

Research on Weather Index-Based Insurance Method Based on EMW-AHP Algorithm

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Abstract. Extreme-weather events are becoming a crisis for property owners and insurers. The world has endured “more than \$1 trillion in damages from more than 1,000 extreme-weather events in recent years.” However, by classifying the risk caused by extreme weather with weather index, weather index-based insurance method can be interesting for both property owners and insurers. This paper investigates the construction of the weather index-based insurance method following the example of two cities that experience extreme weather. This investigation is based on weather situation data form 40 different cities. Furthermore, In this paper, EWM-AHP algorithm is used to process the data, so as to construct the weather index-based insurance method. The results show that the regional weather risk can be divided into four levels according to the weather index calculated by equation given in the insurance method.

Keywords: EMW-AHP, Weather index, extreme weather, risk classification.

1. Introduction

Extreme weather events, intensified by climate change, pose unprecedented challenges to the insurance industry. There is an urgent need for mathematical tools to assess and respond to systemic risks brought about by climate disasters. Curcio and colleagues^[1] innovatively applied the Wilcoxon signed-rank test to evaluate how U.S. banking and insurance systemic risks react to climate catastrophes, highlighting a significant increase in systemic risk on the day of a disaster compared to h days prior^[2].

While Yang Zihui's study^[3] offers valuable insights into the impact of climate risks on China's financial markets, focusing on physical and transition risks, its scope is limited to Chinese data and specific risk types, affecting its global applicability. Both Curcio's and Yang's research, though valuable, fail to fully explore the underlying mechanisms of climate risks, constraining a comprehensive assessment of their impact on global financial markets.

To overcome these constraints, a groundbreaking method is proposed: the Weather Index-based Insurance Method, which employs the EMW-AHP Algorithm^[4]. This approach is designed to enhance the financial sector's grasp of the losses caused by climate change and to aid in crafting effective mitigation strategies. By integrating a sophisticated algorithm with a tailored insurance method, the financial industry can better anticipate and respond to the economic repercussions of climate-related events, thus bolstering its resilience against the uncertainties of a warming world.

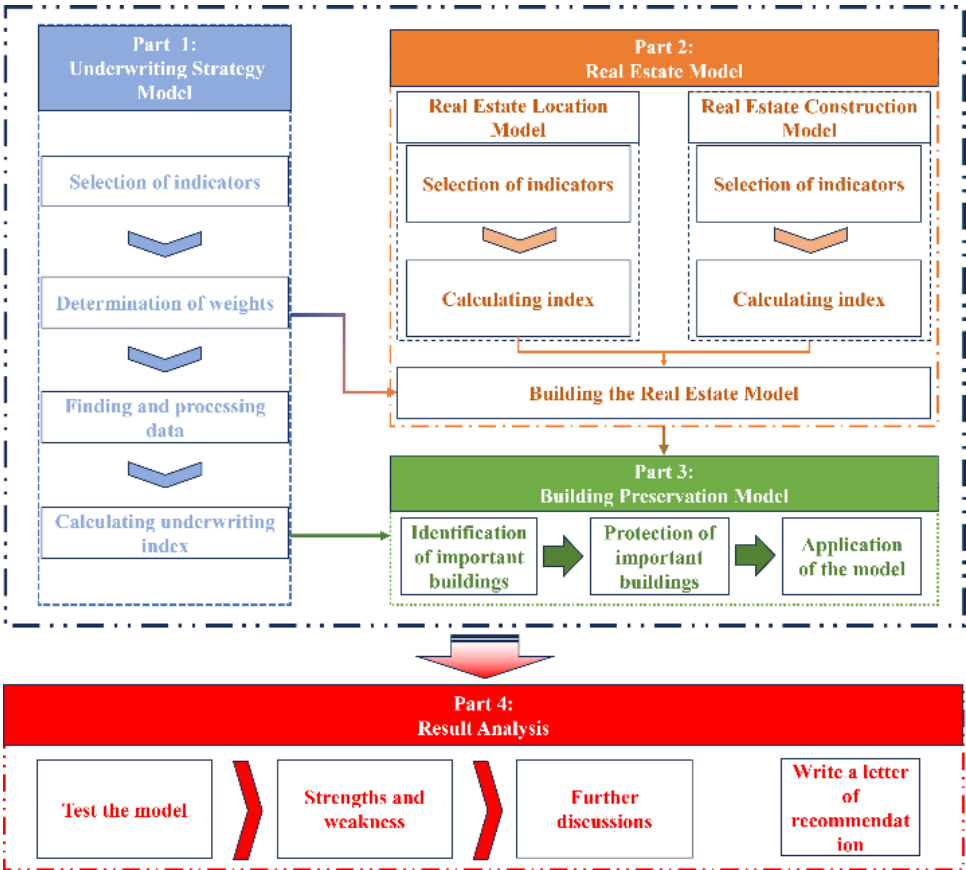


Figure 1. Flow Chart of the Work

2. The construction of index-based insurance method

For the sake of brevity, the main flow of this article is illustrated by Figure 1.

2.1. Indicators Determination

Through the review of related literature, the research choose natural climate conditions, social conditions, and economic conditions as the primary indicators. Then 10 representative secondary indicators are selected to construct the model. The index system constructed is shown in Figure 2.

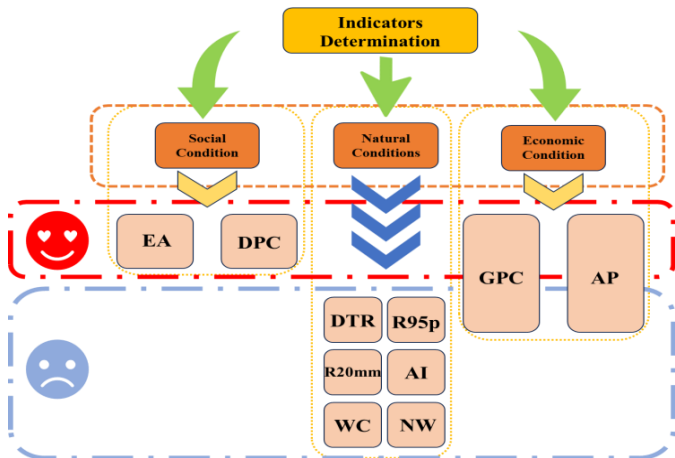


Figure 2. Types of Roles for Different Indicators

The meaning of each of these important indicators is as follows:

- a) Natural Climatic Conditions
 - Daily temperature range(DTR)

The occurrence of extreme weather events is generally recognized as having a significant relationship with the magnitude of local temperature variations^[5]. Due to the large magnitude of temperature change, many extreme weather events^[5] (e.g. heavy rainfall) may be induced. For this reason, the daily difference in temperature (DTR) was used as an indicator to measure the local natural climatic conditions using the available data. Its formula is as follows:

$$DTR = d_{\max} - d_{\min} \quad (1)$$

Where $d_{\max}$ and $d_{\min}$ are the daily maximum and minimum temperatures.

- Total heavy precipitation, Number of days of extremely heavy rain(R95p,R20mm)

The occurrence of extreme weather events, such as floods, is closely linked to sudden heavy precipitation and its frequency^[6]. Thus, the research measure this using the total amount of heavy precipitation (R95p) and the number of days with extremely heavy rainfall (R20mm).

- Aridity index(AI)

Drought, as part of the natural climate of a region, is determined by both rainfall and evaporation. The degree of aridity of a region can be a good description of the natural climatic conditions of the region^[7], so the research use the de°Martonne dryness index calculation method with the formula:

$$l_{dm} = \frac{p}{T + 10} \quad (2)$$

where l_{dm} is the de°Martonne dryness index, p is the average precipitation (mm), and T is the average temperature (°C).

- Number of windy weather days(WC)

Sustained windy weather is a prerequisite for the occurrence of extreme weather, such as hurricanes, in the vast majority of regions, with a certain positive correlation trend between them^[8]. Therefore, the research use the indicator of the number of windy weather days to measure the natural climatic conditions.

- Number of wildfires(NW)

As one of the natural hazards most affected by climate change, wildfires are a large measure of a region's natural weather conditions' risk to insurers. For this reason, the research use the number of wildfires as one of the indicators.

b) Social Condition

- Educational attainment(EA): Years of education per capita

The level of education of residents has a great impact on the disaster prevention capacity of a region. According to China's natural disaster economic losses and national education years per capita from 2010 to 2019. The paper plotted Figure 3 and calculated the Spearman correlation coefficient between them as -0.7091, indicating a negative correlation. Therefore, years of education per capita was used as an indicator to represent the educational level of the population.

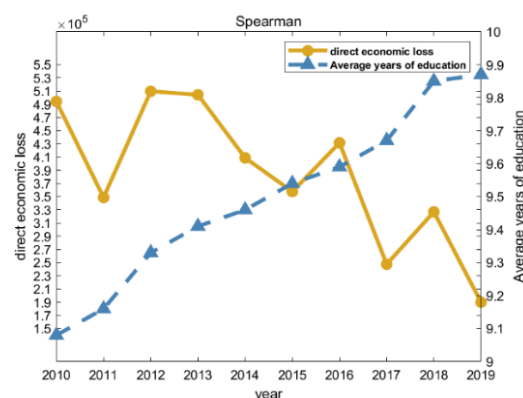


Figure 3. Spearman analysis of economic losses from natural disasters and years of schooling per capita in China

- Disaster prevention capacity(DPC): Building resilience

A society's disaster resilience is determined by many factors, the main one being the average disaster resistance of buildings. According to existing research^[9], disaster prevention capacity can be expressed as the disaster resilience index of a building.

- c) Economic Condition

- GDP per capita(GPC)

In the same disaster situation, regions with higher GDP per capita tend to suffer greater economic losses due to higher levels of consumption^[10]. This results in a greater amount of claims, so GDP per capita was chosen as an indicator to measure the economic conditions of the region.

- Average premium(AP)

Different regions tend to have some disparity in premiums due to different likelihood of disaster and different levels of economic development. Higher premiums provide insurers with considerable profit opportunities while posing risks, making this indicator a useful measure.

2.2. Calculation of the weather index

Firstly, Due to the different types of selected indicators, The investigation first need to process the corresponding data. For cost-type indicators:

$$\tilde{x}_{ij} = \max\{x_i\} - x_{ij} \quad (3)$$

The data for the different indicators are then standardized so that they can be compared on the same scale. The standardization formula is as follows:

$$\tilde{z}_{ij} = \frac{x_{ij} - \min\{x_i\}}{\max\{x_i\} - \min\{x_i\}} \quad (4)$$

Secondly, For the resulting normalized data, the research will use the entropy weighting method to calculate the weights of each indicator. Firstly, the information entropy of the j-th indicator is calculated using the following formula:

$$p_{ij} = \frac{\tilde{z}_{ij}}{\sum_{i=1}^n \tilde{z}_{ij}} \quad (5)$$

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln(p_{ij}) \quad (6)$$

Based on the information entropy obtained above, the research can further calculate the entropy weight of each indicator with the following formula:

$$W_j = \frac{1 - e_j}{\sum_{j=1}^m (1 - e_j)} \quad (7)$$

Through calculations, the weights of the secondary indicators are obtained, and the results are shown in Table 1.

Table 1. Weighting of the Secondary Indicators

Primary Indicator	Secondary Indicator	Weight
Natural Climatical Conditions	DTR	0.019
	R95p	0.077
	R20mm	0.152
	AI	0.057
	WC	0.118
	NW	0.577
Social Condition	EA	0.545
	DPC	0.455
Economic Condition	GPC	0.520
	AP	0.480

Then, in order to calculate the weights of the first-level indicators and thus obtain the district's underwriting index, the research constructed a judgment matrix using the Analytic Hierarchy Process (AHP) and calculated the weights of the first-level indicators as:

$$\delta = (0.4764, 0.3091, 0.2145) \quad (8)$$

where the consistency ratio of the judgment matrix is 0.074, which is within the acceptable range.

From there, the research have an Underwriting Index score of:

$$score = \delta_1 \cdot score_{nature} + \delta_2 \cdot score_{society} + \delta_3 \cdot score_{economy} \quad (9)$$

2.3. Risk level classification

To more clearly and intuitively reflect the magnitude of risk underwritten in a region, the paper have established a risk level model and an evaluation mechanism as shown in Figure 4, based on the weather index for grading.



Figure 4. Risk Evaluation Hierarchy Chart

As shown in figure 4, risk is divided into four levels based on the weather-index, which helps insurance companies to decide whether to insure and property owners to assess the potential risk of the property.

3. Results

3.1. Selection of Presentation Area

To ensure result validity and minimize interference from irrelevant factors, the research chose Zhengzhou, China, and Houston, USA, for model demonstration. Both experienced severe extreme weather events in 2021 and differ in climate, society, and economy. Radar charts for Zhengzhou and Houston data are presented in Figure 5.

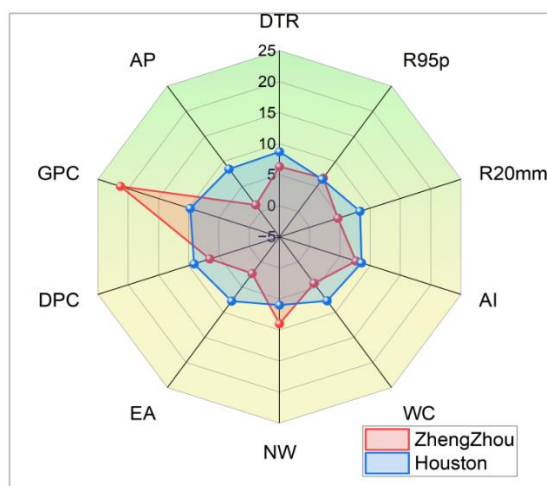


Figure 5. Comparison of data on indicators in Zhengzhou and Houston

As can be seen from Figure 5, The difference in natural scores is mainly due to the fact that Houston has both Various natural disasters occur, but Zhengzhou only suffers from frequent floods. The difference in social and economic scores is mainly due to the fact that Houston is located in a developed country, with a more developed society and greater disaster losses. Zhengzhou is located in a developing country with incomplete social development, but the disaster losses are relatively small.

3.2. Interpretation of Demonstration Results

The model's results show Zhengzhou with a score of 0.5357 and Houston with 0.6301, which is shown in Figure 6. With lower risk, Houston is more recommended to underwriting rather than Zhengzhou These findings closely reflect the real-world insurance industry context.

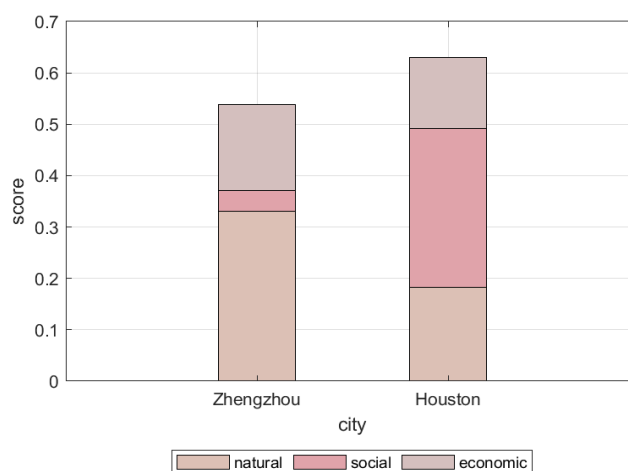


Figure 6. Comparison of Calculation Results between Zhengzhou and Houston

Figure 6 shows that the scores of Zhengzhou and Houston on the three first-level indicators of nature, society and economy are (0.3310, 0.0397, 0.1668), (0.1820, 0.3091, 0.1390) respectively.

4. Conclusions

With the increase of extreme weather events due to global climate change, the insurance industry is facing increasing pressure of claims. In this paper, a weather index-based insurance method is proposed to construct a weather index insurance model by processing weather condition data from 40 different cities through the EMW-AHP algorithm, and the model is demonstrated using two cities, Zhengzhou in China and Houston in the United States, as examples. The results of the study show

that regional weather risks can be categorized into four levels based on the calculated weather index, which helps insurance companies to decide whether to underwrite and property owners to assess potential risks. The study provides the financial industry with a deeper understanding of the losses caused by climate change and the development of sound policies to avoid these losses, and the stability and applicability of the model suggests that it can be applied to scenarios in different regions and with different measures.

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