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Extreme weather insurance underwriting decision model based on break-even theory and Monte Carlo algorithm

Yongmao Li[1,a,#], Shuchang Wang[2,b,#], Xiaowen Liang[3,c], Guorui Zhao[2,d,*]

[1]*School of Materials Science and Engineering, Guangdong Ocean University (Yangjiang Campus), Yangjiang City, China*
[2]*School of Computer Science and Engineering, Guangdong Ocean University (Yangjiang Campus), Yangjiang City, China*
[3]*Business School, Guangdong Ocean University (Yangjiang Campus), Yangjiang City, China*
[a]*silica_200@foxmail.com*, [b]*ayratswa408700@foxmail.com*, [c]*Catherine.L08@outlook.com*, [d]*zhaoguoruimath@foxmail.com*
[#]*Co-first author*
[*]*Corresponding author*

Abstract: *Extreme weather events such as floods, hurricanes, and wildfires are increasingly impacting the world, thereby driving reforms in the property insurance industry. This paper addresses the challenge of making insurance underwriting decisions in the context of extreme weather. To this end, the Monte Carlo algorithm was employed to optimize the risk assessment method for individual natural disasters, while the Loss-Cost Ratio (LCR) method was integrated to construct a comprehensive risk assessment model (ARA). An insurance underwriting strategy tailored to varying risk levels was developed by incorporating the break-even model. A representative sample of 722 regions worldwide was analyzed. The Monte Carlo algorithm was applied to optimize the risk index for each locality under extreme weather conditions. Likewise, using the LCR method and break-even theory, the long-term profitability of insurance companies was evaluated. The findings indicate that when the number of policies increases or the claim rate decreases, profitability remains favorable, suggesting that underwriting remains feasible despite the rising risks posed by extreme weather events. Finally, the decision model was applied to Henan Province and New York City for validation, demonstrating results that align closely with real-world data.*

Keywords: *Property insurance, extreme weather, risk assessment, Monte Carlo algorithm*

1. Introduction

Extreme weather refers to rare weather phenomena that have profoundly destructive impacts on human societies and ecosystems. In recent years, the intensification of the greenhouse effect has significantly increased the frequency and severity of extreme weather events worldwide, leading to substantial economic losses for property owners and insurance companies. According to statistics, over 1,000 extreme weather events globally have caused fiscal losses exceeding $1 trillion [1]. For instance, Hurricane Andrew resulted in $20 billion in damages in 1992, while natural disasters in 2004 incurred insurance payouts totaling $35 billion. Consequently, establishing a robust risk assessment and management strategy has become a critical priority for the insurance industry.

Reviewing literature shows that many studies have used traditional statistical methods, like extreme value theory [2] and ARIMA models, to assess extreme weather risks. These methods, however, require strict data distribution and quality, which are often lacking in practice. This limits their effectiveness in providing comprehensive risk assessments and developing effective strategies. In contrast, the Monte Carlo algorithm provides a novel approach through stochastic simulation, avoiding the rigid data requirements of traditional methods. Still, it faces challenges in addressing the complexities of underwriting decision-making due to its limited consideration of underlying mechanisms.

To address problems, this paper integrates the Monte Carlo algorithm and LCR method to construct an ARA model. It also incorporates a break-even model to propose insurance underwriting strategies based on actual losses, costs, and profit factors for different risk scenarios. The contributions are: First,

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the innovative application of the Monte Carlo algorithm to insurance underwriting overcomes data scarcity issues in traditional methods. Second, the blend of LCR and break-even theory identifies high-risk, high-return characteristics under extreme weather, providing new insights into insurers' sustainable strategies.

2. Review of relevant literature

Currently, extensive research has been conducted on the impact of extreme weather on the insurance industry, with a primary focus on premium rate setting, underwriting strategy development, and risk assessment. For instance, Han Sinan [3] employed extreme value theory to determine agricultural insurance rates; Zhu Jiayi [4] and colleagues proposed an optimization model to balance risk and return; Deng Haoqian [5] and collaborators developed a novel insurance model tailored to the needs of different hazards; and Hudson [6] and co-authors explored strategies to enhance resilience to extreme weather events by incorporating practical experience.

Nevertheless, research on underwriting decisions by insurance companies in the context of complex extreme weather scenarios remains insufficient. Moreover, most existing studies rely heavily on statistical methods or mathematical models for risk assessment and decision-making. Among the specific techniques, Chen Dihong [7] et al. optimized underwriting strategies using the TVaR method; Zhou Yunzhi [8] et al. applied LSTM and random forest models to predict risk indicators; Wang Yukai [9] et al. developed a robust risk assessment model based on the ARIMA-KMEANS algorithm; and Guo Meijia [10] et al. integrated the PCA-AHP algorithm with the ARIMA model to evaluate underwriting risk. While these studies offer valuable theoretical support, several limitations persist. First, the models are relatively complex. Although advanced algorithms improve accuracy, they significantly increase the difficulty of data processing. Second, the methods lack dynamic adaptability, making it difficult to capture changes in disaster frequency and severity over time. Third, the analysis is often narrow, with most studies focusing only on specific events such as floods [3] or hurricanes [7], and limited consideration of multiple extreme weather events, which restricts their broader applicability.

This paper presents a risk assessment model (ARA) that merges the Monte Carlo algorithm with the loss-cost ratio method and integrates the break-even theory. It improves model flexibility and accuracy by including multi-dimensional risk factors, aiding insurers in making scientific underwriting decisions amidst complex extreme weather conditions.

3. Our work

To visually illustrate the research framework of this paper, an overall flow chart (see Figure 1) is provided, enabling readers to systematically and clearly understand the research content.

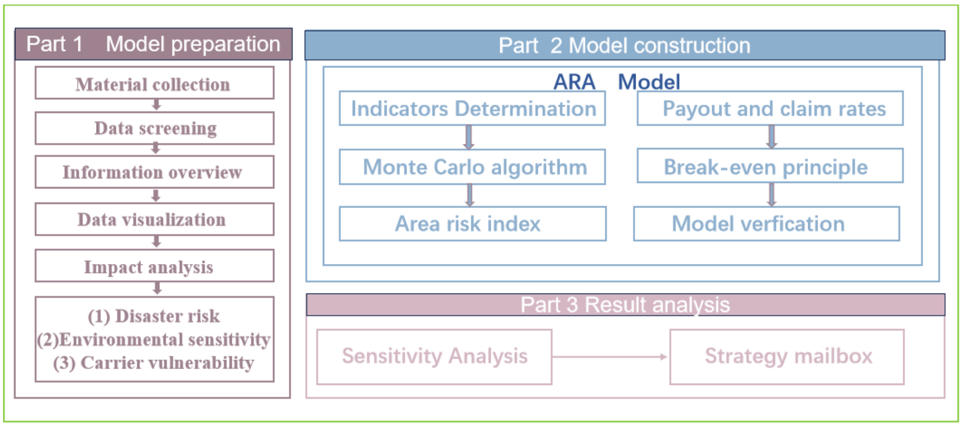

Figure 1: Flow Chart of Our Work

4. Indicator system construction and data description

4.1 Indicator system construction for extreme weather risk assessment

This paper constructs a benchmark index system for extreme weather risk assessment by integrating

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literature with background knowledge of such risks as shown in Figure 2. The system includes two indicators that reflect the causes of disasters: probability of occurrence and intensity of events, which represent the likelihood and impact of extreme weather, respectively. In assessing environmental vulnerability and resilience, the indicators cover the number of regional disaster prevention measures and the disaster prevention Capacity index, which reflects the vulnerability and response capacity of the region. The vulnerability of carriers is assessed using a vulnerability index, which reflects the sensitivity of economic and social systems to disasters.

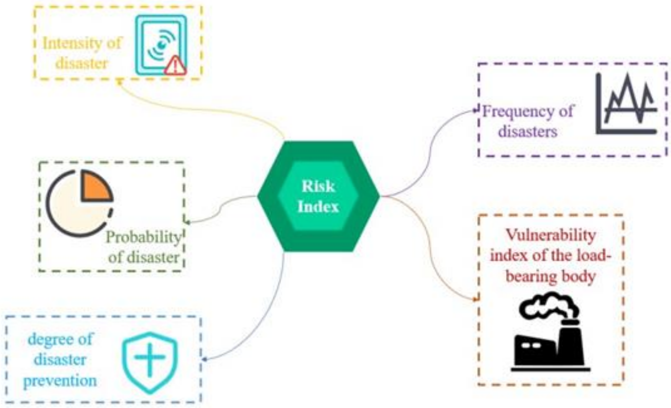

Figure 2: Chart of the risk index indicator system

4.2 Data description for extreme weather risk assessment

In this paper, to facilitate the empirical study, the data were preconditioned as follows: firstly, the missing values of the probability, intensity, and number of occurrences of extreme weather events were filled into zero. Second, the data collected for the five indicators were processed with 3δ outliers to eliminate invalid data. The data comes from official authoritative websites, as shown in Table 1.

Table 1: Main date description and source

Data description	Data source
Indicators related to area risk assessment	https://ourworldindata.org/
	https://www.emdat.be/
	https://data.worldbank.org.cn/
	https://www.stats.gov.cn/sj/ndsj/
	https://www.census.gov/
	https://clima.cbe.berkeley.edu/
Resilience to disasters	https://www.mohurd.gov.cn/
	https://www.archdaily.com/
Remaining Mentioned Data	Various Related Literature

5. Introduction to the research methodology and modeling

5.1 Construction of a composite risk index

In the mid-20th century, as research on natural hazards advanced, scholars began focusing on risk assessments for individual types of natural hazards. These methods remain widely applied in disaster risk analysis to this day. Based on a review of the literature [11][12], this paper develops a regional disaster risk assessment index, with its f-value calculated as follows:

$$f = Y \times Y_X \times (1 - Z_X) \times P_X \times (1 + \sigma) \times C_v \tag{1}$$

Where f is the risk value of different extreme weather conditions, Y is the number of extreme weather occurrences, and Y_x is the intensity of the disaster. Z_X is the degree of disaster preparedness, defined as the amount of disaster damage as a proportion of GDP. P_X is the probability of occurrence of the disaster, and σ is the coefficient of variation. C_v is the vulnerability index of the disaster-bearing body, which is defined according to the literature and consists of the V_a, V_b, V_c.

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$$V_{ai} = 0.1 \times 0.9 + \frac{min(A_i - A_1, A_2, A_3 \cdots A_{722})}{max(A_1, A_2, A_3 \cdots A_{722}) - min(A_1, A_1, A_1 \cdots A_{722})} \tag{2}$$

Where i represents the 722 regions selected globally, V_a denotes the potential vulnerability due to population density, V_b signifies the built-up area per unit area, and V_b can be calculated using Equation 2. Additionally, the potential susceptibility of land-per-capita GDP, denoted as V_c, can be determined as follows:

$$V_{ci} = 1 - 0.9 \times \frac{min(C_i - C_1, C_2, C_3 \cdots C_{722})}{max(C_1, C_2, C_3 \cdots C_{722}) - min(C_1, C_1, C_1 \cdots C_{722})} \tag{3}$$

Final C_v is defined as follows:

$$C_v = 0.295V_a + 0.357V_b + 0.348V_c \tag{4}$$

Firstly, this paper examines key factors in extreme weather risk assessment and simplifies theoretical models to reduce complexity and uncertainty, enhancing their explanatory power. The simplified regional disaster risk index function is given by $\sigma = 0$.

$$f = Y \times C_v \times Y_X \times (1 - Z_X) \times P_X \tag{5}$$

Finally, this paper considers the diversity of extreme weather occurrences and the global characteristics of disaster risks. It assigns weights to and averages the risks of different hazards to derive the following composite disaster risk values for the region:

$$f = \frac{f_1 + f_2 + f_3 + \cdots f_n}{n} \tag{6}$$

5.2 Prediction of composite disaster risk values - Monte Carlo algorithm

This paper's Monte Carlo algorithm aims to predict disaster risks for the next year by considering the randomness of extreme weather and the likelihood of regional disasters. As shown in Figure 3, It optimizes the assessment index for regional disaster risk. The specific research ideas and calculation steps are as follows.

The principle of the Monte Carlo algorithm [13] is to use random numbers to solve deterministic problems. By sampling a large number of random numbers, we can obtain an approximate solution to the problem. The Monte Carlo algorithm usually consists of the following four steps:

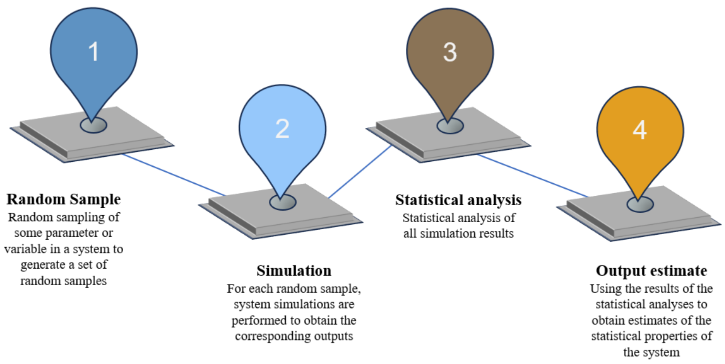

Figure 3: Monte Carlo algorithm flowchart

First, historical data on regional disasters and climate factors is collected to select the most suitable probability model. Then, the Monte Carlo algorithm is used to conduct simulations, refining the estimation results to closely match the actual probability of regional disasters P as follows.

$$P(Disasters\ occur) \approx \frac{1}{N} \sum_{i=1}^{N} I(x_i) \tag{7}$$

Where N is the total number of random samples and $I(x_i)$ is an indicator function to determine whether a disaster occurred in the i random sample. By summing and normalizing the results of all random samples, if a disaster occurs, then $I(x_i) = 1$; otherwise $I(x_i) = 0$.

Next, the prediction of the number of occurrences is carried out for different extreme weather

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events. The number of occurrences of extreme weather events in the region is estimated by weighting the disaster intensity of each simulation result. Here, N is the number of simulations conducted. And fx_i is the result of calculating the extreme weather disaster intensity for the i random sample as follows.

$$Y(Intensity\ of\ disaster) \approx \frac{1}{N}\sum_{i=1}^{N} f(x_i) \tag{8}$$

Finally, the confidence interval for the number of disasters, designated as $(A-B)$, indicates a $(A-B)$ % probability that future disasters will fall within this range.

Using the Monte Carlo algorithm to predict the vulnerability index, disaster preparedness, and disaster intensities allows for estimating the region's vulnerability to extreme weather in the upcoming year. These parameters can then calculate the disaster risk value for the new year, denoted as f_{n+1}. The growth rate of the regional disaster risk index can be expressed as follows:

$$q_n = \frac{f_{n+1}-f_n}{f_n} \tag{9}$$

5.3 Calculation of pure rates - loss-cost rates

In light of rising natural disaster risks, this paper examines the conditions under which insurers should make underwriting decisions. From an economic standpoint and in line with profitability goals, underwriting profit is the key indicator to assess whether an insurer should cover a specific region or type of risk. Using the Loss-Cost Ratio (LCR) [14] and extensive business data, the pure premium rate for a given area can be calculated as follows:

$$\pi^{n+1} = E[\frac{\tilde{L}}{\tilde{C}}] = \frac{1}{n}\sum_{i=1}^{n} \frac{L_i}{C_j} \tag{10}$$

The formula calculates a pure rate without accounting for extreme weather risk. Given the rising risk of such events, this traditional method is outdated. This paper updates the pure rate for a region by incorporating an extreme weather risk factor using the Monte Carlo algorithm, resulting in a corrected pure rate formula.

$$\backslash\pi^{n+1} = E[\frac{\tilde{L}}{\tilde{C}}] = \frac{1}{n}\sum_{i=1}^{n} \frac{L_i}{C_j} * (1+q_n) \tag{11}$$

Where q is the regional risk index growth rate in year n. Meanwhile, the premium growth rate of approximately 4.06 percent was calculated using the Swedish Reinsurance Company's premium rate for 2023 as a proxy for the formula below:

$$G = \pi \times (1+0.0406) + b \tag{12}$$

It follows that the risk index growth rate q indirectly affects total premiums and rate growth by affecting pure rates.

5.4 Construction of the break-even decision-making model

The break-even point [15] is a key metric in insurance for evaluating underwriting feasibility. It helps insurers determine the policy volume needed for profitability, considering factors like coverage, claim rates, and premiums to make informed decisions.

First, the formula for calculating the claim rate for the new year based on the revised net rate is as follows:

$$e = \frac{L}{M} = \frac{L}{\pi \times C} \tag{13}$$

Next, the following formula was created by balancing the number of policies against each factor:

$$G = b + M \times n \tag{14}$$

$$\tilde{L} = e \times n \times u \times N \tag{15}$$

$$r = G - \tilde{L} \tag{16}$$

$$e = \frac{L}{M} \tag{17}$$

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To consider the time value of money, this paper uses the present value formula:

$$S = E \times \frac{1}{(1+i)^n} \tag{18}$$

Table 2: Symbol Descriptions

Symbol	Meaning	Symbol	Meaning
$\tilde{L}$	*Total Benefit Amount*	$\tilde{C}$	*Total Insurance Amount*
G	*Total Premium*	π	*Pure Rate*
L	*Claim Amount*	e	*Claims ratio*
M	*Premium*	u	*Average claim amount*
C	*Insurance Amount*	N	*Single payment*
n	*Number of Policies*	r	*Profit*
S	*Principal*	E	*Principal interest*
i	*Interest Rate*	b	*Fixed cost*

Finally, by fixing the insurance amount, the paper calculates the claim rate for the new year and assesses the equilibrium point between policies and the claim rate through break-even analysis (see Table 2 for symbol descriptions). By adjusting the number of policies or claim rates while holding other factors constant, the paper predicts profitability. Specifically, an increase in policies or a decrease in claim rates, with other factors constant, indicates that the region can maintain underwriting profitability despite rising extreme weather risks.

6. Analysis of empirical results

6.1 Case study—based on Henan Province and Los Angeles.

The United States and China, each prone to frequent extreme weather events, were selected as case studies due to their large populations and diverse climates. The paper begins with a macro analysis using global data, then focuses on New York City and Henan Province to assess disaster risk through the proposed insurance decision-making model. Data collection included local comparisons and analysis of regional conditions. For example, the paper uses the Monte Carlo algorithm to predict the probability and frequency of diverse extreme weather events for the coming year, followed by analysis based on the simulation results. See Table 3 for the results.

Table 3: Forecast of risk index of two regions in 2025

Los Angeles	**Frequency**	**Average disaster intensity**	**Probability**	Z_{Xi}	**Exposures**
Droughts	0.490	1	0.389	0.039	0.183
Cyclones	4.940	2	0.992	0.016	9.644
Wildfires	7.740	3	0.938	0.110	6.865
Thundering	15.160	5	1.000	0.521	36.273
⋮					
Floods	5.630	1	0.489	0.010	0.305
Henan	**Frequency**	**Average disaster intensity**	**Probability**	Z_{Xi}	**Exposures**
Heatwaves	10.620	2	0.721	0.017	0.604
Floods	7.730	3	1.000	0.104	20.766
Wildfires	0.180	1	0.158	0.140	0.073
Thundering	8.370	1	1.000	0.017	8.222
⋮					
Cyclones	0.380	1	0.311	0.014	0.116

Finally, by fixing the amount of insurance, the paper can calculate the claim rate for the new year and assess the equilibrium point between the number of policies and the claim rate through a break-even analysis. The index results are shown in Table 4. If you set a certain number of policies or change in claim rates and hold other factors constant, you can predict profit realization. Specifically, when the number of policies increases or the claim rate decreases, all other factors are equal. This

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implies that the region can sustain underwriting profitability amid increasing extreme weather risks.

Table 4: Display the calculation results of each index

Region	Los Angeles	Henan
V_a	0.134768	0.017480
V_b	0.100185	0.104099
V_c	0.761570	0.142031
C_v	0.342352	0.017106
Z_X	0.696300	0.058500
f	10.65400	5.956260
q_{2023}	0.015778	0.014247
π	0.146261	0.098532
e	0.264057	0.166202

6.2 Case evaluation results - based on break-even decision model

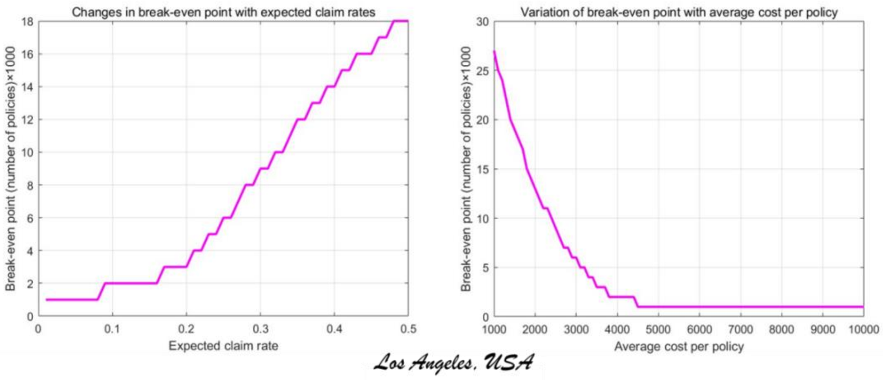

Figure 4: Break-even map of Los Angeles, USA

The expected claim rate, policy costs, and profit-loss analysis for Los Angeles are presented in Figure 4. The average claim amount was $78,320, the interest rate was 4.2%, the average premium per policy was $1,544, and the fixed cost per contract was $466. Based on this, the following conclusions can be drawn:

As shown in the left chart, an increase in the expected claim rate significantly raises the number of policies required to break even. For example, at a claim rate of 0.2645, an insurer must write 4,912 policies to break even. If the claim rate remains stable, exceeding the equilibrium point allows the insurer to achieve profitability by adjusting premiums. The right chart shows that rising average policy costs gradually reduce the number of policies needed to break even. When expenses exceed $4,506, the required number of policies approaches zero. While higher costs can yield greater returns, they also elevate risks, potentially compromising insurer stability. Therefore, managing costs is critical in pricing strategy.

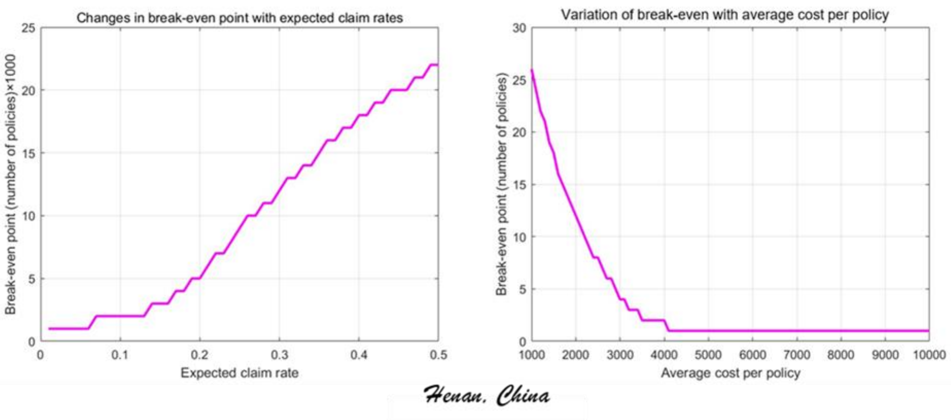

Figure 5: Break-even map of Henan Province, China

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When the insurance company developed the Henan insurance plan, the average claim amount was 6,825 yuan, the interest rate was 3.9%, the average premium per policy was 1,203 yuan, and the fixed cost per policy was 646 yuan(see Figure 5). Based on this, the following conclusions can be made:

As shown in the left chart, the number of policies required to break even increases with the claim rate. Higher claim rates demand more policies to achieve profitability. At low claim rates, the break-even point rises gradually, but once a threshold is reached, it increases sharply, reflecting an accelerated risk accumulation. As seen in the chart on the right, the increase in the average policy cost has caused a gradual reduction in the number of policies required to break even. When the cost exceeds \$4,500, the number of policies needed to break even approaches zero. This implies that while high costs may yield higher returns, they also substantially increase the risk of loss. Therefore, insurance companies must carefully balance costs and benefits based on specific circumstances to ensure sustained profitability.

7. Sensitivity and robustness analysis

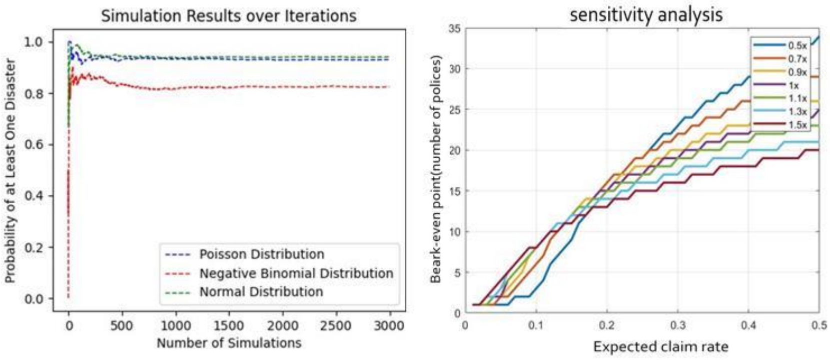

Figure 6: Sensitivity analysis of Monte Carlo model and break-even theory

The sensitivity analysis of the ARA model was conducted using the Monte Carlo algorithm to calculate the risk index, simulating the extreme weather occurrence process with a Poisson distribution to introduce randomness and volatility. To test the model's stability and sensitivity to different factors, we replaced the random number distribution with negative binomial and normal distributions. As shown in Figure 6, changes in the random number distribution have minimal impact on the overall extreme weather probability, with fluctuations staying within an acceptable range, consistent with actual conditions. This indicates that the ARA model is stable across different distribution scenarios and accurately quantifies extreme weather risks, providing a solid foundation for future risk assessments.

Additionally, sensitivity tests were performed on the break-even model to assess its responsiveness to parameter changes. By adjusting the expected claim rate and sensitivity factor, the break-even point was recalculated. The results demonstrate that regardless of changes in the expected claim rate or sensitivity factor, the trend of the break-even point remains consistent with the original situation, with fluctuations staying within acceptable error ranges. This indicates that the break-even model is stable and can effectively address the decision-making challenges faced by insurance companies.

8. Conclusion

In this paper, the ARA model is used to quantify the risk of extreme weather, and the break-even point is analyzed to provide a foundation for pricing and claim rate-setting in insurance. The findings are as follows: First, the ARA model quantifies extreme weather risk factors Precisely and produces visually distinct results. The evaluation indices are well-supported by literature, ensuring scientific rigor and reliability. Second, the model predicts that by 2025, due to precipitation instability caused by climate change, Los Angeles will experience a significant increase in wildfires, which may lead to severe flooding and landslides, amplifying flood risks. Third, the model can simulate extreme weather risks across different regions, and adding indicators can improve its predictive accuracy, showcasing its adaptability. Finally, sensitivity analysis shows that the model remains stable despite changes in the risk index, claim rate, or sensitivity coefficient, demonstrating strong applicability.

Based on these conclusions, the following recommendations are made: First, regarding model improvement, the current assumption of zero variation coefficient may introduce bias, so future studies should refine this assumption for better accuracy. Additionally, government intervention, which significantly affects disaster losses, should be included in the model for more accurate results. Second, insurance companies should use the ARA model to quantify extreme weather risks and optimize pricing and claim rates. In high-risk regions, underwriting strategies should be dynamically adjusted based on the risk index to reduce potential losses. The model index system should be enhanced by incorporating multidimensional data, such as government intervention and climate change trends, to improve adaptability. These recommendations show that the ARA model is an effective tool for analyzing extreme weather risks and supporting decision-making in the insurance industry, enabling better management of future risks and contributing to the sustainable development of the industry and the broader economy.

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