Research on Catastrophe Insurance Based on Multi-layer Analysis

Yanji Qian [1,*], Yifeng Hou [2], Yitao Zhu [2], Haoyu Zhang [1], Boyan Jia [1]

[1] School of Materials Physics, China University of petroleum, Qingdao, China, 266400

[2] School of Storage and Construction Engineering, China University of petroleum, Qingdao, China, 266400

* Corresponding Author Email: 17660639118@163.com

Abstract. In recent years, extreme weather events have occurred frequently around the world, which has caused the insurance industry to face the dual dilemma of insurance company profitability and customer affordability. Therefore, a risk assessment and management model should be developed to adapt to the current new climate reality, and a PD model should be established, combined with analytic hierarchy process and weighted average model. The combined weights of each index were calculated, and the PD risk index was obtained by using the TOPSIS evaluation method. Considering the influence of owners on insurance income, the index factor of owner's age structure α and the owner's awareness factor of prevention β are introduced to optimize the calculation formula of the loss ratio, and the solution model of catastrophe insurance income evaluation index V is obtained. According to the comparison between the evaluation area and the reference area V, the data envelopment evaluation of the 10 regions that the real estate company intends to α and β achieve is judged to determine whether the best input-output ratio is achieved. Finally, according to the optimal target value θ, 10 regions are graded, and the real estate investment policies of each level are given.

Keywords: Analysis Hierarchy Process, Entropy Weight Method, Technique for Order Preference by Similarity to Ideal Solution, Prediction Model.

1. Introduction

With the intensification of global climate change, the frequency and intensity of extreme weather events are increasing, bringing unprecedented challenges to the property and casualty insurance industry. and the accessibility and affordability of insurance coverage have become a common concern in society [1].

In summary, it is of great theoretical and practical significance to explore and develop new models and strategies that can accurately assess and manage extreme weather risks. Gao Yang, Linda· Nozick, Jamie· Cruise, Rachel· Davidson et al, studied the structure of the primary natural catastrophe insurance market, and discussed the impact of market competition on the business decisions and profitability of insurance companies and applied the model framework to a hurricane risk (flood and wind) case study of residential buildings in eastern North Carolina. On this basis, this paper believes that there is another evaluation system model that can assess the risk of natural disasters in the region and provide an evaluation plan for the business decision-making and profitability of insurance companies [2].

Recently, the PD model (P) was established, the combined weights of each index were calculated by combining the analytic hierarchy process (AHP) and the weighted average model (EWM), and the PD risk index was obtained by using the TOPSIS evaluation method to help insurance companies evaluate whether policies should be underwritten in areas facing an increase in extreme weather events in the context of climate change. The model is demonstrated using two regions on different continents experiencing extreme weather events at the same time. According to the comparison between the evaluation area and the reference area V, the data envelope evaluation of the 10 regions that the real estate company intends to make is evaluated to determine whether the best input-output ratio is achieved. Finally, according to the optimal target value θ, the 10 regions are graded, and the corresponding underwriting strategies of the insurance company are given.

2. The basic fundamental of Multi level evaluation analysis method

2.1. Establishment of AHP-EWM-TOPSIS

2.1.1. Establishment of evaluation system

This paper have identified two key factors that affect the underwriting of catastrophe insurance by insurance companies in this area: the probability of extreme weather occurrence (P) and the intensity of extreme weather damage (D), which are used as the first-level indicators in the evaluation system. Seven specific indicators are selected as the second-level indicators in the evaluation system. Among them, the second-level indicator economic loss N is further refined into six third-level indicators (including building damage $N_{bu.}$, agricultural loss $N_{ag.}$, industrial and commercial loss $N_{ie.ij}$, reconstruction and repair wecosts $N_{re.\,ij}$, production and service interruption loss $N_{ps.ij}$, and international trade interruption loss $N_{it.\ ij}$ [3].

The probability of extreme weather occurrence is a key factor in assessing the risk level of an area. This paper have collected and analyzed the number of occurrences Ω and the total number of days T of specific types of extreme weather events in a particular area over the past 10 years. These two indicators can reflect the potential trend of extreme weather changes and the persistence of its impact on a region [4].

The intensity of extreme weather damage is an important factor in determining the amount of compensation from insurance companies.Using the EM-DAT evaluation criteria, this paper have identified the following five factors that affect it and showed in the following Figure 1:

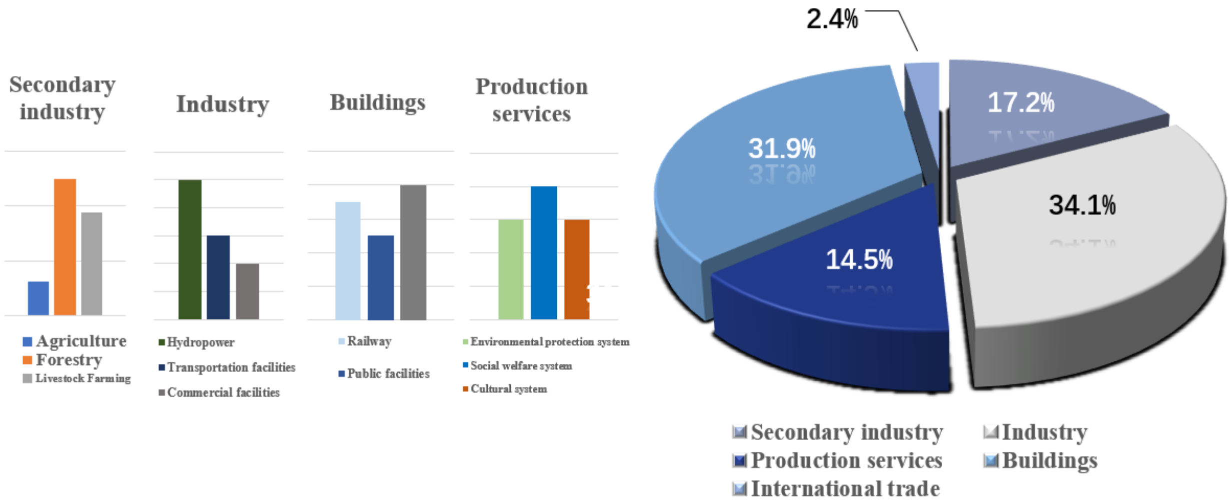

Figure 1. Diagram of the composition of economic losses from disasters

① Economic loss N. In the PD model, six main indicators are selected, including building damage $N_{bu.}$,agricultural loss $N_{ag.}$, industrial and commercial loss $N_{ie.ij}$, reconstruction and repair costs $N_{re.\,ij}$, production and service interruption loss $N_{ps.ij}$, and international trade interruption loss $N_{it.\ ij}$.

② P_a The lower the number of affected people, the more likely it is that the area has a more robust early warning system and more effective emergency response measures.

③ P_d The number of fatalities reveals the direct threat to life safety from extreme weather.

④ P_i The number of displaced people; the more people are displaced, the higher the PD index of the area.

⑤ θ The disaster resistance performance of local buildings is assessed using the earthquake performance rating system introduced by the Earthquake Engineering Research Institute (EERI). The average disaster resistance performance score of the buildings in the area is used as an indicator [5].

2.1.2. AHP-EWM-TOPSIS evaluation model

First, the Analytic Hierarchy Process (AHP) and the Entropy Weight Method (EWM) are used comprehensively to calculate the weights of the indicators. The combination of the two can improve the accuracy of weight calculation [6-7]. Subsequently, the TOPSIS method is used to evaluate the regions to be evaluated. At the same time, this paper selects three regions that are representative of the performance of catastrophe insurance, Tokyo in Japan, Chicago in the United States, and New Delhi in India, as reference regions. Lyon in France and Beijing in China are chosen as the regions to be evaluated. The relevant data of these five regions constitute the database of our model [8-9].

2.1.3. EWM

Step 1. To summarize the indicator data in the database, an original matrix x is formed and normalized. The normalized matrix is then standardized to ultimately obtain the matrix X.

Step 2. Calculate the probability matrix Pij.

According to the concepts of self-information and entropy in information theory, this paper can calculate the information entropy of each evaluation indicator and obtain:

$$\boldsymbol{E_j = -\frac{1}{ln\,5}\sum_{i=1}^{5} P_{ij}\, ln\left(P_{ij}\right)} \tag{1}$$

Step 3. By normalizing the information utility values, the weight of each indicator is obtained.

2.1.4. AHP

Step 1. Construct the hierarchy of indicators.

Step 2. Construct the judgment matrix for the first-level indicators and the second-level indicators respectively:

$$A = \left(\omega_{ij}\right)_{n\times n} \tag{2}$$

Where ω_{ij} represents the relative importance of X_i compared to X_j and n is the number of indicators in each group.

Step 3. Determine the weight of each indicator ε_j'' and perform consistency check

Take $\varepsilon_j=\frac{\varepsilon_j''+\varepsilon_j'}{2}$ as the final weight.

2.1.5. TOPSIS

Step 1. Normalize the original matrix by converting all types of indicators into positive indicators, which are considered as benefit-type indicators. For 5 evaluation subjects and 7 normalized evaluation indicators, the normalized matrix X is formed.

Step 2. Standardize each element in X to obtain the matrix Z.

Step 3. Define the positive ideal solution and the negative ideal solution and then define the distance of the ith (where i = 1, 2…5) evaluation object from the minimum values.

Step 4. Calculate the score of the evaluation object.

2.2. Catastrophe Insurance AIM Model

2.2.1. The calculation of the payout ratio

In the insurance industry, the ratio of claims expenses to premium income over a certain period is usually defined as the insurance payout ratio.

(1) Calculate insurance profits V_{in}:

$$V_{in} = \overline{S_{in}} \times P \times \overline{\gamma} \tag{3}$$

Where $\overline{S_{in}}$--The average sales price of catastrophe risk,P--Total population.,$\overline{\gamma}$--Average insurance penetration rate.

(2) Calculate insurance claim payments V_{out}:

$$V_{out} = \overline{S_{out}} \times P \times \overline{\gamma} \tag{4}$$

Where $\overline{S_{out}}$-- Average individual claim amount.

(3) Calculate insurance claim payments.

2.2.2. Introducing correction factors

Optimize the payout ratio formula to derive the benefit evaluation indicator V introduce the following three correction factors:

(1) PD value, in the catastrophe risk assessment model, the PD index of an area reflects the likelihood and destructive power of extreme weather events.

(2) Age structure evaluation factor α; the age structure factor, where the proportion of policyholders aged 30-60 accounts for the main part of the total number of policyholders [10].

(3) Owner's prevention awareness evaluation index β, the awareness and response capabilities of property owners to extreme weather will directly affect the degree of damage caused by extreme weather in the area, thereby affecting the amount and probability of claims for catastrophe insurance.

Therefore, this paper derives a formula for approximately calculating the benefit evaluation index:

$$V = \frac{PD \times \beta \times \overline{S_{out}} \times P \times \overline{\gamma}}{\alpha \times \overline{S_{in}} \times P \times \overline{\gamma}} \tag{5}$$

2.3. Catastrophe Insurance AIM Model

Data Envelopment Analysis (DEA) is a systematic analysis method based on the concept of “relative efficiency”, particularly suitable for complex systems with multiple inputs and outputs [11]. This study uses the C2R model of DEA to evaluate the investment value of real estate plots through data envelopment analysis.

Step 1.Determine the input α_i and output β_i vectors of the decision-making unit.

Step 2. Determine the weight vectors of input u and output v.

Step 3.Determine the mathematical model of the i0 efficiency of the evaluation object and transform a model into an equivalent linear programming problem:

$$Max\ V_{i0} = \beta_{i0}^T \mu \tag{6}$$

$$s.t.\begin{cases} \alpha_{i0}^T \omega - \beta_i^T \mu \geq 0, i = 1,2,\cdots,m \\ \alpha_{i0}^T \omega = 1 \\ \omega \geq 0, \mu \geq 0 \end{cases} \tag{7}$$

Step 4.Result Analysis After the result is obtained, if the optimal target value of the linear programming problem is Vi0=1, then the evaluation object i0 is said to be DEA valid.

3. Results

3.1. AHP-EWM-TOPSIS Evaluation of the model results

Here, only data from Tokyo, Japan over the past 10 years is selected for demonstration, as shown in the Table. 1.

Table 1. Data on indicaators over a10-year period in Tokyo

Year	Ω	θ	P_d	P_i	P_α	T	N
2013	5	6.27	400	23514	131028	10	75093
2014	5	5.21	301	25689	61075	52	6681000
2015	7	4.9	71	5541	120946	35	1630200
2016	5	4.44	101	23991	436528	22	58200000
2017	5	5	49	44148	300	9	2202000
2018	4	4.93	435	43152	1602397	37	31000000
2019	5	5.04	288	513602	1520342	45	26210000
2020	5	5.12	84	250000	521420	38	6000000
2021	5	5.05	62	39447	60	20	10600000
2022	5	5.01	112	26571	524163	37	11693000
2023	6	4.23	15	10557	54	15	10723000

The weights obtained by the EWM method are as follows:
[0.132, 0.147, 0.238, 0.069, 0.183, 0.081, 0.150];
The weights obtained by the AHP method are as follow:
[0.126, 0.124, 0.231, 0.113, 0.151, 0.132, 0.123];
The final indicator weights are as follows:
[0.129, 0.135, 0.234, 0.091, 0.167, 0.1065, 0.1365];
After visualizing the weights, you can obtain the following Figure 2:

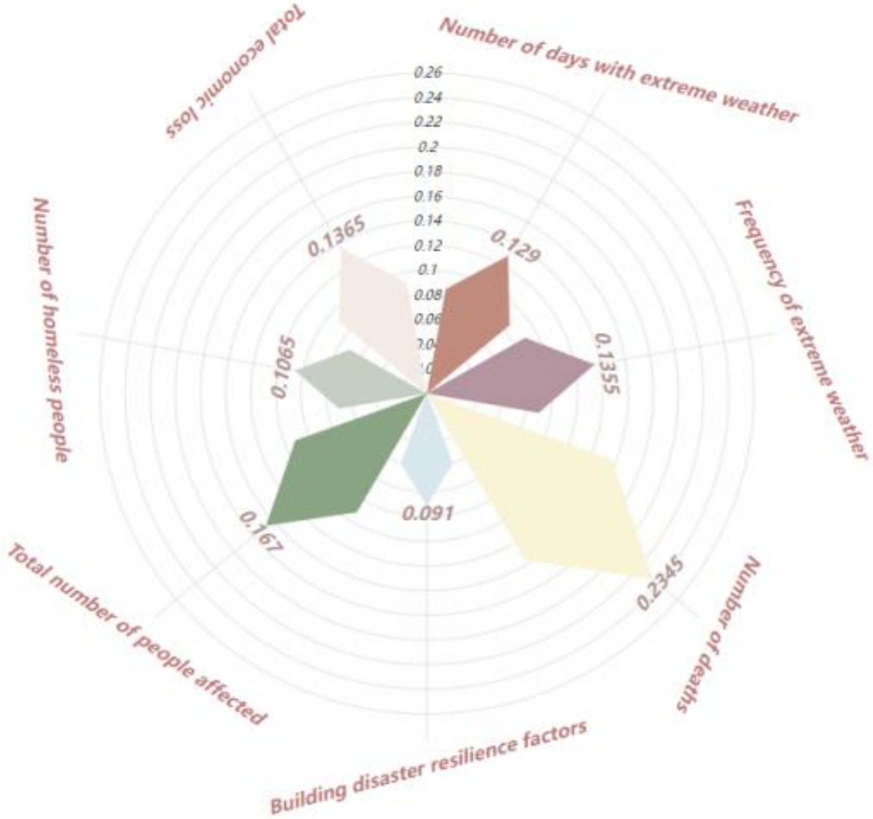

Figure 2. Schematic diagram of the weighting indicator

The calculated list of $Score_i$ is shown in the Table. 2.

Table 2. PD index by region over a 10-year period

Year	Tokyo,Japan	Beijing, China	Madrid, India	Chicago, America	Lyon, France
2013	0.038354	0.27296	0.544643	0.286964	0.1
2014	0.016383	0.328551	0.700601	0.39	0.13
2015	0.009992	0.265265	0.856553	0.56	0.14
2016	0.00753	0.294606	0.871912	0.59	0.11
2017	0.011348	0.267992	0.75	0.357365	0.12348
2018	0.036838	0.265486	0.68	0.326637	0.12
2019	0.085	0.264022	1	0.55	0.11
2020	0.076087	0.267254	0.558275	0.48	0.11
2021	0.010329	0.269057	0.545975	0.45	0.12456
2022	0.011747	0.265624	0.807885	0.46	0.1
2023	0.005142	0.26365	0.735284	0.607836	0.027594

It is worth noting that the number of reference regions and which regions are selected as references can be adjusted based on specific circumstances. In theory, the more reference regions there are, the greater the reference value.

3.2. The Catastrophe Insurance AIM Model Based on the PD Index results

Due to the large volume of data, only the evaluation indicator data for Beijing and France is presented in Table. 3.

Table 3. Beijing and Lyon Indicator Data

Region	Beijing, China	Lyon, France
Days	354	136
Number of deaths	283	4817
Number of injuries	478	78
Total number of people affected	6309457	60379
Number of homeless people	118	54
Total economic loss /$	16000000	5083798
Building disaster resilience factors	6.2	8.7
Total population /billion people	14.1	0.67
Average catastrophe insurance	5.4	64.5
rate /%	7.7	8.3
Age structure evaluation factor	91.32	778.32

The final V value calculation results for the five regions are shown in the Table. 4.

Table 4. V index for regions

Name	Tokyo,Japan	Beijing,China	Madrid,India	Chicago,America	Lyon,France
V	9.5	6.4	1.4	6.7	8.8

3.3. Hierarchical investment policy for real estate companies

By selecting the load prediction results of 403 and 411 lines. This paper can see that the actual values of the lines basically match the predicted values, but there are also some errors, especially in the peak period of electricity consumption, as shown in Table. 5.

Table 5. Comparison of power load forecasting of 403 line

Comparison	Power	Forecasting
A	12937	92387
B	928735	29837
C	894523	23894

This paper considers three input variables: the amount spent in the past five years to improve disaster resilience in buildings a_{i1},the real estate investment amount in the region in recent years a_{i2},and the proportion of the total amount allocated by real estate companies to enhancing disaster resilience in construction projects a_{i3}.

As for output variables, two are considered: the current average return on investment for the real estate sector in the region b_{i1},and the current insurance value evaluation index b_{i2}.

The database composed of input and output variables for 10 regions shown in Table. 6.

Table 6. Data information for the 10 intended investment regions

Region	a_{i1}	a_{i2}	a_{i3}	b_{i1}	b_{i2}
Sydney, Australia	224990	243090	0.125	160654	5.8
Gwangju, Korea	309185	262178	0.024	536070	6.3
Oulu, Finland	125320	198147	0.043	311740	7.2
Vientiane, Laos	303772	262128	0.159	240252	5.1
Changsha,China	160654	205481	0.075	533908	8.2
Cuenca, Ecuador	200805	21386	0.034	271427	6.4
ClujNapoca,Romania	272330	27142	0.027	497241	7.4
Moscow, Russia	349035	29341	0.018	376878	7.9
Madrid, India	124347	10342	0.003	103485	1.4
Rio de Janeiro, Brazil	314921	21385	0.015	150873	3.7

By using MATLAB to solve the efficiency evaluation index h_i and the linear programming problem converted from it, the optimal objective value θ for each region is finally calculated. The closer θ is to 1, the higher the investment-to-output ratio of real estate in disaster-resistant construction for that region, making it more valuable for investment. The θ values for the 10 regions are as shown in Table. 7.

Table 7. θ for the 10 intended investment regions

Region		Region	θ
Sydney, Australia	0. 946	Cuenca, Ecuador	0.476
Gwangju,Korea	0.768	ClujNapoca,Romania	0.658
Oulu, Finland	1	Moscow, Russia	1
Vientiane, Laos	0.846	Madrid, India	0.241
Changsha,China	0. 978	Rio de Janeiro, Brazil	0.884

Consequently, this paper can give some granded investments for real estate companies. The strategies corresponding to different θ values are shown in Table. 8.

Table 8. Schematic diagram of the tiered commissioning policy

Level	θ interval	Given Strategy
A	0. 9~1	Invest here and develop an investment plan according to the recent local real estate trends a_{i2} and a_{i3}.
B	0.5~0.8	Consider investing here, referencing recent local real estate trends a_{i2} and a_{i3} to formulate the investment plan.
C	0.1~0.5	Do not invest here.

From the information above, this paper can see that among the 10 selected potential investment regions:

Four regions are classified as Grade A, where real estate companies should invest. These regions are Moscow, Russia, Sydney, Australia, Oulu, Finland, and Changsha, China.

Four regions are classified as Grade B, where real estate companies can consider investing. These regions are Gwangju, South Korea, Vientiane, Laos, Cluj-Napoca, Romania, and Rio de Janeiro, Brazil.

Two regions are classified as Grade C, where real estate companies should not invest. These regions are Madrid, India, and Cuenca, Ecuador.

At the same time, it can also analyze regional differences and data anomalies in risk management in each region, as well as specific years. An in-depth analysis of data from these years can help determine the types of extreme weather events and their impact on the risk index.

4. Conclusions and outlooks

In this study, this paper successfully assessed the catastrophe risk levels in different regions under the background of climate change by constructing and applying the AHP-EWM-TOPSIS model. This model not only provides a scientific basis for insurance companies to make underwriting decisions, but also provides guidance for governments and real estate investors when facing extreme weather risks.

When this model uses analytic hierarchy process to determine the weights, it will inevitably be affected by subjective factors, which will change in real time according to the different conditions of different regions, and when this model divides the multi-level scheme into hierarchies, there are only approximate scheme suggestions.

Future research should continue to improve the model, consider more influencing factors, and introduce more field data into the analysis to improve the prediction accuracy and practicability of the model.

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