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Research on Insurance Company Underwriting Decisions based on Breakeven Analysis Multi-Objective Planning Model

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Abstract. Extreme weather events are increasingly becoming a crisis for insurance companies, posing significant challenges to their financial stability. These events lead to higher claim frequencies and magnitudes, demanding more robust risk assessment and management strategies. This paper constructs a multi-objective programming model based on breakeven analysis, determines the regional risk level through risk assessment, and calculates the breakeven point. When the number of insurance policies exceeds the breakeven point, the insurance company will underwrite the region. The underwriting plan is the Pareto optimal solution, and the insurance company can choose the plan with a large number of insured but low profit, or choose the plan with a high insurance profit but low quantity. This model aims to provide underwriting decision-making guidance for insurance companies, ensuring their long-term healthy operation.

Keywords: Insurance Company, Underwriting Decisions, Breakeven Analysis, Multi-Objective Planning, NSGA-II.

1. Introduction

Extreme-weather events are wreaking havoc on insurers and property owners alike, with over $1 trillion in damages from 1,000+ events [1].Claims surged by 115% in 2022, and premiums are expected to spike 30-60% by 2040 due to climate change. Insurance is becoming pricier and scarcer, with insurers reevaluating underwriting policies. The global protection gap averages 57%, exacerbating the industry's profitability crisis and property owners' affordability concerns [2].This escalating challenge underscores the imperative for innovative risk underwriting criteria and robust underwriting approaches [3].

Current domestic and international research on the impact of extreme weather on the insurance industry focuses on the determination of pure insurance rates, insurers' strategies, insurance benefits, incentives to purchase insurance, and insurance valuation. Liu et al [4] used an information diffusion method model to determine the pure premium rates for weather index insurance against low-temperature damage to open-air cherries in Shijiazhuang under different triggering conditions. Chen et al [5] proposed strategies for coping with extreme weather from two perspectives: reducing post-disaster losses and mitigating climate change. Hudson et al [6] explored how lessons learned from current best practices in insurance can enhance resilience to extreme weather events. Doherty et al [7] analyzed the attractiveness of publicly supported climate risk insurance products to farmers and examined their preferences for purchasing insurance. Collier et al [8] studied the increasingly important mechanisms by which insurance shapes the impacts of climate change on local economies and lifestyles. However, existing research does not address whether insurance companies should underwrite policies for users or the specific underwriting methods to be used.

Addressing the current issue of whether and how insurance companies should underwrite policies for customers, this paper establishes a multi-objective planning model based on breakeven analysis. The breakeven point can determine the conditions for underwriting, and the model's solutions can yield Pareto optimal solutions, providing different underwriting schemes for the company. This study aims to assist catastrophe insurance companies in better deploying property insurance, making the system resilient enough to cover future claims costs while ensuring the long-term health of the insurance company.

2. The basic fundamental of multi-objective programming model

2.1. Dateset

The paper collected data on the intensity and frequency of various natural disasters in all 51 states of the United States from the website of the Federal Emergency Management Agency [9], as well as data on climate, social, and environmental categories for the 51 states from the Statista website to support the research [10].

2.2. Establishment of evaluation system

The paper proposes three key factors reflecting the level of climate risk: climatic conditions[11], social and governmental factors [12], and environmental factors[13], which are used as primary indicators for the evaluation system. After further reflection and summarization, the indicators are specified, and 10 specific indicators are selected as secondary indicators in the evaluation system, as shown in Figure 1.

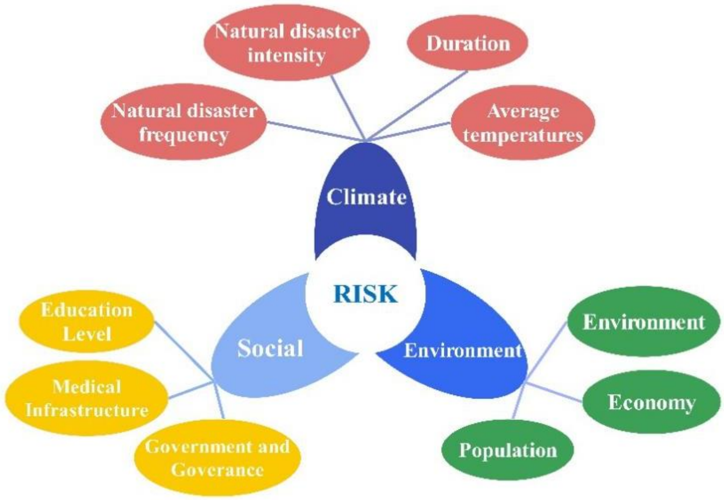

Figure 1. Evaluation system diagram.

Climatic factors are the most crucial determinants of climate risk levels. As shown in Figure 1, climatic factors primarily include natural disaster frequency (C_1), natural disaster intensity (C_2), duration (C_3), and average temperatures (C_4). Social and governmental factors also significantly influence climate risk. Figure 1 indicates that social and governmental factors primarily include education level (S_1), medical infrastructure (S_2), and government and governance (S_3). Environmental factors affect the impact and resilience to natural disasters to some extent. As depicted in Figure 1, environmental factors mainly include population (E_1), economy (E_2), and forest coverage rate (E_3).

2.3. Data Analysis and Processing

The consistent direction of action of the indicators is important for the evaluation results. Analysis of the collected data revealed that indicators $C_1, C_2, C_3, E_1, E_2, S_3$ are positive indicators, S_1, S_2, E_3 are negative indicators and C_4 is an interval indicator. In order to simplify the calculations this paper have chosen to convert all indicators into positive indicators.

First, the indicator data from the 51 states in the database were aggregated to form the original matrix X. Because the types of indicators are different, normalization of the original matrix was required. Subsequently, to eliminate the influence of dimensionality, standardization of the normalized matrix was conducted, resulting in the matrix L. Combined with the process of normalization and standardization of the indicators, this paper has the following formulas:

For interval-type data, research has found that the optimal range of intervals for average annual temperatures in U.S. states is 60 to 70 degrees Fahrenheit. Then, the formula for normalizing the interval-type indicator is as follows:

$$M=\max\{60-\min\{x_1,\cdots,x_i\},\max\{x_1,\cdots,x_i\}-70\}$$
$$x_i'=\begin{cases}1-\dfrac{60-x_i}{M}, & x_i<60\\ 1, & 60\leqslant x_i\leqslant 70\\ 1-\dfrac{x_i-70}{M}, & x_i>70\end{cases} \tag{1}$$

For indicators S_1, S_2, E_3 the normalization formula for converting negative indicators into positive indicators is as follows:

$$x_{ij}'=\frac{\max\{x_{1j},\cdots,x_{ij}\}-x_{ij}}{\max\{x_{1j},\cdots,x_{ij}\}-\min\{x_{1j},\cdots,x_{ij}\}} \tag{2}$$

Also, to eliminate the effect of different indicator scales, it is necessary to normalize all the positively normalized indicator matrices:

$$L=\frac{x_{ij}'-\min\{x_{1j}'\cdots x_{ij}'\}}{\max\{x_{1j}',\cdots,x_{ij}'\}-\min\{x_{1j}',\cdots,x_{ij}'\}} \tag{3}$$

Where $i=1,2,...,51$, x_{ij} represents the jth indicator of the ith region in the previous evaluation system.

2.4. Determination of the Weights for Indicators

Various methods exist for determining the weights of indicators. To enhance the accuracy of the model, the combination weighting method was employed to calculate the weights of the indicators. The combined weighting method proposed in this paper integrates the hierarchical analysis method (AHP) from the subjective weighting method and the entropy weighting method (EWM) and coefficient of variation method (CVM) from the objective weighting method.

Because of the AHP judgment is more subjective, it is easy to change by the subjective influence of the decision maker. At the same time, due to the high sensitivity of the data, it may cause errors due to the data itself. Hence, our combination weighting method synthe-sizes these methods to help us reduce the errors and improve accuracy.

2.4.1. Analytic Hierarchy Process

First, a hierarchy diagram is constructed based on the previously selected metrics, as shown in Figure 2 below.

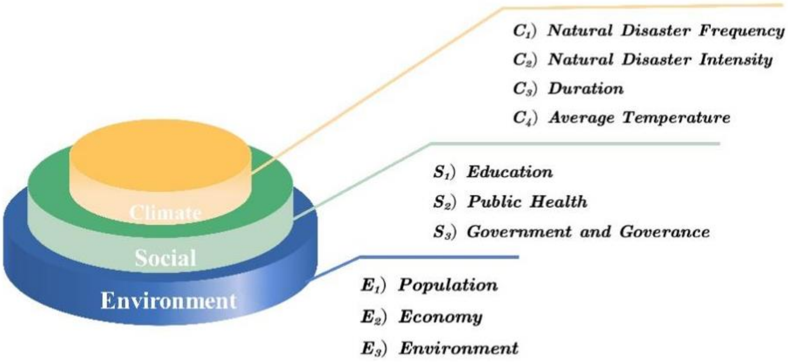

Figure 2. Risk assessment hierarchy diagram.

Judgment matrices were constructed for the primary indicators and each set of secondary indicators separately.

$$A = (a_{ij})_{n \times n} \tag{4}$$

Where a_{ij} represents the importance of x_i relative to x_j, while n represent the quantity of indicators in each group. Due to limited space, the judgment matrix will not be shown.

Calculate the weight of each indicator and perform a consistency check. The weights of each indicator calculated by this method are denoted as ω_{ij}.

2.4.2. Entropy Weight Method

This paper uses the Entropy Weight Method (EWM) to calculate the weights of the indicators and the probability matrix P_{ij}.

According to the concepts of self-information and entropy in information theory, the information entropy of each evaluation indicator can be calculated, as shown in Equation (5).

$$E_j = -\frac{1}{\ln 51} \sum_{i=1}^{51} P_{ij} \ln(P_{ij}) \tag{5}$$

Let $d_j = 1 - E_j$, which is define as the information utility value. The entropy weight of each indicator is given by normalizing the information utility value in the following. The normalization is determined by the equation (6).

$$\omega_j = -\frac{d_j}{\sum_j d_j} \tag{6}$$

The weights of each indicator calculated by this method are denoted as ω_{j2}.

2.4.3. Coefficient of Variation Method

Furthermore, the Coefficient of Variation Method (CVM) is applied to weight the indicators. First, normalize the original matrix X to obtain the matrix Z.

Then, based on the previous database, the mean and standard deviation for the 51 data of each index are found, allowing the calculation of the coefficient of variation as follows:

$$CV_j = \frac{\sigma_j}{\mu_j} \tag{7}$$

Finally, normalize the coefficient of variation to get the weights of each index:

$$\omega_j = \frac{CV_j}{\sum_j CV_j} \tag{8}$$

The weights of each indicator calculated by this method are denoted as ω_{j3}.

2.4.4. Combination weight

By the above three methods, three different weights(ω_{j1} , ω_{j2} , ω_{j3}) were calculated for each indicator. To enhance the model's accuracy, the mean value of the three weights was selected as the final weights of each indicator to minimize the error.

$$\omega_j = \frac{\omega_{j1} + \omega_{j2} + \omega_{j3}}{3} \tag{9}$$

Final results of the weighting of the indicators are shown in Figure 3 below.

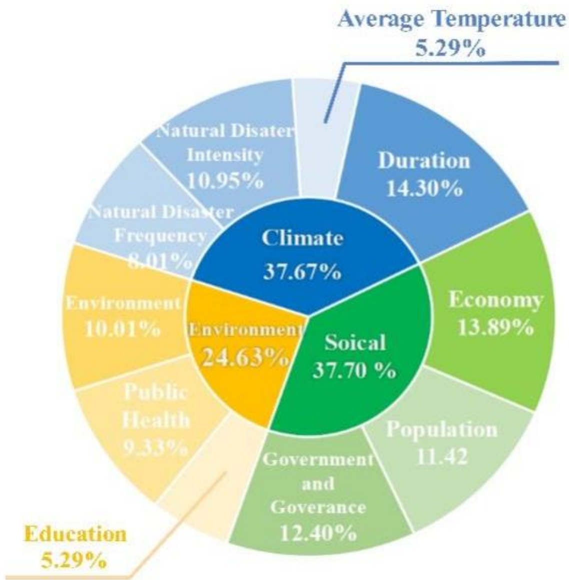

Figure 3. The combination weight diagram of each indicator.

As shown in Figure 3, climatic factors, social and governmental factors, and environmental factors account for 37.67%, 37.70%, and 24.63%, respectively.

2.5. The establishment of CSE Evaluation Model

Considering the impact of Climate, Society, Government, and Environment on climate risk, the CSE Evaluation Model was developed. In this model, URI (Underwiring Risk Index) is introduced to quantitatively describe the risk level of climate risk. Additionally, based on the selected database, the values of CSE were divided into three intervals using fuzzy cluster analysis, effectively categorizing the light pollution risk level into three levels.

2.5.1. Calculation of Light Pollution Index（CSE）

After the previous efforts, the data source of each indicator and its calculation method can be identified. The weight of each indicator is obtained by the combination weighting method. The weights corresponding to indicators C, S, and E are regarded as the extent of the influence of these three indicators on CSE, that means, the greater the weight, the more serious the influence of the corresponding indicator on CSE. Accordingly, this paper reasonably and extremely creatively constructs the formula for calculating CSE:

$$CSE = 100 \times (\omega_C \times C + \omega_S \times S + \omega_E \times E) \tag{10}$$

Similarly, based on the same lines, the formulas for C, S, and N are constructed by equation (11).

$$\begin{cases} C = \omega_{C_1} \times C_1' + \omega_{C_2} \times C_2' + \omega_{C_3} \times C_3' + \omega_{C_4} \times C_4' \\ S = \omega_{S_1} \times S_1' + \omega_{S_2} \times S_2' + \omega_{S_3} \times S_3' \\ E = \omega_{E_1} \times E_1' + \omega_{E_2} \times E_2' + \omega_{E_3} \times E_3' \end{cases} \tag{11}$$

Where $C_1', C_2', C_3', C_4'; S_1', S_2', S_3'; E_1', E_2', E_3'$ are obtained by standardizing.

2.6. Breakeven analysis of insurance companies

Q is the sum of the number of policies in the 51 U.S. states.

$$Q = \sum_{i=1}^{n} x_i,\ i = 1, 2, \ldots 51 \tag{12}$$

The price of the policy p is the sum of the individual state charges b_i divided by 51.

$$p = \frac{1}{n} \sum_{i=1}^{n} b_i,\ i = 1, 2, \ldots 51 \tag{13}$$

The company's receipt of W_s is equal to the average selling price of insurance p multiplied by the total sales volume Q.

$$W_S = p \times Q \tag{14}$$

The total variable cost W_B is equal to the unit variable cost C_v multiplied by the total sales volume Q.

$$W_B = C_v \times Q \tag{15}$$

Note: C_v is fixed value.

Claims rates r_C in states tied to local natural disasters.

$$r_C = \beta_i \times \lambda_i,\ i = 1, 2, \ldots, 51 \tag{16}$$

Note: β_i is the damage factor for the ith state; λ_i is the coefficient of occurrence of the disaster in the ith state.

The amount of compensation μ is converted from the future value of the compensation

$$\mu = C_a \times \frac{1}{(1+i)^{t}} \tag{17}$$

Note: C_a is the future value of the compensation, j is the annual discount rate, and t is the number of years.

$$W_P = r_C \times Q \times \mu \tag{18}$$

Note: r_C is the policy claim rate; C_a is the future value of individual claims. j is the discount rate.

By calculation, the breakeven point Q_0 is given in equation (19).

$$Q_o = \frac{C_f}{p - C_v - r_C \times \mu} \tag{19}$$

2.7. Establishment of Multi-Objective Planning Model

2.7.1. Objectives

The main factors affecting total insurance policy profit are total revenue W_S and total expenses W_C. The objective function total return is as follows:

$$\max\ W = W_S - W_C \tag{20}$$

Objective Function The summation of the number of insurance policies in the 51 states of the U.S. is given by the following equation. It is expressed by the formula as follows:

$$\max\ Q \tag{21}$$

2.7.2. Constraints

The total cost W_c is equal to the total fixed cost W_G plus the total variable cost W_B plus the total compensation W_p.

$$W_C = W_G + W_B + W_P \tag{22}$$

Wherein:

$$W_G = C_f \tag{23}$$

Note: C_f is the total fixed cost, which is a fixed value.

To ensure that the insurance company is equipped to cover the costs of future claims, the total number of policies must be greater than the break-even point Q_o.

$$Q > Q_o \tag{24}$$

Each state must have no more policies x_i than it has people r_i.

$$x_i \leqslant r_i,\ \ i=1,2,...,51 \tag{25}$$

b_i is between the lower and upper bounds of each state's participation costs.

$$\sigma_{i\_\min} \leqslant b_i \leqslant \sigma_{i\_\max}, i=1,...,51 \tag{26}$$

2.7.3. 2Multi-objective Planning Model (MOPM)

Based on the above step-by-step analysis, our Break-even Analysis Model Based on Multi-Objective Planning can be concluded as follows:

$$\begin{aligned} &\max\ Q \\ &\max\ W = W_S - W_C \\ &s.t.\begin{cases} Q > nQ_o \\ x_i \leqslant r_i, i=1,...,51 \\ \sigma_{\mathrm{i\_min}} \leqslant b_i \leqslant \sigma_{\mathrm{i\_max}} \\ W_C = W_G + W_B + W_P \end{cases} \end{aligned} \tag{27}$$

This paper employs the NSGA-II algorithm to solve multi-objective optimization problems. The algorithmic flowchart is illustrated in Figure 4.

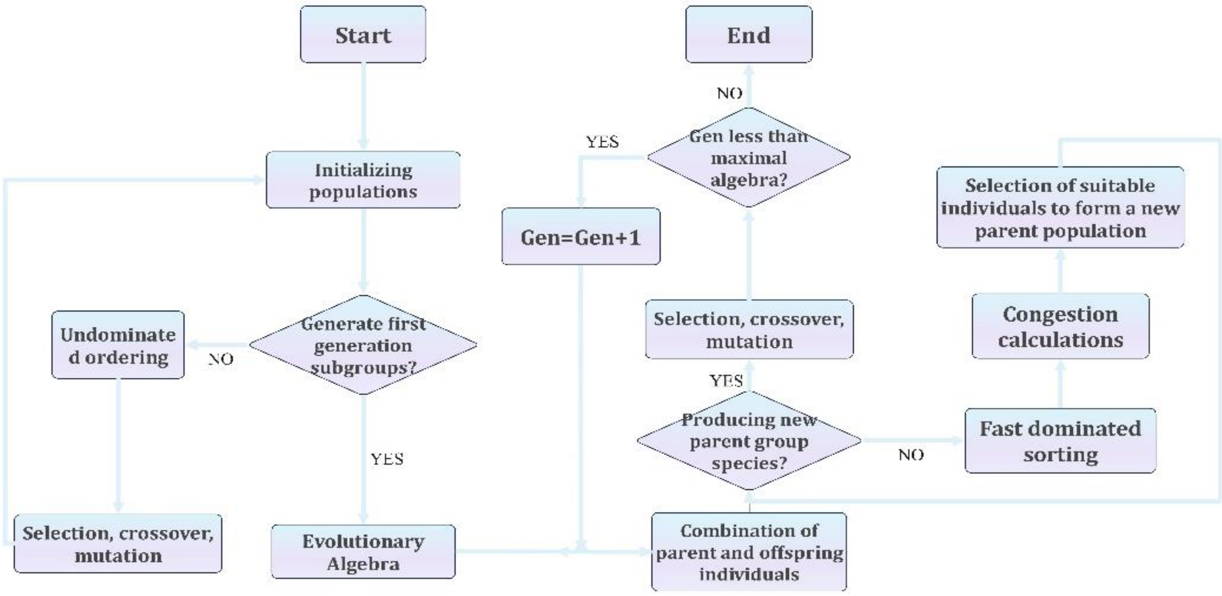

Figure 4. The combination weight diagram of each indicator.

The population is set to 100, and the maximum genetic generation is also set to 100. New solutions are generated through population selection, cross mutation, and dominance relationships to determine the optimal ranking among individuals at different levels. The optimal ranking of individuals on the Pareto front is determined by calculating the crowding distance. The optimal individual is selected to enter the new parent population for inheritance based on two rounds of sorting. Then, the population is continuously filtered and iteratively searched layer by layer to obtain a population with higher fitness, thereby achieving the solution of the optimal solution.

3. Results

3.1. Determination of climate risk levels

The data collected from the 51 states is input into the CSE model to calculate the URI value for each state. Then, fuzzy clustering analysis is utilized to classify all locations into three categories, thereby categorizing climate risk into three classes: Class I: High Risk, Class II: Moderate Risk, and Class III: Low Risk. The specific classification is shown in Table.1.

Table 1. Scale of Climate Risk.

Grade	I	II	III
Climate Risk Level	High Risk	Medium Risk	Low Risk
CSE	$(72, 100]$	$(32, 72]$	$(0, 32]$

According to Table 1, the risk level of a certain location can be determined based on its CSE value. Following the expert judgment method, the coefficients of exposure β for high risk, moderate risk, and low risk are set to 0.4, 0.3, and 0.2, respectively.

3.2. Determination of breakeven point

Through the Climate-Society-Environment (CSE) evaluation model, this paper classifies the 51 states of the United States into high-risk, moderate-risk, and low-risk areas. For these three different risk areas, this paper calculates the values of three break-even points, denoted as Q_{o_1}, Q_{o_2}, and Q_{o_3}. The specific values are as follows: $Q_{o_1} = 143885 \ sheet; Q_{o_2} = 129870 \ sheet; Q_{o_3} = 118343.1953 \ sheet$.

The insurance company can refer to Table 3 to check the breakeven point corresponding to the risk category. If the number of insured individuals exceeds the breakeven point, the company can provide insurance for that area. Conversely, if the number of insured individuals is less than the breakeven point, the company should not offer insurance for that area.

3.3. Determination of constant values in MOPM

Before using the NSGA-II algorithm, this paper assigns values to constants based on practical considerations. The specific values are shown in Table.2.

Table 2. Indicator baseline.

Indicator	value	Indicator	value	Indictor	value
r_C	High Risk: 20%	p	1000	C_v	5
	Medium Risk: 15%	C_a	1500	t	30
	Low Risk: 10%	r_C	30%	W_G	100000000

3.4. Solution of MOPM

This paper constructs a break-even analysis model based on multi-objective programming (MOP) and solves it using the NSGA-II algorithm. The solution results are shown in Figure 5.

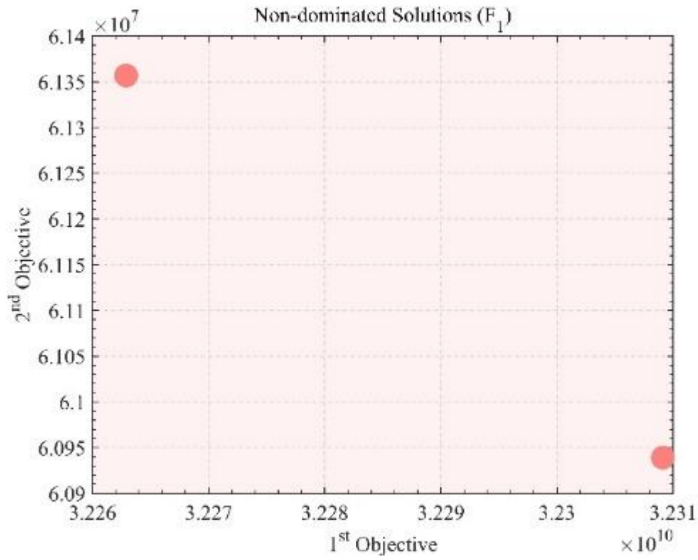

Figure 5. NSGA-II Solution.

As can be seen in Figure 5, there are only 2 solutions in the Pareto frontier, due to the specificity of the catastrophe model and our simplification of the model. The specific solution results are shown in Table.3.

Table 3. The two solutions of MOPM.

W($)	Q(sheet)	p($)
32262897579.38	61356913	525.93
32309105332.15	60939195	530.29

Both solutions here are optimal, the difference being that the first has lower participation costs, more participants, and more security for the property owner; the second firm is more profitable. A company can choose to risk getting more profit by losing customers, Or the opposite, of course. This reflects the idea of gaming.

4. Conclusions

In recent years, the increasing frequency of extreme weather events such as floods, hurricanes, droughts, and wildfires has led homeowners and insurance companies to face crises in both insurance coverage and underwriting. This study established a risk assessment model and a multi-objective planning model based on breakeven analysis. Different regions can determine their risk levels by calculating risk scores. When the number of insured individuals exceeds the breakeven point for that region, insurance companies can consider different underwriting strategies based on actual circumstances. They can opt for the most profitable scheme, which corresponds to higher unit premiums, or they can choose the scheme with the highest number of insured individuals, corresponding to lower unit premiums. Future work should focus on integrating climate change forecasts, advanced data analytics, and collaboration with governmental and non-governmental organizations to enhance the accuracy and adaptability of risk assessment models and insurance strategies.

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