Prediction of Risk Evaluation Prediction Model for the Insurance Industry under Extreme Weather

Shuaichen Ge*

Faculty Office of Science and Engineering, University of Nottingham Ningbo China, Ningbo, China, 315100

* Corresponding Author Email: g2044426910@163.com

Abstract. The insurance industry is one of the indispensable economic sectors of modern society. In recent years, the frequent occurrence and the unpredictable nature of extreme weather have brought economic losses to society reflected in the insurance industry, which prompts people to seek strategies to realize the sustainability of the property insurance industry. This paper addresses the problem by developing a Risk Evaluation Model (REM) for the insurance industry under extreme weather conditions. The model incorporates the Analytic Hierarchy Process (AHP), Entropy Weight Method (EWM), and game theory combination weights to create a comprehensive secondary assessment system. Through fuzzy clustering analysis, risk levels are classified into four categories. The model was validated by applying it to two different regions globally—Florida, USA, and Karachi, Pakistan—determining their insurance risk levels. The results demonstrate that the REM model significantly enhances the accuracy and reliability of risk evaluation, helping to mitigate financial losses and ensure sustainable operations within the insurance industry. The study's significance lies in its contribution to robust risk management and underwriting decisions, with potential applications in urban planning and real estate development, highlighting the model's broader applicability and value.

Keywords: Risk Evaluation, Prediction Model, Insurance Industry, Extreme Weather.

1. Introduction

In recent years, a disconcerting trend has emerged, marked by a rising frequency of extreme weather events. This alarming pattern has not only cast a substantial shadow over the natural environment but has also precipitated a surge in societal losses, prompting an evaluation of its results [1]. Newman and Noy argue that climate change is attributable to $143 billion per year in costs from extreme events. They emphasize the substantial economic burden of climatic changes, highlighting the need for effective mitigation and adaptation strategies. [2] Extreme weather is fast becoming an existential crisis for property owners and their insurers. The world has suffered more than $1 trillion in damages from more than 1,000 extreme weather events in recent years [3]. And across central Europe, a hailstorm caused $1.9 billion in damage. About 50% of these costs are covered by insurance companies [4]. In the face of such large losses, the insurance industry, one of modern society's indispensable economic sectors, has naturally been impacted [5]. Because economic losses are mostly borne by insurance companies. The current situation of losses has prompted the insurance industry to increase premiums, but at the same time, it will also cause certain negative impacts, for example, the profitability of insurance companies and the affordability of homeowners are declining [6-9]. As a result, the insurance industry is seeking a sustainable transformation for the long-term health of insurance companies. This strategy not only mitigates economic losses but also contributes to broader societal resilience.

Some previous research has focused on developing models to predict and evaluate the risks associated with extreme weather in the insurance industry. These models generally combine statistical methods and machine learning algorithms to predict the occurrence and impact of extreme weather events. For instance, Unterberger et al. introduced a two-staged model framework based on the development of flood risk to the insurance industry under extreme weather [10]. This model analyzes the economic losses from public infrastructure and the burden it implies on public budgets. In the first step, the risk model projects flood risks to public infrastructure by combining exposure data and damage curves. In the second step, this model evaluates different compensation arrangements for covering projected flood damages. In general, the study compares the current informal disaster fund with more formalized insurance policies, highlighting benefits such as increased financial certainty and incentivized flood risk reduction measures. According to this model, the financial uncertainty caused by flood losses is reduced since damage can be budgeted for in advance, which brings benefits to the insurance industry.

Despite Unterberger et al.'s study providing methods for the insurance industry, there are still some limitations. Firstly, it focuses on a single flood risk, lacking a comprehensive evaluation of other types of extreme weather events. Secondly, the model does not incorporate a multi-criteria analysis framework, which is essential for a holistic assessment of various extreme weather events' impacts on the insurance industry. This single-risk evaluation approach might not provide the insurance industry with comprehensive risk management strategies, thereby limiting the model's broader applicability in real-world scenarios. To solve these problems, this study develop a new model. In the study, it proposes a Risk Evaluation Model (REM) for the insurance industry, which is used to assess the underwriting risk of insurance companies facing areas subjected to extreme weather. Specifically, the model considers extreme weather, Policy requirements, and social factors. Based on these three indicators, a secondary assessment system was developed. Considering that different methods have their limitations and advantages, the study decided to utilize hierarchical analysis (AHP), and entropy weight method (EWM) game theory combination weights to calculate the weight share of these indicators. Then it determined different risk levels by fuzzy clustering. The study chose different locations in two continents globally to substitute into the model for demonstration and confirm the insurance risk level in these two regions. Additionally, it considered the community and real estate developer factors, added five new indicators to compare with the REM model established at the beginning, and set up a new willingness formula to compare it with the original thresholds, to help the community and real estate developers make decisions.

2. The basic fundamental of Risk evaluation model（REM）

2.1. The hierarchical analysis method (AHP)

The Analytic Hierarchy Process (AHP), which is a systematic decision-making method, decomposes complex decision problems into a hierarchy of goals, criteria, and alternatives. Additionally, it uses pairwise comparison matrices to evaluate the relative importance of each factor. This process calculates the weights of the factors, aiding in making rational decisions among various options. AHP is widely applied in fields such as project evaluation and risk management, helping workers to make scientific and comprehensive choices in complex environments. The method structure is shown in Figure 1.

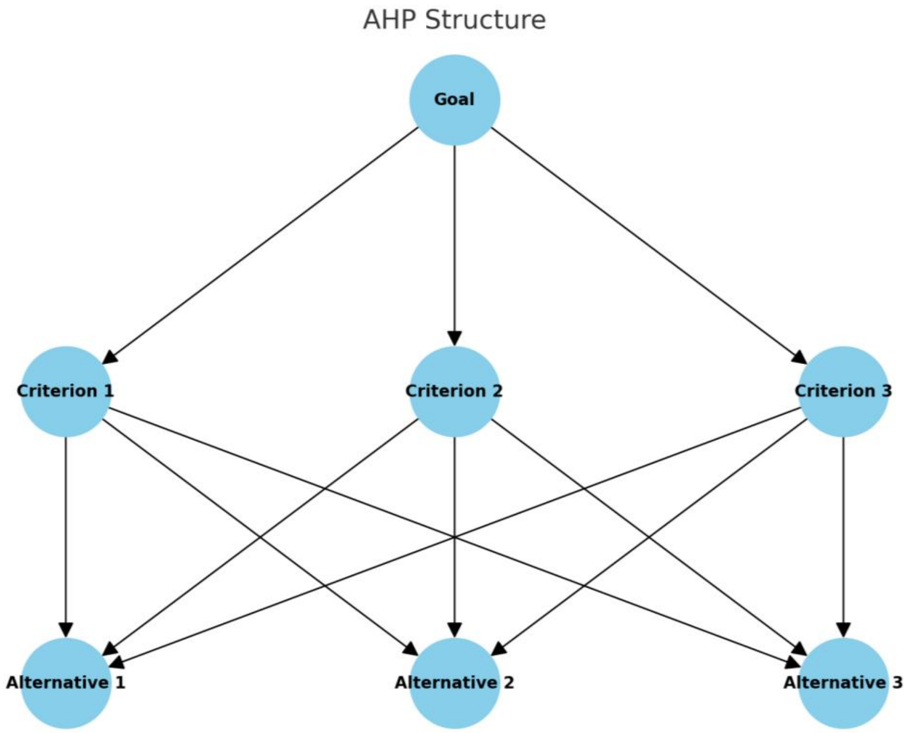

Figure 1. The Analytic Hierarchy Process structure

First, a hierarchical diagram is constructed based on the six indicators, as shown in Figure 2.

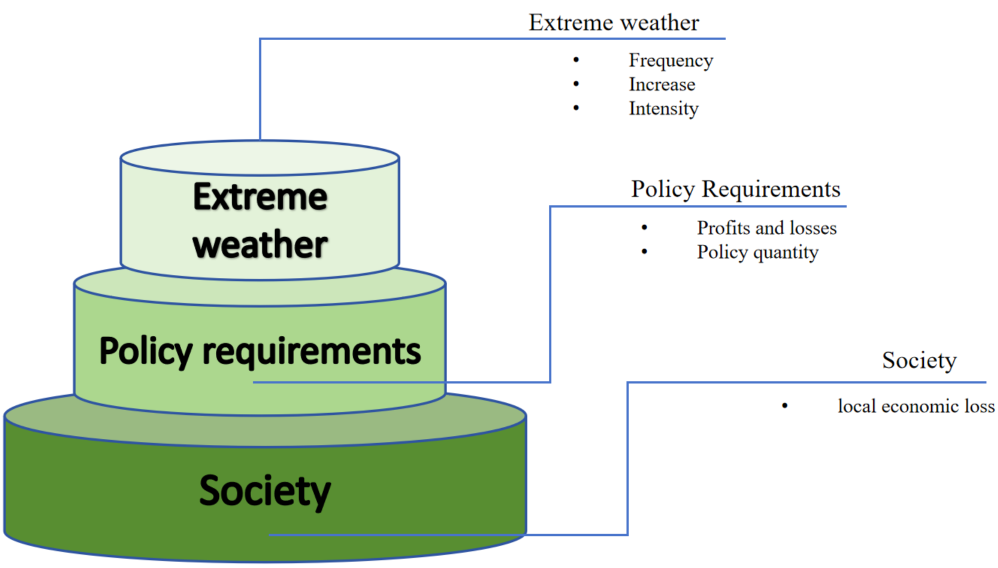

Figure 2. Hierarchical diagram

Then, the study constructed judgment matrices for the primary indicators and each group of secondary indicators separately:

$$A = (a_{ij})n \times n \tag{1}$$

In this matrix, a_{ij} denotes the importance of X_i relative to X_j and n denotes the overall number of indicators in each group.

The model used arithmetic average, geometric average and eigenvalue methods to calculate the indicator weights respectively, and then it combined and optimized the results calculated by these three methods and chose the average of these three weights as the final weight of each indicator in order to minimize the error and make the model more accurate.

The weights of the indicators calculated using this method are denoted as ω_{j_1}.

2.2. The entropy weighting method (EWM)

The Entropy Weighting Method (EWM) is a quantitative analysis technique used to determine the weight of indicators in multi-criteria decision-making problems. It relies on the concept of entropy, a measure of uncertainty, to assess the importance of various criteria based on the diversity of data. By calculating the entropy values for each criterion, EWM assigns lower weights to criteria with less variability and higher weights to those with greater variability. The method structure is shown in Figure 3.

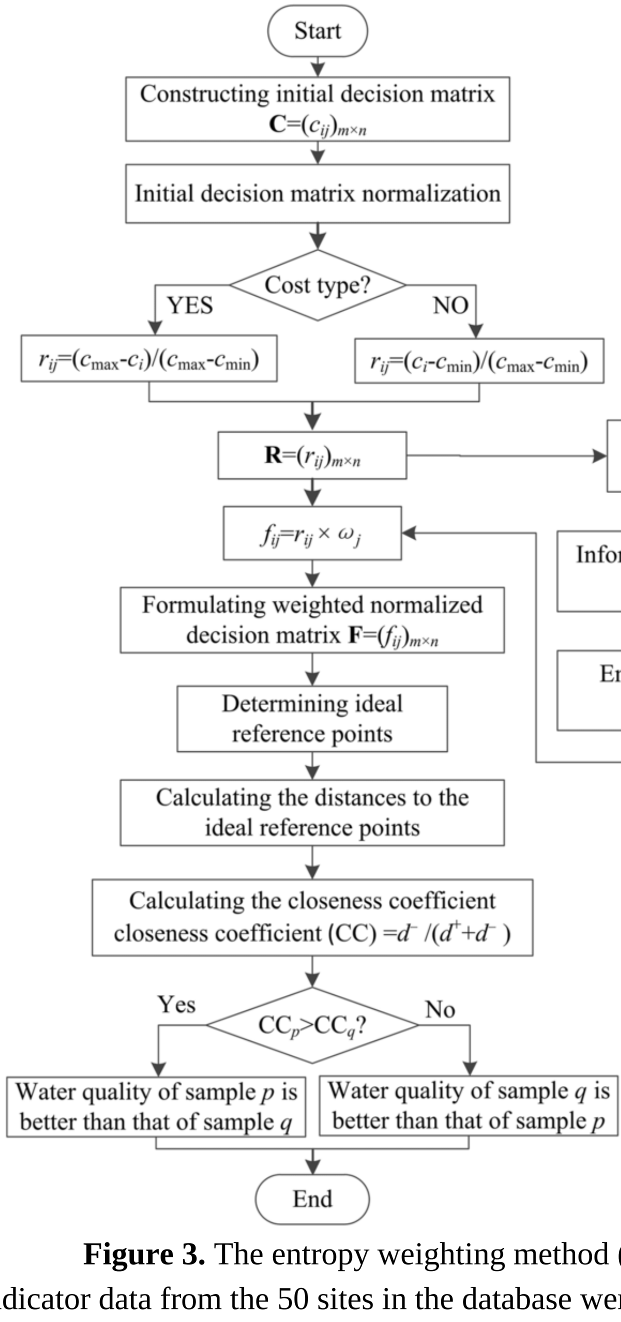

Figure 3. The entropy weighting method (EWM) structure

First, the indicator data from the 50 sites in the database were aggregated to form a raw matrix X. Because of the different types of indicators, the study next normalized the raw matrix. Next, it normalized the normalized matrix, aiming to remove the influence of dimensionality on the data, and then obtained a matrix Y. The study combines the normalization and standardization of the indicators in this paper, calculate the proportion of each sample under each indicator, and regard it as the probability used in the relative entropy calculation, and finally calculate the information entropy of each indicator, and calculate the information utility value, and normalize to get the entropy weight of each indicator.

The weights of the indicators calculated using this method are denoted as ω_{j_2}.

2.3. Game theory combination weights

Game theory combination weights refer to the distribution of weights assigned to different strategies or choices in a game-theoretical context. These weights help determine the relative importance or likelihood of each strategy in scenarios of uncertainty. By optimizing these weights, workers can maximize their payoffs or minimize risks, allowing for more informed decision-making in complex strategic environments.

Through the above two methods, the model calculated two different weights and the percentage of each indicator. To make the model more accurate and persuasive, it chose the game theory combination weights to synthesize the difference between different weights, narrow the gap between each weight and the optimal weight, and make the weights more representative and reasonable. The specific operation is as follows:

Using two weight calculation methods, the model can get two kinds of weights for each indicator, and the corresponding weight matrices are ω1 and ω2 and the calculated weight matrices are subjected to linear combination optimization:

$$minZ = \left\|\sum_{j=1}^{k} a_j w_j^T - w_i^T\right\|, i = 1,2,\cdots,k \tag{2}$$

A first-order derivation of (2) and expansion is obtained:

$$\begin{pmatrix} w_1 w_1^T & \cdots & w_1 w_k^T \\ \vdots & \ddots & \vdots \\ w_k w_1^T & \cdots & w_k w_k^T \end{pmatrix} \begin{pmatrix} a_1 \\ \vdots \\ a_k \end{pmatrix} = \begin{pmatrix} w_1 w_1^T \\ \vdots \\ w_k w_k^T \end{pmatrix} \tag{3}$$

Using equation (3) yields (a_1,a_2,…,a_k), which is then normalized to obtain the linear coefficients a_i^*(i=1,2,…,k).

$$a_i^* = a_i / \sum_{j=1}^{k} a_j, i = 1,2\,,\cdots,k \tag{4}$$

Using equation (4), the matrix ω^* of the final combination weights can be obtained.

$$w^* = \sum_{i=1}^{k} a_j^* \, w_i^T \tag{5}$$

3. Results

3.1. The establishment of the simulation model

Considering the impact of extreme weather, policy demand and society on insurance risk, the study developed a REM model. Inside this model, it chose to calculate scores using indicator weighting as a quantitative to describe the level of risk.

3.2. Analysis of experimental results

After the previous analysis, the study can know the data source of each indicator and its calculation method. The weight of each indicator is synthesized by the combined weight method. The weights corresponding to the indicators W, R and S are taken as the degree of influence of these three indicators for RLS, i.e., the larger the weight, the greater the influence of the indicator on RLS. So, this paper constructs the formula for the risk level score:(W, R, and S are independent variables, derived by comparing the destination point with all areas in the database and calculating the proportion of positively normalized rankings for each indicator in the database.)

$$RLS = \omega_W \cdot W + \omega_R \cdot R + \omega_s \cdot S \tag{6}$$

Similarly, based on the same principle, the model constructed the formula for W, R, and S:

$$w = \omega_{w1} \cdot w_1' + \omega_{w2} \cdot w_2' + \omega_{w_3} \cdot w_3' \tag{7}$$

$$R = \omega_{R_1} \cdot R_1' + \omega_{R_2} \cdot R_2' \tag{8}$$

$$s = \omega_{s_1} \cdot s_1' \tag{9}$$

The data from the 50 locations of the database were compared with the entire database to calculate the percentage of positively normalized ranking for individual locations, which was then used as a dependent variable to substitute into the RLS. Fuzzy cluster analysis was then utilized to classify all locations into 4 classes, thus dividing the insurance rating risk into 5 classes, defined as: Class I: low risk, can be covered; Class II: medium risk, can be covered for the most part; Class III: medium-high risk, less coverage is recommended; Class IV: high-risk, no coverage is recommended.

Table 1. Risk level

Grade	I	II	III	IV
Risk level	Low	Medium	Medium-high	high
RLS	<20%	20-50%	50-70%	>70%

As can be seen from the Table 1 above, the insurance risk level of the location can be determined based on the RLS formula calculation.

ClassI: low risk, the insurance company can choose to underwrite.

Class II: medium risk, insurance companies can underwrite most of it.

Class III: medium-high risk, insurance companies consider coverage.

Class IV: high risk, insurance companies recommend not to underwrite.

3.3. Application of risk evaluation model（REM）

In this section, two different types of locations on different continents were required to be selected globally. To show that the model is somewhat generalizable, it randomly chose two regions one is Florida in the United States of America in North America and the other Karachi in Pakistan in Asia. The study collected data on relevant indicators and applied the model developed to assess the level of insurance risk.

Case 1: Florida

Florida is a state in the southeastern United States, bordered by the Atlantic Ocean to the east and the Gulf of Mexico to the west, with a variety of climate types, and is often affected by hurricanes in July and August due to its proximity to the Gulf of Mexico. It is important to note that the following data are annual averages for this year.

Table 2. Data from Florida

Index	Statistic
Frequency(time)	13
Increase (%)	46
Intensity(1-5)	3
Profit and Losses ($)	7,420,225
Policy quantity	1000000
Local economic loss($)	10000000

Enter the above data, which Table 2 shows, into the RLS formula to calculate the level of insurance risk in the Florida region: the study intend to use the ratio as a dependent variable calculation to compare the location to all regions in the database and to calculate the share of the positive normalized ranking of each indicator within the database.

Florida has an RLS value of 43.26%, which is classified as Class II, indicating moderate risk. Florida is economically developed and densely populated, and in the event of extreme weather social losses are huge, but correspondingly, the early warning system and protection measures in the area are relatively well developed, which can significantly reduce social losses, so the insurance risk is moderate. The insurance profit and loss are shown in Figure 4.

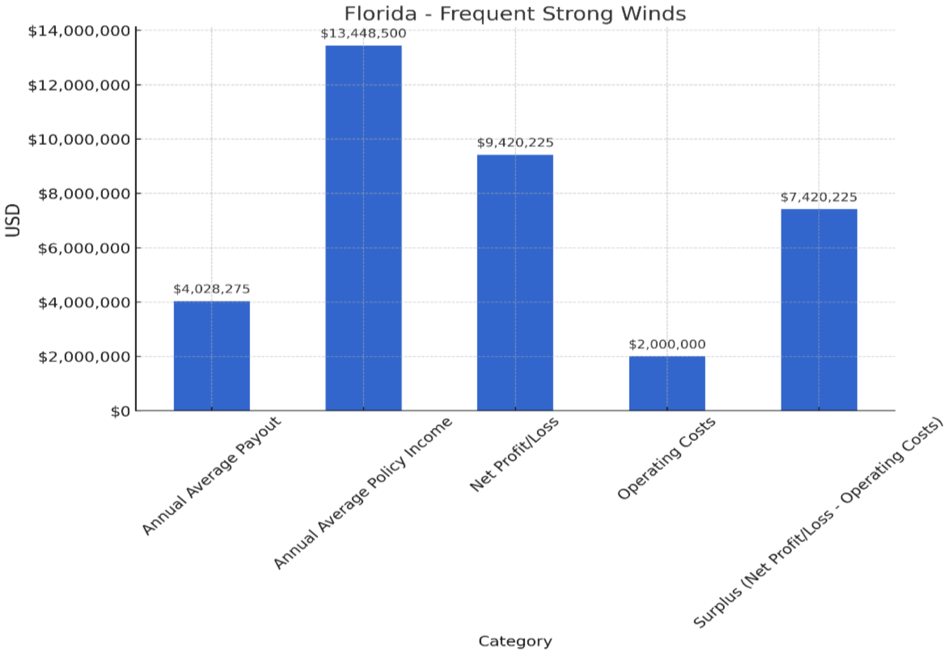

Figure 4. Insurance Profit and Loss in Florida

Case 2: Karachi

Karachi is Pakistan's largest city, located on the southern coast of Pakistan, northwest of the Indus Delta and bordering the Arabian Sea to the south. Karachi is the economic center of Pakistan with important port and air transport facilities. The city is also home to Pakistan's military bases and government institutions. Karachi is an important industrial center of Pakistan, in addition to being a cultural and educational center of Pakistan with many universities and higher education institutions. The data from Karachi is shown in Table 3.

Table 3. Data from Karachi

Index	Statistic
Frequency(time)	18
Increase (%)	34
Intensity(1-5)	3.5
Profit and Losses ($)	2257800
Policy quantity	500000
Local economic loss($)	50000000

Karachi has an RLS value of 57.27%, which is classified as Class III, indicating medium to high risk. Karachi is economically developed and densely populated, in the event of extreme weather social losses are huge, but correspondingly, the early warning system and protection measures in the area are relatively well-developed, which can significantly reduce the social losses, but not as well-developed compared to Florida, so the insurance risk is medium-high.

4. Conclusions and outlooks

In the study, it proposes a Risk Evaluation Model (REM) for the insurance industry, which is used to assess the underwriting risk of insurance companies facing areas subjected to extreme weather. Specifically, the model considers extreme weather and Policy requirements and social factors. Based on these three indicators, a secondary assessment system was developed. Considering that different methods have their limitations and advantages, the model decided to utilize hierarchical analysis (AHP), entropy weight method (EWM) game theory combination weights to calculate the weight share of these indicators. Then it determined different risk levels by fuzzy clustering. And the model chose different locations in two continents globally to substitute into the model for demonstration and confirm the insurance risk level in these two regions. Overall, this study provides a robust tool for risk management and underwriting decisions in the insurance industry, helping to mitigate financial losses and ensure sustainable operations. Future work could expand the model's application scope to include more types of extreme weather events and different regions, enhancing its generalizability and accuracy. Additionally, this model can be extended to other regions prone to extreme weather, and applied in urban planning and real estate development. It can be used by policymakers and corporations for comprehensive risk management too. This versatility underscores the broader applicability of the model and makes a significant contribution to strengthening risk assessment and management practices across sectors.

Although the model can take advantage of decreasing the insurance risk under extreme weather, there are still some limitations. Time constraints did not allow for a large enough database, only 50 districts were selected. The scope of the RLS hierarchy is not clear enough. The data used in this paper is not complete enough, objectively, the study could not get all the data for the required indicators, and there are missing data and accuracy deviations. Since the database in this paper consists of only 50 districts, the study can expand the database sample to collect data from more different districts to reduce data errors and make the RLS more accurate and generalizable.

References

[1] Lin Y H, Wang L J, Shi X Y, et al. Evolution of research on climate risk insurance: A bibliometric analysis from 1975 to 2022[J]. Advances in Climate Change Research, 2023, 14(4): 592-604.

[2] Newman R, Noy I. The global costs of extreme weather that are attributable to climate change[J]. Nature Communications, 2023, 14(1): 6103.

[3] Lyubchich V, Newlands N K, Ghahari A, et al. Insurance risk assessment in the face of climate change: Integrating data science and statistics[J]. Wiley Interdisciplinary Reviews: Computational Statistics, 2019, 11(4): e1462.

[4] Hudson P, De Ruig L T, De Ruiter M C, et al. An assessment of best practices of extreme weather insurance and directions for a more resilient society[J]. Environmental Hazards, 2020, 19(3): 301-321.

[5] Cremades R, Surminski S, Máñez Costa M, et al. Using the adaptive cycle in climate-risk insurance to design resilient futures[J]. Nature Climate Change, 2018, 8(1): 4-7.

[6] Collier S J, Elliott R, Lehtonen T K. Climate change and insurance[J]. Economy and Society, 2021, 50(2): 158-172.

[7] Gupta A, Venkataraman S. Insurance and climate change[J]. Current Opinion in Environmental Sustainability, 2024, 67: 101412.

[8] Agrawal A, Gans J S, Goldfarb A. Prediction machines, insurance, and protection: An alternative perspective on AI's role in production[J]. Journal of the Japanese and International Economies, 2024, 72: 101307.

[9] Behari M. The Future of Foundation Models in Predicting Climate-Related Risks in the Insurance Sector: A Case Study in Louisiana[C]//Fragile Earth: Generative and Foundational Models for Sustainable Development. 2024.

[10] Liu H, Meng J, Li W, et al. Extreme Weather Risk Assessment and Insurance Decision Making Based on ARIMA Model and Visual Analysis[J]. Highlights in Science, Engineering and Technology, 2024, 101: 305-313.