Risk Assessment and Insurance Underwriting Decision Model: A Case Study of Gansu Province and Florida

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Abstract. Extreme weather is driving up economic losses and insurance costs, underscoring the urgency for enhanced disaster risk management and policy reform for sustainability. This study presents a novel Risk Assessment Model for analyzing insurance underwriting risk in specific regions, driven by the increasing economic losses and insurance costs due to extreme weather. The model integrates a comprehensive evaluation system with four primary and twelve secondary indices, applying the Entropy Weighting Method (EWH) and Analytic Hierarchy Process (AHP) to allocate weights and quantify risk (Q_unfavourable) effectively. It also adopts the As Low as Reasonably Practicable (ALARP) principle for setting underwriting decision thresholds, based on risk and profitability. Case studies from Gansu Province, China, and Florida, USA, validate the model's practicality and its potential to enhance insurers' underwriting strategies and policy decisions across varied regions, marking a significant improvement in underwriting risk management and strategic insurance policy formulation.

Keywords: Extreme weather, Insurance, Analytic Hierarchy Process, Exponentially Weighted Harmonic mean.

1. Introduction

Global extreme weather events are increasingly challenging property owners and insurers, leading to significant economic losses and impacting global stability [1]. Swiss Re predicts that weather-related losses in countries like Australia, Canada, France, Germany, Japan, the UK, and due to wildfires, will escalate by 2040, with insurance premiums expected to rise sharply, partly due to climate-induced inflation of 30% to 60% [2]. This situation exacerbates financial instability, affecting the insurance industry's claims liability and profitability, the global real estate market, and necessitating governmental and international policy reassessment for improved disaster risk management and climate mitigation to support sustainable development amidst fiscal pressures [3, 4].

In this work, we first established a robust framework for the Risk Assessment Model by identifying and categorizing four primary indices and twelve secondary indices to comprehensively represent underwriting risks. Following this, we applied the Entropy Weighting Method (EWH) to determine the weights of secondary indices and the Analytic Hierarchy Process (AHP) for the primary indices, ensuring a nuanced and detailed quantification of risks. Lastly, by incorporating the As Low As Reasonably Practicable (ALARP) principle, we delineated clear thresholds for underwriting decisions, providing a strategic basis for insurance companies to make informed policy issuance and risk management decisions in various geographical contexts.

2. Construction of Risk Assessment Models

Firstly, focusing on data related to extreme weather events, we collected relevant information from various online sources, with details of the data presented in Table 1.

Table 1. Main data description and source

Data specification	Data sources
Economic and social indicators related to quantifying the risk	gdpbox.com/countries
Meteorological disaster indicators related to the quantified risk	https://data.un.org/ http://data.cma.cn/
Insurance indicators related to quantifying the risk	gdpbox.com/countries
Meteorological visualization	earth.nullschool.net/

2.1. Quantifying Insurance Underwriting Risk

Figure 1 illustrates our categorization of indicators used to quantify the underwriting risk of insurance companies. We use four major aspects as Level 1 indicators: extreme weather risk, socio-economic vulnerability, coping capacity, and property owner characteristics. We propose a total of four Level 1 indicators and ten Level 2 indicators, taking into account the risk influencing factors and relevant literature.

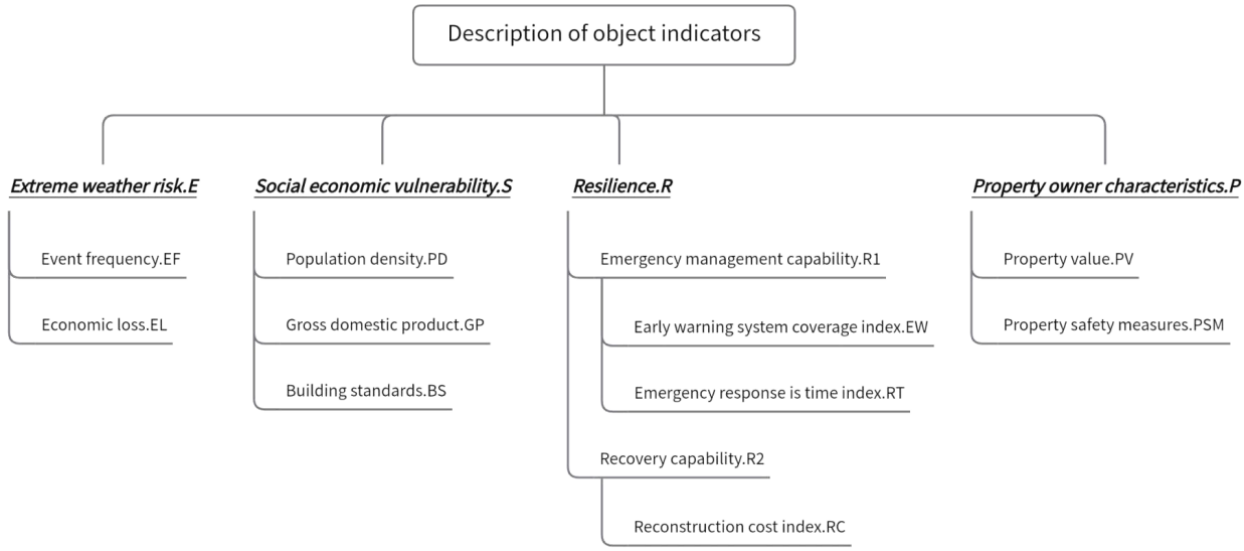

Figure 1. Description of the insurance model risk indicators

2.1.1. Extreme Weather Risk (E)

event frequency (EF):

This indicator is used to assess how common extreme weather exposure occurs in an area. The high frequency of occurrence means that the insurance company may face the risk of insurance claims expenditure, which then produces the liquidity risk, and the damage of the business side of the insurance company is damaged and affects the normal operation risk [5]. This was measured by the average number of extreme weather events in the history of the region.

Economic loss (EL):

The measure measures the severity of the financial impact of an extreme weather event on insurance companies [6]. The higher the average loss amount, the greater the claim amount that may result from a single extreme weather event. This index was measured by the average economic loss of every extreme weather event in history.

2.1.2. Social Economic Vulnerablity (S)

Population Density (PD):

The higher the population density, the more casualties and property damage are incurred in the event of extreme weather events [7]. This exposes insurers to more insurance claims, thereby increasing the risk of payouts.

Gross domestic product (GP):

This indicator is used to assess the regional economic level and the ability to repair the infrastructure. Areas with higher economies often have better infrastructure and emergency management systems that can more effectively respond to extreme weather events and reduce losses; areas with lower economies may lack sufficient resources to prevent and respond to disasters, resulting in greater losses and more insurance claims [8].

Building standards (BS):

This indicator is used to assess the durability of a building and its ability to withstand natural disasters. High home building standards can reduce damage from extreme weather events, thereby reducing the likelihood and size of insurance claims.

2.1.3. Resilience (R)

emergency management capability

Regions with robust emergency management can effectively respond to and lessen the impacts of extreme weather, thereby reducing insurance claims. This capability is measured using the Early Warning System Coverage Index (EW), derived from the ratio of the population within the warning system's coverage to the total population, and the Emergency Response Time Index (RT), which tracks the duration from receiving a warning to initiating rescue efforts.

recovery capability

Resilient areas can quickly bounce back from extreme weather events, restoring economic activities and social order swiftly. This results in fewer insurance claims, lightening insurers' long-term burdens. The Recovery and Reconstruction Cost Index (RC) quantifies a region's resilience by measuring the cost of recovery and reconstruction per unit area.

2.1.4. Property Owner Characteristics(P)

Property value (PV):

Insurance companies adjust coverage and premiums based on property value to ensure adequate protection. Higher-valued properties attract higher insurance rates and premiums. During extreme weather events, these high-value insurance policies elevate the insurer's risk of facing significant claims.

Property safety measures (PSM):

Property owners' security measures, such as surveillance systems, secure doors and windows, and fire protection setups, not only lower damage risks but also affect insurers' risk evaluations and premium costs.

2.2. Secondary-level index weight calculation

In the calculation of $Q_{\text{unfavourable}}$, to make the calculation more reasonable, we need to calculate the weight of the secondary indicators corresponding to the four first-level indicators: extreme weather risk, socioeconomic vulnerability, coping capacity, and property owner characteristics, using the following formula to calculate $Q_{\text{unfavourable}}$:

$$Q_{\text{unfavourable}} = \sum_{i=1}^{\text{Num unfavorable}} \text{indicator}_i \cdot \text{w}_\text{i} \tag{1}$$

Where indicator i is each secondary indicator, w_i is the corresponding weight of each second-level index, and $\text{Num}_{\text{unfavorable}}$ is the total number of secondary indicators. Here we mainly focus on the calculation of w_i:

Since the measurement units of each secondary index are not unified, it is necessary to standardize it before calculating the comprehensive weight,

For forward indicators, standardize using the following formula:

$$\text{x}_{ij} = 0.998\frac{\text{x}_{ij} - \min\{\text{x}_{1j},\text{x}_{2j},\ldots\ldots,\text{x}_{nj}\}}{\max\{\text{x}_{1j},\text{x}_{2j},\ldots\ldots,\text{x}_{nj}\} - \min\{\text{x}_{1j},\text{x}_{2j},\ldots\ldots,\text{x}_{nj}\}} + 0.002 \tag{2}$$

For negative indicators, standardize using the following formula:

$$x_{ij} = 0.998\frac{\max\{x_{1j},x_{2j},\ldots\ldots,x_{nj}\}-x_{ij}}{\max\{x_{1j},x_{2j},\ldots\ldots,x_{nj}\}-\min\{x_{1j},x_{2j},\ldots\ldots,x_{nj}\}} + 0.002 \quad (3)$$

We form a matrix of the collected samples on all secondary indicators$[X_{m\times n}]$, x_{ij} show values of the j th index of i th sample. The purpose of the coefficients 0.998 and 0.002 is to ensure that the value of x_i is greater than 0 and to prevent the occurrence of ln 0 in the subsequent calculation of ln x_i.

Subsequently, calculate the proportion and information entropy for the j-th index of the i-th sample, and determine the weights of each index. The formula is as follows, The specific calculation results are presented in Table 2.

$$w_j = \frac{1-e_j}{\sum_{j=1}^{m}(1-e_j)} \quad (4)$$

Table 2. Weights of secondary indicators corresponding to primary indicators

Primary indicators	Second-level index	e	Weight (%)
Event	EF	0.96	44.174
	EL	0.949	55.826
Characteristic	PV	0.955	56.539
	PSM	0.966	43.461
Vulnerability	PD	0.952	43.821
	BS	0.947	47.592
	GP	0.991	8.587
Resilience	EW	0.969	23.873
	RC	0.958	31.649
	RT	0.941	44.478

2.3. First-level index weight calculation

The first level index was calculated using hierarchical analysis

By collecting the corresponding expert opinions, and comparing the importance of the index, the judgment matrix, as shown in Tables 3 and 4:

Table 3. Judgment matrix

Indicators	Event	Vulnerability	Resilience	Characteristic
Event	1	4	5	5.988
Vulnerability	0.25	1	1.111	1.176
Resilience	0.2	0.9	1	0.4
Characteristic	0.167	0.85	2.5	1

Table 4. First-order index weight

Sum	Feature	Weight (%)	Max feature	CI
Event	2.43	60.761	4.142	0.047
Vulnerability	0.556	13.893		
Resilience	0.408	10.194		
Characteristic	0.606	15.152		

The consistency check is shown in Table 5. The maximum feature value is 4.142, and the corresponding RI value according to the RI table is 0.882. Thus, CR = CI / RI = 0.054 < 0.1, indicating that it passed the test on the first attempt.

Table 5. Consistency test result

Max feature	CI	RI	CR	consistency check
4.142	0.047	0.882	0.054	pass

Four first-level indicators weight: γ = (0.6076, 0.1389, 0.1019, 0.1515)

2.4. Calculate risk quantitative indicators Qunfavourable

The initial step involves employing the entropy weight method to determine the weight of the second-tier indices and the weight of each index. Subsequently, we calculate the quantitative indicators for assessing the underwriting risks of insurance companies in a specific region. These weights are then consolidated into an evaluation vector, referred to as the evaluation vector. The score of each level 1 indicator is:

$$Score_k = \sum_{i=1}^{Num_x} \varphi_i \cdot \theta_i \tag{5}$$

The k represents the primary indicator "Event", "Vulnerability", "Resilience" or "Characteristic". After obtaining the score of the first level index, the calculation formula of the final risk quantification index is obtained, combined with the weight of the first level index

$$\begin{aligned} Q_{unfavourable} &= \gamma_1 \cdot Score_{Event} + \gamma_2 \cdot Score_{Vulnerability} \\ &+\gamma_3 \cdot Score_{Resilience} + \gamma_4 \cdot Score_{Characteristic} \end{aligned} \tag{6}$$

3. Insurance company underwriting risk assessment and decision-making

ALARP (As Low As Reasonably Practicable) principle is called "As Low As Reasonably Practicable". As shown in Figure 2. Risk consists of two lines and three zones, two lines are the "negligible line" and the "intolerable line", the two lines will be divided into three areas, the "intolerable line" above the "intolerable zone", in the "intolerable zone". The two lines divide it into three zones, the one above the "intolerable line" is the "intolerable zone", the one between the two lines is the "ALARP zone", and the one below the "negligible line" is the "widely acceptable zone". The "widely acceptable zone" is the one below the "negligible line".

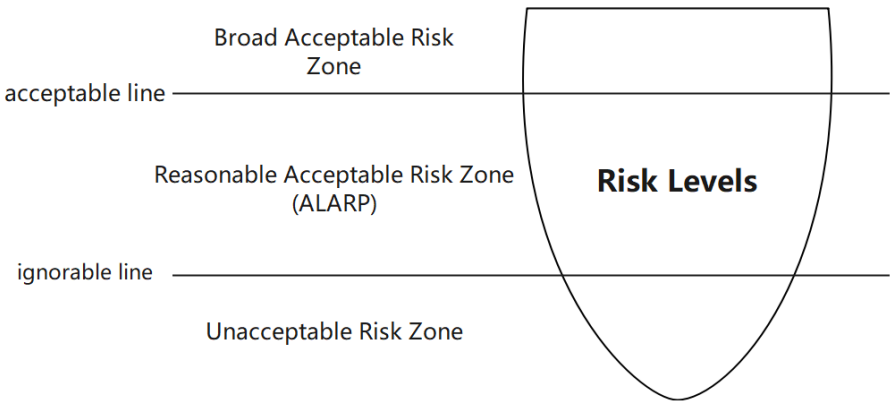

Figure 2. ALARP criterion [9]

Combined with the risk assessment criteria ALARP and the risk quantification index $Q_{unfavourable}$, we obtained the following risk assessment criteria [10]:

$$Q_{unfavourable} = \begin{cases} 0 \sim 0.35 \\ 0.35 \sim 0.9 \\ > 0.9 \end{cases} \begin{matrix} \text{Broad Acceptable Risk} \\ \text{Reasonable Acceptable Risk} \\ \text{Unacceptable Risk} \end{matrix} \tag{7}$$

- If the risk quantification indicator $Q_{unfavourable}$ is in an unacceptable area, the insurance company must choose not to avoid the risk, regardless of the opportunity cost, that is, not considering the income insured in the area.
- If the risk quantification indicator $Q_{unfavourable}$ is in a widely acceptable area, then the insurance company should choose to insure locally, because the risk is at a very low level and is negligible.
- If the risk quantifiers are in a reasonably acceptable area, the insurer needs to conduct a further cost-benefit analysis, i.e. an insurance profitability analysis, to minimize the risk level by adjusting premiums and other strategies. This will be analyzed in detail in the next section.

3.1. Insurance profit analysis

In areas where risk is manageable, analyzing local insurance revenue and claims is essential for assessing profitability. Insurance income is influenced by rates, demand, and population size, with increases in these factors boosting revenue, though market competition can reduce rates and impact income negatively. On the other hand, claims are driven by natural disaster frequency and intensity, the housing price index, and demand, with increases in these factors leading to higher claims. This highlights the need for strategic management to balance profitability and risk in the insurance sector.

Tang Guang and Liu Haitao define insurance underwriting profit as the net and investment income minus claims, taxes, expenses, and reserves from total annual insurance policy sales income. Ma Qingqiang analyzes the profitability of representative global insurance firms from five aspects: operating profit, underwriting profit, investment profit, costs and expenses, and solvency. This paper synthesizes the insights on insurance income and claims to propose a formula for calculating insurance profit, keeping the reference citations intact.

$$W = Q - C \tag{8}$$

Among them, W is insurance profit, Q is insurance income, and C is insurance compensation.

$$Q = D \cdot \sigma \cdot P \cdot (1 + \gamma) \tag{9}$$

Where D represents the market demand for a specific insurance product, indicating its acceptance level. The insurance premium rate reflects the cost per unit of coverage, set by insurers based on risk, costs, and profit. The total population size influences the potential customer base, while the market competition factor accounts for the competitive landscape, including other insurers and market share.

$$C = D \cdot f \cdot E \cdot \mu \tag{10}$$

Increased demand for insurance (D) correlates with higher payout potential. The frequency and intensity of historical natural catastrophes—measured by occurrences and severity, respectively, such as hurricane wind speeds or earthquake magnitudes—indicate greater risk and potential losses. Additionally, the House Price Index, reflecting the price levels of homes in a region, suggests that higher values are linked to larger potential payouts. By analyzing profitability, insurance companies can tailor premium strategies and risk management practices to the unique characteristics of specific regions, aiming to optimize profits, minimize risks, and support sustainable growth.

3.2. Model Demonstration

The risk quantification and decision-making model for insurance companies is applied to Gansu, China in Asia and Europe, and Florida in the Americas, respectively, to determine whether insurance companies choose to underwrite insurance in these regions, or further analyze the profitability of insurance companies in these regions, and give recommendations on risk minimization strategies accordingly.

The data on extreme weather and economic losses in the two regions over the past ten years are presented below, with some of the data related to the secondary indicators, as shown in Table 6:

Table 6. Data related to the secondary indicators

Area	GDP (yuan)	EL (billion yuan)	PD (person/kilometeres)
Gansu Province, China	44968	85	59.33
Florida, United States	64706	1650	330

Further analysis and calculation obtain the corresponding scores of all second-level indicators, and the corresponding first-level indicators are calculated in Table 7:

Table 7. Scores of the Primary index

Area	$Score_{Event}$	$Score_{Vulnerability}$	$Score_{Resilience}$	$Score_{Characteristic}$
Gansu Province, China	0.22051	0.31748	0.59324	0.29764
Florida, United States	0.98821	0.67397	0.84108	0.90247
Level 1 index weight	0.60761	0.13893	0.10194	0.15152

Herein, this study further concludes that the unfavorable underwriting risk score ($Q_{unfavourable}$) for Gansu Province, China, stands at 0.2837, while for Florida it is 0.9166. The scores for the various components are illustrated in Figure 3i. Additionally, the relevant atmospheric conditions for both Gansu and Florida are visualized in Figure 3.

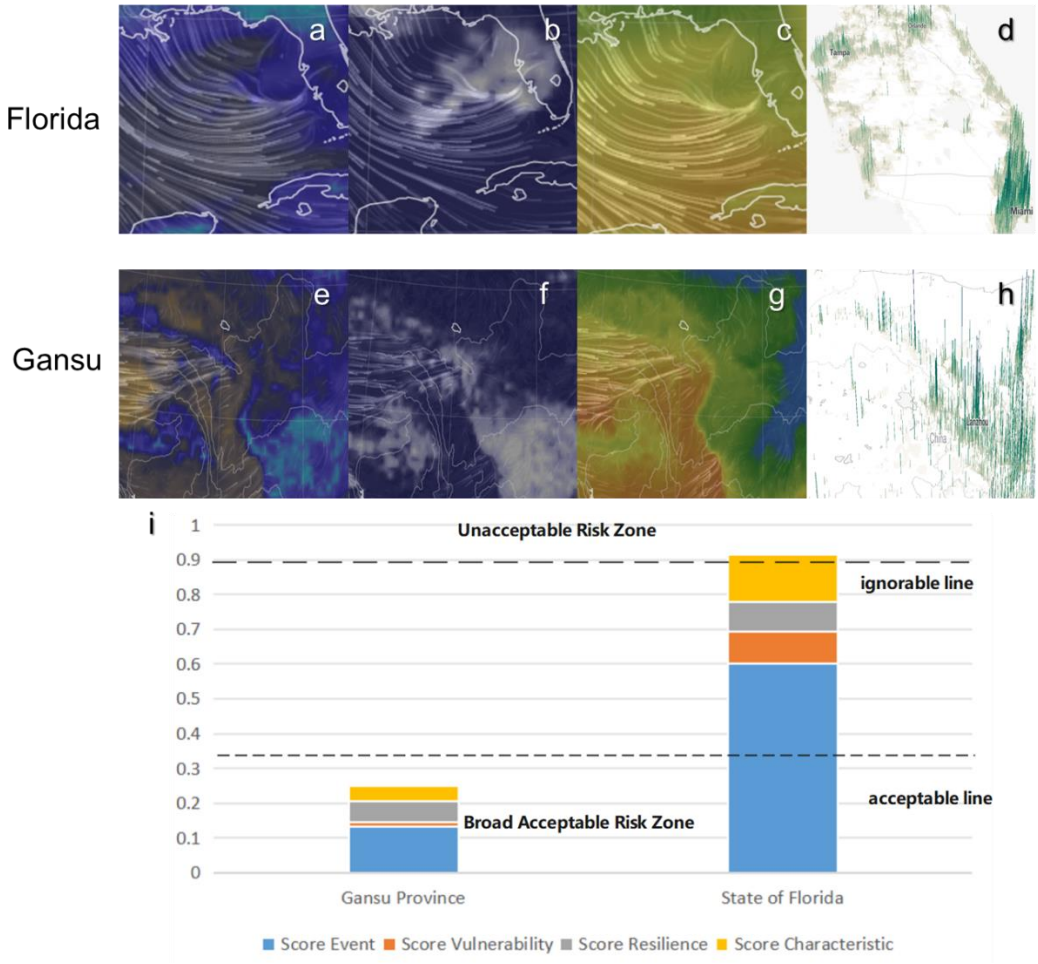

Figure 3. Comparative Meteorological Risk Assessment for Gansu Province and State of Florida

The underwriting risk score for Gansu Province, China, falls comfortably within the acceptable range, suggesting insurers can confidently underwrite in this region due to the minimal level of risk. In contrast, Florida's risk score places it in a zone deemed unacceptable for underwriting, advising insurers to refrain from issuing policies there to avoid high-risk exposure. Accompanying these

findings is a visual representation that highlights the stark differences in climate risk factors such as relative humidity, cloud water content, temperature, and population density between the two regions.

4. Conclusion

This study illuminates the urgent need for better disaster risk management and policy reform in the face of increasing economic losses from extreme weather, leading to higher insurance costs. We developed a Risk Assessment Model incorporating a detailed system of indices, applying the Entropy Weighting Method and Analytic Hierarchy Process for precise risk quantification, adhering to the ALARP principle for decision-making thresholds. Case studies in Gansu Province and Florida demonstrate the model's effectiveness in refining insurers' strategies, representing a significant step forward in managing underwriting risk in the face of climate change.

This study offers a pivotal tool for enhancing global resilience against climate-induced financial risks, steering the insurance industry towards greater sustainability and stability.

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