Strategic Models for Enhancing Insurance Resilience in the Face of Climate-Induced Natural Disasters

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Abstract. As global climate change increases the frequency and intensity of natural disasters, the insurance industry faces significant challenges in risk management and policy affordability. This research develops three models to fortify the resilience of the insurance sector against the intensifying threats posed by climate-induced natural disasters. The Disaster-Affected Model quantifies the immediate impacts of diverse weather extremes, enabling precise risk assessments. The Insurance Bankruptcy Factor Model forecasts the financial sustainability of insurers, factoring in the frequency and severity of these events. The Underwriting Risk Prediction Model utilizes region-specific data to predict underwriting risks accurately, allowing for tailored insurance strategies. Together, these models enhance risk management, optimize underwriting practices, and ensure the financial stability of the insurance industry in a changing climate landscape, thereby promoting the sector's long-term sustainability.

Keywords: Property Insurance, SHAP Value Algorithm, Grey Prediction.

1. Introduction

The physical world faces increasing threats from natural disasters, with significant implications for the insurance industry and the insured due to global climate change[1]. This change not only alters existing risks but also introduces new ones, significantly impacting the interdependencies among these risks and affecting nearly every segment of the insurance and reinsurance industry[2]. As climate change enhances the frequency and intensity of extreme weather events, insurance losses continue to rise, challenging the industry's profitability and the affordability of policies for property owners[3]. This evolving risk landscape necessitates a reassessment of risk management strategies and the development of innovative insurance products that encourage climate-related risk prevention. The property-casualty insurance sector, in particular, must navigate significant sustainability and decision-making dilemmas to balance providing sufficient coverage with maintaining business viability[4][5]. Addressing these complex issues requires a collaborative approach among insurers, governments, and communities, underscoring the need for adaptive measures that can sustain the future of insurance against the backdrop of escalating climate risks. This research employs a multi-model approach integrating empirical data analysis, predictive modeling, and advanced computational methods like Grey Prediction and SHAP Value Algorithms to enhance the insurance sector's resilience against climate change, optimize risk management, and promote sustainable industry practices. (Data Sources: https://www.gddat.cn/newGlobalWeb/#/home).

2. The Establishment of Underwriting Model

2.1. Disaster-Affected Model Establishment

First, it is necessary to determine the main risk disaster criteria brought about by extreme weather. The coefficients for different disaster types are denoted as H_j, The overall coefficient for extreme weather is denoted as H[6].

Drought. Based on the officially announced drought warning criteria, the Disaster-affected coefficient is determined as H_1 .level classification is $i_1 = \{0.05、0.25、0.50、0.80\}$ which Corresponding to mild drought, moderate drought, severe drought, and extreme drought. It is assumed that the Disaster-affected coefficient for drought follows a normal distribution with mean μ and standard deviation σ, with a maximum value of 1. The random probability is as follows:

$$H_1 = \{rand(i_1, \sigma), 1\} \tag{1}$$

Hailstone Impact. With exceptions for certain areas, the coefficient indicating the extent of hail damage is defined as the "Disaster-Affected Coefficient." This coefficient is calculated based on the following random probability model:

$$H_2 = i_2 \cdot min\{rand(\mu, \sigma), 1\} \tag{2}$$

Flooding: The effects of flooding on agriculture are categorized into three phases. The extent of damage is highly dependent on the flood level, r, and can be described by a specific function.

$$\begin{cases} H_{31} = 59.57(r + 0.04)^{0.44} - 10 \\ H_{32} = 47.02(r + 0.25)^{0.83} - 10 \end{cases} \tag{3}$$

Coldwave and Heatwave Disasters: The severity of these disasters is quantified based on established warning criteria, leading to the determination of a Disaster-affected coefficient. The classification of the impact is specified as $i_3 = \{0.05、0.25、0.50、0.80\}$. Random probability is introduced as:

$$H_3 = \{rand(i_3, \sigma), 1\} \tag{4}$$

Wind Disaster: This type of disaster mainly results in crop destruction and damage to infrastructure. The damage coefficient is believed to follow an exponential relationship with the wind speed

$$H_5 = 1 - exp[-0.017(v - 10.8)] \tag{5}$$

The overall disaster coefficient is defined as:

$$H = max\{H_1, H_2, H_3, H_4, H_5\} \tag{6}$$

2.2. Insurance bankruptcy factor model establishment

Suppose the profit process of an insurance company in years t is $U(t)$:

$$U(t) = x + ct - k\sum_{i=1}^{N(t)} Y_i \tag{7}$$

The initial capital x (0 in this article);$c > 0$ represents the premium income rate; $0 < k < 1$ represents the loss payout ratio;$N(t)$ represents the number of extreme weather events that occurred in [0,t], which follows a $\lambda > 0$ Poisson process; $\{Y_i, i \geq 1\}$represents the economic loss caused by the i-th disaster. Let $T = inf\{t: t \geq 0, U(t) < 0\}$be the time when the insurance company goes bankrupt, the probability can be expressed as:

$$\psi(x) = P\{T < \infty | U(0) = x\} \tag{8}$$

2.3. Underwriting conditions

Assuming the insurance capital starting point is (x_0, y_0) , the payout rate is set to $\overline{V}$, so the starting rate is defined as:$\overline{V} = [x_0/y_0]$. Construct the function relationship between insurance capital and insurance bankruptcy factor and premium:

$$E = x - [I_1 \frac{x_0}{y_0}(x - x_0) + I_2 \frac{(x - x_0)^2}{2} + y_0 \cdot \bar{V} \cdot \psi(x)] \tag{9}$$

2.4. Determination of the threshold E

According to the model's prediction, insurance companies only underwrite policies when the risk assessment E exceeds a certain threshold, which is determined using the MFF method to determine profitability. Based on the given data and empirical average exceedance function, the model and threshold can be further optimized to ensure the stability and sustainability of the insurance business. For the given data, the empirical average exceedance function is defined as:

$$e_n(E) = \frac{\sum_{i=1}^{n}(y_i - E)\, I_{\{y_i > E\}}}{\sum_{i=1}^{n} I_{\{y_i > E\}}} \tag{10}$$

2.5. Underwriting model solution

The statistical results of summarizing predictions for various regions (without considering disaster types) are shown in Fig.1.

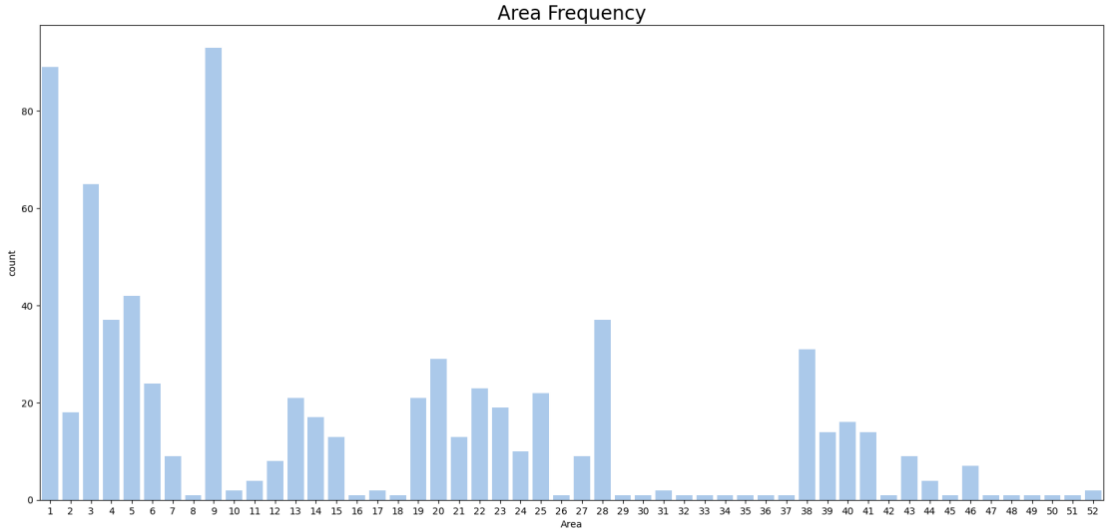


Fig.1: Extreme weather hazard statistics (regardless of type)

Only when the insurance underwriting conditions are near the maximum value E(a) and exceed the threshold $e_n(E)$, the insurance company will underwrite policies. At this time, the probability of the insurance company $\psi(x)$underwriting policies is low, and the insurance company will only make a profit when it undertakes policies. Therefore, insurance companies should only underwrite policies when the bankruptcy rate and the probability of natural disasters are low. For specific factors, please refer to the previous text.

3. Optimizing Insurance Decisions with Grey Prediction Models

Insurance companies need to consider when to take risks based on when the bankruptcy factor of the insurance company is below the threshold. At this time, the risk of insurance underwriting is low and can achieve the goal of profitability. Considering that insurance has a lag (that is, there is a certain period between insurance and claims, it is necessary to con-sider the trend of the bankruptcy factor in the next few years.

3.1. Setting of underwriting risk levels

Using the above model, we calculated the insurance bankruptcy factors for various regions around the world in recent years. Based on the bankruptcy factor (risk level λ), we set the underwriting strategy:

λ > a: Refuse to underwrite or charge high premiums.

b > λ > a: Standard underwriting model strategy with slightly adjusted underwriting fees.

λ > b: Adopt measures such as reducing premiums to obtain underwriting qualifications.

3.2. Underwriting risk prediction mode

For the calculation of risk levels, this article can use region-specific indicators to predict using the gray prediction model. The formula for the gray prediction model is as follows.

Gray prediction is a short-term prediction model for small samples that can achieve relatively accurate prediction results in a limited time series. Therefore, this article uses gray prediction model as a supplement to time series prediction. Gray G, M(1,1) prediction method[7]. G represents gray, M represents model, and $GM(1,N)$ represents a first-order differential equation with N=14 variables.

Assuming that the sequence $X_1^{(0)} = \{x_1{}^{(0)}(1), x_1{}^{(1)}(2), \cdots, x_1{}^{(0)}(n)\}$has n observed values, the accumulated values form a new sequence $\chi^1 = \{\chi^1(1), \chi^1(2), \ldots, \chi^1(n)\}$, corresponding to the model:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = \mu \tag{11}$$

Where the development gray number is α, and the endogenous control gray number is μ. Let the parameter vector to be estimated be:

$$a = \left(\frac{a}{\mu}\right) \tag{12}$$

Solved using the least squares method:

$$a = (B^T B)^{-1} B^T Y_n \tag{13}$$

The prediction model is obtained by solving the differential equation:

$$\hat{\chi}^{(1)}(k+1) = \left\{\chi^{(0)}(1) - \frac{\mu}{a}\right\} e^{-\mathrm{ak}} + \frac{\mu}{a} \tag{14}$$

3.3. Testing and solving the model

According to the a posteriori difference ratio C and the probability of small error P, the prediction model can be divided into four grades, and the specific division basis is shown in Table 1

Table 1: Range of Indicators

Level	C	P
Excellent	0.35	0.95
Good	0.50	0.80
Marginal	0.65	0.70
Unsatisfactory	0.80	0.60

After the a posteriori difference ratio value C and small error probability P test of the grey prediction model, the insurance insolvency factor prediction model is qualified and can be predicted. The prediction results are shown in Table 2:

Table 2: Underwriting Conditions Modelling Results

Total Damage	Total effect	Total Deaths	Mass movement	Flood	Storm	Earthquake	Drought	Extreme temperature
23	243618	127358	120	3	2	0	0	0
9	5889	17801	135	2	1	0	2	0
25	365601	3947216	24	1	0	0	0	0
9	1021766	290067	25	0	2	0	1	0
18	16157325	6297416	517	1	2	0	1	0
68	5913250	15793458	179	1	4	2	1	1
6	300159	80015	47	0	1	1	0	0
26	1394387	300800	79	0	4	0	0	0
4	894267	207689	31	0	0	1	1	0
1	921637	1394217	5	0	1	0	0	0
4	1627158	608742	63	1	1	0	1	0

Based on the assessment of the insurance insolvency factor (risk level) a value of 2.5 and b value of 1.0, we judge that the risk level of extreme weather, such as storms and high winds, is low, low-risk, and suitable for underwriting. Periods of frequent earthquakes and floods (5-6 year cycle) have a high risk rating and should be avoided or subject to strict underwriting conditions. Risks in other years can be referred to the standard model and thresholds and premiums can be adjusted. The visualization results are shown in Fig.2.

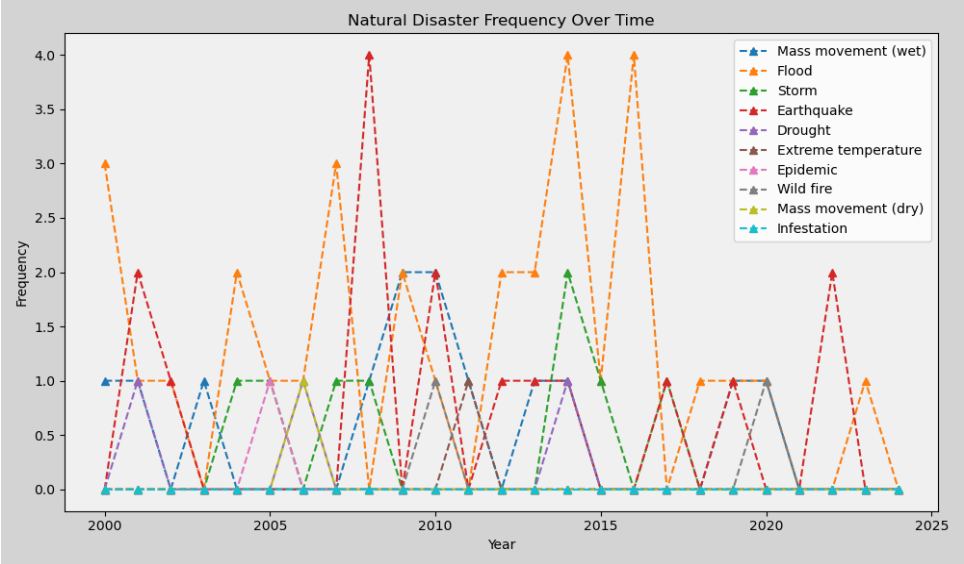


Fig.2 Risk Insolvency Factor Rating Coefficients

4. SHAP Analysis: Enhancing Predictive Accuracy and Interpretability in Insurance Models

The influence of owners on underwriting decisions depends on their adjustments to core parameters in the underwriting model[8]. For example, the importance of flood hazard payouts in extreme weather underwriting models, owner modifications to this parameter may directly affect underwriting decisions

4.1. SHAP modelling

For a trained model $f_x(S) = E[f(x)|xs]$, the output is defined as $f(x)$. S in Shapley Value denotes a subset of the output feature set[9]. To obtain the model's interpretation of a particular sample,

the expectation is computed. In short, the model's interpretation of a given sample can be obtained by determining the model output $f(x)$, S in Shapley Value and calculating the expectation $E[f(x)|x_1, x_2, x_3, x_4]$[10].

Assuming that the value of the feature in the sample is $\{x_1 = a_1, x_2 = a_2, x_3 = a_3, x_4 = a_4\}$, there is:$S = \emptyset$ can be introduced $\psi_0 = f_x(\emptyset) = E[f(x)]$, i.e., a sample-independent expectation of the model's predicted value that can be approximated by the average of the model's predicted value from the training sample. This value is sample-independent.

$S = \{x_1\}$can introduce $\psi_1 = f_x(\{x_1\}) - f_x(\emptyset) = E[f(x)|x_1] - E[f(x)]$, the difference between the predicted expectation at $\{x_1 = a_1\}$ and the sample-independent expectation, this estimate of $E[(x)|x_1]$.

Same for $S = \{x_1, x_2\}$ and $S = \{x_1, x_2, x_3\}$.

Similarly, $S = \{x_1, x_2, x_3, x_4\}$ can be introduced:

$$\psi_4 = f_x(\{x_1, x_2, x_3, x_4\}) - f_x(\{x_1, x_2, x_3\}) = E[f(x|x_1, x_2, x_3, x_4)] - E[f(x|x_1, x_2, x_3)] \quad (15)$$

Note that this is just one of the sorts. Just like the one where we pushed Shapley Value, in order to extrapolate to the general form, we need to apply Shapley Value's formula to push out the explanatory formula:

$$\psi_i = \frac{1}{p!} \sum_{S \subseteq \{x_1, \cdots, x_p\} \backslash \{x_i\}} |S|\,!\,(p - |S| - 1)!\left(f_x(S \cup \{x_i\}) - f_x(S)\right) \quad (16)$$

Where p is the number of total features, αS is a sub-table of SHAPLEY VALUES, and $f_x$is the mean prediction of the coalition, which is the item for example $E[f(x|x_1, x_2, x_3, x_4)] - E[f(x|x_1, x_2, x_3)]$ in the example above, solving for this gives the individual SHAP values.

4.2. Model solution

Using Python, the SHAP values are computed, taking into account the local accuracy, missingness, and consistency features of SHAP. The results are visualized in Fig.3 and Fig.4 using SHAP value visualization.

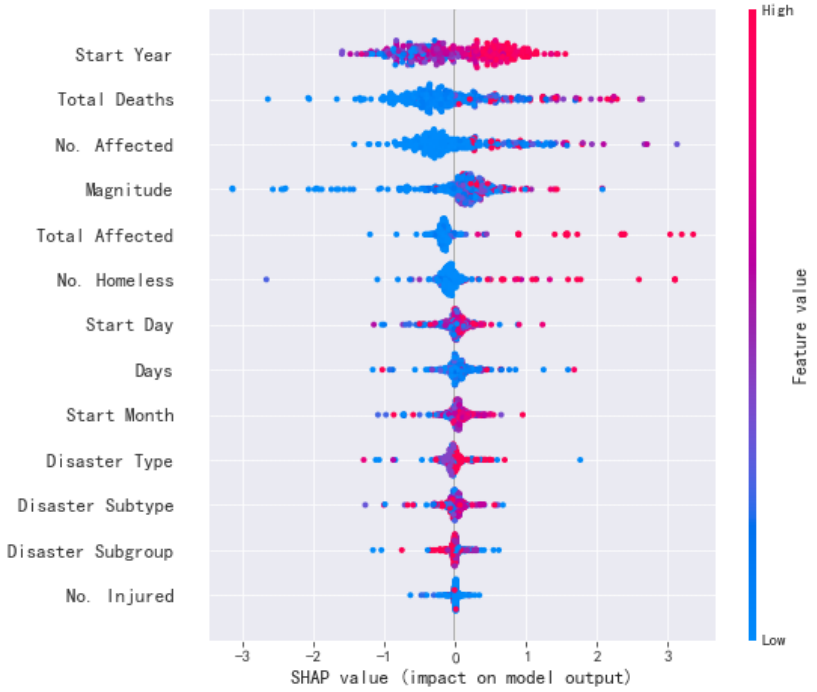


Fig.3: SHAP Value Visualization (Impact On Model Output)

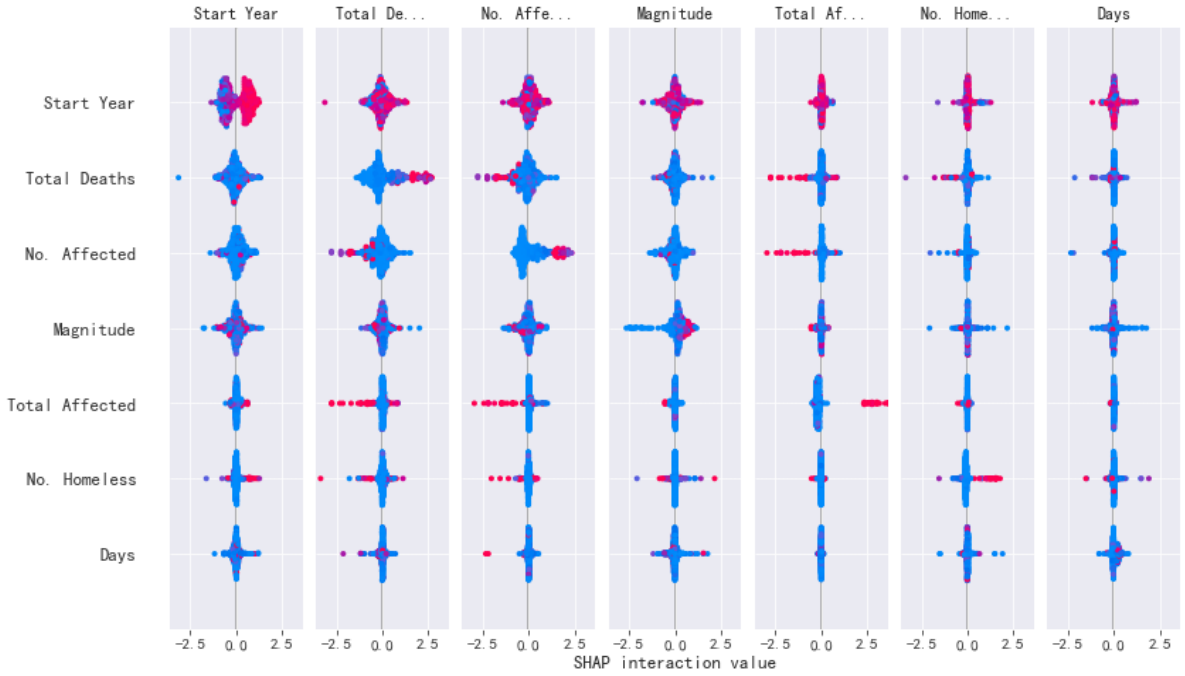


Fig.4: Shap Value Visualization (Interaction Value)

From the SHAP value plot, it can be observed that the indicators "Total Deaths," "Magnitude," and "No Homeless" rank higher, indicating their significant impact on the insurance model. The actions taken by homeowners to reduce the threat to life and property have a strong negative impact on the insurance model and the insolvency factor. This implies that homeowners engaging in disaster knowledge training, strengthening home safety measures, and reducing exposure to extreme weather can effectively lower the threshold for insurance underwriting.

5. Conclusions

This paper has presented three interconnected models designed to enhance the resilience and sustainability of the insurance industry in the face of increased frequency and severity of natural disasters driven by climate change. The Disaster-Affected Model allows for a detailed quantification of the impact of various natural disasters, providing a solid foundation for risk assessment. The Insurance Bankruptcy Factor Model serves as a predictive tool for assessing the financial health of insurance companies, calculating the likelihood of insolvency under stress from extreme weather conditions. This model emphasizes the critical need for robust financial strategies to withstand these pressures.

Furthermore, the Underwriting Risk Prediction Model applies a gray prediction method to accurately forecast underwriting risks based on regional data, enabling insurance companies to tailor their strategies and pricing models to better cope with the variability and unpredictability of natural disasters. This model highlights the importance of adaptive underwriting practices that can respond dynamically to changing risk profiles.

Collectively, these models contribute to a more robust framework for the insurance industry to manage and mitigate risks associated with natural disasters. By integrating comprehensive risk quantification, financial sustainability forecasting, and adaptive underwriting strategies, the proposed models help ensure that the insurance industry remains viable and effective in its role as a key player in risk management and recovery in the era of climate change. This work not only advances the theoretical underpinnings of insurance risk management but also offers practical tools and strategies for enhancing industry practices.

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