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A Study of Property Insurance in Extreme Weather Based on EWM-TOPSIS Modeling

Mingzhong Wei *, Lujie Wang, Jiwei Ye

Department of Information and Electrical Engineering, Xuhai College, China University of Mining and Technology, Xuzhou, China
* **Corresponding author**: Mingzhong Wei (Email: 208429131@qq.com)

Abstract: In recent years, increasing global climate change has led to a rise in the frequency of natural disasters, posing a threat to the safety of human life and property. This trend has put tremendous pressure on insurance companies, so we conducted a related study to more accurately assess the impact of natural disasters on them. We developed two models: the catastrophe-based insolvency probability model and the EWM-TOPSIS model. In the bankruptcy probability model based on the catastrophe model, we introduced the cumulative claim amount to derive the total loss and calculated the bankruptcy probability. And in the EWM-TOPSIS model, we chose seven official indicators to analyze and introduced insurance factors to construct the model. Through our study, we found that insurance factors play an important role in real estate decision-making and have a significant impact on the comprehensive evaluation of the region. In summary, our study provides insights and useful suggestions for understanding the impact of natural disasters on insurance companies.

Keywords: Property insurance; Probability of insolvency model; EWM-TOPSIS model.

1. Introduction

Natural disasters are one of the major challenges facing human society, and their devastating impact is of increasing concern. Global climate change has led to an increase in the frequency and intensity of extreme weather events, exacerbating the occurrence of natural disasters. These disasters not only cause direct damage to individuals and communities, but also have a significant impact on the business and financial sectors, particularly the insurance industry. Insurance companies bear significant risks and need to accurately assess the impact that natural disasters may have on them in order to develop effective risk management strategies [1].

This study aims to explore the impact of natural disasters on insurance companies and to propose corresponding countermeasures. By constructing an insolvency probability model based on the catastrophe model and the EWM-TOPSIS model, we attempt to gain a deeper understanding of the challenges of natural disaster risks on insurance companies and explore the role of insurance factors in risk assessment and decision making. Through this study, we hope to provide useful insights and suggestions for the insurance industry to better adapt to the ever-changing natural catastrophe environment and to ensure the stability and sustainable development of the insurance market.

2. Property Valuation Model

To ascertain whether insurance companies should underwrite policies in areas prone to frequent extreme weather events. We initially establish a catastrophic risk model, which considers the actual claims amount (financial losses for insurance companies) as a function of the magnitude of the catastrophe. Subsequently, utilizing the catastrophic risk model, we derive the probability of bankruptcy for insurance companies. This determination further guides the decision-making process regarding whether to underwrite policies in regions prone to recurrent extreme weather events. Lastly, we exemplify our model through the illustration of two regions [2].

2.1. The Catastrophic Risk Model

Regarding the aforementioned catastrophic risk model. We initially assume that the catastrophic event occurs within a specific domain. In this scenario, there are m regions, each of which has n insurance contracts covering catastrophic risks (assuming these contracts pertain to a specific type of catastrophe, such as wildfires, hurricanes, etc.). During a specific timeframe (e.g., one year), The catastrophic risk loss of the i-th contract in the j-th region can be denoted as L_{ij}^{CR}, then:

$$L_{\mathrm{ij}}^{CR} = \begin{cases} \sum_{\mathrm{k}=1}^{M_{\mathrm{oj}}} Y_{\mathrm{ijk}}^{CR}, & M_{oj} > 0 \\ 0, & M_{oj} = 0 \end{cases} \tag{1}$$

Where M_{oj} represents the number of occurrences of catastrophic risk events for the o-th insurance contract in the j-th region during a certain period of time. Where Y_{ijk}^{CR} represents the insurance claim amount for the k-th occurrence of catastrophic risk for the o-th insurance contract in the j-th region during a certain period of time.

We assume the absence of dependence among catastrophic risks.

For a specific region and a particular insurance contract, we assume L_{ij}^{CR} independence from other factors.

For a specific region and a particular insurance contract, The $Y_{\mathrm{ij1}}^{CR}, Y_{\mathrm{ij2}}^{CR}, \cdots$ follows an independent distribution and is independent of M_{oj}

Based on the aforementioned assumptions, it can be deduced that L_{ij}^{CR} is a function of the occurrence of catastrophic risk events, denoted by M_{oj}, indicating that $L_{\mathrm{ij}}^{CR}\left(i=1,2,\cdots\right)$ is not independent of each other.

In order to facilitate insurance companies in making more informed determinations regarding the provision of coverage in regions susceptible to extreme weather conditions. We introduce a random variable S_{nm}^{CR}, representing the cumulative claim amount for "n" insurance policies across "m" regions with catastrophic risk. Thus, the aggregate loss of the insurance company in a specific time period and region is denoted as:

$$S_{nm}^{CR}=\sum_{i=1}^{n}\sum_{j=1}^{m}L_{ij}^{CR} \tag{2}$$

2.1.1. Insurance Pricing and Options

In order to assist insurance companies in making informed decisions regarding the underwriting of policies in regions prone to frequent extreme weather events, we are discussing the distributional characteristics of the aggregate claims amount, denoted as S_{nm}^{CR}, for catastrophic risks:

$$S_{nm}^{CR}=\sum_{i=1}^{n}\sum_{j=1}^{m}L_{ij}^{CR} \tag{3}$$

Equation (3) can be expressed in the following two forms:

$$S_{nm}^{CR}=\begin{cases}\sum_{j=1}^{n}\sum_{k=1}^{M_{oj}}Y_{1jk}^{CR}+Y_{2jk}^{CR}+\cdots+Y_{njk}^{CR},M_{oj}>0\\ 0, \qquad M_{oj}=0\end{cases} \tag{4}$$

$$S_{nm}^{CR}=\begin{cases}\sum_{j=1}^{m}\sum_{k=1}^{M_{oj}}Z_{njk}^{CR},M_{oj}>0\\ 0, \qquad M_{oj}=0\end{cases} \tag{5}$$

Where $Z_{njk}^{CR}=Y_{1jk}^{CR}+Y_{2jk}^{CR}+\cdots+Y_{njk}^{CR}$.

The equations (3), (4) and (5) can be approached from two perspectives. One perspective is when pricing individual insurance contracts in an insurance company, equations (3) and (4) are utilized. Because we need to model the distribution of individual claim amounts, denoted as $Y_{ij1}^{CR},Y_{ij2}^{CR},\cdots$ On the other hand, when pricing catastrophe options or catastrophe bonds, it is only necessary to know the distributions of variables M_{oj} and Z_{njk}^{CR}. Therefore, when the total loss data for a given catastrophe is known, the problem can be solved using Equation (5) [3].

2.1.2. The Financial Losses Incurred by Insurance Companies.

To determine the financial loss experienced by the insurance company over a specific period of time due to severe weather conditions in a particular location. Moreover, for the sake of convenience in addressing the issue at hand. Under the assumption made, we consider that within the given timeframe, a single catastrophic event occurred in a specific region. The random variable Y_{ij}^{CR} represents the financial losses associated with the risk of a catastrophic event. The amount claimed by the insured party from the insurance company can be denoted as:

$$L_{ij}^{CR}=\begin{cases}Y_{ij}^{CR},M_{oj}=1\\ 0, \quad M_{oj}=0\end{cases} \tag{6}$$

Suppose M_{oj} is a Bernoulli random variable and let $E\left[M_{oj}\right]=q$. represents a portion of the actual losses incurred from a catastrophe. Let us assume that $Y_{ij}^{CR}=P_{ij}^{CR}\times b_{ij}^{CR}$. P_{ij}^{CR} represents the actual losses incurred from a particular catastrophic event. $b_{ij}^{CR}\in\left[0,1\right]$ represents the loss rate. As a result, we arrive at the insurance company's financial loss:

$$L_{ij}^{CR}=b_{ij}^{CR}\times C_{ij}^{CR} \tag{7}$$

Where $C_{ij}^{CR}=\begin{cases}P_{ij}^{CR},M_{oj}=1\\ 0,. \quad M_{oj}=0\end{cases}$

2.2. A Bankruptcy Probability Model Based on CT

In order to ensure the long-term healthy and stable development of an insurance company, we must consider the possibility of bankruptcy after the company has been underwriting in a specific region for a certain period of time. Therefore, by combining the aforementioned elements (CT), we have obtained the probability of bankruptcy for the insurance company, as follows:

Let the equation $\pi_{ij}^{CR}=\pi\left(L_{ij}^{CR}\right)$ represent the catastrophic loss premium of the i-th insurance contract within the j-th region. Here, we assume that the calculation of π_{ij}^{CR} adheres to the principle of separability in premium. However, the simplest principle among them is the pure premium principle, where $\pi(L_{ij}^{CR})=E\left[L_{ij}^{CR}\right]$. However, the safety loading premium is slightly higher than the pure premium, and the difference between them is referred to as the safety loading.as:

$$a_{ij}^{CR}=\pi(L_{ij}^{CR})-E\left[L_{ij}^{CR}\right]>0 \tag{8}$$

The relative safety margin is defined as follows:

$$\eta_{ij}^{CR}=\frac{a_{ij}^{CR}}{E\left[L_{ij}^{CR}\right]} \tag{9}$$

In this context, the probability of bankruptcy refers to the likelihood that an insurance company will be unable to meet its financial losses within a specified period of time. Here, we do not take into account the risks associated with the capital market or transaction costs incurred by the insurance company. In this scenario, we assume that the first and second moments of the random variable y, representing insurance claims, are finite and strictly positive. In other words, there exists a positive constant $a_1,a_2,b_1,b_2>0$,such that:

$$0<a_1\le E\left[L_{ij}^{CR}\right]\le a_2,0<b_1\le Var\left(L_{ij}^{CR}\right)\le b_2 \tag{10}$$

Consequently, we define the bankruptcy probability of the insurance company as:

$$\varepsilon_{nm}^{CR}=P(S_{nm}^{CR}>\sum_{i=1}^{n}\sum_{j=1}^{m}\pi_{ij}^{CR}) \tag{11}$$

Where $\pi_{ij}^{CR} = (1+\eta)E\left[L_{ij}^{CR}\right]$

2.2.1. The Uncertainty of Bankruptcy Probability

As the loss rate, $b_{ij}^{CR} \in [0,1]$, could potentially be a fixed constant (although we won't explore that further), it could also be a deterministic function of catastrophic event intensity. Here, we exclusively discuss the impact of the loss rate, being a deterministic function of catastrophic event intensity, on the probability of bankruptcy for the company. As depicted below:

Let us assume that $b_{ij}^{CR} = \varphi_{ij}(I)(i=1,2,\cdots,n)$,The variable "I" signifies the magnitude of catastrophic event risk intensity. $\varphi_{ij}(\bullet):\Omega \to [0,1]$. The probability distribution function of the random variable I ,denoted as F_1 ,is independent of variable M_{oj} .The definition of variable $\varphi_{ij}(\bullet)$ relies on the characteristics associated with the discussion of damaged properties. Where $\varphi_{ij}(\bullet) > 0$. Suppose the loss function is an increasing function. This implies that if two damaged properties, denoted as l and l', share the same characteristics within the same area.as:

$$\varphi_{ij}(\bullet) = \varphi_{i'j}(\bullet) \tag{12}$$

3. Sustainable Development Assessment Model

As climate patterns continue to shift, the increased occurrence of extreme weather poses challenges to the sustainable growth of both local real estate developers and the insurance industry. Therefore, we aim to refine our insurance models to evaluate the suitable locations for construction. Initially, we have selected seven indicators, such as regional culture and insurance outcomes, and normalized the data associated with them. Subsequently, employing the entropy-weighted TOPSIS method, we derived comprehensive scores for different locations. These scores enable us to offer valuable recommendations to real estate developers [4].

3.1. Data Processing and Analysis

Initially, we meticulously examined 57 relevant official indicators, taking into account various literature sources. After careful consideration, we handpicked the most representative seven indicators to form the foundation of our model. Subsequently, we applied data normalization techniques to these seven chosen indicators.

1)The Ramifications of Governmental Policies

Part of the real estate market is subject to repeated regulation by government policies, with restrictions on financing, taxation and preferential treatment, which will lead to a decrease in the well-being of real estate developers and residents, and the real estate market reacts differently to any government intervention or external influences, which makes real estate projects unstable.

2)The Influence of Regional Culture

Each region has its own unique way of life, which may affect the need for diversity in real estate projects. In addition, the regional culture also affects people's values, which makes locals negatively evaluate buildings that are different from what they think.

3)The Impact of Land Prices

Land supply prices have the most direct and far-reaching impact on real estate prices. The land policy chooses the land purchase area of real estate development enterprises as the representative variable, and the land supply structure and land price have a great influence on real estate site selection. In order to simplify the problem, only land price is used as the main indicator.

4)The Impact of Ecological Environment

Natural landscapes such as mountains, lakes, rivers and seas greatly enhance the attractiveness and home-grown value of real estate.

5)Effects of Aging

As the population ages, we may see a change in demand for different types of properties from home buyers who may choose to sell their properties, which could increase supply in the real estate market, and aging may also provide opportunities for investors.

6)Traffic Impact

With the development of the times, people are more and more attracted to residential areas with fast transportation, so the price of real estate will be affected by the accessibility of transportation and other factors.

7)The Effect of Insurance Results

As the insurance landscape changes, future real estate decisions must ensure that properties are more resilient, especially in the face of extreme weather and natural disasters.

3.1.1. Data Normalization Processing

In order to avoid the bias brought about by the data size, we need to normalize the data of different indicators in order to compare on the same scale. However, we use different normalization methods for different types of data.

For "benefit attribute type", that is, the larger the data type, the better, we use the following formula for normalization:

$$x_{\mathrm{ij}} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{13}$$

For "cost attribute type", that is, the smaller the data type, the better, we use the following normalization method:

$$x_{\mathrm{ij}} = \frac{x_{\max} - x_i}{x_{\max} - x_{\min}} \tag{14}$$

Suppose we have n sets of indicators, such as insurance results, traffic, government policies, etc. x_{ij} represents the normalized data, x_{i} represents the original data, $x_{\max}$ and $x_{\min}$ represent the maximum and minimum values of the indicators respectively.

3.2. Entropy Weight-TOPSIS Method

After obtaining the standardized data, we normalized the data using the following methods (Figure 1):

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} (i=1,2\cdots) \tag{15}$$

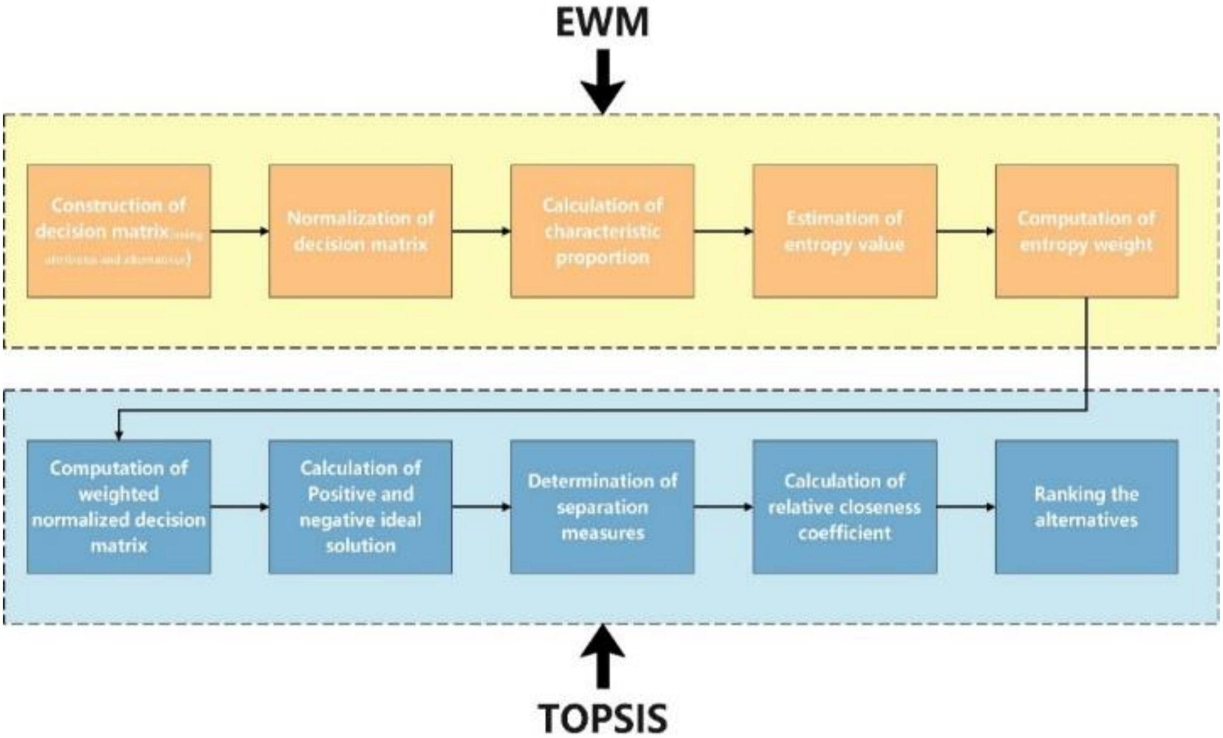

Figure 1. Flow Chart of EWM-TOPSIS

3.2.1. Calculate the Entropy of This Index

By substituting the normalized data of various indicators (such as transportation and environment) obtained from the equation above, we can derive the information entropy for each indicator [5]:

$$E_i = -\frac{\sum_{i=1}^{n} p_{ij} \cdot \ln p_{ij}}{\ln n} (i = 1, 2 \cdots) \tag{16}$$

According to the information entropy, we will further calculate the due weight w of each index:

$$w_i = \frac{1 - E_i}{\sum_{i=1}^{n} 1 - E_i} \tag{17}$$

We incorporated data from seven selected official indicators into the above methodology to derive their respective weights, as shown in Table 1:

Table 1. Indicators Selected

Indicators	Description	Weight
GP	Government policy	0.20
TR	Traffic	0.17
LP	Land price	0.15
IR	Insurance results	0.26
AG	Aging	0.03
RC	Regional culture	0.09
EE	Ecological environment	0.10

3.2.2. Weighted Normalization

First, we will get the weights to form a vector and call it an "evaluation vector", such as $\vec{\lambda} = (\lambda_1, \lambda_2 \cdots)$ .Next, we will make up a vector of different impacts on real estate, which is called the "impact vector", such as $\vec{S} = (S_1, S_2 \cdots)$ .Finally, we get the weighted normalized score:

$$Score_x = \vec{\lambda} \cdot \vec{S} = \sum_{i=1}^{Num_x} \lambda_i \cdot S_i \tag{18}$$

The various indicators represented by x , such as insurance results, traffic, etc., lay the theoretical basis for TOPSIS to evaluate the final score of each place.

3.2.3. The TOPSIS Model

Based on entropy weight method (can be abbreviated), we use TOPSIS model to calculate the final scores of each region [6], and the calculation process is shown as follows.

Determine the best and worst solutions:

$$\begin{cases} A^+ = \left\{\max_i (Score_x) \mid j \in J^+\right\} \cup \left\{\min_i (Score_x) \mid j \in J^-\right\} \\ A^- = \left\{\min_i (Score_x) \mid j \in J^+\right\} \cup \left\{\max_i (Score_x) \mid j \in J^-\right\} \end{cases} \tag{19}$$

A^+ and A^- stand for the optimal and worst solutions respectively, J^+ stands for the optimal criterion set, J^- stands for the worst criterion set.

Calculate the distance of each scheme to the ideal and negative ideal solutions:

$$\begin{cases} d_i^+ = \sqrt{\sum_{x=1}^{m} (Score_x - A^+)^2} \\ d_i^- = \sqrt{\sum_{x=1}^{m} (Score_x - A^-)^2} \end{cases} \tag{20}$$

d_i^+ represents the distance from the i th solution to the ideal solution, d_i^- represents the distance from the i-th solution to the negative ideal solution, and m represents the number of evaluation indexes.

In the end, we got the following scores for district construction:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{21}$$

CC_i represents the relative proximity of the i scheme, and the larger the value, the better the scheme.

4. Conclusions

In this study, we provide insights into the impact of natural disasters on insurance companies and the importance of insurance factors in risk assessment by constructing an insolvency probability model based on the catastrophe model and the EWM-TOPSIS model. Our study finds that the increase in the frequency of natural disasters triggered by global climate change poses a great challenge to the insurance industry, and effective measures need to be taken to mitigate the risks and safeguard the sustainable development of companies.

By using an insolvency probability model based on catastrophe modeling, we are able to more accurately assess the insolvency risk that an insurance company may face in the face of natural disasters, which helps the company to better plan its risk management strategy. The application of the EWM-TOPSIS model, on the other hand, emphasizes the key role of insurance factors in real estate decision-making and provides a new perspective for regional risk assessment.

In summary, our study provides the insurance industry with an in-depth understanding of natural disaster risks and coping strategies. In the future, we recommend that insurance companies further strengthen their risk management capabilities, increase their monitoring and assessment of natural disaster risks, and focus on the role of insurance factors in risk decision-making. In this way, they can better face the changing natural disaster environment, ensure the healthy development of the insurance industry and provide more reliable risk protection for the society.

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