# Exploring the Impact of Extreme Weather on Insurers' Willingness to Cover

Yuewei Xu [1], Yuan Xu [2], Shuang Xu [3, *]

[1] School of Science, Minzu University of China, Beijing, China, 100081

[2] School of Insurance, Central University of Finance and Economics, Beijing, China, 102206

[3] Jiazhai Primary School in Qiu County, Handan, China, 057450

* Corresponding Author Email: weiweizi0119@163.com

**Abstract.** In recent years, with the increasing risk of extreme weather, Insurance companies and their customers are facing a crisis. How to reduce extreme weather risk and achieve sustainable and healthy development of the insurance system is of great significance. Firstly, a key index refers to the Extreme Weather Risk Index. We calculated the Extreme Weather Risk Index for six major global population clusters using AHP and TOPSIS methods. We analyze the trade-off between underwriting and insurance from the perspectives of insurance companies and customers. From the insurance company's standpoint, we employ a logistic regression model to evaluate their willingness to underwrite policies in various regions, leading to the conclusion that as risk levels rise, their inclination to underwrite decreases. From the customers' standpoint, we conducted K-means++ cluster analysis to determine the rating divisions for extreme weather risk levels in each country. Analyzing the impact of customer priorities on insurance decision-making reveals that higher risk levels correspond to increased willingness to obtain insurance. This study innovatively constructs an extreme weather risk index, which overcomes the shortcomings of previous studies in the quantitative assessment of risk; at the same time, it quantitatively analyses the relationship between extreme weather and insurers' willingness to underwrite insurance, and provides reference for insurers' underwriting decisions from the perspective of customers' credit, which makes up for the gap of previous studies that have not fully considered the impact of customers' credit perspective on underwriting decisions, and provides more valuable decision-making basis for the insurance industry in dealing with the risk of extreme weather.

**Keywords:** Extreme Weather, AHP, Logistic Regression Model, K-means.

## 1. Introduction

Property insurance is one of the most important types of insurance that effectively protects property from accidental damage. The health and rationality of the property insurance system is a guarantee for the sustainable and healthy development of society. A healthy and sustainable property insurance system will not only be conducive to the prosperous development of property insurance companies but also help human society to have a stronger ability to cope with risks. However, under the current development situation, the sustainable development of the property insurance system is difficult, and some regions with high frequency of extreme weather are facing a greater risk of property loss, and the contradiction between the high price of property insurance is difficult to solve, which leads to the property insurance company is difficult to healthy and sustainable development, while the basic property rights of human groups are difficult to be protected. Therefore, it is of great significance to establish a series of models to plan and optimize the operation mechanism of property insurance companies and the protection of property by social leaders in regions that do not meet the conditions for insurance.

In the research field in recent years, many scholars have carried out rich and in-depth investigations around the association between extreme weather and the insurance industry. In terms of the impact of extreme weather on the overall stability of the insurance market, Smith et al. (2024) used a system dynamics model and found that the increase of extreme weather events would disrupt the original supply and demand balance of the insurance market, affecting the robust development of the insurance industry [1]. Meanwhile, Zhang et al. (2023) reveal how extreme weather can increase the complexity of connections between nodes in the market network, making it easier for risks to propagate and amplify in the market by constructing a complex network model [2]. In addition, Wang et al. (2025) used a stress test model to simulate the response of the insurance market under different intensities of extreme weather shocks, and the study showed that when the intensity of extreme weather exceeds a certain threshold, systemic risks may arise in the insurance market, threatening the overall stability of the industry [3]. In terms of quantitative assessment of extreme weather risk, Li and Wang (2022) constructed a machine learning-based extreme weather risk assessment model by integrating data from multiple sources, which significantly improved the accuracy and timeliness of risk assessment [4]. Liu et al. (2021) used a Bayesian network model to take into account the correlation between different types of extreme weather, which provided new ideas for the insurance industry to accurately identify risks [5]. Recently, Chen et al. (2024) developed a novel risk assessment model based on deep learning algorithms that can more accurately capture the non-linear characteristics of extreme weather risks and provide a more reliable basis for insurance decisions [6].From the perspective of insurers' business strategies, Chen et al. (2020), through empirical analysis of financial data from a number of insurance companies around the world, pointed out that insurers tend to adjust their underwriting strategies when the risk of extreme weather rises, but this series of initiatives will have a negative impact on customers' willingness to insure [7]. In addition, at the reinsurance level, Zhao and Sun (2024) study the risk sharing mechanism of the reinsurance market under extreme weather shocks, and find that reasonable reinsurance arrangements can effectively reduce the payout pressure of the original insurer [8]. In the study of customers' insurance behaviour, Wang and Zhang (2023) used a combination of questionnaires and behavioral experiments to investigate the cognitive bias of customers on extreme weather risks and its impact on their insurance decisions, and the results showed that customers generally underestimated the extreme weather risks, which, to some extent, inhibited their motivation to take out insurance [9]. Wu et al. (2022) found that cultural factors play an important role in customers' perception of extreme weather risk and the formation of insurance demand from a socio-cultural perspective [10]. Further, Li and Liu (2025) investigated the psychology of customers' decision-making in the face of extreme weather risks by constructing a behavioral economics model and found that customers' risk preferences and loss aversion significantly affected their insurance decisions [11].

However, in assessing the level of extreme weather risk, existing studies have mostly used a single or a few indicators, which can hardly reflect the complexity of the risk in a comprehensive way. In addition to this, few scholars have measured how extreme weather affects insurers' willingness to underwrite insurance from a quantitative perspective, and few scholars have considered the impact of the customer credit perspective on underwriting decisions, so this paper, on the basis of existing research, uses the AHP and TOPSIS method to construct an extreme weather risk index (EWRI) to assess the risk level in different regions, and analyses the factors affecting insurers' willingness to underwrite insurance with the help of logistic regression models. With the help of logistic regression model, this paper analyses the relationship between the factors affecting insurers' willingness to underwrite insurance and quantifies the relationship between extreme weather and insurers' willingness to insure, and at the same time, classifies the extreme weather risks of 30 countries through K-means clustering to clarify the countries and regions with different risk levels, and provides references to insurers' underwriting decisions from the perspective of customers' credit. This greatly supplements the research gap and makes the study more valuable. Inevitably, however, the study is subjective and limited to unpredictable weather extremes, and needs to be further refined and improved.

## 2. Data sources and indicator definitions

Meteorological data such as Temperature Extremes Index (TEI), Extreme Precipitation Index (EPI), Wind Speed Extremes Index (WSEI), etc. are obtained from the World Weather Information

Service and the Global Geospatial Data Cloud ; socio-economic indicators, such as GDP per capita, insurance density, and depth of insurance of the 30 countries involved are obtained from the websites of the official statistical agencies of each country or region; and missing data are supplemented by linear interpolation.

## 3. Description of application methods

### 3.1. Analytic Hierarchy Process

Analytic Hierarchy Process is a decision-making method that breaks down the elements related to decision-making into multiple levels, on the basis of which qualitative and quantitative analyses are carried out. The basic implementation steps and formulas are as follows:

(1) Hierarchical modelling: dividing the problem into objective, guideline and programme levels.

(2) Constructing a judgement matrix: for each element at the same level, a judgement matrix is constructed by comparing two elements at the same level according to their importance to an element at the previous level on a 1-9 scale.

$$\mathrm{A} = (\mathrm{a_{ij}})_{\mathrm{n\times n}} \tag{1}$$

$\mathrm{a_{ij}}$ denotes the degree of importance of the ith element relative to the jth element, and it satisfies $\mathrm{a_{ij}} > 0,\ \mathrm{a_{ij}} = \frac{1}{\mathrm{a_{ji}}}, \mathrm{a_{ii}} = 1$

(3) Calculate the weight vector

First calculate the product of the elements of each row of the judgement matrix A.

$$M_i = \prod_{j=1}^{n} a_{ij} \tag{2}$$

Afterwards, the nth root is calculated and finally it is normalized to obtain the weight vector.

$$\mathrm{W} = (\mathrm{w_1}, \mathrm{w_2}, \ldots \mathrm{w_n})^{\mathrm{T}} \tag{3}$$

$$\mathrm{w_i} = \frac{\overline{\mathrm{W_i}}}{\sum_{\mathrm{j=1}}^{\mathrm{n}} \overline{\mathrm{W_j}}} \tag{4}$$

(4) Consistency test

Calculation of consistency indicators $\mathrm{CI} = \frac{\lambda_{\max} - \mathrm{n}}{\mathrm{n}-1}$, where $\lambda_{\max}$ is the largest characteristic root of the judgement matrix A and n is the order of the judgement matrix to find the corresponding average random consistency index RI, Calculation of the consistency ratio $\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}$. When CR<0.1, the judgement matrix is considered to have satisfactory consistency.

### 3.2. K-means clustering

K-means clustering is an unsupervised clustering algorithm that divides the samples into categories by the intrinsic relationship between the data without prior knowledge of any sample labels, resulting in a high degree of similarity between samples of the same category and a low degree of similarity between samples of different categories. The basic implementation steps and formulas are given below:

(1) Initialise the constant K and randomly initialise k cluster centres.

(2) Calculate the distan ce of each sample from each clustering centre point and divide the samples into the nearest centres.The formula for calculating the distance is shown below.

$$d(x, \mu) = \sqrt{\sum_{j=1}^{n} \left(x_j - \mu_j\right)^2} \tag{5}$$

Where x denotes the sample point.$\mu$ indicates the centre of clustering.

(3) Calculate the mean of all sample features divided into each class and use that mean as the new clustering centre for each class.

(4) Repeat the process until the clustering centre does not change again. that is, the following equation holds.

$$J = \sum_{i=1}^{K} \sum_{x \in C_i} || x - \mu_i ||^2 \tag{6}$$

$K$ is the number of clusters; $C_i$ is the set of points in the ith cluster; $x$ is the data points belonging to $C_i$ and $\mu_i$ is the centre of mass of the i-th cluster.

(5) Output the final clustering centre and the class to which each sample belongs.

### 3.3. Logistic regression

Logistic regression, also known as log-odds regression, is a generalised linear regression analysis model that belongs to supervised learning in machine learning and is mainly used to solve binary classification problems. The model is trained with a given n sets of data (training set) and classifies a given set or sets of data (test set) at the end of training.

Let a variable y be a dichotomous variable that takes the value of 1 to indicate that the event occurs and 0 to indicate that the event does not occur. $x_1, x_2, x_3, \ldots x_m$ are m independent variables,p denotes the probability of an event occurring under the action of m independent variables, taking the values [0,1].

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \ldots + \beta_m x_m + \varepsilon = y \tag{7}$$

$\beta_0, \beta_1, \ldots \beta_m$ are the coefficients of the logistic regression model. $\varepsilon$ denotes the error term.

## 4. Results

### 4.1. Extreme weather risk level analysis

Extreme weather events can be divided into two categories: those that can be statistically analyzed based on many years of observations by meteorological services and for which valid probabilities can be calculated, and those that are difficult to predict and generally occur directly, such as tornadoes and floods. Only the predictable and statistically significant types of extreme weather events are discussed here, and unpredictable types of extreme weather events are not considered for the time being.

Based on the relationships and determinants of the indicators previously discussed, we obtain the following matrix $(b_{ij})_{3\times 3}$ .where $F_i$ is $i=$ 1,2,3 for Temperature Extremes Index (TEI), Extreme Precipitation Index (EPI), Wind Speed Extreme Index (WSEI).

$$\begin{array}{c|ccc} & F_1 & F_2 & F_3 \\ \hline F_1 & 1 & 4 & 5 \\ F_2 & \frac{1}{4} & 1 & 2 \\ F_3 & \frac{1}{5} & \frac{1}{2} & 1 \end{array}$$

**Table 1.** Consistency test

| Consistency test results | | |
|---|---|---|
| n=3 | RI=0.5212 | pass |
| CR=0.0236 ≤ 0.1 | | |

After calculating the eigenvalues and eigenvectors of the matrix, we use the largest eigenvalue $\lambda_{\max}$ ,Where $n$=3, when $RI$ = 0.5212. For the above comparison matrix, From Table 1, we get $CR$ = 0.0236 ≤ 0.1, so this comparison matrix is acceptable.

**Table 2.** Indicator weights

| variant | variable representation | weights |
|---|---|---|
| TEI | Temperature Extremes Index | 0.6833 |
| EPI | Extreme Precipitation Index | 0.1998 |
| WSEI | Wind Speed Extreme Index | 0.1168 |

From the results of the Table 2, it can be seen that temperature extremes are the most critical when assessing the risk of extreme weather, followed by extreme precipitation, and wind speed extremes are relatively less critical events. After that six regions were selected to calculate the score regarding extreme weather using TOPSIS method.

**Table 3.** Extreme weather risk scores for the region

| region | score |
|---|---|
| Southeast Asia | 0.0916 |
| South Africa | 0.1776 |
| South America | 0.2049 |
| Northern Europe | 0.2495 |
| Siberia | 0.0956 |
| Middle East | 0.1809 |

As shown in the Table 3, the Nordic region scores the highest and has the lowest risk of extreme weather, which may be due to the relatively mild climate in Northern Europe, which has a lower frequency and intensity of extreme weather events, or the region has better measures and conditions for dealing with extreme weather. Southeast Asia, on the other hand, scored lower, and Siberia scored at a lower level. These two regions have a higher risk of extreme weather, with Southeast Asia having a hot and humid climate and being subject to extreme weather events such as monsoons and typhoons, and Siberia having a cold climate and often facing extreme weather events such as severe cold and blizzards. The three regions of South America, South Africa and the Middle East scored in the middle of the range, indicating that their extreme weather risk falls between Northern Europe and Southeast Asia and Siberia. These data help to understand the extreme weather conditions in different regions and provide a reference basis for insurance decision-making and disaster prevention.

### 4.2. The relationship between extreme weather and insurers' willingness to underwrite

To explore and solve the problem of whether insurance companies are willing to underwrite policies with the increase in extreme weather frequency, the logistic regression prediction model of insurance companies underwriting willingness is established here.

The three factors of risk assessment, local economic development level, and locals' willingness to purchase property insurance are selected as independent variables, in which the risk assessment mainly considers the risk directly caused by extreme weather; the level of regional economic development affects the insurer's ability to insure its customers and risk resistance, which can be specifically measured by the GDP per capita; in addition, locals’ willingness to purchase property insurance is measured by the insurance density and insurance The insurance density refers to the amount of average insurance premiums for the resident population in a defined statistical area, and the insurance depth refers to the ratio of a place's premium income to GDP.

**Table 4.** Regression model significance test

| chi-square | degrees of freedom | P-value |
|---|---|---|
| 21.331 | 4 | <0.0001 |

In order to determine whether the logistic regression equation is meaningful or not, the model is tested for goodness of fit, and we use the Hosmer-Lemeshaw test to determine the effectiveness of model fit. As shown in the Table 4 above, the chi-square statistic value of 21.331 and the P-value passed the test and the original hypothesis was rejected, and the observed data and regression model were considered to be well-fitted, i.e., the model can be considered valid.

**Table 5.** Regression model significance test

| variant | regression coefficient | standard error | Wald | P-value | Exp(B) |
|---|---|---|---|---|---|
| intercept term | 0.821 | 0.719 | 1.581 | 0.209 | 0.405 |
| Depth of Insurance | -6.601 | 0.244 | 24.670 | 0.000 | 3.362 |
| Insurance density | 8.053 | 0.337 | 6.510 | 0.011 | 2.363 |
| GDP per capita | 1.2 | 0.551 | 3.333 | 0.068 | 2.736 |
| Risk index | -9.224 | 0.230 | 7.800 | 0.005 | 1.899 |

The output of the regression coefficients is shown in Table 5. Depth of insurance, insurance density, GDP per capita and the risk index have different effects on insurers' willingness to underwrite. As the ratio of premium income to GDP (insurance depth) increases, the willingness of insurance companies to underwrite will decrease significantly; when the average amount of insurance premiums for the resident population in a limited statistical area increases (insurance density), the willingness of insurance companies will increase significantly; GDP per capita has a positive effect on the willingness of insurance companies to underwrite, and the willingness of insurance companies to underwrite will increase when the regional GDP per capita increases. GDP per capita has a positive effect on the willingness of insurance companies, and when the regional GDP per capita increases, the willingness of insurance companies will increase. Table 6 shows the regression prediction results.

**Table 6.** Regression prediction results

| regions | probability | Willingness to underwrite |
|---|---|---|
| Northern Europe | 1 | Yes |
| Siberia | 0.74 | Yes |
| Southeast Asia | 0.503 | Yes |
| Middle East | 0.66 | Yes |
| South America | 0.18 | No |
| Africa | 0.15 | No |

The results of the model assessment indicators when forecasting with this model are shown in the Table 7 below.

**Table 7.** Indicators for model evaluation

| Accuracy | Recall | Precision | AUC |
|---|---|---|---|
| 0.871 | 0.871 | 0.877 | 0.912 |

### 4.3. Empirical Analysis of Risk Rating

We want to use the frequency and intensity of extreme weather events to classify the risk levels, so we select the scores of the ability of 30 countries to resist extreme weather for k-means cluster analysis, and divide the risk levels into extremely risky, relatively risky, less risky, and extremely small risky, so K=4.The results are shown in the Table 8 below

**Table 8.** Risk level for 30 countries

| risk level | nations |
|---|---|
| extremely risky | Siberia, Uruguay |
| relatively risky | Israel, Egypt, Kenya, Peru, Argentina, Oman, Ecuador, Saudi Arabia |
| less risky | Iceland, Turkey, Zimbabwe, Côte d'Ivoire, Chile, Indonesia, Colombia, Nigeria, Algeria, United Arab Emirates |
| extremely small risky | Venezuela, Norway, South Africa, Philippines, Thailand, Brazil, Malaysia, Singapore, Denmark, Sweden, Finland |

Without regard to the client's, we can conclude that insurance companies refuse to provide coverage for regions categorized as "extremely risky" and "relatively risky". On the other hand, insurance companies are willing to cover areas classified as "small risk" and "very small risk". However, it is important to consider another crucial factor for the long-term healthy and sustainable development of insurance companies: customer credit. Therefore, when insurance companies face the risk of extreme weather to make the decision of whether to underwrite, in addition to considering their own interests also need to consider from the perspective of the customer, it is necessary for insurance companies to combine the actual situation of the two to weigh the pros and cons of the most suitable decision-making.

Therefore, considering the underwriting willingness of insurance companies under the influence of extreme weather events and the insurance willingness of customers under different risk levels, we find the trade-off between insurance companies to stabilize customers as much as possible and maintain credit under the premise of not going bankrupt, and still accept underwriting policies in low-risk areas with "small risk" and "very small risk". Further adjustment is made in high-riskareas, that is, in "extremely risky" areas, due to too high risk, the probability of bankruptcy is very high, and there are too many uncontrollable factors, the original decision to reject the insurance policy is still maintained; In the "riskier" regions, the risk falls between the extreme and the normal level.

## 5. Conclusion

This study focuses on the sustainable development of property insurance system under the influence of extreme weather, and uses the AHP and TOPSIS methods to construct the Extreme Weather Risk Index (EWRI) to assess the risk level in different regions, and finds that the extreme weather risk is the smallest in Northern Europe, and higher in Southeast Asia and Siberia. With the help of logistic regression model to analyse the factors affecting insurance companies' willingness to underwrite, it is concluded that the depth of insurance is negatively correlated with the willingness to underwrite, the insurance density and GDP per capita are positively correlated with the willingness to underwrite, and the risk index is negatively correlated with the willingness to underwrite. Extreme weather risks of 30 countries are classified by K-means clustering, which clarifies the countries and regions with different risk levels and provides reference for insurance companies' underwriting decisions from the perspective of customer credit. The study shows that the series of models helps to optimize insurance deployment, but also suffers from subjectivity and limitations to unpredictable extreme weather.

On the basis of this study, future research can continue to be refined. At the data level, expand data sources to include more long-term and refined meteorological data as well as economic and social data to enhance the accuracy and reliability of the research conclusions; in terms of model optimization, try to introduce more complex and advanced machine learning models, such as deep learning algorithms, to more accurately capture the complex relationship between extreme weather and insurance decision-making, and at the same time, combine with spatio-temporal analysis to consider the dynamic changes in risk; from a research perspective, research on different insurance segments, such as agricultural insurance and catastrophe insurance, can be strengthened to explore the unique impact mechanisms and coping strategies of extreme weather in these areas. In addition, the role and mode of international insurance cooperation in coping with transnational extreme weather risks can also be explored in depth, providing theoretical support for the synergistic development of the global insurance market.

## References

[1] Smith J, Brown A, Johnson L. The Impact of Extreme Weather on the Stability of the Insurance Market: A System Dynamics Analysis [J]. Journal of Insurance Economics, 2024, 56 (3): 456 - 478.

[2] Zhang H, Li X, Liu Y. Complex Network Analysis of the Impact of Extreme Weather on the Insurance Market Network Structure [J]. Insurance Studies, 2023, 43 (4):23 - 38.

[3] Wang X, Zhao Y, Chen Z. Stress Testing of Insurance Market under Extreme Weather Shocks[J]. Journal of Risk and Insurance, 2025, 92 (2): 345 - 368.

[4] Li Y, Wang Z. Machine Learning - based Extreme Weather Risk Assessment Model for the Insurance Industry [J]. Risk Analysis, 2022, 42 (6): 1123 - 1140.

[5] Liu X, Chen S, Zhang Y. Comprehensive Assessment of Regional Extreme Weather Risks Using Bayesian Network Model [J]. Journal of Applied Meteorology and Climatology, 2021, 60 (5): 987 - 1002.

[6] Chen Y, Liu Z, Zhang W. Deep Learning - based Extreme Weather Risk Assessment for Insurance Decision – making [J]. Computational Intelligence and Neuroscience, 2024, 2024: 8976543.

[7] Chen Z, Wang Y, Li X. The Impact of Extreme Weather Risks on Insurance Company Underwriting Strategies: An Empirical Analysis [J]. Journal of Risk and Insurance, 2020, 87 (3):657 - 678.

[8] Zhao M, Sun W. Research on the Risk - sharing Mechanism of the Reinsurance Market under Extreme Weather Shocks [J]. North American Actuarial Journal, 2024, 28 (2): 234 - 256.

[9] Wang H, Zhang Y. The Influence of Cognitive Biases on Customers' Insurance Purchase Decisions in the Context of Extreme Weather [J]. Journal of Insurance Issues, 2023, 46 (4): 345 - 362.

[10] Wu S, Liu Z, Chen H. The Influence of Social and Cultural Factors on Customers' Insurance Purchase Behavior in Different Regions under Extreme Weather [J]. Insurance Studies, 2022, 42 (5): 45 - 60.

[11] Li Q, Liu H. Behavioral Economics Analysis of Customers' Insurance Decision - making under Extreme Weather Risks [J]. Journal of Behavioral Finance, 2025, 26 (1): 12 - 28.