

Integrating Disaster Risks: A Comprehensive Catastrophe Risk Assessment Model and Its Empirical Validation

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Abstract. The increasing frequency and severity of catastrophic events worldwide highlight the urgent need for the insurance sector to enhance risk assessment strategies. This study introduces a novel Catastrophe Risk Assessment Model that integrates three critical dimensions of risk: disaster-causing factors, disaster-bearing carriers, and disaster-pregnant environments. Utilizing the Grey System Theory and the Entropy Weight Method (G2-EWM), the model evaluates 11 indicators to assess the profitability for insurance companies ($Q_{profitability}$) and affordability for property owners ($Q_{affordability}$). An empirical analysis across ten randomly selected regions demonstrates the model's effectiveness, with a Pearson correlation coefficient of 0.8342 validating its accuracy. This research offers a comprehensive framework for understanding and managing catastrophe risk, providing valuable insights for insurance companies and policymakers to enhance risk management strategies and develop more tailored insurance products. By addressing the multi-dimensional nature of disasters, the model aims to contribute to the resilience of communities and economies against catastrophic events.

Keywords: Catastrophic events, Insurance, Catastrophe Risk Assessment Model, G2-EWM.

1. Introduction

In recent years, the world has witnessed an alarming increase in the frequency and severity of catastrophic events, ranging from natural disasters like hurricanes and earthquakes to man-made crises^[1]. These events pose significant risks to communities, economies, and the environment, highlighting the urgent need for effective risk assessment and management strategies^[2]. The insurance sector, in particular, faces the challenge of accurately evaluating catastrophe risk to ensure financial stability and to offer affordable coverage to property owners^[3]. Traditional risk assessment models often fall short of capturing the complex, multi-dimensional nature of disasters, leading to gaps in risk management and financial planning^[4].

Employing Grey System Theory and the Entropy Weight Method (EWM) as our main analytical tools, this research addresses issues related to incomplete information, which is particularly prevalent in systems analysis and forecasting when data is scarce or incomplete^[5]. Grey System Theory is adept at handling such challenges, while the Entropy Weight Method leverages entropy theory to ascertain the importance of various factors within a comprehensive evaluation. These approaches have been effectively utilized in diverse areas such as environmental science, economic forecasting, risk management, and engineering technology, offering nuanced data analysis and decision-making support to navigate the complexities of uncertain systems^[6].

In this work, we first collected a wide range of data from various sources and defined the theoretical framework for the catastrophe risk assessment model, clarifying three key dimensions: disaster-causing factors, disaster-bearing carriers, and the disaster-prone environment. Then, using the Grey System Theory and the Entropy Weight Method (EWM), we conducted a comprehensive analysis of 11 related indicators aimed at assessing the profitability of insurance companies ($Q_{profitability}$) and the affordability of insurance for property owners ($Q_{affordability}$). Subsequently, through empirical analysis in ten randomly selected regions, we verified the model's effectiveness and applicability.

2. Analytical Strategies for Catastrophe Risk Evaluation

Catastrophe risk is a very ambitious topic and based on our literature review, we choose to model the macroscopic impact of catastrophe risk mainly on property insurance, using mainly two-dimensional data simplifies the model in the modeling process and uses a small amount of three-dimensional data to improve the model accuracy. This study collected the required data from various websites, as shown in Table 1. To avoid the interference of more unknown factors in the model and simplify the complexity of the model, we mainly collected data from the US, considering the small differences in geography and customs within a country.

Table 1: Primary data description and sources

Data Description	Data Source
Catastrophe risk-related indicators	https://ourworldindata.org/natural-disasters https://www.fema.gov/ https://www.usgs.gov/ https://www.emdat.be/
Natural disaster	https://www.undrr.org/ https://earthquake.usgs.gov/
Remaining mentioned data	Various Related Literature

2.1. Indicator Determination

Natural disasters pose a huge risk to property insurance. To improve risk management, reduce loss, and increase insurance benefits, a natural disaster risk assessment method is proposed considering disaster-causing factors, disaster-bearing carriers, and a disaster-pregnant environment. Disaster-causing factors include floods, hurricanes, earthquakes, drought, and other natural disasters involved in property insurance. The disaster-bearing carriers are buildings, PP&E(Property, Plant, and Equipment), means of production, transportation tools, and inventory goods. Disaster-pregnant environment refers to the environmental factors, human factors, and technical factors that affect the probability and severity of structural accidents. Based on the satisfaction criterion, the severity of structural accidents is established. The probability of an accident is evaluated by experts^[7].

Primary indicators are disaster-causing factors, disaster-bearing carriers, and disaster-pregnant environment. The second-level indicators are the factors affecting the first-level indicators, such as the influence of environmental factors and human factors on the disaster-pregnant environment. The specific effects are shown in Figure 1, the catastrophe risk can be mainly divided into disaster-causing factors, disaster-bearing carriers, and disaster-pregnant environment. Therefore, we used these three main aspects as first-level indicators.

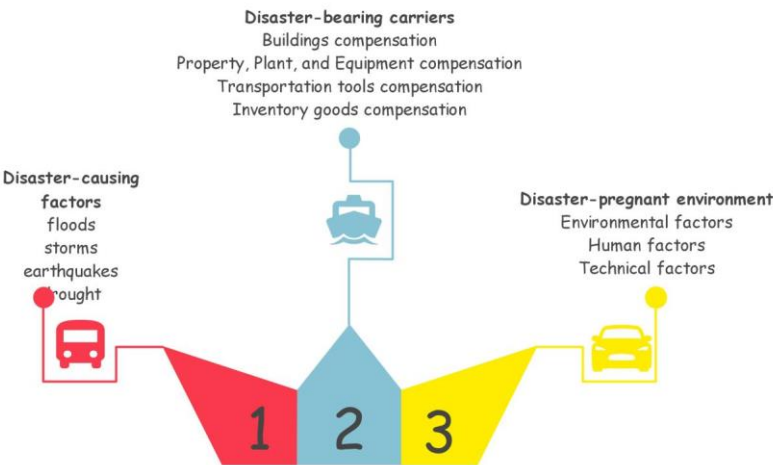


Figure 1: Effects of Catastrophe Risk

For disaster-causing factors, we considered 63 officially relevant indicators in combination with the literature and finally retained the 8 most representative second-level indicators to construct our model. On this basis, we improved our quantitative model by supplementing three secondary indicators related to the disaster-pregnant environment from the ecological components. The specific description and the selected indicators are shown in Table 2.

Table 2: Selected indicators

Object	Indicators	Description
disaster-causing factors (%)	FR	Total economic damages from floods
	SR	Total economic damages from storms
	ER	Total economic damages from earthquakes
	DR	Total economic damages from drought
disaster-bearing carriers	BC	Buildings compensation
	PC	Property, Plant, and Equipment compensation
	TC	Transportation tools compensation
	IC	Inventory goods compensation
disaster-pregnant environment	EF	Environmental factors
	HF	Human factors
	TF	Technical factors

2.2. Weight Calculation

Determining the Weights of Disaster-causing Factors by G2-EWM

(1) Entropy Weight Method(EWM)

In this study, the data for various indicators were standardized and normalized before being weighted using the entropy weight method. Furthermore, we form a vector to obtain the weight and call the vector an "evaluation vector", expressed as $\vec{\Phi}$. The influence of different aspects is obtained by composing a vector, and the vector is called the "influence degree vector" and represented as $\vec{S}$ then the final assessment value:

$$Score_x = \vec{\Phi} \cdot \vec{S}^T = \sum_{i=1}^{Num_x} \phi_i \cdot S_i \quad (1)$$

Among x represents "DCF", "DBC", or "DPE".

(2) G2-EWM Method

Step 1: Selection of the least important indicator under the disaster-causing factors. The expert selects the only index DR that he thinks is the least important from the evaluation index set $\{X_1, X_2, \dots, X_m\}$ under the disaster-causing factors, and records it as X_{jm} . At this time, the evaluation index set is rewritten as $\{X_{j1}, X_{j2}, \dots, X_{jm}\}^{[8]}$.

Step 2: Quantitative characterization of the importance of each index under the disaster-causing factors. Calculate the entropy value $X_{jr}(r = 1, 2, \dots, m)$ of each evaluation index under the disaster-causing factors, and calculate the importance ratio of X_{jr} to X_{jm} with the least important indicator X_{jm} as the only reference:

$$a_r = \begin{cases} e_{jm} / e_{jr}, & e_{jr} < e_{jm}, \\ 1, & e_{jr} \geq e_{jm}, \end{cases} \quad r = 1, 2, \dots, m \quad (2)$$

Step 3: Determine the weight of each indicator under the disaster-causing factors. The weight of the index X_{jr} is:

$$w_r = a_r / \sum_{i=1}^m a_i, \quad r = 1, 2, \dots, m \quad (3)$$

Table 3: The weight of each indicator

Indicators	Entropy of information	a_r	or
FR	0.2846	2.7607	0.3642
SR	0.2840	2.7665	0.3650
ER	0.7459	1.0534	0.1390
DR	0.7857	1.0000	0.1319

Ultimately, as shown in Table 3, our weights of disaster-causing factors are calculated as follows:

$$Score_{DCF} = 0.3642FR + 0.3650SR + 0.1390ER + 0.1319DR \quad (4)$$

Determining the Weights of Disaster-bearing Carriers by GDM

According to previous studies, disaster-bearing factors are related to the probability of risk occurrence(β_1), risk loss rate(β_2), and risk exposure(β_3). In the above dataset, we can obtain a combination of the three parameters of the four disaster-bearing factors^[9].

In each dimension, experts compare the size of each two indicators and rate them resulting in a complementary judgment matrix. By solving the eigenvectors of these matrices, we will get the weights, as shown in Table 4.

$$S_j = \beta_1 \cdot \beta_2 \cdot \beta_3 \quad (5)$$

$$\omega_j = \frac{S_j}{\sum_{j=1}^n S_j} \quad (6)$$

Table 4: Sensitivity index weights

Indicators	β_1	β_2	β_3	S_j	w_j
BC	0.20	0.45	0.37	0.0333	0.4849
PC	0.23	0.24	0.25	0.0138	0.2010
TC	0.44	0.19	0.23	0.0192	0.2800
IC	0.13	0.12	0.15	0.0023	0.0341

$$Score_{DBC} = 0.4849BC + 0.2010PC + 0.2800TC + 0.0341IC \quad (7)$$

Determining the Disaster-pregnant Environment by AHP

We used AHP to determine the weights of the disaster-pregnant environment. First, a paired comparison matrix was established based on the relevant literature and theory. Then, we calculate the maximum eigenvalues of the matrix as well as the corresponding eigenvectors. After that, the weights can be obtained by normalizing the resulting eigenvectors:

$$\omega_i = \frac{\omega'_i}{\sum_{i=1}^n \omega'_i} \quad (8)$$

$$Score_{DPE} = 0.6483EF + 0.1220HF + 0.2297TF \quad (9)$$

A consistency test was performed. Results indicate $CI = 0.001847 < 0.1$. This means that our model is acceptable.

Ultimately, our profitability of insurance companies is calculated as follows:

$$Q_{profitability} = \frac{Score_{PCF} + Score_{DBC} + Score_{DPE}}{3} \quad (10)$$

3. Strategies for Assessing Catastrophic Risks

In short, risk is the uncertainty between investment and return over time to come. The ALARP (as low as possible) standard is a common standard for risk assessment and is still widely used to select acceptable risks and develop a reasonable risk control plan^[10]. ALARP The standard divides the risk into three regions: unacceptable, reasonably acceptable, and widely accepted, as shown in Figure 2 (a).



Figure 2: Schematic diagram of the risk assessment criteria. (a) ALARP criterion. (b) Cost-Risk Curve

As insurers change the way and where they are willing to write insurance, property insurance is not only becoming more expensive but also harder to find. Assuming that future socioeconomic development will bring about human, social, and ecological progress, we believe that the risk of property insurance comes from the mutual relationship between the profitability of insurance companies and the affordability of property owners.

Property insurance contributes to the economic level and development of a region to some extent, so property insurance plays a positive role in the economy, and we use the regional "per capita GDP" (PCG) to measure the affordability of property owners.

$$Q_{affordability} = PCG \quad (11)$$

We have tentatively defined the risk factor Ω :

$$\Omega = \frac{Q_{affordability}}{Q_{profitability}} \quad (12)$$

Considering that the risk needs to be combined with the prediction and judgment about the future, we defined the risk assessment period as one year. As it is difficult for human and biological beings to change in the short term, the negative effects, mainly the ecological environmental indicators change during the evaluation period, and the change of environmental indicators drives the change of positive impact.

Combined with the above analysis to correct the definition of Ω , we obtain the Ω :

$$\Omega = \frac{Q_{affordability} \cdot (1 + C_{negative})}{Q_{profitability} \cdot (1 + C_{positive})} \quad (13)$$

Among them, the degree of variation of the ecological environment indicators $C_{negative}$ we assumed to meet the normal distribution, while the variation of $C_{positive}$ was more stable. Thus, the actual definition of risk factors is:

$$\Omega = \frac{Q_{affordability} \cdot \left(1 + \frac{e^{\frac{(C_{positive} - \mu)^2}{2\sigma^2}}}{\sqrt{2\pi}\sigma} \right)}{Q_{profitability} \cdot (1 + C_{positive})} \quad (14)$$

Where μ is the expectation of $C_{positive}$, and σ^2 is the variance of $C_{positive}$.

4. Validation of Catastrophe Risk Models

We randomly selected 10 regions, normalized the natural disasters with negative effects, visualized the line diagram shown in Figure 3, and calculated the Pearson correlation coefficient of the two values, the correlation coefficient is 0.8342, higher than 0.8, indicating that the correlation between the two data is very strong, indicating that our model can effectively measure the influence of natural disasters to a greater extent.

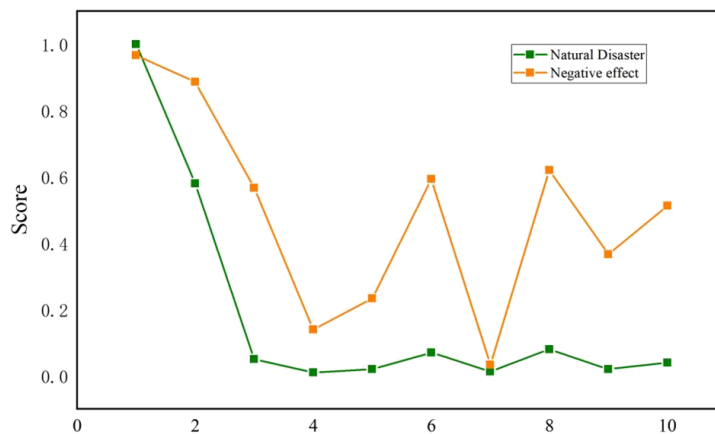


Figure 3: Model validation data

Combined with the risk assessment criteria ALARP and the risk factor Ω , we obtained the following risk assessment criteria^[10]:

$$\Omega = \begin{cases} 0 \sim 0.3 & \text{Broad Acceptable Risk} \\ 0.3 \sim 0.8 & \text{Reasonable Acceptable Risk} \\ > 0.8 & \text{Unacceptable Risk} \end{cases} \quad (15)$$

Two regions are particularly vulnerable to extreme weather events on different continents. The southeastern United States, is often threatened by hurricanes, tornadoes, and floods, weather disasters that pose a significant risk of property damage to residents and businesses. Another example is Bangladesh and the Ganges Delta in Asia, where the annual monsoon season causes severe flooding and extensive damage to farmland, villages, and infrastructure. In both areas, the need for property insurance is particularly important because effective insurance strategies can help reduce the economic burden of disasters and help communities recover and rebuild more quickly.

We selected the southeastern US and Bangladesh as the main study subjects, taking one site in each of the two different regions, and the two different types of sites are shown in Table 5.

Table 5: Information on the Selected Location

Type	Location	Land Area
North America	Florida	170400
Asia	Bangladesh	147570

Applying the CRA model to these two sites, combined with the risk factor Ω . The values of the three aspects of catastrophe risk evaluation are shown in Figure 4.

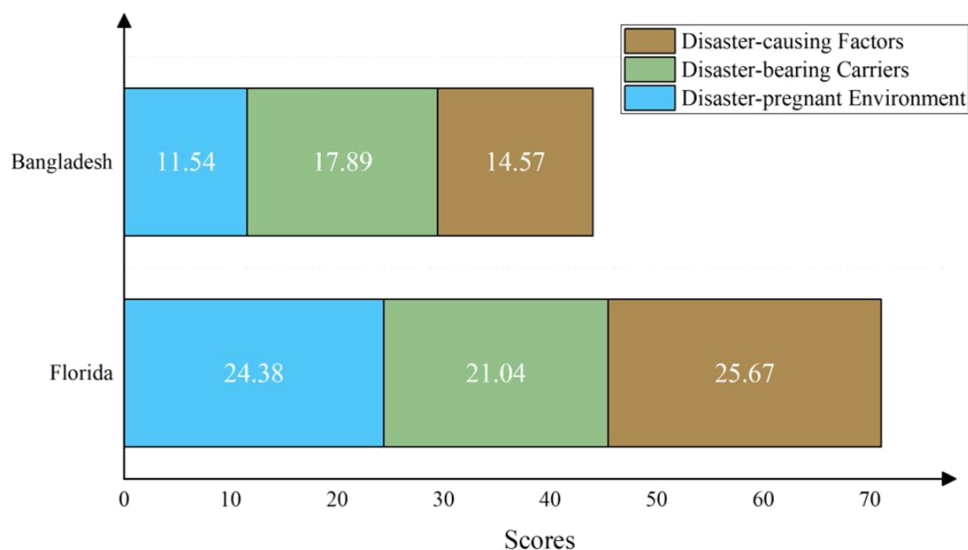


Figure 4: Results of the CRA application

Herein, we can intuitively see that the level of disaster-causing factors in the two regions is not much different. Our analysis shows that natural disasters in both sites are severe and the economic loss of natural disasters to property insurance is huge. When comparing the severity of property damage between different regions or countries, the differences in their risk occurrence probability, risk loss rate, and risk exposure should be taken into account. In conclusion, Bangladesh may face a greater risk of property loss due to the differences in the economic base, industrial structure, and infrastructure. Florida and Bangladesh all face certain disaster risks in terms of environmental, human, and technological factors. While Florida has advantages in some ways, it cannot ignore the risk of disasters. Bangladesh, on the other hand, needs to strengthen its efforts in early warning systems and infrastructure construction to reduce disaster risk.

5. Conclusions

In conclusion, this study has developed and validated a comprehensive Catastrophe Risk Assessment Model, leveraging a multi-dimensional approach that encompasses disaster-causing factors, disaster-bearing carriers, and the disaster-pregnant environment. Through the application of the G2-EWM method to analyze 11 critical indicators, our findings not only quantify the financial impact of natural disasters on property insurance but also offer insights into the differential resilience capacities across regions. The empirical analysis, substantiated by a Pearson correlation coefficient of 0.8342, underscores the robustness of our model in forecasting risk exposure and insurance implications.

In light of these findings, we advocate for policymakers, insurance companies, and stakeholders to integrate the insights from our Catastrophe Risk Assessment Model into their strategic planning and risk mitigation efforts. By doing so, they can better anticipate potential losses, enhance affordability and profitability metrics for property insurance, and ultimately reduce the economic and human toll of natural disasters.

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