Risk Quantification-based Underwriting Assessment Model

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Abstract. With extreme weather events increasingly causing losses in regions, the insurance sector is confronted with a growing dilemma. Insurance companies urgently need to develop risk quantification-based underwriting assessment model (RQ-UA) to keep pace with the evolving environment. The underwriting risk index β is partitioned into 11 indicators, and the AHP combined with GRA is utilized to calculate the weights of these indicators. This paper employ the Capital Asset Pricing Model (CAPM) from Economics to develop the RQ-UA assessment model. Applying Japan and Ecuador to this model, the acceptable thresholds for β were calculated to be 0.3291 and 0.1843, indicating that underwriting can proceed when values remain below these figures. To enhance the model's flexibility in specialized regions, this paper introduce two new factors: the Housing Resilience Index (HRI) and the Government Subsidy Index (GSI). By combining the GE matrix with the model, can β' be calculated. Further validation with Japan and Ecuador showed that, with the intervention of property developers, the thresholds for β in the two countries increased by 32.9% and 17.8%.

Keywords: Uderwriting risk index, AHP, Gray Relation Analysis, CAPM, GE matrix.

1. Introduction

Frequent natural disasters resulting from extreme weather have significantly impacted the insurance industry. As of 2022, the frequency of weather-related events such as floods, hurricanes, droughts, and wildfires, has led to a significant surge in natural disaster claims within the insurance industry, rising by approximately 115% compared to the average over the past three decades. It is projected that by 2040, the situation will deteriorate further, with climate change driving insurance premiums to increase by 30% to 60%. In addition, the global insurance coverage gap currently averages 57% and continues to widen, posing an unparalleled challenge to the operational stability of insurance companies. This has triggered a crisis in both profitability and the financial resilience of property owners. Currently, scholars are engaged in research focused on developing risk assessment models to evaluate the resilience of the insurance and financial sectors under diverse extreme weather conditions, while also forecasting and analyzing the likelihood of future disasters.

Qiao et al. [1] established a multidimensional, comprehensive evaluation system using the TOPSIS method, incorporating key factors such as climate change, socio-economic conditions, and financial stability, and constructing corresponding evaluative indicators. This model was applied to regions in southeastern China and the southeastern United States, effectively demonstrating its utility and applicability. Wang et al. [2] employed Bayesian formulas to estimate the probability of extreme weather events, calculated event weights using the traditional TF-IDF algorithm, and developed an LSTM model to forecast compensation losses in the region. Lv et al. [3] identified typical fires and wildfires as key indicators and utilized the ARMA forecasting model to assess real estate insurance. Zhu [4] employed the Monte Carlo method to simulate catastrophic loss thresholds and integrated a Generative Adversarial Network-based Attention Long Short-Term Memory (GAN-ALSTM) model for precise loss prediction, alongside a comprehensive profit model for profitability analysis. Shen [5] use the Entropy Technique for Order of Preference by Similarity to the Ideal Solution (EW-TOPSIS) Model and Logistic Regression to assess underwriting risks and probabilities, the planning model focused on optimizing revenue generation and reducing customer attrition. Raffaella Calabrese [6] compared the survival model with the flexible logistic model and extreme gradient boosting algorithm, estimated the model of the Florida mortgage portfolio, and provided an estimate of the impact of extreme event features on mortgage risk.

There have been many previous studies on related models. Wang [7] studied the Fuzzy Analytic Hierarchy Process (AHP) and the Improved Grey Relational Analysis (GRA) to evaluate construction projects based on sustainable development standards. Mills E. [8] proposed the need for convergence between sustainability and resilience, and clarified the role that regulatory agencies will play in driving the market. Tsanakas A, Desli E. [9] proposed the concept of risk measurement, which can be interpreted as a representation of risk ranking and an absolute monetary quantification of risk. Rowan S, Kwiatkowski K. [10] found in his research that the Social Vulnerability Index has statistical significance in explaining changes in the impact of housing.

Karydas C. [11] developed a dynamic asset pricing framework for rare disasters related to climate change, linking carbon emissions and portfolio composition to the random probability of these events. Härdle W K. [12] transformed the non tradable risk factor of weather into a tradable financial asset, establishing a link between market risk premium and risk market price. Tsakalerou M. [13] reexamined the GE matrix, a strategic tool used for portfolio analysis, and explored its application in Multi-Criteria Decision Analysis (MCDA). Okoko C O. [14] applied the McKinsey matrix to evaluate the attractiveness of different routes for Kenya Airways.

This study innovatively integrates traditional evaluation models by combining the AHP with GRA, enhancing the applicability of the model to uncertain systems, such as environmental assessments. The incorporation of GRA strengthens the model's capacity to address uncertainty, effectively managing vague information in scenarios of incomplete data. Unlike traditional research, this study highlights the importance of regional specificity and human activities by considering the architectural structures and anthropogenic interventions specific to certain areas. This approach leads to the development of an innovative risk index model for extreme weather impacts, filling a notable gap in the existing literature. The proposed comprehensive indicator system enhances the scientific rigor and adaptability of the model, providing targeted disaster prevention and mitigation recommendations for local governments. Furthermore, this research raises public awareness of extreme weather risks and their moderating factors, contributing significant academic value and societal relevance.

2. The basic fundamental of RQ-UA model

2.1. Analytic Hierarchy Process (AHP)

Analytic Hierarchy Process (AHP) is proposed by Thomas Shatty in the 1970s. It’s core principle involves breaking down decision-making issues into hierarchical levels of constituent factors and establishing a multi-layered structural model. Experts assess and quantify the relative importance of each factor using a standardized scale, thereby constructing a judgment matrix A:

$$A = \left(a_{ij}\right)_{n\times n} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \tag{1}$$

In this matrix, a_{ij} represents the importance of the criterion layer elements A_i and A_j. To compare elements in the criterion layer, their relative importance is typically assessed using Saaty's 1-9 scale method.

The judgment matrix necessitate a consistency check. Calculate the maximum eigenvalue of the A using the formula $\lambda_{max} = \sum_{i=1}^{n} \frac{(AW)_i}{nW_i}$, where W is the eigenvector, i.e. the weight value. Calculate the random consistency ratio using the formula $C_R = \frac{C_1}{R_1}$, where C_1 is the consistency indicator of the judgment matrix, the calculation formula is,

$$C_1 = \frac{\lambda_{max} - n}{n-1} \tag{2}$$

Among them, R_1 is the average random consistency index (1-9) order judgment matrix value, see Table 1.

Table 1. Average random consistency index

Matrix order	1	2	3	4	5	6	7	8	9
R_1	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

If criterion layer A has m indicators $A_1, A_2, \cdots, A_m$ with associated weights $a_1, a_2, \cdots, a_m$, and sub-criterion layer B includes n indicators $B_1, B_2, \cdots, B_n$ with weights $b_{1k}, b_{2k}, \cdots, b_{nk}$ for indicator A_k in layer A, then the total ranking weights of the target layer for sub-criterion B can be denoted as,

$$\sum_{k=1}^{m} a_k b_{1k}, \sum_{k=1}^{m} a_k b_{2k}, \cdots, \sum_{k=1}^{m} a_k b_{nk} \tag{3}$$

Similarly, the total weights for each candidate solution related to the decision objective can be derived.

2.2. Gray Relation Analysis (GRA)

Gray Relation Analysis (GRA) can get the objective weight of each secondary indicator. First, the indicator data in the database are summarized, and all the indicator types are normalized, and then the elements of each indicator are divided by the average of the elements of the indicator, and then the parent sequence is constructed to calculate the gray relation coefficient. The parent sequence is X_0:

$$X_0 = \left(x_0(1), x_0(2), \cdots, x_0(n)\right) \tag{4}$$

This represents the target value of the system under ideal conditions. The behavior sequence is X_i:

$$\begin{gathered} X_1 = \left(x_1(1), x_1(2), \cdots, x_1(n)\right) \\ X_2 = \left(x_2(1), x_2(2), \cdots, x_2(n)\right) \\ \cdots \\ X_m = \left(x_m(1), x_m(2), \cdots, x_m(n)\right) \end{gathered} \tag{5}$$

These are actual observed sequences used for comparison and correlation analysis with the parent sequence. Subsequently, the calculation steps for the grey correlation degree will be derived.

(1) Define the Initial Sequences:

$$X_i^* = \frac{X_i}{x(1)} = \left(y_i(1), y_i(2), \dots, y_i(n)\right),\ i = 0,1, \dots, m \tag{6}$$

Divide each system sequence X_i by its first value $x(1)$ to obtain the standardized sequence X_i^*.

(2) Compute the Absolute Difference Sequence:

$$\Delta_i(k) = |x_0(k) - x_i(k)|, \Delta_i = \left(\Delta_i(1), \Delta_i(2), \cdots, \Delta_i(n)\right), \qquad i = 1,2, \cdots, m$$

(3) Calculate the Grey Correlation Degree:

$$\gamma\left(x_0(k), x_i(k)\right) = \frac{\min\limits_i \min\limits_k |x_0(k) - x_i(k)| + \xi \max\limits_i \max\limits_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \xi \max\limits_i \max\limits_k |x_0(k) - x_i(k)|}, \xi \in (0,1) \tag{7}$$

According to formula (7) calculate the average correlation coefficient of all sequences, which is the grey correlation degree between the parent sequence and the behavior sequence.

$$r_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) = \frac{1}{n} \sum_{k=1}^{n} r\left(x_0(k), x_i(k)\right) \tag{8}$$

2.3. Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) is an important theory in finance that relates asset pricing to the relationship between risk and return, providing a method for quantifying asset risk. In CAPM, the Market Portfolio is defined as the optimal combination of all risky assets, with the assumption that all investors hold this portfolio. The expected return of the Market Portfolio is denoted as $E(r_m)$.

The β is an indicator that measures the risk of an individual asset relative to the Market Portfolio, reflecting the sensitivity of the asset's returns to changes in market returns.

$$\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)} \tag{9}$$

In this equation, r_i denotes the actual return of the i-th asset and r_m denotes the actual return of the market portfolio. β_i denotes the systematic risk coefficient of the i-th asset.

Based on the linear relationship between risk and return, the CAPM formula is expressed as follows:

$$r_i = r_f + \beta_i(r_m - r_f) \tag{10}$$

Where r_f denotes the interest rate in the riskfree case, which we can set as a constant. We can substitute the r_i and r_f with their respective expected values:

$$E(r_i) = r_f + \beta_i(E(r_m) - r_f) \tag{11}$$

The expected return of an asset is expressed as a function of the risk-free rate and the asset's sensitivity to market movements, encapsulated by its β coefficient.

3. Risk Quantification-based Underwriting assessment model (RQ-UA)

3.1. The establishment of Hybrid AHP-GRA Framework

(1) Primary indicators

For the determination of the weights of the primary indicators, we summarized the evaluation scores of the experts and obtained the weights of the first tier of the vulnerability indicators. Natural and socioeconomic were both given a weight of 0.3 and extreme weather was given a weight of 0.4.

(2) Secondary indicators

The Analytic Hierarchical Process (AHP) can get the subjective weight of each indicator. For the secondary indicators, we synthesize the experts' scores to construct a judgment matrix. The weights of each indicator were calculated and checked for consistency. The weights of the secondary indicators calculated using this method are shown in the Table 2 below.

Table 2. The weights of the secondary indicators

Indicator	Weight
GDP	0.2450
Fiscal Income	0.2467
Population Density	0.3830
Type	0.2480
Intensity	0.2463
Frequency	0.2523
GDP	0.2450
Rainfall Amount	0.1454
Soil Quality	0.1536
Terrain	0.1460
Vegetation coverage	0.1490
Temperature	0.1480

(3) Combination Weighting

Combined subjective and objective weights obtained by Analytic Hierarchical Process (AHP) and Gray Relation Analysis (GRA). Assuming that the preference coefficient of the weights is λ, we take the preference coefficient λ to be 0.65. The formula for calculating the composite weights is:

$$w_j = \lambda w_j^{(1)} + (1-\lambda) w_j^{(2)} \tag{12}$$

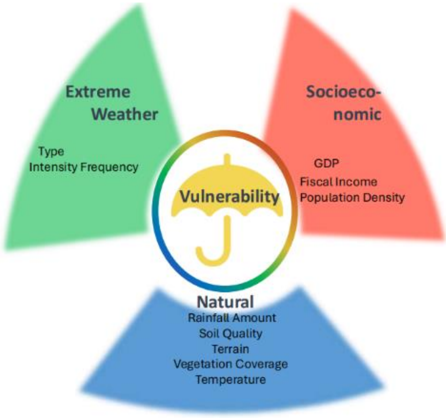


Figure 1. Indicators

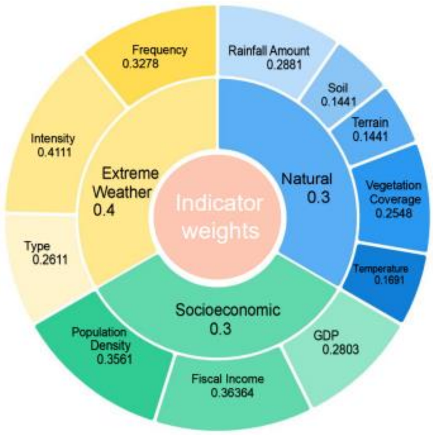


Figure 2. Factors Influencing vulnerability

Figure 1 presents the three primary first-level indicators for vulnerability assessment: Extreme Weather, Natural Factors, and Socioeconomic Factors, which are divided into 11 second-level indicators. Figure 2 visualizes the weight distribution of the indicators. In Extreme Weather, Intensity (weight 0.4111) is clearly the most critical influencing factor; in Socioeconomic Factors, Fiscal Income (0.3636) and Population Density (0.3561) dominate; in Natural Factors, Rainfall Amount (0.2881) and Vegetation Coverage (0.2548) have higher weights, indicating that these environmental factors play a significant role in vulnerability. This framework comprehensively covers the key dimensions of vulnerability assessment.

3.2. Analysis of the Applicability of CAPM to Property Insurance Premium Determination

The CAPM model has been introduced earlier, and now we will further derive the formula for periodic returns.

Assuming that Y denotes net income, I denotes investment income, π_u denotes premium profit, r_a denotes the rate of return on the investment of assets, A denotes assets, r_u denotes the rate of return on underwriting, and p denotes premium income, the income can be expressed in the following form:

$$Y = I + \pi_u = r_a A + r_u p \tag{13}$$

By weighting the financial leverage coefficients of investment returns and underwriting returns, we obtain the expected return on underwriting in the insurance capital asset pricing model:

$$r_u = kr_f + \beta_u (r_m - r_f) \tag{14}$$

Where kr_f denotes the interest rate in the risk-free case obtained by the premiums paid by the policyholder as an insurance fund, β_u denotes the systematic risk coefficient, and $r_m - r_f$ denotes the market portfolio risk premium rate. To evaluate future underwriting returns, we considered the bank discount rate and obtained the formula for calculating the average expected underwriting return, as shown in Formula (15).

$$R_u = \frac{1}{n}\sum_{t=1}^{n} r_u p_t \frac{1}{(1+i)^t} = \sum_{t=1}^{n} r_u p_t \frac{kr_f + \beta_u (r_m - r_f) p_t}{(1+i)^t} \tag{15}$$

Where p_t is the premium income for the t-th period. Only when the risk compensation mechanism of insurance companies is included will r_u be higher than the market risk-free rate. In the investment industry, a fundamental principle is the balance between returns and risks. Therefore, we have developed the following underwriting risk assessment criterion, as depicted in formula (16).

$$R_u = \begin{cases} 0 \sim 0.25 & \text{Unacceptable Return} \\ 0.25 \sim 0.35 & \text{Reasonable Acceptable Return} \\ > 0.35 & \text{Broad Acceptable Return} \end{cases} \tag{16}$$

If the expected return rate Ru falls into the unacceptable zone, significantly lower than the risk-free return rate, the decision could be to refuse underwriting in that location, regardless of the profit potential. If Ru is close to the risk-free return rate, indicating very low-risk returns, the options could include increasing premiums or reducing risks. If Ru is slightly above the risk-free interest rate, it suggests that the measure has achieved investment returns in terms of the time value of money, making it viable to underwrite in that location.

3.3. Application of the Assessment Model

We collected data on relevant indicators for different regions and applied the model developed to determine the expected rate of return, and from there, assessed whether an insurance company should choose to underwrite locally. By using Matlab, we have plotted a representation of the global expected rate of return, as shown in Figure 3.

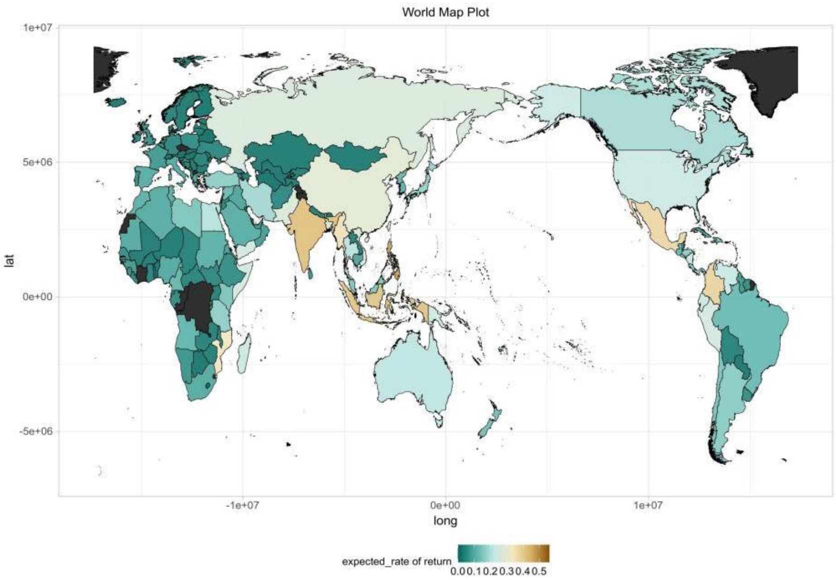


Figure 3. Degree of Global Expected Rate of Return

As can be seen from the figure, countries such as India, Myanmar, Indonesia, Mexico, and Colombia have relatively high expected yields, while regions such as Mongolia, Kazakhstan, and Finland Bolivia have low expected yields.

We chose Japan and Ecuador as representative examples. Weighted by the AHP-GRA model combination, we arrive at the extreme weather event risk indices of 0.203 and 0.342 for the two countries, which are both at relatively high levels. Due to the difference in the degree of economic development, the risk coefficients of their claims β are quite different, which leads to the different expected returns on property insurance in the two countries.

Assuming that all current market risk-free rates are 3%, combining this with r_m, we can compute from the underwriting model that Japan's expected rate of return, r_u , is now as high as 4.265%, which is represented as a darker color in Figure 4. This stems from the fact that Japan has established a good disaster prevention and mitigation policy, which greatly reduces the risk of economic loss.

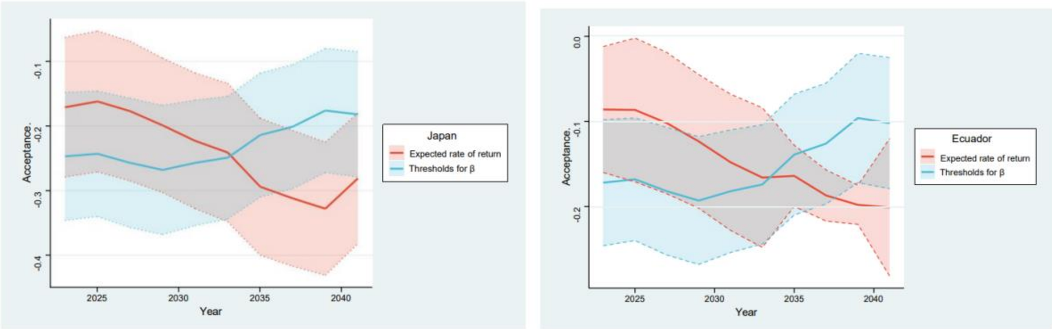


Figure 4. Range of risk acceptance values

When projecting future returns, we find that a rise in the underwriting risk index β above 0.3291 results in an expected return r_u that falls below the risk-free rate in Japan, significantly increasing the likelihood of insurer losses in Japan. In Ecuador, the current return stands at 1.679%, slightly below the market risk-free rate, indicating potential investment losses. Additionally, the risk factor for future claims β is expected to rise, further exacerbating losses for insurers in the region.

3.4. Risk-resistant Intervention Model

While the current underwriting evaluation model holds universal significance, we aim to enhance its flexibility for real-time adjustments in response to human factors. To this end, we identified some human intervention factors and summarized them into two categories — Housing Resistance Index (HRI) and Government Subsidy Index (GSI) — to further refine the underwriting evaluation model. The hierarchical structure diagram of specific factors is shown in Figure 5.

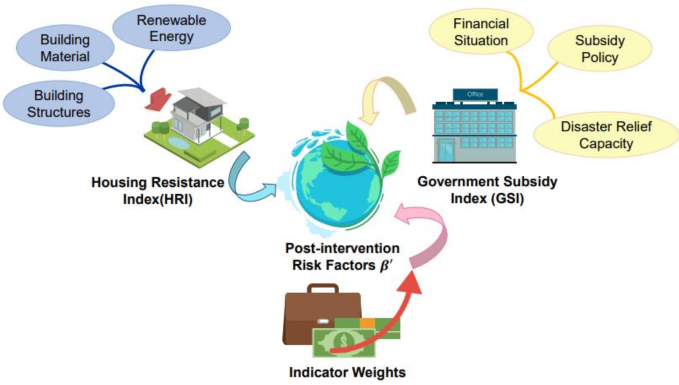


Figure 5. Factors affecting β

HRI reflects the resilience and recovery ability of a region in the face of extreme weather, and can be seen as an assessment of market risk. It can be calculated using formula (17):

$$H_i = \frac{\sum_{j=1}^{n} w_j x_{ij}}{\sum_{j=1}^{n} w_j} \tag{17}$$

Where H_i is the HRI for the year i, n is the number of extreme weather events considered, w_j is the weight of the j-th extreme weather event, x_{ij} is the level of house reinforcement in response to the j-th extreme weather event in the year i, taking values between 0 and 1.

This paper roughly make a grading by clustering for the level of house: level 1 reinforcement, level 2 reinforcement, and level 3 reinforcement. HRI shows a certain functional relationship with the cost of reinforcement, and the real estate developer should ensure the reinforcement material is not less than 1 under the premise of cost-effectiveness.

GSI reflects the level of government support for the region. This can be seen as an important indicator of market attractiveness. It can be calculated by formula (18):

$$G_i = \frac{\sum_{k=1}^{m} \nu_k y_{ik}}{\sum_{k=1}^{m} \nu_k} \tag{18}$$

Where G_i is the GSI for year i, m represents the number of financial inflows and outflows, ν_k is the weight of the k-th financial source or use, and y_{ik} is the level of government subsidy in the i-th region for the k-th financial source or use, taking values between 0 and 1.

We utilize HRI and GSI as two dimensions of the GE matrix to analyze the market environment from a fresh perspective. HRI is recorded as the first variable and GSI as the second, both categorized into low, medium, and high levels. These levels reflect the degree of impact from anthropogenic changes, ranging from low to high. Figure 6 illustrates the classification criteria for HRI and GSI in the GE matrix.

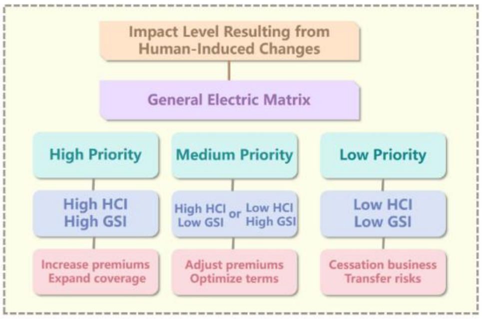


Figure 6. Potential Coverage Options

Based on the classifications of the GE matrix, we can make corresponding decisions, as illustrated in Figure 7. By calculating the GSI and HRI values for each country, representative countries are selected, and their corresponding points are traced in the GE matrix as shown in Figure 8:

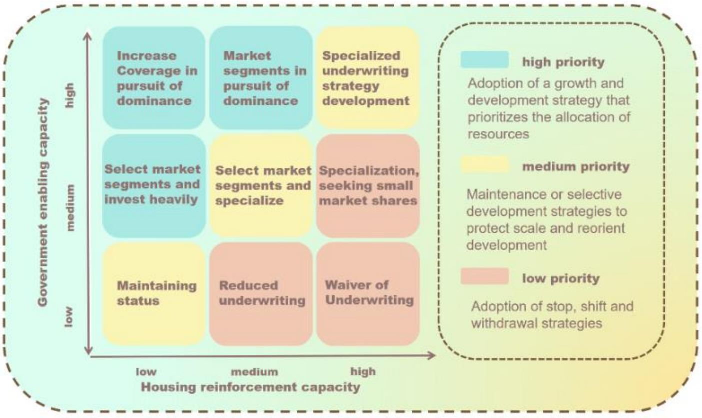


Figure 7. GE matrix

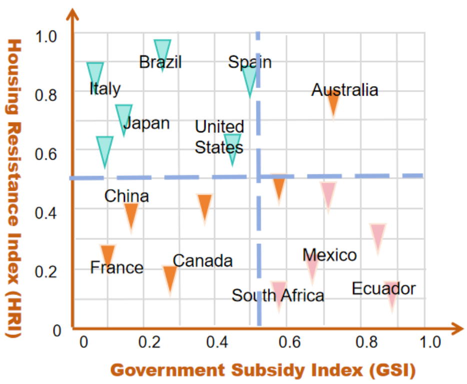


Figure 8. Index distribution for different countries

High Priority region: includes Japan, Brazil, Italy, Spain and the United States. These countries have strong housing resilience and high government subsidy capacity, representing lower risk and stronger recovery support.

Medium Priority region: includes China, France, Canada and Australia. These countries have relatively low housing resilience and government subsidy capacity, implying potential vulnerability to extreme weather and limited recovery support.

Low Priority Region: Includes Mexico, South Africa and Ecuador. These countries may face challenges in recovering from extreme weather events.

3.5. This adjusted premium pricing model

Under the influence of HRI and GSI, the expected rate of return changes. The following equation can represent the effect of this coupled intervention:

$$\beta_i' = \beta_i - \alpha_i \times (h_i + g_i) \tag{19}$$

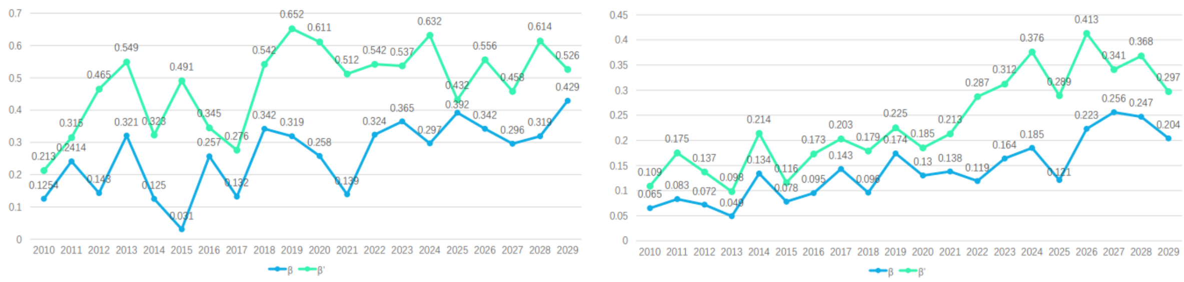
Where β_i' is the underwriting risk index after coupled interventions, α_i is the coefficient of intervention in year i, reflecting the intensity and effectiveness of the intervention, h_i is the HRI in year i, and g_i is the index of GSI in year i.

Finally, we have to adjust the premium pricing model so that it can output more evaluation metrics, to facilitate the assessment of a building's ability to withstand extreme weather and combine it with the results of the GE Matrix to formulate an appropriate underwriting strategy. This adjusted premium pricing model can be represented by the following formula:

$$E(r_i) = r_f + \beta_i'\left[E(r_m) - r_f\right] + \gamma_i \times (L_i + T_i + C_i) \tag{20}$$

γi is the risk premium coefficient in the i-th region, L_i is the indicator of personnel loss in the i-th region, T_i is the indicator of building rehabilitation time in the i-th region, and C_i is the indicator of building rehabilitation cost in the i-th region.

We still choose Japan and Ecuador as representatives. The GSI and HRI values for Japan are 0.729 and 0.821, and for Ecuador the GSI and HRI are 0.138 and 0.252. Based on the adjusted premium pricing model, we predicted the value of β_i' for Japan and Ecuador respectively, as represented in Figure 9.



(a) β_i' of Japan (b) β_i' of Ecuador

Figure 9. Pridiction of β_i'

We combine the optimized intervention model with the values of GRI and HSI in Japan and substitute them into the premium pricing model calculation, and find that the decision threshold of the coefficient of β_i' reaches 0.4374, which shows that with the intervention of real estate developers and governmental communities, etc., when the β is located between the values of 0.3291 and 0.4374, the insurance companies can continue to choose to underwrite in that location.

Ecuador has a low value of GSI and HRI, which belongs to the region of low priority. Substituting the value of GSI, HRI in Ecuador into the premium pricing model calculations, we find that the expected rate of return is 2.793%, is close to the market risk-free rate with the intervention of the community, the government, and real estate developers, at which time the insurance company can choose to underwrite in that place with the adjustment of raising premiums or reducing the economic risk.

Insurance companies must choose different regions when underwriting, and reasonably diversify risks rather than concentrating on high-risk areas, which would pose a serious challenge to the solvency of insurance companies in the event of a major extreme weather disaster in the region.

4. Conclusion

This study integrates the AHP-GRA method to determine the vulnerability assessment indicators of regions affected by extreme weather and derives the underwriting risk index β. Furthermore, the CAPM model is introduced to quantify the risk-return relationship in insurance underwriting, an evaluation standard for underwriting return rates r_u is established, enabling the formulation of specific underwriting decision strategies based on varying return rates.

Applying Japan and Ecuador to this model, we calculated that the acceptable thresholds for β in the next 20 years are 0.3291 and 0.1843, respectively. This indicates that when β is below these data, the region can be insured. By reasonably increasing the model factors to improve the model, β' can be calculated. Further verification of Japan and Ecuador shows that with the intervention of real estate developers, the β thresholds of the two countries have increased by 32.9% and 17.8%, respectively.

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