Underwriting Decision Modeling Based on Regional Hazard Assessment and Urban Resilience

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Abstract. In recent years, frequent extreme weather disasters have posed serious challenges to the economic social, and post-disaster recovery capabilities of places such as the United States, and original insurance models and payout strategies are difficult to adapt. Scientific assessment and response to natural disaster risks have become a key topic. This paper presents the Urban Resilience Index (URI) derived from 18 indicators. The ability of the city itself is rationally assessed for disaster resilience, which better helps insurance companies predict the loss compensation caused by disasters. This study starts by analyzing the risk of disasters in various regions of the United States, takes the intensity and frequency of disasters and the toughness of the city's resistance to disasters into account, and uses nonlinear multi-objective optimization to derive the threshold value of the payout strategy in a certain region to be around 0.21 and 0.94, respectively, and at the same time, after the control of the scalar function of the number of iterations is between 10 and 15 times, the final determination of the insurance model that responds to the different regions and verifies. The insurance model to cope with other areas is finally determined and its feasibility is verified.

Keywords: Insurance Model, Urban Resilience, Nonlinear Multi-objective Optimization, Disaster Assessment.

1. Introduction

For the insurance industry, extreme weather events are currently a serious crisis. In recent years, more than 1,000 extreme weather events have caused more than $1 trillion in global losses. Property insurance premiums have not only risen rapidly but have also become more expensive and harder to obtain as insurers have changed their underwriting practices. The study aims to configure property insurance optimally so that its system can withstand the cost of future claims while ensuring the long-term health of insurers and property owners.

Hierarchical analysis and entropy weighting were used to determine the weights of the model's indicator sets to address the issue of indicator selection [1]. The geographic locations were rasterized through field tests of specific geographic locations [2], while the GE matrix was combined to calculate building health scores from four aspects [3]. From there, different insurance strategies are developed based on specific situations. The study first established a regional disaster assessment system from four aspects and modeled the frequency distribution of regional extreme weather disasters based on historical data. K-means clustering determines the intensity of the four types of catastrophes [4]. Relevant indicators of disaster resilience of 18 cities were proposed in six aspects, such as economic and social [5], and the weights were determined by using hierarchical analysis and the weighting method. Then, the resilience indices of U.S. states were evaluated through the weighted topsis model and grouped into four categories. Based on the consideration of resilience, the queue-step payout and time-value-based premium setting were set. A nonlinear optimization model for maximizing insurance surplus is developed. Finally, a proposal for insurance premium rate adjustment is derived.

2. Data Sources and Preparation

The regional hazard assessment model consists of two parts, disaster risk prediction and urban resilience assessment. The time-sliding average of the most likely disasters in the region over ten years is calculated by counting data sourced from the US National Bureau of Statistics www.bea.gov. Based on the k-means clustering model, the intensity of disasters is categorized into four classes. In exploring urban resilience assessment, secondary and tertiary indicators are proposed to measure the city's resistance in the event of a disaster. In this study, the urban resilience index was explored by combining the hierarchical structure with the analysis method and entropy weight method, and the urban resilience was divided into four levels of standard values according to the classification method.

To better analyze whether or not to underwrite in a certain area, this paper needs to analyze the likelihood of disaster and the severity of this area. Then in conjunction with the area's resistance to such a disaster, further underwriting decisions can be made. The research history is shown in Figure 1.

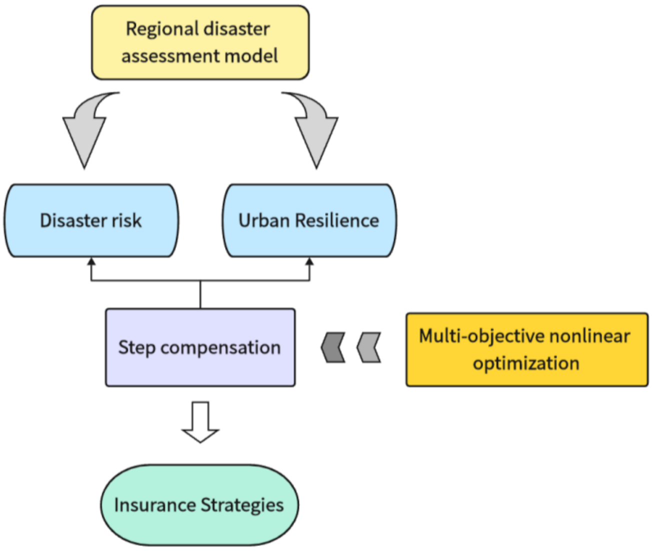

Figure 1. Research history

3. Results

3.1. The establishment of the simulation model

Regional disaster likelihood and severity analysis combines disaster resilience and underwriting decisions [6]. The assessment model includes disaster risk prediction and urban resilience assessment. The probability of disasters is obtained through statistical data, and common types of disasters determine the amount of insurance payments. Accurate prediction of disaster occurrence and magnitude is a prerequisite for underwriting. Insurance companies have the option to cover frequent or large disasters that increase risk. U.S. data show an increase in the probability and severity of disasters. Ecologist Holling pioneered the term resilience, which has been expanded into engineering, social, and economic fields for disaster management. Resilience refers to the ability of a system, community, or society to resist, absorb, adapt, and recover from rapid exposure to hazards [7]. It includes infrastructure protection, functional recovery, and overall system resilience.

We introduce the Urban Resilience Index (URI). The ability of the city itself to reasonably assess resilience can better help insurers predict compensation for losses caused by disasters. Urban resilience is categorized into six secondary indicators: social resilience, economic resilience, organizational resilience, infrastructure resilience, environmental resilience, and community resilience. Based on this, we propose 18 tertiary indicators as shown in Figure 2.

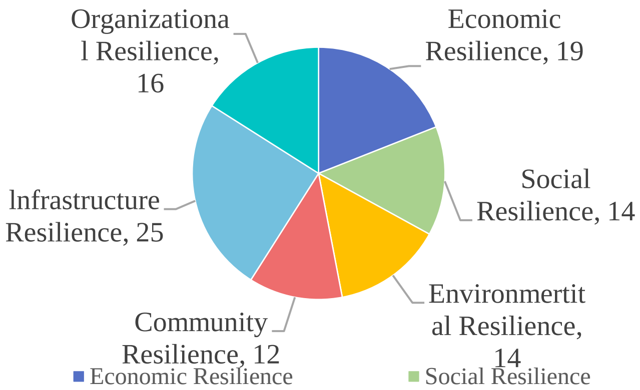

Figure 2. Six sub-indicators of urban resilience

To better analyze whether or not to underwrite in a particular area, we need to analyze the likelihood and severity of the disaster in that area.

(1) Data standardization:

For positive indicators, the standardization formula is:

$$Y_{ij} = \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})} \tag{1}$$

For negative indicators, the standardization formula is:

$$Y_{ij} = \frac{\max(X_{ij}) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})} \tag{2}$$

Where X_{ij} is the raw data for the evaluation indicators and Y_{ij} is the standardized data. After processing the data, we tested the standardized data, and the reliability coefficient of the urban resilience index (URI) is 0.826 using Kronbach, which indicates that the reliability of each evaluation index is high and can be used for further analysis.

Indicator weights:

A combination of hierarchical analysis and entropy weighting method was used to obtain the weights as shown in Table 1.

Table 1. Indicator weights

Indicators	Weights	Portfolio
GDP	0.324	0.062
Per capita gdp	0.258	0.049
Number of large-scale enterprises	0.177	0.034
Percentage of urban private and self-employed workers	0.241	0.047
Number of cell phone subscribers	0.139	0.019
University students per 10,000 population	0.222	0.030
Number of doctors per 10,000 population	0.257	0.035
Percentage of the population covered by the subsistence minimum	0.382	0.052
The proportion of nature reserves to the area under the jurisdiction	0.409	0.059
Greening coverage in built-up areas	0.034	0.005
Urban water consumption per capita	0.557	0.079
Health, social security, and social welfare personnel as a percentage	0.384	0.044
Percentage of personnel in public administration and social organization	0.616	0.071
Number of schools	0.418	0.108
Number of hospital beds per 10,000 population	0.320	0.082
Number of public motor vehicles(trams) per 10,000 persons	0.262	0.055
Unemployment insurance coverage	0.468	0.075
Medical insurance coverage	0.532	0.085

(3) Evaluation method:

We adopted the more commonly used comprehensive evaluation method, where the urban resilience index is equal to the sum of the product of the standardized values of each indicator and the corresponding weights. The formula is as follows:

$$R = \Sigma_{J=1}^{18} \omega_J Y_{ij} \left(i = 1、2 \ldots 6, j = 1、2 \ldots 18\right) \tag{3}$$

Where ω_J denotes the combined weight of the three-level indicator to the first-level indicator, Y_{ij} denotes the standardized value of the three-level indicator, and R denotes the Urban Resilience Index (URI).

Based on the disaster data from the National Bureau of Statistics (NBS), we calculated the URI index for the 50 states in the United States. In this study, the U.S. is divided according to each state, the smallest resilience index is 0.032, and the largest resilience index is 0.56. The maximum value of the urban disaster resilience index is 10 times the minimum value, which shows that there is a significant difference in resilience index between different cities. According to the classification method of standard value, the urban disaster resilience index is divided into four categories, and the index interval is 0 to 0.16, 0.16 to 0.29, 0.29 to 0.42, 0.42 to 0.56, and the corresponding urban disaster resilience intensity is lowest resilience, low resilience, medium resilience, and high resilience, respectively. The results of the classification can be represented in Figure 3, where the green-labeled states have high disaster resilience intensity, while the red-labeled states generally have low disaster resilience intensity.

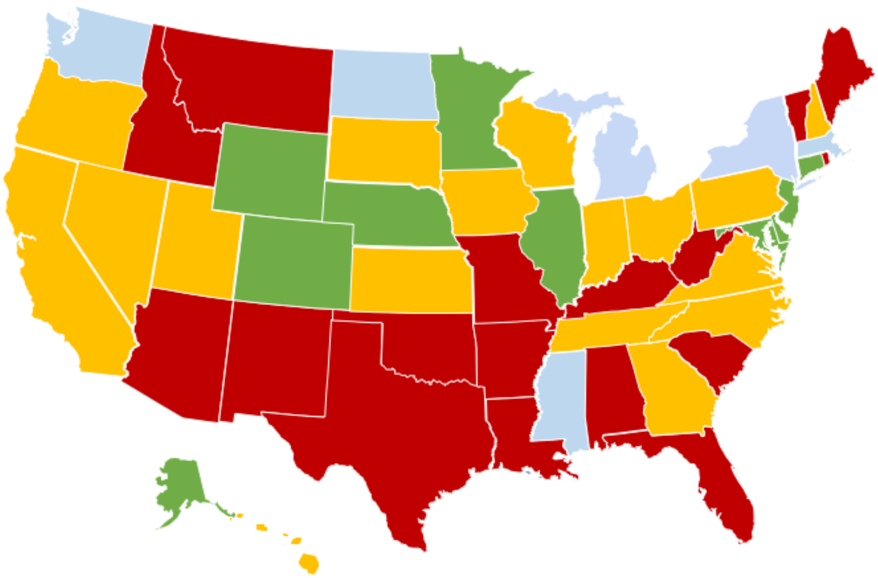

Figure 3. Distribution of Disaster Resilience Intensity by U.S. State

3.2. Optimizing Insurance Returns Through Market Supply and Demand Analysis

Disaster risk reduction and climate change adaptation are crucial [8]. The International Panel on Climate Change (IPCC) has emphasized the need for financial instruments for disaster risk management and climate change adaptation [9]. Catastrophe insurance is aimed at these events that cause events that can cause great damage and are less frequent. A huge problem facing catastrophe insurance is the extreme uncertainty of the occurrence of catastrophic events, which makes it extremely difficult for insurers and institutions to price premiums. Unlike traditional insurance, which spreads the risk across the insured, catastrophe insurance faces a timing problem of matching the regular annual influx of premiums with the irregular and unforeseen distribution of loss payments [10]. For example, the U.S. National Flood Insurance Program (NFIP) is the primary provider of flood insurance in the U.S., assuming more than 95% of the underwritten risk, but as of 2023, the program has an operating deficit of $19 billion [11]. The NFIP's main goal is to provide coverage to more people with its maximum limits for residential property damage, now set at $250,000 for buildings and $100,000 for contents. So, for catastrophe insurance, setting thresholds to control a more reasonable payout range is a necessary step to ensure the healthy survival of insurance companies [12]. Climate change will increase the frequency and severity of natural disasters [13], and at the same time bring about an increase in premiums for insurance companies. Once the increase in premiums becomes too large, it may exceed the willingness to pay for insurance, leading to a decrease in the number of catastrophe insurance policies purchased. The insurance industry aims to absorb individual losses by spreading the risk over time and space, hoping that by creating a larger pool of risk there is a lower associated risk. So, setting a premium growth rate that is consistent with the market, as well as a reasonable balance between rising premiums and declining willingness to purchase is an important issue in catastrophe insurance actuarial.

Aiming at the realistic problems encountered by catastrophe insurance actuarial, the study proposes an insurance decision model with nonlinear multi-objective optimization as the core based on disaster intensity and urban resilience above. By comparing the levels of damage intensity and resilience, the payout amount is divided into stepped payouts. Considering the unstable factors of the economy, the time value of money is added to the model to accurately reflect the significant changes in the value of money over an investment cycle [14]. Finally, the optimal solution of the set payout threshold is obtained by maximizing the net profit of the insurance company. Figure 4 shows a schematic of the payout thresholds.

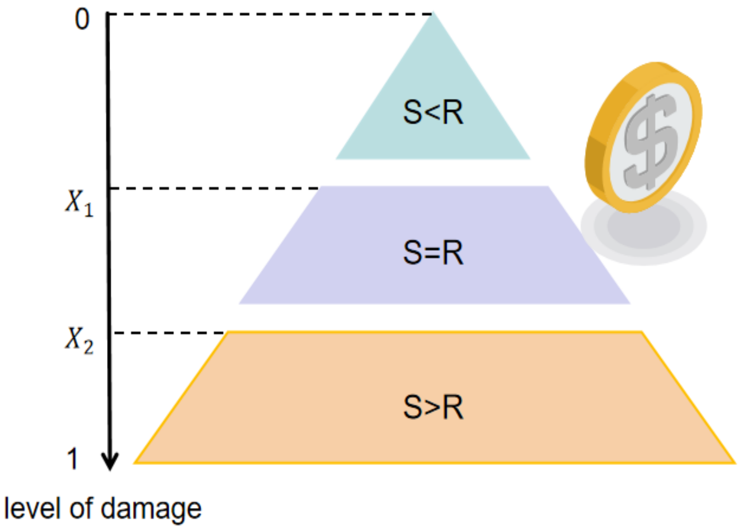

Figure 4. Payout thresholds

When the loss is less than the first threshold X_1, the insurance will not pay. When the loss is between the first threshold X_1 and the second threshold X_2, the insurance will pay a percentage of X_1. When the loss is greater than the second threshold X_2 the insurance will pay out in proportion to X_2. This step setup reduces the risk to the extent that it reduces the expected cost to the insurance company.

Insurance terms are usually measured in years, so we adjust for inflation. Longer coverage periods lead to higher premiums for the insurer without a proportional increase in damages costs, boosting expected profits. Expected costs are computed using the outlined stepped compensation scale. The results of the multi-objective optimization are reflected in Figure 5.

$$\mathrm{Min}\{W = 100S \times (P_1 \times 0 + P_2 \times X_1 + P_3 \times X_2)\} \tag{4}$$

$$\mathrm{Max}\{E = S \times (1 + I)^Y\} \tag{5}$$

$$\mathrm{s.t.} = \begin{cases} 0 < X_1 < 0.5 \\ 0.5 < X_2 < 1 \\ I < 0.2 \end{cases} \tag{6}$$

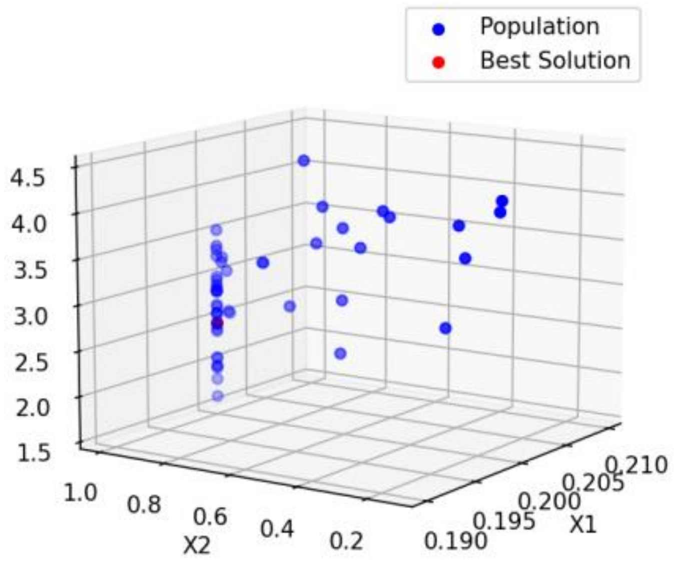

Figure 5. Optimization results.

The x, y, and z axes represent the values of the three optimizations, we found that there are many sets of optimal solutions for these three optimization problems, but many of the optimal solutions do not match the actual market situation. The best case is found to be desirable as 0.21, 0.94, and 2.53.

The market supply and demand situation is analyzed to select the best solution that best meets the demand. We find that the value of the objective function gradually converges to zero as the number of iterations increases. The optimal solution is obtained through the process of Figure 6, the optimal solution is obtained when the number of iterations is 10-15.

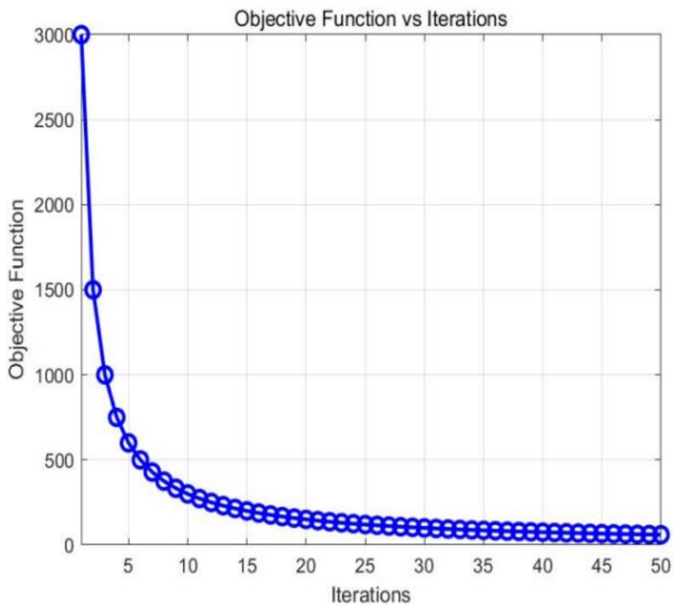

Figure 6. Relationship between the scalar function and the number of iterations

Market equilibrium is the state in which supply and demand are perfectly matched and represent relative price stability [15]. When insurance policies are adjusted, the demand curve AD shows the price consumers are willing to pay for the good. As the annual standard rate increases, consumer demand decreases, and the amount they are willing to pay decreases. Reducing rates increases consumer surplus, but the return on premiums decreases. Rates can be lowered to increase willingness to consume when fewer people are insured and raised to increase the rate of return when more people are insured. The equilibrium price forms the demand curve and consumer surplus equilibrium price forms are shown in Figure 7.

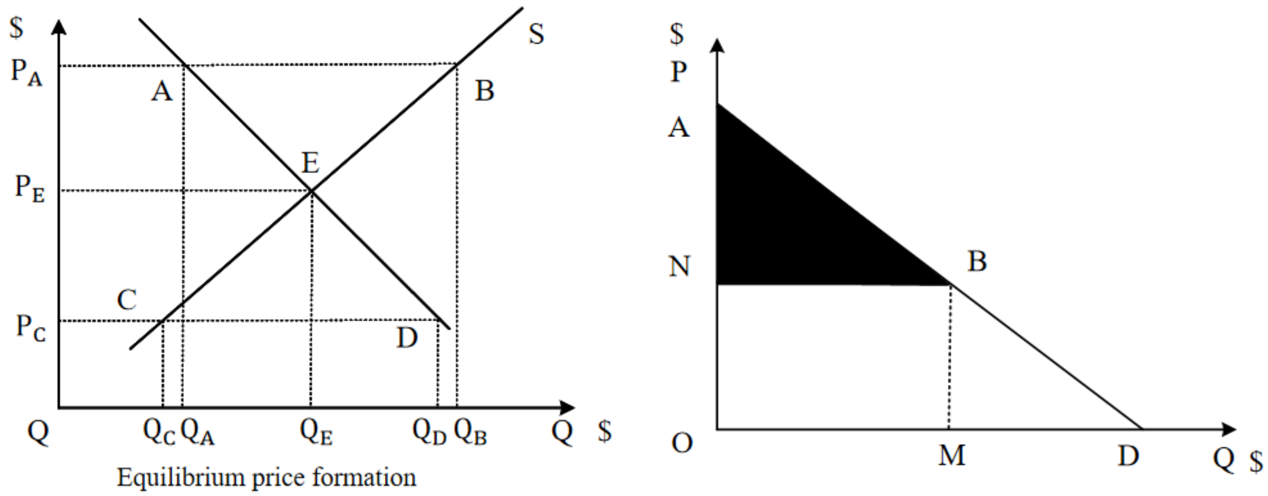

Figure 7. Equilibrium price and Demand curve and consumer surplus

3.3. The region was selected for model validation

We chose the North American city of Portsmouth to demonstrate our model, and based on the above multi-objective optimization results, we analyzed the optimal coverage scenarios for the coverage year Y=3 as x1=0.21 and x2=0.94. Next, we calculated the total cost and total benefit of the area under this scenario, and the results are shown in Table 2, we arrived at the judgment that the area is suitable for real estate development. Figure 8 shows Portsmouth.

Figure 8. Portsmouth

Table 2. Portsmouth Insurance Costs as Revenue

S	Y	I	X_1	X_2	E	W
100.00	3.00	0.09	0.21	0.94	129.50	118.44

4. Conclusions

This paper provides a research idea and framework applied to the related field of insurance assessment, using a multi-objective nonlinear optimization model to calculate the optimal solution for insurance decision-making, combined with the market supply and demand, to select the best solution that best meets the demand desirable payout thresholds of 0.21, 0.94 respectively. The calculations performed with data from the actual location, Portsmouth, taking into account the conditions of inflation over time, yielded a local insurance profitability of about 9.3% for the best solution, demonstrating the feasibility of the methodology.

There are multiple directions to consider for the future development of underwriting decision models. Data-driven decision-making models that utilize big data technology to improve the accuracy of the model by integrating data from multiple sources, such as meteorology, geography, and socioeconomics. Introducing real-time monitoring data to dynamically adjust underwriting strategies and improve the ability to respond to sudden disasters.

In addition, predictive modeling can be used to apply machine learning algorithms to improve the ability to predict the probability and impact of disasters. Second, increase the multi-risk assessment framework, integrate different types of disaster risk assessment, consider socio-economic factors and vulnerable groups, assess their impact on the city's resilience, and construct a comprehensive assessment model to reflect the city's overall resilience.

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