A Study on the Assessment of the Impact of Extreme Weather on the Insurance Industry and Response Strategies Based on SEIR Modeling

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Abstract. This paper investigates the impact of extreme weather on the insurance industry and proposes a new model for assessing the value of insurance underwriting. The study first collected data on nine indicators from 50 regions, categorized these indicators into three categories: extreme weather, insurance, and region, and then used the hierarchical analysis method (AHP), entropy weighting method (EWM), and CRITIC method to calculate the composite weights to derive the Underwriting Value Index (UVI). In addition, underwriting values for St. Louis and Kingman were evaluated using the ALARP criteria and the EIR model. In order to help communities and real estate developers to carry out rational development, the EIR model was improved to form the SEIR model, which was applied to score the development value of nine municipalities in Fujian Province, which showed that Xiamen scored the highest and was recommended to be developed and built in Xiamen. The methodological validation of this study shows that there is a significant correlation between the UVI score and the insurance coverage gap (Pearson correlation coefficient R=0.869), which indicates that the model has good rationality and practicality.

Keywords: Insurance Industry; Indicator System; EIR model; SEIR model.

1. Introduction

Extreme weather has been frequenting in recent years. According to the World Meteorological Organization, global warming may exceed the warming thresholds set by the Paris Agreement in the next five years as the effects of climate change become more pronounced. As climate change intensifies, extreme weather events are becoming more frequent globally [1]. Climate change affects all aspects of society. For the insurance industry, the dramatic rise in insurance claims due to extreme weather is forcing insurers to change their decision-making to avoid the risk of large claims, but it is also leading to a larger global insurance coverage gap; For communities and real estate developers, with changes in insurance policies, it is important to know where to develop in order to be able to develop for self-sufficiency and to meet the needs of the growing population of a community.

To address the impact of extreme weather on insurers, in this paper we collected data on nine metrics for 50 regions and categorized these nine metrics into extreme weather, insurance, and region, and then used a combination of weighting methods (including APH, EWM, and CRITIC) to calculate the combined weights of these metrics to obtain the Underwriting Value Index (UVI). The ALARP criteria were also used to simultaneously evaluate the underwriting value of St. Louis and Kingman using the EIR model. For communities and real estate developers, we will improve the EIR model to obtain the SEIR model and use it to calculate the scores for the nine municipalities in Fujian Province.

2. Using the EIR model to assess the value of coverage

2.1. Establishing an Indicator System

Based on the study of the problem, we believe that the underwriting value assessment can be considered mainly from three aspects: insured amount, area, and extreme weather. Therefore, we established the Extreme Weather-Insurance-Region model (EIR model for short). After comprehensively considering 22 officially mentioned relevant indicators, we finally retained the 9 most representative secondary indicators to construct the model. In the following, we will introduce the quantification method of each indicator separately.

2.1.1. Extreme weather

Extreme weathers are a direct cause of risk to insurance companies. We will analyze three aspects of extreme weather: frequency, main types, and average intensity.

Frequency: the total number of occurrences of each type of extreme weather in the region on average per year from 2013 to the present. The greater the number of extreme weather occurrences, the greater the loss to insurers and the more unfavorable it is for insurers to underwrite in that location. The average number of extreme weather events per year per country or region can be found on the relevant website.

Main Types: Based on the idea of data downscaling, we have grouped the four main types of extreme weather - floods, storms, wildfires and droughts - into one set of data. In order to retain the original basic information of these extreme weather types, combined with the collected data, we have established a corresponding scoring system for the four major extreme weather types with the following formula:

$$E_2 = (\alpha \cdot \frac{X_i}{\sum_{i=1}^{50} X_i} + \beta \cdot \frac{E_{1i}}{\sum_{i=1}^{50} E_{1i}}) \times 100 \tag{1}$$

Average intensity: Due to the variety of extreme weather types around the world, in order to make our model generalizable, we harmonize the intensity of different extreme weather types into a single metric based on the idea of downscaling the data. When determining the intensity of extreme weather in a region, we consider the average intensity of all extremes in the region.

2.1.2. Insure

The insurance industry plays a dual role in responding to climate change: to minimize the negative impacts of climate change on underwriting business and asset business, and to seize the opportunities in adapting to climate change by providing insurance products and services to manage climate risks, and contributing to the mitigation of climate change by providing financial support to new energy, energy-saving and environmental protection, new energy automobile, and other strategic emerging industries [2]. Insurance indicators are the most important factors that insurance companies should consider when underwriting. We will consider three aspects: conventional cost, average risk of loss, and insurance compensation rate.

Routine costs: this is a negative indicator for insurance companies; the higher the costs required for routine operations, the harder it is for the insurance company to maintain operations in the area

Average Risk of Loss: It specifically refers to the average amount of money an insurance company pays out per disaster in the area. The larger this amount is, the more unfavorable it is for the insurer.

Insurance recovery rate: It specifically refers to the probability that an insurance company will pay out a customer's loss when extreme weather affects the customer's property at the time the customer is insured.

2.1.3. As suffix city name, means prefecture or county

District indicators are one of the most important indicators for assessing the value of coverage. We will consider district population, GDP per capita, and the level of policy support in the district.

Population: District population refers to the number of people living in a particular district and is closely related to the revenue of an insurance company. Generally speaking, the more populated an area is, the higher the insurer's revenue will be. Conversely, in less populated areas, insurers' revenues will decline.

Gross Domestic Product (GDP) per capita: GDP per capita is a useful tool to understand and capture the macroeconomic performance of a country or region. It depends on two factors, population size and GDP, and can be calculated using the following formula: GDP refers to the gross domestic product, which can be obtained for different regions from each country's national statistical yearbook.

Policies: The policies of a country or region can also have a profound impact on the underwriting policies of insurance companies. We assessed local policies mainly in terms of prevention of extreme weather and support for insurance. There are three levels: almost no action (assigned a value of 1), moderate (assigned a value of 2), strong (assigned a value of 3)

2.2. Determining indicator weights

We will use a comprehensive weighting method to extreme the weight of all indicators, the comprehensive weight calculation methods include hierarchical analysis method (AHP), entropy weight method (EWM) and CRITIC method.

2.2.1. AHP

The hierarchical analysis method (AHP), as a comprehensive evaluation method combining qualitative and quantitative analysis methods, has been widely used in many fields of safety and environmental research [3]. We will construct judgment matrices for as well as indicators and each group of secondary indicators with the following formulas:

$$A = (a_{ij})_{n\times n} \tag{2}$$

We can use co-twelve to find the weight of each indicator, and we define the weight of the jth indicator obtained by the APH method as w_{j1} .

2.2.2. EWM and CRITIC

Figures 1 and 2 show the flowcharts of EWM and CRITIC, respectively, and we define the weight of the jth indicator obtained by the EWM method as w_{j2} and the weight of the jth indicator obtained by the CRITIC method as w_{j3}.

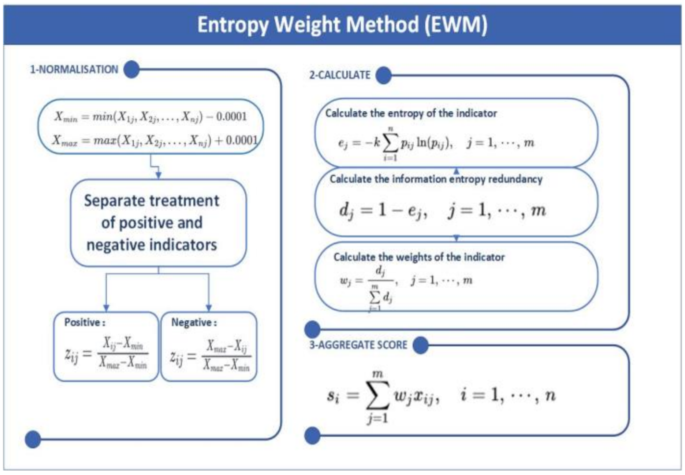

Fig 1. EWM Method.

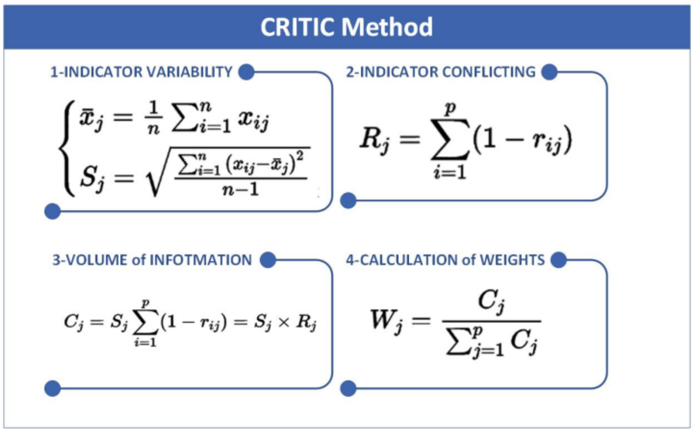

Fig 2. CRITIC Method.

2.2.3. Comprehensive weights

We can derive the composite weight of each indicator through Equation 3, and Figure 3 shows the composite weight value of each indicator we obtained.

$$w_j = \frac{w_{1j} + w_{2j\_}w_{3j}}{3} \tag{3}$$

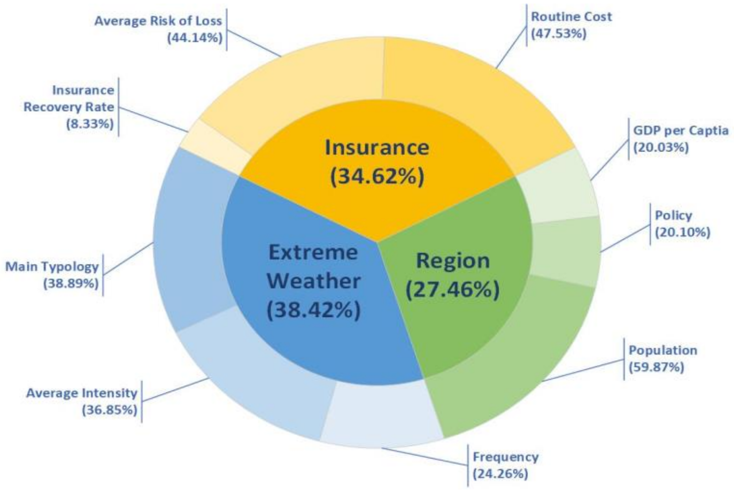

Fig 3. Combined weights of indicators.

2.3. Building the EIR Model

2.3.1. Calculation of the Underwriting Value Index (UVI)

We can utilize the three level 1 indicators and their weights (extreme weather, insurance and region) to derive the UVI score for a region. The UVI score can be used to obtain the underwriting value of a region under the current conditions, and is calculated using the following:

$$UVI = (E \cdot \omega_e + I \cdot i + r \cdot \omega_R) \times 100 \tag{4}$$

2.3.2. Future Risk Prediction

Figure 4 shows the ALARP criteria, which are commonly used in risk assessment and are still widely used for selecting acceptable risks. The ALARP criteria categorize risks into three classes: unacceptable, reasonably acceptable, and generally acceptable. The ALARP criteria categorize risks into three regions: unacceptable, reasonably acceptable, and generally acceptable.

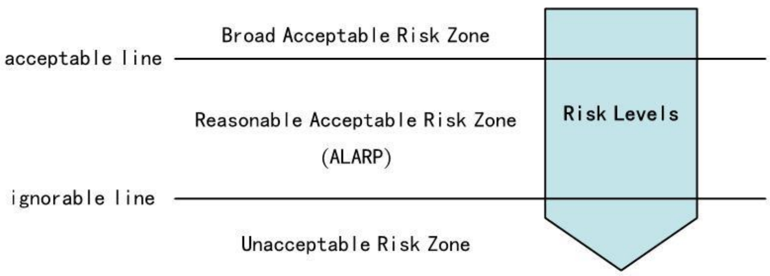

Fig 4. ALARP criterion.

We will use the ALARP model to predict the future underwriting risk of an area by introducing a hazard factor with the following equation:

$$\mathcal{X} = \frac{\mathcal{Q}_{negative'}}{\mathcal{Q}_{positive'}} \tag{5}$$

Considering that the determination of risk needs to be combined with forecasts and judgments about the future, we set the risk assessment period at 5 years and optimized the risk factors as follows:

$$\mathcal{X} = \frac{\mathcal{Q}_{negative'}(1 + C_{E+I})}{\mathcal{Q}_{positive'}(1 + C_R)} \tag{6}$$

The risk factors are optimized as follows:

$$\mathcal{X} = \begin{cases} 0\sim0.35 \text{ Broad Acceptable Risk} \\ 0.35\sim0.9 \text{ Reasonable Acceptable Risk} \\ > 0.9 \text{ Unacceptable Risk} \end{cases} \tag{7}$$

It can be concluded that after introducing the data of a region into the EIR model, two data can be obtained, one is the UVA score and the other is the value of the risk factor.

2.4. Model checking

In order to test whether our model can more accurately reflect the local situation and help insurance companies make reasonable decisions, we conducted a correlation analysis between UVA scores and insurance coverage gaps. We randomly selected 10 countries for analysis and plotted them in Figure 5. Figure 6 shows the normal distribution graphs. After the normality test, the two sets of data basically conform to the normal distribution, and their Pearson correlation coefficient R=0.869, which is greater than 0.8, indicates that there is a good correlation between the two sets of data and the modeling is reasonable.

Location	Score	Insurance Protection Gap
Tanta	34	45
Cairo	53	54
Texas	69	85
Illinois	92	95
Alabama	72	80
Glarus	45	67.8
Niteroi	36	36
Sichuan	52	45
Jiangxi	64	54
Valais	75	90

Fig 5. Original Data.

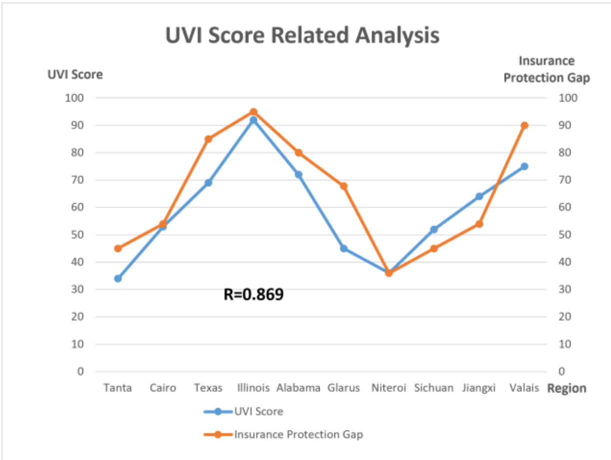

Fig 6. Correlation analysis.

3. Using the SEIR model to assess the value of the development

3.1. Establishment of the indicator system

In this section, we apply the results derived from the EIR model to identify three first-level indicators: the UVI score, the $\mathcal{X}$-value, and the social indicators [3]. Social indicators include three secondary indicators: population density, road density and hospital density. These three secondary indicators can well reflect the infrastructure construction and service guarantee construction in the area. When determining the weights of the indicators, we adopted the comprehensive weight TOPSIS method. Its principle is shown in Figure 7:

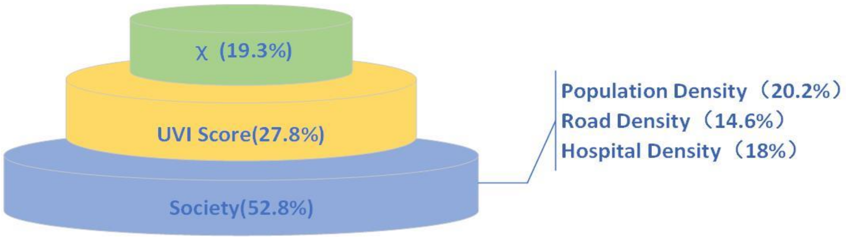

Fig 7. The weights of indicators.

3.2. Establishment of SEIR model

The TOPSIS algorithm is a commonly used finite-scenario, multi-attribute decision analysis method, which uses the degree of proximity to the ideal solution and the degree of distance from the negative ideal solution as an evaluation metric [5]. In this section, we will use the TOPSIS algorithm to derive the SEIR score, the larger the SEIR value, the more favorable the community and real estate developers choose to develop in the area. The comprehensive evaluation formula for each indicator is as follows:

$$SEIR = W_U \cdot W_X + w_x \cdot C_x + w_{PD} \cdot C_{PD} + w_{RD} \cdot C_{RD} + w_{HD} \cdot C_{HD} \tag{8}$$

3.3. Using the SEIR model

We use the SEIR model to analyze Fujian Province and calculate the SEIR scores for each city in Fujian Province, and the scores for each city are shown in Figure 8, and for a more intuitive observation, we use Figure 9 to show them.

We can see from Figures 8 and 9 that Xiamen has the best score. After considering the social factors, risk factors and UVI scores, we recommend that the community and put down the Azen developers to develop and build in Xiamen. This will allow them to realize their own benefits with controlled risks and also solve the problems caused by the increase in population.

Loaction	SEIR Score	Interval
Xiamen	0.63	0.6~1 Recommend Developing
Quanzhou	0.57	0.4~0.6 Generally Recommend Developing
Putian	0.46	
Fuzhou	0.43	
Longyan	0.42	
Ninde	0.41	
Sanming	0.40	
Nanping	0.37	0~0.4 Not Recommend Developing
Zhangzhou	0.29	

Fig 8. Scores and corresponding intervals for each region. **Fig 9.** Score distribution.

4. Summary

According to the World Meteorological Organization, global warming may exceed the warming thresholds set by the Paris Agreement in the next five years as the effects of climate change become more pronounced. As climate change intensifies, extreme weather events are becoming more frequent globally [1].

The insurance industry plays a dual role in responding to climate change: not only to minimize the negative impact of climate change on underwriting and asset business, but also to seize the opportunities in adapting to climate change, provide insurance products and services to manage climate risks, and contribute to mitigating climate change by providing financial support to new energy, energy-saving and environmental protection, new energy automobiles, and other strategic emerging industries [2].

The hierarchical analysis method (AHP), as a comprehensive evaluation method combining qualitative and quantitative analysis methods, has been widely used in many fields of safety and environmental research [3].

In this section, we apply the results derived from the EIR model to identify three first-level indicators: the UVI score, the $\mathcal{X}$-value and the social indicators [4].

The TOPSIS algorithm is a commonly used finite-scenario multi-attribute decision analysis method, which uses the degree of near-ideal and far-negative ideal solutions as evaluation indexes [5].

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