Research on Comprehensive Assessment Model of Insurance Industry Based on Environmental Risk Matrix and Entropy Method-TOPSIS

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Abstract. With the increasing frequency of extreme weather events, the insurance industry faces a major challenge of how to balance risk and return. In this study, a risk-return assessment model is constructed with the aim of providing scientific decision support for insurance companies. The model quantifies risk severity and risk probability through risk matrix, calculates risk index by linear interpolation, and generates comprehensive risk index by combining Borda method and hierarchical analysis method. For the benefit assessment, the direct benefit index was calculated by regional emergency management budget normalization and tanh function mapping, and the indirect benefit index was generated by using expert scoring and sigmoid function mapping, which led to the comprehensive benefit index. Finally, the entropy method-TOPSIS method is used to generate the underwriting priority ranking by calculating the geometric distances of regions from positive and negative ideal solutions. Taking eight U.S. states and the Wenchuan earthquake as examples, the model demonstrates its applicability in macro-regional assessment and specific disaster scenarios. Sensitivity analysis verifies the robustness of the model and shows its strong adaptability to input changes. This study provides theoretical basis and practical guidance for the insurance industry's decision-making in high-risk environments.

Keywords: Environmental Risk Matrix, Composite Risk Index, Composite Return Index, Entropy Method-TOPSIS.

1. Introduction

As global climate change intensifies, the frequency and intensity of extreme weather events have risen significantly, with natural disasters such as hurricanes, floods, droughts and wildfires posing an unprecedented threat to socio-economic and human life and property security. According to the World Meteorological Organization, global economic losses due to extreme weather events have exceeded trillions of dollars over the past decade, and the affected population continues to grow. The insurance industry, as a central player in risk management and transfer, is faced with the challenge of effectively responding to these highly uncertain and destructive events in its underwriting decisions. Extreme weather events not only increase the pressure on insurance payouts, but also place higher demands on the pricing, market competitiveness and long-term sustainability of insurance products [1]. However, traditional risk assessment methods tend to focus only on a single risk dimension, such as the probability of a disaster occurring or the scale of potential losses, ignoring the dynamic balance between risk and return. This makes insurance companies often face problems such as information asymmetry, assessment bias or inefficient resource allocation when formulating underwriting strategies, making it difficult to realize a win-win situation of financial soundness and market expansion in the complex and changing climate environment [2-3].

To address this problem, it is particularly urgent to build a comprehensive risk-benefit assessment framework. The framework should be able to quantify the multidimensional risk characteristics of extreme weather events and assess their potential impact on insurance returns, so as to provide a scientific basis for underwriting decisions. In this paper, an analysis method based on the Risk-Revenue model is proposed, which integrates the risk matrix, Analytic Hierarchy Process, Entropy Weight Method and TOPSIS. for Order Preference by Similarity to Ideal Solution method to systematically analyze the risk characteristics of extreme weather events and their impact on insurance company revenue. The risk matrix is used to identify and categorize the risk levels of different types of extreme weather events; the combination of AHP and EWM is used to determine the weights of each risk factor and revenue indicator to ensure the objectivity and scientificity of the assessment; and the TOPSIS method is used to screen the optimal underwriting strategy through the multi-criteria decision analysis [4-5]. In addition, typical areas are selected for case studies in this paper to verify the practicality and robustness of the model. Ultimately, this study aims to provide an operational quantitative tool for the insurance industry to optimize underwriting decisions, enhance risk management capabilities, and provide theoretical support and practical guidance for the sustainable development of the industry in the context of addressing climate change.

2. Risk-Revenue model

This section will establish the model by considering the risk of extreme weather events that insurance companies are exposed to, as well as their likely revenue.

2.1. Selection of Indicators

We set two criteria for comprehensive risk assessment: the Risk index of extreme weather events and the revenue of insurance company in the process of establishing the composite risk assessment, we used following indicators.

2.1.1 Extreme Weather Events

The combined impact of extreme weather events mainly depends on the severity of the consequences of the event and the probability of the event occurring. Based on this situation, we introduce three indicators for this system [6].

Risk Severity (RS): RS refers to the severity of the impact of an extreme weather event or natural disaster.

Risk Probability: RP refers to the probability of an extreme weather event or natural disaster. RP is divided into five ranges, which are

$$(0,10\%), (11\%, 30\%), (31\%, 70\%), (71\%, 90\%), (91\%, 100\%) \tag{1}$$

Risk Index: RI refers to the risk level index of event nodes in the risk matrix constructed by RS and RP.

Composite Risk Index: CRI refers to the final result given by the model after combining the risk index and the importance, which is the index ultimately used to judge the risk level of a certain country or region.

$$CRI = \sum_{i=1}^{N} R_i \times \omega_i \tag{2}$$

2.1.2 Revenue of Company

According to the business model of insurance companies, we divide the income and evaluate it by the following indicators [7]:

- Direct income: DI refers to the payment of insurance by a government, organization or individual directly purchasing insurance.
- Indirect income: II refers to the gains or loss deduction obtained by the insurance company after part of the income through investment, reinsurance, etc.

2.2. Construction of Risk Assessment Model

In this section, we will build a Risk-Revenue model to help insurance companies make decisions. By calculating the Composite Risk Index of a certain region, the RR model helps insurance companies to decide whether to underwrite policies in the region [8-9].

Firstly, after selecting the indicators, we build the Risk Assessment model and the Revenue model respectively. RA calculates the CRI of extreme weather events for a country or region. The Revenue model will be used to estimate the revenue of the insurance company in this region. Finally, based on the above two models, we build a RR model for helping to make reasonable decision. We show the whole process in Figure 1.

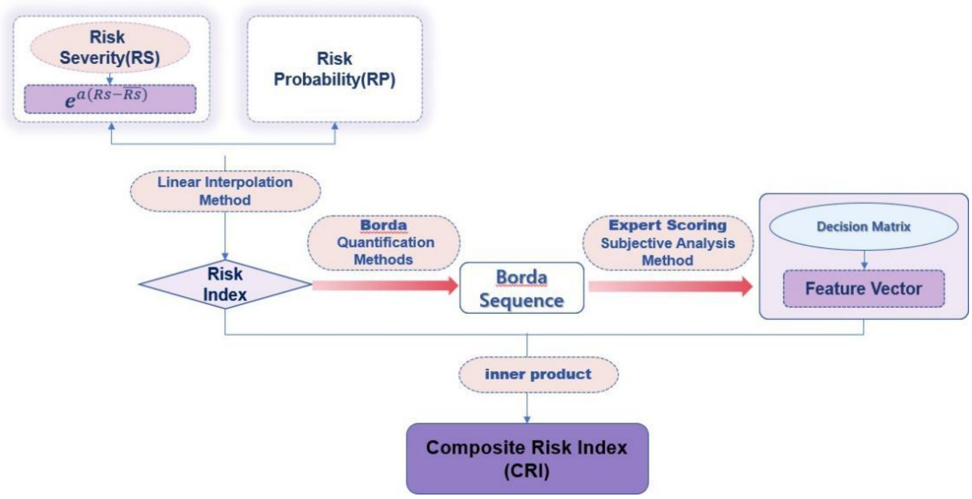

Figure 1. The Flow Diagram of Risk Assessment Model

2.2.1 Construction of Initial Risk Matrix

In this system, RS is quantified into five scales. We construct the Initial Risk Matrix by considering the severity of risk consequences and the probability of risk occurrence. To distin- guish the severity level more clearly, based on research from the University of Calgary, we divide the RS into five levels, as shown in Figure 2.

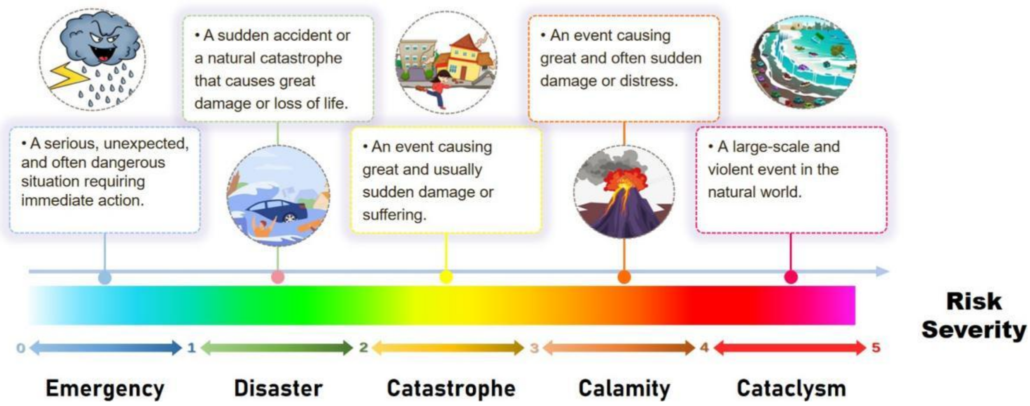

Figure 2. Risk Severity

In addition, the probability of risk is divided into five levels, as shown in Figure 3.

Risk possibility	Statement
0-10	Extremely Unlikely to Happen
11-30	Somewhat Unlikely to Happen
31-70	Possible to Happen
71-90	Likely to Happen
91-100	Highly Likely to Happen

Figure 3. Risk Probability

The Initial Risk Matrix based on the different severity and likelihood are shown in Figure 4. In the initial matrix, the level of risk is measured on a low, medium and high scale [10]. To address this shortcoming, the risk matrix needs to be quantitatively improved.

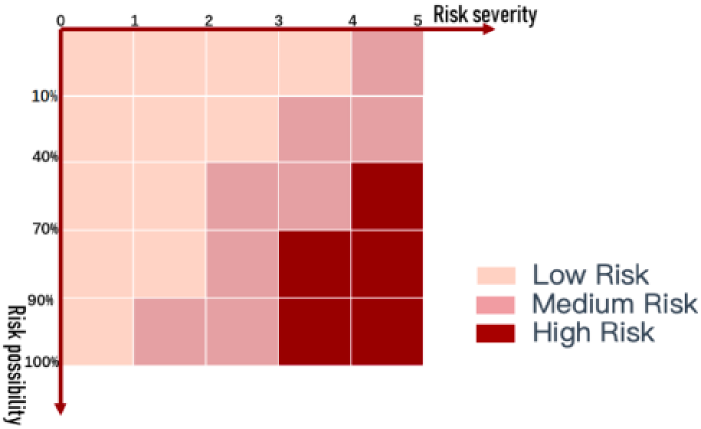

Figure 4. Initial Risk Matrix

2.2.2 The Calculation of Risk Index

Based on resarch Combined with the initial risk matrix, the event risk quantization table is obtained as shown in Table 1.

Table 1. Risk Level Classification Comparison

Risk Probability/%	Emergency	Disaster	Catastrophe	Calamity	Cataclysm
0~10	0	[0, 0.5)	[0.5, 1)	[1, 1.5)	[2, 2.5)
11~30	0	[0, 0.5)	[1, 1.5)	[1.5, 2)	[2.5, 3)
31~70	[0, 0.5)	[0.5, 1)	[1.5, 2)	[2, 3)	[3, 4)
71~90	[0, 0.5)	[1, 1.5)	[2, 2.5)	[3, 3.5)	[4, 4.5)
90~100	[0, 0.5)	[1.5, 2)	[2.5, 3)	[3.5, 4)	[4.5, 5)

According to Table 1, the risk level obtained is only a range. In order to obtain the specific *RI* (Risk Index) under a certain *RS* and *RP*, linear interpolation method is adopted for the calculation. Assuming that $RS \in (RS_1, RS_2), RP \in (RP_1, RP_2), RI \in (RI_1, RI_2)$, then

$$RI = RI_1 + \frac{(RS-RS_1)-(RP-RP_1)}{(RS-RS_2)-(RP-RP_2)}(RI_2 - RI_1) \tag{3}$$

Considering that in the case of a large RI, even if the probability of occurrence is small, the possible loss is extremely serious. The following formula to calculate the new Risk severity, referred to as RS′, to enhance the impact of the risk severity.

$$RS' = e^{(RS-m)} \tag{4}$$

Where c is a constant, m is the mean value of all RS.

Replace RS with RS′ in formula (1), the final risk index calculation formula is as follows.

$$RI = RI_1 + \frac{(RS\prime-RS\prime_1)-(RP-RP_1)}{(RS\prime-RS\prime_2)-(RP-RP_2)}(RI_2 - RI_1) \tag{5}$$

Thus, if RP and RS are known, RV can be computed.

2.2.3 Analysis of node Risk Importance

According to the above evaluation system, there may be cases where events of different importance are at the same risk value. Therefore, we need to consider the importance of events to this model.

To avoid the subjectivity brought by Delphi method, Borda method [8] is used to rank importance. Assume the Borda count of event i is bi, then:

$$b_i = \sum_k^N (N - r_{ik}) \tag{6}$$

Where N is the total number of events, the risk level of event i under criterion k is r_{ik}, and the total number of criteria is n.

In this system, risk severity and probability are taken as criteria, expressed by k=1 and k=2 respectively, thus n=2. r_{ik} is numerically equal to the number of entries with higher probability or higher risk severity than the entries to which the event belongs in the previously constructed risk matrix.

For a specific event, after calculating its borda count, the closer the count is to 0, the fewer events are less severe or less likely than this event, we can consider this event to be of higher importance.

2.2.4 Determination of Comprehensive Risk Index

For a specific region, the Composite Risk Index (CRI) consists of the risk index corre- sponding to various extreme weather events or climate disasters. To quantify the influence weights of different events on the whole system in this region, a parameter ω is introduced into the model.

According to the Borda count of the risk of each disaster event, the impact degree of the event is scored by the experts. Assume the score of event i among N events is a_i, and the relative importance of event i to event j is expressed by a_i. Therefore, the following $N \times N$, judgment matrix A is obtained:

$$A = \begin{bmatrix} a_1/a_1 & a_1/a_2 & \cdots & a_1/a_N \\ a_2/a_1 & a_2/a_2 & \cdots & a_2/a_N \\ \vdots & \vdots & \ddots & \vdots \\ a_N/a_1 & a_N/a_2 & \cdots & a_N/a_N \end{bmatrix} \tag{7}$$

Then, according to the Analytic Hierarchy Process (AHP), the influence weight ω of each event can be obtained. Assume the risk index and influence weight of the i event among the N events are RI_i and respectively, then the Composite Risk Index CRI of the region is

$$CRI = \sum_{i=1}^{N} R\,I_i \times \omega_i \tag{8}$$

2.3. Construction of Revenue model

In this section, according to the business model of insurance companies and the different ways of obtaining income, we divide the revenue of insurance companies into two parts: Direct Revenue (DR) and Indirect Revenue (IR). The whole process is shown in the Figure 5.

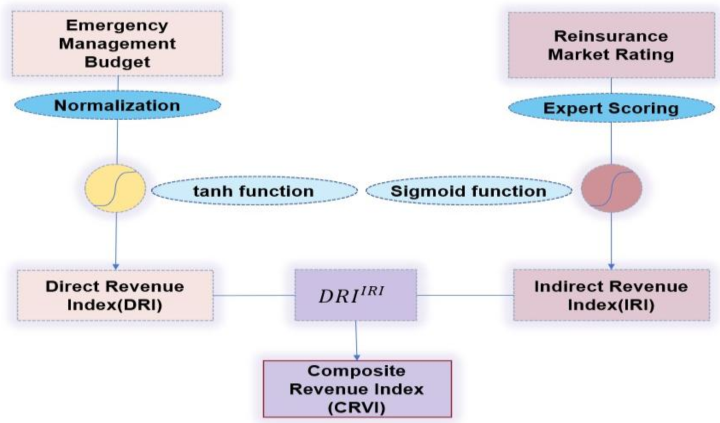

Figure 5. The Flow Diagram of Revenue Assessment Model

2.3.1 Analysis of Direct Revenue

Direct Revenue (DR) refers to the amount paid for the purchase of insurance. For a specific region, to quantify DR, we introduce the regional Emergency Management Budget (EMB).

To help insurance companies make decisions, we introduce decision range, which contains multiple alternative regions. After obtaining EMB for these regions, Min-Max Normalization is used to obtain the Normalized EMB, notated as NEMB.

$$NEMR_k = \frac{EMB_k - \min}{\max - \min} \tag{9}$$

Where min and max are the minimum and maximum in all EMB, respectively.

Finally, we need to get the Direct Revenue Index. Considering subsequent modeling, DRI needs to be squashed in to a certain interval. Therefore we use the modified tanh function to map NEMB as follows to get DRI:

$$DR_l = a \times \tanh(NEMR_l) + b,\ a \text{ and } b \text{ are constants.} \tag{10}$$

Through process above, we can obtain the DRI squashed into $(b-a, b+a)$.

2.3.2 Analysis of Indirect Revenue

In addition to Direct Revenue, Indirect Revenue (IR) is also considered in this model. We measure IR by the revenue or loss deduction obtained by the company using a portion of the Direct Revenue to invest or reinsurance. Firstly, through Delphi method, the scores s in different regions can be obtained. Assume the scores for region l is si, and the Indirect Revenue Index (IRI) is IRIi. The following formula is used to map the s to IRI.

$$IR_l = \frac{a}{1+e^{-ks_l}} + b \tag{11}$$

Where a, b and are constants.

The constant k is used to adjust the sensitivity to s of IRI. Through process above, we can obtain the IRI squashed into $(b, b+a)$.

2.3.3 Determination of Composite Revenue Index

The Composite Revenue Index (CRVI) is calculated by following formula:

$$CRVI = DRI^{IRI} \tag{12}$$

Where DRI and IRI are the Direct Risk Index and Indirect Risk Index, repectively.

CRVI is an important indicator in this model, used to measure the possible revenue for insurance company in one region

2.4. The construction of Risk-Revenue model

TOPSIS method is an method to realize the scheme selection by calculating the geometric distance of a solution to the positive ideal solution, and that to the negative ideal solution. TOPSIS method has no strict restrictions on sample size and indicators, and its calculation method is simple. Therefore, this method is selected to build the Risk-Revenue model. We also use Entropy Weight Method to calculate the weight used in TOPSIS. The whole process is as Figure 6.

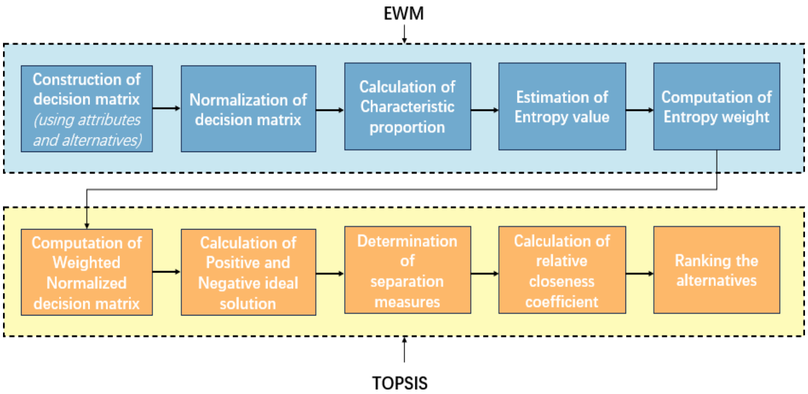

Figure 6. The Flow Diagram of EWM-TOPSIS

2.4.1 Forward Conversion of Data

Since the comprehensive risk coefficient is a smaller, better indicator, here we use the following formula for Forward Conversion. Assume the initial data is DRI, then

$$DR = max - DR \tag{13}$$

2.4.2 Decision Matrix

Assume there are n objects to be evaluated, each of which has mindicators. In this system, the indicators are the Composite Risk Index and Composite Revenue Index, thus m=2. The initial data matrix is:

$$X = \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \\ \vdots & \vdots \\ x_{n1} & x_{n2} \end{bmatrix} \tag{14}$$

Then normalize each entry is by dividing it by the norm of its column vector.

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{15}$$

A standard decision matrix can be obtained by:

$$Z = (z_{ij})_{N\times N} = \begin{bmatrix} z_{11} & z_{12} \\ z_{21} & z_{22} \\ \vdots & \vdots \\ z_{n1} & z_{n2} \end{bmatrix} \tag{16}$$

The Positive Ideal Solution $Z+$ consists of the maximum value of each element in the column. Similarly, the Negative Ideal Solution $Z-$ consists of the minimum value of each element in the column.

$$Z^{+} = (\max\{z_{11}, z_{21}, \cdots, z_{n1}\}, \min\{z_{12}, z_{22}, \cdots, z_{n2}\}) \tag{17}$$

$$Z^{-} = (\min\{z_{11}, z_{21}, \cdots, z_{n1}\}, \min\{z_{12}, z_{22}, \cdots, z_{n2}\}) \tag{18}$$

2.4.3 Determination of Solution

We use following formula:

$$D_l^{+} = \sqrt{\sum_{j=1}^{2} \omega_j \left(Z_j^{+} - z_{ij}\right)}, \tag{19}$$

$$D_l^{-} = \sqrt{\sum_{j=1}^{2} \omega_j \left(Z_j^{-} - z_{ij}\right)} \tag{20}$$

The ω_j is the weight of the j-th indicator. It can determined by Entropy Weight Method.

The closer the solution is from the PIS and the farther it is from the NIS, the better it is. In order to compare the advantages and disadvantages of each solution, we introduce the closeness degree C. The greater C_i is, the closer the solution i is to the PIS.

$$C_i = \frac{D_i^{+}}{D_i^{+} + D_i^{-}} \tag{21}$$

By ranking the closeness degree C of each plan, we help insurerance company get a ranking of the areas they may underwrite.

3. Application of Risk-Revenue Model

In this section, we will choose two countries, the United States and China, to apply our model. For both countries, we selected areas that were more affected by extreme weather events or natural disasters.

3.1. Application in Eight States of USA

As mentioned above, the RR model ranks the various possible choices in order of merit. To demonstrate this feature of the RR model, we select eight states in the United States. We present RI and RP of these states in the following figure 7.

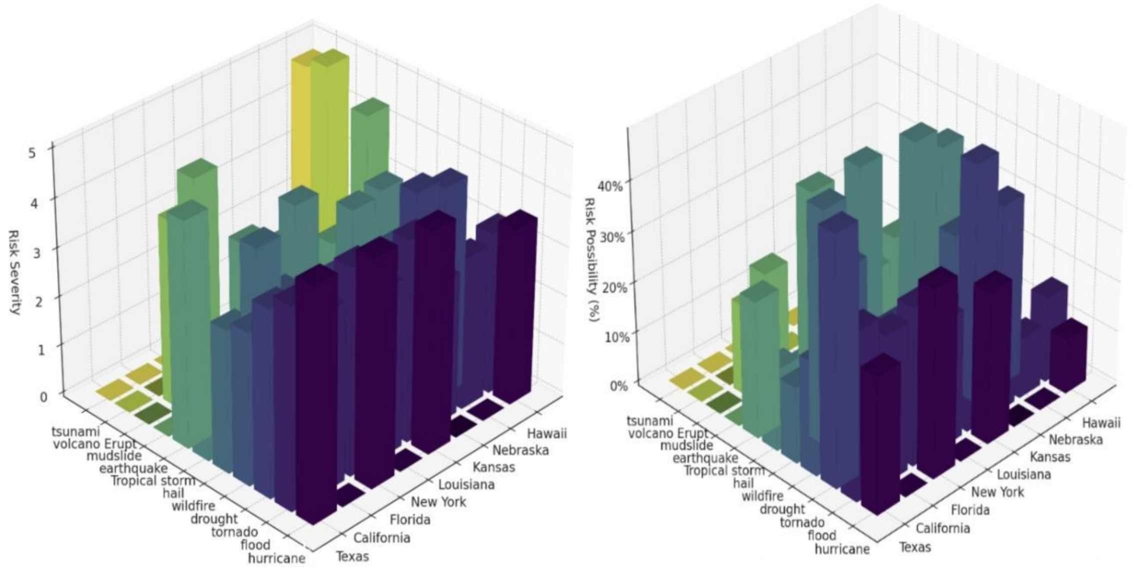

Figure 7. Risk Severity and Risk Probability of Eight States

Then, the Composite Risk Index and Composite Revenue Index of eight states can be obtained by replacing all data into the RR model and the results are as the Figure 8 and Figure 9.

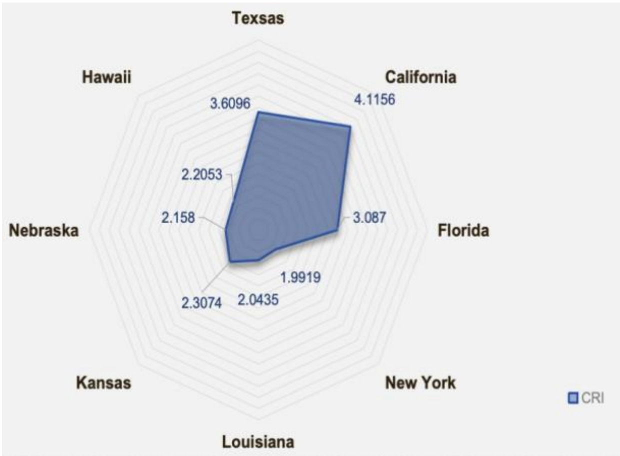

Figure 8. Composite Risk Index

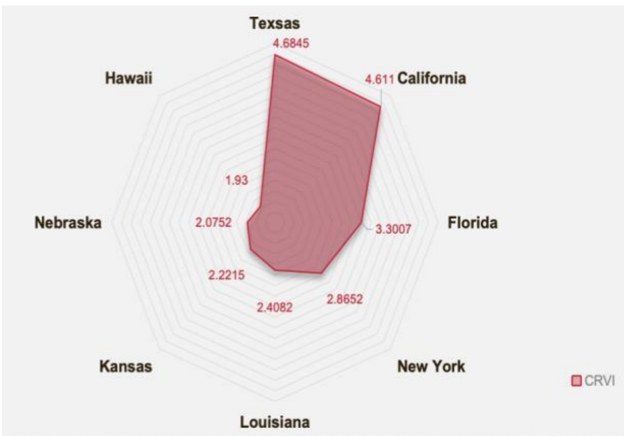

Figure 9. Composite Revenue Index

After evaluating CRI and CRVI by TOPSIS method, we obtained a rank of eight regions into four parts according to the underwriting priority from high to low, as shown in the Figure 10.

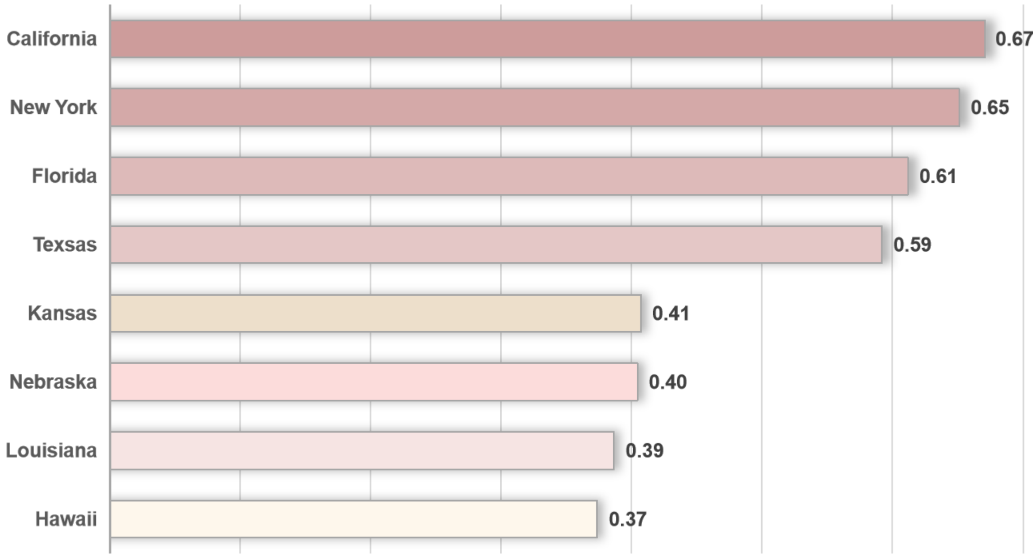

Figure 10. The Rank of Closeness Degree of Eight States

We can give the advice by the closeness degree of eight states.

3.2. Application in Wenchuan, China

In the application of China, we choose a representative region which is Wenchuan city. On May 12, 2008, a massive earthquake struck Wenchuan, killing nearly 70 thousand people and affecting more than 46 million people. Based on the data of Wenchuan earthquake disaster in literature, the results are obtained as the Table 2.

Table 2. Indices of Wenchuan Earthquake

Event Number	Disaster Event	Risk Probability/%	Risk Severit	Risk Index	Borda Count	Borda Value	Influence Weight
1	After shock	80	3.2	3.07	18	1	0.17
2	Damage to Road	40	2.4	1.75	5	8	0.02
3	Landslide	80	4.2	4.07	20	0	0.26
4	Collapse	60	3.8	2.84	16	3	0.12
5	Traffic Block	30	2.4	1.13	4	10	0.01
6	Formed a barrier lake	50	2.2	1.51	5	8	0.22
7	House Collapse	60	3.2	1.85	13	7	0.04
8	Impact on Rescue	80	3.4	3.19	18	1	0.17
9	Flood	50	4.6	3.67	15	5	0.05
10	Casualty	60	3.8	2.84	16	3	0.08
11	Property Loss	80	2.6	1.81	15	5	0.05

To reflect the generality of the model, we do not consider Revenue Assessment.Here we consider the various disasters in the earthquake in detail instead of considering the earthquake, hurricane and other disasters. The indicators can also be obtained.

4. Conclusion

As global climate change intensifies, extreme weather events pose increasing threats to socio-economic stability and human safety, presenting significant challenges for the insurance industry in underwriting decisions. Traditional risk assessment methods, which often overlook the dynamic balance between risk and return, lead to assessment biases and inefficient resource allocation. To address this, this paper proposes a Risk-Revenue model framework, integrating risk matrix, Analytic Hierarchy Process, Entropy Weight Method, and TOPSIS to systematically quantify the multidimensional risk characteristics of extreme weather events and their impact on insurance revenue. The model incorporates indicators such as Risk Severity, Risk Probability, Composite Risk Index, Direct Income, and Indirect Income, constructing risk and revenue assessment models, and using TOPSIS to select optimal underwriting strategies. Case studies in eight U.S. states and Wenchuan, China, validate the model's practicality and robustness. This framework provides a scientific tool and practical guidance for insurers to optimize underwriting decisions, enhance risk management capabilities, and support the industry's sustainable development amid climate change.

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