Research on Extreme Weather Insurance and Real Estate Risk Assessment by Integrating EWM-ARIMA and AHP Methods

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Abstract: This study aims to address the risk challenges brought by increasingly frequent extreme weather events and to build a comprehensive assessment model to provide scientific support for insurance companies, real estate developers and community managers in disaster prevention and risk decision-making. The study is divided into two core tasks. In Task 1, an extreme weather risk assessment model is constructed by combining the entropy weight method and time series analysis (EWM-ARIMA) to quantitatively predict the intensity and frequency of extreme weather events in different regions. At the same time, the Premius-Policyholder risk assessment framework is introduced, and the analytic hierarchy process (AHP) is used to integrate economic, social and sustainability risks to form a decision support model for insurance companies to optimize their underwriting strategies. Task 2 is based on principal component analysis (PCA) and decision tree algorithm to establish a real estate construction risk assessment model, and combine house building types and geographical zoning to complete model integration. Finally, the stability and robustness of the model under key parameter fluctuations are verified through sensitivity testing. The results show that the errors are all controlled within 5%, indicating that the model has good practicality and reliability.

1. Introduction

In recent years, as the trend of global warming becomes increasingly significant, the frequency and intensity of extreme weather events (such as hurricanes, floods and heavy rainfall) continue to rise. Such natural disasters not only cause serious casualties and infrastructure damage, but also have a great impact on regional economic development and social stability. According to the assessment report of the Intergovernmental Panel on Climate Change (IPCC), the economic losses caused by climate-related disasters are increasing year by year, and extreme climate factors are gradually evolving into key variables affecting national economic stability and social resilience.

Against this background, the insurance industry, as an important pillar of the modern risk management system, is facing increasingly severe challenges. The large amount of compensation caused by natural disasters continues to compress the profit margins of insurance institutions, and some small and medium-sized insurance companies have even fallen into bankruptcy or market exit.Traditional insurance pricing and risk assessment models are difficult to accurately respond to the high uncertainty and complexity of climate risks, and often have prediction bias and response lag in underwriting strategies and compensation forecasts, further weakening their role in risk buffering and transfer. Therefore, it is urgent to build a more scientific, dynamic and regionally adaptable extreme weather risk assessment and insurance support model, which will not only help improve the decision-making quality of insurance companies in underwriting and claims, but also provide reasonable financial protection and development support for residents and enterprises in high-risk areas, thereby improving the risk resistance and sustainable development level of the whole society.

In response to this research demand, academia and industry have carried out explorations in

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multiple dimensions. From the existing research, Jahn[1] systematically classified the economic impact of extreme weather events and constructed a regional impact model, providing macro-theoretical support for risk assessment models; Lubchenco and Karl[2] emphasized the urgency of improving extreme weather prediction and management capabilities, and pointed out the prospects of combining meteorological data with policy tools; Kron et al.[3] further pointed out that the extreme climate risk in Europe is increasing, emphasizing that risk models should have regional adaptability. In addition, in the study of multi-index evaluation methods, Yang et al. [4] combined the AHP and EWM methods to construct an education evaluation model, which provided a reference for multidimensional weight modeling in insurance scenarios; while Jiang et al. [5] introduced principal component analysis (PCA) into extreme precipitation event modeling, effectively identifying the dominant factors in climate variables, which provided inspiration for the method selection in real estate risk modeling in this study.

However, most existing studies focus on the prediction and risk trend analysis of extreme climate itself, and rarely systematically integrate climate risks with insurance underwriting strategies, regional construction planning and other factors. Therefore, this paper takes improving the insurance industry's ability to cope with extreme climate risks as its core goal, and constructs a comprehensive, multi-stage, multi-method integrated risk assessment and insurance decision support framework. The research is divided into two main tasks: first, based on the entropy weight method and ARIMA time series analysis (EWM-ARIMA), an extreme weather risk assessment model that considers time dynamics and autocorrelation is constructed to predict the intensity and frequency of extreme weather events; second, an insurance and real estate integrated risk model combining AHP and PCA methods is constructed to assist insurance institutions in formulating precise underwriting strategies by introducing factors such as premium payment ability, wealth protection ability, building type and sustainable development factors, and optimize the site selection and development planning of real estate projects in high-risk areas. Finally, the stability and robustness of the model are verified through sensitivity analysis, providing scientific decision-making basis for insurance companies, real estate developers and regional managers when facing extreme weather risks.

2. Model building and solving

2.1. Extreme Weather Risk Evaluation Model with EWM-ARIMA

In areas where extreme weather occurs frequently, optimizing the allocation of property insurance resources has become a key issue to ensure claims settlement capabilities, improve system flexibility, and maintain the long-term stable operation of insurance companies. To achieve this goal, it is necessary to comprehensively consider multiple influencing factors and systematically analyze the decision-making strategies adopted by insurance companies when selecting underwriting areas, so as to build a comprehensive and scientific insurance assessment model.

This study aims to establish a multi-dimensional risk assessment scoring model to meet the challenges of insurance configuration in extreme climate environments. The model uses two key algorithms in combination: one is the EWM-ARIMA algorithm, which is used to capture trends and volatility in historical data; the other is the analytic hierarchy process (AHP) to achieve weight evaluation and decision optimization under the influence of multiple factors. Through the combination of these two algorithms, the model can more accurately assess the regional risk level and resource allocation efficiency, and provide strong support for insurance companies to formulate scientific underwriting strategies in high-risk areas.

This paper uses EWM-ARIMA to build a risk level assessment model for extreme weather events. The model takes into account three common extreme weather events: floods, tropical cyclones, and wildfires, and comprehensively considers multiple factors to predict the risk level corresponding to extreme weather. This paper uses the analytic hierarchy process to build the final comprehensive risk assessment scoring model, which will integrate the extreme weather risk level assessment model obtained in the first step, as well as other factors such as the insured's own risk model, economic development, and social policy conditions. The model will provide insurance companies with intelligent underwriting decision support, ensuring that the system has sufficient flexibility to pay future claims costs while maintaining the company's long-term health.

Based on historical meteorological data and related auxiliary information, this paper constructs a comprehensive model for assessing the extreme weather risk level. The model comprehensively describes the regional risk characteristics of extreme weather events from the two dimensions of risk frequency and intensity. In the process of constructing the index system, various factors affecting extreme weather risks are fully considered, including meteorological conditions, geographical terrain characteristics, and human activities.

In order to effectively integrate multidimensional factors and quantify their relative importance, the model introduces the entropy weight method to assign weights to each indicator. The entropy weight method calculates weights through objective data distribution characteristics, overcomes the human bias that may be introduced by traditional subjective weighting methods, and thus enhances the scientificity and accuracy of the evaluation results. In addition, this method can highlight the dominant role of variables with larger information entropy in risk assessment, and improve the model's adaptability and explanatory power to highly complex environments.

After data preprocessing, we obtained data from 12 regions with frequent extreme weather events over the past five years. Based on the intensity of extreme weather risk, we established positive and negative indicators:

$$x_{ij}^{'} = \frac{x_{ij} - min(\sum x_j)}{max(\sum x_j) - min(\sum x_j)} (i = 1, \ldots, n, j = 1, \ldots, m) \tag{1}$$

$$x_{ij}^{'} = \frac{\max(\sum x_j) - x_{ij}}{max(\sum x_j) - min(\sum x_j)}, (i = 1, \ldots, n, j = 1, \ldots, m) \tag{2}$$

Calculate the entropy of each dimension:

$$E_j = -k \sum_{i=1}^{n} p_{ij} ln(p_{ij}) \tag{3}$$

$$p_{ij} = \frac{x_{ij}^{'}}{\sum_{i=1}^{n} x_{ij}^{'}}, i = 1, \ldots, n, j = 1, \ldots, m, k = \frac{1}{ln(n)} > 0, E_j \geq 0 \tag{4}$$

Calculate redundancy (difference):

$$d_j = 1 - E_j \tag{5}$$

Calculate weights:

$$w_j = \frac{d_j}{\sum_j d_j} \tag{6}$$

Object	factors	Indicator	Weight	Object	factors	Indicator	Weight
Floods	Meteorological	Flood season's Average precipitation	0.11348	Tropical cyclones	Meteorological	Sea level temperatures (June)	0.21892
		Flood season's precipitation Average days number	0.21759			Sea level temperatures(July)	0.18676
	Geographical	River network Density	0.09280			Sea level temperatures(August)	0.18594
		hardened land Proportion	0.09339		Geographical	latitude	0.21171
		Percentage of terrain with a slope of less than 5%.	0.21059		Human	Urbanization degree	0.19666
		Vegetation coverage	0.09298	Wildfires	Meteorological	Average daily maximum temperature	0.20465
	Human	Urbanization degree	0.17917			Air humidity	0.20185
						wind velocity	0.20466
					Geographical	Vegetation coverage	0.20043
					Human	Urbanization degree	0.18841

Figure 1 Weights with EWM.

We used the above algorithm to obtain the weights of various influencing factors, as shown in the following Figure 1.

Based on the weights in the figure we can obtain the risk scores for the intensity of floods typhoons and wildfires.

$$S_i = \sum_j w_1 j x'_{ij}, i = 1, 2, 3 \tag{7}$$

In extreme weather risk modeling, temporal dynamics is a key factor that cannot be ignored. The occurrence of extreme weather events is not only significantly affected by time variables such as seasonality, periodicity, and long-term trends, but also often exhibits a certain degree of autocorrelation, that is, the probability of current or future events may be statistically related to past observational data. In order to more comprehensively reveal this dynamic evolution feature, this paper introduces the time series analysis method to systematically model historical meteorological data.

Time series analysis can effectively capture the changing trends and fluctuation patterns of data over time, and has significant advantages in predicting the occurrence time of future extreme weather events. In particular, for event types with obvious periodicity, such as seasonal floods or tropical cyclones, time series modeling can identify stable periodic structures, thereby improving the accuracy and foresight of predictions. At the same time, considering the autocorrelation characteristics of extreme weather events, time series models can help improve the accuracy and robustness of overall risk assessment by integrating the dependencies between historical data points, and provide more scientific decision-making support for the dynamic allocation of insurance resources and risk response strategies.

AR autoregressive model:

$$X_t = \sum_{i=1}^{p} a_i X_{t-i} + \varepsilon_t, t \in \mathbb{Z} \tag{8}$$

MA moving average model:

$$X_t = \varepsilon_t + \sum_{i=1}^{p} b_i \varepsilon_{t-i}, t \in \mathbb{Z} \tag{9}$$

Differential model:

$$X_t = \sum_{i=1}^{d} (-1)^{i+1} C_d^i x_{t-i} + \nabla^d x_t \tag{10}$$

We obtained the following results using ARIMA, as shown in the Figure 2-4.

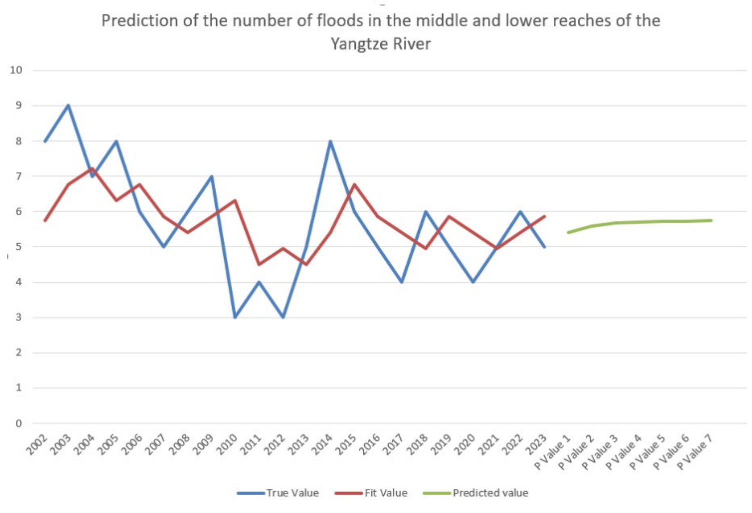

Figure 2 Flood: F1(t) = 3.123 + 0.456 * F1(t − 1).

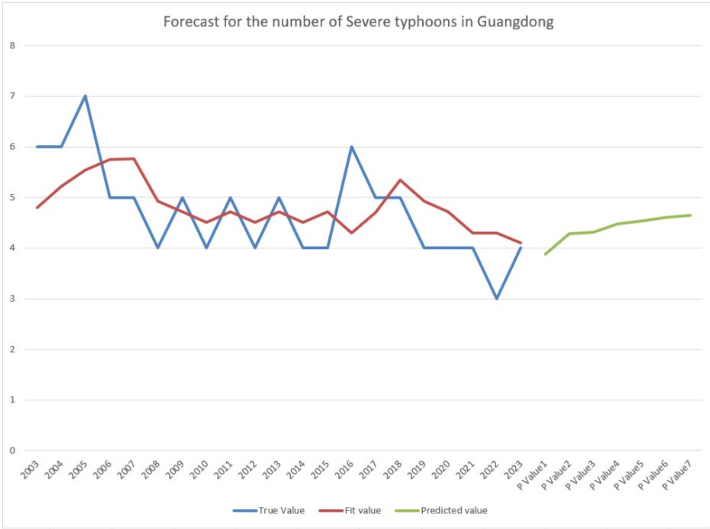

Figure 3 Typhoon: F2(t) = 1.822 + 0.202 * F2(t − 1) + 0.418 * F2(t − 2)

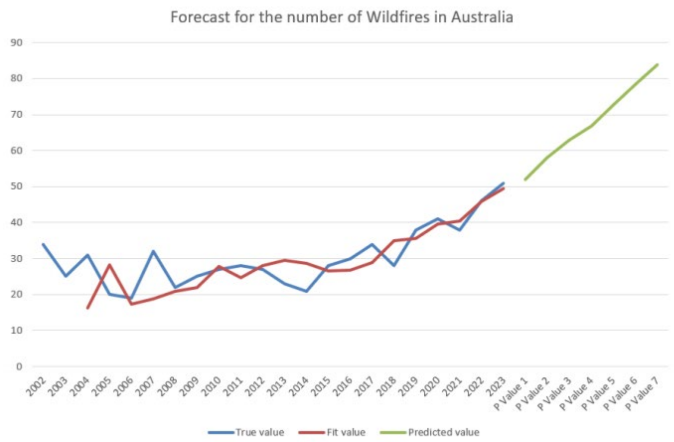

Figure 4 Wildfires: F3(t) = 0.659 − 0.739 * F3(t − 1) − 0.497 * F3(t − 2)

The calculation formula for extreme weather assessment is as follows:

$$R_i = Si * Fi, i = 1,2,3 \tag{11}$$

(1,2, and 3 represent the indices corresponding to floods, typhoons, and wildfires, respectively)

The Google search index ranking over the past five years to some extent reflects the ranking of the impact of floods, typhoons, and wildfires during these five years.

This is because when natural disasters occur, people often turn to Google search for related information, including understanding the situation, coping measures, and donation assistance. Therefore, the Google search index of that region may reflect an increase in people's attention and search frequency for these disaster events.

Based on this, we can obtain the weight relationship of these three through the Analytic Hierarchy Process(AHP).

We obtained weights of 0.28, 0.06, and 0.66 for floods, typhoons, and wildfires, respectively.

Our final formula for extreme weather risk evaluation model is

$$Q_R = 0.28 * R_1 + 0.06 * R_2 + 0.66 * R_3 \tag{12}$$

(R1, R2, andR3 represent the comprehensive indices corresponding to floods, typhoons, and wildfires, respectively) To sum up, this model ultimately obtain a risk evaluation score for extreme weather in a region ,which will helps quantify the likelihood of extreme weather events and provide insurance companies with a quantitative assessment of risk.

2.2. Policyholders Premius Risk Evaluation Model

In a sound legal, technological environment, property is more likely to be effectively protected, thereby reducing the personal assessment risk of policyholders. Therefore, it is necessary to discuss the property protection ability of policyholders. We obtained weights of 0.25, 0.30, and 0.45 for online fraud rate, loan default rate, and crime rate by EWM.

Based on the above we can obtain the policyholder's property protection risk score:

$$H_R = \sum_{i=1}^{3} H_i * w_2 i \tag{13}$$

The premium payment capability of the policyholder directly influences the insurance company's decision to underwrite a policy. A policyholder with a strong ability to pay premiums implies higher policy persistency, reducing the insurance company's risk of claims. Additionally, for high-sum insured policies, the premium payment capability directly determines whether the policyholder can timely and fully meet the payment obligations, thus impacting the insurance company's operational stability.

We obtained weights of 0.41 0.28 and 0.31 for floods typhoons and wildfires respectively. We get the Premium payment risk score:

$$M_R = \sum_{i=1}^{3} M_i * w_3 i \tag{14}$$

Above all, we will obtain the policyholder-premium risk evaluation score(*PR*):

$$P_R = H_R + M_R \tag{15}$$

Table 1 Score level

Score Range	Self-Risk Level	Underwriting Decision
0.20~0.60	Low	Proceed to comprehensive assessment
0.60~0.75	Moderate	Further observation required
Over 0.75	High	Reject the application

It should be noted that as premiums directly affect the profits of insurance companies once the risk evaluation of policyholders-premiumsin a certain region exceeds a certain level, insurance companies will directly abandon underwriting in that region! Based on regional data analysis and experience we have divided the score into the following three levels, as shown in the Table 1.

Risk Assessment and Pricing: Economic conditions directly impact a region's sensitivity to natural disasters. In economically vulnerable areas, disasters may have a more significant impact on individuals and businesses. Insurance companies need to consider these factors to ensure that their underwriting and risk assessment for policies are reasonable.

Claim Frequency and Amount: Economic conditions also correlate with claim frequency and amount. In economically depressed areas, homeowners may struggle more to bear the losses caused by disasters, leading to higher claim frequency and amounts. This directly affects the insurance company's costs and profitability.

We obtained weights of 0.22507,0.29357,and 0.48136 inflation rate long term decline in per capita income growth rate and decline in labor conductivity respectively with EWM. We get the Economic Conditionres (ER):

$$E_R = \sum_{i=1}^{3} E_i * w_4 i \tag{16}$$

Social Responsibility along with Sustainability scores

Insurance companies are increasingly focusing on social responsibility and sustainability in underwriting decisions. In economically challenging regions, insurance companies may face greater responsibility pressures, requiring a balance between risk assumption and considerations for social support.

Public Image and Reputation: The performance of insurance companies in terms of social responsibility and sustainability directly affects their public image and reputation. Actively fulfilling social responsibility helps establish a positive image, influencing consumer and industry trust in the company.

Risk Management: Neglecting social responsibility and sustainability factors may lead to additional risks, such as societal resistance and legal disputes. By actively fulfilling social responsibility, companies can mitigate these potential risks, protecting their economic interests.

While these factors are crucial, they cannot be solely accomplished through mathematical modeling because they involve subjectivity, ethical judgments, and complex societal dynamics. So we did not include it in the comprehensive risk score.

2.3. Breakeven score Model with the Analytic Hierarchy Process

Employing the Analytic Hierarchy Process (AHP), the evaluation of extreme weather risk levels, evaluation of policyholders-premiums scores, economic condition scores, and social responsibility along with sustainability scores are integrated to directly influence the insurance company's decision-making regarding policy underwriting.

Construct a judgment matrix A (orthogonal matrix) and use aij to represent the comparison result of the i-th relative to the j-th:

$$A = (a_{ij})_{n\times n} = \begin{Bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{Bmatrix} \tag{17}$$

Perform geometric averaging (root square method) on the row vectors of matrix A, and then normalize them to obtain the weights of each evaluation indicator and the eigen vector W:

$$\mathrm{w}_i = \frac{\overline{\mathrm{w}_i}}{\sum_{i-1}^{n}\overline{\mathrm{w}_i}}\ \mathrm{w}\overline{\mathrm{w}_i} = \begin{Bmatrix} \mathrm{w}_1 \\ \mathrm{w}_2 \\ \vdots \\ \mathrm{w}_n \end{Bmatrix} \tag{18}$$

$$\mathrm{CI} = \frac{\lambda max - n}{n-1} \tag{19}$$

$$CR = \frac{CI}{RI} \tag{20}$$

Based on a large amount of data investigation and experience summary, we set parameters and use AHP to obtain the following weights, as shown in the Table 2.

Table 2 Final Weights

Scores Analysis	Weight(%)
extreme weather risk level	47.911
policyholders-premiums scores	44.293
economic condition scores	7.796

In summary we have obtained the final comprehensive evaluation score model for insurance company underwriting policy decision-making strategies, as shown in the Table 3:

$$C_R = \begin{cases} 0.47911 * Q_R + 0.44293 * P_R + 0.07796 * E_R \ ,if \ P_R < 0.6 \\ Further \qquad observcation \ required, if \ 0.6 < P_R < 0.75 \\ \quad Reject \ the \ underwriting \ policy \ ,if \ P_R > 0.75 \end{cases} \tag{21}$$

Table 3 Final Evaluation Level

Score Range	Self-Risk Level	Underwriting Decision
0~0.55	Low	decide to underwrite the policy
0.55~0.65	Moderate	further observation required
over 0.65	High	reject the application

We choose Zhanjiang in Eurasia and Perth in Australia as locations for evaluating the comprehensive risk of extreme weather mainly due to their significant characteristics in extreme weather events. Zhanjiang is frequently affected by typhoons, while Perth experiences frequent bushfires. These two extreme weather phenomena can have a substantial impact on local communities and economies, especially in the insurance industry, where these risks need effective assessment and management.

In Zhanjiang, due to its geographical location, the influence of monsoons, and a warm and humid climate, typhoons regularly make landfall, causing significant losses and risks to local residents and businesses. Therefore, understanding and assessing the extreme weather risk in the Zhanjiang region is crucial for insurance companies to better design insurance policy strategies and pricing.
Simultaneously, the Perth region often faces the threat of bushfires, especially during dry seasons. Bushfires not only cause damage to the natural environment but can also result in substantial losses to homes, farmlands, and infrastructure. Insurance companies need a comprehensive understanding of the bushfire risk in the Perth region and develop corresponding insurance strategies to mitigate potential economic losses.

Considering that the final score in Zhanjiang are low-risk, we believe that insurance companies can underwrite policies here Due to Perth's PR score exceeding 60, we recommend that insurance companies do not underwrite policies here.

2.4. the sub model of Real Estate Construction with PCA

We plan to establish a sub-model for evaluate the risks of real estate construction(SREC)by considering various factors such as basic resources and sustainability, using the principal component analysis(PCA). Subsequently, we will integrate this sub-model with the insurance model from Task 1 using the decision tree algorithm to create the final real estate construction evaluation(REC) model.

Principal Component Analysis (PCA) is used to consider the reasons for weighting various aspects of real estate risk assessment. There are several reasons for this:

Dimensionality Reduction and Simplification: PCA can identify the most important variables in a dataset, reducing the dimensions of the data. In real estate risk assessment, there may be multiple factors involved, such as underlying resources, sustainability, etc. Through PCA, these factors can be condensed into a few principal components, simplifying the model and improving its interpretability.

Reducing Collinearity: In the real estate field, different risk factors may exhibit some correlation, known as collinearity. Principal Component Analysis helps eliminate collinearity, ensuring that variables in the model are independent of each other, providing a more accurate reflection of the impact of various factors on real estate risk.

Table 4 PCA test

KMO		0.708
Bartlett	Approx.Chi-Square	93.204
	df	45
	P	0.000***

KMO test was performed between variables, **, *, * respectively indicate the significance level of 1%, 5% and 10%. If the KMO test is passed (KMO> 0.6), it indicates that there is a correlation between the variables, which meets the requirements of PCA. If the Bartlett test is performed with P < 0.05, it shows significance, and PCA can be performed. The results are shown in Table 4 below, from which it can be concluded that PCA can be performed.

Therefore, the principal component analysis(PCA) is deemed effectiveis deemed effective, with a moderate degree of correlation. Subsequently, we calculate the score of each component based on its factor score coefficient (principal component load), obtain the factor formula, and finally normalize it to obtain the factor weight score, as shown in the Table 5:

Table 5 Factor load matrix heatmap

N15	-0.546	0.298	N7	0.264	0.070
4	-0.720	0.518	N6	0.199	0.040
N1 3	-0.187	0.035	N5	0 710	0.505
N12	0.672	0.451	4	-0.437	0.191
N11	0.182	0.033	N3	-0.030	0.001
N1 0	0.236	0.056	N2	0.721	0.520
N9	-0.691	0.478	N1	0.740	0.548
NB	-0.729	0.531			

Then we will obtain the sub model of real estate construction(S-REC):

$$N_R = \sum_{i=1}^{15} u_i * N_i \tag{22}$$

Decision trees provide intuitive decision rules that are easy to interpret and understand. This allows the information extracted from different models to be communicated to decision makers and stakeholders in a clear manner. The structure of the constructed decision tree is shown in Figure 5.

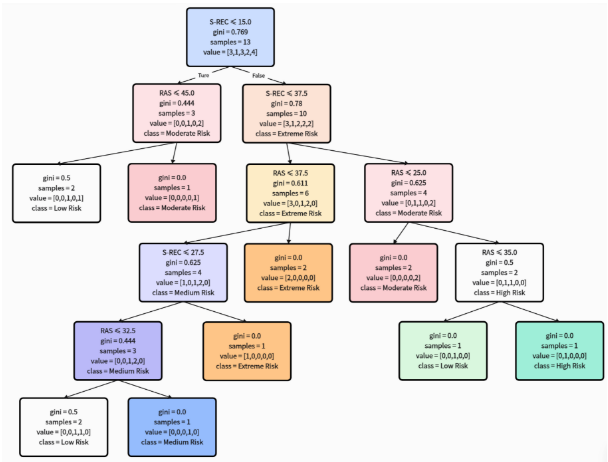

Figure 5 Decision Tree Structure

Then we will obtain the narrowly defined REC model:

$$O_R = 0.542 * C_R + 0.458 * N_R \tag{23}$$

A robust real estate construction evaluation model, capable of addressing extreme weather conditions, should not only consider the feasibility of construction but also take into account the specific types of construction. Therefore, we will elaborate on two aspects: house construction types and construction area types.

Geographical factors play a vital role in urban planning and architectural design to cope with the risks of extreme natural disasters. In order to enhance the adaptability of buildings to natural disasters, different regions need to adopt targeted engineering measures and design concepts according to local conditions.

In areas prone to floods, residential buildings should focus on improving flood control performance, such as raising the foundation, using waterproof building materials, and building efficient drainage systems to reduce property losses and personnel risks caused by floods. In areas where wind disasters frequently occur, wind-proof architectural design strategies should be adopted, including strengthening building structures, selecting wind-resistant materials, and rationally planning emergency evacuation routes to improve disaster response capabilities. For areas with frequent seismic activities, building planning should focus on seismic resistance, and effectively improve safety and structural stability in earthquake events by adopting structural designs and material configurations that comply with seismic standards.

At the same time, the spatial layout of urban functional areas also needs to fully consider the dual impact of geographical factors on safety and functionality. Commercial areas are usually located in the core areas of cities to maximize customer traffic, facilitate transportation, and promote economic activities. Industrial areas tend to be located in urban fringe areas, which not only helps reduce interference with residents' lives, but also facilitates the implementation of environmental governance measures. Residential area planning should be rationally laid out with public service facilities as the core to ensure that residents can easily access basic service resources such as education and medical care in their daily lives.

By incorporating disaster response capabilities into the overall consideration framework of urban space and architectural design, the climate adaptability and infrastructure resilience of the region can be effectively improved, laying a solid foundation for sustainable development in the context of frequent extreme weather.

3. Conclusion

In summary, this study has built a set of systematic and forward-looking assessment and decision support models around the risk assessment and resource allocation issues under the background of frequent extreme weather events. By combining the entropy weight method with time series analysis, the risk level of extreme weather in different regions is accurately identified, providing a data basis for insurance companies to formulate scientific underwriting strategies. At the same time, the introduction of methods such as AHP and PCA effectively integrates insurance risk assessment with real estate construction planning, realizing the overall linkage from individual property protection to regional sustainable development. The sensitivity test results of the model further verified its stability and applicability, showing good promotion potential in actual scenarios. Future research can introduce social, environmental and policy variables in more dimensions, continuously optimize the model structure, and provide more in-depth decision support for disaster response and urban resilience construction.

References

[1] Jahn M. Economics of extreme weather events: Terminology and regional impact models[J]. Weather and Climate Extremes, 2015, 10: 29-39.

[2] Lubchenco J, Karl T R. Predicting and managing extreme weather events[J]. Physics today, 2012, 65(3): 31-37.

[3] Kron W, Löw P, Kundzewicz Z W. Changes in risk of extreme weather events in Europe[J]. Environmental Science & Policy, 2019, 100: 74-83.

[4] Yang X, Yang J, Lu Y. Higher education evaluation system based on AHP & EWM[J]. Advances in Educational Technology and Psychology, 2022, 6(10): 75-93.

[5] Jiang Y, Cooley D, Wehner M F. Principal component analysis for extremes and application to US precipitation[J]. Journal of Climate, 2020, 33(15): 6441-6451.