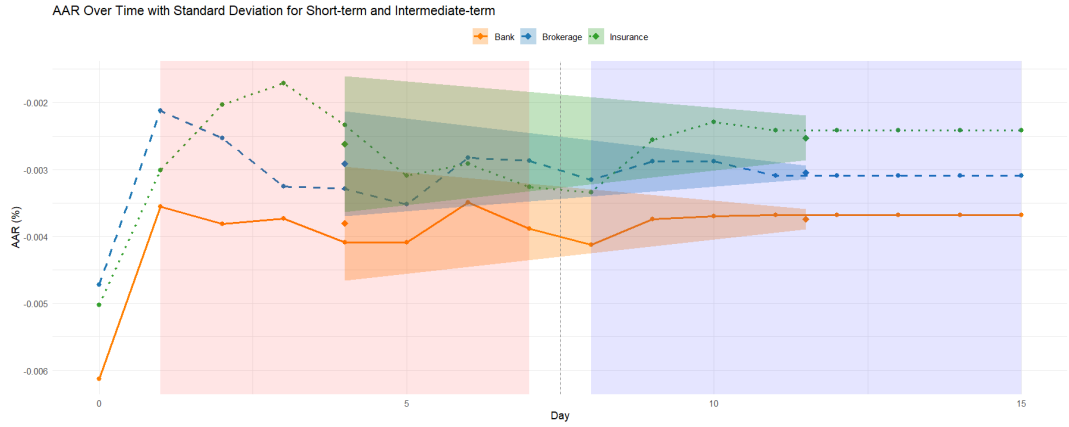
Response to all natural disasters	**Market model**		**XGBoost**					
	intermediate–window event 15–day AAR	short–window event 7–day AAR	intermediate–window event 15–day AAR	short–window event 7–day AAR	intermediate–window event		short–window event	
					SD	Range	SD	Range
Insurance firms	–0.018%	0.027%	–0.241%**	–0.326%**	0.015%	0.044%	0.085%	0.264%
Brokerage firms	0.048%	–0.020%	–0.309%***	–0.287%***	0.010%	0.027%	0.078%	0.260%
Banks	0.051%	0.056%	–0.368%***	–0.388%***	0.033%	0.105%	0.101%	0.331%

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's table.

Figure 4 reveals persistent negative AARs for 15 days post-disaster. In the short-term window (days 1–7), volatility was significantly higher than in the intermediate-term (days 8–15). For insurance firms, S.D. declined from 0.085% to 0.015%, ranging from 0.264% to 0.044%. Brokerage firms showed similar reductions, with S.D. falling from 0.078% to 0.010%, ranging from 0.260% to 0.027%. Banks experienced the largest decline, with S.D. dropping from 0.101% to 0.033%, range from 0.331% to 0.105%. These findings indicate that the short-term period is characterized by greater volatility and dispersion in AAR, reflecting erratic investor behavior and intense speculative activity following the event[10]. In contrast, the intermediate-term period is marked by stabilization in market responses, as volatility diminishes and investor reactions become more deliberate, suggesting that initial chaos gives way to calculated decision-making over time.

Figure 3: Average Abnormal returns (AAR) of different financial institutions—Insurance companies, brokerage firms, and commercial banks—7–day window (short–window) and 15–day (intermediate–window) reaction to all events.



*Note: This figure illustrates the Average Abnormal Returns (AAR) calculated by XGBoost over a 15-day event window for Banks (orange line), Brokerage firms (blue dashed line), and Insurance firms (green dotted line) in response to natural disasters in Vietnam. The shaded areas around each line represent the standard deviation of AAR, indicating the volatility of returns. The red shaded region (Days 0-7) denotes the short-term window, capturing immediate market reactions, while the blue shaded region (Days 8-15) represents the intermediate-term window, reflecting more stabilized responses. The vertical dashed line at Day 7.5 marks the transition between the short-term and intermediate-term periods.

[10] In the immediate aftermath of a disaster, investors often engage in speculation, attempting to anticipate its financial impact. For example, they may sell stocks in expectation of losses (e.g., insurance firms facing high compensation payouts) or buy in, predicting a swift recovery. These speculative actions drive heightened volatility and AAR dispersion (Robles, Torero, & Von Braun, 2009)

Source: Author's figure.

4.2. Robustness of XGBoost Relative to Traditional and Alternative Models in Event Study Analysis

We compare our Correlation-Enhanced Bayesian-Optimized XGBoost against three benchmark models: (1) LightGBM, a state-of-the-art gradient boosting method; (2) GARCH, a traditional volatility model; and (3) the market model, the standard event study baseline. All models are evaluated over a 15-day event window using RMSE, MAE, and SMAPE metrics.

This study employs a GARCH model for financial time series data, ideal for capturing time-varying volatility and clustered price movements (Bollerslev, 1986; Peer, Katoch, & Sidhu, 2025; Tsay, 2010). We evaluate GARCH(m,n) models with ARCH orders $m \in (1,2)$ and GARCH orders $n \in (1,2)$, using stock returns from 120-day estimation windows before events. Candidate models (GARCH(1,1), GARCH(1,2), GARCH(2,1), GARCH(2,2)) are evaluated using the Bayesian Information Criterion (BIC), selecting the model with the lowest BIC for optimal fit and complexity. The Ljung-Box test on squared standardized residuals is used to check for residual autocorrelation (Table 3). If no model converges, GARCH(1,1) is used for its robustness in financial analysis (Hansen & Lunde, 2005; Queiroz & David, 2024).

For LightGBM, this model stands out for its high performance and efficiency, particularly with large datasets, primarily due to its innovative techniques: Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) (Ke et al., 2017). GOSS effectively reduces the number of data instances by focusing on those with larger gradients, which are more critical for learning. EFB, on the other hand, minimizes the number of features by grouping mutually exclusive features, thereby optimizing computational speed without significantly compromising accuracy. In this study, LightGBM was configured with fixed hyperparameters based on default values[11] and common recommendations found in LightGBM's official documentation and

[11] A default learning rate of 0.1, a maximum tree depth of 6, and 31 leaves were set for the LightGBM model, which was trained over 100 iterations.

widely adopted practices within the machine learning community (Caballero Castro, 2024; Liu, 2022).

Table 3 demonstrates the superior performance of XGBoost compared to other models. For instance, when analyzing the Insurance companies' dataset, XGBoost achieved an RMSE of 0.0012, an MAE of 0.00010, and a SMAPE of 1.09512. This significantly outperforms LightGBM (RMSE: 0.00196, MAE: 0.00152, SMAPE: 14.62057), the market model (RMSE: 0.03841, MAE: 0.02587, SMAPE: 125.58621), and the GARCH model (RMSE: 0.02328, MAE: 0.01658, SMAPE: 174.78533). XGBoost across all metrics presented in Table 3 confirm its effectiveness in predicting normal returns (Jain, 2024; Prasad et al., 2021; Wang et al., 2023). This finding also underscores the limitations of both the market model and the GARCH model in accurately capturing stock price dynamics. While LightGBM shows competitive performance compared to traditional models, its inferior results relative to XGBoost may be attributed to the lack of Bayesian optimization for hyperparameter tuning.

Table 3: Performance Comparison: XGBoost with Bayesian optimization, Market Model, LightGBM, and GARCH

Model	Insurance firms			Brokerage firms			Banks		
	RMSE	MAE	SMAPE	RMSE	MAE	SMAPE	RMSE	MAE	SMAPE
XGBoost	0.00012	0.00010	1.09512	0.00196	0.00034	5.08740	0.00013	0.00011	1.53304
Market Model	0.03841	0.02587	125.5862	0.02418	0.01806	118.5086	0.02445	0.01818	111.8719
LightGBM	0.00196	0.00152	14.6205	0.00200	0.00057	11.9999	0.00039	0.00030	4.35643
GARCH	0.04164	0.02888	174.5005	0.03002	0.02131	174.4464	0.03017	0.02302	163.1870
*Note: BIC identifies the optimal GARCH(m, n) model.	GARCH(1 , 1) BIC: –3.513971 GARCH(1 , 2) BIC: –3.512639 GARCH(2 , 1) BIC: –3.512638 GARCH(2 , 2) BIC: –3.511306 Selected GARCH(1 , 1)			GARCH(1 , 1) BIC: –4.306779 GARCH(1 , 2) BIC: –4.305092 GARCH(2 , 1) BIC: –4.305071 GARCH(2 , 2) BIC: –4.328137 Selected GARCH(2 , 2)			GARCH(1 , 1) BIC: –4.158884 GARCH(1 , 2) BIC: –4.400681 GARCH(2 , 1) BIC: –4.157679 GARCH(2 , 2) BIC: –4.399565 Selected GARCH(1 , 2)		

Source: Author's table.

4.3. Robustness of Sectoral and Disaster-Specific Responses to Floods and Storms

To test the robustness of the adverse effect of natural disasters on the financial sector, the dataset was divided into two subsets—floods and storms. Figure 5 displays the 15-day CAARs for insurance firms, brokerage firms, and commercial banks across all events, storm events, and flood events, comparing the XGBoost model (solid black line) with the market model (dotted line). The study highlights a shared vulnerability to natural disasters in Vietnam, with XGBoost consistently indicating negative CAARs across all sectors. In contrast, the market model exhibits CAARs that vary between positive and negative, suggesting that the traditional model's weakness in predicting normal returns may lead to flawed conclusions and misguided policy implications.

Tables 4–6 present the AARs, CAARs, and their corresponding t-statistics for all events, storms, and floods. As can be seen in Table 4, among the three sectors, the insurance industry experienced the least impact, with a CAAR of –4.361% on day 15, compared to –4.948% for brokerage firms and –6.271% for banks. The variations in impact magnitude, timing, and recovery patterns provide valuable insights into sectoral resilience when facing floods and storms. The relatively lower impact on the insurance sector may be attributed to Vietnam's underdeveloped insurance market, which maintains a low penetration rate compared to developed economies[12]. In contrast, banks, with their higher financial integration, face greater systemic risks during natural disaster events.

Insurance sector returns (AAR and CAAR) remained statistically insignificant until Day 4, reaching significance only on Day 5. In contrast, both brokerage firms and banks exhibit earlier impacts, showing statistically significant responses from Day 1, which underscores their heightened sensitivity to market disruptions. The delayed reaction of the insurance sector—marked by an AAR stabilizing from –0.309% on Day 5 to –0.241% on Day 11— may indicate Vietnam's emerging insurance market manages

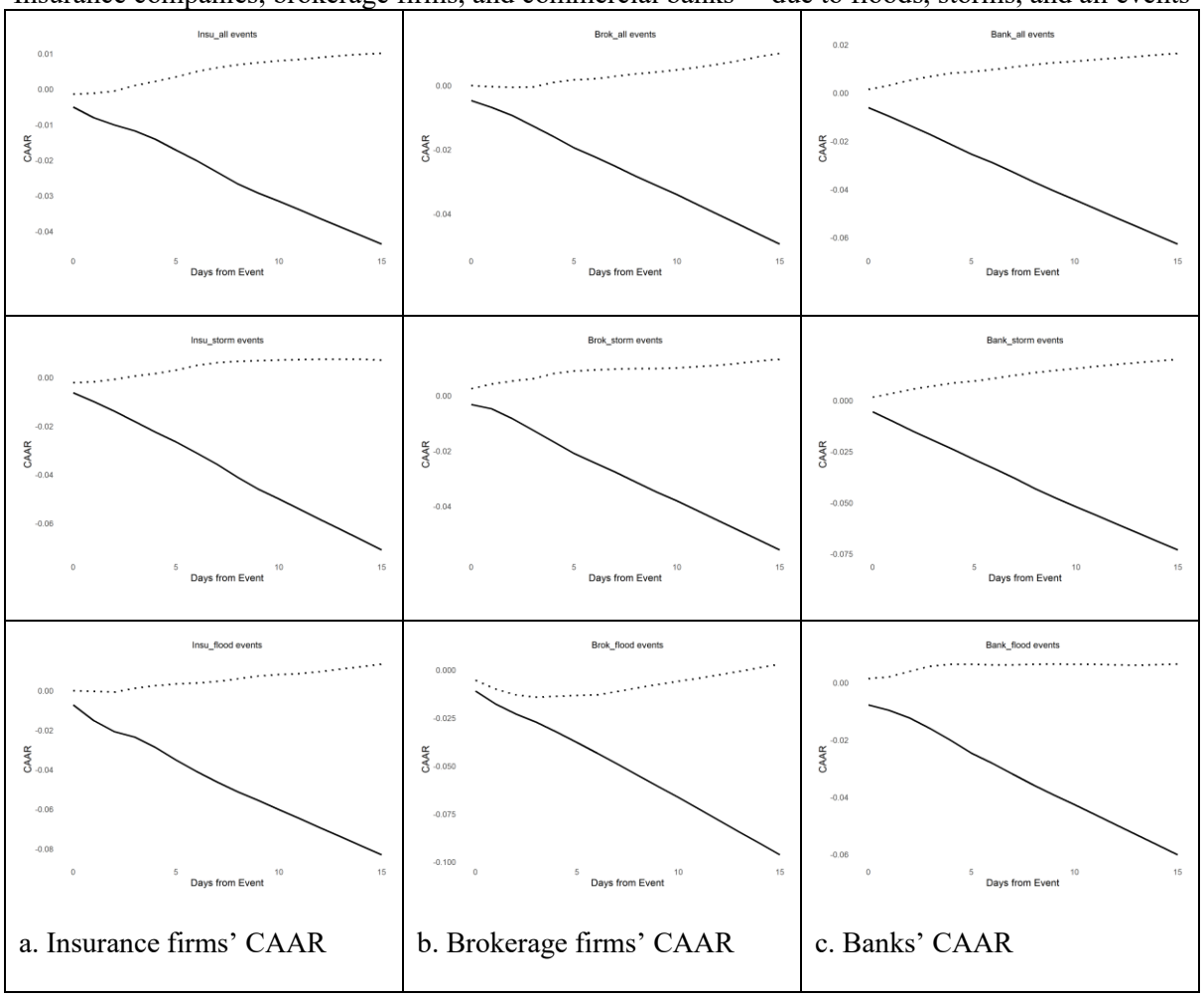
[12] Insurance Industry Struggling with Continued Difficulties.

payout pressures through delayed claims processing, a practice to ease financial strain after natural disasters (Feinman, 2010).

CAARs indicate that floods are associated with more pronounced negative responses in insurance and brokerage firms compared to storms. Brokerage firms, for instance, recorded a CAAR on Day 15 of –9.628% following floods, compared to –5.579% for storms. The sharp initial decline in AAR to –1.099% on Day 1 for brokerage firms highlights a significant economic impact, reflecting their sensitivity to trading disruptions and heightened risk aversion following floods, which often cause prolonged market interruptions in Vietnam. This aligns with the nature of floods, which, due to their extended duration, exert sustained pressure on stock markets and trading volumes, exacerbating volatility. The 2023 EM–DAT report[13] notes floods affected 74.6 million people annually (2003–2022) versus 32.2 million for storms, suggesting their broader impact amplifies financial repercussions. These findings suggest that prolonged disasters cause more severe market disruptions than fast-onset storms, reducing liquidity and increasing volatility, consistent with Yajie Chen et al. (2023), who found predictable storms had weaker financial effects. However, for banks, storms have a stronger negative impact than floods, with a CAAR of –7.31% and an AAR peak of –5.10% on day 8, compared to a CAAR of –6.016% and an initial AAR of –0.775% for floods. One possible explanation is that storms, with their rapid onset, are associated with immediate operational disruptions, while floods, with their prolonged nature, may allow banks time to implement contingency measures, potentially reducing the intensity of immediate negative effects, though cumulative impacts persist. Existing studies primarily focus on asset damage, operational disruptions, and customer effects within the banking sector, but few directly compare the impact of storms and floods. This study fills this gap by providing empirical evidence that storms have a stronger negative impact on banks than floods.

[13] EM-DAT annual reports: 2023 Disasters in Numbers - A Significant Year of Disaster Impact

Figure 4: Cumulative Average Abnormal Returns (CAAR) of different financial institutions—Insurance companies, brokerage firms, and commercial banks— due to floods, storms, and all events



a. Insurance firms' CAAR | b. Brokerage firms' CAAR | c. Banks' CAAR

* Note: The Optimized XGBoost is represented by the solid black line. The market model is represented by the dotted line.

Source: Author's figure.

In summary, the varying CAAR and AAR magnitudes (e.g., –3.19% storms to –9.63% floods in brokerages) highlight significant economic impacts across Vietnam's financial sectors and disaster types, providing critical insights into institutional resilience. To further assess vulnerabilities, stress testing with simulated losses based on sector-specific abnormal returns—such as those observed for insurance firms, which exhibit milder responses to floods compared to brokerage firms—can enhance risk assessment and preparedness. These findings underscore the urgent need for targeted policy interventions to advance SDG 13 by strengthening adaptation to climate-related hazards through improved risk management and proactive financial strategies.

Table 4: Average Abnormal Returns (%) and Cumulative Average Abnormal Returns (%) over a 0 to 15-day window for all disasters, based on the XGBoost model.

XGBoost	Insurance firms				Brokerage firms				Banks			
day	AAR	CAAR	t test_CAAR	t test_AAR	AAR	CAAR	t test_CAAR	t test_AAR	AAR	CAAR	t test_CAAR	t test_AAR
0	–0.502%	–0.502%	–1.5963	–1.59632	–0.472%*	–0.472%*	–1.73287	–1.73287	–0.613%***	–0.613%***	–2.74098	–2.74098
1	–0.301%	–0.803%	–1.5710	–1.20436	–0.212%	–0.684%	–1.62141	–1.19923	–0.355%***	–0.968%***	–2.85347	–2.35961
2	–0.203%	–1.006%	–1.4977	–1.03027	–0.253%**	–0.937%*	–1.91081	–2.29068	–0.381%***	–1.349%***	–3.10939	–2.9797
3	–0.171%	–1.177%	–1.4258	–0.88316	–0.325%***	–1.262%**	–2.26485	–3.0059	–0.373%***	–1.722%***	–3.30565	–3.47369
4	–0.233%	–1.410%	–1.4490	–1.27095	–0.329%***	–1.591%**	–2.52716	–3.09072	–0.409%***	–2.130%***	–3.56236	–4.25504
5	–0.309%*	–1.719%	–1.5492	–1.9224	–0.352%***	–1.944%***	–2.78548	–3.83027	–0.409%***	–2.539%***	–3.81733	–4.89699
6	–0.291%**	–2.010%	–1.6531	–2.13566	–0.282%***	–2.226%***	–2.93615	–3.58489	–0.349%***	–2.888%***	–4.03511	–4.61052
7	–0.326%**	–2.335%*	–1.7831	–2.61598	–0.287%***	–2.513%***	–3.11474	–4.02402	–0.388%***	–3.276%***	–4.31341	–5.62205
8	–0.334%***	–2.669%*	–1.9021	–2.78814	–0.315%***	–2.828%***	–3.32616	–4.9351	–0.412%***	–3.688%***	–4.59479	–5.82288
9	–0.256%**	–2.926%*	–1.9572	–2.23922	–0.288%***	–3.117%***	–3.49486	–4.64453	–0.374%***	–4.062%***	–4.7937	–5.51566
10	–0.229%**	–3.154%*	–1.9984	–2.19408	–0.288%***	–3.405%***	–3.6697	–4.89552	–0.370%***	–4.432%***	–4.97783	–5.61326
11	–0.241%**	–3.396%**	–2.0406	–2.31743	–0.309%***	–3.713%***	–3.84543	–5.40323	–0.368%***	–4.800%***	–5.14204	–5.74019
12	–0.241%**	–3.637%**	–2.0762	–2.31743	–0.309%***	–4.022%***	–4.00063	–5.40323	–0.368%***	–5.167%***	–5.27933	–5.74019
13	–0.241%**	–3.878%**	–2.1065	–2.31743	–0.309%***	–4.331%***	–4.13765	–5.40323	–0.368%***	–5.535%***	–5.39395	–5.74019
14	–0.241%**	–4.120%**	–2.1324	–2.31743	–0.309%***	–4.639%***	–4.25867	–5.40323	–0.368%***	–5.903%***	–5.48961	–5.74019
15	–0.241%**	–4.361%**	–2.1546	–2.31743	–0.309%***	–4.948%***	–4.36565	–5.40323	–0.368%***	–6.271%***	–5.56945	–5.74019

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's table.

Table 5: Average Abnormal Returns (%) and Cumulative Average Abnormal Returns (%) (0,+15 days) due to storms based on the XGBoost model.

XGBoost	Insurance firms				Brokerage firms				Banks			
day	AAR	CAAR	t test_CAAR	t test_AAR	AAR	CAAR	t test_CAAR	t test_AAR	AAR	CAAR	T test_CAAR	T test_AAR
0	–0.634%	–0.634%	–1.4480	–1.4480	–0.319%	–0.319%	–0.8638	–0.8638	–0.556%*	–0.556%*	–1.9499	–1.9499
1	–0.357%	–0.991%	–1.3682	–0.9976	–0.161%	–0.480%	–0.8465	–0.7261	–0.464%**	–1.019%**	–2.1753	–2.1095
2	–0.395%	–1.386%	–1.4206	–1.4254	–0.352%**	–0.832%	–1.2929	–2.3710	–0.498%**	–1.518%**	–2.4681	–2.7078
3	–0.428%	–1.814%	–1.4905	–1.5539	–0.416%***	–1.248%*	–1.7279	–3.0150	–0.441%***	–1.958%**	–2.6158	–2.9092
4	–0.438%	–2.253%	–1.5645	–1.6386	–0.420%***	–1.668%*	–2.0317	–2.8191	–0.458%***	–2.417%***	–2.8059	–3.5496
5	–0.404%	–2.657%	–1.6019	–1.6788	–0.424%***	–2.093%**	–2.2937	–3.3955	–0.474%***	–2.891%***	–3.0546	–4.5376
6	–0.449%**	–3.106%*	–1.6957	–2.2114	–0.339%***	–2.432%**	–2.4565	–3.0722	–0.453%***	–3.344%***	–3.2863	–4.1956
7	–0.471%**	–3.577%*	–1.8008	–2.5223	–0.326%***	–2.758%***	–2.6097	–3.2845	–0.467%***	–3.811%***	–3.5565	–5.2157
8	–0.532%***	–4.109%*	–1.9284	–2.9639	–0.368%***	–3.126%***	–2.7895	–3.8343	–0.510%***	–4.322%***	–3.8656	–5.4548
9	–0.487%**	–4.596%*	–2.0207	–2.7315	–0.349%***	–3.475%***	–2.9369	–3.7028	–0.446%***	–4.767%***	–4.0938	–5.2473
10	–0.405%**	–5.001%**	–2.0784	–2.5378	–0.330%***	–3.806%***	–3.0702	–3.6895	–0.432%***	–5.199%***	–4.3043	–5.4027
11	–0.420%**	–5.421%**	–2.1334	–2.6397	–0.355%***	–4.160%***	–3.2039	–4.0548	–0.422%***	–5.622%***	–4.4948	–5.5913
12	–0.420%**	–5.841%**	–2.1807	–2.6397	–0.355%***	–4.515%***	–3.3184	–4.0548	–0.422%***	–6.044%***	–4.6620	–5.5913
13	–0.420%**	–6.261%**	–2.2216	–2.6397	–0.355%***	–4.869%***	–3.4166	–4.0548	–0.422%***	–6.466%***	–4.8082	–5.5913

14	–0.420%**	–6.681%**	–2.2571	–2.6397	–0.355%***	–5.224%***	–3.5008	–4.0548	–0.422%***	–6.888%***	–4.9357	–5.5913
15	–0.420%**	–7.101%**	–2.2881	–2.6397	–0.355%***	–5.579%***	–3.5731	–4.0548	–0.422%***	–7.310%***	–5.0468	–5.5913

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's table.

Table 6: Average Abnormal Returns (%) and Cumulative Average Abnormal Returns (%) (0,+15 days) due to floods based on the XGBoost model.

XGBoost	Insurance firms				Brokerage firms				Banks			
day	AAR	CAAR	t test CAAR	t test AAR	AAR	CAAR	t test CAAR	t test AAR	AAR	CAAR	t test CAAR	t test AAR
0	–0.725%	–0.725%	–1.635	–1.635	–1.099%**	–1.099%**	–2.385	–2.385	–0.775%**	–0.775%**	–2.156	–2.156
1	–0.783%**	–1.508%**	–2.209	–2.587	–0.683%**	–1.782%**	–2.676	–2.332	–0.187%	–0.962%*	–1.796	–0.817
2	–0.562%*	–2.070%**	–2.428	–1.952	–0.525%**	–2.307%**	–2.825	–2.551	–0.272%	–1.234%*	–1.912	–1.619
3	–0.288%	–2.357%**	–2.256	–0.929	–0.420%**	–2.727%***	–2.957	–2.423	–0.371%**	–1.606%**	–2.135	–2.387
4	–0.516%*	–2.874%**	–2.332	–2.024	–0.513%***	–3.239%***	–3.099	–3.059	–0.412%***	–2.018%**	–2.385	–3.069
5	–0.641%***	–3.515%**	–2.504	–2.900	–0.537%***	–3.776%***	–3.207	–3.286	–0.443%***	–2.462%**	–2.589	–3.205
6	–0.581%**	–4.096%**	–2.627	–2.556	–0.566%***	–4.342%***	–3.347	–4.178	–0.353%***	–2.815%**	–2.735	–3.342
7	–0.530%**	–4.626%**	–2.701	–2.448	–0.563%***	–4.905%***	–3.496	–3.784	–0.380%***	–3.195%***	–2.891	–3.789
8	–0.497%**	–5.123%**	–2.726	–2.465	–0.591%***	–5.496%***	–3.665	–4.996	–0.377%***	–3.572%***	–3.002	–3.902
9	–0.433%**	–5.555%**	–2.735	–2.336	–0.572%***	–6.067%***	–3.817	–5.189	–0.354%***	–3.926%***	–3.062	–3.434
10	–0.458%**	–6.013%**	–2.763	–2.643	–0.574%***	–6.641%***	–3.973	–5.659	–0.337%***	–4.263%***	–3.128	–3.576
11	–0.459%**	–6.472%**	–2.777	–2.574	–0.598%***	–7.238%***	–4.096	–5.391	–0.350%***	–4.614%***	–3.189	–3.733
12	–0.459%**	–6.931%**	–2.786	–2.574	–0.598%***	–7.836%***	–4.204	–5.391	–0.350%***	–4.964%***	–3.241	–3.733
13	–0.459%**	–7.390%**	–2.791	–2.574	–0.598%***	–8.433%***	–4.297	–5.391	–0.350%***	–5.315%***	–3.286	–3.733
14	–0.459%**	–7.849%**	–2.793	–2.574	–0.598%***	–9.031%***	–4.379	–5.391	–0.350%***	–5.665%***	–3.324	–3.733
15	–0.459%**	–8.307%**	–2.793	–2.574	–0.598%***	–9.628%***	–4.451	–5.391	–0.350%***	–6.016%***	–3.358	–3.733

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's table.

5. Conclusion

This study examines the response of Vietnamese financial institutions to natural disasters through an event study integrated with a Correlation-Enhanced Bayesian-Optimized XGBoost Framework. Event dates were selected using the Universal Disaster Severity Classification Scheme (UDSCS) to identify significant storms and floods in Vietnam, improving the focus on impactful climate events. The research demonstrates robust results through comprehensive model comparison, with XGBoost consistently outperforming LightGBM, GARCH, and the market model across all performance metrics, thereby providing reliable insights into climate-related financial shocks in Vietnam.

Key findings suggest that natural disasters are associated with negative effects on the financial sector, with sector-specific variations. Among the three sectors, insurance firms show the least pronounced negative responses, while brokerage firms and banks react more strongly—brokerage firms to floods and banks to storms. Consistent with the ECB research (European Central Bank, 2021), insurance firms face greater exposure to flood-related risks than storm events. The results further indicate that short-term market reactions are volatile, whereas intermediate-term adjustments suggest a shift from panic-driven responses to more calculated decision-making, as noted by Oler et al. (2008).

This study advances SDG 13 by demonstrating how machine learning can transform disaster impact assessments, enabling financial institutions and policymakers to develop sophisticated adaptive strategies against escalating climate risks. The findings reveal critical insights for three key stakeholders. Regulators should mandate sector-specific stress testing that accounts for the heightened vulnerability of brokerage firms and banks to short-term volatility. Investors can capitalize on insurance firms' relative resilience by strategically overweighting these assets during disaster-prone periods. Financial managers should prioritize intermediate-term risk mitigation, leveraging the observed behavioral shift toward calculated decision-making to build institutional resilience. As extreme weather events intensify globally, these machine learning-enhanced models provide essential tools for strengthening financial system

stability through improved stress testing, risk management protocols, and regulatory frameworks.

Despite these contributions, there are clear limitations to address. A critical limitation is the "black box" nature of machine learning, such as XGBoost and LightGBM, which may obscure the interpretability of how specific features (e.g., lag returns or volatility) drive predictions, potentially complicating trust and decision-making for stakeholders. Additionally, Vietnam's underdeveloped insurance market may influence the findings, limiting their applicability to more mature financial systems. Future research should extend the analysis to regional markets and across diverse economic contexts to strengthen global insights and address these interpretability concerns.

Acknowledgements

We thank the editor and anonymous referee(s) for comments and suggestions.

This paper is funded by University of Economics Ho Chi Minh City, Vietnam (UEH).

References

Ahmetoglu, H., & Das, R. (2022). A comprehensive review on detection of cyber-attacks: Data sets, methods, challenges, and future research directions. *Internet of Things, 20*, 100615. doi:https://doi.org/10.1016/j.iot.2022.100615

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics, 61*(1), 43-76.

Antoniuk, Y., & Leirvik, T. (2024). Climate change events and stock market returns. *Journal of Sustainable Finance & Investment, 14*(1), 42-67.

Betrò, B. (1991). Bayesian methods in global optimization. *Journal of Global Optimization, 1*(1), 1-14. doi:10.1007/BF00120661

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327. doi:https://doi.org/10.1016/0304-4076(86)90063-1

Boungou, W., Djatche, M. N., & Biekpe, N. (2025). Chinese Stock Market Performance and Natural Disasters. *Journal of Emerging Market Finance, 24*(3), 281-305. doi:10.1177/09726527251318132

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics, 14*(1), 3-31.

Bui, A. T., Dungey, M., Nguyen, C. V., & Pham, T. P. (2014). The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from Vietnam. *Applied Economics, 46*(15), 1751-1766.

Caballero Castro, J. (2024). *Impact of LightGBM hyperparameters on class imbalance* (Bachelor's thesis, KTH Royal Institute of Technology). Retrieved from https://upcommons.upc.edu/bitstreams/59ce425e-700a-48e4-8964-3095e070a52f/download

Caldera, H. J., & Wirasinghe, S. C. (2022). A universal severity classification for natural disasters. *Natural Hazards, 111*(2), 1533-1573. doi:10.1007/s11069-

021-05106-9

Chen, T., & Guestrin, C. (2016). *XGBoost: A scalable tree boosting system.* Paper presented at the Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785-794). doi:10.1145/2939672.2939785

Chen, Y., Guo, K., Ji, Q., & Zhang, D. (2023). "Not all climate risks are alike": Heterogeneous responses of financial firms to natural disasters in China. *Finance Research Letters, 52*, 103538. doi:https://doi.org/10.1016/j.frl.2022.103538

Chen, Y., Zhang, D., Wu, F., & Ji, Q. (2022). Climate risks and foreign direct investment in developing countries: the role of national governance. *Sustainability Science, 17*(5), 1723-1740. doi:10.1007/s11625-022-01199-8

Corrado, C. J. (2011). Event studies: A methodology review. *Accounting & Finance, 51*(1), 207-234.

Coutts, J. A., Mills, T. C., & Roberts, J. (1994). The market model and the event study method: A synthesis of the econometric criticisms. *International Review of Financial Analysis, 3*(2), 149-171.

Dewenter, K. L., Higgins, R. C., & Simin, T. T. (2005). Can event study methods solve the currency exposure puzzle? *Pacific-Basin Finance Journal, 13*(2), 119-144. doi:https://doi.org/10.1016/j.pacfin.2004.07.002

Dhas, M. M., & Singh, N. S. (2023). Optimized Haar wavelet-based blood cell image denoising with improved multiverse optimization algorithm. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, 11*(4), 1438-1449. doi:10.1080/21681163.2022.2141658

Dolley, J. C. (1933). Characteristics and procedure of common stock split-ups. *Harvard Business Review, 11*(3), 316-326.

Drahokoupil, J. (2022). Application of the XGBoost algorithm and Bayesian optimization for the Bitcoin price prediction during the COVID-19 period. *FFA*

Working Papers, 4.006. Retrieved from https://wp.ffu.vse.cz/pdfs/wps/2022/01/06.pdf

European Central Bank. (2021). *Climate-related risk and financial stability: ECB/ESRB Project Team on Climate Risk Monitoring*. Publications Office of the European Union.

Feinman, J. M. (2010). *Delay, Deny, Defend: Why Insurance Companies Don't Pay Claims and What You Can Do About It.* Penguin.

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics, 19*(1), 3-29.

Hameed, A., & Kusnadi, Y. (2006). Stock Return Cross-Autocorrelations and Market Conditions in Japan. *The Journal of Business, 79*(6), 3029-3056. doi:10.1086/508007

Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: does anything beat a GARCH(1,1)? *Journal of Applied Econometrics, 20*(7), 873-889. doi:https://doi.org/10.1002/jae.800

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and practice* (2nd ed.). Melbourne, Australia: OTexts.

Jain, S. (2024). A Comparative Study of Stock Market Prediction Models: Deep Learning Approach and Machine Learning Approach. In R. Sharma & K. Mehta (Eds.), *Deep Learning Tools for Predicting Stock Market Movements* (pp. 249-269). Beverly, MA: Scrivener Publishing.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., . . . Liu, T.-Y. (2017). LightGBM: A highly efficient gradient boosting decision tree. *Advances in Neural Information Processing Systems, 30, 3146-3154*.

Kim, S., & Kim, H. (2016). A new metric of absolute percentage error for intermittent demand forecasts. *International Journal of Forecasting, 32*(3), 669-679. doi:https://doi.org/10.1016/j.ijforecast.2015.12.003

Kousky, C. (2014). Informing climate adaptation: A review of the economic costs of

natural disasters. *Energy Economics, 46*, 576-592. doi:https://doi.org/10.1016/j.eneco.2013.09.029

Kouzehgar, K., & Eslamian, S. (2023). Chapter 2 - Application of experimental data and soft computing techniques in determining the outflow and breach characteristics in embankments and landslide dams. In S. Eslamian & F. Eslamian (Eds.), *Handbook of Hydroinformatics* (pp. 11-31): Elsevier.

Li, C., Liu, Y., & Pan, L. (2024). A study of impact of climate change on the U.S. stock market as exemplified by the NASDAQ 100 index constituents. *Scientific Reports, 14*(1), 15468. doi:10.1038/s41598-024-66109-7

Li, Q., Yang, J., Hsiao, C., & Chang, Y.-J. (2005). The relationship between stock returns and volatility in international stock markets. *Journal of Empirical Finance, 12*(5), 650-665.

Liu, Y. (2022). *Grocery Sales Forecasting.* Paper presented at the 2022 International Conference on Creative Industry and Knowledge Economy (CIKE 2022) (pp. 215-219). Atlantis Press. doi:10.2991/aebmr.k.220404.040

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature, 35*(1), 13-39. Retrieved from http://www.jstor.org/stable/2729691

McWilliams, A., & Siegel, D. (1997). Event studies in management research: Theoretical and empirical issues. *Academy of Management Journal, 40*(3), 626-657.

Nguyen, D. T. T., Diaz-Rainey, I., Roberts, H., & Le, M. (2024). The impact of natural disasters on bank performance and the moderating role of financial integration. *Applied Economics, 56*(8), 918-940.

Nour, M., Cömert, Z., & Polat, K. (2020). A Novel Medical Diagnosis model for COVID-19 infection detection based on Deep Features and Bayesian Optimization. *Applied Soft Computing, 97*, 106580. doi:https://doi.org/10.1016/j.asoc.2020.106580

Noy, I., & Vu, T. B. (2010). The economics of natural disasters in a developing country: The case of Vietnam. *Journal of Asian Economics, 21*(4), 345-354. doi:https://doi.org/10.1016/j.asieco.2010.03.002

Oler, D. K., Harrison, J. S., & Allen, M. R. (2008). The danger of misinterpreting short-window event study findings in strategic management research: An empirical illustration using horizontal acquisitions. *Strategic Organization, 6*(2), 151-184.

Pagnottoni, P., Spelta, A., Flori, A., & Pammolli, F. (2022). Climate change and financial stability: Natural disaster impacts on global stock markets. *Physica A: Statistical Mechanics and its Applications, 599*, 127514. doi:https://doi.org/10.1016/j.physa.2022.127514

Pandey, D. K., & Kumari, V. (2021). Event study on the reaction of the developed and emerging stock markets to the 2019-nCoV outbreak. *International Review of Economics & Finance, 71*, 467-483. doi:https://doi.org/10.1016/j.iref.2020.09.014

Peer, U. A., Katoch, R., & Sidhu, A. (2025). Dynamics of Volatility Spillovers: Evidence from Implied Volatility Indexes to Conventional and Green Equities in the Indian Context. *Southeast Asian Journal of Economics, 13*(1), 65-97. Retrieved from https://so05.tci-thaijo.org/index.php/saje/article/view/267783

Prasad, V. V., Gumparthi, S., Venkataramana, L. Y., Srinethe, S., Sruthi Sree, R. M., & Nishanthi, K. (2021). Prediction of Stock Prices Using Statistical and Machine Learning Models: A Comparative Analysis. *The Computer Journal, 65*(5), 1338-1351. doi:10.1093/comjnl/bxab008

Queiroz, R. G. d. S., & David, S. A. (2024). *Does Anything Beat a GARCH(1,1)? Evidence from Crypto Markets*. In A. Saha & S. Banerjee (Eds.), Proceedings of the 2nd International Conference on Nonlinear Dynamics and Applications (ICNDA 2024), Volume 3 (pp. 398-408). Cham: Springer. doi:10.1007/978-3-031-69146-1_30

Robles, M., Torero, M., & Von Braun, J. (2009). When speculation matters (IFPRI

Issue Brief No. 57). Washington, DC: International Food Policy Research Institute.

Shi, R., Xu, X., Li, J., & Li, Y. (2021). Prediction and analysis of train arrival delay based on XGBoost and Bayesian optimization. *Applied Soft Computing, 109*, 107538. doi:https://doi.org/10.1016/j.asoc.2021.107538

Tsay, R. S. (2010). *Analysis of Financial Time Series*: John Wiley & Sons.

Ullah, S., Zaefarian, G., Ahmed, R., & Kimani, D. (2021). How to apply the event study methodology in STATA: An overview and a step-by-step guide for authors. *Industrial Marketing Management, 99*, A1-A12. doi:https://doi.org/10.1016/j.indmarman.2021.02.004

Wang, J., Zhao, W., Tsai, F.-S., Jin, H., Tan, J., & Su, C. (2023). A study of crude oil futures price volatility based on multi-dimensional data from event-driven and deep learning perspectives. *Applied Soft Computing, 146*, 110548. doi:https://doi.org/10.1016/j.asoc.2023.110548

Worthington, A., & Valadkhani, A. (2004). Measuring the impact of natural disasters on capital markets: an empirical application using intervention analysis. *Applied Economics, 36*(19), 2177-2186.

Yamori, N., & Kobayashi, T. (2002). Do Japanese Insurers Benefit from A Catastrophic Event?: Market Reactions to the 1995 Hanshin–Awaji Earthquake. *Journal of the Japanese and International Economies, 16*(1), 92-108. doi:https://doi.org/10.1006/jjie.2001.0477

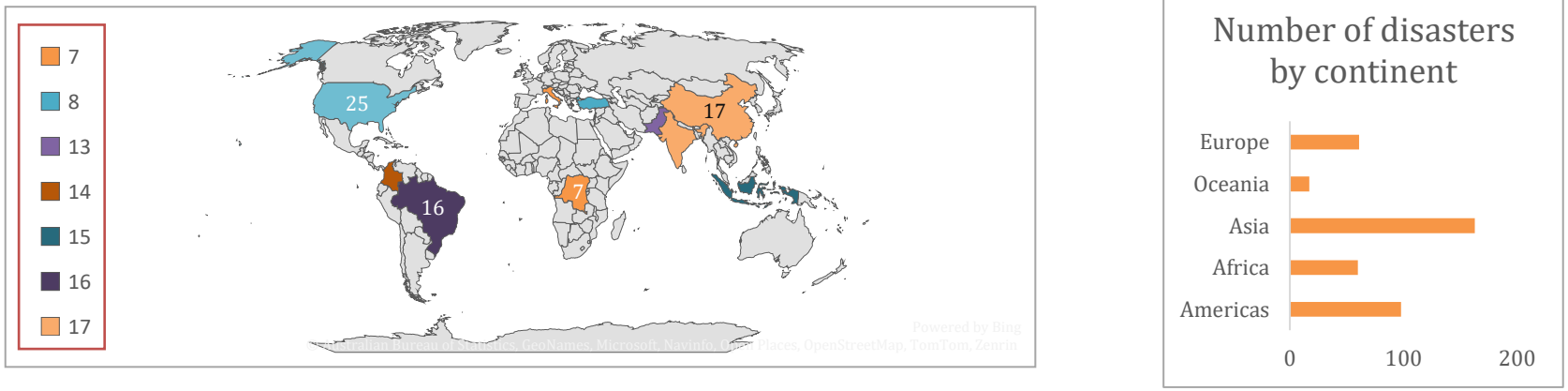
Zhou, F., & Botzen, W. J. W. (2017). *The impact of natural disasters on firm growth in Vietnam: Interaction with financial constraints* (Working Paper No. 17-20). Utrecht School of Economics. Retrieved from https://dspace.library.uu.nl/bitstream/handle/1874/361920/zhou.pdf

Zhou, F., & Botzen, W. J. W. (2021). Firm Level Evidence of Disaster Impacts on Growth in Vietnam. *Environmental and Resource Economics, 79*(2), 277-322. doi:10.1007/s10640-021-00562-0

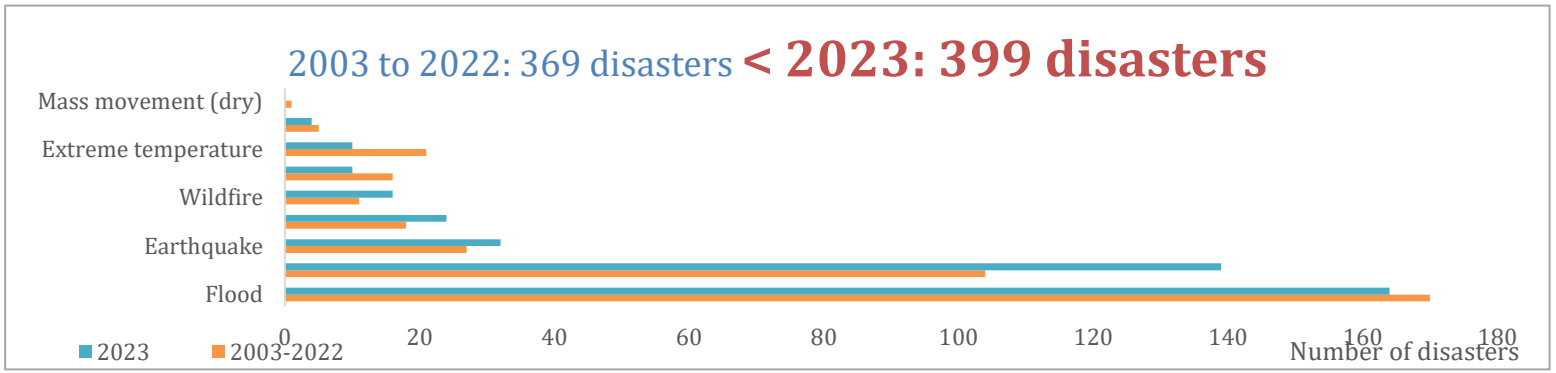
APPENDIX

Appendix 1: a) Number of disasters by continent and top 10 countries in 2022;
b) Occurrence by disaster type: 2022 compared to the 2002–2021 annual average

a.



b.



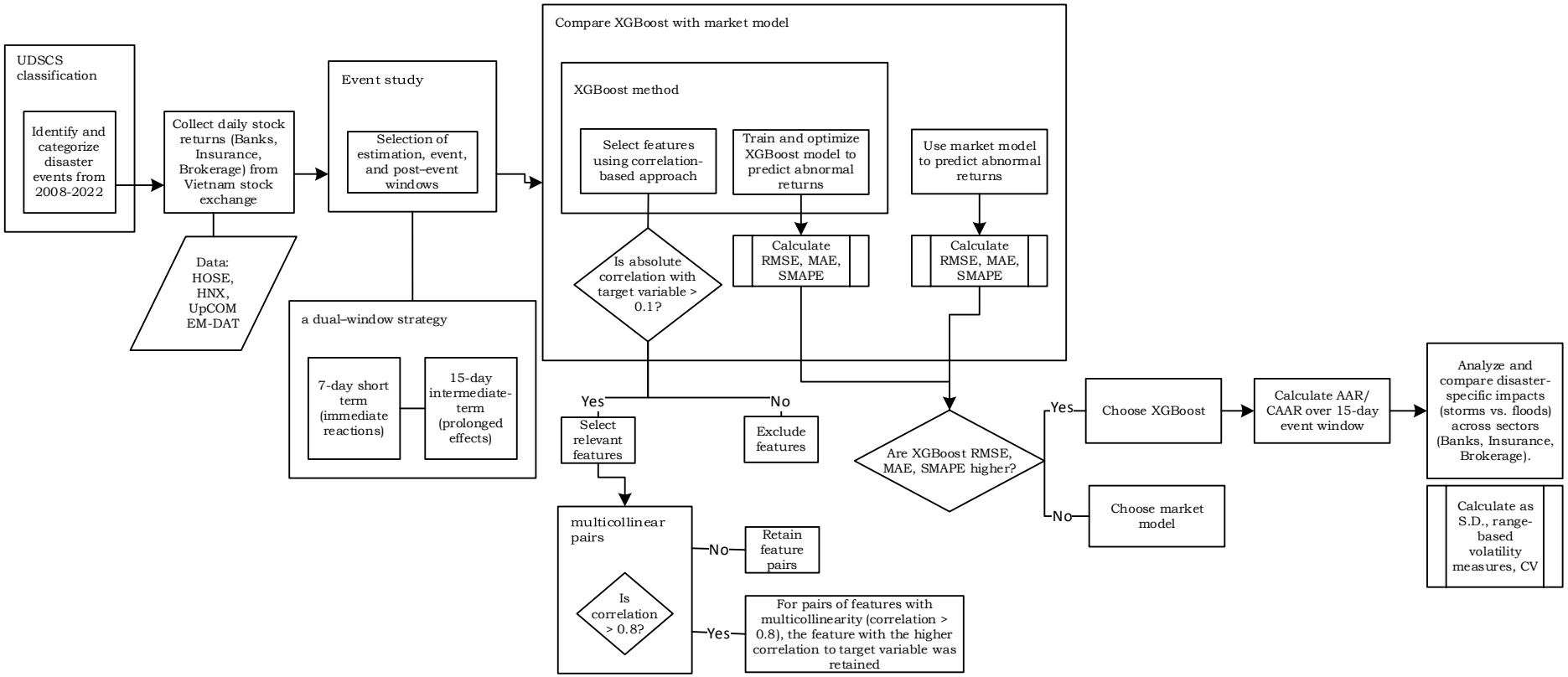
Source: Author's diagrams based on EM–DAT annual reports.

Appendix 2: Ranges of human and damage factors in 0–10 levels and Qualitative Universal Disaster Severity Classification

UDSCS level	Human factors (H)	Damage factors (D)	Proposed word and order	Proposed definition
0	1<H	1<D	None	None
1	1≤H<10	1,000≤D<10,000	Emergencey	A sudden natural event that causes damage, injuries, and some fatalities.
2	10≤H<100	10,000≤D<100,000	Disaster Type 1	A major natural event that causes significant damage, many serious injuries, and many fatalities
3	100≤H<1000	100,000≤D<1M	Disaster Type 2	
4	1,000≤H<10,000	1M≤D<10M	Calamity Type 1	A large-scale natural disturbance that causes severe destruction, a major number of injuries, and great number of fatalities.
5	10,000≤H<100,000	10M≤D<100M	Calamity Type 2	
6	100,000≤H<1M	100M≤D<1B	Catastrophe Type 1	A very large-scale natural disturbance that causes widespread continental destruction, a massive number of injuries, and an extensice loss of life.
7	1M≤H<10M	1B≤D<10B	Catastrophe Type 2	
8	10M≤H<100M	10B≤D<100B	Cataclysm Type 1	An extremely large-scale natural upheaval that causes global devastation, an uncountable number of injuries, and unimaginable loss of life.
9	100M≤H<1B	100B≤D<1T	Cataclysm Type 2	
10	1B≤H	1T≤D	Partial or Full Extinction	A world-scale natural upheaval that causes universal devastation, partial or full extinction of human.
Note: M = Million; B = Billion, T = Trillion				

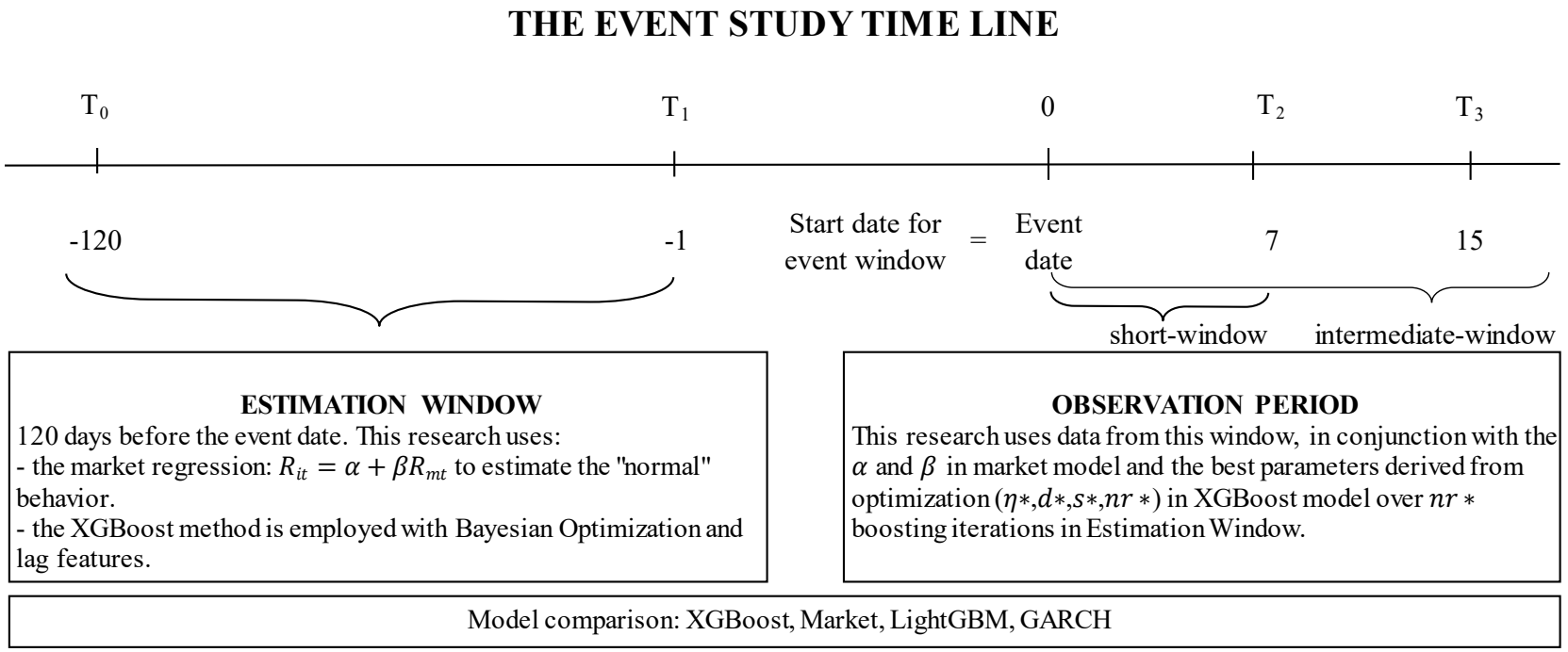
Source: Author's design based on Caldera and Wirasinghe (2022).

Appendix 3: Research Methodology Overview



Source: Author's design.

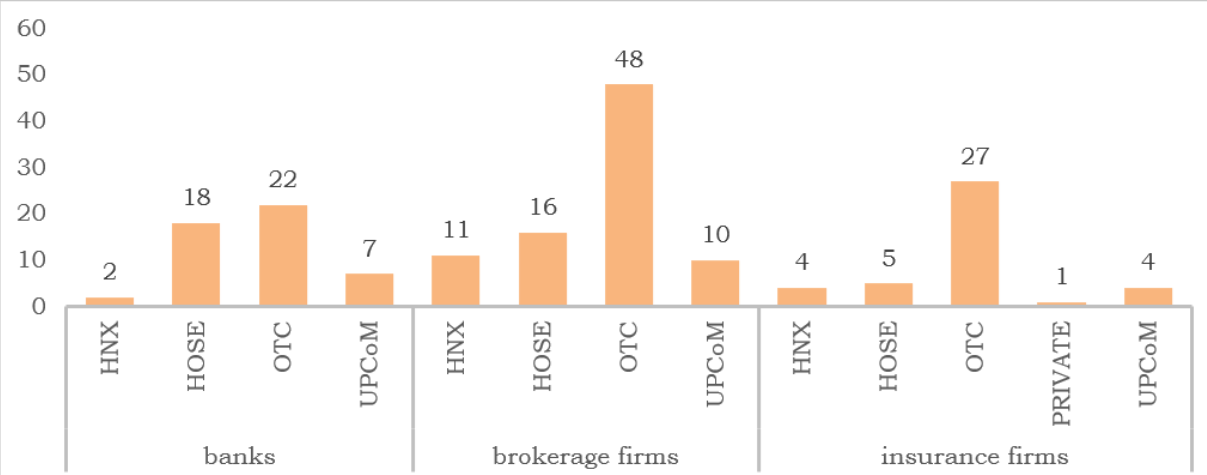
Appendix 4: Selection of estimation window, observation period.



Source: Author's diagram.

*Appendix 5: The descriptive statistics of all financial institutions**

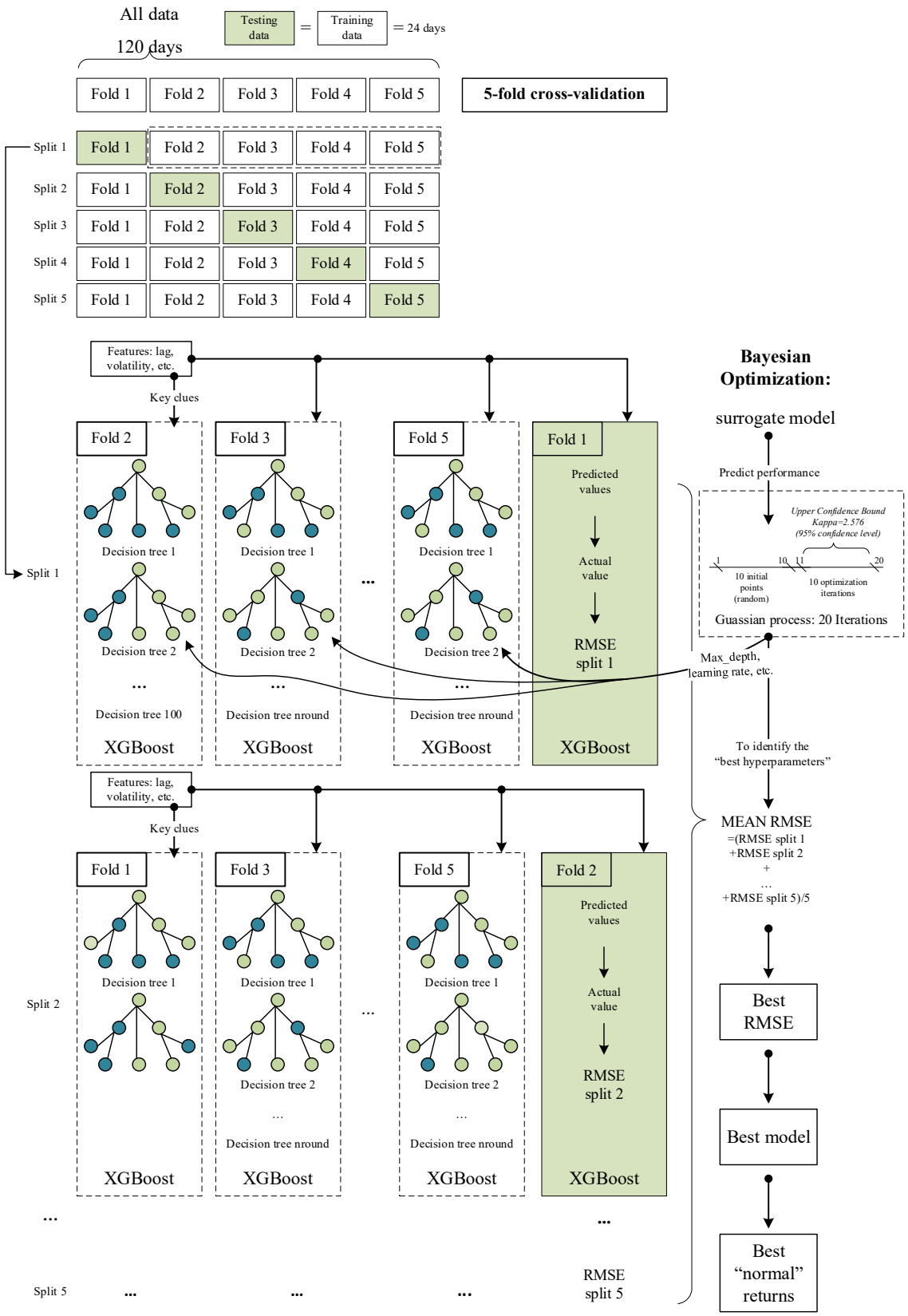
Exchange market	Count of type
banks	49
HNX	2
HOSE	18
OTC	22
UPCoM	7
brokerage firms	85
HNX	11
HOSE	16
OTC	48
UPCoM	10
insurance firms	41
HNX	4
HOSE	5
OTC	27
PRIVATE	1
UPCoM	4
Grand Total	80/175



** Financial institutions in the dataset include those listed on the three major exchanges: HOSE, HNX, and UPCoM. A list of banks, brokerage firms, and insurance companies is available upon request.*

Source: Author's design.

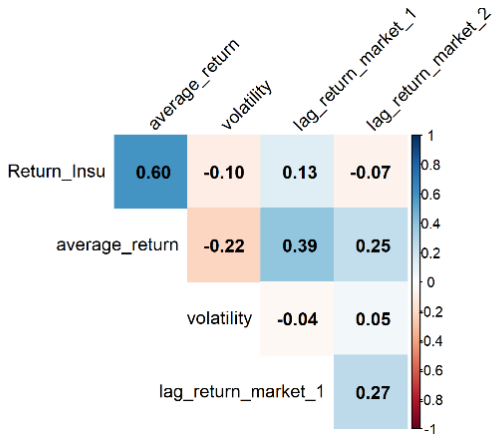
Appendix 6: XGBoost algorithm with Bayesian Optimization and lag features process.



Note: Phase 1: Data undergoes "5-fold cross-validation" → tests its learning with five different data groups to ensure reliability. Phase 2: For each fold, uses "Features" → key clues (like yesterday's stock price or market changes). Builds an "Ensemble of decision trees" → a team of decision guides (like maps showing which way to go based on past data). Phase 3: applies "Bayesian Optimization" → smart tuning to adjust XGBoost's settings (e.g., learning rate, tree depth) based on 5-fold results, minimizing prediction errors (like how far off the "normal" return guess is), with 20 iterations: 10 initial points, 10 optimization iterations. Phase 4: trains the Best Model with optimized hyperparameters on all data (120 days), then predicts the Best Normal Returns for the 16-day event window to analyze disaster impacts.

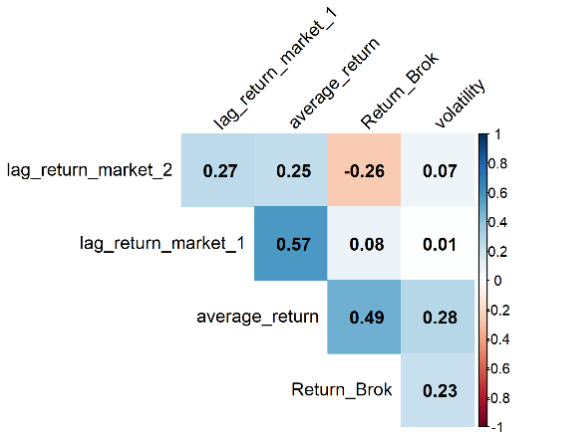
Source: Author's design.

Appendix 7: Correlation plot of features and target variables: market returns (`lag_return_market_1`, `lag_return_market_2`), `average return`, and `volatility`.



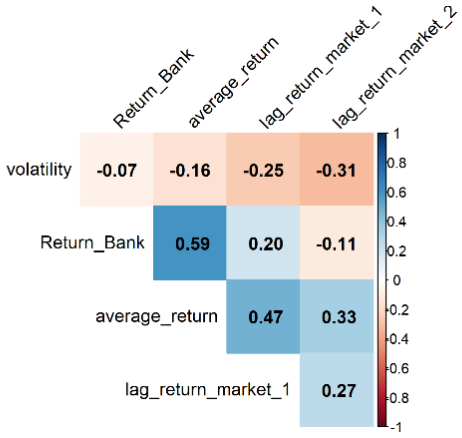
a. Insurance Companies

The final features after removing multicollinearity and based on correlation > 0.1: `lag_return_market_1`, `average_return`



b. Brokerage Companies

The final features after removing multicollinearity and based on correlation > 0.1: `lag_return_market_2`, `average_return`, `volatility`



c. Commercial banks

The final features after removing multicollinearity and based on correlation > 0.1: `lag_return_market_1`, `lag_return_market_2`, `average_return`

Note: lag_return_market_1 = lag(return_market, 1): Market return lagged by one period.

lag_return_market_2 = lag (return_market, 2): Market return lagged by two periods.

average_return = rollmean (Return_Insu, Return_Brok, Return_Bank, k = 3, fill = NA, align = "right"): Three-period rolling mean of Return_Insu, Return_Brok**,** and Return_Bank using the rollmean function in R.

volatility = rollapply (Return_Insu, Return_Brok, Return_Bank, width = 3, FUN = sd, fill = NA, align = "right"): Three-period rolling standard deviation of Return_Insu, Return_Brok, and Return_Bank using the rollapply function in R. Returns for insurance firms (Return_Insu), brokerage firms (Return_Brok), and commercial banks (Return_Bank) were analyzed using a three-period rolling window (k = 3, width = 3). A fixed random seed (set.seed(#)) ensured reproducibility in Bayesian optimization and model training.

Source: Author's figure.

Caldera, H. J., & Wirasinghe, S. C. (2022). A universal severity classification for natural disasters. *Natural Hazards, 111*(2), 1533-1573. doi:10.1007/s11069-021-05106-9