A Study of Insurance Company Underwriting Strategies Based on TOPSIS Entropy Weights and Cost-Benefit Analysis

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Abstract. Frequent extreme weather events triggered by climate change pose an increasing risk to property owners and insurance companies. To address this challenge, this paper explores how to optimize resource allocation strategies for property insurance with the aim of improving the ability of the insurance system to pay future claims while safeguarding the long-term stability of the company. In order to give an underwriting strategy for disaster-prone areas, the number of natural disasters, the number of people affected, and the economic losses are screened as key influencing factors. Subsequently, TOPSIS entropy weighting analysis was used to assign appropriate weights to these factors, and the K-mean algorithm was used to cluster these data into low, medium, and high-risk levels. To more accurately assess underwriting risk, I constructed an underwriting risk assessment model using cost-benefit analysis. Applied to the U.S. and Switzerland, the scores were 0.49 and 0.02, respectively. This suggests that the U.S. is a high-risk country and cannot be insured, while Switzerland is in a low-risk area and can be insured.

Keywords: TOPSIS Entropy Weights, Cost Benefit Analysis, Underwriting Strategy.

1. Introduction

In recent years, extreme weather events have occurred all over the world, which poses a great threat to the safety of property owners and insurance companies Weather disasters, such as hurricanes, floods, droughts, snowstorms, and wildfires, usually lead to many proper-ty losses and casualties These losses are often covered by various insurance policies, such as real estate insurance, vehicle insurance, agricultural insurance, etc., which leads to many claims for insurance. Insurance may have to pay huge compensation after extreme weather events, which directly affects its financial situation. The study found that natural disaster claims increased by 115% in 2022 "compared with the 30-year average [1]." Damages from severe weather events such as hurricanes, floods, droughts, snowstorms, and wildfires may be expected to get worse Due to the impact of climate change, insurance costs are expected to increase by 30-60% by 2040[2].

With extreme weather events and intensity insurance may reassess its risk model and premium rates accordingly In high-risk areas, insurance costs may increase significantly to reflect higher risk levels This rate may cause the cost of insurance coverage to affect consumers' willingness and ability to buy insurance So the change of insurance coverage and the place of coverage property insurance is not only more expensive but also more difficult to find Weather-related events continue to drive the cost of property insurance, depending on where you are in the world In addition, the global insurance coverage gap averages 57% and is still there. This highlights the serious impact climate change is having on the insurance market, which involves the whole process from primary insurance reinsurance to insurance-linked securities. The sharp catastrophe risk has brought challenges to these levels.

To explore how to optimize resource allocation strategies for property insurance, we first collected global data on the impact of natural disasters caused by extreme weather, screened out the number of occurrences of natural disasters, the number of people affected, and economic losses in the three aspects of ecology, society, and economy for correlation analysis, and then carried out entropy weighting analysis of the TOPSIS, and then clustered the resulting composite scores to get the different risk levels by using the K-means algorithm, and then finally used the cost-benefit analysis method to establish a risk assessment model to assess underwriting risks.

2. Determination of risk level assessment indicators

2.1. Ecological

The increase in extreme weather events due to climate change has a direct impact on the type and extent of risks underwritten by the insurance industry. For example, climate change increases the number and intensity of natural disasters, such as floods [3], droughts [4] and hurricanes [5], resulting in a higher risk of claims for insurance companies. Therefore, the ecological impact on underwriting risk cannot be ignored.

We primarily represent ecology as an indicator for risk level assessment by applying the number of natural disaster occurrences in each region. By arranging the collected data in chronological order, it is possible to analyze the number of occurrences of natural disasters in a given country. With the help of ArcGIS, we show the severity of natural disasters around the world, as shown in Figure 1.

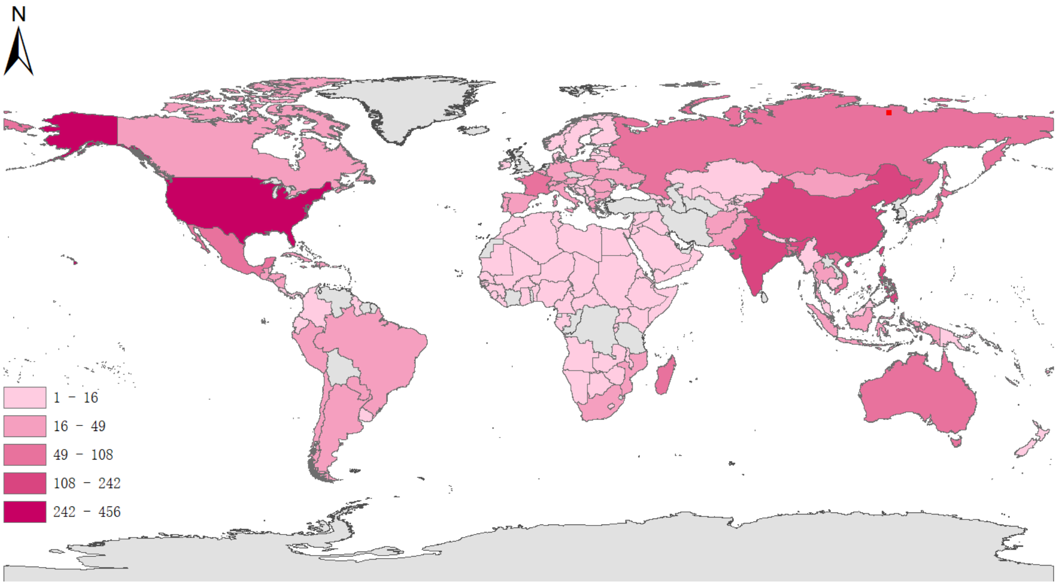

Figure 1. Disasters' Frequency

2.2. Social

Social factors such as social change, demographic change, and increased public awareness of risk affect insurance demand and underwriting risk. Moreover, public concern about natural disaster risks may increase the purchase of related insurance products. One of the most direct impacts of natural disasters is to cause human casualties. Disasters such as earthquakes [6], floods, typhoons [7], and droughts can lead to many deaths and injuries. Therefore, it is also necessary for society to analyses the underwriting risk.

We have mainly adopted the total number of people affected such as deaths, injuries, and homelessness after natural disasters to represent an indicator of society's evaluation of the risk level. With the help of various visualization tools, we show the extent of the number of people affected by natural disasters globally, as shown in Figure 2.

$$P = P_d + P_i + P_h + P_a \tag{1}$$

Where P is the total number of people involved. P_d is the total number of deaths, P_i is the total number of injured, P_h is the total number of homeless, P_a is the total number of being affected by the disaster.

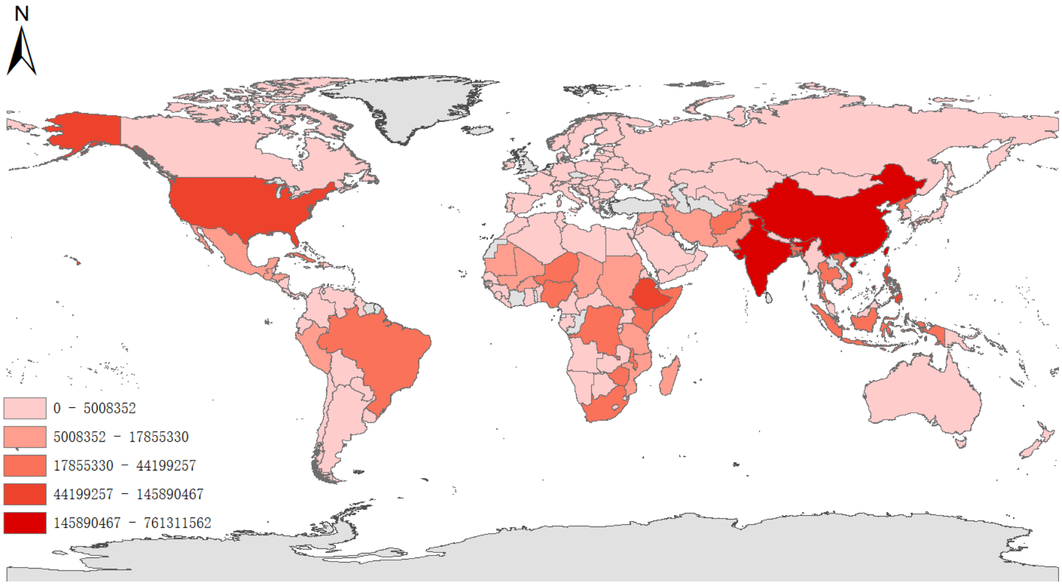

Figure 2. Number of people affected

2.3. Economic

Economic factors such as the level of economic development, industrial structure and the investment climate affect the demand for insurance and the risks underwritten [8]. When the economy is booming, asset values rise, which may increase the demand for property insurance and the associated risks. However, the higher the level of economic development, the higher the amount of loss in the event of a natural disaster, so the impact of the economy on underwriting risk is also critical.

$$E = E_i + E_r \tag{2}$$

Where E represents the total economic losses, E_i is the number of insurance damage, E_r is the cost of reconstruction.

We represent the economy as an indicator of the evaluation of the risk level through the overall economic loss after a natural disaster. With the help of ArcGIS, we show the extent of economic losses due to natural disasters around the world, as shown in Figure 3.

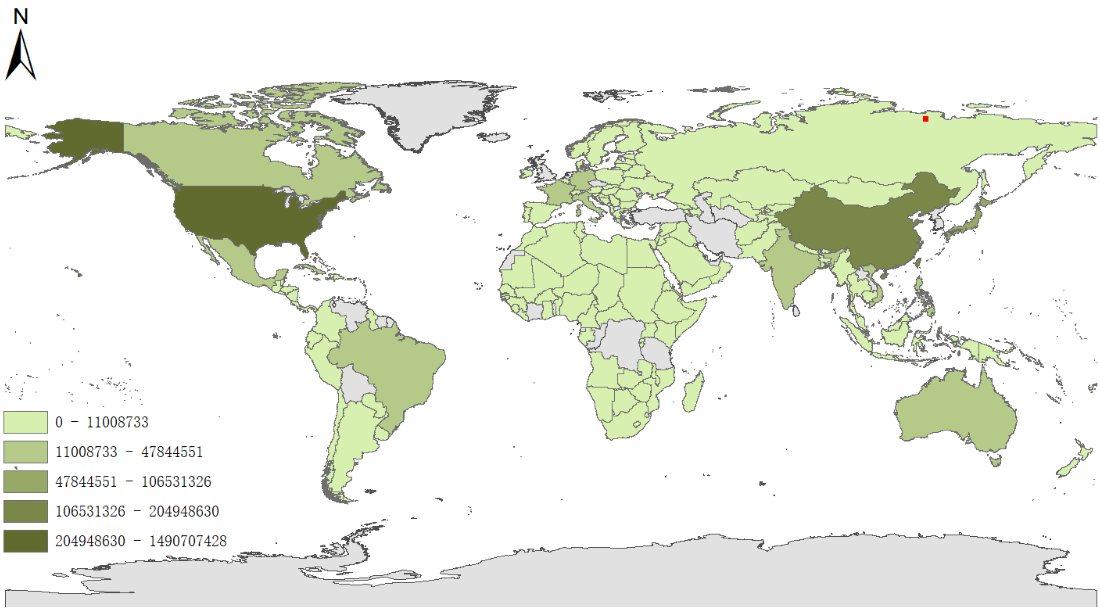

Figure 3. Economic losses

3. Modelling of risk level assessment

3.1. Data pre-processing

We firstly did correlation analysis on the data, the correlation coefficient of the three indicators of the number of natural disasters, the number of people affected and the economic loss are lower than 0.513, the correlation is very low, so we used the TOPSIS entropy weighting algorithm to analyses the weights of the three indicators of the number of natural disasters, the number of people affected and the overall economic loss. the principle of the TOPSIS entropy weighting algorithm is shown in Figure 4.

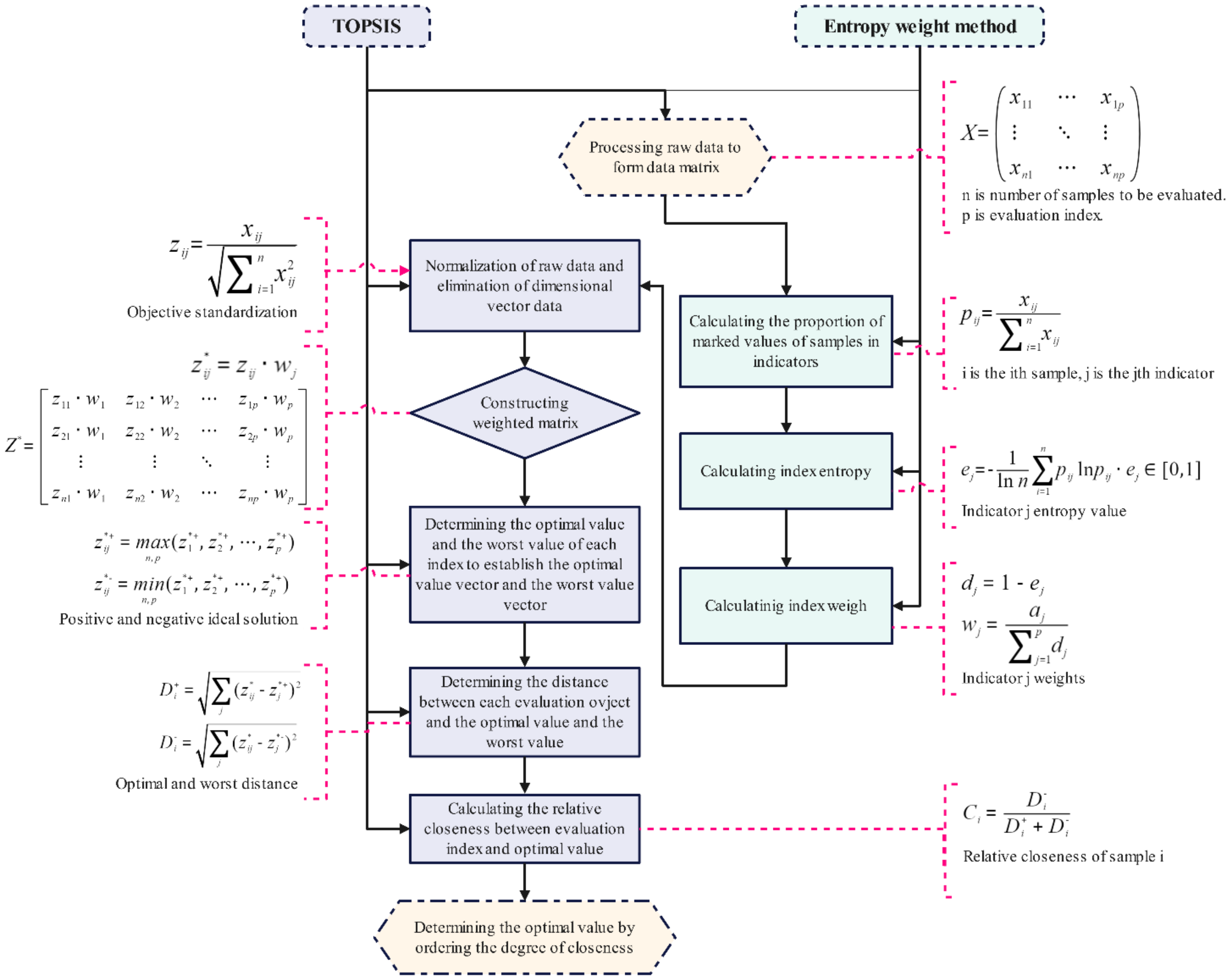

Figure 4. Principle of TOPSIS entropy weight method

Since the three indicators involved in the indicators of this paper, namely the number of natural disasters, the number of people affected and the overall economic loss, are all positive indicators, the extreme value method is adopted to measure the standardized value of each working indicator, and the formula is as follows [9]:

$$X_{ij} = \frac{X_{ij} - min(X_j)}{max(X_{ij}) - min(X_j)} \tag{3}$$

3.2. Weight analysis

The maximum and minimum values of each evaluation queue in the data of each index that has been normalized in the previous entropy value process are counted as the optimal solution Z^- and the worst solution Z^+ respectively, and the positive and negative ideal solution distances D_j^+ and

D_j^- are calculated by calculating the distance of each evaluation index to the optimal solution and the worst solution in the corresponding queue, and then the relative proximity C_i value is calculated. When the relative proximity value is higher, the evaluation object is closer to the ideal value, and the evaluation result is correspondingly better.

Therefore, the TOPSIS method can be used as the basis for judging the advantages and disadvantages. After the comprehensive score was clustered and graded according to the order of C_i value, SPSS software was used to conduct one-way ANOVA, and $P < 0.05$ was set as the difference was statistically significant. Considering the weight difference of each evaluation index in the comprehensive score, this paper adopts the weighted TOPSIS method for comprehensive evaluation [10]. The formula is:

$$\boldsymbol{D_j^+} = \sqrt{\sum_{j=1}^{m} \boldsymbol{W_j}(\boldsymbol{Z_{ij}} - \boldsymbol{Z_{ij}^+})^2} \tag{4}$$

$$\boldsymbol{D_j^-} = \sqrt{\sum_{j=1}^{m} \boldsymbol{W_j}(\boldsymbol{Z_{ij}} - \boldsymbol{Z_{ij}^-})^2} \tag{5}$$

$$\boldsymbol{C_i} = \frac{\boldsymbol{D_j^-}}{\boldsymbol{D_j^+} + \boldsymbol{D_j^-}} \tag{6}$$

The weights of the indicators obtained are shown in Table 1:

Table 1. Ecological, social and economic weightings

Dimension	Factor	Weight
Ecology	Number of natural disasters	0.24631
Society	Number of people affected	0.34446
Economy	Economic loss	0.40923

All CR were tested to be <0.10 and the consistency of the judgement matrix A was acceptable.

3.3. Risk classification

For the three indicators described above, we used a metric formula to factories them into a consistent evaluation criterion,

$$E_m = \frac{I_m}{I} \times 100 \tag{7}$$

Where I_m denotes the actual value of factor m and I denotes the value of factor m in the whole region. For example, the economic loss is the annual economic loss in the selected region divided by the sum of the annual economic losses in the local and other regions.

We chose a representative global data for our study because it spans a wide range. The composite score was categorized into 3 classes by clustering the dataset into 3 clusters using the K-means algorithm. Here, we output a scatterplot of the composite score:

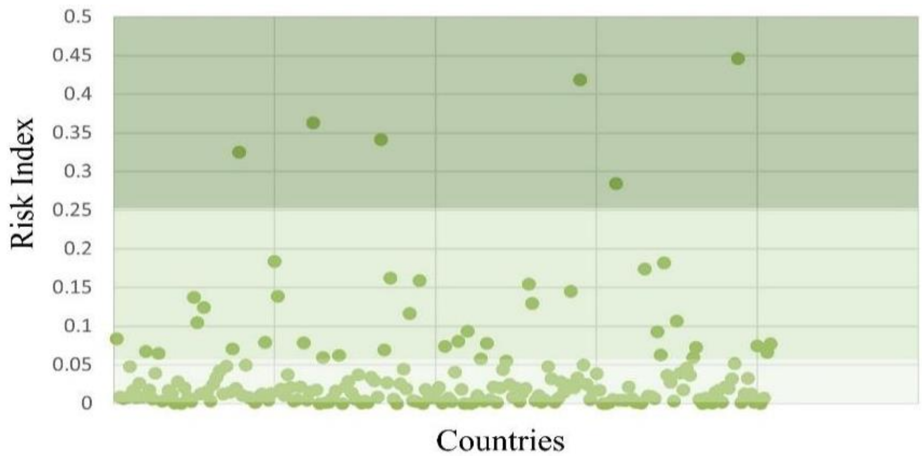

Figure 5. Scatter plot of risk levels

As shown in Figure 5, the risk classes can be divided into three categories, namely low risk, medium risk and high risk.

The RI (Risk Index) of the first risk class is 0~0.06, that is, low-risk areas, which can be widely underwritten;

The RI of the second risk class is 0.06~0.26, that is, medium-risk areas, which have a certain degree of risk, and can be underwritten according to a reasonable ratio.

The RI of the third risk class is 0.26~0.5, that is, high-risk areas, which have a relatively high risk and need to be denied coverage according to the actual situation. The third risk class has an RI of 0.26~0.5, which is a high-risk area, and the risk of this class is relatively high, so it needs to be denied coverage according to the actual situation.

Using the TOPSIS entropy weighting method, we get the weight of each factor in the relevant index. We can calculate the final RI and construct a comprehensive evaluation model. It has the following form:

$$RI = 0.24631 \times RI_{Ecology} + 0.34446 \times RI_{Society} + 0.40923 \times RI_{economy} \tag{8}$$

3.4. Cost-benefit economic models

Let the purpose of the project be the underwritten profit W, which is determined by the difference between the underwritten income x and the economic loss compensation y by the following formula:

$$W = \alpha x - \beta y \tag{9}$$

$$\alpha = 1 - \beta \tag{10}$$

Where underwriting income x and economic loss compensation y are the standardized average of underwriting income x and economic loss compensation y for the last five years in the future according to the time-series forecasting model; β is the risk factor. According to the insurance compensation standard, the relationship between β and RI is shown in Table 2:

Table 2. Relationship between β and RI

β	RI
0.01	0~0.06
0.10	0.06~0.26
0.20	0.26~0.5

According to the underwriting risk assessment model, when the profit $W < 0$ indicates that the insurance company will have economic losses, and should not choose to underwrite the policy, when the profit $W > 0$ indicates that the policy can be profitable, that is, the policy can be underwritten.

Because the relevant factors of the regional risk level assessment model in the underwriting risk model are the number of people affected and the economic loss, so the owners can do a good job of defense in these two aspects, such as building houses more firmly, so that the economic loss caused by the occurrence of natural disasters is greatly reduced, or to improve the owner's self-preventive consciousness, to establish some disaster prevention and mitigation measures, and to set up a disaster early warning, which can reduce the RI.

Therefore, homeowners can influence RI through their own defence measures, which in turn can influence the insurance industry's underwriting decisions.

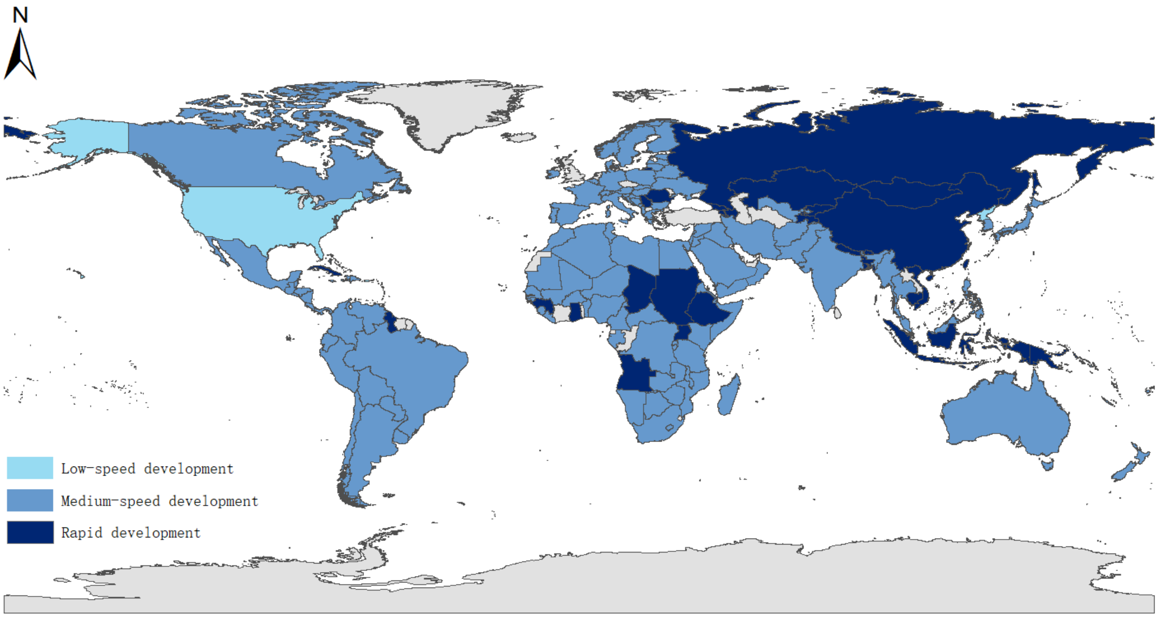

Figure 6. Global distribution of low, medium and high-risk areas

As shown in Figure 6, different shades of blue are used to indicate the risk level of individual countries and regions. Light blue represents low-risk areas, medium blue represents medium-risk areas and dark blue indicates high-risk areas. The distribution of colors on the map suggests that Europe and Oceania are generally at low risk, while the Americas and Asia are relatively high.

4. Model Demonstration

We selected disaster data for the United States and Switzerland for the period 2000-2023, with information on losses due to natural hazards in both countries over a period of more than 20 years, as shown in Figure 7.

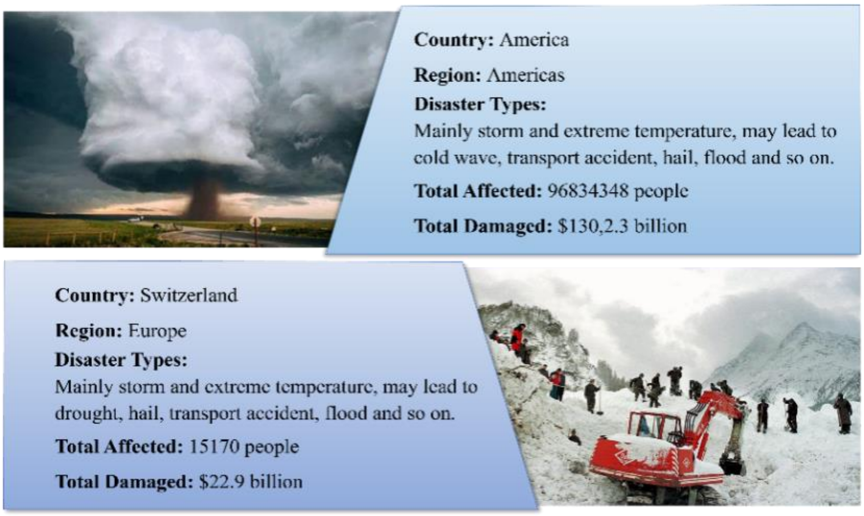

Figure 7. Disaster data for the United States and Switzerland

4.1. United States

We chose the United States as the country for the model demonstration because it has a more visible climate change problem, a more developed economy, and good statistics.

Firstly, the data on the number of natural disasters, the number of people affected and the economic losses were collected, and the score using the risk level assessment constructed above was 0.49 > 0.34, indicating that the United States is in a high-risk area, i.e.

$$\beta = 0.2 \tag{11}$$

Other data were predicted using the Arima model, and the predicted benefits results in USA is shown in Figure 8.

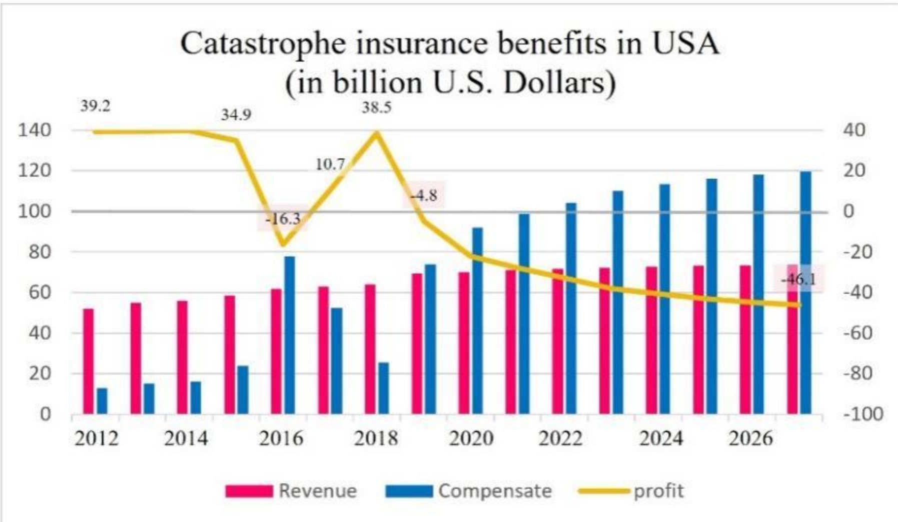

Figure 8. Forecasts of catastrophe insurance benefits in the United States

As shown in Figure 8, economic losses are in blue, underwriting income is in red, and the yellow line is profit. Economic losses in the U.S. will continue to rise in the next few years with respect to natural disasters, and underwriting income will remain flat in the next few years. Substituting the processed data into the underwriting risk model yields a final profit of $W < 0$, indicating that the U.S. is in the range of unacceptable risk, i.e., the insurance industry should refuse to underwrite U.S. catastrophe insurance.

Currently, the United States is facing frequent and diverse natural disasters, including hurricanes, tornadoes, wildfires, and floods. 2023, the United States experienced several major events, such as

Hurricane Idalia, which caused an estimated $2.2 to $5 billion in damage in Florida, and wildfires in Hawaii, which resulted in 110 deaths and approximately $6 billion in damage.

In addition, tornado outbreaks caused significant loss of life and property damage in the southern and midwestern United States. These catastrophic events highlight the increasing frequency and intensity of extreme weather events, which pose a serious threat to the safety of people's lives and property. Therefore, the results of the modelling exercise are within reasonable limits.

4.2. Switzerland

Firstly, data on the number of natural disasters, the number of people affected, and the economic losses were collected, and using the risk level constructed above, Switzerland's score was assessed to be $0.02 < 0.10$, which indicates that the level of natural hazards in Switzerland is very small and that the country is in a low-risk area, i.e.

$$\beta = 0.01 \tag{12}$$

By using ARIMA model, a time series forecast of underwriting income and economic loss compensation for Switzerland is shown in Figure 9.

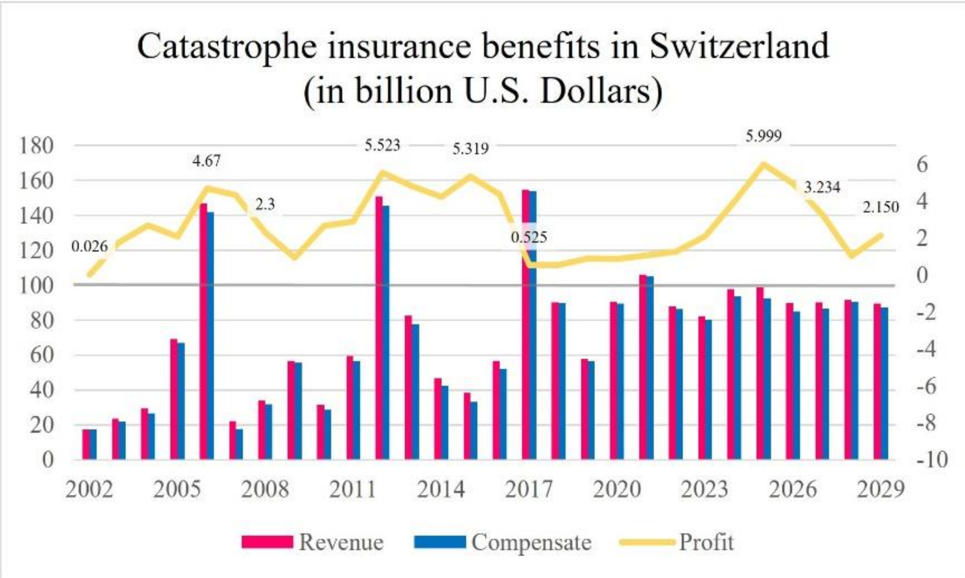

Figure 9. Forecast of Swiss underwriting income, economic losses and profits

As shown in Figure 9, economic losses are shown in blue, underwriting income in red and profits in yellow. Switzerland's economic losses in terms of natural disasters will fluctuate slightly up and down over the next few years, and the underwriting income will be relatively stable over the next few years. Substituting the processed data into the underwriting risk model yields a final profit of $W > 0$, which would indicate that it is widely acceptable for the insurance industry to underwrite catastrophe insurance in Switzerland.

The relatively low level of natural disasters in Switzerland compared to other countries is largely due to its geographical location, advanced disaster prevention techniques and efficient management measures. Although Switzerland, located in the heart of Europe, has a predominantly mountainous terrain, its unique geographical and climatic conditions, coupled with its long-standing emphasis on environmental protection and disaster prevention, have made large-scale natural disasters relatively rare.

The Swiss government and private organizations have invested a great deal of resources in disaster prevention, the construction of early warning systems and the enhancement of emergency management capabilities. For example, Switzerland has world-leading technology and experience in preventing landslides and avalanches.

In addition, the need to mitigate the effects of natural disasters is also taken into account in urban planning and building design, for example in the form of buildings that can withstand earthquakes and floods. As a result, despite natural threats such as floods, landslides and avalanches, Switzerland ensures that the damage and impacts of natural disasters are kept to a low level through effective preventive measures and emergency response mechanisms. The results of the modelling exercise are therefore within reasonable limits.

5. Conclusion

As climate change continues to intensify, the potential for more severe weather and natural disasters grows. It has therefore become critical to optimally deploy property insurance resources to increase the resilience of the insurance system. When assessing underwriting risk, we need to consider not only natural hazards as a single factor, but also delve into the intertwined impacts of natural, social and economic aspects. Their value in underwriting risk assessment should not be overlooked.

In the process of constructing the underwriting risk assessment model, we first use the TOPSIS entropy weighting method to analyze the weights of ecological, social and economic dimensions. This step aims to clarify the relative importance of each dimension in the overall risk assessment. Subsequently, based on the results of these weighting analyses, we use the K-means algorithm to cluster the resulting composite scores and classify the risks into different levels. This step helps us to identify and differentiate between the various types of risks more clearly, so that we can respond more precisely. Finally, we introduce a cost benefit analysis to conduct a comprehensive assessment of underwriting risks. This segment not only focuses on the size of the risk, but also focuses on the costs and benefits of risk response, to provide decision-makers with more informative recommendations.

Finally, we apply the model to the United States and Switzerland. The United States scored 0.49, indicating that the United States is a high-risk country and cannot be insured. Switzerland scored 0.02, indicating that Switzerland is in a low-risk area and can be insured.

References

[1] Boston Consulting Group. (2023, December 4). An Insurance Risk Framework for Climate daptation.

[2] Munich RE. (2022, January 10). Hurricanes, cold waves, tornadoes: Weather dis-asters in USA dominate natural disaster losses in 2021.

[3] Li Huiying. Research on international co-operation of flood insurance in China [D]. Heilongjiang University, 2021.DOI: 10.27123/d.cnki.ghlju.2020. 001373.

[4] XU Jinping, WANG Dandan, LIU Kun. Practice and thinking of drought weather index insurance for Anji white tea--Taking the extreme high temperature drought in 2022 as an example [J]. Jiangxi Journal of Agriculture, 2023, 35 (12): 125 - 131. DOI: 10.19386/j.cnki.jxnyxb. 2023. 12. 018.

[5] Ling Yunzhi. Study on the Development of Disaster Reduction and Recovery Mechanisms in the United States--Taking the Changes in Emergency Response to Hurricane Ian in 2022 and Hurricane Katrina in 2005 as an Example [J]. China Disaster Reduction, 2024 (03): 60 - 61.

[6] Hu Xiaofeng. On the construction of earthquake insurance system in China [D]. Liaoning University, 2012.

[7] Zhao Lingdi. Study on the Construction of Comprehensive Disaster Management Mechanism in China--Taking Storm Surge Disaster as an Example [D]. Ocean University of China, 2004.

[8] Grossi P, Muir-Wood R, Gao Fwang, et al. The 1906 San Francisco earthquake and fire: A super-catastrophe (insurance) model [J]. International Earthquake Dynamics, 2013 (03): 13 - 33.

[9] Zhang Lin, He Jiarui. Research on the evaluation of green city development level based on entropy weight-TOPSIS method: taking Jinan city as an example [J/OL]. Journal of Engineering Management: 1 - 6 [2024-03-10]. https: //doi.org/10.13991/j.cnki.jem.2024. 01. 013.

[10] Tian Yan, Shu Shihai, Ren Jianjun et al. Evaluation of mine fire hazard based on AHP-TOPSIS method [J]. Coal, 2024, 33 (02): 18 - 23.