Problem Chosen	2024 MCM/ICM Summary Sheet	Team Control Number
E		2401748

Catastrophe Insurance Response Strategies: The "Guardian" of Extreme Weather

Summary

As Victor Hugo once said: ' Nature is kind of a loving mother, but also a butcher in cold blood.' Extreme weather events are affecting all aspects of people's daily lives, such as tourism, services, and the insurance industry. This paper provides a corresponding coping strategy for the development of the insurance industry under extreme weather by establishing an insurance company underwriting model and a fuzzy comprehensive evaluation protection model.

For Model I: Based on the results of some international databases and disaster resilience studies, an insurance model (**ICU model**) for assessing catastrophe risk is proposed. The ICP coefficient is obtained by multiplying the regional vulnerability index with the regional risk index, where the risk index is predicted by our innovatively proposed **ARIMA-LSTM** coupling algorithm. The inverse proportionality function of the ICU coefficient is constructed based on the fact that the risk of insurance companies is positively correlated with the regional risk (ICP coefficient) and negatively correlated with the regional purchasing power (CBP coefficient). The CBP coefficients were computed by **K-means clustering,** and the derived ICP coefficients were used to derive the ICU coefficients for each region. Finally, the coefficients were categorized into three intervals to give the insurance company's coverage model.

For Model II: We select the ICP coefficients in the ICU model for disaster risk assessment and introduce the comprehensive development indicators of the community, which are evaluated by the **EWM-TOPSIS** algorithm, and then rank the U.S. states, and the top three states in the ranking are Minnesota, North Dakota, and South The information shows that these three states not only have a pleasant climate but also maintain high urbanization rates and GDP per capita, which are almost consistent with our predictions.

For Model III: We use the **fuzzy comprehensive evaluation model** to give the most worthwhile landmark, the Pennsylvania Independence Memorial, and give relevant suggestions and timetables for the community so that the relevant departments can better protect this historic and unique building. unique significance of the building.

Immediately after that, the research team gradually adjusted the key parameter of regional risk factors in the EWM-TOPISIS model downward by **50%** for sensitivity analysis, and the results showed that the rankings of the top five cities remained almost unchanged under the change of weights, proving that the real estate model has a very strong anti-interference ability. And through the sensitivity test on the weights and affiliation of each factor of the key indicators, the result is basically consistent with the expectation. The research team meticulously analyzed the advantages and disadvantages of the model and made further improvements to the model.

Finally, the research team summarized the problem and provided a timeline and cost proposal for the community regarding the precious landmark preservation plan.

Keywords: ARIMA-LSTM coupling algorithm; K-means clustering; EWM－TOPSIS; Fuzzy Integrated Evaluation

Contents

1 Introduction

1.1 Problem Background

Since the 1990s, a series of natural disasters have caused economic losses in the tens of billions of U.S. dollars. Examples include the Northridge earthquake in 1994, the Kobe (Japan) earthquake in 1995, the 2004 Indian Ocean earthquake that caused the Asian tsunami.[1] In recent years, along with the acceleration of urbanisation and industrialisation, the problem of environmental pollution has become increasingly serious. The enormous impact of natural and man-made disasters on human society has made them one of the topics of great concern.

Figure 1: Mega-hazards: "ghosts" over cities [2]

Although insurance is thought to play a critical role in improving resilience to these events by both promoting recovery and providing incentives for investments in hazard mitigation [3], the situation and development of the insurance industry, which is related to mega-disasters, is still not favourable. On the one hand, the increase in the number of natural disasters has led to a sharp rise in the amount of compensation paid by insurance companies; on the other hand, the crisis in the development of the insurance industry has been aggravated by high premiums, and the purchasing power of the public has continued to decline. Therefore, it is particularly significant to establish relevant models to promote its development.

1.2 Restatement of the Problem

Considering the issues related to the aforementioned mega-natural disasters and the huge impact on the insurance industry, our team addressed the following questions:

- **Problem 1:** Develop an insurance company underwriting model to assess the viability of implementing underwriting in a specific region, aiming to maximize profits amidst the rising frequency of extreme weather events worldwide. Apply the model to two different regions.
- **Problem 2:** Evaluate potential real estate development areas from the viewpoint of a real estate developer, considering factors such as community growth and the influence

of severe weather conditions.

- **Problem 3:** Based on the insurance model, make appropriate adjustments and optimizations to evaluate the worthiness of preserving certain buildings within an area from multiple perspectives.
- **Problem 4:** Choose a historic landmark and apply the model from Question 3 to evaluate whether the landmark should be preserved.
- **Problem 5:** Write a one-page letter to the community outlining future plans, timelines, and cost proposals for the preservation of their treasured landmark.

1.3 Our Work

Our team developed a model to evaluate the risk for insurance companies in a specific area. We utilized the risk assessment from the model to identify optimal building sites for real estate developers and to facilitate accurate cost planning for building reinforcement. Ultimately, the model offers recommendations for the future conservation of important historic landmarks, taking into account multiple metrics. Researchers illustrate the work completed using a simple framework diagram, as depicted in the figure.

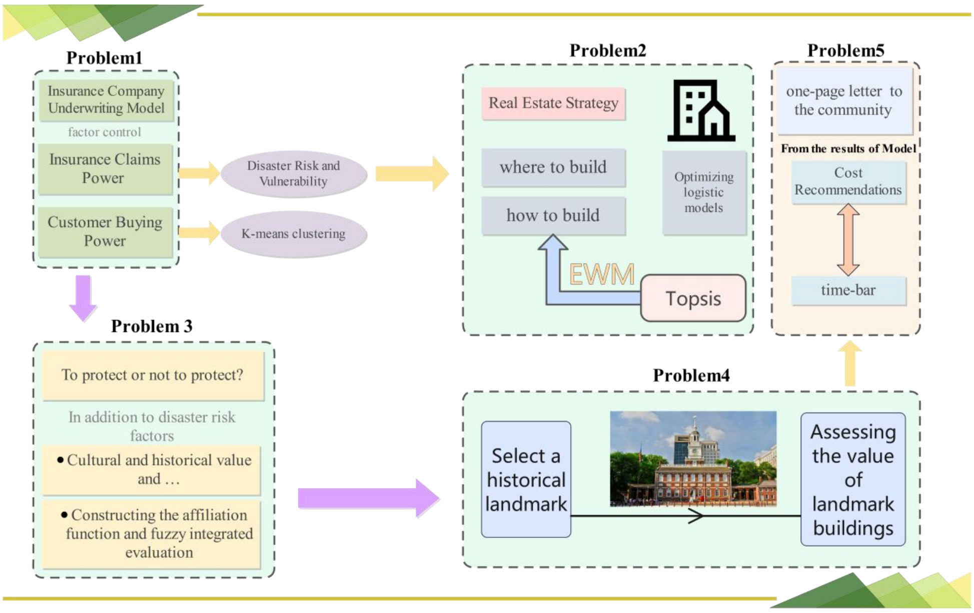


Figure 2: The framework diagram of our work

2 Assumptions and Justifications

- **Assumptions1:** Among the significant natural hazards that are increasingly common, extreme weather events are a relevant variable that can be used to evaluate the trend of natural hazard threats in most regions.

Justifications1: We arrived at the above conclusion after conducting a study using Pearson's correlation coefficient. Global data on various types of disasters from 1970 to 2023 has been extracted. After analyzing the correlation coefficients, we found that the correlation coefficient between extreme weather and total threat is greater than 0.8, indicating a very strong correlation. Therefore, we ultimately selected the frequency data of extreme weather to represent the trends of mega-hazards in each region.

- **Assumptions2:** There is a positive correlation between the severity of a natural disaster and its frequency of occurrence. In other words, the higher the frequency of occurrence, the greater the severity of the hazard.

Justifications2: The above assumptions are derived when the impacts caused by each mega-hazard are close to the average and the error is negligible.

3 Notations and Glossary

3.1 Notations

The key mathematical notations used in this paper are listed in Table 1.

Table 1: Notations used in this paper

Symbol	Description
ICU	Insurance Company Underwriting
ICP	Insurance Claims Power
CBP	Customer Buying Power
C_0	The constant term of the formula ICU
G_i	Economic fragility
m_i	Population density
R_i	Social vulnerability
Y_i	Comprehensive fragility
L_r	Long-term-risk

3.2 Glossary

- **Insurance Protection Gap:** the difference in protection coverage between economic losses brought about by natural disasters and the amount of those losses that are covered.
- **Underwrite:** accept liability for, thereby guaranteeing payment in the case of loss or damage.

4 Model I: Insurance Company Underwriting Model

4.1 Data Description

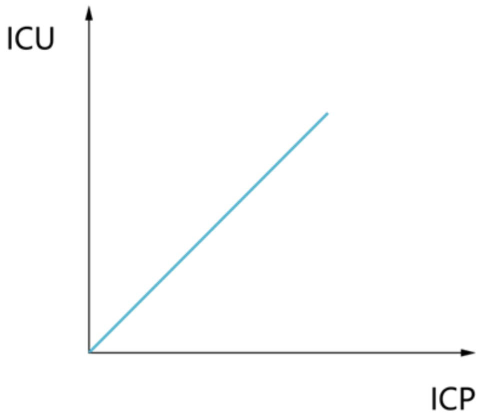
Our team utilized data on the frequency of natural disasters, global GDP[4], and national GDP[5] from the World Bank and an online data-sharing program[6] established by Oxford University economist Max Roser in 2011. Global GDP and national GDP can be used by researchers to study the future development of a region and the adequacy of its infrastructure. The frequency of disasters can be used to validate the accuracy of subsequent models. Data sources are in the table below:

Table 2: Data source collation

Dataset	Website Source
Number of natural disaster events	https://ourworldindata.org/search?q=Extreme-weather
Global GDP data	https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?end=2022&start=2022&type=shaded&view=map&year=1973
GDP of each country	https://www.kylc.com/stats/global/yearly_overview/g_gdp_per_capita.html

4.2 The Establishment of Model I

After gaining a thorough understanding of the profitability model of catastrophe insurance for insurance companies, the ICU model is divided into two components: Insurance Claims Power (ICP) and Customer Buying Power (CBP). ICU is directly proportional to the ICP coefficient and inversely proportional to the CBP coefficient, as illustrated in the figure below:



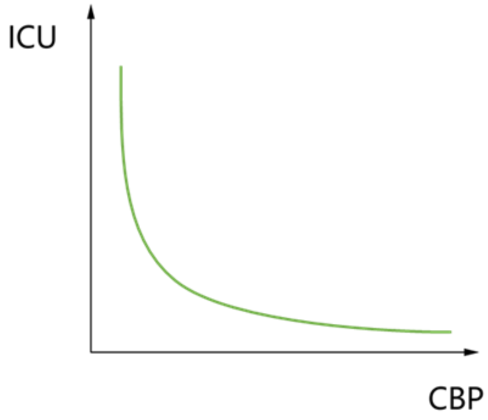


Figure3: ICU-ICP relationship curve **Figure4: ICU-ICP relationship curve**

The figure above indicates that the ICU coefficient directly correlates with the underwriting risk of the insurance company in the region. A larger ICU coefficient suggests a greater underwriting risk, prompting the recommendation that the insurance company refrain from underwriting buildings in the region. Alternatively, the company could consider raising premiums or setting an upper limit on payouts to mitigate the risk. Conversely, a smaller ICU coefficient indicates a lower underwriting risk, allowing for potential adjustments to the insurance company's policies to further incentivize people to purchase insurance in the region.

Based on this assumption, we provide the formula for calculating the ICU coefficient as follows:

$$ICU = C_0 \times ICP/CBP \quad (1)$$

where ICU represents the underwriting factor, ICP denotes the underwriting power factor, CBP signifies the customer purchasing power factor, and C_0 is a constant. We set the value of C_0 to 1 to simplify the calculation in the following sections.

Our team grouped and categorized the factors of ICP and CBP. Among them, ICP is categorized into fragility factor and long-term extreme weather forecasting. The CBP coefficients are categorized into risk perception (R), education level (E), and GDP per capita coefficient (G). The overall flow of the ICU model is illustrated in the following figure:

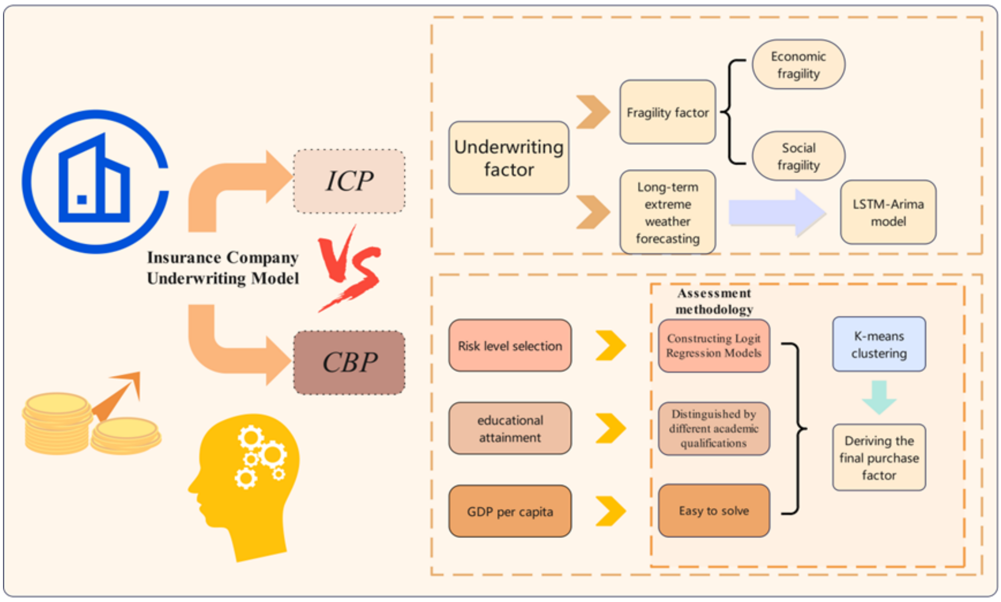


Figure 5: Flow chart of Insurance Company Underwriting Model

4.3 Insurance Claims Power Model

Vulnerability is divided into two parts: **Economic vulnerability** and **Social vulnerability.**[7]

Economic vulnerability: The property damage caused by natural disasters is relatively higher in economically developed and property-rich areas. By the same token, the property losses caused by economically underdeveloped regions are relatively small. Therefore, it is necessary to select the per capita GDP of each judging area as the indicator for judging economic vulnerability.

The formula for calculating the region's vulnerability with the economic vulnerability indicator is as follows:

$$G_i = \begin{cases} \ln(G) - \dfrac{21}{2} & 5\times10^4 \leqslant G < 10^5 \\ 1 & G \geqslant 10^5 \\ 0.3 & G < 5\times10^4 \end{cases} \tag{2}$$

where G_i is the region's economic vulnerability indicator and G represents the region's GDP per capita (measured in dollars).

Social vulnerability: The more densely populated an area is, the greater the loss of life caused by natural disasters. Therefore, population density was chosen as the indicator to judge social vulnerability.

$$\begin{cases} m_i = r_i / s_i \\ R_i = \begin{cases} \frac{m_i}{1300} & m_i < 1300 \\ 1 & m_i \geqslant 1300 \end{cases} \end{cases} \quad \textbf{(3)}$$

where r_i is the actual total number of people in the area, s_i is the actual area of the area, m_i is the population density of the area, and R_i is the social vulnerability indicator for the area.

On one hand, the level of disaster vulnerability increases with the economic development and population density of an area. On the other hand, economically developed areas have a greater capacity to withstand disasters, which partially offsets the increase in disaster losses. Therefore, the relationship between vulnerability and property and population is non-linear, with rapid growth at the initial stage followed by a gradual slowdown. Based on the above assessment, we developed a functional relationship between the giant disaster vulnerability index and the economic and social vulnerability indices:

$$Y_i = \sqrt{\frac{R_i + G_i}{2}} \quad \textbf{(4)}$$

where G_i represents economic vulnerability, R_i represents social vulnerability, and Y_i represents vulnerability to mega-disasters in the area.

Catastrophe risk prediction is a crucial component of ICP coefficient assessment. After collecting disaster and CO2 emission data from various regions in previous years, we utilized the ARIMA-LSTM prediction model. Following the pre-processing of the data using the differential equation structure of the ARIMA model, we observed that the disaster data exhibit multivariate effects, unstable time series, and straightforward seasonality. Finally, we have decided to leverage the complementary advantages and targeted combination of these two algorithms to address the potential time series shift phenomenon in ARIMA time series prediction (Autoregressive Integrated Moving Average Model) and the stochastic nature of the fitting effect of LSTM:

$$\begin{cases} w_1 + w_2 = 1 \\ Y(t) = w_1 y_1(t) + w_2 y_2(t) \end{cases} \quad \textbf{(5)}$$

where $y_1(t)$ represents the time series prediction generated by the ARIMA algorithm, and $y_2(t)$ represents the time series prediction produced by the LSTM neural network. w_1 and w_2 represent the weights of the two algorithms.

The ARIMA model demonstrates excellent performance in handling non-smooth time series, such as the unit root process of order d. It can be applied to the data in various ways. Therefore, we need to first differentiate the data and convert it into a smooth time series before modeling.

Our team selected the neural network based on the Adam optimization algorithm for timing prediction in **LSTM neural networks**. The network construction is depicted below:

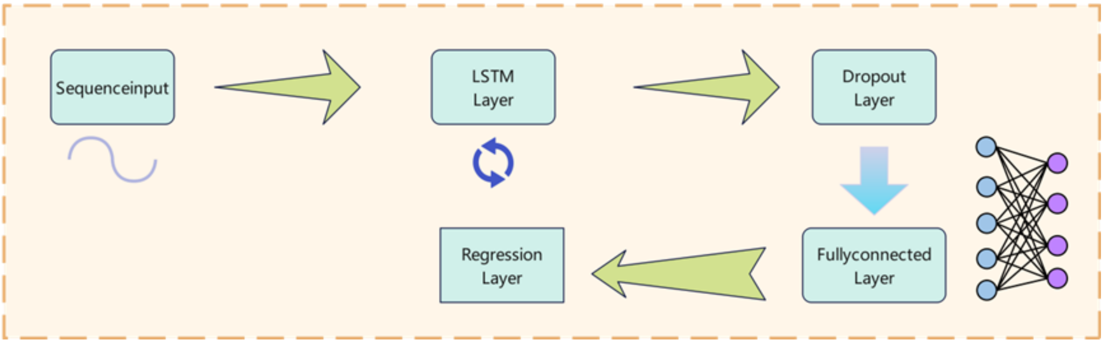


Figure 6: LSTM network structure

Based on the above structure, the input layer of the LSTM model is involved, and it considers the frequency of extreme weather, CO2 emissions, temperature, and economic losses as analyzed in section 4.1. Multiple LSTM hidden layers are added, with each layer learning different time-step patterns within the sequence.

RMSE (Root Mean Square Error) has been selected as the loss function. The formula for the loss function is as follows:

$$\sqrt{1/n \cdot (Z_i - U_i)^2} \tag{6}$$

where n represents the number of samples, Z_i denotes the predicted value, and U_i represents the true value.

During the optimizer configuration phase, the research team selects the Adam optimizer. The traditional gradient algorithm has the drawbacks of maintaining a constant learning rate, oscillating at the saddle point, and easily getting trapped in a local optimal point. In contrast, the Adam algorithm, which incorporates an adaptive gradient descent strategy, can dynamically adjust the learning rate for each parameter based on the estimation of the first-order and second-order moments of the gradient. It avoids using fixed or manually adjusted learning rates, which improves optimization efficiency and stability. At the same time, Adam's algorithm incorporates momentum by utilizing the estimation of the first-order moments of the gradient to introduce an inertia term for the update direction of each parameter. This results in a smoother and more stable update direction. This helps to avoid oscillation or deviation from the optimal solution caused by the gradient descent algorithm when there is noise or curvature inconsistency.

The update rule for the Adam optimizer is shown in the following equation:

$$\begin{aligned} m_t &= \beta_1 m_{t-1} + (1-\beta_1) g_t \\ v_t &= \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \\ \theta_t &= \theta_{t-1} - \frac{\alpha \cdot m_t}{\sqrt{v_t} + \varepsilon} \end{aligned} \tag{7}$$

We acquired the ARIMA-LSTM mega-disaster prediction data, computed the average frequency of disasters in the region for the next five years, and derived the Long-term-risk coefficient (L_r coefficient) through standard normalization of the data for the selected multiple regions. The L_r coefficient was multiplied by the Y_i vulnerability index calculated in 4.3.1 to obtain the final ICP coefficient.

$$ICP = Y_i \cdot L_r \quad \textbf{(8)}$$

The constraints of any one of the three influencing factors— GDP per capita, level of education, and customer's judgment of risk—may cause customers to refuse to purchase insurance.

The analysis of whether customers purchase insurance is shown below:

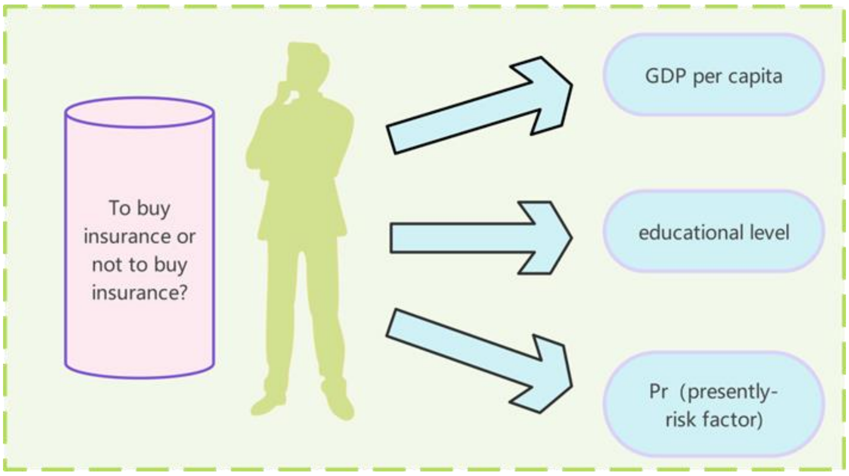


Figure 7: Buy or not to buy

After a thorough analysis by the research team, several factors that influence whether a customer purchases insurance have been identified:

- **GDP per capita level:** Even if the region experiences frequent extreme weather events, lower income levels are linked to reduced purchasing power for insurance.
- **Level of education:** Individuals with higher levels of education are more likely to be aware of insurance and to make insurance purchases.
- **Pr factor (presently-risk factor):** The higher the risk factor of the region, the more likely it is to purchase catastrophe insurance.

To simplify the calculation of the coefficient of purchasing power (CBP), we categorized purchasing power into three groups, assigning values of 1, 2, and 3 to the CBP. After conducting a preliminary analysis of the data, no significant outliers were identified. Therefore, it is reasonable to establish a hierarchical system based on K-means clustering.

4.4 The Result of Model I

Using the global disaster frequency as the sample set for algorithm validation, we tested the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the data. After analyzing the results, we determined the differential order of the ARIMA model to be "d" and selected the ARIMA (0, 1, 1) model for prediction.

By substituting into the ARIMA model, we obtain the relationship between y_t and y_{t-1} as follows:

when p=0, d=1, and q=1:

$$\begin{cases} \Delta y_t = \varepsilon_t + 0.366\varepsilon_{t-1} \\ \varepsilon_t = 0.038 \end{cases}$$

$$\Rightarrow y_t = y_{t-1} + 0.366\varepsilon_{t-1}$$

And finally, the ARIMA predicted time series was obtained, followed by the LSTM neural network prediction as shown below:

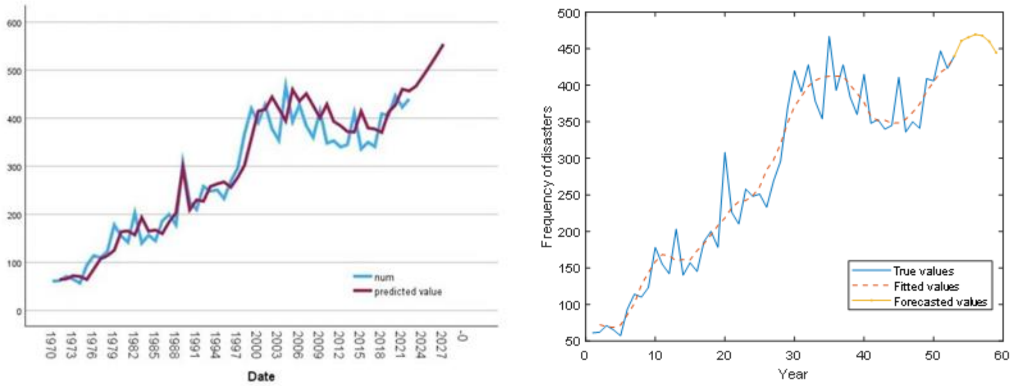


Figure 8&9: Prediction plots for ARIMA and LSTM

ARIMA predicts more fluctuations, while LSTM predicts a smoother sequence. Based on this, we finally provide the following weight assignment formula:

$$\begin{cases} w_1 = 0.8, w_2 = 0.2 \ t < \dfrac{T}{2} \\ w_1 = 0.2, w_2 = 0.8 \ t \geqslant \dfrac{T}{2} \end{cases}$$

After obtaining the two columns of predicted timings, the allocation is reorganized based on the weights, ultimately resulting in the predicted timings of the coupled algorithm:

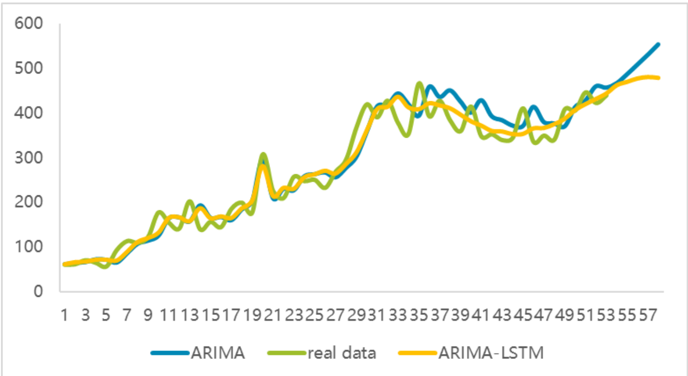


Figure 10: Coupled ARIMA-LSTM algorithm for time prediction

Through the above comparisons, we can intuitively see that the coupling algorithm has achieved satisfactory results in both pre- and post-prediction.

The ARIMA-LSTM coupling algorithm calculates the L_r coefficient, which in turn determines the ICP coefficient and the ICU coefficient. This approach provides a more accurate reflection of the risk associated with insurance companies underwriting in a specific region. We collected data from key regions in the United States for standardization. According to the three-level insurance strategy, the major regions of the United States are divided into three categories based on the size of the ICU coefficient, and different insurance policies are implemented. In the category with higher ICU coefficients, it is not recommended to underwrite or the fee is increased to **1%** of the claim fee, and the insurance cap is set at word-sub **50,000** per single case. The middle category maintains the original insurance strategy (the fee accounts for **0.5%** of the claim fee). The category with the lowest ICU factor encourages customers to purchase insurance by reducing the ratio of premiums to benefits to **0.1%**.

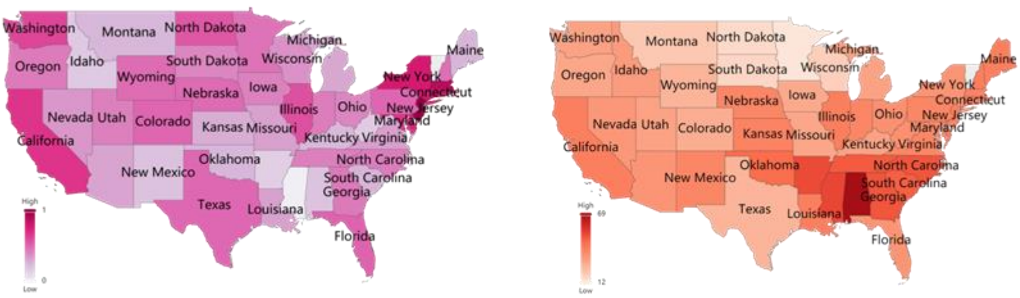


Figure 11&12: Data visualization on Y_i and L_r coefficients

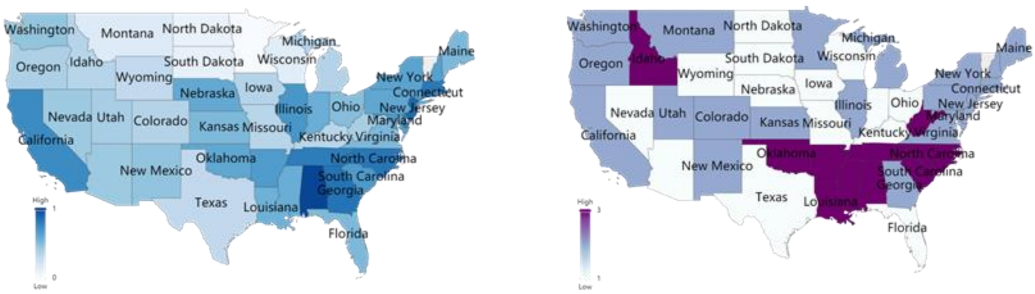


Figure 13&14: CBP and ICP coefficients

We selected two states, New Jersey and Oregon, for the analysis of insurance metrics. As depicted in the figure below, New Jersey has a higher ICU coefficient, while Oregon has a lower ICU coefficient.

Therefore, our model suggests that insurers should not underwrite in the New Jersey area. Alternatively, they could achieve cost control by significantly increasing the insurance purchase amount and setting the maximum cap of a single insurance claim at no more than

$500,000.

In the Oregon region, insurers face an extremely low underwriting risk. Therefore, we encourage insurers to expand their market presence in this region by, for example, further reducing the insurance purchase amount to incentivize customers to buy insurance.

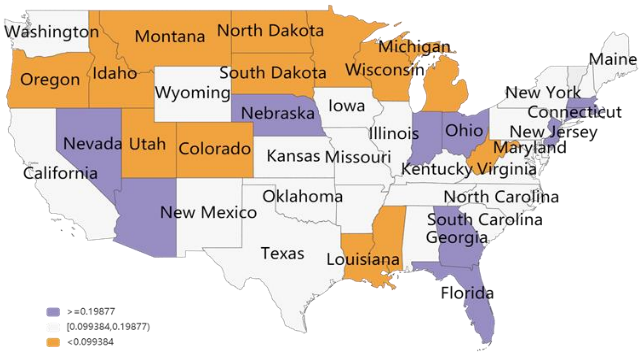


Figure 15: ICP coefficients for major U.S. states

5 Model II: Realtor Model

5.1 Model Assumptions

- First of all, without considering the influence of city type, city climate, and city population, the urbanization rate and GDP per capita can intuitively reflect the level of development and social welfare index of a region. These factors can also help determine the future development of the community in the region and the social services it can provide. After careful consideration, the research team decided to use the urbanization rate and GDP per capita of a community to represent the level of sophistication of the community's supporting facilities and services.
- Secondly, appropriate regional risk factors enable real estate developers to reduce the cost of inputs for mega-disasters and extreme weather events. Higher urbanization rates also help meet the various social needs of a growing population. Based on the above facts, the research team hypothesized that the selection of construction sites by real estate developers depends solely on the risk factor (i.e., ICP coefficient) and the urbanization rate.

5.2 The Establishment of Model II

Real estate developers select building sites based on a variety of factors. As the focus of this section's research, a comprehensive evaluation model will be developed by integrating the Topsis and EWM entropy weighting methods, utilizing three evaluation indices that impact the construction model. Subsequently, the suitable areas for real estate development are identified and evaluated. A logistic optimization model is developed to simulate the percentage of return on revenue resulting from the reinforced construction of houses in areas with varying risk coefficients. In this model, the risk assessment of the buildings in the area can still be evaluated using the ICP coefficients obtained in 4.3.3.

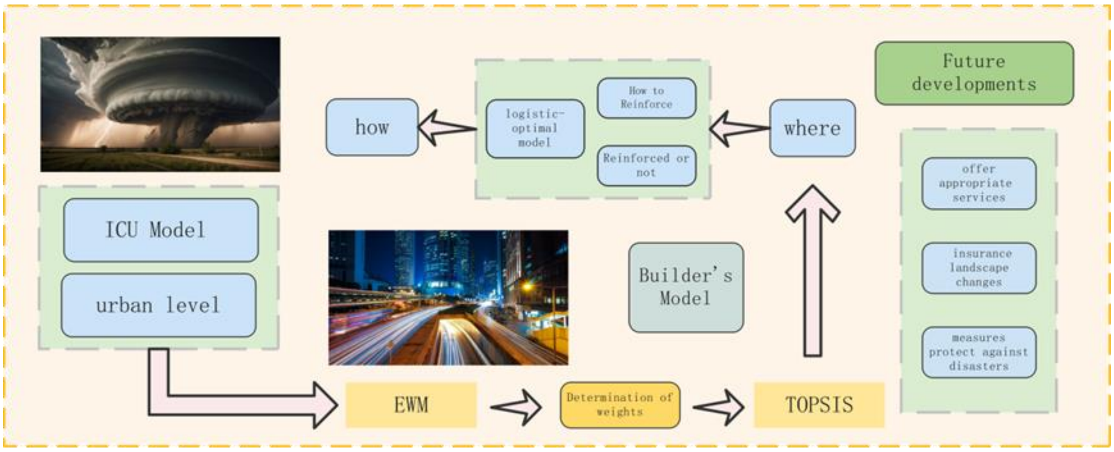


Figure 16: Flow chart of Model II

The entropy weight method is an objective approach that reflects the information of indicators based on their variability, allowing for the assignment of weights. In this chapter, after determining the weight of each indicator using the entropy weight method, the TOPSIS method is used to evaluate the objects. The basic process of TOPSIS involves unifying the original data matrix with the type of indicator (general normalization process) to obtain the normalized matrix. Then, the normalized matrix is standardized to eliminate the influence of each indicator's scale. The optimal and worst solutions are found in the limited program, and then the distance between each evaluation object and the optimal and worst programs is calculated. This process yields the relative proximity between each evaluation object and the optimal program, which serves as the basis for evaluating their advantages and disadvantages.

The specific construction steps of WM-TOPSIS are as follows:

Step 1: Construct the evaluation matrix, transform the three indicators of GDP per capita, urbanization rate, and risk coefficient into extremely large ones, and standardize them.

Step 2: Calculate the weight of the ith sample under the jth indicator and regard it as the probability used in the relative entropy calculation.

Step 3: Calculate the information entropy of GDP per capita, urbanization rate, and risk coefficient, and calculate the information utility value, normalized to obtain the entropy weight of each indicator.

Step 4: Calculate the relative proximity of the selected GDP per capita, urbanization rate, and risk factor.

Step 5: Ultimately, the entropy weights and Topsis scores obtained from the above algorithm are multiplied to obtain a composite indicator score for each state and ranked according to the score.

5.3 Model Results

After conducting the EWM-Topsis ranking, there may be a high risk factor in the final calculation of suitable construction areas. Subsequently, specific construction scenarios can be proposed for different construction areas.

When evaluating the construction sites, we identified three potential scenarios for improving the buildings in each area.

- **Scenario 1:** In areas with a high-risk factor, reinforcing buildings can enhance their resilience. However, the return on investment is slower to materialize because most reinforcement measures have limited impact when the building is exposed to extreme weather events.
- **Scenario 2:** Located in an area with a moderate risk factor, increased investment in strengthening the building can lead to a significant increase in return on investment. This is because the impact of extreme weather in the area is often not significant and can be mitigated through human intervention.
- **Scenario 3:** Located in a region with a low risk factor, where extreme weather is not a year-round occurrence or, if it does occur, the return on investment grows slowly due to its minimal impact on society.

Based on the above analysis, we propose a logistic regression optimization model [8], which is based on the following formula:

$$y = \frac{e^{2x-5}}{e^{2x-5}+1} \tag{9}$$

Based on the above findings, the research team graphed the relationship between return on investment and risk factor, as depicted in the figure below:

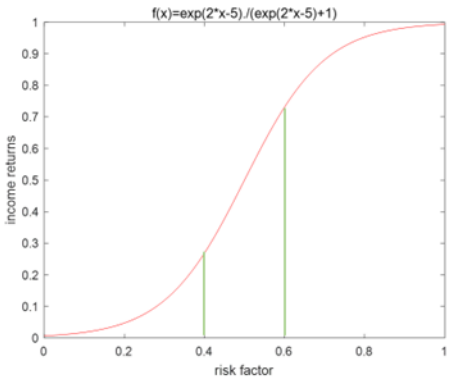


Figure 17: Input-Return Growth Curve

After normalizing the risk coefficients, we divide the intervals into three categories: [0, 0.4), [0.4, 0.6), and [0.6, 1]. If the preferred city falls in the first interval, it is recommended to reduce the building reinforcement investment and ensure profits. If it falls in the second interval, it is advisable to invest in reinforcing the building within the profit-allowed range to achieve maximum return on earnings. In the third interval, it is important to focus on basic disaster prevention measures for the building. Too much investment in the prevention and treatment of mega-disasters may yield little results and greatly reduce the profit space.

The following chart displays the ranking of different U.S. states based on EWM-Topsis scoring. A higher ranking indicates that builders are more likely to consider developing projects in that location, as it can handle extreme weather conditions, cater to the needs of a growing population, and offer a diverse range of complementary community services.

Table 3: the rank of state

State	score	rank
Minnesota	0. 0378617	1
North Dakota	0. 036595644	2
South Dakota	0. 035387127	3
Wisconsin	0. 034476226	4
Montana	0. 03296886	5
Alaska	0. 029542787	6
Texas	0. 028899398	7
Wyoming	0. 028690233	8
Colorado	0. 02709972	9
Missouri	0. 026902781	10

The analyzed areas for building are Minnesota, North Dakota, and South Dakota.

A review of the risk factor maps shows that all three areas are pleasant places to live, with high levels of urbanization and GDP per capita, so there is no need to invest too much in building reinforcement in these three states.

6 Model III: Fuzzy Integrated Evaluation Protection Model

6.1 Construction of Fuzzy Comprehensive Evaluation System

In the fuzzy comprehensive evaluation, three sets are introduced:

Factor set (set of evaluation indicators): a collection of all the influencing factors, denoted as:

$$U=\{u_{1,}u_2\cdots,u_n\}$$

Set of judgments (results of evaluations): Different grades are often formed as each indicator is assessed at a different value. The set of different verdicts is denoted as:

$$V=\{v_1,v_2,\cdots,v_m\}$$

Weight set (weights of the indicators): In general, the factors in the factor set play different roles in the comprehensive evaluation. The results of the comprehensive evaluation are not only related to the evaluation of the factors but also rely to a large extent on the role played by the factors in the comprehensive evaluation. This requires the determination of a weight distribution among the factors, which is a fuzzy vector on U, denoted as:

$$A=[a_1,a_2,\cdots,a_n]$$

where a_i represents the weight of the ith factor and meets the condition: $\sum_{i=1}^{n} a_i=1$.

According to the problem analysis, we can consider the set of relevant factors influencing building protection as a factor set. "Yes" and "No" are considered as categories in the rubric set, and weights are assigned to each factor.

The fuzzy comprehensive evaluation problem involves selecting an optimal program by considering the objects in the domain as a set of rubrics corresponding to the rubric set of a formulated rubric or program.

Therefore, based on the above inference, it can be observed that it fulfills the definition of fuzzy comprehensive evaluation. Thus, we can create a fuzzy comprehensive judgment matrix: for each indicator, the degree of association with each domain is a fuzzy subset of the above. The indicator's judgment is documented as:

$$R_i = [r_{i_1}, r_{i_2}, \cdots, r_{i_m}]$$

The fuzzy comprehensive judgment matrix of each index is:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix}$$

It is a matrix of fuzzy relationships from u to v.

Suppose there is a fuzzy relation from u to v:

$$R = (r_{ij})_{n \times m} \tag{10}$$

A fuzzy transformation can be obtained using the relation R:

$$T_R : F(U) \rightarrow F(V) \tag{11}$$

The resulting transformation yields the combined judgment result B:

$$B = A \cdot R \tag{12}$$

The synthesized judgment can be viewed as a fuzzy vector, denoted as:

$$B = [b_{1,} b_2, \cdots, b_m]$$

If $\max\{b_1, b_2, \cdots, b_m\} = b_k$, The object to be evaluated should be divided into the category of comment k.

6.2 The Solution of Model III

Based on the above reasonable assumptions and modeling process, the steps to solve the problem are as follows:

First, determining the set of factors: we considered the probability and intensity of risk(u_1), cultural and historical values(u_2), community identity and emotional ties(u_3), economic values and community development(u_4), and physical conditions and preservation costs(u_5). These factors are denoted as:

$$U = \{u_1, u_2, u_3, u_4, u_5\}$$

Second, determine the set of rubrics: protection needed (v1), protection not needed (v2), notated as:

$$V = \{v_{1,} v_2\}$$

Third, determining the weight of each factor: According to the hierarchical analysis method, the weight of each factor is determined as follows: the probability and intensity of risk are weighted as a_1, cultural and historical values are weighted as a_2, community identity and emotional ties are weighted as a_3, economic values and community development are weighted as a_4, and physical conditions and the cost of protection are weighted as a_5. These weights are recorded as:

$$A = [a_1, a_2, a_3, a_4, a_5]$$

The table below shows the relevant rubrics for each factor:

Table 4: Importance Evaluation Form

1	equal importance
3	slightly important
5	clearly important
7	overriding importance
9	extremely important
2, 4, 6, 8	medium value

By comparing the factors on a one-to-one basis in terms of importance, the following table was completed based on the importance assessment:

Table 5: Importance matrix

	u_1	u_2	u_3	u_4	u_5
u_1	1	3	7	5	4
u_2	0. 33	1	5	3	2
u_3	0. 14	0. 2	1	0. 25	0. 2
u_4	0. 2	0. 33	4	1	0. 5
u_5	0. 25	0. 5	5	2	1

Select the weights obtained using the eigenvalue method, The actual form of the matrix A is as follows.:

$$A = [0.4863, 0.2267, 0.0402, 0.0971, 0.1497]$$

Finally, determining the fuzzy composite judgment matrix:the researcher assigned a default score of 10 to the factors.

- Affiliation functions include risk probability and intensity, cultural and historical values, community identity and emotional ties, and economic values and community development:

$$\mu_A = \frac{x}{10} \tag{13}$$

- Affiliation functions for physical conditions and protection costs:

$$\mu_B = 1 - \frac{x}{10} \tag{14}$$

The construction of the affiliation function reveals that the affiliation functions of the five factors have been positively normalized. This means that the greater the degree of affiliation, the more protection is required.

The specific form of the fuzzy judgment matrix we obtained is as follows:

$$R = \begin{pmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \\ r_{31} & r_{32} \\ r_{41} & r_{42} \\ r_{51} & r_{52} \end{pmatrix} \tag{15}$$

Determine the comprehensive evaluation results: $B = A \cdot R = [b_1, b_2]$

If $\max\{b_1, b_2\} = b_1$, the object to be evaluated, is classified according to a rubric. Otherwise, protection is not required.

6.3 Model Application and Results

The research team chose Independence Hall in Pennsylvania. The researchers applied an insurance model to assess the risk in the area and to determine the fundamental factors at play in the area. By applying the protection model constructed in Section 6.2, we obtained the matrix for assessing the affiliation of each factor. According to the relevant conclusions in section 6.2, the specific form of the A matrix is derived.

Based on the ratings from relevant experts, the researchers systematically analyzed the significance of five landmarks (Pennsylvania Independence Memorial, Statue of Liberty in New York, Washington Monument, Wyoming State Capitol, and California Lighthouse). According to the relationship between the comprehensive judgment results, the weights assigned to the decisions, and the landmark affiliations in section 6.2, the final judgment scores for each landmark were obtained, as shown in the table below:

Table 6: Final judgment scores for each landmark

Region	b1	b2
Pennsylvania Independence Memorial	0.6416	0.3584
Statue of Liberty in New York	0.6085	0.3915
Washington Monument	0.5567	0.4433
Wyoming State Capitol	0.5265	0.4735
California Lighthouse	0.635	0.3665

It is evident that the all survey landmarks need to be protected. The preservation efforts will commence with the Pennsylvania Independence Memorial, followed by the California Lighthouse, then the Statue of Liberty in New York, then the Washington Monument, and finally the Wyoming State Capitol.

7 Sensitivity Analysis

In the Realtor Model realtor model, to verify the effectiveness of the EWM-topsis algorithm, we conduct a sensitivity analysis for the key indicator risk factor. By changing the weights of the riskiness of the key influencing factor areas, we observe the changes after the EWM-topics ranking. Here we selected the top five states among all states in the U.S. for testing and found that the top five rankings remain almost unchanged in the range of weights from 0.4 to 0.7, and the ranking order gradually changes abruptly after 0.4 because the weights of the key factors' riskiness have declined to the extent that they affect the global judgment. However, within a reasonable range of variation, our Realtor Model is considered to be robust and accurate.

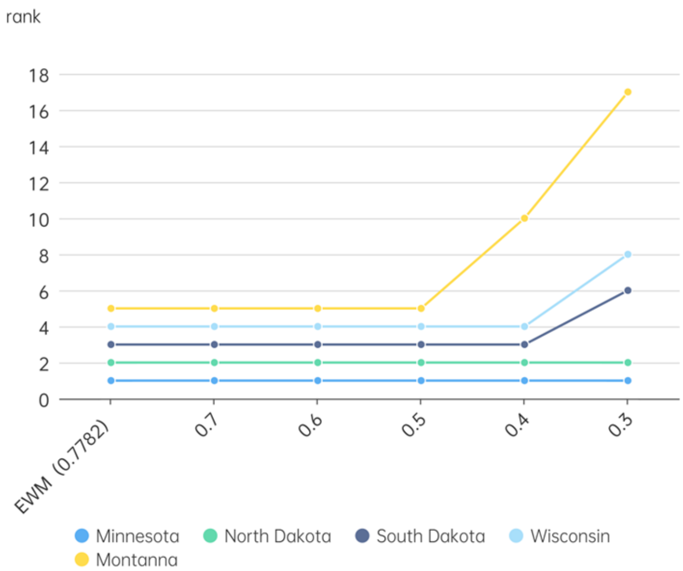


Figure 18: Sensitivity analysis of weight allocation

Changing the weights of the factors within a reasonable range, we changed the weights of the factors to $A = [0.4132, 0.3218, 0.0312, 0.0879, 0.1459]$.

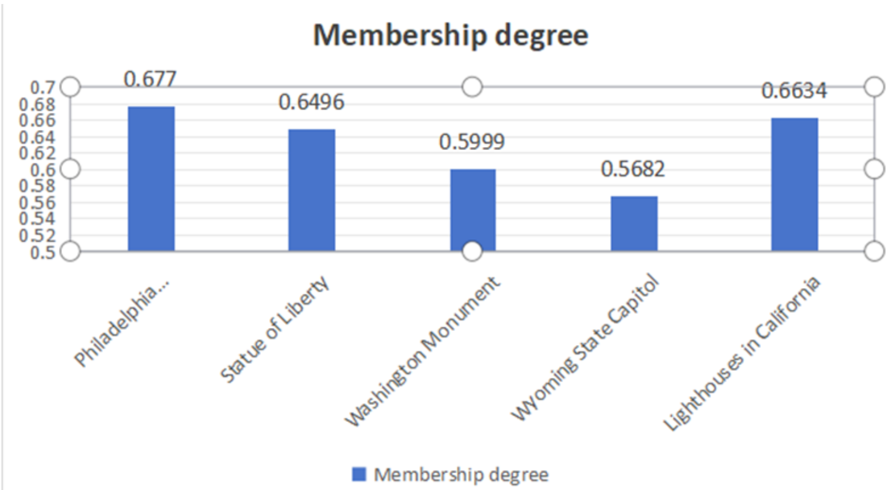


Figure 19: Sensitivity analysis on fuzzy comprehensive evaluation

As can be seen from the graph, changing the weights of the factors gives us the result that the Pennsylvania Independence Memorial, the California Lighthouse, the Statue of Liberty in New York, the Washington Monument, and the Wyoming State Capitol need to be protected; the Pennsylvania Independence Memorial is the first to be protected, followed by the California Lighthouse, then the Statue of Liberty in New York, then the Washington Monument, and lastly, the Wyoming State Capitol. The results are the same as the previous results, thus verifying that the model has good stability.

Changing the affiliation degree of each factor within a reasonable range, the affiliation degree of each factor of Pennsylvania Independence Memorial to different rubrics is modified as follows:

Table 7: Pennsylvania Independence Memorial Affiliation Chart

	Need for protection	No need for protection
Risk probability and intensity (u_1)	0. 6723	0. 377
Cultural and historical value (u_2)	0. 8675	0. 1325
Community identity and emotional ties (u_3)	0. 7632	0. 2368
Economic value and community development (u_4)	0. 8523	0. 1477
Physical conditions and protection costs (u_5)	0. 4619	0. 5381

Based on the above data, the R matrix takes the specific form:

$$R=\begin{bmatrix}0.6723 & 0.3770\\ 0.8675 & 0.1325\\ 0.7632 & 0.2368\\ 0.8523 & 0.1477\\ 0.4619 & 0.5381\end{bmatrix}$$

According to the expert evaluation, the weight of each factor in the decision:

$$A=[0.4863,0.2267,0.0402,0.0971,0.1497]$$

The composite evaluation of the rubric: $B=A\times R=[0.7062,0.3178]$

It can be seen that: the Pennsylvania Independence Memorial needs to be protected, which is the same as the previous results, the stability of the model is better.

8 Model Evaluation and Further Discussion

8.1 Strengths

- The evaluation algorithm based on EWM-TOPSIS ensures that the assignment of indicator weights is reasonable and effective.
- The Adam algorithm can converge quickly and is suitable for large-scale data sets and models.
- The fuzzy comprehensive evaluation method considers the influence of multiple factors and can provide a more comprehensive reflection of the real situation of things.
- The fuzzy comprehensive evaluation method can handle uncertainty and ambiguity. In reality, many things are ambiguous and cannot be precisely described. The fuzzy comprehensive evaluation method can address this uncertainty and provide relatively objective evaluation results.

8.2 Weaknesses

- Adam's algorithm may converge to a local optimal solution instead of the global optimal solution.

- In the process of fuzzy comprehensive evaluation, the determination of weights and the construction of a fuzzy matrix rely on the experience and judgment of experts. As a result, the evaluation results may be affected by subjective factors.

8.3 Further Discussion

Recommendations for insurance companies may vary from the modeled ideal depending on the policies and circumstances of different countries.

In this paper, we have only considered a simple input-benefit model for the "how to build" question, while the actual situation may be more complicated. In the future, we will continue to delve deeper into the theory of engineering structures and cost-benefit analysis in order to achieve continuous optimization.

9 Conclusion

The Pearson correlation coefficient between extreme weather and disasters was experimentally analyzed to be as high as 0.8. This indicates that the frequency of extreme weather can serve as a proxy for the severity of mega-disasters:

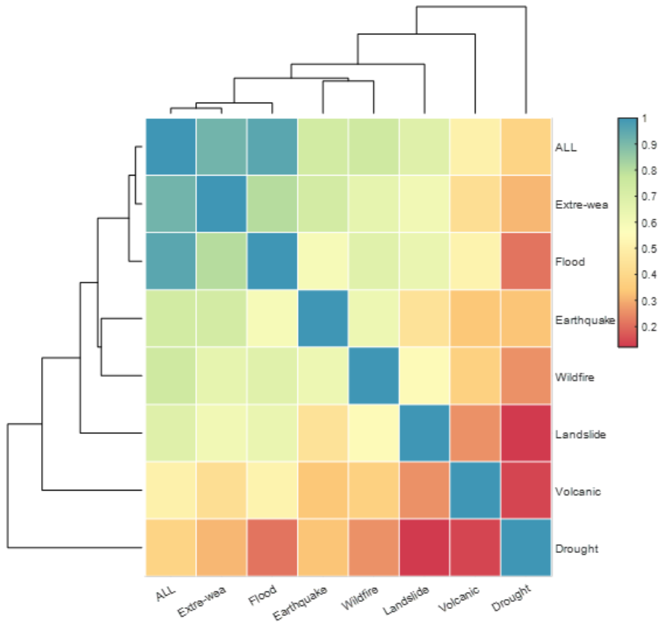


Figure 20: Heat map of correlation coefficients for different categories of extreme

In this paper, we present an insurance model for evaluating catastrophic risk that has broad practical value. We selected the 48 contiguous states in the United States as the standard database. All the data is included in the assessment insurance model. The CBP coefficients are calculated using K-means clustering. The ICU coefficients for each region are derived from the ICP coefficients, and finally, the coefficients are categorized into three intervals, which forms the insurance company's underwriting model. The states of New Jersey and Oregon were selected for evaluation to assess high-risk areas in New Jersey and low-risk areas in Oregon. Recommendations will be provided based on the analysis.

In order to effectively address real estate distress, utilized selected portion part of the ICU model for disaster risk assessment and introduced comprehensive indicators. These indicators which were using by the EWM-TOPSIS to rank ranked the states. The the top three ranked states were Minnesota, North Dakota, and Dakota. We provided giving advice reinforcing re-inforce building and encouraged encouraging real estate developers to build in these areas. Since these areas are situated in habitable zones with pleasant climates, they do not necessitate excessive reinforcement of buildings.

At the end of our study, we utilized a fuzzy integrated evaluation model to identify the most deserving landmark, the Pennsylvania Independence Memorial, and provided recommendations and timelines for the community to effectively preserve this historic and unique building.

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Watching over each other: Preserving the common landmarks

Dear Community Members,

As researchers in the catastrophe insurance and related industries, and considering the impact that precious landmarks have on a community's ability to cope with extreme weather, the research team writes this letter and proposes future plans, a timeline, and cost recommendations to the community regarding precious landmarks.

Figure 1: State House

First, the research team will address the development and implementation of a plan for the landmarks of the community. Researchers plan to use the reinforcement of precious landmarks to resist the damage of extreme climate to a lesser extent, to minimize the loss and protect the integrity of the precious landmarks. We also plan to use the relocation of the precious landmarks to the areas which are free from the extreme climate or less affected by the extreme climate, to better protect the precious landmarks.

Second, the research team set the threshold of the risk factor, obtained the future risk factor through the risk prediction of the areas where different valuable landmarks are located, and based on the prediction results, identified in advance the year when the threshold of the risk factor would be reached, to determine by which year the restoration plan of the valuable landmarks would be perfected. The specific timeline is shown in the table below:

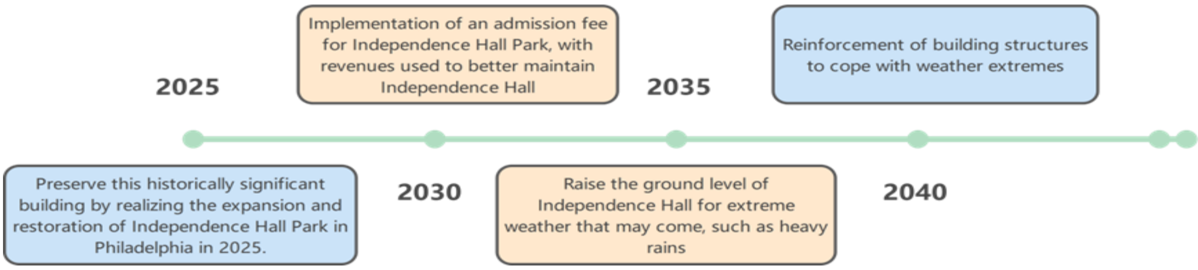

Figure 2: The timeline of landmarks

Finally, based on the analysis and study of the problem, the research team puts forward a cost proposal: before reaching the threshold of the hazard factor, combining the local economic impacts and maintenance costs of the precious landmarks before and after their relocation, judging how many years in the future they will be repaired and perfected before relocating them. For some valuable landmarks, even though the risk factor has not reached the risk factor threshold, the sum of the maintenance costs will be greater than the cost of relocation in the next few years, and the research team suggests relocating the landmarks immediately to reduce the cost.

The research team firmly believes that with the joint efforts of the community workers and the research team members, the precious landmarks can be properly preserved, and the quality of the community can be pushed forward with the least amount of time and cost. In the end, the glorious fruits of community work and construction will be harvested!

Sincerely,

Team #2401748