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Research on Insurance Industry Based on AR3 Multi Risk Model

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Abstract. The increasing frequency of extreme weather events presents challenges for the insurance industry, necessitating the construction of models for its development and offer insights and inspiration for real estate and community. In the current climate, aiming to enhance decision-making for insurance companies, this paper firstly establishes the AR3 Multi-Hazard Insurance Model incorporates three primary indicators of resilience, recovery, and adaptability, as well as secondary and tertiary indicators such as Insurance Penetration Rate (IPR), to evaluate regional disaster coping capabilities, whose weights are calculated using the E-AHP model. Additionally, the Climate Risk Insurance Model (CRIM) is established which utilizes the ARIMA model for data forecasting over the next 10 years and calculates the relationship between insurance costs and claims to indicate that it's unfeasible for insurance policies to be held in the California from 2029 to 2033 and in Queensland for 2028, and from 2031 to 2033. The results of the models are also used to determine the insurance company's risk strategies and how individuals can influence such strategies.

Keywords: Disaster Insurance, Real Estate, E-AHP, ARIMA

1. Introduction

In recent years, there has been an alarming increase in the frequency and intensity of extreme weather events, which have resulted in significant losses for countries worldwide. These extreme weather phenomena, including heat waves, cold snaps, and heavy precipitation, not only directly threaten public safety but also give rise to a series of man-made disasters that pose a substantial risk to human life and property.

The insurance industry has been profoundly impacted by the losses caused by such weather-related events. Not only have natural disaster claims surged, but insurance costs have also risen considerably. Consequently, insurers are now compelled to meticulously assess their risk-taking capacity. This disruption has upset the delicate balance between supply and demand in the insurance market, presenting a formidable challenge: how can insurance companies effectively balance profitability and risk? Furthermore, the insurance models employed today will significantly influence the decisions made by future real estate brokers and leaders. Considering these circumstances, it is imperative for the insurance industry to adopt a forward-looking approach. This necessitates the development of comprehensive long-term strategies to address these challenges and the formulation of integrated policies for the future.

The objective of this research is to provide insights and inspiration for the insurance industry and for the real estate and community sectors by constructing models that facilitate the understanding and development of the insurance industry. This paper introduces the AR3 Multi-Risk Insurance Model, which incorporates three primary indicators: resilience, recovery, and adaptability. Additionally, secondary and tertiary indicators, such as the Insurance Penetration Rate (IPR), are included to evaluate regional disaster coping capabilities. The weights of these indicators are calculated using the E-AHP (Evidential Analytic Hierarchy Process) model. Furthermore, this research establishes the

Climate Risk Insurance Model (CRIM), which utilizes the ARIMA (Autoregressive Integrated Moving Average) model for data forecasting over the next 10 years. This model calculates the relationship between insurance costs and claims, providing insights into the feasibility of holding insurance policies in specific regions during certain time periods. The study specifically suggests that it would be unfeasible to hold insurance policies in California from 2029 to 2033 and in Queensland from 2028 to 2033. The results obtained from these models not only aid in determining risk strategies for insurance companies but also shed light on how individuals can influence these strategies.

By developing comprehensive models and strategic policies to address the challenges posed by extreme weather events, the insurance industry can better navigate the complexities of balancing profitability and risk. Furthermore, these efforts will have a profound impact on the decision-making processes of real estate brokers and leaders, shaping the future of these industries.

The following sections of this paper will examine the research on the AR3 Multi-Risk Insurance Model, the analysis of primary and secondary indicators, the forecasting results using the ARIMA model, and the application of these findings in determining risk strategies. The comprehensive approach presented in this research aims to provide valuable insights for the insurance industry, real estate market, and community planning.

2. Research on AR3 Multi Risk Insurance Model

Since the Industrial Revolution, human activities have led to a large amount of greenhouse gas emissions into the atmosphere, causing the Earth's temperature to gradually rise, resulting in greenhouse effects and extremely low amplification effects, leading to an increase in the frequency of natural disasters. Extreme weather is not only a test of urban building quality, but also a test of its ability to rebuild after disasters and organize and plan new response strategies, which in turn can affect the impact of extreme weather on cities [5]. The concept of urban resilience is to measure the ability of a city to adapt, resist, recover, and transform in the face of various pressures and impacts. Here, this article will introduce the AR3 multi risk insurance model to consider the city's response to extreme weather. This article takes resilience, adaptability, and resistance as the primary indicators.

Resilience refers to the ability of a city to quickly and effectively reduce the impact of disasters in the event of extreme weather events. This involves post-disaster reconstruction, rapid recovery of services and supply chains, as well as the swift normalization of community and economic activities.

Adaptability demonstrates a city's capacity to learn, adapt, and improve strategies and measures based on experiences with extreme weather events, to better prepare for potential future disasters. It requires continuous learning, updates to planning, and the implementation of innovative coping strategies. By being adaptable, a city can enhance its resilience and response to extreme weather events [6].

Resistance refers to the ability of a city to quickly and effectively restore itself to a pre-disaster state after experiencing extreme weather events. This involves post-disaster reconstruction, rapid recovery of services and supply chains, as well as the rapid normalization of community and economic activities. It focuses on the restoration and revitalization of the city's systems and functions.

In summary, resilience, adaptability, and resistance are essential components for cities to effectively respond to extreme weather events, ensuring the reduction of disaster impacts, prompt recovery, and continuous improvement in preparation for future challenges.

A larger capacity means that various assets in the city are less likely to be damaged, which means that insurance payments will be lower. To measure the resistance, resilience, and adaptability of cities, we introduced secondary and tertiary indicators to quantify these concepts, as shown in figs 1 and 2.

Fig 1 Multi-Hazard Insurance Model Index.

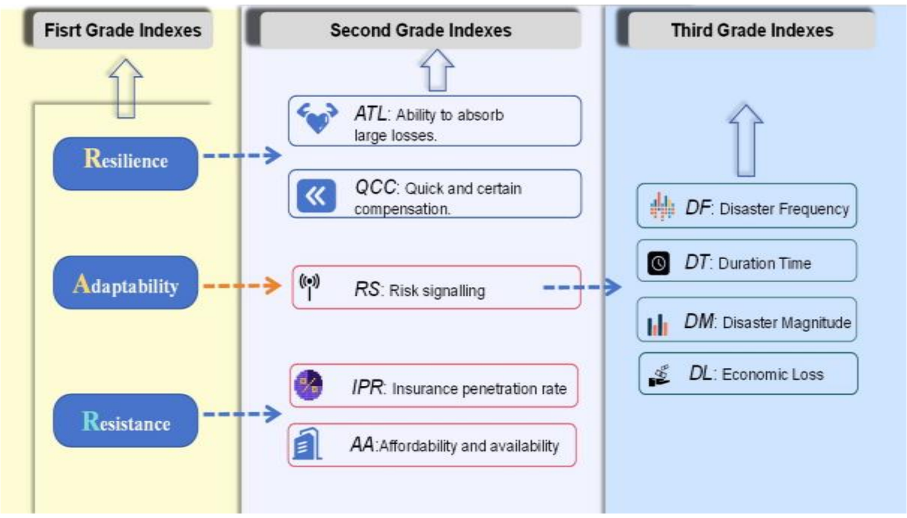


Fig 2. Description of indicators at all levels.

This study selected California, USA, and Queensland, Australia as representative case studies to ensure their representativeness and applicability. To obtain reliable and relevant data, we utilized reputable sources and publicly available information.

For the data concerning California, we accessed the official website of the Consortium for Mathematics and Its Applications (COMAP), which hosts the Mathematical Contest in Modeling (MCM) and Interdisciplinary Contest in Modeling (ICM). This website provides a wide range of data resources, including meteorological data, population statistics, economic indicators, and more. The data offered on the website are sourced from reputable institutions and undergo a rigorous collection and verification process. In this study, we utilized the data from this website to analyze the relationship between extreme weather events and insurance costs in California.

Regarding the data for Queensland, we relied on official government websites, such as the Australian government's official website, the Bureau of Meteorology, and other reliable sources. These sources provide comprehensive meteorological records, reports on natural disasters, and relevant insurance data for Queensland.

To ensure consistency and comparability, we performed minimum-maximum normalization on the collected data. This normalization technique accounts for variations in amplitudes and orders of magnitude among the data points. Additionally, we calculated the scaling matrix to further standardize the data. To prevent division by zero errors, a very small number ε was added.

By employing these reliable data sources and employing appropriate data preprocessing techniques, our study maintains representativeness and applicability. It provides valuable insights into the insurance industry and the relationship between extreme weather events and the associated costs in both California and Queensland.

$$z = (x - min)/(max - min) \tag{1}$$

Afterwards, this article found that the annual data of each indicator from 2013 to 2023 was relatively stable, without obvious trends or seasonal changes. Therefore, the paper chose the ARIMA model to predict the future value of this indicator.

$$\hat{Y_t} = c + \phi_1 Y'_{t1} + \phi_2 Y'_{t2} + \cdots + \phi_P Y'_{tp} + \theta_{1et-1} + \theta_{2et-q} + \theta_{qet-q} + e_t \tag{2}$$

$\hat{Y}_t$ is the predicted value of the time series at time *t*. *C* is the constant term of the model, $Y'_{t-1} Y'_{t-2} \cdots Y'_{t-p}$ are the first p lag values of the difference sequence, indicating that p is the order of the autoregressive part. Et-1, et-2, et-q are the first lagged prediction error q, where q is the order of the moving average part. ϕ 1, ϕ 2, ξ P is the coefficient of the autoregressive term. θ_1, θ_2, θ_Q is the coefficient of the moving average term [7]. Et is the prediction error of time t. P represents the order of the autoregressive term. D is the number of non-seasonal differences required to stabilize the time series. Q represents the order of moving average terms.

The predicted results for each indicator are shown in fig 3.

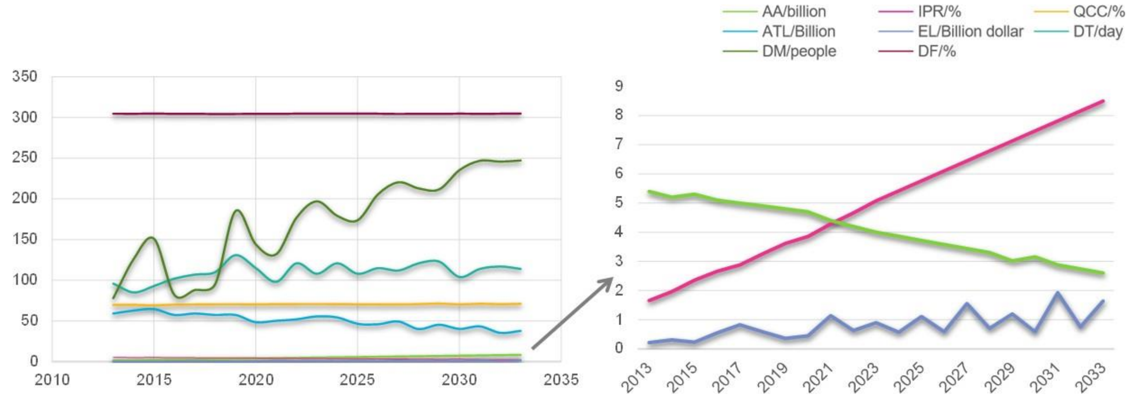


Fig 3. QLD forecast results.

The analysis of fig 4 shows that the vast majority of indicators in Queensland remain stable or show an upward trend within the forecast area.

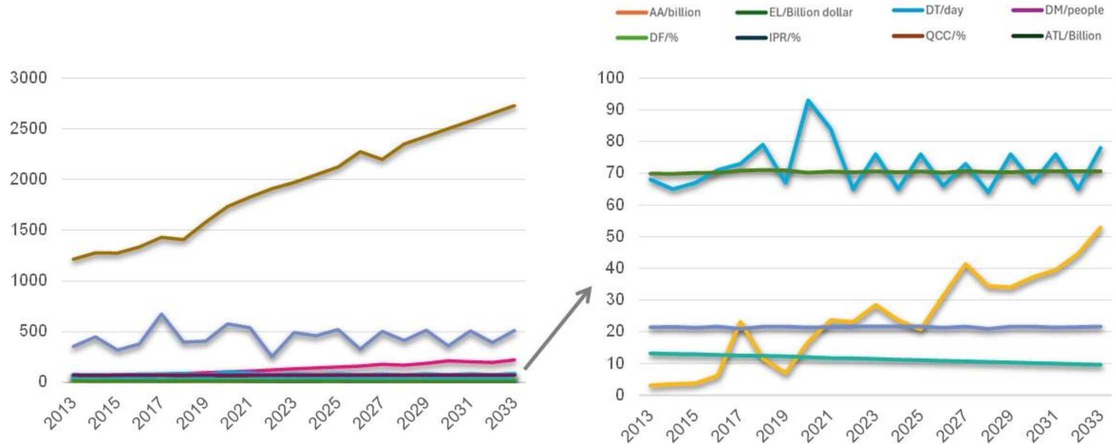


Fig 4. CA forecast results.

Then, for each secondary indicator under the primary indicator, the entropy weight method is used to determine its objective weight. This includes calculating the information entropy and coefficient of variation of indicators to obtain objective weights for each secondary indicator.

First calculate the weight of each sample p_{ij}.

$$p_{ij} = \frac{x_{ij}}{\sum_{k=1}^{n} x_{kj}} \tag{3}$$

Where x_{ij} represents the value of the i-th sample on the j-th indicator, and n is the total number of samples.

Next, calculate the entropy value e_j

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} p_{ij} \ln(p_{ij}) \tag{4}$$

Finally, entropy weights are calculated w_j

$$w_j = \frac{1-e_j}{\sum_{j=1}^{m}(1-e_j)} \tag{5}$$

Where m is the total number.

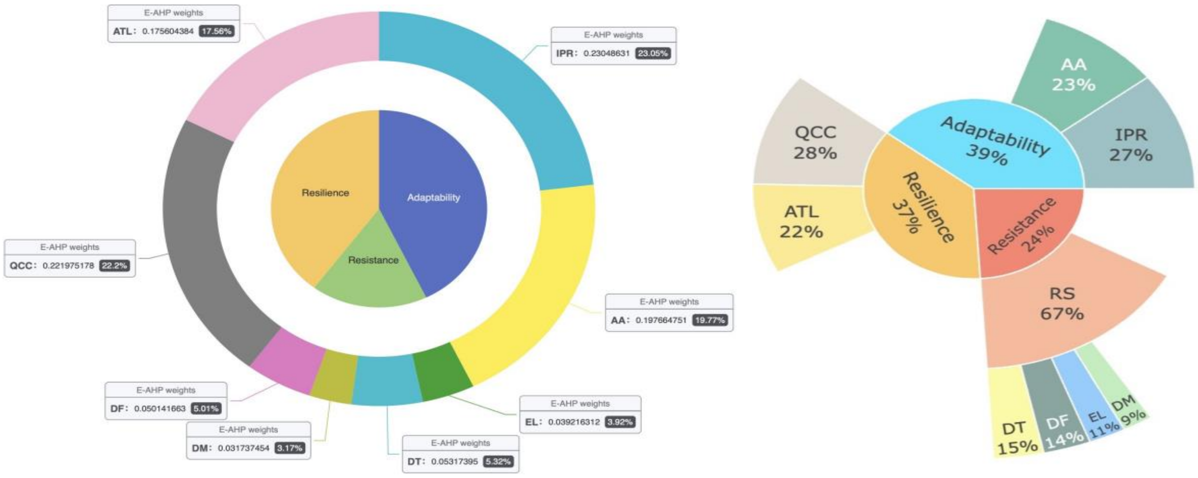
Then, this article uses the Analytic Hierarchy Process to construct a decision hierarchy model, which includes the objective hierarchy, the standard hierarchy (three primary indicators), and the plan hierarchy (corresponding secondary and tertiary indicators). Compare the first level indicators one by one and judge them based on their relative importance to construct a judgment matrix. Finally, the subjective weight is obtained.

Then calculate the weight vector of the AHP judgment matrix and test its consistency. The calculation of the consistency ratio indicates that both CRs are less than 0.1, indicating that they are within the confidence interval of the results.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{6}$$

$$CR = \frac{CI}{RI} \tag{7}$$

Finally, this article synthesized the objective weight obtained by entropy weighting and the subjective weight obtained by AHP in a ratio of 70% and 30% to obtain the final weight, as shown in fig 5.



(a) QLD Indicator weights. (b) CA Indicator weights.

Fig 5. Indicator Weights.

2.1. Climate Risk Insurance Model

After measuring the resilience of regional cities, in order to provide a decision-making tool for the insurance industry to evaluate the feasibility of underwriting specific policies in different scenarios, this paper developed a climate risk insurance model, as shown in fig 6.

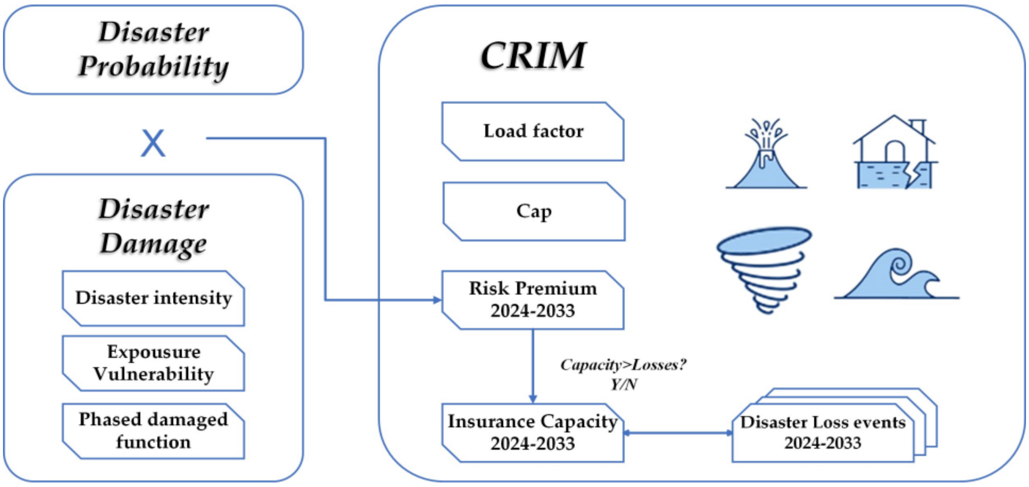


Fig 6. Climate Risk Insurance Model Idea diagram.

As shown in fig 6, this article will first calculate the disaster and disaster loss probabilities at different locations, and then multiply them to obtain the risk premium. Afterwards, the climate risk insurance model enables risk simulation to calculate the premiums required at different locations during different time periods and evaluate how the financial reserves of the insurance fund will change over time. The climate risk insurance model enables risk simulation to calculate the insurance premiums required for each location over time and evaluate how the financial reserves of the insurance fund will develop over time. Finally, decide whether to insure by comparing the claim amount and insurance cost. Then, we will discuss the various components of the diagram in more detail [8] [9].

2.2. Solution process and result analysis

In order to predict the probability of disasters from 2024 to 2033, this paper proposes a weighted comprehensive prediction model based on historical data. This model uses four key indicators: disaster frequency (DF), disaster management (DM), duration (DT), and economic loss (EL). That is to say, the weights of each of the four tertiary indicators under the previous RS secondary indicators were calculated using the E-AHP model mentioned above. This article uses the ARIMA algorithm to predict four indicators and calculates the weighted values of the predicted values, ultimately obtaining the probability of disasters.

$$S = w_{DF} \cdot DF + w_{DM} \cdot DM + w_{DT} \cdot DT + w_{EL} \cdot EL \tag{8}$$

$$P_t = \alpha + \beta_1 \cdot DF_t + \beta_2 \cdot DM_t + \beta_3 \cdot DT_t + \beta_4 \cdot EL_t + \epsilon_t \tag{9}$$

Among them, P_t represents the probability of disasters occurring in year t, α It is a constant term, β Is the coefficient for each indicator, ε T is the error term.

Next, the paper utilizes the Damage Scanner model, a multidimensional disaster economic loss assessment framework, to quantitatively estimate the direct and indirect economic impacts of a given hazard event. The model consists of three main components: a hazard intensity module, an exposure and vulnerability module, and a stage-damage function. The Damage Scanner model uses the stage-damage function to calculate the direct losses caused by natural hazards, and then a conversion factor is added to calculate the indirect losses caused by natural hazards, which is then summed up to calculate the total economic losses [10].

$$L = L_{direct} + \alpha \cdot L_{direct} \tag{10}$$

L_{direct} denotes the direct economic loss, which is calculated from the stage-damage function. α is a conversion factor used to estimate indirect damages from direct damages. L denotes the total economic loss, including both direct and indirect losses.

In calculating the Insurance premiums for different districts, we have chosen to use the Comprehensive Assessment Method to calculate the insurance cost per household as follows.

$$\text{Premium}_{it} = \frac{l \times h \times \text{Total expected damage}_{it}}{\text{Total houses}_{it}} \times \text{Disasters probability}_{it} \tag{11}$$

In this equation, l represents the premium load factor. When l=1, it represents the actual fair premium, which means that the premium for each policy covers the expected loss value. If l>1, it indicates additional expenses used to pay for management or transaction costs as well as the economic return (profit) of the insurance company. The total estimated loss refers to the total estimated loss caused by disasters in the i-th region within a year *t*.*h*(1>0) represents the proportion of house and furniture losses to the total direct losses [11]. The total number of houses is the total number of all houses in region i at time t. Based on predictions of climate change and expectations for socio-economic development, we anticipate that disaster losses, disaster probabilities, and housing numbers will occur over time.

The capital reserve of the insurance department depends on the accumulation of insurance premiums over time and insurance claims after natural events; Simply put, capital accumulation is equal to the integral of net income minus costs, and the costs of the insurance industry mainly come from insurance claims. Therefore, the total funds of the insurance department at a specific time point are calculated as follows.

$$\begin{aligned} \text{Insures funds}_t = \sum_{i=1}^{I} \square \sum_{t=1}^{T} (\text{Premium}_{it} \times \text{Totalhouses}_{it}) + \\ + \textstyle\sum_{i=1}^{T} \text{Disaster premium}_{it} - \sum_{i=1}^{T} \square \sum_{i=1}^{T} c\text{Damage}_{it} \end{aligned} \tag{12}$$

The capital growth assumption of insurance funds is based on the annual expected investment return rate, and this article assumes a 4%. To simplify the model, we did not consider reinsurance mechanisms and viewed insurance funds as the capital pool of the entire insurance industry. Families bear a certain proportion of losses through a deductible ratio 1c, and the insurance department pays the remaining losses based on the set maximum CAP. The total amount of disaster losses borne by the family at time *t* is:

$$\text{Householdlayer}_{it} = (1 - c) \times \text{Damage}_{it} \tag{13}$$

The insurance department shall pay the remaining losses up to the predetermined maximum limit (CAP). The total amount of flood losses paid by the insurance department is defined as follows.

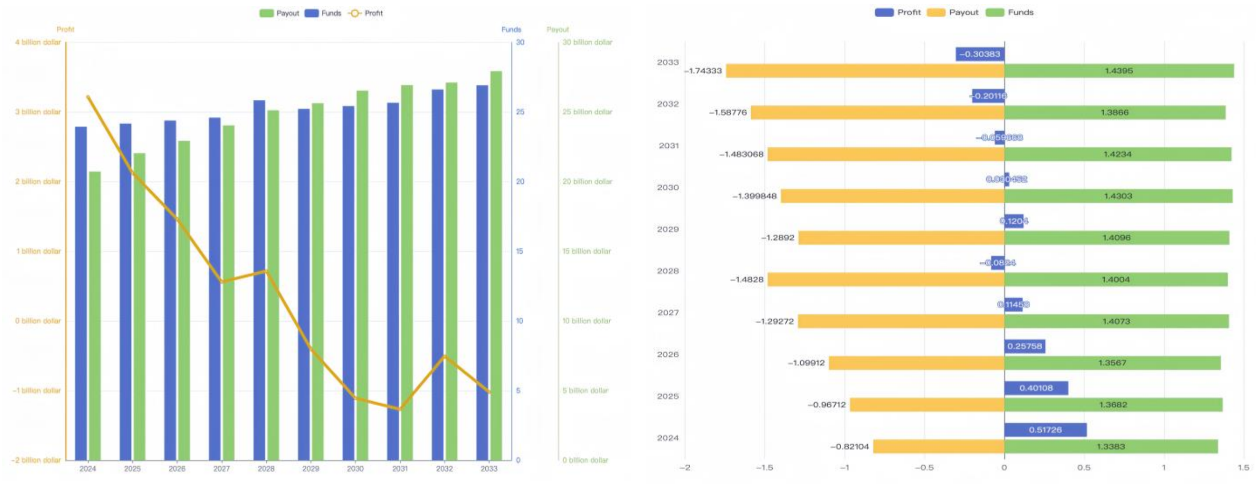
$$f(x) = \begin{cases} \text{CAP, if } \sum_{\mathrm{i}=1}^{\mathrm{I}} \text{damage}_{\mathrm{it}} - \text{household layer}_{\mathrm{t}} > \text{CAP} \\ \sum_{i=1}^{I} \text{damage}_{it} - \text{household layer}_t, if \ \sum_{i=1}^{I} \text{damage}_{it} - \text{household layer}_t < CAP \end{cases} \tag{14}$$

According to the original data, the estimated total flood losses for California, USA from 2027 to 2029 and 2031 to 2033 are estimated to be CAP, while the predicted total flood losses for Queensland, Australia from 2032 to 2033 are shown in Table 1. In the darkness, the maximum compensation can reach the highest premium.

Table 1. 2024-2033 CA and QLD payout projections.

Year	2024	2025	2026	2027	2028
CA/billion	20.726808	22.046376	22.929936	24.036344	25.125648
QLD/billion	0.82104	0.96712	1.09912	1.29272	1.4828
Year	2029	2030	2031	2032	2033
CA/billion	25.628288	26.536734	26.93076	27.114248	27.932224
QLD/billion	1.2892	1.399848	1.483068	1.58776	1.74333

Ultimately, insurance funds and payment for household claims are derived from data and compared to determine if they are profitable, As shown in fig 7.



(a) Comparison of CA Revenue Expenses. (b) Comparison of QLD Revenue Expenses.

Fig 7. Comparison of Revenue Expenses.

According to predictions, it was found that insurance companies will not be responsible for policies in California, USA between 2029-2033, Queensland, Australia between 2028 and 2031-2033. However, for both of these states, the derivative of the profitability function is positive, indicating an upward trend in profitability, although it may be negative at certain times. In addition, the spatial spillover effects of disasters may also have an impact, as cities close to the location of extreme weather events may share losses with that city, resulting in smaller losses for the city.

2.3. Risk management in the insurance industry - risk-taking

It is not difficult to see from the above research that we can quantify the urban resilience and insurance investment return of a region to determine whether to conduct business in that area. In this way, avoidance seems to be the answer to all risks. Risk avoidance also means avoiding potential benefits. However, although there is no doubt that there is a clear positive correlation between customer numbers and company performance for insurance companies, avoiding all risks is impractical. Faced with areas with high urban resilience, based on previously developed models, it is evident that some cities have a high ability to respond to natural disasters due to their high importance and experience. This city can respond and recover more effectively. This reduces the likelihood of large-scale losses and high claims, thereby lowering the potential financial risk of insurance companies. Insurance companies can not only increase their potential profits by providing insurance for such regions, but also enhance their business visibility and reputation by increasing insurance coverage. In some countries, laws or regulatory agencies require insurance companies to provide insurance to all regions to protect all consumers. This makes it necessary for insurance companies to provide at least a certain level of insurance coverage for these areas in order to expand the market without considering risks.

In order to maintain market share and attract customers, insurance companies may seek unique market opportunities, such as serving high-risk areas that other companies typically do not want to cover.

In addition to traditional one-year term insurance, insurance companies can also offer multi-year term insurance such as three-year and five-year terms. Long term insurance helps stabilize a company's income and risk distribution, and reduces potential claims pressure in the short term. Long term insurance can also provide long-term protection for customers, improve customer loyalty and stickiness. In addition, long-term insurance can provide companies with healthier cash flow.

Insurance companies can expand their business to different regions, countries, or markets to minimize excessive reliance on any specific region. In this way, even if an extreme event occurs in one region, businesses in other regions can still provide revenue, thereby reducing the overall risk of the company. In addition, this model allows insurance companies to have more data to filter customers.

Reinsurance is the practice of an insurance company transferring part of its risk to another insurance company to limit its potential losses. By purchasing reinsurance, insurance companies can reduce their exposure to large-scale losses by transferring some or specific types of claim risks to reinsurers. Reinsurance can help reduce losses and reduce insurance companies' exposure to catastrophic events.

3. Conclusions

This study employs the AR3 Multi-Risk Insurance Model and the Climate Risk Insurance Model to analyze the impact of extreme weather events on the insurance industry and to evaluate the coping capacity of different regions in the face of natural disasters. The two models have enabled a more nuanced understanding of risk management in the insurance industry and have provided decision support for insurance companies in the development of long-term strategies.

The AR3 model places emphasis on the resilience, adaptability, and resistance of cities, which are key indicators for assessing whether a region can respond effectively in the face of natural disasters. By empirically analyzing the cases of California and Queensland, it can be observed that although there are differences in insurance penetration and disaster resilience between the two regions, both demonstrate the necessity to further strengthen urban infrastructure and community emergency management capacity in the face of future risks.

Furthermore, the application of climate risk insurance modelling has demonstrated the significance of temporal windows for insurance policy holdings and region selection. The projections indicate that insurance policies may be infeasible in specific time periods, such as 2029 to 2033 in California and 2028 and 2031 to 2033 in Queensland.

In conclusion, the findings of this study provide insurance companies with a scientific foundation for operational modelling and strategic decision-making. Furthermore, they offer policy makers and urban planners' valuable insights on how to enhance urban resilience. As the impact of climate change persists, the continued advancement of research in this field will have a long-term impact on the insurance industry and the global capacity to cope with extreme weather events.

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