Research on Extreme Weather Risk Management Based on Gray Prediction and Multi-Criteria Evaluation Models

Dingshu Fan, Hongye Wu*

International School, Beijing University of Posts and Telecommunications, Beijing, China, 100876

* Corresponding Author Email: jp2022213348@qmul.ac.uk

Abstract. This study investigates the growing challenges faced by the insurance industry due to extreme weather events and climate change, with a focus on the widening global insurance gap. We propose a novel dual-model approach to address these complex issues. First, we develop a Gray Prediction-Based Risk Assessment Framework (GPRAF) that integrates multidimensional data on natural disasters, economic development, population dynamics, and agricultural trends. This framework enables insurance companies to make more informed underwriting decisions in the context of increasing climate-related risks. Through case studies in Japan and Mexico, we demonstrate the practical applications and implications of our approach. Our research contributes to the growing body of literature on climate risk management in the insurance sector and provides valuable insights for policymakers and industry practitioners. By bridging the gap between risk assessment and community preservation needs, this study offers a holistic perspective on adapting insurance strategies to the challenges of climate change while preserving community values.

Keywords: Extreme Weather, Insurance, Gray Prediction Model.

1. Introduction

Climate change and extreme weather events pose increasingly severe challenges to the insurance industry, leading to a widening global insurance coverage gap. Accurate assessment and prediction of climate-related risks are crucial for insurance companies' underwriting decisions, risk management, and the overall sustainability of the industry [1,2]. Traditional risk assessment methods, primarily based on historical data and linear models, have limitations in addressing the complex impacts of climate change [3,4]. In recent years, as climate change intensifies, the frequency and severity of natural disasters have been increasing, putting unprecedented pressure on the insurance industry [5,6]. In recent years, scholars have proposed various approaches to improve climate risk management in the insurance industry. For example, Linnerooth-Bayer et al. explored the possibility of insurance as a response to climate change loss and damage [7], while Gatzert et al. examined sustainability risks and opportunities facing the insurance industry [8]. To address these challenges, this study proposes an innovative dual-model approach. First, we develop a Gray Prediction-Based Risk Assessment Framework (GPRAF) that integrates multidimensional data on natural disasters, economic development, population dynamics, and agricultural trends. Grey system theory has shown excellence in dealing with uncertain and information-incomplete systems [9], making it particularly suitable for application in the complex field of climate risk assessment. Through case studies in Japan and Mexico, we demonstrate the practical applications and implications of this approach. This research not only provides a new perspective on climate risk management for the insurance industry but also offers valuable insights for policymakers and industry practitioners. By bridging the gap between risk assessment and community preservation needs, this study presents a comprehensive perspective on adapting insurance strategies to the challenges of climate change while preserving community values.

2. The Gray Prediction-Based Risk Assessment Framework

2.1. Framework design

The Gray Prediction-Based Risk Assessment Framework (GPRAF) is designed to address the challenges of predicting extreme weather events and their associated risks in the context of climate change. This framework leverages the strengths of gray system theory, particularly its applicability to scenarios with limited and uncertain data.It contains two parts which are Gray Prediction and Risk Assessment.

2.1.1. Gray Prediction

The gray prediction model is a data forecasting methodology predicated on small samples and incomplete information. Through the generation of cumulative sequences, non-negative sequences exhibit exponential patterns, enabling prediction via exponential curve fitting. This model is particularly applicable for forecasting data series with exponential growth or declining trends, demonstrating unique advantages in scenarios with limited data and incomplete information.

Despite the low occurrence frequency of extreme weather events, their trends often manifest certain regularities. Consequently, the gray prediction model can be applied to forecast the probability of extreme weather occurrences. A notable characteristic of this model is its minimal data requirements, typically necessitating no fewer than four data points for prediction. Given the scarcity of extreme weather data, the application of gray prediction models for forecasting is feasible.

The accuracy of gray prediction models can be evaluated by comparing actual values with predicted values. Commonly employed evaluation metrics include Mean Absolute Error (MAE), Mean Square Error (MSE), and Relative Error (RE). When applying this model, particular attention must be paid to accuracy issues. Should the predictive accuracy fail to meet requirements, further optimization of model parameters or consideration of alternative prediction methods may be necessary.

This study employs the gray prediction model to forecast extreme weather events, aiming to explore its potential applications in the field of meteorology. Through analysis of the model's predictive results and errors, we can assess the efficacy of this method in extreme weather prediction and provide valuable insights for future research in this domain.

The core of GPRAF is the GM(1,1) model, a first-order, single-variable gray model [10]. It consists of four basic elements, which are:

(1) The collected initial data (known as the raw data sequence) is expressed as $X^{(0)}$, and $\left(x^0(1), x^0(2), \cdots, x^0(n)\right)$represents the historical data sequence.

$$X^{(0)} = \left(x^0(1), x^0(2), \cdots, x^0(n)\right) \tag{1}$$

(2) The raw data sequence was generated once to generate a new sequence $X^{(1)}$, called Accumulated generated sequence (AGO), namely $X^{(1)} = \left(x^1(1), x^1(2), \cdots, x^1(n)\right)$, where $x^1(k) = \sum_{i=1}^{k} x^0(i), (k = 1, 2 \cdots, n)$. Plus operation helps to show the trend of data and reduce randomness.

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i), (k = 1, 2, 3, \cdots, n) \tag{2}$$

(3) Establish the GM (1,1) model. A first-order differential equation model is established for the AGO sequence $X^{(1)}$, where (a) is the control coefficient and (b) is the gray action amount.The parameters (a) and (b) are estimated by least squares, and the data series is fitted by solving this set of equations.

$$\frac{dx^1}{dt} + ax^1 = u \tag{3}$$

$$\hat{a} = \begin{bmatrix} a \\ u \end{bmatrix} = \left(B^t B\right)^{-1} B^T y_n \tag{4}$$

$$B=\begin{bmatrix} -\frac{1}{2}\left(X^{(1)}(1)+X^{(1)}(2)\right) & 1 \\ -\frac{1}{2}\left(X^{(1)}(2)+X^{(1)}(3)\right) & 1 \\ \cdots\cdots\cdots & \\ -\frac{1}{2}\left(X^{(1)}(n-1)+X^{(1)}(n)\right) & 1 \end{bmatrix} \tag{5}$$

(4) Establish the time-response equation. According to the model parameters a and u, the time response equation of the GM (1,1) model is able to describe the dynamical behavior of the system.The time-response equation usually takes the form of: ($X^{(1)}$)

$$\hat{x}^{(1)}(k+1)=\left[x^{0}(1)-\frac{u}{a}\right]e^{-ak}+\frac{u}{a} \tag{6}$$

After finding $\hat{x}^{(1)}(k+1)$ the predicted value can be obtained by the following equation

$$x^{0}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k) \tag{7}$$

The GM(1.1) is suitable for data series with exponential growth or decreasing trends, especially in cases of small data volume and incomplete information. It requires a minimum of four data points for prediction, making it particularly valuable for analyzing rare events like extreme weather.

2.1.2. Risk assessment

Risk assessment is used to identify and assess the risk of extreme weather. It can help insurance companies to identify the risk factors that may have a negative impact on their operations and business, and to take corresponding risk management measures. Depending on the data of the insurance model, based on the possibility of risk occurrence and the possible degree of loss after the risk occurs, the higher the risk level means that the greater the possibility of risk occurrence, or the worse the loss may be caused after the risk occurs. Therefore, the insurance company will decide whether to cover a certain risk based on the risk level.

The specific steps are described as follows. First define the average claim cost $x_a=50000$, $x_b=100000$, that is, the money we need topay the customer if an extreme event occurs, and then define the premium rate : $r_a=0.1$, $r_b=0.15$ Next, define the financial threshold f =0.9, the financial threshold represents the lowest or highest value that an effect can produce. If the financial indicators exceed the set threshold, it may mean that the enterprise has financial risks, requiring corresponding risk management and control. The next step calculates the risk value (number of risk events * average claim cost) $R_a=w_a\times ac_a, R_b=w_b\times ac_b$. Next, calculate the annual insurance cost (risk value * insurance rate) $ic_a=R_a\times ir_a, ic_b=R_b\times ir_b$. The next step is to calculate the risk proportion (risk value divided by the total value), first define the total risk value tv=100000.

$$ra_a=\frac{R_a}{tv} \tag{8}$$

$$ra_b=\frac{R_b}{tv} \tag{9}$$

Finally, predict the insurance cost in the next few years, and the total future insurance cost will be the sum of the insurance cost in the next few years. Final decision by comparing the total future insurance cost and the financial threshold, if the former is less than the latter, the insurance company can insure, but not otherwise.

2.2. Data collection and result analysis

Data collection. The paper mainly collect the frequency of extreme weather in regional history annually, but it should be noted that the variety of extreme weather extreme weather definition. Extreme climate events into two categories: one based on simple climate statistics, these extreme events happen every year, such as very high or very low daily temperature, strong daily or monthly precipitation; the other is more complex directly determined by the occurrence of events, such as flood, hurricane, such events do not occur every year for a given location. Here, we take the extreme weather that produces large economic losses.

Data sources: Google Scholar, GLOBAL DISASTER DATA PLATFORM, NOAA. Fig.1 below shows the frequency chart of major natural disasters in 2015-2022; Fig.2 shows the proportion of several meteorological disasters

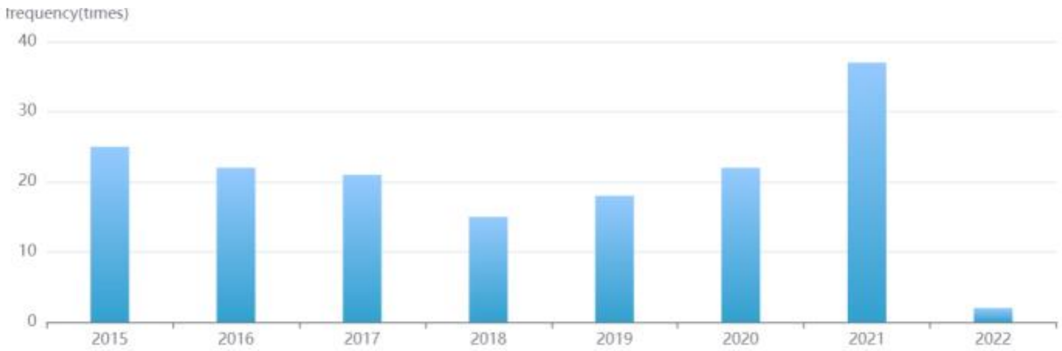

Fig. 1 Frequency of major natural disasters in 2015-2022

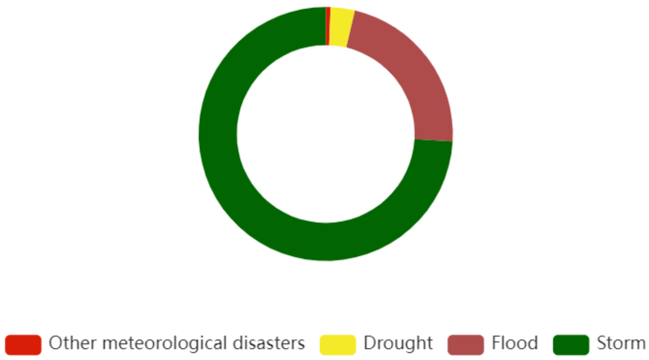

Fig. 2 The proportion of disaster types

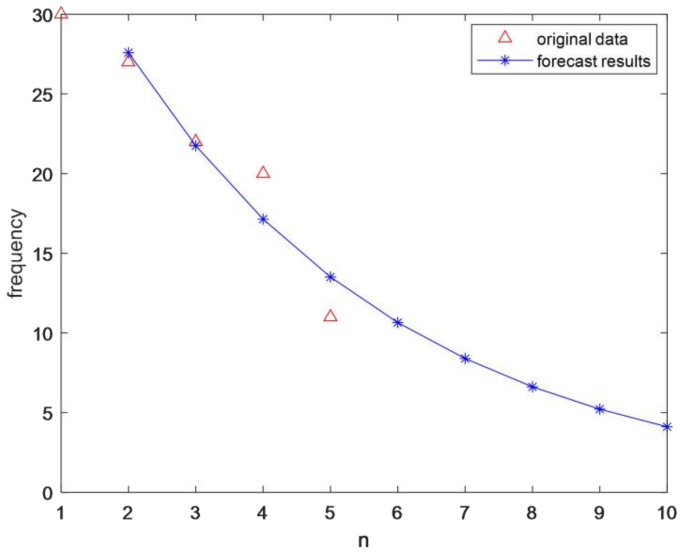

Fig. 3 Comparison of prediction results

Result analysis. First, the paper utilized the data on meteorological disasters in China from 2015 to 2019 as a foundation and employed the gray prediction model to forecast the frequency of meteorological disasters for the years 2019 to 2022. The original data points are marked with red triangles, while the forecast results are denoted by blue star markers connected by a blue line.The result is shown in Fig.3.

The graph indicates a general declining trend in the frequency of meteorological disasters over the specified years. Notably, the red triangles representing the original data from 2015 to 2019 align with the initial segment of the blue curve, demonstrating the model's capacity to accurately capture the historical trend. This alignment substantiates the credibility of the gray prediction model in reflecting the actual data trends.

The gray prediction has demonstrated effectiveness in predicting the frequency of meteorological disasters with a high degree of fidelity to historical trends. The declining pattern predicted for 2019 to 2022 is consistent with the model's interpretation of past data. Future studies might focus on refining model parameters and incorporating larger datasets to enhance predictive accuracy. This research underscores the gray prediction model's potential applicability in meteorological forecasting, providing valuable insights for disaster preparedness and mitigation strategies.

Second, The paper synthesize and analyze the results of our comprehensive study that combines gray prediction with risk assessment to understand the impact of extreme weather events on insurance operations. The analysis integrates insights from our gray prediction results and detailed risk assessment metrics, providing a cohesive view of future insurance costs and risk levels.

This study focuses on predicting the frequency of meteorological disasters and assessing the corresponding risks for insurance operations. The data involves, the frequency of meteorological disasters in Mexico from 2015 to 2022 as shown in Fig.4 and in Japan from 2015 to 2021 for risk assessment as shown in Fig.5.

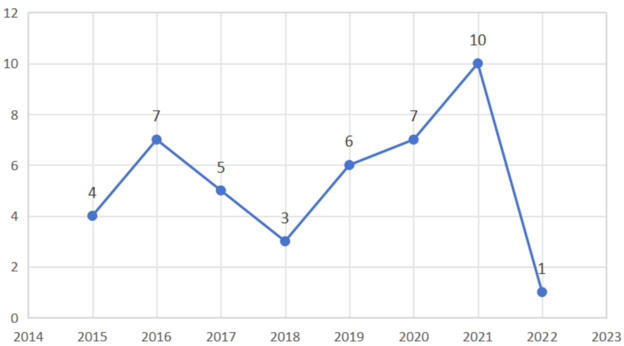

Fig. 4 Meteorological disasters in a Mexico city

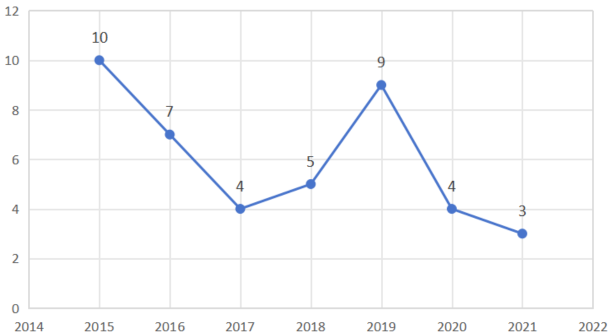

Fig. 5 Meteorological disasters in a Japan city

For the final result, the paper present Table 1 and Table 2, which provide a detailed breakdown of the future insurance costs and risk assessment metrics for two regions over a five-year period, based on gray prediction data. The result shows the forecasted insurance costs for Region A and Region B over the next five years. These values are crucial for budgeting and financial planning in the insurance sector, as shown in Table.1 and the key risk metrics for the two regions, including predicted events, risk value, annual insurance cost, risk proportion, and suggested strategies, as shown in Table.2.(Region A for a Mexico city, Region B for a Japan city).

Table 1. Future Insurance Costs by Region and Year

Region	Year 1	Year 2	Year 3	Year 4	Year 5
Region A	\$31414.38271	\$36558.41621	\$42544.77345	\$49511.38304	\$57618.75906
Region B	\$30180.03148	\$27692.86388	\$25410.66633	\$23316.54705	\$21395.00629

Table 2. Risk Assessment Metrics

Region	Predicted Events	Risk Value	Insurance Cost	Risk Proportion	Risk Level	Strategy
Region A	12.57	$628,288	$31,414	62.83%	High Risk	Careful assessment needed. Consider higher premiums or limited coverage.
Region B	3.77	$377,250	$30,180	37.73%	Medium Risk	Consider slight premium increase and review policy terms.

The assessment process includes defining the average claim cost, premium rate, financial threshold, and calculating the risk value, annual insurance cost, and risk proportion. The total risk value is pre-defined as $100,000.

The results of the integrated analysis show that the grey forecast is highly consistent with the risk assessment data, which provides a reliable framework for meteorological disaster trend prediction. In Region A, the insurance cost is increasing year by year, and the predicted events are frequent (12.57 times). The risk value is as high as $628,288, and the risk ratio is 62.83%, far exceeding the financial threshold. In contrast, Region B has a medium risk, with the insurance cost decreasing year by year and fewer predicted events (3.14 times). These findings highlight the need for differentiated risk management strategies, with Region A carefully evaluated and potentially raising premiums or limiting coverage, while Region B recommends small premium adjustments and reviewing policy terms. Conclusion.

This study highlights the importance of integrating forecasting models with risk assessment to improve forecasting accuracy and risk management reliability. Future work should focus on refining these models and incorporating larger datasets to further improve forecasting accuracy and optimize risk management strategies. By continuously updating and improving forecasting models, insurers can better prepare for and mitigate the financial impacts of extreme weather events, ensuring long-term sustainability and resilience.

3. Conclusions

This study provides a comprehensive analysis of the impact of extreme weather events on insurance business by combining grey prediction models and multi-criteria evaluation methods. The study shows that the grey prediction model shows high accuracy in predicting the frequency of meteorological disasters, which is highly consistent with the historical trend. By combining the forecast results with the risk assessment, the study provides a holistic perspective on future insurance costs and risk levels. This highlights the importance of integrating forecasting models in risk management to help improve the accuracy of forecasting and the reliability of management. Future research should focus on further optimizing these models and introducing larger datasets to improve forecasting accuracy and optimize risk management strategies to better cope with the financial impacts of extreme weather and ensure the long-term sustainability and resilience of insurers.

References

[1] Henstra D, Thistlethwaite J, Vanhooren S. The governance of climate change adaptation: stormwater management policy and practice[J]. Journal of environmental planning and management, 2020, 63(6): 1077-1096.

[2] Battiston S, Dafermos Y, Monasterolo I. Climate risks and financial stability[J]. Journal of Financial Stability, 2021, 54: 100867.

[3] Ward P J, Blauhut V, Bloemendaal N, et al. Natural hazard risk assessments at the global scale[J]. Natural Hazards and Earth System Sciences, 2020, 20(4): 1069-1096.

[4] Kolstad C D, Moore F C. Estimating the economic impacts of climate change using weather observations[J]. Review of Environmental Economics and Policy, 2020.

[5] Botzen W J W, Martinius M L, Bröde P, et al. Economic valuation of climate change–induced mortality: age dependent cold and heat mortality in the Netherlands[J]. Climatic Change, 2020, 162: 545-562.

[6] Botzen W J W. Economics of insurance against natural disaster risks[M]//Oxford Research Encyclopedia of Environmental Science. 2021.

[7] Linnerooth-Bayer J A, Surminski S, Bouwer L M, et al. Insurance as a Response to Loss and Damage?[J]. Loss and damage from climate change: Concepts, methods and policy options, 2019: 483-512.

[8] Gatzert N, Reichel P, Zitzmann A. Sustainability risks & opportunities in the insurance industry[J]. Zeitschrift für die gesamte Versicherungswissenschaft, 2020, 109: 311-331.

[9] Liu S F, Yang Y J, Forrest J. Grey Systems Analysis[M]. Springer-Verlag, Berlin, 2022.

[10] Liu S, Lin Y. Grey prediction[M]. Springer London, 2006.