

Navigating Insurance Challenges: A Decision Tree Model for Insurance Pricing and Risk Strategy

Dongling Fu^{1, *, #}, Qianran Hong^{2, #}, Xuechun Xu^{3, #}

¹ School of Mathematical Sciences, Soochow University, Suzhou, China, 215000

² School of Electronic and Information Engineering, Soochow University, Suzhou, China, 215000

³ Business School, Soochow University, Suzhou, China, 215000

* Corresponding author: 2107402056@stu.suda.edu.cn

#These authors contributed equally.

Abstract. Amid escalating natural disasters intensified by climate change, accurately assessing risks and determining insurance rates in disaster-prone areas present significant challenges to the insurance industry, impacting the underwriting decisions and strategies correspondingly. This article employs a frequency-loss degree framework to quantify meteorological disaster risk as the Annual Average Loss (AAL), which was classified into three categories (severe, moderate, and mild) further. Utilizing a Poisson Distribution to process extreme event data and integrating it with data from typical years into a comprehensive prediction model, this approach facilitates enhanced risk assessment and premium estimation. A decision tree model was further established to explore insurance institution's underwriting decisions and risk strategies on the basis of monetary benefits and mental utility respectively, highlighted by case studies in Australia and the Philippines. The findings underscore the necessity for insurers to incorporate advanced decision-making tools taking utility factors into account, to navigate the complexities of risk and pricing in vulnerable areas efficiently. A tendency was observed among insurers to prefer conservative strategies in medium-risk areas, like the Philippines, over aggressive underwriting in high-risk zones, such as Western Australia. This suggests further research into expanding the model's applicability and delving into the evolving influence of climate change on the insurance industry.

Keywords: Risk Evaluation, Insurance Pricing, Underwriting Strategy, Decision Tree Model.

1. Introduction

Recent years have seen an increase in the frequency of extreme weather events, which has increased the risk of catastrophes, harmed the property of individuals, and presented obstacles to governments. The issue is emerging as one of the main barriers to sustainable regional economic and social growth. In addition to raising the likelihood of natural disasters, climate change also places a great deal of strain on property insurance.

In response, navigating insurance complexities in disaster-prone areas and setting accurate rates have gained urgency due to climate change, elevating the topic's importance. Initially engaging insurers and researchers in the 1990s, recent climatic shifts have widened the focus in both academia and industry. Catastrophe insurance pricing research has employed diversified and innovative computational methods, like machine learning [1], to address multivariate considerations. Targeted research on specific disaster types [2] [3] and regional analyses [4] [5] has uncovered distinct regional risks, highlighting the necessity for precise pricing. Additionally, the research has delved into discussions within the economic sphere, investigating behavioral strategies related to economic incentives, market behaviors, and pricing fairness [6] [7], which has further deepened the comprehension of disaster risk management with new insights.

In order to provide a comprehensive sight of the system, the paper proposes an integrated model: (1) Utilizing a risk quantification framework to quantify Annual Average Loss, which is then categorized into different levels aiming to quantify risks more precisely. (2) Refining insurance rate prediction through historical data analysis and Poisson Distribution, creating a model that combines extreme and typical situations for risk assessment and insurance premium estimation. (3) Establishing

a Decision Tree Model to assess insurers' underwriting and risk strategies integrating benefits and utility. (4) Selecting Western Australia and the Philippines for case studies to demonstrate the model's adaptability and validity in diverse regions.

2. Risk Quantification and Premium Calculation

Based on the "Frequency-Loss Magnitude" framework [8], this study rigorously quantifies risk for insurance purposes. As a method used for risk assessment, it divides risk analysis into two critical dimensions: the frequency of the occurrence of an event and the magnitude of loss each event could potentially cause. This framework facilitates a thorough comprehension and evaluation of both the possibility and consequence of particular occurrences or phenomena in a system or organization.

Recognizing the diversity in the frequency and type of extreme weather events across regions, this paper posits a categorization for analytical clarity. In this paper, it is assumed that there are n types of extreme weather that may occur in a given place, with each extreme weather event i having an annual probability of occurrence is p_i . The risk, as previously defined in the framework, is the product of frequency and loss magnitude. It reflects the likelihood of an event occurring over a certain period and the potential loss each event could cause. The risk can be mathematically represented by the following formula:

$$Risk = p_i \times LS \quad (1)$$

Where, *Loss Severity*(LS) represents the degree or intensity of loss that may be caused by each event across economic, human, social, and environmental aspects, typically expressed in monetary units. To facilitate calculation, the model's loss severity is improved by replacing LS with the expected loss amount for each event, denoted as L_i . The formula is then:

$$\begin{cases} L_i = LS \times GDP \\ W_i = p_i \times L_i \end{cases} \quad (2)$$

Where, GDP is the annual gross domestic product of the place, W_i is the disaster risk quantified as the amount of loss from the event within a year.

Then, the cumulative risk in a given area is expressed as *Annual Average Loss*(AAL), and the amount of loss for all potential random events in a year is calculated as annualized cost.

$$AAL = \sum_{i=1}^n W_i = \sum_{i=1}^n p_i \times L_i \quad (3)$$

As described, AAL represents the average annual loss for all extreme weather hazards. It is the average annual expected loss over several years.

Since most insurance policies have a one-year term, the insurance cost comprises AAL , expense load, and risk load. Excluding reinsurance costs for simplification, the premium is:

$$Premium = AAL + Expense Load + Risk Load \quad (4)$$

Where, *Expense Load* refers to the operational expenses, administrative and other overheads, *Risk Load* refers to an additional charge added to the premium to compensate the insurer to cover the potential for catastrophic loss. According to the American Academy of Actuaries Extreme Events and Property Lines Committee, *Expense Load* is calculated as 27 percent, and *Risk Load* is estimated with the standard deviation of the modeled losses, which is presumed to include a provision for profit.

3. Disaster Loss Prediction Integrating Poisson Processes

To enhance the accuracy of the prediction model, the paper compiled and processed data on the losses caused by meteorological and other natural disasters in various countries and regions over recent years are obtained. This preprocessing selects valid information for subsequent analysis.

Observations based on the obtained data reveal exceptionally high losses in certain years, contrasted with a trend towards stabilization in other periods. The difference between the two patterns often exhibits an order of magnitude disparity. It is thus inferred that, this irregularity is likely caused by low-probability events leading to significant losses, such as extreme weather phenomena. In order to streamline the model, it is posited that all severe extreme weather events within the same year follow an identical distribution function. For prediction purposes, let the frequency of occurrence of major natural disasters be X , which follows a distribution with Poisson distribution [9] with parameter $\lambda(t)$. The probability density function is:

$$p_i(X = k) = \frac{\lambda^k}{k!} \cdot e^{-\lambda} \quad (5)$$

In processing the data, total economic loss is bifurcated into the regular losses caused by ordinary natural disasters, and the other part is the losses controlled by the probability density of major natural disasters. Thus, the anomalies (extreme value points) in the data are eliminated and then the remaining data points are fitted. The fitting function obtained is considered the best approximation of losses caused by ordinary meteorological hazards. Let the anomalous data points be $x_i = 1, 2, 3 \dots$, and the data points be y_i . The fitting function to the remaining points is $y = g(x)$, then the formula below represents the economic impact caused by major extreme weather events:

$$\Delta y = y_i - g(x_i), i = 1, 2, \dots \quad (6)$$

Let the total average loss from all major natural disasters be $L = \sum_i L_i$. Since climate change increases the likelihood of more severe weather and natural disasters, the frequency of natural disasters shows an upward trend. Therefore, assume that $\lambda(x) = \lambda \ln x$ as the mean of the Poisson distribution, where λ is a constant parameter to be determined. By applying least squares to the product of λ and L , the result can be obtained as:

$$(\lambda \cdot L)_{est} = \frac{1}{N} \sum_{i=1}^N \frac{\Delta y_i}{\ln x_i} \quad (7)$$

Where, N denotes the number of all the years involved in the prediction.

Combining all of the above, the average annual disaster loss within the interval spans $[t_1, t_2]$ for a given year can be calculated as:

$$AAL = \frac{1}{t_2 - t_1 + 1} \sum_{i=t_1}^{t_2} [g(x_i) + (\lambda \cdot L)_{est} \cdot \ln x_i] \quad (8)$$

4. Underwriting Strategy on Decision Tree Model

Data-based decision-making has become increasingly sophisticated as a response to the complexities and uncertainties inherent in real-world scenarios, which often challenge the accuracy of conventional predictive models. The decision tree method stands out as a versatile and commonly employed approach within the realm of risk-based decision-making, which can handle not only single-stage but also multi-stage decision problems. The combination of monetary benefits and psychological utility provides a comprehensive framework, reflecting the risk attitude and decision of the insurance institution.

4.1. Underwriting Strategy by Monetary Benefits

With reference to the international standard specification for classifying meteorological disasters [10], meteorological disasters can be classified into three categories, namely, mild, moderate and severe loss, and the AAL amount in the standard is adopted for categorization:

$$\begin{cases} AAL > 5 \times 10^8, \text{Severe Loss} \\ 1 \times 10^8 < AAL < 5 \times 10^8, \text{Moderate Loss} \\ AAL < 1 \times 10^8, \text{Mild Loss} \end{cases} \quad (9)$$

For this problem, the losses caused by meteorological disasters are first categorized as A_1 (mild), A_2 (moderate), and A_3 (severe), and their probabilities of occurrence are a_1 , a_2 and a_3 , and the amounts of losses caused are a , b , and c . The premiums paid by the insurer for these three degrees of meteorological disasters are a' , b' , and c' respectively, and the probabilities of participation are b_1 , b_2 , and b_3 , respectively. The preliminary evaluation is shown in figure 1:

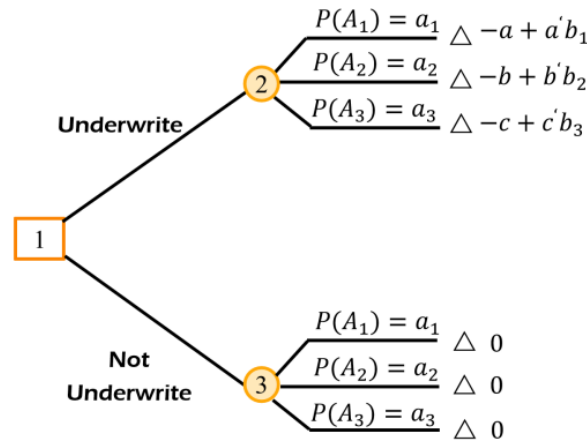


Figure 1. Decision Tree Model on Underwriting Strategy

Then calculate the expected value for each node:

$$\begin{cases} \text{Node 2: } a_1(-a + a' \cdot b_1) + a_2(-b + b' \cdot b_2) + a_3(-c + c' \cdot b_3) \\ \text{Node 3: } 0 \end{cases} \quad (10)$$

When $E_2 > E_3 = 0$, the insurance company is willing to cover it. The methods discussed above and the examples given basically use the expected value of gain or loss as the criterion for selecting a program.

4.2. Risk Strategy by Psychological Utility

In previous models, where the insurance institution was assumed to be absolutely rational, the decision-making criterion was solely based on the expected monetary value of gain or loss. This approach simplifies the decision-making process to a mechanical calculation, potentially disregarding the insurer's actual behavior and strategic considerations. However, in reality, insurance companies have diverse risk profiles, thus the paper introduces the concept of utility, a subjective preference not just the gain or loss itself, into the decision tree model.

The utility curves depict different risk attitudes: Curve A reflects a conservative decision maker who is risk-averse, Curve C is the opposite, suggesting a risk-seeking behavior, and Curve B indicates a balanced, expectation-based approach. Utility curves are shown in figure 2.

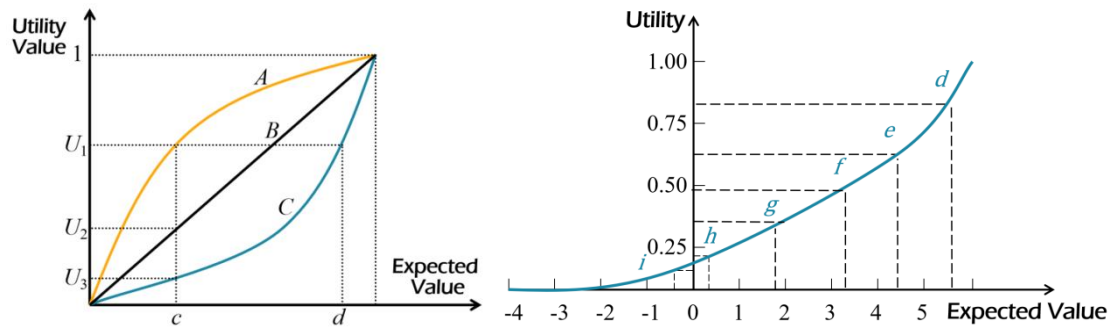


Figure 2. Utility curves

Here, the paper assumes a risk-seeking attitude and convex utility curve for the insurance company, which may be due to the ample capital reserves and intense competition in the industry, it can be acknowledged that insurers are more willing to undertake risks. This reflects a more aggressive market stance where seeking higher profits is often accompanied by a readiness to accept higher risks. Here, for convenience, assume that the utility value $d < e < f < g < h < i$ in the curve. Draw the decision tree as shown in figure 3.

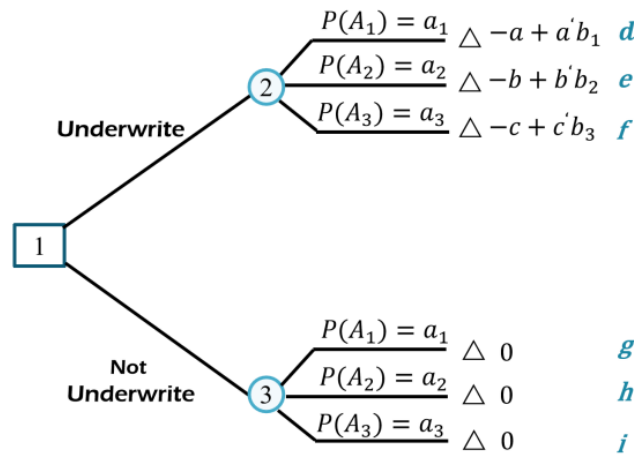


Figure 3. Decision Tree Model on Risk Strategy

Then calculate the utility value of each node:

$$\begin{cases} \text{Node 2: } a_1 \cdot d + a_2 \cdot e + a_3 \cdot f \\ \text{Node 3: } a_1 \cdot g + a_2 \cdot h + a_3 \cdot i \end{cases} \quad (11)$$

When $EU_2 > EU_3$ the insurance company chooses to take the risk, i.e., it prefers to take a greater risk for a greater return. The insured, on the other hand, influences the company's decision through their intention to insure, i.e., the larger the value of b_1 , b_2 , and b_3 , the more the company is willing to take a risk.

5. Case Study

To apply the aforementioned models in practice, this paper selects Western Australia in Atlantic and Philippines in Asia for detailed studies. The comparison underscores how different economic and infrastructural backgrounds can influence the management of disaster risks and the strategic decisions of insurance companies. Historical data are obtained from the website Our World in Data, and then fitted and predicted according to the model described above.

5.1. Western Australia in Oceania

Western Australia, Australia's largest state, encompasses vast lands with diverse natural geographic conditions. Despite its robust economy, the region is prone to extreme weather events due to its vast lands and diverse natural conditions, necessitating sophisticated risk management strategies.

The data is initially preprocessed, resulting in the retention of a total of twenty-three years of valid data spanning from 2000 to 2022. After removing the extremely large values in the two years of 2010 and 2022, a function is fitted to the remaining 21 years of data.

$$g(x) = g(x_0) + Ae^{\frac{-x}{t_0}} \sin\left(\pi \frac{x-x_c}{\omega}\right) \quad (12)$$

Where, $g(x_0) = 2.56 \times 10^9$, $x_c = 0.375$, $\omega = 1.05$, $t_0 = 18.1827$, $A = 1.869 \times 10^{57}$.

Assuming that insurers conduct risk assessments and policy adjustments every five years. Bringing the above equation into equation (severe), the average annual loss for all extreme weather events from 2024 to 2028 is:

$$AAL = \frac{1}{5} \sum_{i=2024}^{2028} [g(x_i) + (\lambda \cdot L)_{est} \cdot \ln x_i] = 2.8636 \times 10^9 \quad (13)$$

Due to the frequent wildfires and dust storm disasters in Australia, the risk load is about 1.5 times the AAL based on the premium formula. These two figures are then used to derive the expense load.

$$Premium = \frac{2.5 \cdot AAL}{0.73} = 9.8068 \times 10^9 \quad (14)$$

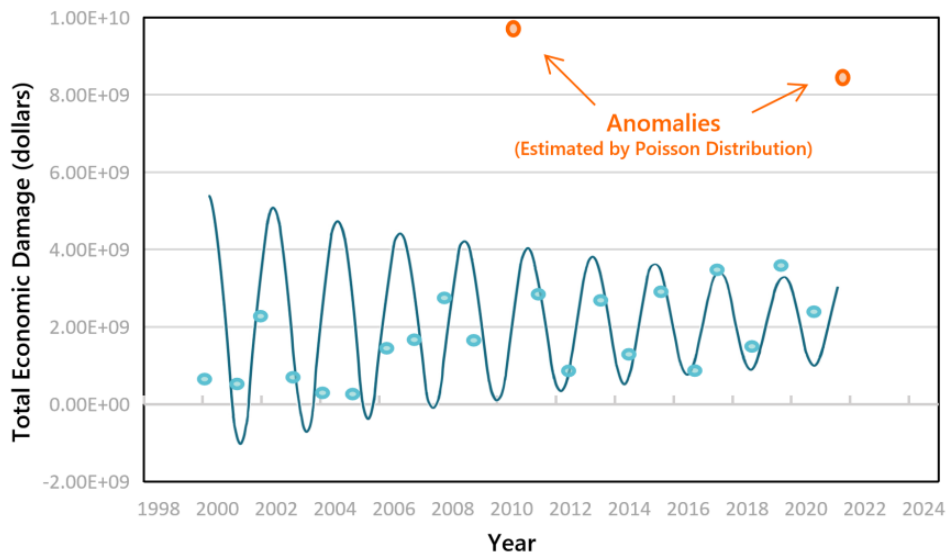


Figure 4. AAL and fitted plot for Western Australia for previous years

Based on figure 4, $AAL > 5 \times 10^8$, which is a severe loss, it can be calculated that $E_2 < 0$ using the decision tree model. Thus, the insurance company won't underwrite.

This indicates that while developed regions like Western Australia may have greater financial resilience, they also face significant potential losses that lead to the insurer's decision to deny coverage. The calculated insurance premium and underwriting decision reflect this, as a higher risk load and system instability are applied due to frequent severe weather events like wildfires and dust storms.

5.2. Philippines in Asia

The Philippines, in contact, a developing archipelago in Southeast Asia, is endowed with rich natural geographic conditions but also exposed to a wide range of meteorological disasters and extreme weather events such as typhoons and hurricanes, floods, and drought.

Similar to the above process, through data preprocessing, fitting, and adding Poisson process for adjustment, the fitting function can be obtained whose fitting effect is depicted in figure 5.

$$g(x) = a_0 + a_1 \cos \omega x + b_1 \sin \omega x \quad (15)$$

Were, $a_0 = 3.371 \times 10^8$, $a_1 = -1.481 \times 10^8$, $b_1 = -2.512 \times 10^9$, $\omega = 0.2453$.

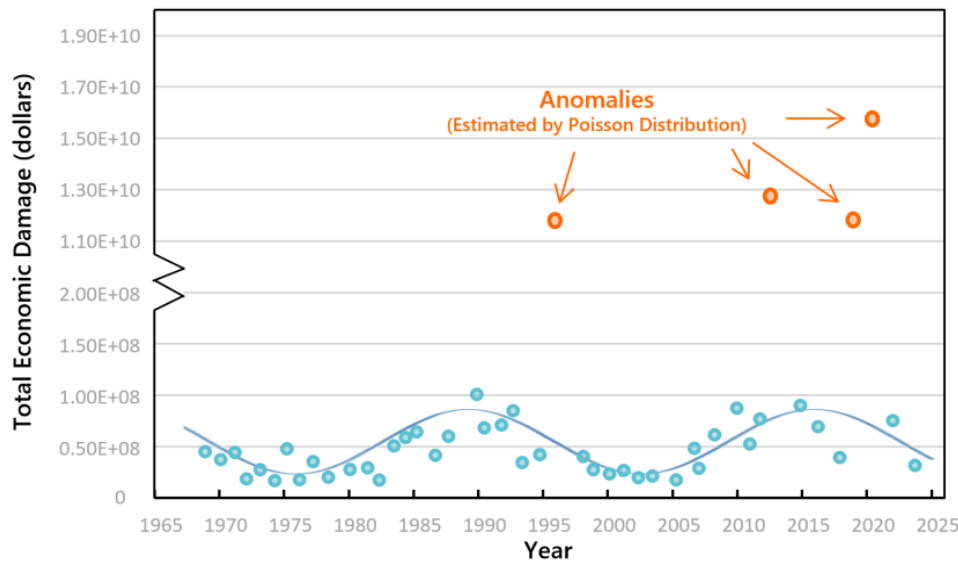


Figure 5. AAL and fitted plot for Philippines for previous years

The average annual losses and premiums for extreme weather disasters for the next five years are:

$$\begin{cases} AAL = \frac{1}{5} \sum_{i=2024}^{2028} [g(x_i) + (\lambda \cdot L)_{est} \cdot \ln x_i] = 3.1088 \times 10^8 \\ Premium = 1.2776 \times 10^9 \end{cases} \quad (16)$$

Thus, it can be calculated $E_2 > 0$, indicating that the insurance company is willing to underwrite.

For developing regions like the Philippines, the balance between managing disaster risks and economic growth is delicate. The premiums calculated for the upcoming years, while lower than those of a developed region, are still a significant consideration for insurers who must balance the risk and returns facing the challenge of increasingly frequent and enormous climate disasters.

6. Conclusion

The study delineates an integrated approach to risk assessment and insurance pricing in the face of natural disasters, emphasizing the need for insurers to consider both empirical data on losses and their own risk preferences, as dictated by utility theory.

The model first quantifies the level of natural disaster risk as annual natural disaster economic losses, and predicts the future level of risk by handling outliers through a function fitting and Poisson process. Then the decision tree model is used to decide whether the insurance company will underwrite or not. This model has a good application to help insurance companies to anticipate risk and make underwriting decisions. The findings from case studies in Western Australia and the Philippines illustrate the practical application of these models, highlighting the contrast between insurance strategies in developed and developing regions.

In essence, this research stresses the importance of tailoring insurance models to regional specifics and acknowledges the varied risk tolerances of insurers. It advocates for dynamic, regionally adapted strategies in insurance underwriting, urging a shift towards models that are both data-informed and reflective of the complex landscape of global climate risk.

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