# A Study of Insurance Company Underwriting Risk Based on EWM and TOPSIS Methods

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**Abstract.** This study proposes a risk assessment model called CPSF, which aims to assess insurance risk in areas where extreme weather is frequent. The model adopts a multidimensional and comprehensive assessment system, considering climate change, demographic and socio-economic, and financial conditions as the main factors, and constructs corresponding assessment indicators. The study establishes a scientific and reliable risk assessment system through the steps of data source, data pre-processing, indicator establishment, weight determination, and comprehensive assessment. By applying the model to two regions, namely, Southeast China and Southeast United States, where extreme weather often occurs, the insurance risk situation of these regions is analyzed and the future trend is predicted, which provides an important reference for insurance companies and policy making.

**Keywords:** TOPSIS, Entropy weight method, Insurance Risks.

## 1. Introduction

The insurance industry plays a vital role globally, providing important risk protection for individuals and businesses. However, the insurance industry is facing unprecedented challenges as climate change intensifies and extreme weather events become more frequent. Extreme weather events, such as hurricanes, floods and droughts, not only put enormous pressure on insurers to settle claims, but also have far-reaching implications for the economic stability of society as a whole [1-2].

Against this backdrop, effective risk assessment modeling becomes critical. Traditional risk assessment methods often face the problems of insufficient data, single indicator and high subjectivity, which make it difficult to comprehensively and accurately assess insurance underwriting risks. To address this challenge, we have introduced the 4CPSF risk assessment model, which aims to provide insurers with a more accurate and comprehensive underwriting risk analysis through comprehensive data analysis and scientific methodology, thus providing a scientific basis for policy making and urban planning [3].

This report will introduce the construction process and application effect of the 4CPSF risk assessment model in detail, aiming to provide strong support to the insurance industry in facing complex challenges such as climate change and promote the sustainable development of the industry.

# 2. CPSF Risk Assessment Model

## 2.1. Data Description

### 2.1.1. Data Description

The collection of sufficient data is the basis for a complete indexing system. Our data come mainly from the World Bank, the National Bureau of Statistics, and the National Oceanic and Atmospheric Administration (NOAA). These data sources are summarised in Table 1.

**Table 1.** Data Sources

| Data sources | Data website |
|---|---|
| World Bank public data | https://data.worldbank.org.cn/ |
| National Bureau of Statistics (NBS) | https://www.stats.gov.cn/ |
| National Oceanic and Atmospheric Administration (NOAA), USA | https://psl.noaa.gov/data/gridded/index.html |
| Sanya Statistics Bureau | https://tjj.sanya.gov.cn/ |

### 2.1.2. Data preprocessing

Data preprocessing is divided into three steps: data padding, handling outliers and normalization.

Data filling: regression interpolation is used if there is a strong correlation with other years, or the average of other years is used to fill in missing years.

Handling outliers: we analyzed each metric and deviated from outlier data that could compromise the accuracy and validity of our models.

Data normalizatiozn: We normalize the data for different indicators so that they can be compared on the same scale. We categorized the indicators used into benefit attributes and cost attributes.

## 2.2. CPSF model - a prism to measure the level of insurance risk

### 2.2.1. Establishment of indicators

In order to more comprehensively measure the risk of insurers underwriting insurance in regions where extreme weather is common, we have adopted a multidimensional and comprehensive assessment system. We believe that climate change, demographics and socio-economics, and finances are the main factors that can reflect the risk of insurance in a region, and we have therefore created indicators for assessing the risk in these three dimensions. The purpose of this assessment method is to provide insurance companies with a more accurate and comprehensive underwriting risk analysis, which in turn provides a scientific basis for policymaking and urban planning [4-5].

Climate: In terms of climate change, we believe that in regions where extreme weather occurs frequently, historical climate information can be a good indicator to assess the risk of extreme weather in the region, mainly in terms of the historical number of extreme weather events (NEWE), the number of typhoons suffered (NT), and the average typhoon intensity (ATI). In terms of the number of extreme weather, by analysing the number of historical extreme weather times occurring in a region, it can be used as an indicator to evaluate the risk of extreme weather occurrence. For typhoon-prone areas, it is crucial to record the number of typhoon occurrences, and by analysing the intensity of typhoons it is possible to more accurately assess the impact of typhoons on properties. Therefore the number of typhoons and the average intensity of typhoons can be a good indicator for evaluating risk.

Population and socio-economy: In terms of demographic and socio-economic aspects, we believe that population density (PD), per capita GDP (PCGDP), degree of urbanisation (UR), and annual inflation rate (AIR) can be used as indicators for evaluating the underwriting risk; in terms of population density, densely populated areas will have a higher demand for insurance, and may suffer greater losses in extreme weather events; in terms of per capita GDP, more economically developed areas property buildings are more resistant to extreme weather and help to mitigate the impact of extreme weather events, and residents in areas with higher GDP per capita may be more willing to invest in insurance and will have a higher demand for insurance; and in terms of the degree of urbanisation, buildings and infrastructure in urbanising areas may be more susceptible to extreme weather. In addition, urbanisation may exacerbate the heat island effect and affect climatic conditions. With regard to the annual inflation rate, the inflation rate reflects changes in the purchasing power of money, which is crucial for assessing the real value of insurance products and the ability to pay out claims, as well as influencing the purchasing power of the population [6].

Financial situation: In terms of financial situation, we believe that an insurer's Property and Casualty Insurance Premium Income (PCIPI), Combined ratio of property and casualty insurance (CRPCI) and Expense Ratio of Property and Casualty Insurance ( ERPCI) can be used as indicators of underwriting risk. In terms of Property and Casualty Insurance Premium Income, the stability and growth of premium income is an important indicator of an insurer's financial health, as well as its ability to take on new risks and pay out claims. In Combined ratio of property and casualty insurance:The lower the comprehensive cost ratio, the better the insurer has done in controlling costs and the more profitable it is. In Expense Ratio of Property and Casualty Insurance:A lower expense ratio usually means that the insurer is doing a better job of controlling expenses and is able to devote more resources to risk management and customer service.Indicator classification is shown in table 2.

**Table 2.** Indicator classification

| Climate | Population and socio-economy | Financial situation |
|---|---|---|
| NEWE | PD | PCIPI |
| NT | PCGDP | CRPCI |
| ATI | UR | ERPCI |
| | AIR | |

Through the comprehensive analysis of these secondary indicators, we are able to construct a more detailed underwriting risk model, which not only helps insurers to assess the risk of underwriting in areas prone to extreme weather, but also predicts future trends and supports the development of effective strategies. Such an assessment system will contribute to the achievement of the Sustainable Development Goals, as well as to the risk management and growth of the insurer's own business, and will also have a positive impact on society [7-8].

### 2.3. Entropy method for determining indicator weights

Entropy is a certain degree of chaos, defined as the more chaotic things are, the greater the entropy value, and the tidier things are, the greater the entropy value. The entropy method uses the concept of entropy to assign weights to indicators.

We have established the entropy method based on the idea of attraction. It assigns based on the fluctuation of the data itself and has no subjectivity. Therefore, using the entropy method for the assignment of weights ensures that the objectivity of the weights of the indicators is obtained.

Once we had completed the pre-processing of the data, we created a raw data matrix using the 10 types of data collected for the last 11 years for the 19 districts:

$$x_{ij} = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \tag{1}$$

We selected three positive and five negative indicators based on the information from the relevant papers and executed dimensionless for each indicator data to make the raw data comparable. The presence of ln0 was avoided and 0.001 was added to the data for error avoidance.

For positive indicators:

$$X'_{ij} = \frac{X_{ij} - min\{X_{ij}\}}{max\{X_{ij}\} - min\{X_{ij}\}} + 0.001 \tag{2}$$

For negative indicators:

$$X'_{ij} = \frac{max\{X_{ij}\} - X_{ij}}{max\{X_{ij}\} - min\{X_{ij}\}} + 0.001 \tag{3}$$

After completing the dimensionless, the weighted indicator array is calculated:

$$(P_{ij})_{m \times n} = \frac{X'_{ij}}{\sum_{i=1}^{m} X'_{ij}} \tag{4}$$

Then, the entropy value of each indicator is calculated:

$$e_j = -k \sum_{i=1}^{m} P_{ij} \ln P_{ij}, k = \frac{1}{\ln m} \tag{5}$$

Finally, the coefficient of variation is calculated:

$$g_i = 1 - e_j \tag{6}$$

After completing the above steps, we can find the weights by using the following equation:

$$w_j = \frac{g_i}{\sum_{j=1}^{n} g_i} \tag{7}$$

As shown in table 3, we obtained the weights of the 10 indicators used to judge the risk of underwriting coverage for areas with frequent extreme weather events:

**Table 3.** Weights

| Climate | Population and socio-economy | Financial situation |
|---|---|---|
| NEWE 9.71% | PD 14.36% | PCIPI 15.53% |
| NT 7.62% | PCGDP 17.48% | CRPCI 7.34% |
| ATI 6.3% | UR 10.61% | ERPCI 8.32% |
| | AIR 2.73% | |

## 2.4. Topsis method to construct a comprehensive evaluation system

After determining the weight of each indicator by entropy value method, combining the weights to get the weighted standardised matrix of each indicator as the raw data of each indicator, calculating the degree of proximity of each evaluation object to the optimal solution, Ci, as the basis for evaluating the strengths and weaknesses [9-10].

First, we need to standardise the indicators:

$$(Z_{ij})_{m \times n} = \frac{X'_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{8}$$

Once the normalisation is complete, the raw data from the tosopsis is obtained by multplying the weights and the normalised data to determine the optimal and worst soltions:

$$R_{ij} = W_j * X'_{ij} \tag{9}$$

Before determining the optimal and worst solutions, we need to determine the optimal solution Z+ and the worst solution Z-.

The optimal solution Z+ consists of the maximum value of each column in Z:

$$Z+= (maxZ_{i1}, maxZ_{i2}, \cdots maxZ_{in}) \tag{10}$$

The worst case is that Z- consists of the minimum value of each column in Z:

$$Z-= (minZ_{i1}, minZ_{i2}, \cdots minZ_{in}) \tag{11}$$

We then calculate the distance between z+ and z- for each evaluated object:

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(Z_j^- - Z_{ij}\right)^2} \tag{12}$$

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(Z_j^+ - Z_{ij}\right)^2} \tag{13}$$

Finally, we calculated the proximity of the optimal solution for each evaluated object

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{14}$$

The value of $Ci$ is in the range of (0, 1) and the closer to 1, the higher we consider the underwriting risk to be.

To make the observation and analysis of the data more intuitive, we scaled the underwriting risk score $Ci$ for each region by multiplying it by 100, thus converting the original $Ci$ value to the range of (0,100). This conversion makes the assessment of the level of underwriting risk more intuitive. Larger values indicate higher underwriting risk in that area, i.e., closer to 100 means higher underwriting risk.

By sorting Ci by order of magnitude, i.e., by clustering the scores of the 19 regions, we can classify the level of underwriting risk into four degrees: potential risk, low risk, medium risk, and high risk. The division indicators are as figure 1:

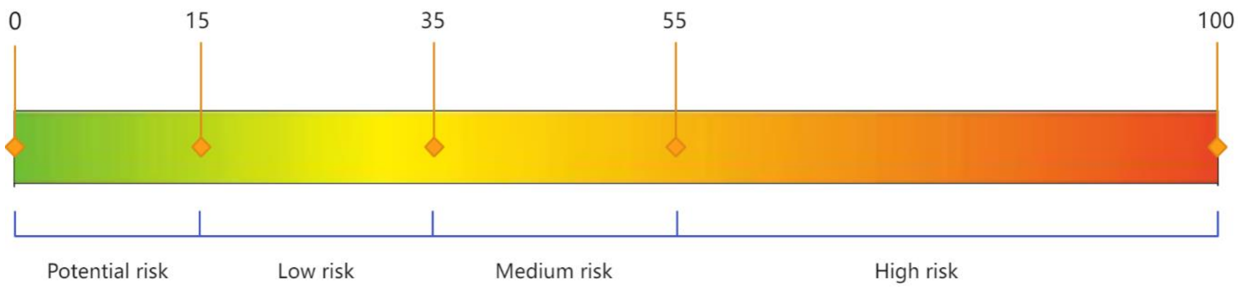


**Figure 1.** Division indicators

Our views:

Potential risk areas: do not have much profit margins, the impact of extreme weather in such areas, although much less than in other areas, tends to be characterised by low GDP per capita, low urbanisation rates and high annual inflation rates, which have a negative impact on the health of companies

Low-risk areas: market niches that are worth exploring, most of which have low urbanisation rates, potentially huge purchasing power and low exposure to extreme weather, which can bring more profit to the company's financial position.

Medium-risk areas: more frequently exposed to extreme weather than low-risk areas, companies should maintain a stable financial income when taking on policies, appropriately increase the policy price, and reduce the combined cost ratio and the combined expense ratio in order to gain more profits

High-risk areas: the most strongly affected by climate and the most devastated, often the ones where the company has to face high and frequent claims, resulting in high combined expense ratios. We recommend that in these types of places, companies increase the price of their policies, reduce their indemnity coverage or reduce policies in the area in a way that is sufficiently resilient.

### 2.5. Applications on two different continents

After completing the CPSF model, we applied it to Southeastern China and Southeastern U.S.A., where extreme weather often occurs. Due to their special geographic location and climatic conditions, these two areas are often subject to different degrees of extreme weather impacts, such as typhoons and floods, which have caused huge losses to local properties and other properties. We used the model to assess the underwriting risk in these two locations, with the specific scores below figure 2:

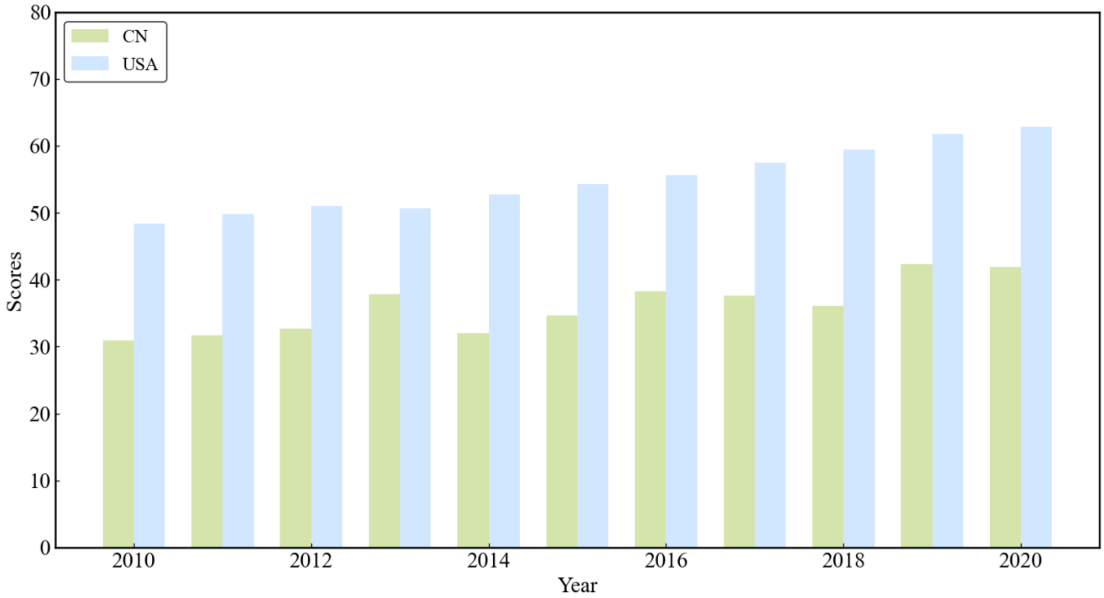


**Figure 2.** Risk level scores for the United States and China

We intuitively find that the underwriting risk in the southeastern U.S. is much higher than that in southeastern China during this 11-year period, while both the southeastern U.S. and southeastern China are facing an increase in underwriting risk due to climate change being affected by global warming, and the southeastern U.S. suffers from heavy rainfalls and hurricanes more often than ever before, so the underwriting risk of the southeastern U.S. has shifted from a medium to a high risk, and at the same time, the southeastern China is subjected to catastrophic weather brought about by typhoons, and the southeastern China is getting closer and closer to a high risk.

The increased frequency of extreme weather events has had a significant impact on the financial position of insurance companies. Against the backdrop of global warming, extreme weather events, such as extreme precipitation, extreme heat, drought and typhoons, are occurring more frequently. In the case of typhoons, the intensity of typhoons has remained high while the number of typhoons has continued to increase, and the impact of extreme weather on insurers has been significant.

In the southeastern U.S., insurers' comprehensive property and casualty cost ratios have risen sharply due to the frequency of catastrophes, which has a direct impact on insurers' profitability and long-term growth. Although premium income is increasing at an average rate of 4 per cent per year, this is not enough to compensate for the increase in costs due to disasters, and insurers are facing enormous financial pressure.

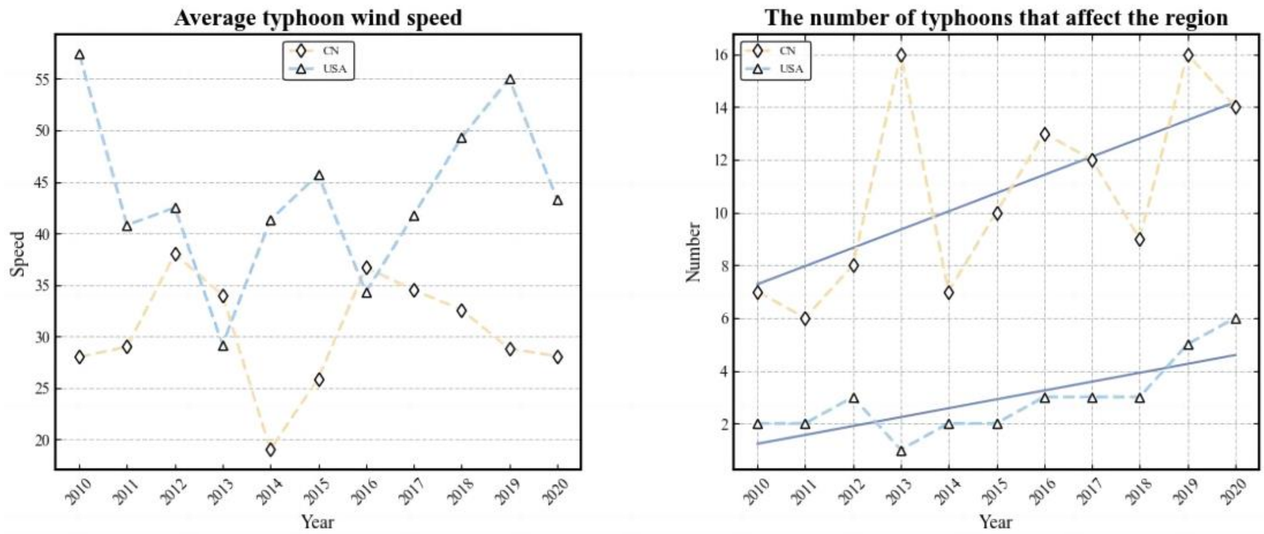


**Figure 3.** Typhoon intensity/number of typhoon impacts

According to figure 3, through specific financial analyses, we note that extreme weather-prone regions tend to have high urbanisation rates and high population densities, which exposes insurers to a high volume of compensation claims in the event of a disaster, potentially leading to higher-than-expected payouts. Nonetheless, the southeastern U.S. region shows greater economic resilience due to higher property and casualty insurance premium income, lower population density and higher GDP per capita. However, the impact of extreme weather cannot be ignored and insurers still need to take steps to counter the risk. In southeastern China, high population densities increase the pressure on insurers to pay out during extreme weather events, despite currently being at a medium risk level. We recommend that for high-risk areas, insurers should raise property and casualty premiums to increase revenues, while reducing comprehensive costs by optimising management processes and improving comprehensive expense ratios to ensure financial health. Reducing the number of policies written is also an effective means of ensuring company resilience where necessary. For medium-risk areas, insurers should maintain normal premium income and control costs by improving management efficiency to increase resilience to potential risks. These strategies aim to balance risk and return to ensure that insurers are able to maintain robust operations under changing climatic conditions.

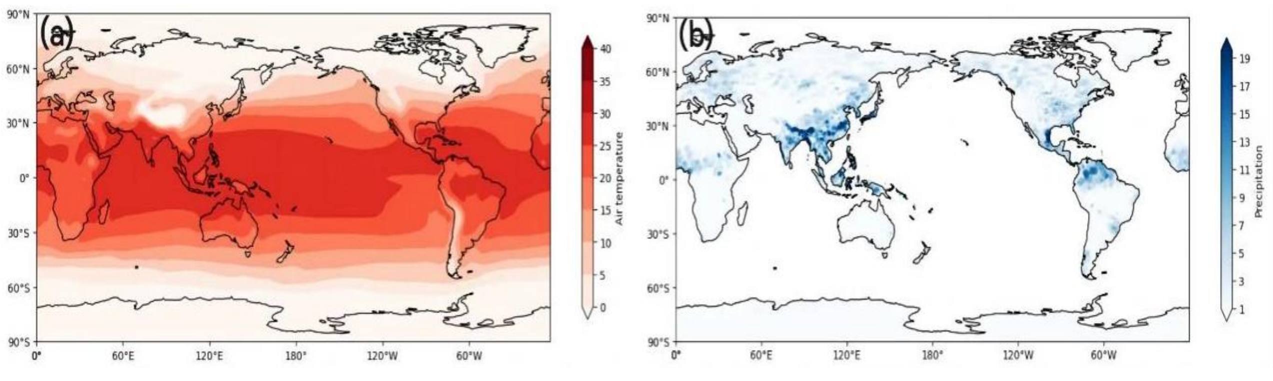


**Figure 4.** Global temperature distribution(a) & precipitation(b)

According to figure 4, the Southeastern U.S. has a higher climate impact score than the Southeastern China, which is consistent with the two regions' performance on extreme weather impact factors. The southeastern U.S. is experiencing an increase in the frequency and intensity of extreme weather events such as heavy rainfall, hurricanes, and heat waves as a result of climate change. In contrast, the southeastern region of China, while also affected by extreme weather such as typhoons, has a relatively low level of risk. However, with global warming, extreme weather events are increasing in south-eastern China.

Estimation:We took a grey forecasting approach and predicted the underwriting risk of insurance companies in the southeastern United States over the next few years regarding areas prone to extreme weather, and the results are shown in figure 5:

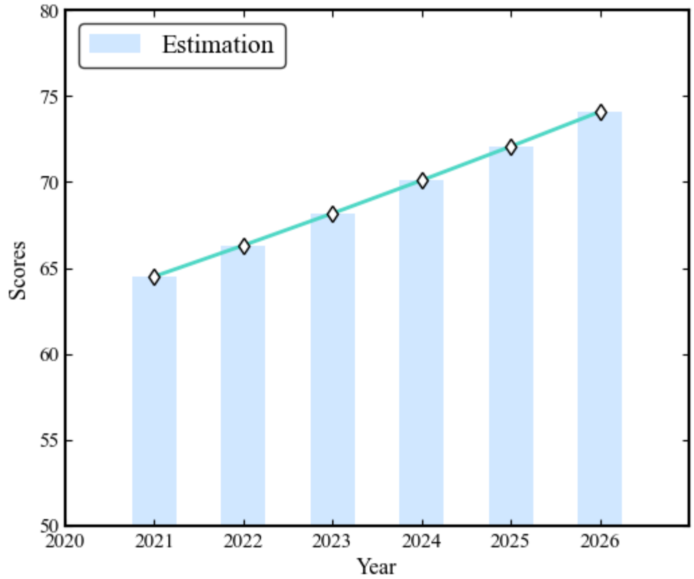


**Figure 5.** Projected trends for the coming years

It can be observed that the region will continue to be exposed to high and increasing levels of risk, which will lead to severe damage to property from extreme weather events, which will have a negative impact on the health and sustainability of the insurance industry.

## 3. Conclusion

Through the details presented in this report, we delve into various aspects of the 4CPSF risk assessment model, from data collection and pre-processing to indicator building, weighting, and application in different geographic contexts. With its comprehensiveness, science and adaptability, the model provides a powerful tool and support for the insurance industry in facing the challenges posed by climate change and extreme weather events.

By comprehensively utilizing data from authoritative data sources such as the World Bank and the National Bureau of Statistics, combined with advanced data preprocessing and weight determination methods, we have constructed a multi-dimensional underwriting risk assessment model. The model not only comprehensively assesses climate, demographic, socio-economic and financial risks, but also customizes risk management strategies according to specific situations, providing insurers with more accurate and reliable risk assessments.

In terms of model application, we have successfully applied the model to regions with frequent extreme weather, such as Southeast China and Southeast America, to provide insurers with comprehensive risk assessment and strategic guidance. Through comparative analysis, we found that risk levels vary significantly across regions, influenced by factors such as climate, economy and population density. These insights provide important references for insurers in formulating risk management strategies and business expansion, helping to maintain their robust growth in a changing climate.

In summary, the introduction and application of the 4CPSF risk assessment model provides new ideas and solutions for the insurance industry in addressing the challenges posed by climate change and extreme weather events. We expect this model to contribute more to the sustainable development of the insurance industry and the stability of the society and economy.

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