Research on Insurance Underwriting Decision Optimization Based on Multi-dimensional Risk Assessment

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Abstract. Against the background of climate change exacerbating extreme weather events, the traditional insurance underwriting model is difficult to cope with complex risks, and scientific decision-making models are urgently needed to safeguard the sustainable development of the insurance industry. In this study, regional climate risk is assessed by calculating the Climate Extreme Index (CEI) and five underwriting strategies are formulated by combining the risk matrix.Meanwhile, a multidimensional community resilience evaluation system is constructed by using the Entropy Weighting Method (EWM), and the results are categorized into four levels by fuzzy C-mean (FCM) clustering. The results show that the model can effectively identify high-risk areas, optimize underwriting decisions, and maintain the solvency of insurance companies. This study innovatively integrates the multidimensional factors of climate, economy and community resilience to provide a scientific basis for the insurance industry to respond to climate change.

Keywords: Risk Matrix Method, Underwriting Decision, Community Resilience.

1. Introduction

In the context of escalating global climate change, the frequency of extreme weather events has resulted in significant economic losses and social impacts across various regions worldwide. As a fundamental tool for risk management, the insurance industry is facing unprecedented challenges. On one hand, the rising costs of natural disaster claims driven by climate change compel insurance companies to increase premiums to address heightened risks. On the other hand, risk-adjusted pricing is one of the primary objectives of capital allocation[1]. This dual pressure poses a serious challenge to the sustainable development of the insurance sector. Traditional underwriting decisions primarily rely on historical data and unidimensional risk assessments, which have proven inadequate in the current complex environment. Factors such as the uncertainty of climate change, regional disparities in socio-economic development and community resilience significantly influence insurance risks. Therefore, establishing an underwriting decision-making model based on multidimensional risk assessment is of considerable theoretical significance and practical value.

The model presented in this paper focuses on the resilience of property insurance, aiming to balance the impacts of severe weather on insurance companies and homeowners, ensuring the ongoing operation of the insurance industry while safeguarding the interests of property owners [2]. Initially, the model assesses the types, frequency, and losses associated with extreme weather events through the Extreme Climate Index (CEI), and establishes an underwriting decision model using a risk matrix approach, resulting in five distinct underwriting decisions. The model's effectiveness is validated in regions experiencing extreme climate conditions in California, USA, and Guangdong Province, China. Subsequently, eight relevant indicators are selected to create a multidimensional community resilience evaluation framework. Based on this framework, a mathematical model is derived by integrating the entropy weight method and fuzzy mean clustering to assess the relationship between community resilience and insurance policies, thereby assisting insurance companies in determining which areas and environments to underwrite property insurance.

2. Climate Extreme Event Risk Assessment and Insurance Underwriting Decision Framework

2.1. Calculation of Climate Extremes Indices

This paper selects the assessment of extreme climate event risks through climate extreme indices. According to the National Centers for Environmental Information (NCEI 2024), the following data categories are currently included in the U.S. Climate Extremes Index (CEI): monthly maximum and minimum temperatures, daily precipitation, monthly hurricane and tropical storm wind speeds, and the Palmer Drought Severity Index (PDSI) [3]. Therefore, this paper defines the monthly maximum temperature as d_1, monthly precipitation as d_2, and monthly PDSI values as d_3 to describe climate change, withφ φ_1, φ_2, and φ_3 representing temperature, precipitation, and PDSI, respectively. The specific calculation expressions are as follows:

$$\varphi_i = \begin{cases} e^{\frac{\ln 1.1}{\sigma_i}|d_i|} - 1, 0 \leq |d_i| \leq \sigma_i \\ \frac{0.4}{\sigma_i}|d_i| - 0.3, \sigma_i \leq |d_i| \leq 2\sigma_i \\ \frac{0.5}{\ln 2.5}\ln\left(\frac{|d_i|}{5\sigma_i}\right) + 1, 2\sigma_i \leq |d_i| \leq 5\sigma_i \end{cases} \tag{1}$$

Non-Gaussianity, as an atmospheric variable, is primarily described through skewness and kurtosis to characterize climate extreme events and their variations. Ruiz et al. (2021) applied non-Gaussianity to address the issue of cloud sensitivity[4], utilizing the Kullback-Leibler divergence (KLD, 1951) to quantify the degree of non-Gaussian characteristics in the assessment of error distributions. The specific calculation method is as follows:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{2}$$

Subsequently, integrating over the areas of abnormal probability yields the probability values for the three factors $p(t)$, $p(p)$ and $p(pd)$. Here, t represents the monthly maximum and minimum temperatures, p denotes daily precipitation, and pd refers to the Palmer Drought Severity Index (PDSI). Through calculations, the Kullback-Leibler Divergence (KLD) can be determined.

$$KLD(P\|Q) = \int_{-\infty}^{\infty} p(x) \ln \frac{p(x)}{q(x)} dx \tag{3}$$

Ultimately, these indicators need to be integrated and weighted into a composite index, which is considered to reflect the extent of climate change. Given the challenges in determining the precise proportions of these variables, the study assume that they hold equal significance.

$$CEI = \int KLD(P\|Q) = KLD(P_t\|Q_t) + KLD\left(P_p\|Q_p\right) + KLD(P_{Pd}\|Q_{Pd}) \tag{4}$$

Therefore, the CEI can be derived from the aforementioned analysis. By aggregating annual precipitation, temperature, and PDSI data from various regions, one can calculate the local climate extremes index to assess the risks associated with climate extreme events.

2.2. Underwriting decision model based on risk matrix

In recent years, over 1,000 extreme weather events have occurred globally, resulting in losses exceeding $1 trillion. The total amount of natural disaster claims in the insurance industry in 2022 was "115% higher than the average level of the past 30 years."[5]Therefore, to ensure the long-term health and sustainability of insurance companies, a risk matrix-based underwriting decision model has been proposed to predict underwriting risks and determine whether to provide coverage.

2.2.1 Application of Risk Matrix

The risk matrix illustrated in Figure 1[6] is a tool utilized in risk management to assess and prioritize risks based on the likelihood of an event occurring and the severity of its consequences. In the context of underwriting, the risk matrix aids insurance companies in determining whether to accept a risk, the premiums to be charged, and any specific terms or conditions applicable to the policy. High-risk scenarios may result in increased premiums or even denial of coverage.

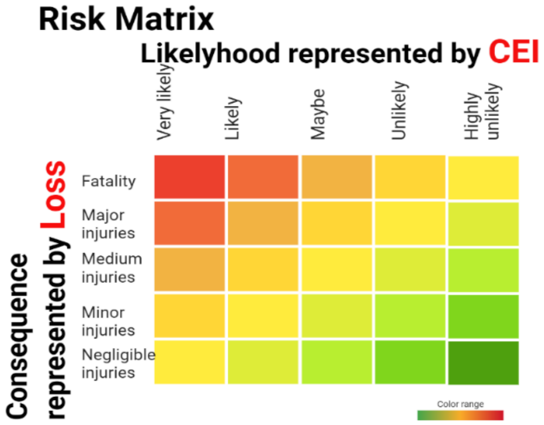


Figure 1. Risk matrix

2.2.2 Risk Identification and Quantification

In the realm of risk identification, it is essential to determine the extreme weather risks that insurance policies must cover, such as hurricanes, floods, and wildfires, while also calculating the Climate Extremes Index (CEI), which is categorized into five levels.

In the context of loss assessment, We analyze the potential impacts of extreme weather on assets or personnel and categorize the severity of losses based on the intensity of the events, approximating the relationship between loss and risk as proportional. The injuries are classified into five levels: severe, moderate, minor, and negligible.

2.2.3 Risk Exposure and Characterization Assessment

First, assess the probability of weather events occurring in specific regions and the exposure levels of assets or populations. The Climate Exposure Index (CEI) is categorized into five tiers: the top 10%, the top 30%, the middle third (from 30% to 67%), the bottom 30%, and the bottom 10%, arranged in descending order. Subsequently, conduct a risk characteristic evaluation by integrating information on consequences and likelihood to comprehensively describe the overall risk. This analysis serves as a basis for underwriting decisions, including policy terms, pricing, or coverage limitations.

2.2.4 Risk level and underwriting strategy

Based on the assessment results of losses and the Climate Exposure Index (CEI), risks are categorized into different levels of zones, as illustrated in Figure 2.

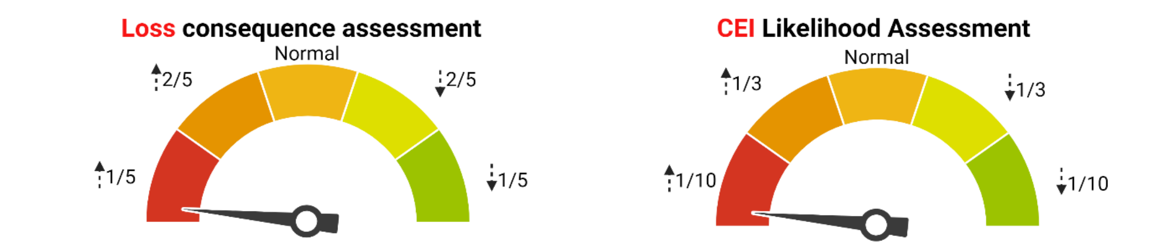


Figure 2. Assessment of loss consequences and CEI likelihood assessment

High-risk areas (red, orange) indicate significant potential losses and/or a high Climate Exposure Index (CEI), suggesting that underwriting risks in these regions is inadvisable and requires careful decision-making. Risk areas (dark green, light green) represent the lowest risk levels, where underwriting decisions or increased ongoing underwriting investments may be considered. Moderate risk areas (dark yellow, yellow, yellow-green) necessitate the development of underwriting strategies based on the specific circumstances of the region.

2.3. Validation of Underwriting Decision Models

By collecting data on property loss rates around the world from 2004 to 2023, and combining the above calculated CEI index data, the study tested the model in the regions of two different countries experiencing extreme climate, California and Guangdong Province of China.

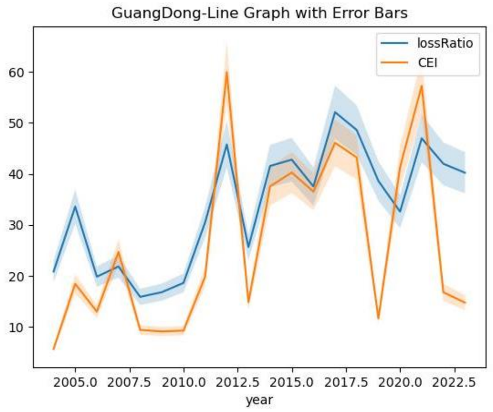
2.3.1 Correlation between CEI and Loss rate

By 2040, insurance premiums are expected to increase by 30% to 60% due to climate change[7]. To gain a deeper insight into the impact of climate change on insured losses, we used Pearson Correlation Analysi of annual loss rate and CEI to derive the resilience index and Pearson's correlation numbers for the three variables presented in Table.1.

Table.1. Pearson's coefficient between loss and CEI and its significant index in California

Independent Variable in California			
Implicit Varia-Bles	Year	Loss rate	CEI
Year	1(0.000***)	0.841(0.000***)	0.574(0.038*)
Loss rate	0.841(0.000***)	1(0.000***)	0.729(0.000***)
CEI	0.574(0.038*)	0.729(0.000***)	1(0.000***)

Where, * * *, * *, * indicate the significance levels of 15%, 10% and 5%, respectively. In addition, $P < 0.05$ indicates the correlation.



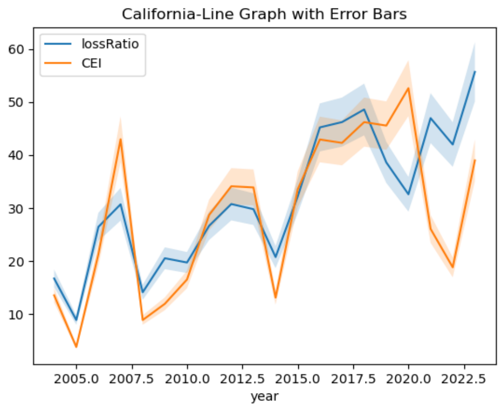


Figure 3. CEI and property loss rate(%) in Guangdong and California from 2004 to 2023

Based on the analysis in Figure 3, it is clear that there is a correlation between the loss ratios and CEIs in the two regions, but this correlation is not linear and varies over time and with other factors. For example, loss ratios and CEI in the two regions rise or fall in parallel in some years, while in other years they may show opposite trends. This may suggest that factors other than the CEI influence property loss rates. In summary, the data suggest that property loss rate and CEI are not static and unchanging in either Guangdong Province or California, but are influenced by a variety of factors, and further research is needed to identify these factors and their interactions.

2.3.2 Underwriting decision risk index

To provide a clearer picture of the risk ratings of the two regions over the 20-year period, a three-dimensional view is plotted as shown in Figure 4.Around 2005, Guangdong had the highest underwriting risk index, which is shown in dark red in Figure 4. Although the CEI data for Guangdong in 2005 was below the historical average, socioeconomic factors lagged behind two decades ago, increasing the uncertainty of underwriting decisions at that time. California's underwriting risk reached hazardous level around 2012 when the CEI peaked, validating the impact of CEI underwriting decisions when socioeconomic factors were more stable.

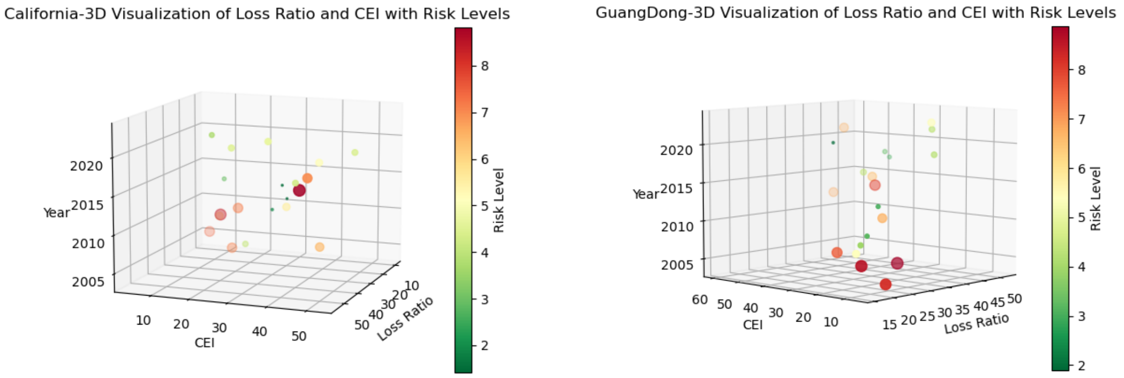


Figure 4. Annual underwriting risk index from 2004 to 2023 in 3D visualization.

3. Multi-dimensional Community Resilience Evaluation Framework and Insurance Policy Optimization

3.1. Indicator construction

A suitable insurance risk framework should include multiple indicators other than CEI, which to some extent reflect the risk index in the ecosystem. Therefore, the indicators need to be further adapted to build a community resilience assessment model to assess the sustainability of a community in terms of social sustainability, ecosystem sustainability and economic growth[8].

3.2. Sources of date

Regarding social sustainability, the Population Index, the Community Services Index and the Building Resilience Index are collected through government websites, the home building sector and other sources to assess the size, services and building resilience of a community.

For ecosystem sustainability, we obtained the Climate Extremes Index, Carbon Dioxide Index from the National Oceanic and Atmospheric Administration (https://www.noaa.gov/), and crawled geographic indices through remote sensing imagery to assess the community's exposure to climate risk, environmental sustainability, and resilience to natural hazards.

For economic growth, homeownership rates and GDP were crawled through the National Bureau of Statistics, the World Bank, and others to assess the economic health of the community. Homeownership rates correlate with wealth accumulation among residents, while GDP reflects employment opportunities and income levels.

3.3. Entropy Weight Method for finding weights

In order to determine the weights of the previously defined assessment indicators to generate the combination of the main indicators, according to the Entropy Weighting Method (EWM) a normalization process will be applied, which results in the best and worst values of 1 and 0 for each variable after alternation. the assessment indicators are denoted as x_i $(i\epsilon[1,8], i\epsilon Z)$, k and n denote the number of assessment indicators and the number of regions we identified respectively.

$$y_{ij} = \frac{x_{ij}-\min(x_i)}{\max(x_i)-\min(x_i)}, v_{ij} = \frac{\max(x_{ij})-x}{\max(x_i)-\min(x_i)} \; j = 1,2,\cdots,n \tag{5}$$

Among these indicators, there are positive and negative indicators, for example, GDP, human resources, resilience of buildings and community services are positive indicators, while population size, carbon dioxide and CEI are negative indicators.

Later, q was introduced as a quantitative indicator of the importance of community resilience in each region.

Then the entropy of each criterion is determined using normalized data.

$$q = \frac{y_{ij}}{\sum_{j=1}^{n} y_{ij}} \tag{6}$$

$$E = -\ln(n)^{-1} \sum_{j=1}^{n} p_{ij} \ln(p_{ij}) \tag{7}$$

Based on the entropy, the weights are calculated as follows:

$$w_i = \frac{1-E_i}{k-\sum E_i} i = 1,2,\dots,k \tag{8}$$

In this case, indicators with lower entropy (less variability) are considered to have less impact and are given lower weights, while indicators with higher entropy (more variability) are considered to have more impact and are given higher weights. The expressions for the three metrics ESI, SSI and EGI can finally be obtained.

$$\begin{cases} ESI = w_1 y_1 + w_2 y_2 + w_3 y_3 \\ SSI = w_4 y_4 + w_5 y_5 + w_6 y_6 \\ EGI = w_7 y_7 + w_8 y_8 \end{cases} \tag{9}$$

3.4. Community Resilience Index

In addition, the three indicators were weighted and combined into a composite index using the coefficient of variation method[9]. In order to make the insurance model more generalizable, eight indicators from 51 U.S. regions were selected for the construction of the community resilience index. The results are shown in Table.2.

Table.2. Weight values of 8 indicators from fifty-one regions

	Indicators(I)	Weights	Indicators	Weights
Community Resilience Index	Society sustainability	0.451	Demographic Index	0.435
			Community Services Index	0.304
			Building Resilience Index	0.261
	Ecosystem sustainability	0.299	Climate Extreme Index (CEI)	0.341
			Carbon Dioxide Index	0.240
			Geographic index	0.581
	Economic growth	0.250	Homeownership Rate	0.268
			GDP	0.732

As can be seen in Table 2, social factors have the greatest impact on the resilience index, with the population size index having the greatest weight of 0.435. Geography and GDP, with weights of 0.581 and 0.732, respectively, are the most important indicator economic categories in ecosystems.

3.5. Fuzzy C-means (FCM)

Due to the different insurance strategies used in regions, Fuzzy C-means[10]was introduced and 51 regions in the U.S. were selected to introduce the fuzzy clustering method to better determine the coverage patterns, which was optimized based on the following objective function.

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2 \tag{10}$$

By iteratively updating the affiliation degree and clustering center until the objective function converges to a minimum value, the optimal clustering result can be obtained, and the clustering result is shown in Figure 5.

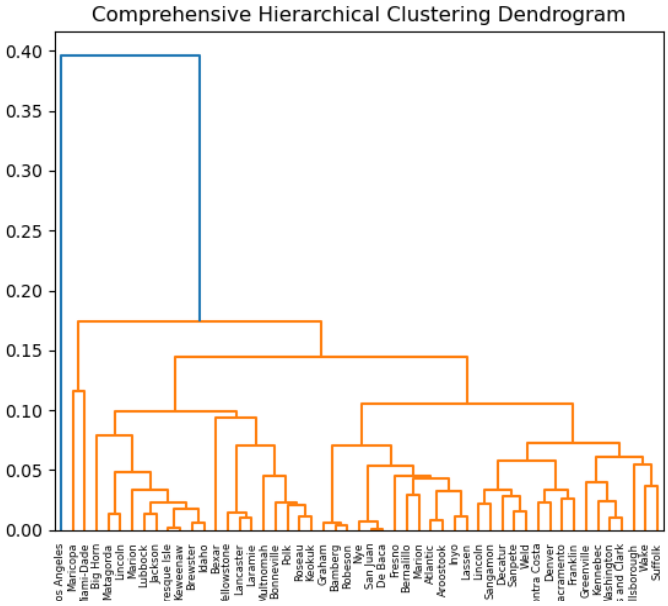


Figure 5. FCM results for the comprehensive index

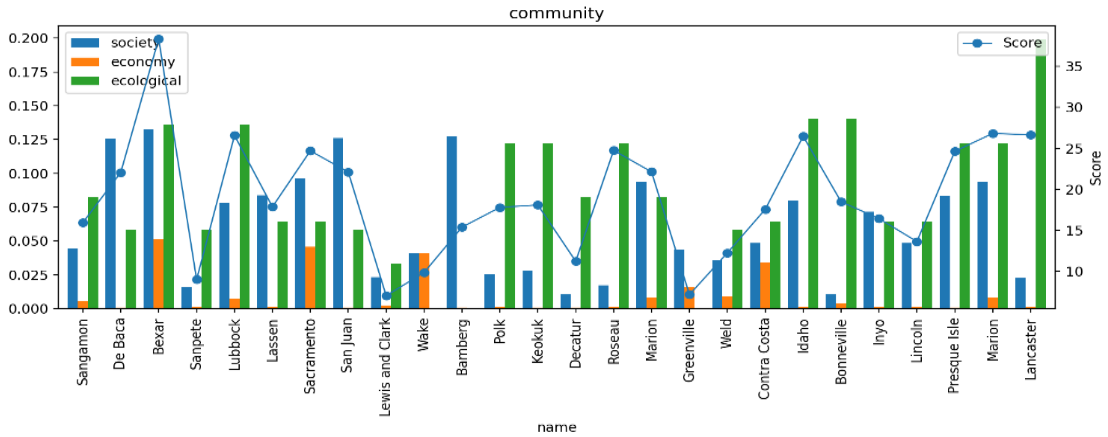


Figure 6. Weight of three indicators and scores of 51 regions.

The results shown in Figure 5 are for the composite clusters. Based on the scores and weights of the indicators, the community resilience index for the 51 regions of the United States is categorized into four levels in Figure 5, which are 0,1,2, and 3, representing high resilience, second-highest resilience, second-low resilience, and low resilience, respectively. Meanwhile, the weight of three indicators for partial regions are shown in Figure 6. There are different resilience assessment models in different regions of the United States, with different weights for economic, social, and ecological as shown in the Figure 6. Locally adapted insurance policies allow for the sustainability of the local insurance industry.

4. Conclusions

The research establishes a comprehensive framework for climate extreme event risk assessment and insurance underwriting decisions. Through the refined Climate Extremes Index (CEI) calculation and risk matrix-based underwriting model, the study reveals significant correlations between climate extremes and loss rates across different regions. The multi-dimensional community resilience evaluation framework demonstrates that social sustainability factors have the greatest impact on community resilience, followed by ecosystem sustainability and economic growth. The application of Fuzzy C-means clustering to 51 U.S. regions provides insurers with a practical tool for optimizing underwriting strategies and policy designs, enabling more accurate risk assessment and sustainable insurance practices in response to increasing climate challenges.

The study's innovation lies in the construction of a multidimensional community resilience evaluation framework, which optimizes insurance policies to ensure companies can better cope with future risks. This framework not only enhances the accuracy of risk assessment but also provides a scientific basis for sustainable insurance practices in the context of climate change.Future work will focus on improving the evaluation system by incorporating personal and enterprise-related data indicators to enhance its comprehensiveness and applicability. This will further strengthen the framework's ability to address large-scale data challenges and support the development of robust insurance strategies in a changing climate.

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