# Regional Disaster Vulnerability Analysis and Insurance Selection Analysis Based on AHP-EWM-TOPSIS Group Method

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**Abstract.** Floods, hurricanes, cyclones, and droughts are the most common types of weather, and they have a profound impact on insurance. To specifically analyse the impact, the paper first introduces the concept of Regional Resilience Index (RRI), and then use the AHP-EWM-TOPSIS Method to derive the *RRI* scores and categorize all regions into five categories based on the size of *RRI*, which are rock-solid, stable, moderate, weak and vulnerable. Next, the Insurance Break-even Index Evaluation Model is built through the analysis. Insurers should increase their coverage in rock-solid, stable and moderate areas in line with the equilibrium curve, where they should invest in extensive publicity. In weak and vulnerable areas, insurance companies should appropriately reduce policy investment, build a multi-level insurance portfolio such as reinsurance mechanism, and invest a certain amount of funds in regional disaster prevention and loss prevention to maximize the win-win situation between the insurance company and the insured.

**Keywords:** BP Neural Network, TOPSIS, AHP, EWM.

## 1. Introduction

Extreme-weather events are becoming a crisis for property owners and insurers. The world has endured more than $1 trillion in damages from more than 1,000 extreme-weather events in recent years. Therefore, it is urgent to make a plan on how to insure for an insurance company. Many experts and scholars have used some evaluation systems to quantify the impact of natural disasters on insurance companies. For example, Guo Yunchao uses AHP to analyze the agricultural insurance situation in M province in his article [1] and Wen Chao and Xiaotao Qian utilize the EWM-TOPSIS method in their paper to analyze the typhoon disaster vulnerability assessment in Fujian Province and give the determination of insurance premium [2]. However, the use of a single evaluation system will be too subjective, resulting in insufficient quantification coefficient. In addition, some scholars have visualized the number or intensity of extreme weather by constructing some indexes, which can be used as a bridge to analyze the impact of extreme weather on insurance companies. For instance, Jerry R. Skees first proposes the method of weather indexing, using the weather index as the trigger condition for insurance claims [3]. World Bank Summarizes the relevant research results of weather index insurance and summarize the general process of product design [4]. Wang Yanping constructs the relationship between crop loss and climate factors, and provides a general process for the design of weather index insurance products [5]. Zeng Xiaoyan and Guo Xingxu describes the relationship between climate change and extreme weather events, and the major climate risks posed in China's agricultural production [6]. However, the index constructed by scholars contains relatively simple indicators. Inspired by these scholars and in order to solve the drawbacks mentioned above, this paper creatively puts forward the concept of Regional Resilience Index and includes 12 indicators for quantitative analysis, and then this paper uses the combination of AHP, BWM and BP neural network to show the impact of extreme weather on insurance companies, which can combine subjective and object evaluation to render the quantitative more convincing. And through the division of regional disaster resistance, this paper can propose different strategies that insurance companies should adopt in different regions.

## 2. The basic fundamental of AHP-EWM-TOPSIS Method

The paper introduces a novel concept Regional Resilience Index to indicate a region's capability to resist the extreme weather, short for *RRI*. Apparently, *RRI* depends on a variety of factors, so the paper will construct a hierarchical interactive evaluation model using 4 first-level evaluation indicators and 12 second-level evaluation indicators. The data are got from http://www.dsac.cn/DataProduct/Index, https://baijiahao.baidu.com, https://zhuanlan.zhihu.com, https://bbs.hupu.com/622956024.html, http://disaster.casnw.net/#/root/view. The paper then uses this information to construct a *RRI* evaluation model using a complete evaluation method that combines the TOPSIS method and the hierarchical analysis method [7].

### 2.1. Establishment of Interactive Evaluation Indicators

Combined with the actual situation, the authors comprehensively consider demographic features, economic level, infrastructure density and catastrophe disruptiveness to construct the Regional Resilience Index evaluation index system[8,9]. *Ci* is used in this paper to refer to the weight of each of these four first-level indicators and *Cij* is to refer to the weight of each of the second-level indicators under the first-level indicators. The principles of indicator selection are as follows.

Demographic Features **(***C1***)**: The impact of demographic features on *RRI* is multifaceted. The paper introduces population density **(***C11***)**, proportion of adults **(***C12***)** and education level **(***C13***).**

Economic Level **(***C2***)**: The level of economy largely determines how quickly and efficiently a region can respond to and recover from a major catastrophe. The paper introduces Gross Domestic Product **(**GDP**)** **(***C21***),** industrial structure **(***C22***)** and urbanization level **(***C23***).**

Infrastructure Density **(***C3***)**: Increased infrastructure density strengthens the capacity for emergency rescue and catastrophe recovery, and is critical in supporting the enhancement of an region's *RRI*. The paper introduces digitization level **(***C31***),** medical level **(***C32***)** and road density **(***C33***).**

Catastrophe Destructiveness **(***C4***):** The more destructive a catastrophe is, the more effort is needed for a region to recover from that catastrophe, which reduces the region's *RRI*. The paper introduces the catastrophe frequency **(***C41***)**, catastrophe intensity **(***C42***)** and economic losses **(***C43***).**

### 2.2. The AHP-EWM-TOPSIS Method for RRI Evaluation

#### 2.2.1. Data normalization

Different types of indicators can be categorized into the largest indicator, the smallest indicator, the medium-type indicator and the interval-type indicator according to their characteristics; this paper only discusses the largest indicator and the smallest indicator. The rating of the evaluation object increases as the value of the largest indicator increases and the value of the smallest indicator decreases.

First the data are subjected to dimensionless processing, and the principle equation is shown in (1). Where $x_i$ is the index value, $x_{i0}'$ is the dimensionless value of the index.

$$x_{i0}' = \frac{x_i}{\sqrt{\sum_{i=1}^{n} x_i^2}} \tag{1}$$

No processing is required for maximum value indicators. For minimum value indicators, a forwarding process is required to convert them to maximum value indicators, as shown below

$$x_i = M - x_{i0}' \tag{2}$$

Where M is the permissible upper limit of the index, a dimensionless number that takes the value 1. And $x'_{i0}$ is the result of the normalization of the minimum index.

### 2.2.2. Calculate weights using AHP and EWM

The paper uses AHP-EWM to jointly assign weights to the indicators. AHP can derive the subjective weights of the indicators while EMW can derive the objective weights, and the average of the subjective and objective weights is taken to get the final weights, which can make our weights more realistic.

First, this paper uses AHP to derive subjective weights. All indicators are categorized into three levels: the first level is the regional risk index, which is the object of our assessment, called the target level; the second level is the first-level factors affecting the regional risk index, called the criterion level; and the third level is the various sub-factors with the same attributes under the first-level factors, called the scenario level. To illustrate this structure more explicit, a hierarchical structure is formed as shown in *Figure 1*. By constructing a judgment matrix and performing consistency tests this paper derives subjective weights for all indicators.

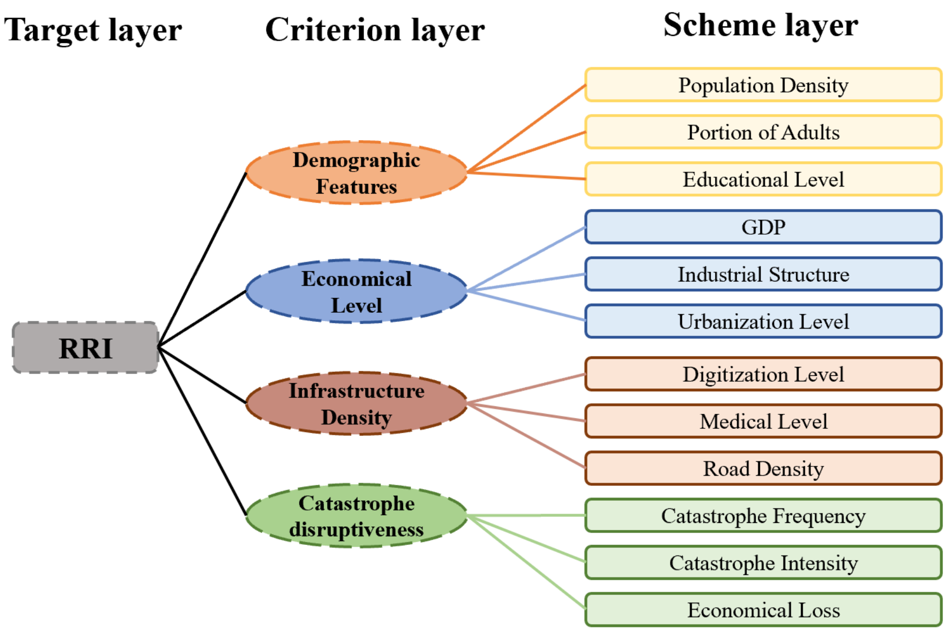


**Figure 1.** Hierarchical Structure

Then this paper analyzes the objective weights of the indicators using EMW. By constructing an evaluation matrix with a weighted normalization matrix it’s easy to derive objective weights for all indicators.

Finally, the subjective and objective weights are averaged to obtain the final weights of these indicators. This paper uses *Ci* to refer to the weight of the first-level indicators and *Cij* to refer to the weight of the second-level indicators under the first-level indicators. The results are presented in *Table 1*.

**Table 1.** Weight Values of the Twelve Indicators

| | Indicator | Weight ($C_i$) | indicator | Weight ($C_{ij}$) |
|---|---|---|---|---|
| RRI | Demographic Features | 0.0649 | Population Density | 0.0216 |
| | | | Portion of Adults | 0.0367 |
| | | | Educational Level | 0.0063 |
| | Economical Level | 0.3927 | GDP | 0.1300 |
| | | | Industrial Structure | 0.2236 |
| | | | Urbanization Level | 0.0391 |
| | Infrastructure Density | 0.1206 | Digitization Level | 0.0197 |
| | | | Medical Level | 0.0651 |
| | | | Road Density | 0.0368 |
| | Cata Disruptiveness | 0.4219 | Cata Frequency | 0.0663 |
| | | | Cata Intensity | 0.2493 |
| | | | Economical Loss | 0.1055 |

### 2.2.3. Calculate the relative proximity of the pre-selected points Ai

First the data is standardized to obtain dimensionless results $Z_{ij}$.

$$Z_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{m}\left(X_{ij}\right)^2}} \tag{3}$$

Then the paper defines the distance of the $i^{th}$ evaluation object from the maximum value as $D_i^+$, and the distance from the minimum value as $D_i^-$.

$$D_i^+ = \sqrt{\sum_{j=1}^{m} c_{ij}\left(Z_{ij}^+ - z_{ij}\right)^2}$$
$$D_i^- = \sqrt{\sum_{j=1}^{m} c_{ij}\left(Z_{ij}^- - z_{ij}\right)^2} \tag{4}$$

Where $c_{ij}$ is the weight (degree of importance) of corresponding indicators.

The larger the $D_i^+$ value of the research object is, the greater the distance from the optimal solution is; the larger the $D_i^-$ value is, the greater the distance from the worst solution is. The ideal research object is the smaller $D_i^+$ value while the larger $D_i^-$ value.

$$A_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{5}$$

The relatively larger the $D_i^-$ value is, the further away the object is from the worst solution, the better the object is. And the larger $A_i$ value is, the better the object is evaluated is. It is considered that the value of $A_i$ to be the size of the *RRI* in the $i_{th}$ region.

### 2.2.4. BP Neural Network

The structure of BP Neural Network is shown in *Figure 2:*

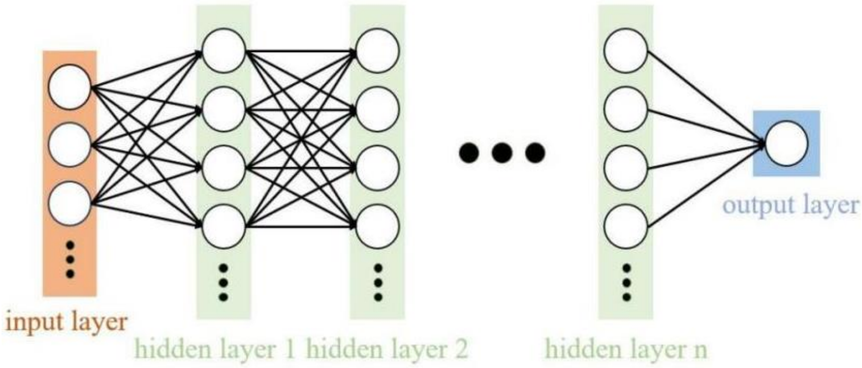


**Figure 2.** BP Neural Network Structure

Once the data set is input into the input layer, the system will input the above input data set into the neural network model for training a large amount of data within n hidden layers, and then output the results in the output layer.

In the above section, a data set is obtained by constructing a regional resilience evaluation model, which includes the data of various indicators related to the *RRI* of the region. The authors input the data set into the neural network model and calculate the estimated value $\hat{y}$ . Then the weights of *Cij* keep changing, so that the error between $\hat{y}$ and *RRI* can be as small as possible. After a large amount of data training, new data for each indicator in a region are then input into the network, and the system can find the *RRI* for that region.

### 2.2.5. Application & Inspection

Applying the model to evaluate the *RRI* of each province in China, it can be found that Shanghai and Tianjin have the highest scores among all provinces which shows that their *RRI* is strongest, mainly due to the fact that they have one of the highest levels of economic development in China and their infrastructure is well developed. However, Tibet and Sichuan have the lowest scores, mainly due to their low population densities and the devastating nature of disasters. Overall, the coastal provinces in China generally score higher, while the central and western provinces score lower, which is consistent with the overall development trend in China, and indicates that the model is relevant to the real situation and has a strong application value. The values are presented in *Table 2* and *Figure 3.*

**Table 2.** Scores for Some Provinces in China

| Province | Points | Province | Points |
|---|---|---|---|
| Shanghai | 0.7523 | ... | … |
| Tianjin | 0.5783 | Henan | 0.4063 |
| Jiangsu | 0.5723 | Yunnan | 0.4002 |
| Zhejiang | 0.5267 | Sichuan | 0.4001 |
| … | … | Tibet | 0.3962 |

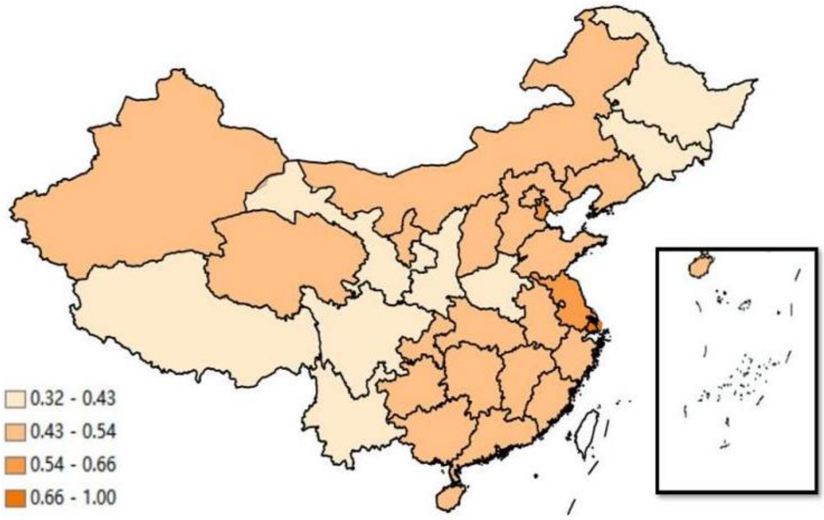


**Figure 3.** RRI Level of Each Province in China

## 3. Insurance Break-even Model

The paper establishes RRI Evaluation Model in the last section, which quantitatively analyzes the resilience level of a region and provides some reference for insurance companies to choose insurance. However, it is not scientific enough to judge whether a region can be insured based on *RRI* alone. If an insurance company refuses to insure in a region with low resilience level, it will lose some potential markets, reduce profitability or even go out of business due to insufficient profitability. Therefore, it is necessary to build a more comprehensive model based on *RRL* Evaluation Model to decide how insurance companies should insure. The model mainly considers profitability, so it is named Insurance Break-even Model.

### 3.1. The Preparation and Construction of the Model

The primary concern in running a company is cost. $Cost_1$ is defined as the production costs for insurance companies, which satisfies the following equation [10]:

$$Cost_1 = F + \bar{M}_1 \times Q_{sell} \tag{6}$$

Where $F$ is the fixed cost, including house rent etc. $Q_{sell}$ is the total amount of sold insurance, and $\bar{M}_1$ is a constant which means the average cost of per sold insurance policy, such as labor costs, etc.

The most important feature of insurance companies is that the success of selling insurance does not necessarily mean that it is profitable, because insurance companies need to pay out to their customers. The paper counts the amount of money that the insurance companies need to pay out to the customers as the costs as well, which is called $Cost_2$ and satisfies the following equation:

$$Cost_2 = M_2 \times Q_{claim} \times \lambda \tag{7}$$

Where $M_2$ is the payout amount which is related to claim rate $r$. $Q_{claim}$ is the total amount of insurance to be paid out. $\lambda$ is the compound present value coefficient, defined as follows

$$\lambda = \frac{1}{(1+i)^t} \tag{8}$$

Where $i$ is the discount rate and $t$ is time. In this model $t$ is took to be 1 for ease of computation.

The paper defines the ratio of $Q_{claim}$ to $Q_{sell}$ as the claim rate $r$.

$$r = \frac{Q_{claim}}{Q_{sell}} \tag{9}$$

*Rev* is defined as the revenue of an insurance company, which satisfies the following equation:

$$Rev = P \times Q_{sell} \tag{10}$$

Where *P* is the average price of per insurance policy.

The break-even point for insurance companies is when costs and revenues are equal.

$$Rev = Cost_1 + Cost_2 \tag{11}$$

Expand it and write it as:

$$P \times Q_{sell} = F + \bar{M}_1 \times Q_{sell} + M_2 \times Q_{claim} \times \lambda \tag{12}$$

Then the paper introduces *RRI* into the model and consider *r* to be inversely related to *RRI*. This is because the smaller the *RRI*, the more $Q_{claim}$ will be in the area for the same $Q_{sell}$.

$$r = \frac{1}{RRI} - 1.15 \tag{13}$$

It is considered that $M_2$ is exponentially related to *r* [11].

$$M_2 = 10000 \times exp(-2 \times r - \mu) \tag{14}$$

After substituting (13)(14) into (12) and (15) can be obtained:

$$Q_{sell} = \frac{F}{P - M_2 \times r \times \lambda - \bar{M}_1} \tag{15}$$

Equation (15) is revised to obtain (16)

$$Q_{sell} = Q_0 - \frac{F}{M_2 \times r \times \lambda + \bar{M}_1 - P} \tag{16}$$

Where $Q_0$ is the minimum number of sold insurance policies that insurance companies should sell to break even when *RRI* is 0. Similarly, the paper modifies the definition of $Q_{sell}$ to be the minimum number of insurance policies that insurance companies should sell in order to break-even under an arbitrary *RRI*.

### 3.1.1. Model Solving and Analysis

From the above analysis the paper obtains the relationship between *RRI* and $Q_{sell}$ as shown in *Figure 4*.

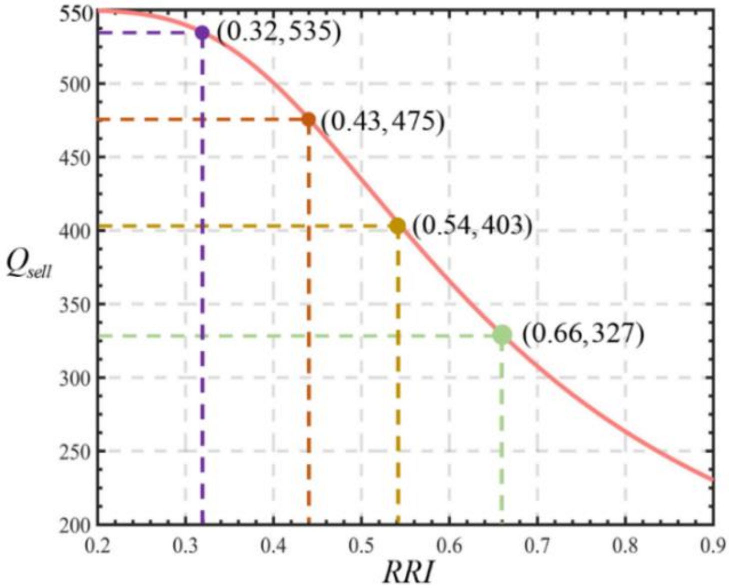


**Figure 4.** Relationship Between RRI and $Q_{sell}$

It is clear to see that $Q_{sell}$ decreases as *RRI* increases. This shows that if the *RRI* of an area is smaller, insurance companies need to sell more insurance policies to reach break-even, which is consistent with the reality.

Through K-means clustering the $Q_{sell}$ is divided into five classes, and each segmentation point of $Q_{sell}$ has a corresponding *RRI*, so *RRI* is divided into five classes as well, as shown in *Figure 5.*

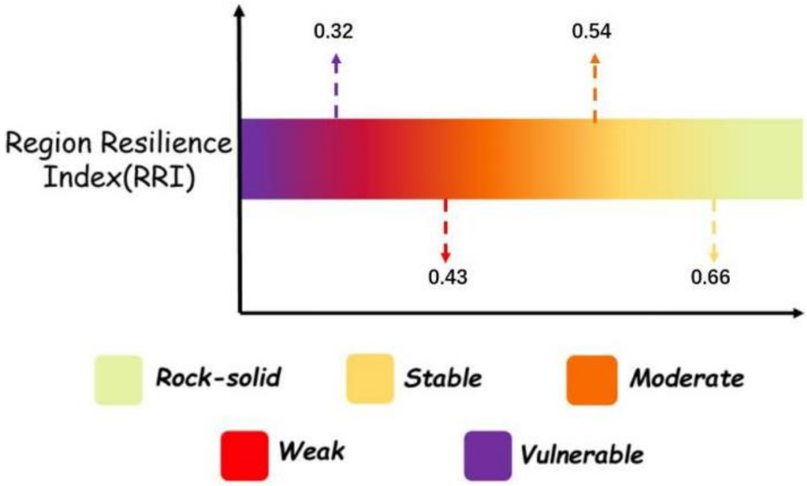


**Figure 5.** RRI classification

The darker the color is, the smaller the *RRI* of the area is, which means that the less resilient the region is, As a profit-oriented insurance company, insuring in these places means that they will have to bear more insurance claims and will be exposed to a greater risk of insolvency. Therefore, it is recommended that insurance companies focus on areas with high *RRI* -- that is rock-solid, stable and moderate regions -- and curtail insurance in vulnerable and weak areas. However, in order to avoid having too few customers in high *RRI* areas, insurance companies should not completely give up insuring in low *RRI* areas, but should open up submarkets in these areas. Economists have developed a method of "reinsurance" in which insurance companies share a portion of their premiums to purchase reinsurance. Reinsurance can reduce the risk of large claims by sharing the risk between the original insurance companies and the reinsurers[12].

## 4. Conclusion

This paper focuses on the impact of extreme weather on the insurance industry. In order ensure the RRI scores has both subjectivity and objectivity, the combination of AHP and EWM is utilized to calculate the weight of RRI. However, the application of this model needs a large amount of data to support, and the classical forecasting method cannot bear such a huge consumption of time and computing resources. Therefore, this paper uses BP neural network to migrate the model. After using AHP-EWM-TOPSIS to calculate the RRI of various regions in China, it can be found that the RRI of the economically developed coastal areas is generally higher than that of the economically backward inland areas, which is consistent with the reality. Then, this paper constructs the relationship between RRI and Qsell, and finds that insurance companies should reasonably give up part of their market share in areas with low RRI according to the equilibrium curve, and focus on areas with high RRI. This study can provide some guiding opinions for insurance companies to rationally insure.

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