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Underwriting Risk Prediction Based on Moran Process and Fourier Fitting

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Abstract. Extreme-weather events are becoming a crisis for property owners and insurers, which has drawn widespread attention. For insurance companies, predicting regional losses from Extreme-weather events and studying the participation decisions of insurers can inform insurance strategies. This paper primarily focuses on the impact of extreme-weather events on insurance behavior, based on ten years of extreme-weather data of Michigan, we use Fourier fitting to predict the frequency of extreme-weather events in the subsequent year. Next, to measure underwriting risk, this paper considers economic losses and pay-out ratios, etc. to apply Biotic community Strategy-updated Moran process to simulate the social leaning and reciprocal mechanism in catastrophe insurance purchase decision-making combined with the prediction results and consumers with different levels of risk-aversion and expected utility perception. Based on the above analysis, the URA model is developed, and the validity of the model is demonstrated using Michigan as an example. The evolutionary dynamic analysis based on Moran process expands the research perspective of the insufficient demand for Extreme-weather insurance, and can be a reference for insurance company's insurance strategy.

Keywords: Insurance; Fourier Fitting; Moran Process.

1. Introduction

With the intensification of global climate change and the rapid increase of human activities, extreme weather events are becoming more frequent, posing a serious threat to the safety of human lives and property [1-2]. Under such circumstances, the insurance industry plays an important role in disaster risk management as an economic shock absorber and social stabilizer [3-4]. The changes in total losses and the amount of insurance compensation losses from 1970 to 2021 are shown in Figure 1 [5].

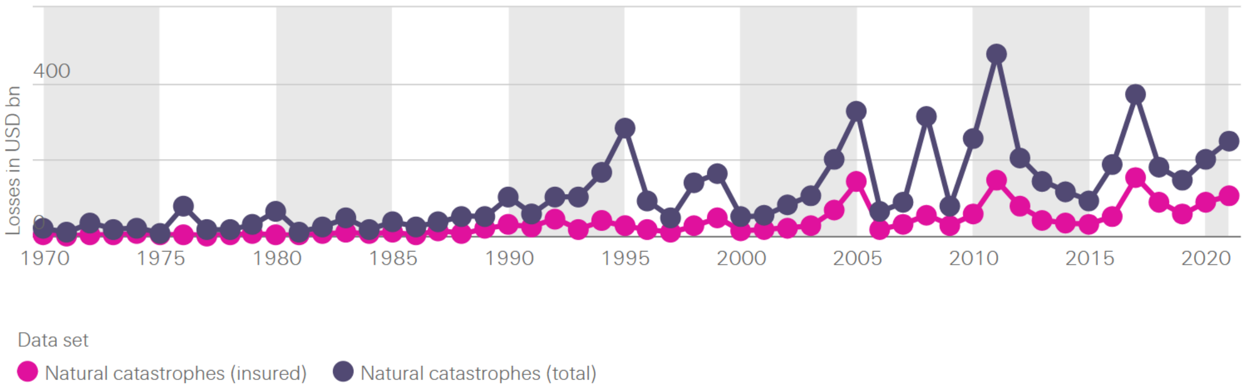


Figure 1. Comparison of total losses and insurance recoveries

As seen, there is an upward trend in economic losses from extreme weather events as the number of years increases. However, the rise in the amount of insurance compensation also tends to bring about a rapid rise in insurance premiums. According to Swiss Re, by 2040, losses from weather-related events in regions such as Australia, Canada, and France could increase by 35% to 120%, and premiums for primary insurance coverage could in-crease by 30% to 60% [6]. At the same time, the global insurance coverage gap is gradually growing as major insurers continue to narrow insurance coverage in disaster-prone regions following an increasing number of extreme events [7]. Therefore, for the long-term health of the insurance industry in each region, how to model the deployment of property insurance while focusing on the affordability of homeowners and the global coverage gap has become a top priority.

Liu et al. combined future climate scenarios with a quantitative assessment model of natural disaster risk to assess socio-economic risks and determining the integrated risk levels [8]. Hu et al. highlight the influence of precipitation on economic flood risk by developing a linear regression model to predict precipitation patterns, estimating financial loss risk several months in advance [9]. Jacob Pastor-Paz examined the impact of extreme weather events on residential insurance policies by projecting climate change [10].

In this paper, based on ten years of extreme-weather data of Michigan, we use Fourier fitting to predict the frequency of extreme-weather events in the subsequent year. Next, to measure underwriting risk, we consider economic losses and payout ratios, etc., combined with the prediction results, we conducted an evolutionary analysis of willingness to insure using Moran process, define the URA factors and build the URA model. Our model was demonstrated using Michigan, and the URA factor was calculated to be 6.183, indicating that Michigan is not suitable for underwriting, which is in line with reality, and the model was validated.

2. The fundamental of Underwriting Risk Assessment (URA) Model

2.1. Establishment of URA factors under dynamic analysis of Moran process evolution

Insufficient demand for property insurance is an important issue that hinders the development of the insurance market in regions prone to extreme weather. Since the insurance behavior of a limited group of consumers can be regarded as a social learning and social reciprocity mechanism, the Moran process can be used to study the evolutionary law of the group's participation rate and analyze the moderating effect of each factor on the participation rate. The conditions and paths for the evolutionary advantage of the participation strategy are solved after considering various factors.

2.1.1. Basic Assumptions and Parameter Definitions of the Moran Process.

Let the total number of residents in the study area be N and categorize their decisions about property insurance into participation and non-participation, where participation is denoted as 1 and non-participation is denoted as 0. The insurance issued by the region's insurance is short-term and the enrollment strategy can be updated by the consumer at the end of each insurance contract.

The initial wealth of the residents in the study area is W, the probability of extreme weather is P, and the total economic loss per resident due to extreme weather is L. Let residents choose to enroll in the insurance, each of them pays a premium I, and the payout rate K is the ratio of the total amount of compensation received to the amount paid for the premium I. If they do not enroll in the insurance, the residents do not have to pay premiums and naturally cannot receive compensation from the insurance company. However, they can receive a certain percentage of post-disaster relief from the government, which is set to t.

According to the expected utility theory, a Constant Relative Risk Aversion utility function can be used to measure the residents' fear of extreme weather occurrences with the following formula:

$$U(x) = \frac{x^{1-\gamma}}{1-\gamma} \tag{1}$$

Where γ ($0 < \gamma < 1$) is the relative risk aversion coefficient.

To reduce the probability of claims, the insurance company contributes a portion of the premium to the government's extreme weather preparedness efforts. In this way, the premiums paid by the insured also provide an indirect benefit to the uninsured residents, i.e., the "free-rider" benefit [11], denoted as F.

2.1.2. Frequency-dependent Moran processes.

(1) Expected returns

Based on the above assumptions as well as homogeneity, we constructed a symmetric payment matrix for the residents of the area A, B to represent their expected utility, as shown in Table.1.

Table 1. Symmetric payment matrix for resident enrollment strategies

Resident A	Resident B	
	Enrollment (1)	Non-insurance (0)
Enrollment (1)	EU_1, EU_1	$EU_1, E[U_0\|U_1]$
Non-insurance (0)	$E[U_0\|U_1], EU_1$	$E[U_0\|U_0], E[U_0\|U_0]$

Where $E[U_1]$ is the expected utility of the insured residents, $E[U_0|\ U_1]$ is the expected utility of the uninsured individuals when the other party is insured, and $E[U_1|\ U_0]$ is the expected utility of the uninsured individuals when the other party is not insured. The specific formula is as follows:

$$EU_1 = PU(W - I - L + IK) + (1-P)U(W - I) \tag{2}$$

$$E[U_0|\ U_1] = PU(W - L + tL) + (1-P)U(W) + F \tag{3}$$

$$E[U_0|\ U_0] = PU(W - L + tL) + (1-P)U(W) \tag{4}$$

If the number of insured residents among the number N is i, then the expected returns of strategy 1 and strategy 0 are respectively:

$$S_1(i) = \frac{i-1}{N-1}EU_1 + \frac{N-i}{N-1}EU_1 = EU_1 \tag{5}$$

$$S_0(i) = \frac{i}{N-1}E[U_0|\ U_1] + \frac{N-i-1}{N-1}E[U_0|\ U_0] = E[U_0|\ U_0] + \frac{iF}{N-1} \tag{6}$$

(2) Fitness

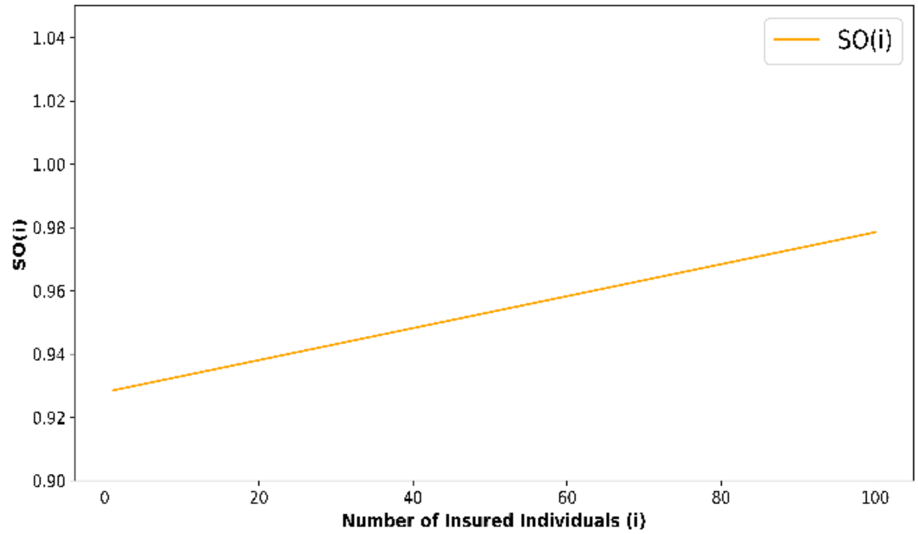
Fitness is the basis for updating the strategies of residents in extreme weather prone areas, denoted as $f(i)$, where a larger fitness indicates a higher chance of the strategy being selected.

The linear relationship chooses ω $(0,, \omega < 1)$ to denote the random disturbances, then the fitness $f(i)$ of strategy 1 and strategy 0 is related to the expected return $S(i)$ as follows:

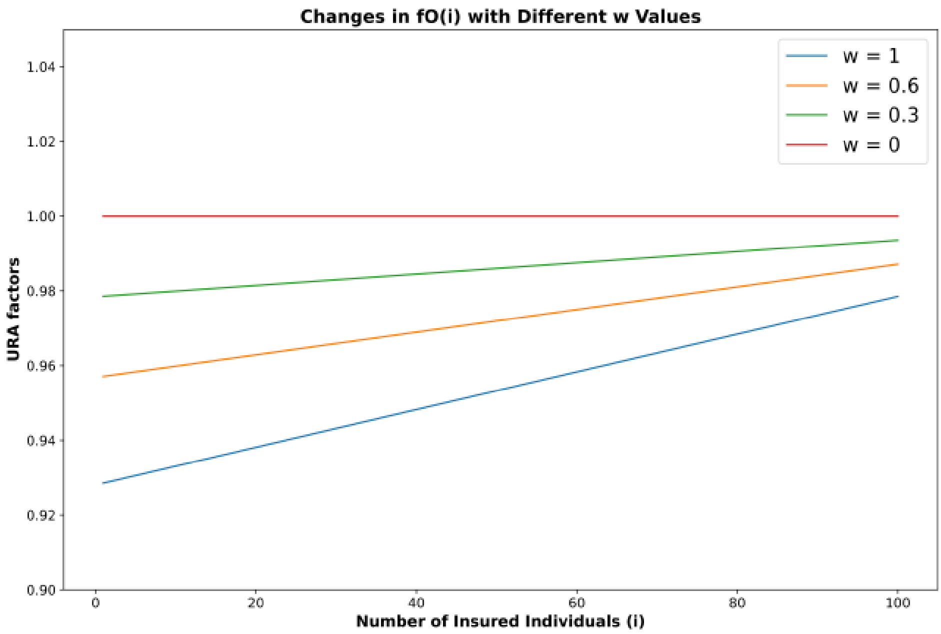
$$f_1(i) = 1 - \omega + \omega S_1(i) \tag{7}$$

$$f_0(i) = 1 - \omega + \omega S_0(i) \tag{8}$$

The images of $S(i)$ and $f(i)$ are in Figure 2:



(a) Expected return $S_0(i)$



(b) The change in $f_0(i)$ for increasing ω

Figure 2. The relationship between the effect of ω on strategy choice

As ω increases, the more similar the two function images are, the expected return has a greater influence on strategy choice. When $\omega = 1$ the two function images are identical, indicating that strategy choice is dominated by expected returns, i.e., by residents who have an accurate perception of the risk of extreme weather in the region and can make accurate judgments about the expected returns from insurance. When $\omega = 0$, the two are unrelated and individual decisions depend on random factors, i.e., the insurance participation behavior is dominated by people whose behavior is completely influenced by random factors.

The exponential function, denoted by α $(\alpha..0)$ for choice intensity, is used to characterize the sensitivity of residents' strategy choices to expected returns. The relationship between the fitness $f(i)$ and the expected return $S(i)$ for strategy 1 and strategy 0 is as follows:

$$f_1(i) = e^{\alpha S_1(i)} \tag{9}$$

$$f_0(i) = e^{\alpha S_0(i)} \tag{10}$$

From the expression, it follows that as α gets larger, individual strategy choices become more sensitive to expected returns. Residents who are extremely sensitive to expected returns make active participation decisions in the short run after suffering extreme weather losses.

In summary, different functional relationships and parameter values of fitness and expected return can separately describe the insurance enrollment behavior of residents in realistic extreme weather-prone areas. Taking a completely random group as a benchmark, this paper focuses on the evolutionary dynamics of insurance participation strategies of three types of residents: those dominated by random factors (ω tends to be close to 0 in the linear relationship), those dominated by expected returns ($\omega = 1$ in the linear relationship), and those who are extremely sensitive to the expected returns ($a > 0$ in the exponential relationship).

(3) Fixation probability

The fixation probability is an important indicator of the evolutionary dynamics of the Moran process, by which the probability that a given strategy will eventually become the only strategy of the group can be calculated [12].

Denote by ϕ_i the probability that i residents choose strategy 1 at the beginning of the development to all choose strategy 1, which is obtained by the full probability formula brought to the boundary conditions $\phi_0 = 0$, $\phi_1 = 1$:

$$\phi_i = \left(1 + \sum_{j=1}^{i-1} \prod_{k=1}^{j} \frac{f_0(k)}{f_1(k)}\right) \Big/ \left(1 + \sum_{j=1}^{N-1} \prod_{k=1}^{j} \frac{f_0(k)}{f_1(k)}\right) \tag{11}$$

So, the fixation probability that only one person in the region chooses to enroll develops to the point where enrollment becomes the only strategy for all residents in the region is:

$$\rho_1 = \phi_1 = 1 \Big/ \left(1 + \sum_{j=1}^{N-1} \prod_{k=1}^{j} \frac{f_0(k)}{f_1(k)}\right) \tag{12}$$

Similarly, the fixation probability that only one person in the region chooses to be uninsured develops to the point where the uninsured strategy becomes the only strategy for all residents in the region is:

$$\rho_0 = 1 - \phi_{N-1} = 1 \Big/ \left(1 + \sum_{j=1}^{N-1} \prod_{k=j}^{N-1} \frac{f_1(k)}{f_0(k)}\right) \tag{13}$$

(4) Indicators of evolutionary dynamics

The criteria adopted in this paper for judging the direction of individual strategy choice and the trend of group strategy evolution consist of two kinds:

Judgment based on fitness: when there are i people enrolled in the region, the difference in fitness of the two strategies can be used as a change in how the strategies are selected, copied, and reproduced. I.e.:

$$h_i = f_1(i) - f_0(i) \tag{14}$$

If the result is greater than 0, it means that the fitness of strategy 1 is greater than that of strategy 0, and residents are more likely to choose strategy 1. Conversely, they are more likely to choose strategy 0.

Judging by fixation probability: we define the strategy fixation probability ratio R as the ratio of ρ_0 to ρ_1, i.e.:

$$R = \frac{\rho_0}{\rho_1} = \prod_{K-1}^{N-1} \frac{f_0(k)}{f_1(k)} \tag{15}$$

$R > 1$, i.e., $\rho_0 < \rho_1$, means that the participation strategy is more likely to be selected for replication and reproduction. The opposite implies that the non-participation strategy is more likely to take root in the region. For residents with a dominant random factor (ω tends to 0 in the linear relationship), $f_1(i) = f_0(i) = 1$, bringing in the above equation yields the fixation probability of the two strategies for this type of resident as $\rho_0 = \rho_1 = 1/N$.

2.1.3. Evolutionary advantage and establishment of URA factors.

For the proportion of participation strategies being selected in the region, three evolutionary advantages are generally defined [13]:

Definition 1: Define a strategy as an evolutionarily stable strategy (ESS) when it can resist the intrusion of other strategies. Measured by the difference h_i between the FITNESS of the two strategies.

Definition 2: When the fixation probability of strategy 1 is greater than the fixation probability of strategy 0, i.e., $\rho_1 > \rho_0$, define strategy 1, i.e., enrollment, as a risk-dominant strategy (RD).

Definition 3: An individual's choice favors strategy 1 in place of strategy 0 when the fixation probability of strategy 1 is greater than the fixation probability of the random-factor-dominant resident, i.e., $\rho_1 > 1/N$. Define this time as when strategy 1 is an AD strategy.

Since the evolutionary tendency is obtained by considering the factors affecting the underwrite behavior of insurance companies such as economic losses and payout rates, this tendency can be used to qualitatively measure the URA factor, which is quantitatively represented by R in this paper. The larger the URA factor is, the higher the underwrite risk is proved.

2.2. Fourier series extreme weather frequency prediction models

Different disaster-causing factors play different roles in extreme weather, but they can be generally categorized into two aspects: on the one hand, there are disaster-causing factors that play long-term and decisive roles, such as precipitation, temperature, etc.; on the other hand, there are disaster-causing factors that show cyclical and seasonal effects, such as seasonal precipitation and hurricanes, etc. Therefore, we can establish the following time series trend fitting model to describe the damage caused by extreme weather:

$$S(t) = a_0 + b_0 t + \sum_{n=1}^{N} \left(a_n \cos \omega_n t + b_n \sin \omega_n t \right), t = 1, 2, \ldots \tag{16}$$

Where a_0, b_0 are determined by the causative factors that play a long-term role; a_n, b_n are measured by the causative factors that show periodicity and seasonality, and also affect the amplitude and phase of this model; N is the total number of causative factors, and its increase can improve the accuracy of the model during the fitting process.

3. Results

3.1. Validation of the model

By setting the intensity of choice ω in the linear function of FITNESS and EX-PECTED RETURNS to be 1, the consumer decision at this point is completely dominated by EXPECTED RETURNS. In this setting, we assume that there are 100 people in the area and 50 people initially choose to be insured. The evolutionary change in the number of insured people is shown in Figure 3.

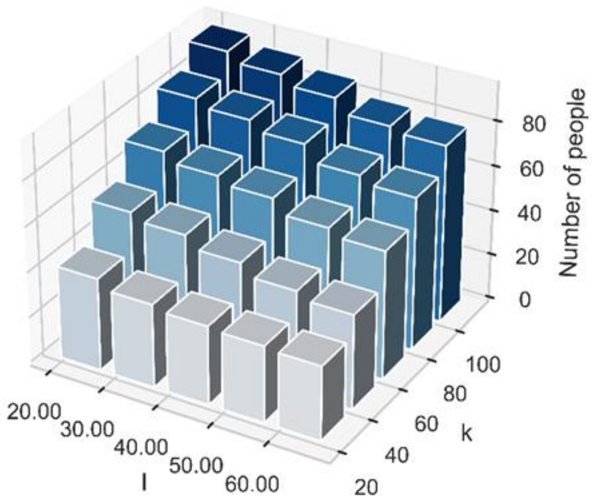


Figure 3. Evolutionary changes in the number of insured people

It shows the change in the number of insured people after 20 rounds of evolution under different conditions of premium (I-axis) and insurance payout ratio (k-axis). When the premium is lower, the number of people choosing to insure is higher, which indicates that low-er premiums are more attractive to consumers. At the same time, the number of people choosing to insure increases as the insurance payout rate increases, especially when premiums are low, suggesting that higher payout rates may increase the attractiveness of insurance. These observations are in line with our expectations and validate the model, as well as being an important reference for insurers in pricing and designing payout strategies, which can help develop more attractive insurance programs to attract more customers.

3.2. Analysis of experimental results

We have collected the number of days in each of the last eleven years that extreme weather has occurred in Michigan as shown in Table.2.

Table 2. Michigan extreme weather statistics

Year	2013	2014	2015	2016	2017	2018
Number of extreme weather days	46	39	35	45	45	43
Year	2019	2020	2021	2022	2023	2024
Number of extreme weather days	51	42	45	43	37	Predict

The prediction curve is plotted according to the data in Table.2 as shown below:

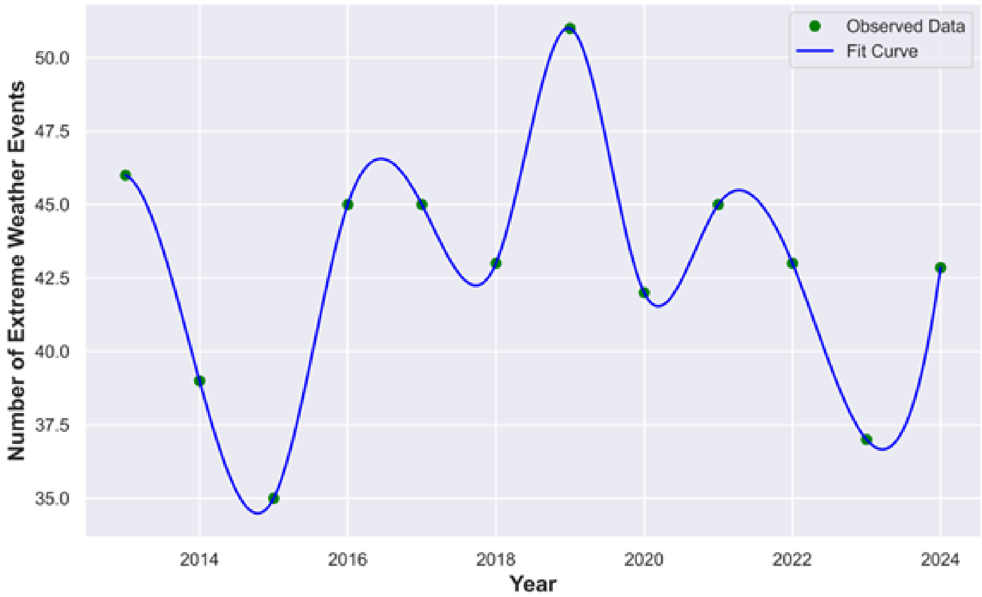


Figure 4. Michigan extreme weather prediction curve

From figure 4, the predicted number of extreme weather days in 2024 is 42.85. Therefore, the probability of extreme weather occurring in Michigan in 2024 is 11.7%. The prerequisite coefficients $R^2 = 0.932$, $F = 86.256$, and the critical values required for the test was passed.

3.3. Analysis of experimental results

From the analysis, it can be obtained that in 2024, the probability of extreme weather in Michigan is 11.7% The data are brought into the evolutionary dynamic analysis model of Moran process, and finally the URA factors of Michigan is 6.183. This corresponds to the local climate and the actual initiatives of the insurance companies: Michigan has a long history of high property losses due to the occurrence of extreme weather, and insurance companies have been reluctant to underwrite in the region.

4. Conclusion

In our URA model, we meticulously analyze various factors including the probability of extreme weather events and the relative severity of risk to the public. The results derived from our model are comprehensive, shedding light on the multifaceted aspects of urban risk assessment. The Moran evolution, a pivotal component of our model, adeptly captures the propagation dynamics of strategies within different societal groups. Its inherent sensitivity enables it to discern subtle shifts in patterns, thereby yielding results of remarkable stability. This underscores the robustness of our approach in evaluating urban risk scenarios. Furthermore, in our endeavor to forecast extreme weather events, we recognize the influence of enduring factors such as global warming and seawater temperature. To effectively model these stability-inducing elements, we have employed Fourier series for fitting and forecasting. This strategic choice allows us to tangibly articulate the influence of stability factors that are otherwise challenging to quantify, thus bolstering the persuasiveness of our predictions.

References

[1] Weilnhammer V, Schmid J, Mittermeier I, et al. Extreme weather events in Europe and their health consequences–A systematic review [J]. International Journal of Hygiene and Environmental Health, 2021, 233: 113688.

[2] Cruz J, White P C L, Bell A, et al. Effect of extreme weather events on mental health: a narrative synthesis and meta-analysis for the UK [J]. International journal of environmental research and public health, 2020, 17 (22): 8581.

[3] Alam A S A F, Begum H, Masud M M, et al. Agriculture insurance for disaster risk reduction: A case study of Malaysia [J]. International Journal of Disaster Risk Reduction, 2020, 47: 101626.

[4] Zhao J, Lee J Y, Li Y, et al. Effect of catastrophe insurance on disaster-impacted community: Quantitative framework and case studies [J]. International Journal of Disaster Risk Reduction, 2020, 43: 101387.

[5] Swiss Re's interactive sigma exploration tool [online] Retrieved at: sigma explorer - catastrophe and insurance market data | Swiss Re Institute (sigma-explorer.com).

[6] Boston Consulting Group. (2023, December 4). An Insurance Risk Framework for Climate Adaptation. Retrieved at: https://www.bcg.com/publications/2023/an-insurance-risk-framework-for-climate-adaptation.

[7] Washington Post. (2023, September 3). Home insurers cut natural disasters from policies as climate risks grow. Retrieved at: https://www.washingtonpost.com/business/2023/09/03/natural-disaster-climate-insurance/.

[8] Liu L, Gao J, Wu S. Warming of 0.5° C may cause double the economic loss and increase the population affected by floods in China[J]. Natural Hazards and Earth System Sciences, 2022, 22(5): 1577-1590.

[9] Hu X, Wang M, Liu K, et al. Using climate factors to estimate flood economic loss risk [J]. International Journal of Disaster Risk Science, 2021, 12: 731 - 744.

[10] Pastor-Paz J, Noy I, Sin I, et al. Projecting the effect of climate change on residential property damages caused by extreme weather events[J]. Journal of Environmental Management, 2020, 276: 111012.

[11] Zhang Zhuo, LI Bingkun, Yin Hang. Evolutionary game analysis of low-level equilibrium in China's policy agricultural insurance market [J]. Journal of Harbin University of Commerce (Social Science), 2021(1): 117 - 128. Journal of Harbin University of Commerce (Social Science), 2021 (1): 117 - 128.

[12] Wang Xianjia. A review of evolutionary games on complex networks and their learning mechanisms and evolutionary dynamics [J]. Journal of Reading River, 2021, 13 (3): 70 - 84 + 131 - 132.

[13] Liu Wei, SUN Shuanglin. Research on the problem of insufficient demand for catastrophe insurance--an analysis of evolutionary dynamics based on the Moran process [J]. Insurance Research, 2023, (06): 46 - 61.