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Insurance Company's Undertaking Model Based on ARIMA Algorithm

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Abstract. Extreme weather can cause economic losses to residents which can be reduced by purchasing insurance. From the perspective of insurance company, to earn maximum profit, they need to carefully consider whether to provide insurance services in a region, especially for where natural disasters happen frequently. The paper puts forward Natural disaster prediction model and Insurance company undertaking model. In the first part, the paper uses ARIMA algorithm to forecast when will the natural disasters happen, including extreme high and low temperature, droughts and floods, and tornadoes. Data form four different regions follow as example. In the second part, the paper applies C-L risk model, and converts it into Compensation forecast model. As an example, this model is also used to value the insurance details in Tempa, America and Jakarta, Indonesia. When the total insured value of the two places is greater than 44 billion dollars and 143 billion dollars respectively, the insurance company can make a profit.

Keywords: ARIMA; Natural Disaster; Forecast; Insurance.

1. Introduction

Extreme weather such as high temperatures, droughts, and tornadoes can cause economic losses to residents. Losses can be reduced by purchasing insurance. Pagano et al. [1] believe that insurance companies can use climate prediction models to develop measures to predict climate change and adjust undertaking measures. Gizzi et al. [2] found that big data can provide useful information for decision-makers and stakeholders to implement residential property insurance systems. Rufat et al. [3] used effects regression and interaction analysis to reveal a positive correlation between household adaptation to floods and comprehensive insurance coverage. Miroshnikova et al. [4] designed a financial resource allocation mechanism for flood prone areas and proposed the establishment of an effective flood insurance system in Russia.

Most studies only focus on natural disasters such as floods, demonstrating the role of purchasing insurance in reducing economic losses. This paper collects climate data from multiple locations such as Beijing, Jakarta, Canberra, Chicago, and predicts the occurrence of various extreme weather events. And from the perspective of insurance companies, an undertaking model has been developed to maximize the interests of insurance companies.

2. Natural disaster prediction model

The paper collected data on temperature, rainfall, and hurricanes from 1982 to 2022 in four regions: Beijing, China; Jakarta, Indonesia; Canberra, Australia; and Chicago, USA. In terms of temperature, high temperatures can significantly contribute to the occurrence of droughts or mountain fires. Concerning rainfall patterns, heavy precipitation often leads to floods while low levels of rainfall result in drought conditions. As for hurricanes, they typically inflict severe damage upon infrastructure and buildings. These extreme weather events have the potential to unleash catastrophic consequences globally and incur substantial economic losses.

The upper and lower limits of temperature standards vary significantly across different regions due to variations in climate conditions, leading to varying degrees of temperature adaptation [5]. To accommodate these climate differences, different countries and regions have implemented distinct standards for defining high and low temperatures.

The paper fit extreme weather conditions to temperature data from 1982-2022 according to the high and low temperature boundaries of these four regions, as shown in Table.1 and Fig.1.

Table 1. Temperature boundaries of four regions

District	High temperature limit	Low temperature limit
Beijing, China	22°C	0°C
Jakarta, Indonesia	27.5°C	No limit
Canberra, Australia	20°C	No limit
Chicago, USA	22°C	0°C

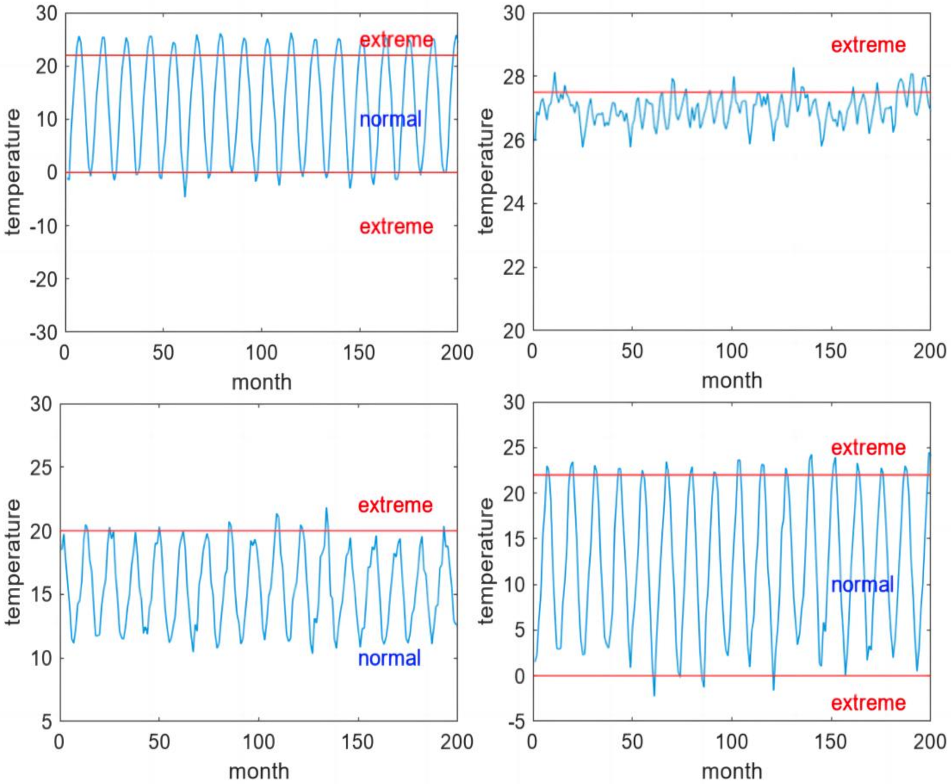

Figure 1. Temperature boundaries of four regions

The Bureau of Meteorology classifies regions with annual precipitation below 250 mm as arid, while those receiving annual precipitation exceeding 1200 mm are categorized as wet and rainy [6]. Extreme weather is either below the minimum annual precipitation standard or above the maximum annual precipitation standard. Our team used precipitation data from 1982 to 2022 in four regions: Beijing, China; Jakarta, Indonesia; Canberra, Australia; and Chicago, USA, to analyze the precipitation conditions of previous years, as shown in Fig.2.

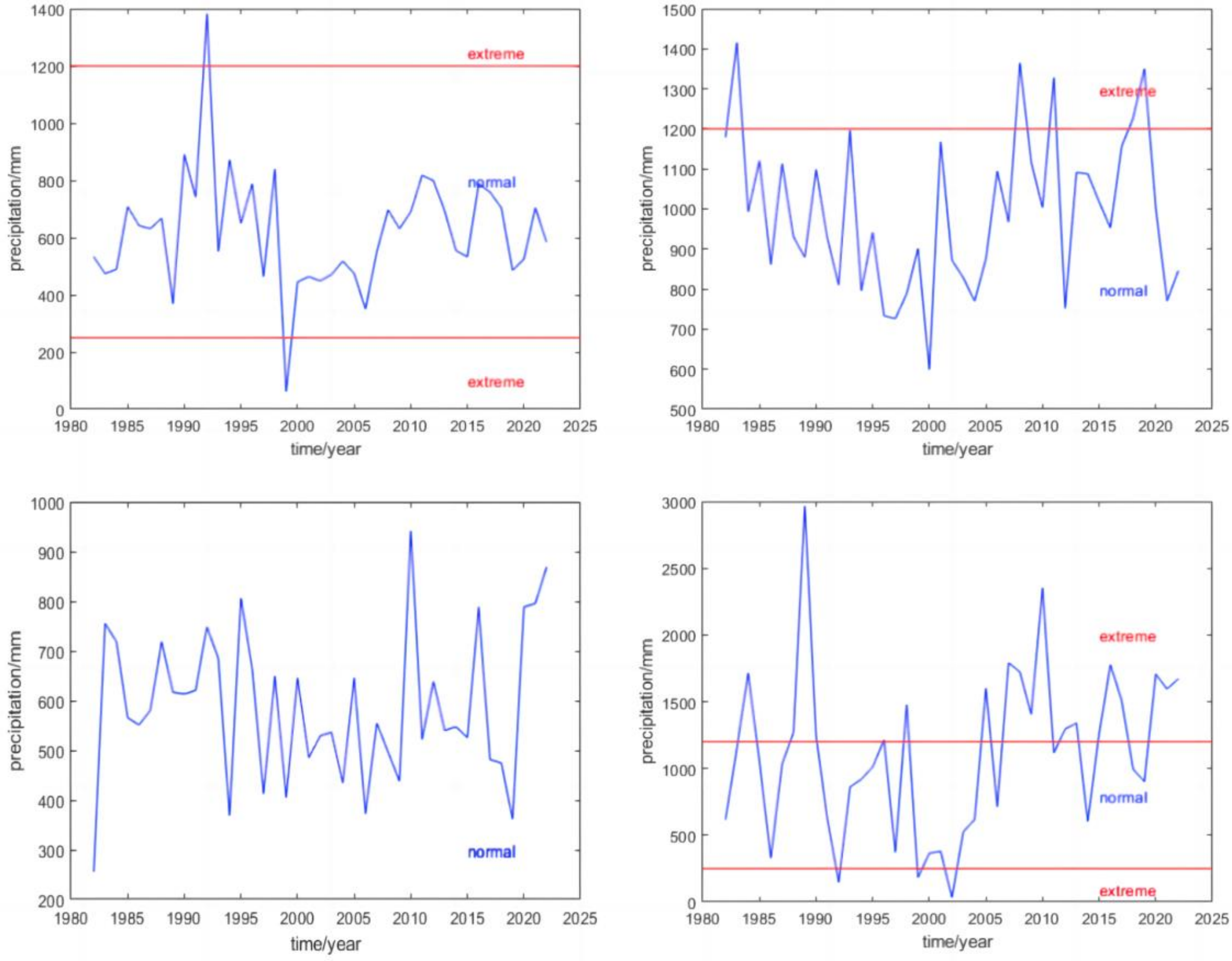

Figure 2. Precipitation boundaries of four regions

In the United States [7], for example, the paper collected data on the location and frequency of tornadoes from 2012 to 2022. As shown in the Fig.3, the red dots indicate the number of tornadoes in the last ten years. The redder dots a region has, the more likely it is to experience extreme weather events like hurricanes.

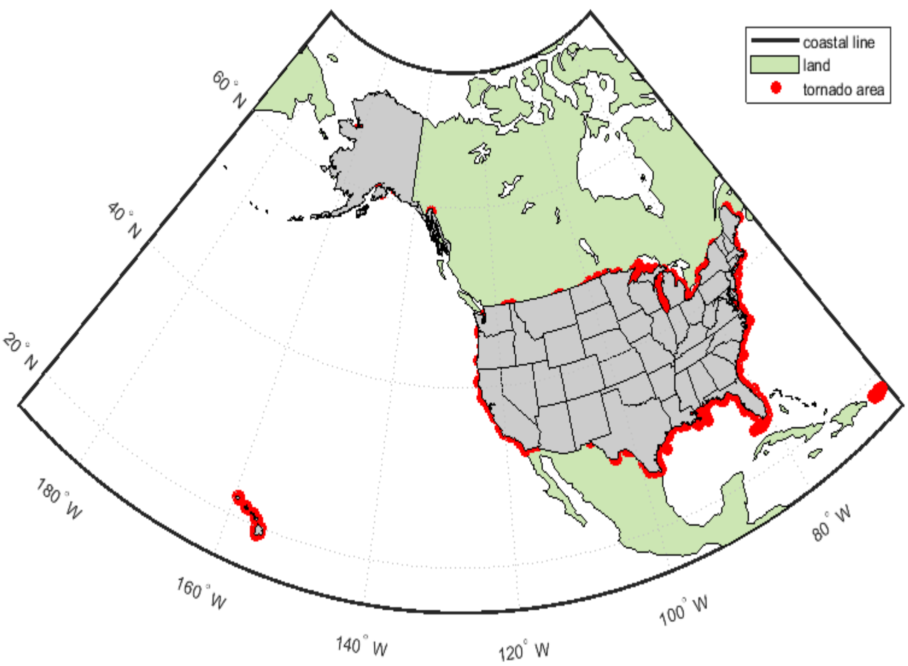

Figure 3. Tornado scatter in United State

As shown in the Fig.4, the paper extracted the top four cities SanJuan, Fairview, Playalin, and Springfie from the data for comparison. It can be seen from the figure that the annual frequency of tornadoes in these four regions is more than 20, and the frequency of tornadoes in region SanJuan is often much higher than that in the other three regions. The Fairview region had more than 120 tornadoes in both 2018 and 2019.

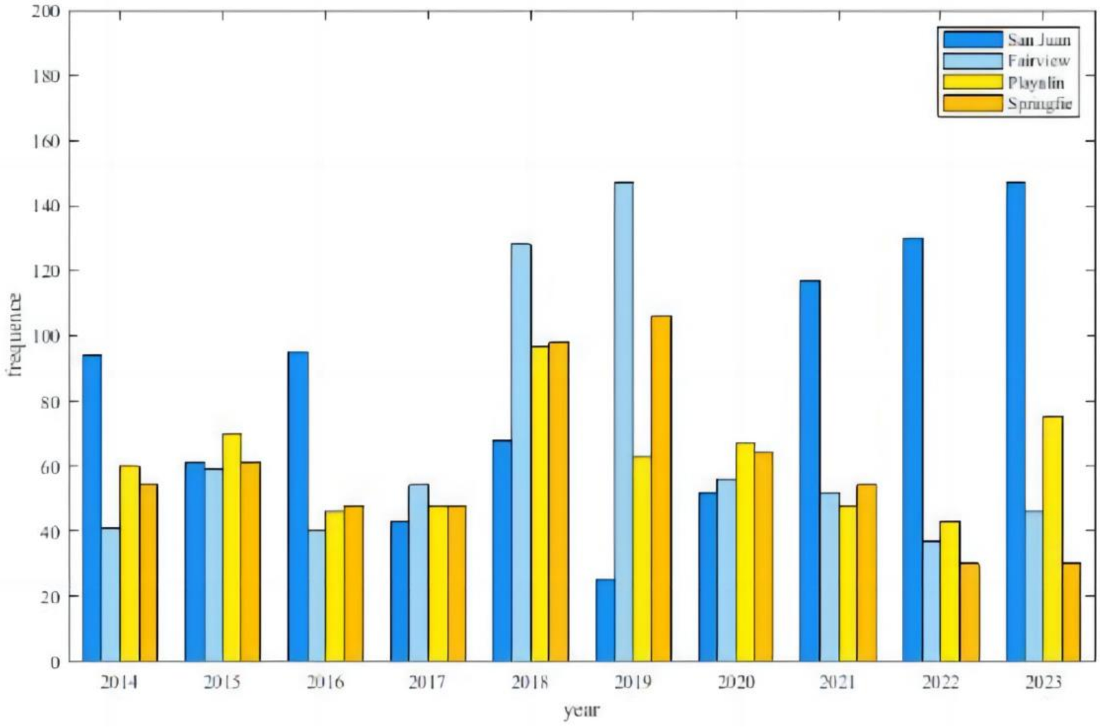

Figure 4. The bar chart of some regions in United State

3. Insurance company's undertaking model

Without considering reinvestment scenarios, the surplus process of the insurance company is determined by the classical C-L risk model, R_t represents the insurance company's surplus [8].

$$dR_t = cdt - \sum_{i=1}^{N_t} Y_i \, c \tag{1}$$

Where c is the premium rate, N_t is a homogeneous Poisson process with intensity λ_N, representing the number of claims occurrences.$Y_i$is a random variable representing the amount of a single claim.

Assuming a proportion α of the premium is earmarked for investment, with an investment return rate of β, the investment income generated over n years is $I\alpha(1+\beta)^n$.

Through a time, series ARIMA model, this paper forecasts the expected number of claims within the insurance period, replacing the previously assumed homogeneous Poisson process. The premiums charged by insurance companies are simply summarized in terms of different premium rates.

Let Y represent the annual loss due to a single occurrence of extreme weather, N be the number of claims, and t_i denote the corresponding claim proportion. Assuming the total insured asset value is P, and the premium rate for the i-th type of insurance is C_i, the premium based on the claim amount is calculated as $YN{*}t_i{*}\ C_i$, and the total premium [9] collected by the insurance company is $I = Pt_i{*}\ C_i$.

$$R_t = I(1-a) + Ia(1+\beta)^n - \sum_{i=1}^{4} YN * t_i * \ C_i \tag{2}$$

To validate the established insurance revenue model, we selected two regions from different continents that experienced extreme weather. They are Tampa in North America and Jakarta in Asia, respectively.

Tampa is a seaport city located on the west coast of the Florida Peninsula in the United States, the main meteorological disaster faced by the Tampa region is hurricanes, which belong to the category of "storms" in meteorological disasters.

The trend of the maximum instantaneous value of wind speed in the training set is shown in the Fig 5.

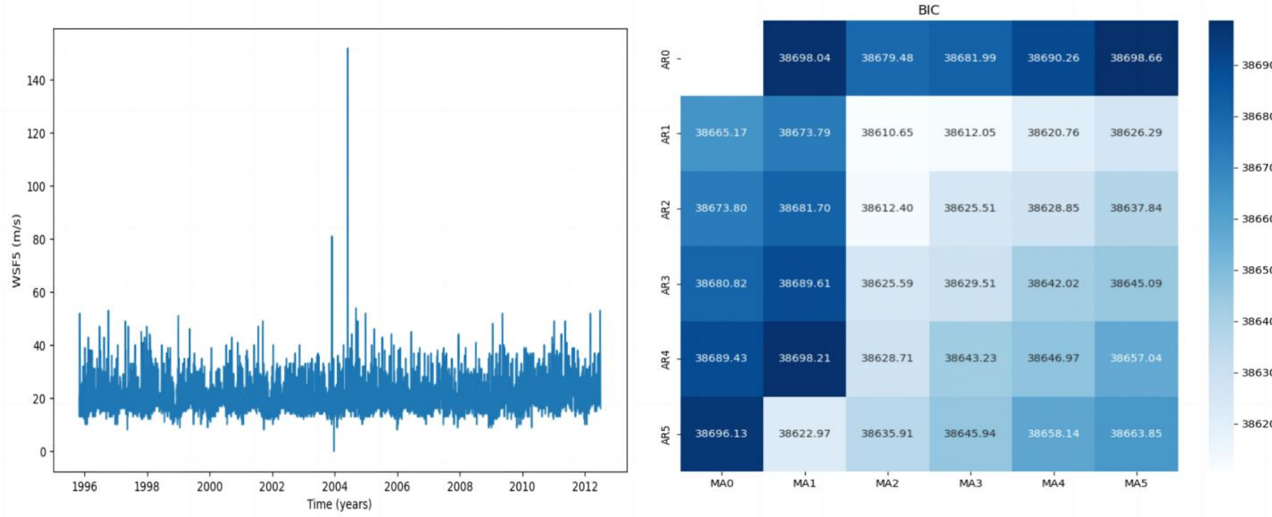

Figure 5. Speed training set (Left) and Heat map (Right)

The grid search method of ARIMA model searches for the optimal value of BIC (Bayesian Information Criterion) by traversing different parameter combinations, corresponding to the lightest colored area in the heat map: The order to obtain the optimal ARIMA model is: AIC (1, 3), BIC (1, 2).

After determining the parameters of the ARIMA model, predict the maximum daily wind speed for the next year. The red part represents the prediction result, and the blue part represents the original data.

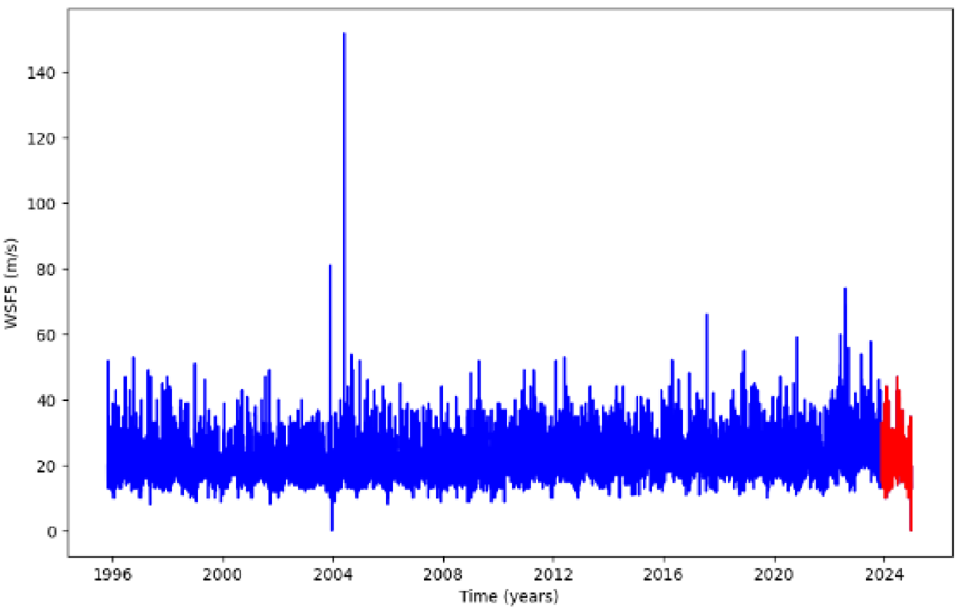

Figure 6. Time Series (ARIMA) Forecast Values

From the Fig 6, the predicted results are in good agreement with the volatility and periodicity of historical data. But individual extreme situations are difficult to predict.

Process and analyze the prediction results: predict the maximum daily wind speed in the Pattan area for the next three years, and calculate the frequency of hurricane occurrences. with a three-year insurance period, it is predicted that there will be 7 hurricanes in the Tampa area within three years, with an average property loss of 4.17 million US dollars each time.

Assuming that the average premium rate of different insurance products is [0.02, 0.01, 0.015, 0.012], corresponding purchase ratios are [0.1, 0.6, 0.2, 0.1], compensation ratios are [0.9, 0.6, 0.5, 0.4], investment period is three years, annual return rate is 0.5%, and the proportion used for investment is 0.2. The insurance surplus under different total insured assets is shown in Fig 7:

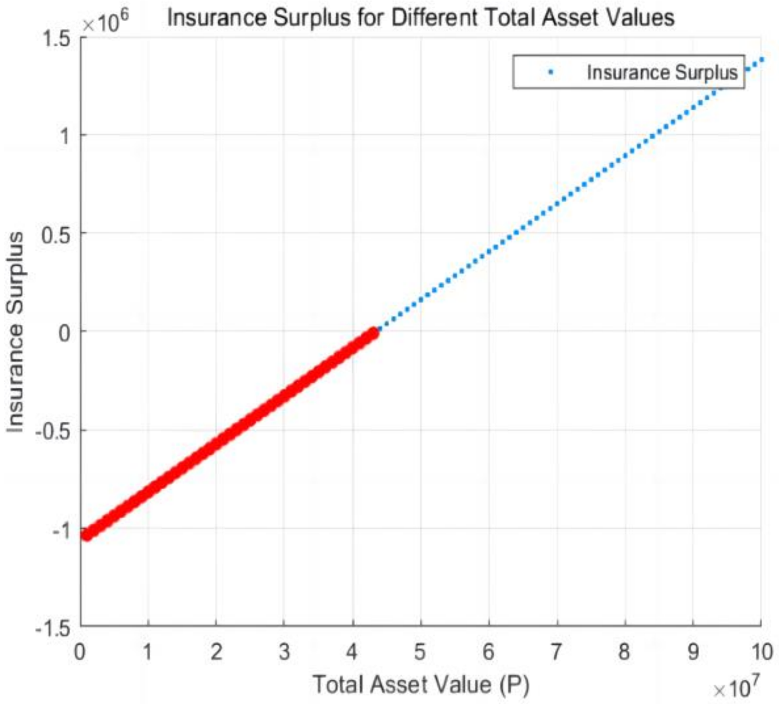

Figure 7. Insurance surplus for different total asset values in Tampa

Highlighted in red indicates a deficit. Based on the Fig 7, in the case where the total insured asset value in Tampa is less than $44,050,000, purchasing insurance in that area would result in a deficit. The purchase ratio represents the proportion of insured individuals purchasing different insurance products, typically with higher premium products corresponding to higher compensation ratios. Assuming a new purchase ratio F1 as [0.3, 0.6, 0.1, 0.0], corresponding to the observed purchase ratio, this paper examines the insurance surplus under different purchase ratios.

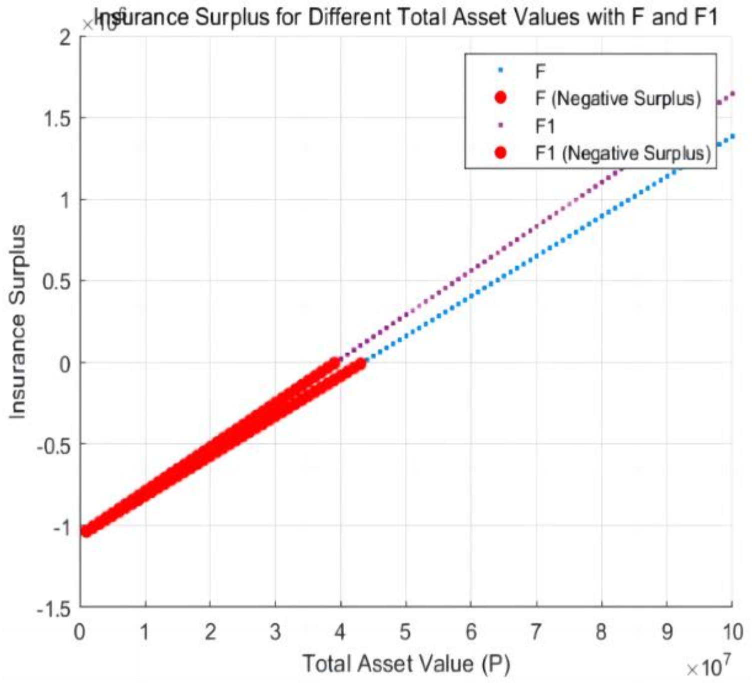

Figure 8. Insurance surplus for different total asset values with F and F1

From the Fig 8, it can be observed that when policyholders are more inclined to purchase products with higher premium rates and higher compensation ratios, the insurance company's surplus under the same insured asset value will be higher. The purchase ratio significantly influences the model's output.

For the second region, this paper selected Jakarta, Indonesia, located in Asia. Jakarta has a tropical rainforest climate, and due to its low-lying terrain and the influence of tropical monsoons, it faces the threat of flooding disasters. Like Tampa, this paper utilizes a time series (ARIMA) algorithm to predict the frequency of potential flooding disasters in Jakarta in the future.

Assuming a three-year insurance period, the forecast for the number of flooding disasters in Jakarta in the next three years is 6, with each event causing an estimated property loss of approximately $15,912,500. The insurance surplus under different insured asset values is as Fig 8 follows:

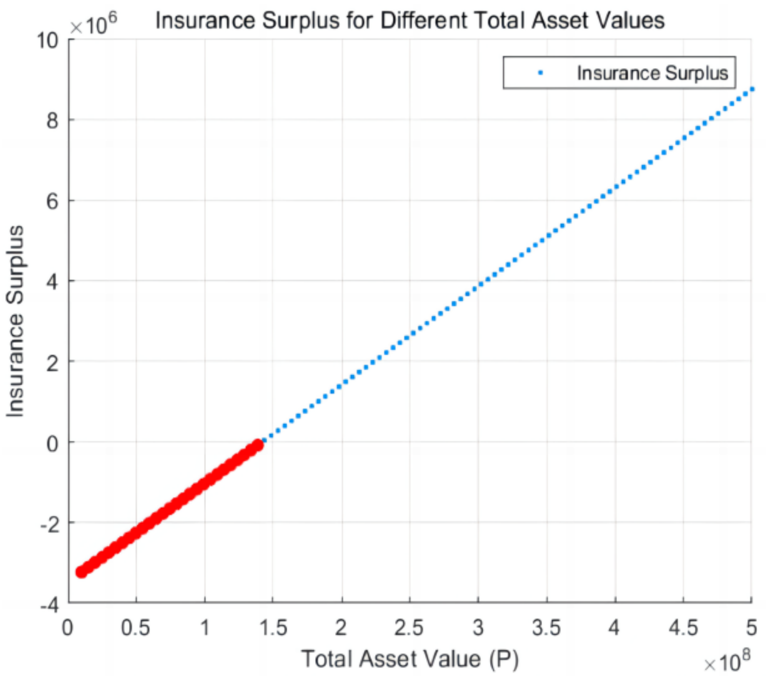

Figure 9. Insurance surplus for different total asset values in Jakarta

Observing the Fig 9, it is evident that insurance in Jakarta will result in a deficit when the total insured property value is below $143,636,000.

When surplus is generated from insurance and the expected annual claims amount is within the acceptable range, it is feasible to undertake insurance business in that region. The model primarily focuses on the entire insurance industry and the entire region, determining whether to insure in that area and under what conditions to do so. According to the model results, this depends on the frequency of natural disasters and the economic level in the region [10].

For property owners, they can influence the insurance company's decision by taking the following measures: Increase willingness to purchase insurance products with higher premium rates and higher payouts, or increase the total value of insured assets.

In summary, residents can influence the decision of whether insurance companies will insure by enhancing their willingness to purchase insurance.

4. Conclusion

Based on the maximization of the interests of insurance companies, this paper designs a complete underwriting model for insurance companies. The model comprehensively uses the ARIMA algorithm and the C-L surplus model to comprehensively consider the seasonality and volatility of meteorological disasters caused by extreme weather. Its simplicity and ease of use, along with convenient data accessibility, give it strong practicality. In cases where the insurance generates a surplus and the expected annual claim amount is within an affordable range, this paper recommends that the insurance company take on the insurance business in the region to maximize the benefits. In addition, the model is not only applicable to the insurance industry and region, but also assists insurers in determining under what conditions to insure in the region. With an in-depth analysis of factors such as the frequency of natural disasters in the region, the level of the economy, and the level of development of the insurance industry, the model provides insurers with comprehensive decision support to help reduce risk and maximize profits.

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