Research and Application of Underwriting Decision Model Based on Climate Risk Factor

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Abstract. In recent years, the frequency of extreme weather has led to an increase in claims costs for the insurance industry resulting in higher insurance premiums. This paper addresses how to strike a balance between the profitability problem of insurance companies and the affordability of customers. Firstly, we construct an underwriting decision model based on the climate risk coefficient, then we use the entropy weight topology to measure multiple types of climate risks, then we estimate the disaster loss and insurance claim probability by ARIMA and random forest; we use the data envelopment analysis model to assess the underwriting efficiency, and we use the gray prediction model to predict the gap trend, and secondly, we derive the decision function. Finally, we chose the Statue of Liberty as the object for risk assessment object, using the established model to calculate, and concluded that the Statue of Liberty faces a climate risk index of 0.624 and proposed protection measures.

Keywords: Climate Risk Underwriting Decision Models, Random Forests, Underwriting Decision Models, ARIMA.

1. Introduction

With the increasing frequency of weather disasters, the rational underwriting decision to strike a balance between the profitability of insurance companies and the affordability of their customers has become a highly controversial topic [1]. Therefore, this paper will establish a model for determining whether insurance should be underwritten in areas where extreme weather events are increasing so as to achieve optimal asset allocation and strike a balance between the profitability of insurance companies and the affordability of customers to effectively allocate property insurance so as to safeguard the long-term development of insurance companies.

This paper successively derives data on climate risk, catastrophic loss and insurance claim probability, gap trend, etc., and in the decision-making stage, such as the owner's behavioral influences are cited, and a decision-making model is deduced for the purpose of not going bankrupt to derive the profitability of climate insurance in Guangzhou and Florida from 2020 to 2022, which determines that Florida will be underwritten in April 2022 and Guangzhou will not be underwritten in March 2021, reaching a maximum value of $1,140.8 million, which is the highest value. The maximum value of $1,140.8 million is reached. Finally, the Statue of Liberty is chosen as the object for risk assessment and protection measures, according to which the insurance company can obtain a profit of 1.53 million dollars.

2. Climate risk underwriting decision models

2.1. Estimating disaster losses and insurance claim probabilities

2.1.1 ARIMA predicts the impact of extreme weather

In this section, we will use an explicit time-series dataset to record the total monthly losses due to extreme weather so that we can use an ARIMA model to predict the impact of extreme weather over time [2].

Two plots are constructed identifying the three necessary components of the autoregressive model (AR(p)), the difference (d), and the moving average model (MA(q)), which will be integers, usually ranging from 0-3. Using MATLAB, we can obtain the autocorrelation (ACF) plot and the partial autocorrelation (PACF) plot for Figures I and II. We can see from the two residual plots that both fluctuate around 0, so we can choose ARIMA(1, 1, 1) as the target model.

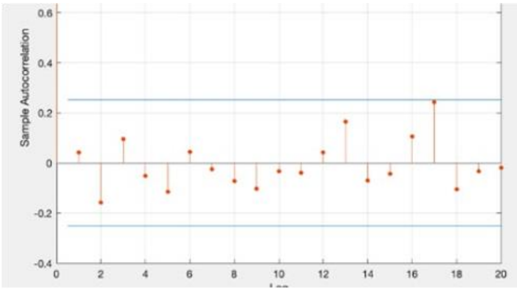

Figure 1. ACF

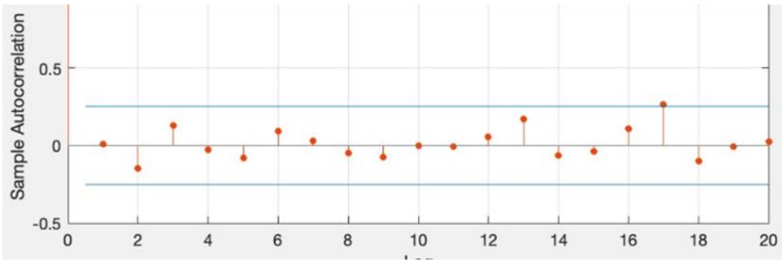

Figure 2. PACF

Figure 3 shows the prediction plot of the ARTMA model, from building the ARIMA(1, 1, 1) model shows that the recent past error is a significant predictor of the current year's losses due to extreme weather, and that if the frequency and magnitude of extreme weather occurrences increase, so do the losses, in order to come to more informed conclusions about the relationship between climate change and economic losses, we have combined the weather indices with the losses.

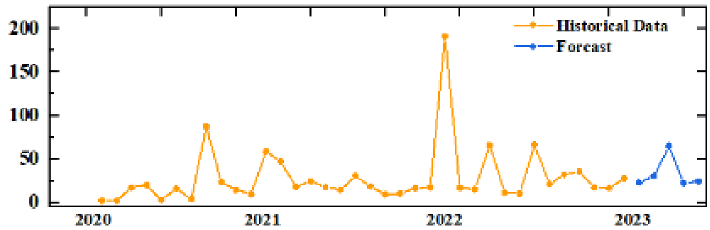

Figure 3. ARIMA Predict

2.1.2 Random Forest

Random forest (random forest) model is a classification tree-based algorithm proposed by Breiman and Cutler in 2001 [3]. It improves the prediction accuracy of the model by summarizing a large number of classification trees, and is a new model that replaces traditional machine learning methods such as neural networks. Random forests are fast and excel in handling large data [1]. In this section, we apply Random Forest is based on the probability of all the factors that may affect the amount of insurance that the insurance provider has to pay after certain events.

Table 1 shows the results of the Random Forest where MSE and RMSE are key to assessing the performance of the model, where a lower value indicates a better fit. The R-squared (R^2) value is the coefficient of determination in a regression model [4], which is used to determine the proportion of the variance in the dependent variable that can be predicted by the independent variable, where a higher value of R^2 indicates a better performance of the model. We can see that the MSE and RMSE in the table are low, so we can infer that our prediction of the loss ratio is very close to the actual value. It can also be concluded that the sample data matches well with its prediction.

Table 1. Result of Random Forest

MSE	RMSE	MAE	MAPE	r^2
0.001	0.038	0.017	23.965	0.951

In Figure 4 the blue line represents the true compensation rate and the green line represents the compensation rate predicted by the machine, it is clear from the figure that the two lines are very similar. So by using the model of random forest we can provide stakeholders with valuable insights into the factors affecting loss rates, which in turn can guide risk management and policy decisions in the insurance industry.

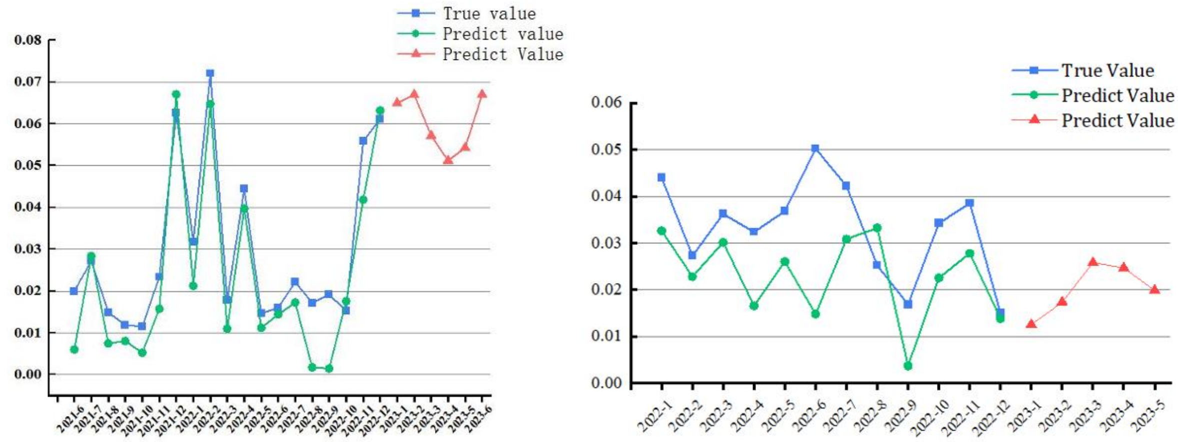

Figure 4. True Value and Predict Value

2.2. Insurance coverage gap

2.2.1 Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a method for evaluating relative effectiveness based on input-output data [5]. There are a number of key elements in the methodology, including: production possibility set, measurement, preferences, type of variable, level of the problem, and whether the data are deterministic or not. The combination of these elements can lead to different DEA models for solving different problems. [2] In this section, the data envelopment analysis model is used to assess the efficiency of insurance coverage in different regions, and then the gray prediction model is used to predict the development trend of insurance coverage gap.

The period of 2020-2022 is selected as the study period, and the empirical study related to efficiency is conducted by utilizing the data of climate disaster insurance in Guangdong Province of China and Florida State of the United States. The DEA method is selected for efficiency measurement, and according to the research results of Ma Zhanxin scholars [3], a comparative base period is selected as the efficiency measurement period, so that the efficiency calculations of DMU in other periods are based on the base period, and the inter-period comparisons of efficiency are realized, and the data model is as follows:

$$\begin{cases} max\theta(t) - \varepsilon(\hat{e}^T S^- + e^T s^+) \\ s.t. \sum_{j=1}^{n(0)} X_j(0)\lambda_j + S^+ = Y_0(t) \\ \sum_{j=1}^{n(0)} Y_j(0) - S^- = \theta Y_0(t) \\ \sum_{j=1}^{n(0)} \lambda_j = 1 \\ S^- \geq 0, S^+ \geq 0, \lambda_1, \lambda_2, \cdots, \lambda_n \geq 0 \end{cases} \tag{1}$$

We normalize the output of the DMU to produce results for the two cities of Fig 5.

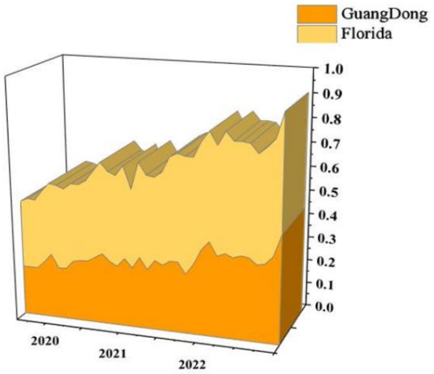

Figure 5. Insurance Cover Rate

2.2.2 Gray system

Gray system is an applied mathematical discipline that studies the phenomenon of information that is partially clear, clear and with uncertainty [6]. One of the models of gray theory is GM(1, 1), which uses equations and AGO to generate a series of data and used to predict future data. The specific public steps are as follows:

Data with a quasi-exponential law is the theoretical basis for modeling using the gray system, defining the smooth ratio of the series as:

$$p(k) = \frac{x^{0}(\mathrm{k})}{x^{(1)}(k-1)} \tag{2}$$

We can find that for the series to have a quasi-exponential law, it is only necessary to ensure that the smooth ratio p(k) ∈(0, 0.5)∈(0, 0.5), and the smooth ratios in the present data are 0.13 and 0.31. respectively. have quasi-exponential laws.

Gray prediction solution: the specific formula for generating the series is as follows:

$$x^{(1)}(i) = \{\textstyle\sum_{j=1}^{i} x^{0}(j) | i = 1,2, \ldots, n\} \tag{3}$$

A GM(1, 1) model is then built:

$$\frac{dx_t^{(1)}}{dt} + \hat{a}x_t^{(1)} = \hat{b} \tag{4}$$

A GM(1, 1) model is then built:

$$\hat{x}^{(1)}(t)|_{t-1} = x^{0}(0) \tag{5}$$

Where the parameters a and b can be found by least squares. The initial values are then entered into the prediction results:

$$\hat{x}_{k=1}^{(0)} = \hat{x}_{k=1}^{(1)} - \hat{x}_{k}^{(1)}, k = 1,2, \ldots, n-1 \tag{6}$$

According to the above gray prediction model [5], the predicted results of insured efficiency in Guangzhou and Florida for the last three years are shown in Fig:

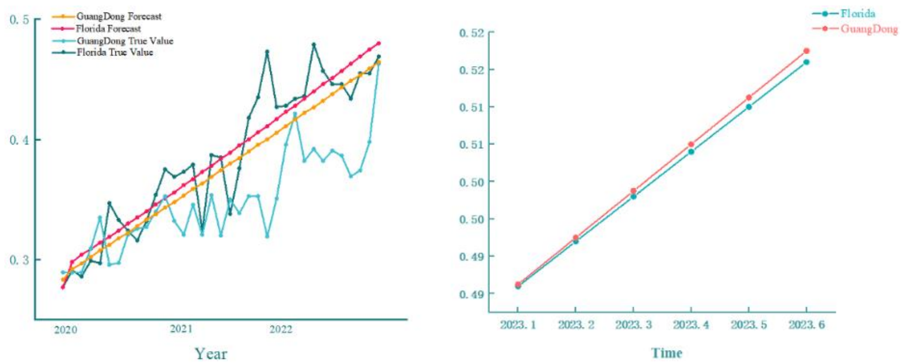

Figure 6. Insurance Coverage

From Figure 6, it can be seen that Florida has a mean extreme deviation of 0.0235, indicating that the model fits the data very well. The average extreme deviation for Guangdong is 0.0345, indicating that the model fits the data well.

The trend of insurance coverage gap can be obtained by simply processing the resulting insurance coverage efficiency.

2.3. Customer Behavior Factors

Considering the influence of customer behavior on insurance underwriting decisions, we will introduce two types of customer behavior that affect insurance underwriting decisions as customer influence factors.

(1) The level of disaster prevention system already in place for the user's insured property. We introduce the weights of the urban disaster mitigation capacity indicator to measure the level of the property's disaster prevention system, which comprehensively covers factors such as the structure of the house, the degree of newness and oldness of the house, the floors and spacing, the type of the house, and the building materials.

(2) Whether the property insured by the user has an indemnity history or not, we tend to think that properties with an indemnity history have a higher probability of being indemnified again, so appropriately increasing the guaranteed price of a property with an indemnity history is a reasonable and effective means of guaranteeing the profitability of the insurance company.

2.4. Profitability Decision Function

Summarizing the above data, we derive the profitability decision function:

$$K = P_{\text{price}} * Q_{\text{sales}} - P_{\text{claim}} * \omega_{\text{hisitory}} * (1 - \varsigma_{\text{disaater prevention}}) * \sigma_{\text{Claima costs}} \tag{7}$$

3. Statue of Liberty Climate Risk Analysis

3.1. Climate Analysis of the Statue of Liberty

The full name of the Statue of Liberty is “Lady Liberty Shining on the World”, which is a gift from France to the United States in 1876 to commemorate the 100th anniversary of the victory of the United States in the War of Independence from the British rule. The Statue of Liberty is one of the largest statues ever constructed [6]. Recently, it has suffered from multiple events caused by climate change, such as rising sea levels and the famous Hurricane Sandy. We collected precipitation, temperature, and wind data for the Statue of Liberty, i.e., Manhattan area in New York, and substituted them into the above model to construct the typhoon risk coefficient, high temperature risk coefficient, flood risk coefficient, etc., and finally the final climate risk coefficients were derived by entropy weighting method TOPSIS. And the climate risk composition of each risk factor measured in Manhattan, New York, Figure 7 shows the various data we collected.

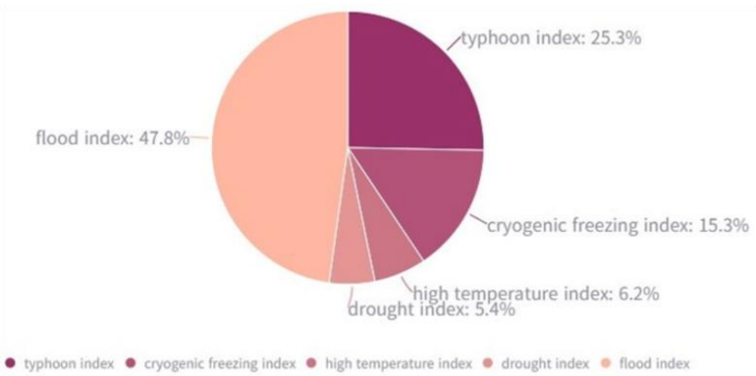

Figure 7. Index rate

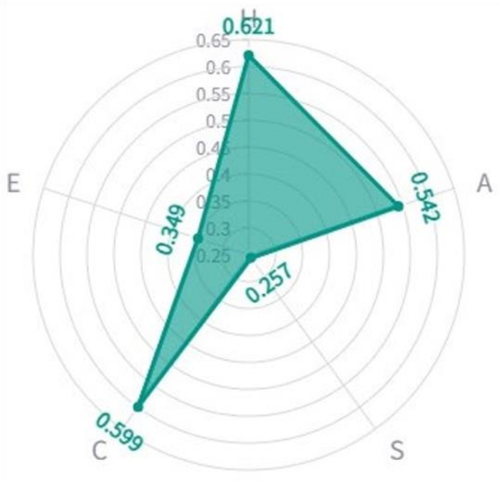

Figure 8. Radar Chart

3.2. Analysis of the heritage value of the Statue of Liberty and conservation measures

As can be seen in Figure 7, the flood index corresponds to the sea level problem and the typhoon index represents the hurricane problem. Although the challenges we encounter do not seem to be easy to solve, there is no doubt that we cannot just give up. Therefore, we must look at the cost of preserving American symbols and find viable ways to preserve the American spirit. This would be accomplished through our Architectural Heritage Value Assessment Model, and since the Statue of Liberty is an iconic landmark of New York, we expected to score higher in terms of historical and cultural value. Unsurprisingly, we obtained the following results, with the highest historical and cultural values:

Next, for the specific implementation of each heritage value, we can use linear programming to maximize the benefits. Due to space constraints, we will omit the computational process and go directly to the explanatory part. Ideally, according to our model, we could obtain a benefit of $1.53 million. Even though the damage from the hurricane is estimated to be as high as $77 million, this is still a sizable budget that can be saved for future restoration efforts.

For a historic landmark such as the Statue of Liberty, which is located in the middle of the ocean and is susceptible to saltwater and wind erosion, preservation and restoration of materials and structures should be a priority, while the Statue of Liberty's erosion-prone paintwork and changeable colors should be prioritized. In addition, since the Statue of Liberty is one of the most important landmarks in the United States, the establishment of a Statue of Liberty Documentation Center to document and present the history of the Statue of Liberty will help visitors learn more about the Statue of Liberty, both for preservation and development, i.e., conservation development of the Statue of Liberty.

4. Summary

Through the research in this paper, we constructed an insurance underwriting decision model based on climate risk coefficients, successfully integrating various technical tools such as entropy weighting method, ARIMA model, random forest method, data envelopment analysis (DEA), and gray prediction model. The results show that the model can effectively predict the probability of climate risks, disaster losses and insurance claims, and accurately assess the efficiency of insurance underwriting and coverage gaps. An empirical analysis using the Statue of Liberty as a case study further validates the practicality and accuracy of the model, which yields a climate risk index of 0.624 and proposes corresponding protection measures. This study provides scientific decision support for insurance companies when facing the challenge of climate change, which helps to protect profitability while rationally controlling the premium burden of customers and realizing the sustainable development of the insurance industry. Future research can further extend the application scope of the model by exploring more climate risk factors and specific cases in different regions to enhance the generalizability and accuracy of the model.

References

[1] Xinhai. Application of random forest model in classification and regression analysis [J]. Journal of Applied Entomology, 2013, 50 (4): 1190-1197.

[2] YANG Guoliang, LIU Wenbin, ZHENG Navy. An overview of data envelopment analysis (DEA) [J]. Journal of Systems Engineering, 2013, 28 (6): 840-860.

[3] Smith, Adam & Katz, Richard. (2013). US billion-dollar weather and climate disasters: data sources, trends, accuracy and biases. natural Hazards. 67. 10.1007/s11069-013-0566-5.

[4] Zhao, Xiaofen. An overview of gray system theory [J]. Journal of Jilin Institute of Education, 2011, 27 (3).

[5] Navigating the climate risk sustainability horizon: climate risk and sustainability in Re/insurance USA 2023 [J]. M2 Presswire, 2023.

[6] Zhong Kochen. Statue of Liberty [J]. Children's Stories and Pictures: The Discovery Encyclopedia, 2010 (12): 18-23.