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DYNAMIC RISK ASSESSMENT IN THE INSURANCE INDUSTRY BASED ON A HIGH-RISK UNDERWRITING DECISION MODEL

BinHao Guo, ShuJie Shi*, GuoLiang Wen, XingPeng Zhuo
School of Electronic Countermeasures, National University of Defense Technology, Hefei 230000, Anhui, China.
Corresponding Author: ShuJie Shi, Email: 17730001109@163.com

Abstract: With the increasing frequency of extreme weather events, dynamic risk assessment has emerged as a crucial research topic for the sustainable development of the insurance industry. To address the underwriting decision-making challenges faced by insurers in high-risk areas, this study develops a risk assessment model that integrates historical data to predict property loss ratios in such regions for the coming year. By considering the perspectives of both insurers and policyholders, we propose a utility value model that evaluates the utility values of risk-free and risk-exposed properties separately. This framework derives the conditions for insurance underwriting and identifies a reasonable range for premium rates, thereby determining the optimal underwriting strategy for insurers. Finally, the model is applied to two regions in China—Fujian and Guizhou—for validation. Simulation results demonstrate that the proposed model exhibits high predictive accuracy and sensitivity in risk assessment, confirming the feasibility of the proposed underwriting strategy.
Keywords: Extreme weather; Insurance industry; Risk assessment; Grey time series prediction; Utility value

1 INTRODUCTION

In recent years, the frequent occurrence of extreme weather events and their associated economic losses have become a global concern. Ben J. Clarke et al. highlighted that global losses caused by extreme weather events over the past decade have exceeded $1 trillion, encompassing thousands of natural disasters, including floods, hurricanes, tornadoes, droughts, and wildfires [1]. According to the IPCC, the frequency and intensity of such events are likely to escalate further due to climate change [2].

Multiple studies indicate that extreme weather events not only cause significant damage to personal property but also pose unprecedented challenges to the insurance industry. The increasing frequency of these events has directly led to a surge in insurance claims. For instance, in 2022, the insurance industry's payout for natural disasters was 115% higher than the 30-year average [3]. This trend is projected to continue until 2040, with premium prices expected to rise by 30%–60% over the next two decades [4]. Peter Zweifel noted that such rapid premium increases not only make insurance more expensive but also reduce its accessibility in many regions [5]. Many insurers are adjusting their underwriting strategies by limiting coverage in high-risk areas, further exacerbating market tensions. Research by Ganesan and Reva reveals that the global insurance protection gap averages 57%, and this figure continues to rise [6]. This gap signifies that a substantial portion of properties damaged by extreme weather events lack adequate insurance coverage, threatening insurers' profitability and exposing property owners to significant financial risks [7].

Academic interest in this phenomenon is growing, with existing literature exploring the causes and mitigation strategies from multiple perspectives. For example, Peterson et al. argued that climate change is redefining the risk landscape of the insurance industry, rendering traditional actuarial models inadequate for accurately predicting the frequency and impact of extreme weather events [8]. Chloe H. Lucas et al. reviewed 175 studies on extreme weather and household insurance, emphasizing that flood insurance dominates current research and calling for expanded focus on storms and wildfires [9]. Additionally, Smith and Johnson examined the potential impacts of extreme weather on the sustainable development of the insurance industry, proposing novel risk-sharing mechanisms to address future uncertainties [10]. Tian-Zhen Hua et al. advocated for leveraging fiscal policies to amplify support and establish agricultural insurance mechanisms under extreme weather conditions [11]. Yang-Xiao Tong summarized strategies for building robust catastrophe insurance systems and multi-layered risk protection frameworks to enhance the "stabilizing role" of catastrophe insurance [12].

However, traditional insurance models rely on static risk assessments, failing to account for the dynamic impacts of climate change. This shortcoming has led insurers to reduce coverage in extreme weather-prone regions due to mounting underwriting pressures, aggravating market failures in high-risk areas. Consequently, insurers urgently need to enhance their risk assessment and prediction capabilities to make informed underwriting decisions. This study establishes a high-risk underwriting decision model that combines historical data to forecast risk parameters, evaluates underwriting conditions in extreme weather-prone regions through utility value analysis, and identifies optimal underwriting strategies to balance the insurer's need for profit maximization and risk minimization. Finally, the model is validated through case studies in Fujian and Guizhou provinces, China.

2 HIGH-RISK UNDERWRITING DECISION MODEL

Insurance companies face a contradiction between underwriting risks and profitability: Generally, refusing to underwrite catastrophe policies may lead to insufficient profits and potential bankruptcy, while underwriting excessively risky policies could result in substantial claim payouts that exceed revenues. Therefore, this paper first establishes a risk assessment model to predict risk scenarios and then constructs a utility value model to determine underwriting decision conditions in regions prone to extreme weather events.

2.1 Risk Assessment Model

Using historical data on the frequency of extreme weather events, direct economic losses, and Gross Regional Product in a specific area over recent years, the annual economic loss rate caused by a specific extreme weather event is calculated. The grey prediction model GM(1,1) is employed to forecast the economic loss rate for the next year, thereby quantifying the underwriting risk of the policy.

The damage rate time series $X^{(0)}$ contains four observed values:

$$X^{(0)} = \left\{ X^{(0)}(1), X^{(0)}(2), X^{(0)}(3), X^{(0)}(4) \right\} \tag{1}$$

By accumulating the original data to reduce volatility and randomness in the damage rate sequence, a new sequence is generated:

$$X^{(1)} = \left\{ X^{(1)}(1), X^{(1)}(2), X^{(1)}(3), X^{(1)}(4) \right\} \tag{2}$$

where,

$$X^{(1)}(t) = \sum_{k=1}^{t} X^{(0)}(k) \tag{3}$$

A first-order linear differential equation for the GM(1,1) model is established for $X^{(1)}(t)$:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = \mu \tag{4}$$

Here, a is the development coefficient, and μ is the grey action quantity.

Let $\hat{\alpha}$ denote the parameter vector to be estimated. Construct the mean generation matrix B and constant term vector Y for the accumulated data:

$$\begin{cases} \hat{\alpha} = (\dfrac{a}{\mu}) \\ B = \begin{bmatrix} 0.5\left(X^{(1)}(1) + X^{(1)}(2)\right) \\ 0.5\left(X^{(1)}(2) + X^{(1)}(3)\right) \\ 0.5\left(X^{(1)}(3) + X^{(1)}(4)\right) \end{bmatrix} \\ Y_n = \left(X^{(1)}(2), X^{(1)}(3), X^{(1)}(4)\right)^T \end{cases} \tag{5}$$

Using the least squares method, solve for the parameter vector $\hat{\alpha}$:

$$\hat{\alpha} = (B^T B)^{-1} B^T Y_n \tag{6}$$

Substituting $\hat{\alpha}$ into the differential equation yields the predicted time sequence:

$$\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{\mu}{a} \right] e^{-ak} + \frac{\mu}{a} \quad \left(k = 0, 1, 2, \cdots, n \right) \tag{7}$$

Discretize the predicted sequence $\hat{X}^{(1)}(k)$, and subtract $\hat{X}^{(1)}(k+1)$ from $\hat{X}^{(1)}(k)$ to restore the predicted sequence for $X^{(0)}(k)$:

$$\hat{X}^{(0)}(k+1) = \hat{X}^{(1)}(k+1) - \hat{X}^{(1)}(k) \tag{8}$$

2.2 Utility Value Model

2.2.1 Economic principles

From the client's perspective, failure to purchase insurance exposes their future personal assets to potential risks and losses, termed "risky assets". However, by obtaining insurance coverage with full compensation provisions, their future assets become fixed-value and risk-free, thus classified as "risk-free assets".

Conversely, for insurance companies, underwriting policies introduces probabilistic losses to their future corporate assets, making them "risky assets", whereas declining coverage maintains fixed-value future assets without risk exposure, hence making them "risk-free assets".

In practice, individuals do not make straightforward comparisons between risky and risk-free assets but exhibit a preference for risk-free options. Consequently, decision-making requires the conversion of actual asset values into utility-based measurements for proper evaluation.

2.2.2 Client perspective

Assume a client's protected asset is E_1, potential loss is X, and the premium paid is Y. Define the client's risky asset utility rate l_1 and risk-free asset utility rate k_1. The subjective value of assets is determined by:

$$\begin{cases} E_{Y1} = k_1\left(E_1 - Y\right) \\ E_{N1} = l_1\left(E_1 - X\right) \end{cases} \tag{9}$$

where E_{Y1} is the subjective value of the client's assets with insurance, and E_{N1} is the subjective value without insurance.

The condition for a client to purchase insurance is:

$$E_{Y1} \geq E_{N1} \tag{10}$$

Define the damage rate $\eta = X/E_1$ and premium rate $r = Y/E_1$. The above condition becomes:

$$r \leq 1 - \frac{l_1}{k_1}\left(1-\eta\right) \tag{11}$$

2.2.3 Insurer Perspective

Assume the insurer's asset is E_2, and the number of policyholders is n. The subjective value of assets is determined by:

$$\begin{cases} E_{Y2} = l_2\left(E_2 + nY - nX\right) \\ E_{N2} = k_2 E_2 \end{cases} \tag{12}$$

where E_{Y2} and E_{N2} are the subjective values of the insurer's assets with and without underwriting, respectively, l_2 and k_2 are the insurer's risky and risk-free asset utility rates.

The condition for the insurer to underwrite the policy is:

$$E_{Y2} \geq E_{N2} \tag{13}$$

Combining the damage rate η and premium rate r, assuming $E_2 = nE_1$, the above condition becomes:

$$r \geq \eta + \frac{k_2}{l_2} - 1 \tag{14}$$

Define the client's risk attitude index $u_1 = l_1/k_1$ and the insurer's risk attitude index $u_2 = l_2/k_2$. The condition further simplifies to:

$$\eta < \eta_{\max} = 1 - \frac{\frac{1}{u_2} - 1}{1 - u_1} \tag{15}$$

where $\eta_{\max}$ is the maximum allowable damage rate.

3 CASE ANALYSIS

3.1 Case Setup

Taking Fujian Province and Guizhou Province in China, which frequently experience extreme weather, as examples (as shown in Tables 1 and 2), data on economic losses caused by typhoon disasters and Gross Regional Product (GRP) in Fujian Province from 2016 to 2024, as well as data on economic losses caused by floods and hailstorms and GRP in Guizhou Province from 2018 to 2024, were collected from publicly accessible web sources (https://www.fujian.gov.cn/, http://fjnews.fjsen.com/, https://www.guizhou.gov.cn/, https://yjgl.guizhou.gov.cn/). Simulations were conducted to evaluate the effectiveness of the high-risk underwriting decision model, considering whether insurance companies should provide catastrophe insurance for these regions.

Table 1 Impact of Typhoon Disasters in Fujian Province (2016–2024)

Year	Direct Economic Loss (100 million CNY)	Gross Regional Product (100 million CNY)	Economic Loss Rate (%)
2016	382.34	28519.15	1.3406
2017	9.54	32298.28	0.0295

2018	29.04	38687.77	0.0751
2019	0.13	42395.00	0.0003
2020	12.10	43903.89	0.0276
2021	0.49	48810.36	0.0010
2022	67.31	53109.85	0.1267
2023	198.09	54355.10	0.3644
2024	26.41	57761.02	0.0457

Table 2 Impact of Flood and Hailstorm Disasters in Guizhou Province (2018–2024)

Year	Disaster Type	Direct Economic Loss (100 million CNY)	Gross Regional Product (100 million CNY)	Economic Loss Rate (%)
2018	Flood	6.29	14806.45	0.0425
	Hailstorm	13.78		0.0931
2019	Flood	43.56	16769.34	0.2598
	Hailstorm	1.63		0.0097
2020	Flood	86.03	17826.56	0.4826
	Hailstorm	4.5		0.0252
2021	Flood	19.88	19586.42	0.1015
	Hailstorm	8.18		0.0418
2022	Flood	43.2	20164.58	0.2142
	Hailstorm	9.9		0.0491
2023	Flood	10.2	20913.25	0.0488
	Hailstorm	11.3		0.0540
2024	Flood	61.08	22667.12	0.2695
	Hailstorm	12.22		0.0539

3.2 Underwriting Decision

Considering that different property owners possess varying total assets, insurance companies tend to be more risk-averse compared to policyholders [13,14], therefore, the risk attitude index of the insurance company is set as $u_2 = 0.751$, and that of the policyholder as $u_1 = 0.667$. The maximum acceptable loss rate for the insurance company, calculated using the utility value model, is $\eta_{\max} = 0.4331\%$.

3.2.1 Underwriting decision for typhoon disasters in Fujian Province

First, the risk assessment model was used to predict the economic loss rates caused by disasters in Fujian Province from 2020 to 2024. A comparison between predicted and actual values is shown in Table 3. The results indicate high model accuracy, with errors controlled within 15%, meeting the requirements for addressing uncertainties in extreme weather risks.

Table 3 Comparison of Predicted vs. Actual Economic Loss Rates in Fujian Province (2020–2024)

Year	Predicted Loss Rate (%)	Actual Loss Rate (%)	Relative Error (%)
2020	0.0288	0.0276	4.35
2021	0.0009	0.0010	10.00
2022	0.1165	0.1267	8.05
2023	0.3126	0.3644	14.22
2024	0.0482	0.0457	5.47

Furthermore, the expected loss rate for Fujian Province in 2025, denoted as $\hat{\eta}$, is calculated to be 0.2095%, which is less than the maximum acceptable loss rate $\eta_{\max}$. Therefore, the insurance company may choose to provide typhoon catastrophe insurance. Based on the utility value model, the premium rate range is determined as $r \in [3.337\%, 3.344\%]$. Thus, a premium rate of 3.344% can be selected for insurers.

3.2.2 Underwriting decision for flood and hailstorm disasters in Guizhou Province

Table 4 Comparison of Predicted vs. Actual Economic Loss Rates in Guizhou Province (2022–2024)

Year	Disaster Type	Predicted Loss Rate (%)	Actual Loss Rate (%)	Relative Error (%)
2022	Flood	0.2215	0.2142	3.41
2023		0.0541	0.0488	10.86
2024		0.2517	0.2695	6.60
2022	Hailstorm	0.0516	0.0491	5.09
2023		0.0523	0.0540	3.15
2024		0.0530	0.0539	1.67

A comparison of predicted versus actual economic loss rates in Guizhou Province from 2022 to 2024 is shown in Table 4. The model's accuracy improves further when historical loss rates exhibit minimal fluctuations.

The predicted combined loss rate for floods and hailstorms in Guizhou Province in 2025, denoted as $\sum \hat{\eta}$, is 0.2439%, which is also less than the maximum acceptable loss rate $\eta_{\max}$. Therefore, the insurance company may choose to provide a combined catastrophe insurance package for these disasters.

3.2.3 Analysis of underwriting conditions

By analyzing the conditions under which customers choose to purchase insurance and insurers decide to underwrite risks in the model, it can be observed that insurers' decisions on corporate assets determine the lower bound of premium rates, while customers' decisions on personal assets determine the upper bound. This aligns with real-world scenarios. From the insurer's perspective, catastrophic risks may lead to substantial payouts, necessitating relatively high premium rates. However, customers' limited capacity and willingness to bear premiums constrain excessive rates, as overly high premiums would deter purchases and deprive insurers of revenue.

Furthermore, the underwriting decision criteria derived from the model are consistent with economic principles. Against the backdrop of increasing extreme weather events, loss ratios rise over time. On one hand, risk-averse customers will opt for insurance when their fixed assets without coverage equal their expected assets with coverage, thereby mitigating risks. On the other hand, insurers, also risk-averse, will decline underwriting if their expected assets from underwriting equal their fixed assets without underwriting. Therefore, the aversion coefficient must be less than 1, and a maximum loss ratio exists. Insurers may underwrite risks only when the expected loss ratio remains below this threshold.

3.3 Optimal Underwriting Strategies

3.3.1 Single extreme weather region

Using utility value theory, the utility values of assets for both insurers and customers are converted. By comparing the utility values of purchasing versus not purchasing insurance (for customers) and offering versus not offering insurance (for insurers), acceptable premium rate ranges for both parties are derived.

If the two ranges do not overlap, insurers cannot balance their interests with customer demand and should refrain from offering coverage.

If the ranges intersect, insurers may select an appropriate premium rate within the overlapping interval. The optimal scheme is to adopt the maximum value in this interval to maximize profits.

3.3.2 Multiple extreme weather regions

For regions prone to multiple extreme weather events, insurers must categorize risks and design distinct insurance products for each type. The total predicted loss ratio across all covered risks is compared against the maximum allowable loss ratio.

If $\sum_{i=1}^{N} \hat{\eta}_i \leq \eta_{\max}$, full coverage is offered, assuming all risks.

If $\sum_{i=1}^{N} \hat{\eta}_i > \eta_{\max}$, the combined risk exceeds acceptable thresholds, leading to unaffordable premium rates. In such cases, insurers should sequentially exclude underwriting for extreme weather events with higher loss ratios in descending order until the total loss ratio falls below the maximum allowable threshold. The resulting insurance combination at this stage represents the optimal underwriting scheme.

3.4 Sensitivity Analysis

Statistical data and model inputs in practical applications often contain errors, which may affect output reliability. To assess the model's robustness, a sensitivity analysis was conducted.

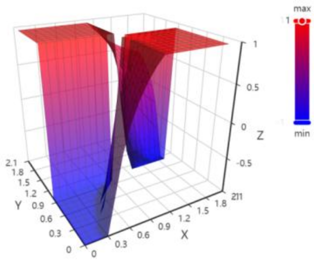

Figure 1 Sensitivity Analysis of Risk Attitude Index Model

The sampling diagram initially selected four sample points, yet the probability distribution across the entire region exhibited uniformity. By altering sampling points, variations were analyzed (Figure 1).

Adjusting the policyholder's risk attitude index X and the insurer's risk attitude index Y generated different risk attitude combinations. Figure 1 reveals that the model's maximum loss ratio may fall below 0 or exceed 1: a maximum loss ratio below 0 implies insurers may reject all extreme weather risks, while a ratio above 1 suggests insurers might underwrite all risks. Moreover, the surface plot trend indicates that the loss rate is highly sensitive to changes in the risk attitude indices of both parties. Any variation in either risk attitude index triggers significant fluctuations in the corresponding maximum loss rate, with the loss rate frequently exceeding the reasonable range of [0,1]. The analytical results demonstrate that the model exhibits robust sensitivity characteristics.

Practically, policyholders' risk attitude indices depend on their subjective perception of current risks, which is directly influenced by extreme weather events. Thus, precise quantification of extreme weather risks is critical for decision-making. Insurers can leverage this model to accurately assess risk levels and ensure informed underwriting decisions.

4 CONCLUSION

This study establishes a high-risk underwriting decision model to address insurers' challenges amid escalating extreme weather risks. Key conclusions include: (1) Insurers should provide coverage when the expected loss rate is below the maximum allowable threshold and assume risks when the premium rate falls within a feasible range. (2) For single extreme weather regions, the optimal scheme is to adopt the maximum premium rate within the overlapping acceptable range of both customers and insurers. (3) For regions with multiple extreme weather events, insurers should categorize risks and design coverage combinations where the total loss ratio remains below the maximum threshold, maximizing profitability. This model provides data-driven and theoretical support for insurers in risk assessment and underwriting decisions in high-risk regions, demonstrating practical applicability. While the current study focuses on underwriting strategies for single versus multiple extreme weather events, future research could explore coupling risk quantification methods for compound disasters and incorporate stochastic processes to simulate time-varying loss rate characteristics.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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