Bridging the Insurance Gap in Extreme Weather: A Multidimensional Risk Assessment Framework Integrating Socioeconomic Indicators and Cultural Preservation for Sustainable Property Insurance

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Abstract. Extreme weather events have intensified the insurance gap, posing significant challenges to the sustainability of the property insurance industry. To address this issue, we propose the Catastrophes Insurance Underwriting (CIU) Risk Assessment Model, optimized from the perspectives of property development and landmark preservation. Our model integrates social, economic, and natural indicators into an evaluation system and classifies risk levels using Projection Pursuit and the GE matrix. We employ AHP-CRITIC to evaluate candidate sites, aiding real estate decision-making. Furthermore, for historical and culturally significant sites, we propose a Preservation Model, incorporating a Building Value Evaluation Model (BVEM) to assess protection levels. Our comprehensive framework balances insurance profitability, real estate feasibility, and cultural preservation, providing data-driven strategies for sustainable insurance practices. Future research should explore innovative insurance solutions and dynamic preservation policies to enhance industry resilience.

Keywords: Property Insurance, Projection Pursuit, Underwriting Risk Assessment.

1. Introduction

Extreme weather events have become increasingly frequent and severe, significantly impacting the global insurance industry, real estate sector, and cultural heritage conservation efforts. Climate change has intensified the occurrence of hurricanes, wildfires, floods, and other natural disasters, leading to greater economic losses for property owners and insurers. According to Swiss Re, by 2040, losses from weather-related disasters are projected to increase by 35% to 120%, with the share of catastrophe risk in property insurance premiums expected to rise from 20% to 30%. This surge in losses threatens the profitability and sustainability of the insurance industry, as insurers struggle to manage growing risks while maintaining affordable coverage for consumers [1][2].

One of the most pressing challenges is the insurance gap, which arises when insurers withdraw from high-risk regions to mitigate financial losses. As a result, property owners in these areas may find it difficult or impossible to obtain insurance coverage, leaving them financially vulnerable in the event of a disaster. This situation not only affects residential and commercial properties but also puts at risk culturally and historically significant landmarks [3]. Many of these landmarks hold deep economic, social, and historical value for communities, yet they are often located in disaster-prone areas where insurance coverage is either unavailable or prohibitively expensive. The loss of such properties could have far-reaching consequences, affecting local economies, tourism, and cultural identity [4][5].

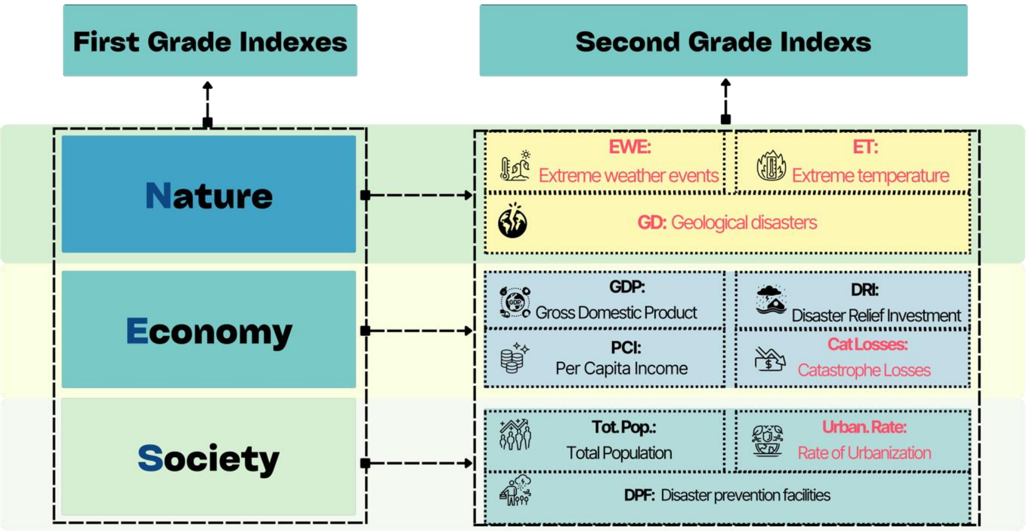
Given these challenges, this study proposes an integrated approach to property insurance underwriting, real estate feasibility assessment, and cultural landmark preservation. We introduce the Catastrophes Insurance Underwriting (CIU) Risk Assessment Model, which systematically evaluates insurance risks, pricing strategies, and site suitability for development. Furthermore, we propose a Building Value Evaluation Model (BVEM) to assist in the identification and prioritization of historically significant structures for preservation. By incorporating machine learning, statistical modeling, and economic analysis, our approach provides a comprehensive decision-making framework for insurers, property developers, and policymakers facing the impacts of extreme weather.

2. Methodology

2.1. CIU Risk Assessment Model

In older to achieving a comprehensive evaluation of CIU risk, we select a variety of indicator metrics as comprehensively as possible and reorganizing them.

Using science direct, PubMed, Google Scholar and other journal search sites to review related literature with catastrophe insurance as the keyword, we finally obtained 41 related documents. The keywords involved in these 41 literatures were frequency tagged, and the indicators with higher frequency of occurrence were finally selected as the judgement indicators. To establish the most suitable evaluation system for assessing the risk of catastrophes insurance underwriting, indicators were identified from three aspects, including nature, economic and social factors. Then we extract these 3 primary indexes and 10 secondary indexes, and preliminarily establish the CIU risk system as shown in the Figure 1:



- PS: Indexes belonging to the profit system are marked in black, while indexes **belonging to the loss system are marked in red.**

Figure 1. Indexes

In the follow-up, we cannot directly compare the data given the different dimensions of the indicators. Therefore, we standardize the data and remove the detrimental effects of a single sample, we transformed all the data into numbers between 0 and 1 by min-max normalization:

$$x'_{ij} = \frac{X_{ij} - min(X_{1j}, X_{2j}, \ldots, X_{nj})}{max(X_{1j}, X_{2j}, \ldots, X_{nj}) - min(X_{1j}, X_{2j}, \ldots, X_{nj})} \tag{1}$$

In general, risk assessment needs to take into account the advantages and disadvantages, supply and demand relationship and other factors. The measurement of CIU risk should be based on two perspectives:

1. Insurance loss is caused by extreme-weather events (EWE), geological disaster (GD), urbanization level (UL), etc.
2. The profitability with greater stability of insurance companies. This is mainly reflected in GDP, disaster prevention facilities (DPF), among others.

Considering the relationship between the secondary index and the CIU risk, we reclassify the secondary index and separate the two valuation subsystems of LS (Insurance loss system) and PS (Insurance profitability system). Indicators belonging to the loss system and profit system are shown in the following table:

Table.1. Symbolic Notation of the secondary indicators

LS Indicators	EWE	ET	GD	Cat Losses	Urban. Rate
Symbolic Notation	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
PS Indicators	GDP	DRI	PCI	Tot.Pop	DPF
Symbolic Notation	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}

Therefore, the linear relationship between each system and the classified indicators can be obtained. The scores of the two subsystems are used as the benefit index to assess the risk of CIU and are calculated as LSI and PSI respectively. The calculation formula is as follows:

$$LSI = \sum_{k=1}^{5} w_{1i} x_{1i}^{*} \tag{2}$$

$$PSI = \sum_{k=1}^{5} w_{2i} x_{2i}^{*} \tag{3}$$

Where x_{1i}^{*}, x_{2i}^{*} refer to the data after min-max normalization particularly.

Next, we select 51 countries in the world that exist CIU risk to varying degrees, and use projection pursuit method (PP) to solve and analyze the LS and PS evaluation models.

The basic principle of projection pursuit model is map the high-dimensional data to a one-dimensional or low-dimensional space, and then the distribution characteristics or patterns of the data are searched for in the low-dimensional space. We can analysis and understand the structure of high-dimensional data in the low-dimensional space more intuitively.

Step 1: Analyze the index of the sub-system (LS and PS).

The indicators are processed in a positive and standardized way.

Step 2: Construct linear projections.

To find the optimal projection direction, observe the data from different direction that fully reflects the characteristics of the indicators. We calculate the size of the projection index function. Then, the maximum index function as the optimal projection direction is determined from our random selection of projection directions $w = (w_1, w_2, w_3 ... w_m)$. For the i th sample, its one-dimensional space projection can be expressed as:

$$z_i = \sum_{j=1}^{m} w_j x_{ij} \tag{4}$$

Step 3: Construct the projection index function.

According to the definition of the optimal projection direction, we need to project the distribution of eigenvalues z_1 to satisfy:

a. The projection cluster is spread out as far as possible.

b. Local projection points are as dense as possible.

Thus, the objective function may be constructed as:

$$maxQ(w) = S_w D_w \tag{5}$$

Where S_w refers to the standard deviation of the projected eigenvalue, and D_w is the local density of the projected eigenvalue. The formula is as follows:

$$S_w = \sqrt{\sum_{i=1}^{n} (z_i - \bar{z}_w)/(n-1)} \tag{6}$$

$$w = \sum_{i=1}^{n} \sum_{j=1}^{n} (R - r_{ij}) u(R - r_{ij}) \tag{7}$$

Where r_{ij} means the distance between the projection eigenvalue, $r_{ij} = |z_i - z_j| (i, j = 1,2,3 ... n)$. $u(t)$ is the step function which is $u(t) = \begin{cases} 0, t < 0 \\ 1, t \geq 0 \end{cases}$. R is the parameter for estimating the local scatter density, and we take $R = 0.1max(r_{ij})$.

Step 4: Optimize the projection direction.

In summary, to find the optimal projection direction w, we establish a nonlinear optimization model:

$$maxQ(w) = S_w D_w \tag{8}$$

$$s.t.\begin{cases}\sum_{j=1}^{m} w_j^2 = 1\\ 0 < w_j < 1\\ S_w = \sqrt{\frac{\sum_{i=1}^{n}(z_i - z_w)}{(n-1)}}\\ D_w = \sum_{i=1}^{n}\sum_{j=1}^{n}\left(R - r_{ij}\right)u\left(R - r_{ij}\right)\\ u(t) = \begin{cases}0, t < 0\\ 1, t \geq 0\end{cases}\\ r_{ij} = \left|z_i - z_j\right|\\ R = 0.1\max\left(r_{ij}\right)\end{cases} \tag{9}$$

2.2. Building Site Evaluation Model (BSEM)

This chapter evaluates suitability for property development from five aspects: Economic Benefit, Construction Probability, Ecological Level Value, Facility Improvement, and Location Convention. Based on extensive data collection, an AHP-CRITIC model was established to calculate the weights of indicators.

CRITIC: The CRITIC method comprehensively assesses the objective weight of an indicator based on the evaluation indicator's comparative strength and the conflict between indicators.

The complete flow of CRITIC is shown in Figure 3.

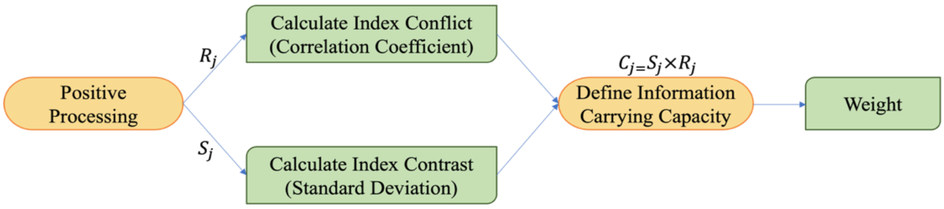


Figure 2. CRITIC flow chart

Weighted Combination of AHP and CRITIC: The final weights of the indicators are computed using the Mon formula, which integrates the AHP and CRITIC methods of indicator weighting. The resulting weights take into account both subjective and objective perspectives, enabling the calculation of a comprehensive weight vector of indicators based on AHP-CRITIC.

$$\omega_{\text{total}} = \beta * \omega_{\text{AHP}} + (1 - \beta) * \omega_{\text{CRITIC}} (0 \leq \beta \leq 1) \tag{10}$$

3. Results

3.1. Radar map and Risk assessment via GE matrix

We consider using GA algorithm to optimize the solution process. Then, we obtain the optimized projection weight $w = (w_1, w_2, w_3 \ldots w_m)$. Finally, the weight results are represented by radar map (Figure 5).

Figure 3. Weight radar map

We hold the view that LSI and PSI reflect the relative risk (benefits and harms) of CIU across two distinct aspects, analogous to the correlation between business competitive prowess and the allure of a market in the formulation of corporate business strategies. Subsequently, we use LSI as the horizontal axis and PSI as the vertical axis to delineate the risk level of CIU, categorizing it based on its placement on the GE matrix. Both LSI and PSI metrics are normalized to ensure their values fall within the range of (0,1). In alignment with the specific circumstances, DSI and RSI are classified into three grades (Table.4).

Table.2. Index classification

The value of LSI	Level	The value of PSI	Level
0~0.34	Low	0~0.34	Low
0.34~0.67	Medium	0.34~0.67	Medium
0.67~1	High	0.67~1	High

We visualize the GE matrix (Figure 6). Since both LSI and PSI are divided into three levels, the GE matrix is divided into nine parts. Then we combine GE matrix to evaluate the risk of CIU.

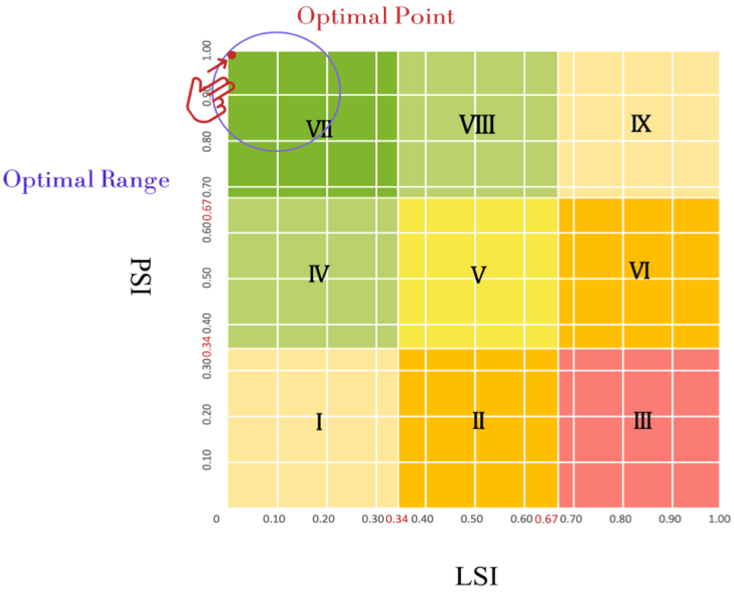


Figure 4. GE matrix diagram

4. Conclusions

In this study, we address the challenges posed by extreme weather events on the insurance industry, real estate development, and cultural landmark preservation [6]. The increasing frequency and severity of climate-related disasters have led to a widening insurance gap, where insurers withdraw from high-risk areas, leaving property owners financially vulnerable [6]. To ensure the sustainability of catastrophe insurance, we propose the Catastrophes Insurance Underwriting (CIU) Risk Assessment Model, which evaluates underwriting risks using social, economic, and natural indicators. The model provides a quantitative approach to risk classification, enabling insurers to make data-driven decisions regarding premium pricing and policy coverage [7][8].

Furthermore, recognizing the need for climate-adaptive real estate planning, we introduce the Building Site Evaluation Model (BSEM), site assessment (AHP-CRITIC), and risk classification (K-means clustering). By applying this framework to Yunnan and Texas, we demonstrate how real estate developers can make informed decisions on where, how, and whether to build in high-risk regions [7][9].

Additionally, to address the preservation of culturally and historically significant landmarks, we propose the Building Value Evaluation Model (BVEM). This model assesses the historical and economic significance of structures and recommends tiered protection strategies. Our case study on the Jagannath Temple illustrates how insurers and policymakers can balance financial risk with the preservation of cultural heritage [8][10].

Overall, our study provides a comprehensive framework that integrates insurance risk assessment, real estate decision-making, and landmark preservation, offering a data-driven solution for insurers, developers, and policymakers. The findings highlight the importance of flexible insurance strategies, sustainable urban planning, and proactive preservation efforts in mitigating the effects of extreme weather events.

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