ISSN 2522-3488 Vol. 9, Issue 2: 46-50, DOI: 10.25236/IJNDES.2025.090208

A Study on Insurance Decision-Making Based on Extreme Weather Conditions and Regional Resilience Assessment

Haochong Xie[1,*], Yiyang Wu[1], Jiayu Shen[2]

[1]*School of Science, China University of Mining and Technology-Beijing, Beijing, China, 102206*
[2]*School of Mechanical and Electrical Engineering, China University of Mining and Technology-Beijing, Beijing, China, 102206*
[*]*Corresponding author: xhc18069858145@outlook.com*

Abstract: *In recent years, with the increase of extreme weather events, the financial crisis of insurance companies and residents has become more and more serious, this paper stands in the perspective of insurance companies to provide the optimal choice for the profitability of insurance companies. For the construction of the model, this paper first applies the Poisson distribution to construct the extreme weather forecasting model to describe its probability distribution. Then, in the disaster resilience assessment model, this paper constructs a two-layer assessment index system, and combines subjective and objective values through hierarchical analysis method (AHP) and entropy weight method (EWW). The entropy weight method (EWM) is used to combine subjective and objective values, and the calculation formula is used to derive the regional disaster resistance coefficient. Then, combining the above two models, this paper derives the core index of insurance company's decision-making - payout ratio. The paper also constructs a regional risk index model and a break-even analysis model to determine appropriate policy bands.*

Keywords: *Comprehensive Evaluation, Resilience to Disasters, Insurance Payout*

1. Introduction

Influenced by the uncertainty of extreme natural disasters, insurance companies have overpayment in some areas if they follow the original payout strategy. In order to help insurance companies to reasonably underwrite insurance and at the same time reasonably bear the risk for local residents, this paper combines a variety of analytical methods, prediction models and diversified influencing factors for disaster risk prediction and regional disaster resilience assessment, and constructs relevant models to provide insurers with a basis for decision-making.

2. Extreme Weather Prediction Model - Predicting the Frequency of Extreme

Because we are only projecting for the next three years, we idealistically ignore changes in the incidence of extreme weather due to climate change. We use the Poisson distribution for forecasting. We recommend that insurance companies count the frequency of extreme weather occurrences over the past n (n cannot be too large) years to obtain the frequency vector X, based on actual conditions[1]. Then, according to the probability distribution equation:

$$\begin{gathered} X = (x_1, x_1, \cdots, x_n) \\ P(x = i) = \frac{\lambda^i}{i!} e^{-\lambda} (i = 0,1,2,\cdots) \\ \lambda = E(x) = \frac{1}{n} \sum_{i=1}^{n} x_i \end{gathered} \tag{1}$$

Obtain a probability distribution of the number of extreme weather events in a year. Next, we analyze the profit and loss of the insurance company by taking the extreme value F of the curve obtained from the prediction as the predicted value of the number of occurrences in a year. According to the Three Sigma principle, we use MD, the maximum number of disasters with a probability close to three in a thousand, as a worst-case scenario for the risk assessment of insurance companies [2].

ISSN 2522-3488 Vol. 9, Issue 2: 46-50, DOI: 10.25236/IJNDES.2025.090208

3. Disaster Resilience Assessment Model - Calculation of Resilience Factor for the area

3.1 Construction of evaluation index system

Clarifying the concept of urban disaster resilience is an important prerequisite for constructing the evaluation index system. The urban disaster resilience referred to in this paper is based on the resilience theory. Resilience refers to the ability of a city to prevent floods before a disaster, to make self-adjustment to reduce the impact of floods during a disaster to eliminate the adverse effects of floods, and to restore the normal order of the city promptly after a disaster. We construct the disaster resilience evaluation index system from four dimensions: exposure, sensitivity, adaptability, and resilience[3].

Target Layer	System Layer	Factor Layer	Indicator Layer	Index
Development and construction coefficient	Livability coefficient	Social security level	Number of participants in basic pension insurance for enterprise employees	(+)
			Number of participants in unemployment insurance	
			per capita GDP	
		economic prosperity	Per capita disposable income	(+)
			Share of tertiary employment in total employment	(+)
			Engel's coefficient for households	(+)
			Urban registered unemployment rate	(+)
			Average wage of urban employed persons	(+)
			Green space per capita in parks	(+)
		environmental beauty	Greening coverage in built-up areas	(+)
			Public Library Book Collection	(+)
			General undergraduate enrollment	(+)
			Total water resources	(+)
			Daily capacity of non-destructive treatment plants	(+)
		Convenience of life	Measures for urban community services	(+)
			Housing area per capita	(+)
			Cell phone penetration rate	(+)
			Road space per capita	(+)
			Water penetration rate	(+)
	Disaster resilience	exposure leve	Urbanization index	(-)
			annual rainfal	(-)
			altitude	(-)
		sensitiveness	GDP per unit area	(-)
			population density	(-)
			The proportion of construction land	(-)
		adaptability	Investment in experimental and research and development funds	(+)
			road density	(+)
			Proportion of undergraduate population	(+)
		recovery force	Medical resource density	(+)
			per capita GDF	(+)
			The proportion of the tertiary industry	(+)

Figure 1 Analytical Table

Exposure: refers to the risks and pressures faced by urban systems, reflecting the likelihood of urban systems being exposed to disasters. We selected urbanization rate, annual precipitation, and elevation as secondary evaluation indicators.

Sensitivity: refers to the degree to which an urban system or its components are likely to be affected when subjected to a disturbance. We selected population density, construction land share GDP per unit area, as its secondary indicators[4].

Adaptability: refers to the ability of urban systems to self-regulate to mitigate potential damage,focusing on the state of a city to maintain normal levels of functioning.Focuses on the state of the city to maintain a normal level of functioning. We choose road area, adaptation, R and D investment, and percentage of undergraduate students as secondary indicators.

ISSN 2522-3488 Vol. 9, Issue 2: 46-50, DOI: 10.25236/IJNDES.2025.090208

Below we establish a two-tier evaluation indicator (Figure 1).

3.2 Data and processing

Due to the differences in the type, scale, and order of magnitude of the indicators in the urban flood resilience assessment index system, it is necessary to standardize the raw data of each indicator.differences, it is necessary to standardize the raw data of each indicator, and the standardized values can more effectively reflect the impact of indicators on disaster [5]. The standardized values can more effectively reflect the magnitude of the impact of the indicators on the resilience of disasters. The formulas for standardizing the positive and negative indicators are as follows:

$$\begin{aligned} \mathrm{Y_{ij}} &= \frac{\max(\mathrm{x_{ij}})-\mathrm{x_{ij}}}{\max(\mathrm{x_{ij}})-\min(\mathrm{x_{ij}})}(\mathrm{j}=1,2,3,\cdots,\mathrm{n}) \\ \mathrm{Y_{ij}} &= \frac{\mathrm{x_{ij}}-\min(\mathrm{x_{ij}})}{\max(\mathrm{x_{ij}})-\min(\mathrm{x_{ij}})}(\mathrm{i}=1,2,3,\cdots,\mathrm{m}) \end{aligned} \tag{2}$$

x_{ij} and Y_{ij} denote, respectively, the raw and standardized values of j indicators in i regions.

3.3 EWM-AHP method combination for determining fixed weights

First, we use the entropy weight method to determine the objective weights in the Analytical Table like Figure 1. The entropy weight method utilizes the existing objective data to obtain the objective assignment of weights of the evaluation indicators method. It is not affected by the subjective will of the evaluator and can reflect the change sin the data of the indicators and the relationship between the weights, so it can objective and effective evaluation [6]. We calculate the weight of the its data under the metric P. We consider this as the probability to be used in the relative entropy calculation to obtain the probability matrix.

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{m} Y_{ij}}(i=1,2,3,\cdots,m)(j=1,2,3,\cdots,n) \tag{3}$$

We calculated the information entropy for each metric:

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} P_{ij}\ln(P_{ij})(j=1,2,3,\cdots,n) \tag{4}$$

Finally we we find the weighting coefficients for each indicator:

$$\varepsilon_j = (1-e_j)/\sum_{j=1}^{n}(1-e_j)(j=1,2,3,\cdots,n) \tag{5}$$

Next, we used hierarchical analysis for subjective empowerment.

We constructed judgment matrices and scored the importance of each of the secondary indicators under each of the four primary indicators[7]. Then, we apply the eigenvalue method to calculate the eigenvectors (obtained by MATLAB function). We obtain the weight vector:

$$W = (w_1, w_2, \cdots w_n) \tag{6}$$

Next, we do the consistency test. We use the Consistency Index (CI) and Consistency Ratio (CR) to assess the consistency of the judgment matrix.

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{7}$$

When CR<0.10 , we consider the consistency test to hold.

$$W_j = \frac{\sqrt{w_j\varepsilon_j}}{\sum_{j=1}^{n}\sqrt{w_j\varepsilon_j}}(j=1,2,3,\cdots,n) \tag{8}$$

Finally, we combine the weights.As show in the figure above The subjective weights and objective weights of the flood disaster resilience evaluation indexes are obtained by hierarchical analysis and entropy weighting method respectively. The method of combining the subjective and objective weights is used to calculate the combined weights of the urban disaster resilience evaluation indexes:

Therefore, by combining the weights obtained above with the data from the local indicators, the resilience coefficient for a region can be obtained.

The disaster resilience of our study refers to the integrated function of four dimensions of exposure, sensitivity, adaptability, and resilience of the urban system to various disasters, in which exposure and

ISSN 2522-3488 Vol. 9, Issue 2: 46-50, DOI: 10.25236/IJNDES.2025.090208

sensitivity are negatively correlated with resilience, and adaptability and resilience are positively correlated with resilience [8]. The urban disaster resilience assessment model can be calculated by the following formula:

$$D_i = \sum_{j=1}^{n} W_j Y_{ij}$$
$$TC = (AC \times RC)/(E \times S) \tag{9}$$

AC, RC, E, and S are the resilience index, resilience index, exposure index, and sensitivity index, respectively. Di is the score of each sub-dimension (AC, RC, E, and S) for i districts.

4. Pricing Strategies for Insurance Companies

4.1 Risk index modeling - analyzing whether insurers can absorb maximum losses

Now, we've got the maximum compensation rate:

Next, we evaluate the underwriting risk using the maximum indemnity ratio. We know that insurance companies have an internal underwriting risk index threshold q. When the risk exceeds q, the insurance company considers it likely to lead to insolvency and will not underwrite the policy. Therefore, insurance companies can decide whether to underwrite or limit the number of insurance policies (QI) based on this model .

$$IRM = k \times MD \times TC \times \text{ year} \tag{10}$$

We calculate the max present value of compensation PCM using the time value of money theory and get:

$$PCM = \frac{IRM \times QI \times AP}{(1+i)^{year}}$$
$$Q = \frac{PCM}{TA} \times 100\% < q \tag{11}$$

Finally, we get the maximum amount of insurance that can be sold.

$$NI < \frac{q \times TA \times (1+i)^{year}}{IRM \times AP} \tag{12}$$

Accordingly, insurance companies can assess the level of risk and limit the maximum number of policies to be sold.

4.2 Break-even analysis model - analyzing when an insurance company is solidly in the black

From economics, we know that for an insurance company to make a profit it needs to make its sales revenue greater than the sum of its production costs and claims. Next, we obtain the total cost of production (TC), the present value of the estimated claim (PC), and the revenue (SI), respectively, based on economic principles.

$$TC = C_f + C_v \times QI$$
$$PC = \frac{IR \times QI \times AP}{(1+i)^{year}} \tag{13}$$
$$SI = AS \times QI$$

When revenues and expenses are equal we get the break-even point.

$$SI = PC + TC \tag{14}$$

We use the number of policies that must be sold to reach breakeven (QI*) to reflect breakeven status.

$$QI^* = \frac{C_f(1+i)^{year}}{(AS-C_v)(1+i)^{year} - IR \times AP} \tag{15}$$

QI* is the minimum number of insurance policies that need to be sold for the program to be able to preserve its capital. The lower its value, the greater the program's ability to adapt to market changes [9]. Below we examine the relationship between policy metrics and QI* to assist insurers in developing policy pricing programs.

So, the insurance company can get the right pre-sale interval of the policy by adjusting the

ISSN 2522-3488 Vol. 9, Issue 2: 46-50, DOI: 10.25236/IJNDES.2025.090208

corresponding parameters of the policy. Combining these two models, we conclude that when the number of pre-sold policies is within this range, the insurer is profitable while not at great risk of insolvency [10]. The insurance company can appropriately increase the number of policies sold within this range.

$$QI^{*} < NI < \frac{q \times TA \times (1+i)^{year}}{IRM \times AP} \tag{16}$$

5. Conclusions

Extreme weather events have become more common in recent years. The property-casualty insurance industry faces significant sustainability and decision-making issues in the face of climate change and extreme weather events. In this new environment, insurers will have to reassess risks to reflect new climate phenomena, which could result in higher premiums, fewer policyholders in high-risk areas or, in extreme cases, insurers choosing not to offer coverage anymore. In short, insurers need to find new ways to balance profitability with homeowner affordability. This paper constructs an extreme weather forecasting model and a disaster resilience assessment model through multiple influencing factors such as the level of economic development, disaster capacity, and convenience of life, and obtains the core indicator of insurance company's decision-making - payout ratio. Setting the payout amount and policy price according to the payout ratio allows the insurance company to ensure profitability and also minimise the risk of extreme weather. This in turn, shares the risk and improves protection for the local population.In the future, through the refinement and application of this model, we can better protect our cities from natural disasters and reduce the damage caused by them.

References

[1] Liu F ,Xu E ,Zhang H .Assessing typhoon disaster mitigation capacity and its uncertainty analysis in Hainan, China[J].Natural Hazards,2024,120(11):9401-9420.

[2] Mehdi J B ,Mohsen A ,Yousof S A , et al.Evaluating the disaster preparedness of emergency medical services (EMS) facilities: a cross-sectional investigation in Iran[J].BMC Emergency Medicine, 2024,24(1):48-48.

[3] N. L U .Capacity Assessment Spatialization to Disaster Risk Reduction in Semarang Coastal Area[J].IOP Conference Series: Earth and Environmental Science,2023,1264(1):35-47

[4] Mohammad S ,Qureshi M S .An Assessment of the Relationship between Cultural Diversity and Disaster Preparedness[J].Journal of Scientific Research and Reports,2023,29(8):59-64.

[5] Ara G P ,Rajarshi D ,Anwarul M A , et al.Disaster experiences, associated problems and lessons in southwestern coastal Bangladesh: exploring through participatory rural appraisal to enhance resilience[J].Sustainable and Resilient Infrastructure,2023,8(sup1):223-236.

[6] Chao F ,Yanze C ,Haoran F, et al.On the resilience assessment of complementary transportation networks under natural hazards[J].Transportation Research Part D,2022,109

[7] Zavareh S H .Build Back Better and Long-Term Housing Recovery: Assessing Community Housing Resilience and the Role of Insurance Post Disaster[J].Sustainability,2022,14(9):5623-5629.

[8] Pauline J T ,Stephen M ,Devendra S .Whose resilience matters? A socio-ecological systems approach to defining and assessing disaster resilience for small islands[J].Environmental Challenges, 2022,7

[9] Nikola B ,Božidar S .A demand-supply framework for evaluating the effect of resource and service constraints on community disaster resilience[J].Resilient Cities and Structures,2022,1(1):13-32.

[10] Mohamed S ,Wael E ,J. M T , et al.Dynamic Network Flow Model for Power Grid Systemic Risk Assessment and Resilience Enhancement[J].Journal of Infrastructure Systems,2022,28(2).