

Research on Underwriting Risk Based on EWM-TOPSIS and SARIMA Models

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Abstract. Recent climate change-induced extreme weather events have heightened property insurance claims, prompting the development of an insurance model utilizing advanced mathematical models. Utilizing the EWM-TOPSIS model, a comprehensive framework for underwriting risk assessment was developed and applied to determine the 20-year Insurance Claim Risk Index (ICRI) for both Beijing and Guizhou Province. Predictive modeling using the SARIMA model produced ICRI values for Beijing (0.134, 0.154, 0.149) and for Guizhou Province (0.265, 0.304, 0.169). Assuming the ICRI follows a normal distribution, a statistical analysis was conducted on 40 ICRI data points. Based on this, the ICRI was categorized into three levels, providing a foundation for the insurance company's decision-making. In Beijing, it is suggested to insure for the next three years, while in Guizhou, it is advised not to insure for the first two years or to start the business in the third year.

Keywords: EWM, TOPSIS, SARIMA, Insurance Model.

1. Introduction

A concerning trend is emerging amidst the escalating global climate change [1], characterized by a surge in extreme weather events that are inflicting substantial economic losses worldwide, as evidenced by a rapid increase in insurance claims. Against the backdrop of mounting environmental concerns and a rise in environmental disasters, extreme weather events are evolving into an imminent crisis for property owners and insurance companies. Consequently, there has been a growing interest in recent years in studying the impact of extreme weather and other natural disasters on the insurance industry. Stephen Barnes [2] and others have explored the influence of natural disasters on individuals' willingness to purchase insurance. José-María Montero [3] and colleagues have investigated the correlation between natural disasters and the stock prices of insurance markets. Researchers such as Stricker, L [4], Goncalves [5], Mills [6], and R. Waddell [7] and others have delved into the measures taken by insurance companies to address climate disasters. G. Dionne [8], M. Ghafory-Ashtiany [9] and colleagues have analyzed insurance companies' ability to withstand natural disasters. B. A. Brotman [10] and others have examined insurance losses resulting from natural disaster events. Shea [11] and colleagues have explored the importance of environmental factors on underwriting syndicates. While enthusiasm for related research is increasing, the literature remains relatively sparse, with much of it focusing on the impact of individual natural disaster events or qualitative analysis. This paper aims to analyze whether insurance companies underwrite in the face of high occurrences of extreme weather events using methods such as EWM, TOPSIS, and SARIMA.

2. Insurance Model - A Framework for Evaluating Underwriting

To model and analyze the underwriting feasibility of insurance policies in regions affected by an upsurge in extreme weather events, the process commences with predicting the loss risk for insurance companies in the area. The first step involves establishing a comprehensive evaluation model for loss risk, followed by forecasting the trajectory of risk indicators. Ultimately, decisions regarding policy underwriting can be informed by these assessments.

2.1. Establishment of EWM-TOPSIS Assessment Model

Developing an assessment model utilizing the Entropy Weight Method (EWM) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to evaluate insurance claims risk in a region.

Construct the model following the steps below:

(1) Select various indicators, gather data, and perform scaling and normalization processes to acquire the standardized matrix P.

Insurance Claims Risk Index:

Direct Economic Losses from Natural Disasters

Flood, Geological Disaster, and Typhoon Affected Areas

Frequency of Earthquake Disasters

Property Insurance Expenditure

Frequency of Forest Fires

Direct Economic Losses from Earthquake Disasters

(2) Compute the weight for each indicator using the EWM and derive the weight vector W. The outcome is depicted in Table1 and Fig1.

Table 1. Results of EWM

Indicators	Information Entropy	Information Utility Value	Weights (%)
Direct Economic Losses from Natural Disasters	0.688	0.312	14.603
Flood, Geological Disaster, and Typhoon Affected Areas	0.649	0.351	16.455
Frequency of Forest Fires	0.784	0.216	10.095
Frequency of Earthquake Disasters	0.658	0.342	15.993
Direct Economic Losses from Earthquake Disasters	0.13	0.87	40.76
Property Insurance Expenditure	0.955	0.045	2.094

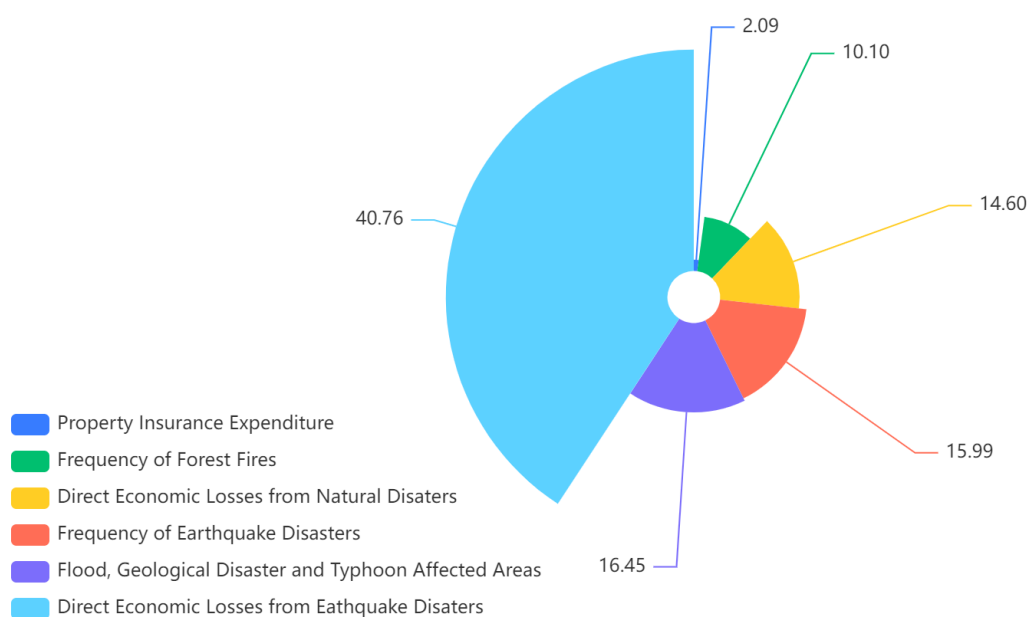


Figure 1. Weights of Indicators

(3) Compute the weighted normalized matrix Z using the following calculation formula:

$$Z = (z_{ij})_{n \times m} = (p_{ij} \times w_j) \quad (1)$$

(4) Identify positive and negative ideal solutions. A positive ideal solution implies that each indicator attains the best value within the sample, while a negative ideal solution suggests that each indicator reaches the worst value within the sample.

(5) Compute the distance of each sample from both the positive and negative ideal solutions using the following formula:

$$D_i^+ = \sqrt{\sum_{j=1}^m (z_{ij} - z_j^+)^2}, D_i^- = \sqrt{\sum_{j=1}^m (z_{ij} - z_j^-)^2}, (i = 1, 2, 3 \dots n) \quad (2)$$

(6) Calculate the proximity of each evaluation object to the optimal solution, represented by the comprehensive score index C value, using the following formula:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (3)$$

The value range of C_i is $[0, 1]$. The closer the value is to 1, the higher the sample score.

(7) The Insurance Claim Risk Index (ICRI) has been introduced and is computed utilizing the following formula:

$$ICRI = \frac{C_i}{C_{max} - C_{min}} \quad (4)$$

According to the principles of the TOPSIS evaluation method, when the natural disaster risk is at its highest, it is treated as the positive ideal solution, i.e., D^+ equals 0 and C equals 1. Similarly, when the natural disaster risk is at its lowest, it is considered the negative ideal solution, i.e., D^- equals 0 and C equals 0.

(8) Assuming a normal distribution of risk factors, conduct data analysis to derive the mean(μ) and variance(σ). Utilizing the interval on the horizontal axis ($\mu - \sigma$, $\mu + 2\sigma$), three distinct regions are delineated to suggest coverage, indicate insurable risk, and discourage coverage, respectively.

2.2. Establishment of SARIMA Model

The Seasonal Autoregressive Integrated Moving Average(SARIMA) model is employed for forecasting time series with periodic and seasonal patterns. It comprises three essential components:

Enhance the analysis by decomposing the time series into trend data, seasonal data, and random data to make an initial assessment of the seasonal effects.

Conduct a unit root test on the time series using the Augmented Dickey-Fuller (ADF) test to assess stationarity. If the time series is found to be non-stationary, apply differencing operations to transform it into a stationary time series. Subsequently, establish a SARMA model for the stationary time series. Reviewing the final differenced sequence plot and concurrently performing autocorrelation and partial autocorrelation analysis on the time series. Using the truncation patterns to estimate the values of p, q, P and Q.

(a) The AutoRegressive model (AR) elucidates the connection between past values and current values, utilizing historical time data of the variable for prediction. To be effective, it necessitates the time series data to exhibit stationarity and possess autocorrelation. Specifically, it is most applicable when the autocorrelation coefficient is less than 0.5. The p-order autoregression is defined as follows:

$$y_t = \mu + \sum_{i=1}^p \gamma_i y_{t-i} + \varepsilon_t \quad (5)$$

In the equation, y_t represents the current value, μ is the constant term, p is the order, γ is the autocorrelation coefficient, ε_t signifies the error, and y_{t-i} denotes the previous value of y_t .

(b) The Moving Average model (MA) concentrates on aggregating error terms from the autoregressive model, aiming to effectively mitigate random fluctuations in predictions. The definition of the q-order regression is as follows:

$$y_t = \mu + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t \quad (6)$$

(c) Utilize SAR and SMA models to incorporate seasonality in determining their respective orders

P and *Q*.

Verify whether the model residuals display characteristics indicative of white noise. If the model passes the test, it is considered reasonable; otherwise, the model's form needs to be modified and retested.

Utilize the established SARIMA model for forecasting.

3. Case Demonstration

Beijing and Guizhou Province have been selected as case studies for demonstration due to their distinct characteristics as regions with low and high underwriting risks, respectively. Gather relevant data for the selected indicators in both regions. Conduct analyses for each region utilizing the aforementioned models and present the results. A partial display of the outcomes is as follows:

3.1. Trend of ICRI

Gather relevant data for the selected indicators in both regions. Conduct analyses for each region utilizing the aforementioned models and present the results. A partial display of the outcomes is as shown in Fig2, Fig3, and Table2.

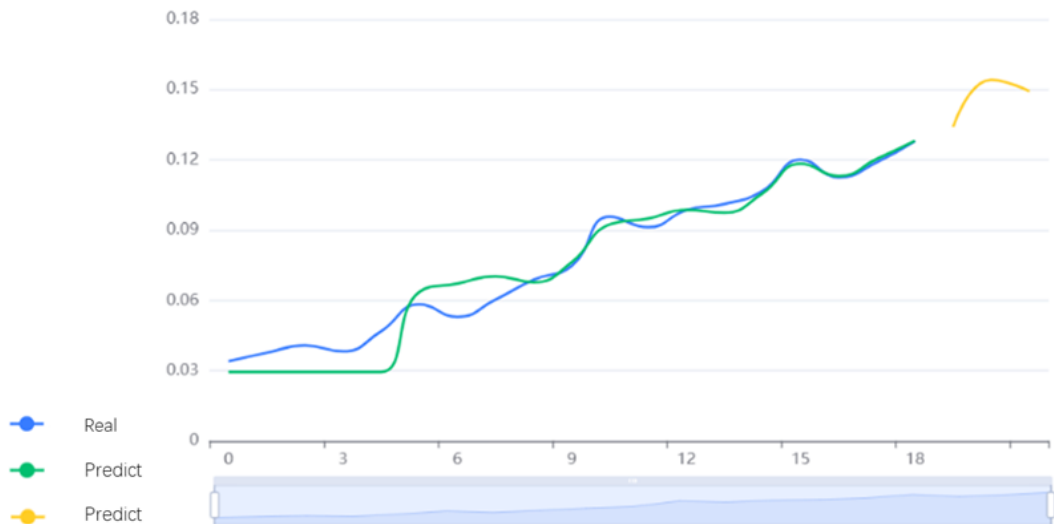


Figure 2. Time Series Graph of Beijing

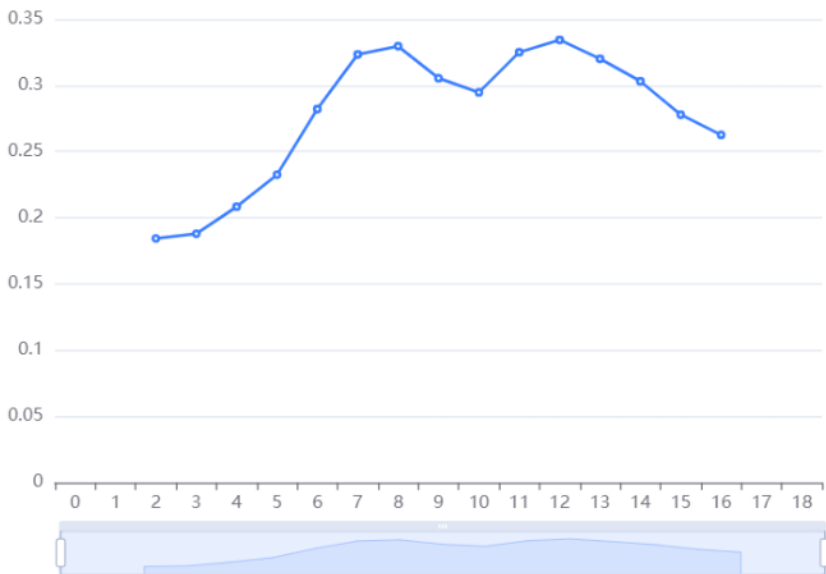


Figure 3. Trend Time Series of Guizhou Province

Table 2. Forecasted Values for ICRI of Beijing and Guizhou Province in the Next Three Years

Time	Beijing	Guizhou Province
1 year later	0.13407779419161164	0.26504169963131236
2 years later	0.15407631367482116	0.30464295520634443
3 years later	0.14924868463473023	0.16864537961588333

3.2. Analysis of Results and Recommendations

Assuming a normal distribution for ICRI, the paper collect data for analysis and calculate the mean and variance.

$$\mu = 0.206, \sigma = 0.016$$

Utilizing the horizontal axis interval $(\mu - \sigma, \mu + 2\sigma)$, particularly (17.47%, 23.12%),for differentiation, three regions are generated as illustrated in Fig4: the recommended underwriting zone, the underwriting risk zone, and the not recommended underwriting zone.

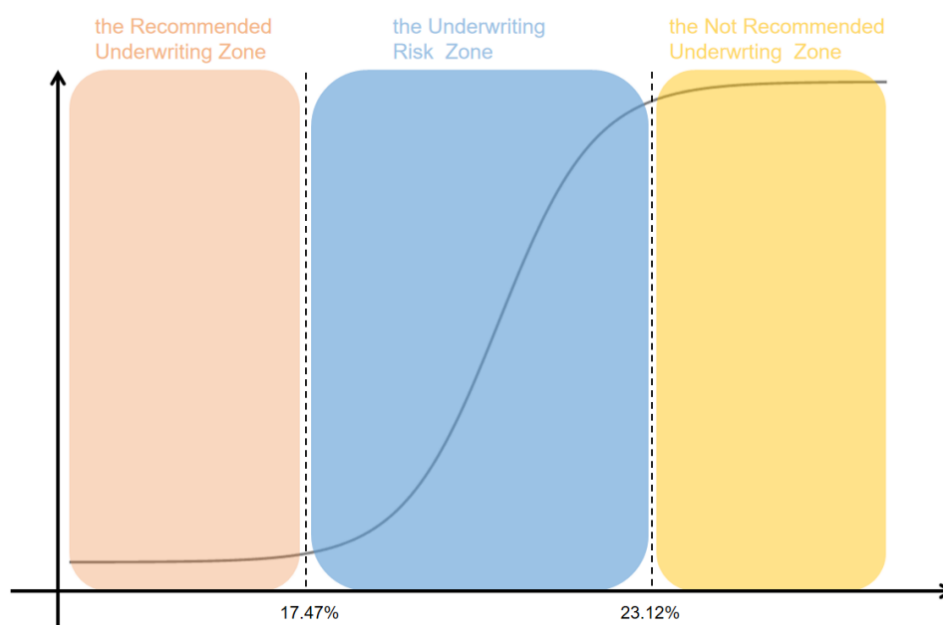


Figure 4. Underwriting Zone Division Chart

The ICRI for Beijing in the next three years are 13.4%, 15.4%, and 14.9%, exhibiting an upward fluctuation trend, but all still fall within the recommended insurable zone. As for Guizhou Province, the ICRI for the next three years are 26.5%, 30.5%, and 16.8%, placing it in the not recommended underwriting zone and the recommended underwriting zone. It is advisable to consider not underwriting in the first two years or initiating business in the third year.

4. Conclusion

Based on the pre-established insurance model, the ICRI for Beijing in the next three years are 13.4%, 15.4%, and 14.9% with an excellent fit ($R^2 = 0.95$), exhibiting an upward fluctuation trend, but all still fall within the recommended insurable zone. As for Guizhou Province, the ICRI for the next three years are 26.5%, 30.5%, and 16.8% with a good fit ($R^2 = 0.81$), placing it in the not recommended underwriting zone and the recommended underwriting zone. It is advisable to consider not underwriting in the first two years or initiating business in the third year. Furthermore, the pre-established insurance model offers numerous advantages. To begin with, the first advantage is its advanced nature. Various models have been established and integrated to form a comprehensive model, incorporating the strengths of each individual model. Besides, the second benefit lies in our provision of innovative solutions tailored for insurance companies. By exploring differentiated

premium structures and introducing financial instruments such as catastrophe bonds, research has provided new perspectives for insurance product innovation. This contributes to enhancing the risk management capabilities and market competitiveness of insurance companies. In addition, the third strength lies in the model's comprehensive capabilities. The model takes into account multiple aspects, providing a comprehensive framework for evaluating risks or values. It offers a holistic approach to assess and forecast challenges and opportunities faced by the insurance industry.

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