Research on the Sustainability of Property Insurance Based on Region Under Extreme Weather

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Abstract. In the context of global climate change, the increasing frequency of extreme weather events poses significant challenges to the property insurance industry. In order to determine whether the companies should underwrite the insurance in extreme weather conditions, the paper builds the risk level evaluation model and ALARP risk assessment criterion to solve this problem. Through calculating the risk factor Ω in our model, the paper could decide whether the companies should underwrite. Then the paper chooses China and USA to conduct risk level evaluation. The paper gets the result that Ω is 0.64 in China and 1.13 in USA. The paper concluded that insurance companies will choose to underwrite policies to take the risk in many locations in China and not to do so in USA. In order to develop community building and development strategies to adapt to risks posed by climate change in specific locations, This paper builds the MGWR model in order to decide the best strategies to develop the community corresponding to the calculated loss and minimize the loss. Finally, the paper chooses Asia and North America to show our simulation results and provide strategies like “infrastructure development, emergency preparedness” to promote the community development. These results are straightforward to interpret, facilitating acceptance by decision-makers.

Keywords: ALARP, MGWR Model, Climate Change, Community Development.

1. Introduction

Recent data indicate that the past seven years are on track to be the hottest on record (WMO, 2023). Climate change has led to an increase in the frequency and severity of extreme weather events, including tropical cyclones, heatwaves, floods, and droughts, which are becoming the new norm. These extreme events have profound societal impacts, resulting in approximately 35,000 fatalities annually and causing substantial economic losses. For example, in 2016, flash floods and storms in Germany, Belgium, and Switzerland led to financial damages amounting to $2.2 billion, with only about 50% of the costs covered by insurance companies [1]. The rising frequency and intensity of natural disasters place an increasing financial strain on insurance and reinsurance companies, which have experienced record-breaking losses over the past 15 years. In response to the growing risks associated with climate-induced extreme weather events, the property insurance industry must adopt innovative risk mitigation models. This adaptation is essential as insurers face escalating natural catastrophe risks, necessitating the development of more resilient underwriting frameworks.

In the context of insurance industry pricing strategies under extreme weather conditions, existing literature identifies several key approaches. Insurance companies are enhancing internal methodologies to improve risk assessment and pricing accuracy. This includes the development of advanced predictive capabilities and the integration of artificial intelligence with spatial imaging technologies to refine asset vulnerability assessments. For example, the Canadian technology company Riskthinking has employed such methods to enhance risk evaluation [2]. Moreover, insurers are actively collaborating with policymakers, regulatory bodies, and industry stakeholders to adapt to evolving climate challenges. These efforts encompass advocating for regulatory reforms, facilitating data sharing, and investing in climate-adaptive infrastructure projects [3]. The increasing variability of climate risks has rendered traditional models that rely solely on historical data less reliable, necessitating a transition toward predictive risk assessment frameworks. For instance, Risk Management Solutions (RMS) has refined its models to incorporate the changing frequency and severity of extreme weather events, such as hurricanes and floods [4]. In recent years, insurers have also prioritized financial resilience by accounting for low-probability catastrophic events and diversifying their investment portfolios. This strategy involves employing dynamic risk models that consider non-fixed risks, thereby reducing dependence on historical data. Such an approach enables insurers to more effectively quantify and mitigate the financial impacts of climate-related risks [5].

In the previous work, the researchers didn't consider the enough risk influencing factors to build the model to assess the risk level which could lead to the inaccurate results. Therefore, our work developed a Risk Level Evaluation Model to determine underwriting in regions with frequent extreme weather events. To build the model, paper takes four key indicators and twelve secondary indicators to build the evaluation system. By combining Entropy Weight Method [6] and ALARP risk assessment criterion [7], paper defines a risk factor Ω to quantify the risk level: when Ω exceeds 0.9, the insurance companies will not choose to take the risk; Conversely, they are more likely to assume the risk. In order to develop community building and development strategies to adapt to risks posed by climate change in specific locations, previous studies didn't calculate the optimal level of intervention based on risk and cost considerations. Therefore, our work developed a Multi-scale Geographically Weighted Regression(MGWR) model by integrating geographical locations and financial data from insurance comapnies. The model incorporates protective measures and calculates the optimal level of intervention based on risk and cost considerations. Through this model, paper gives the corresponding location community building and development strategies.

2. Model establishment

2.1. Risk level evaluation model

The impact of extreme weather can be mainly divided into the impact on humans, environments, economy and insurance. Therefore, paper uses these main aspects as the first-level indicators and choose some second-level indicators. In the first-level indicators, human impact includes death rate(DR), injury rate(IR), affected rate(AR) and population number(PN); Environment impact includes flood index(FI), hurricane loss(HI), drought index(DI) and wildfire area(WA); Economic impact includes GDP per capita(GDP), economy loss(EL); Insurance indicator includes insurance income(IC) and loss ratio(LR).

Since the paper needs to calculate Q_{positive} and $Q_{negative}$ from these first-level indicators. Based on the above analysis, the paper gets the $Q_{negative}$ is:

$$Q_{positive} = PN + EL + IC \tag{1}$$

Q_{positive} indicates the quantitative results of positive impacts. And when calculating $Q_{negative}$, to make the model reasonable, the paper needs to calculate the weights of the 9 second-level indicators corresponding to the four first-level indicators of human impacts, environment impact, economic impacts and insurance impact to obtain the $Q_{negative}$ in the following equation:

$$Q_{negative} = \sum_{i=1}^{Num_{negative}} Indicator_i \bullet w_i \tag{2}$$

where $Indicator_i$ is the i-th negative indicator, w_i is the weight corresponding to the i-th negative indicator and $Num_{negative}$ is the number of negative indicators. In the following, the paper will focus on the calculation of the weights of each negative indicator:

The paper normalizes the collected data and process the second-level indicators, which can be divided into two categories: benefit attributes, cost attributes. For the "benefit attribute type", the larger the better type of data, the paper uses the following normalization:

$$\bar{x}_{ij} = \frac{x_{ij} - min\{x_i\}}{\max\{x_i\} - \min\{x_i\}} \tag{3}$$

For the “cost attribute type”, the smaller the better type of data, the paper uses the following equation:

$$\bar{x}_{ij} = \frac{\max\{x_i\} - x_{ij}}{\max\{x_i\} - \min\{x_i\}} \tag{4}$$

Suppose the paper has m sets of data with $\mathrm{Num}_{\mathrm{Human}}$ / $\mathrm{Num}_{\mathrm{Environment}}$ / $\mathrm{Num}_{\mathrm{Economy}}$/ $\mathrm{Num}_{\mathrm{Insurance}}$ indicators above in each set. $\bar{x}_{ij}$ represents the *j*-th data in *i*-th group; max{ x_i } represents the maximum data in *i*-th group; min{ x_i } represents the minimum data in *i*-th group.

According to the definition of information entropy, the entropy value can be used to judge the degree of dispersion of an indicator. The smaller the information entropy value is, the greater the degree of dispersion of the indicator, and the greater the influence, or weight, of the indicator on the comprehensive evaluation. Therefore, the weight of each indicator can be calculated by using the tool of information entropy to provide a basis for comprehensive evaluation.

After standardizing each indicator to obtain standard data, the paper normalizes the data by the following equation:

$$p_{ij} = \frac{\bar{x}_{ij}}{\sum_{j=1}^{m} \bar{x}_{ij}} \tag{5}$$

Getting the information entropy:

$$E_{\mathrm{i}} = -\frac{\sum_{j=1}^{m} p_{ij} \bullet \ln p_{ij}}{\ln m} \tag{6}$$

Through the information entropy, the paper would get the weight of w_i of each indicator we defined as follows:

$$\mathrm{w}_i = \frac{1 - E_i}{\sum_{i=1}^{n} (1 - E_i)} \tag{7}$$

the paper forms a vector of the obtained weights and call the vector as "evaluation vector", denoted as $\vec{\mathrm{w}} = (\mathrm{w}_1, \mathrm{w}_2, ..., \mathrm{w}_{\mathrm{Num}_{\mathrm{Human}}/\mathrm{Num}_{\mathrm{Environment}}/\mathrm{Num}_{\mathrm{Economy}}/\mathrm{Num}_{\mathrm{Insurance}}})$; By composing a vector of the obtained influences of different aspects and calling this vector as "influence degree vector", denoted as $\vec{S} = (\mathrm{S}_1, \mathrm{S}_2, ..., \mathrm{S}_{\mathrm{Num}_{\mathrm{Human}}/\mathrm{Num}_{\mathrm{Environment}}/\mathrm{Num}_{\mathrm{Economy}}/\mathrm{Num}_{\mathrm{Insurance}}})$, then the final evaluation value is:

$$S\mathrm{core}_x = \sum_{i=1}^{Num_x} \mathrm{w}_i \bullet S_i \tag{8}$$

where x represents “Human”, “Environment” , “Economy”or “Insurance”.

To assign weights to these four first-level indicators to obtain the $Q_{negative}$, the paper used AHP(hierarchical analysys) to obtain the weights of the four first-level indicators:

$$\alpha = (0.1384, 0.2564, 0.3513, 0.2539) \tag{9}$$

Eventually, our risk evaluation value of quantitative results of negative impacts is :

$$Q_{negative} = \alpha 1 \bullet Score_{Human} + \alpha 2 \bullet Score_{Environment} + \alpha 3 \bullet Score_{Economy} + \alpha 4 \bullet Score_{Insurance} \quad (10)$$

The risk to insurance companies in deciding whether to underwrite policies is fundamentally rooted in the uncertainty brought about by natural extreme weather events. The ALARP (As Low As Reasonably Practicable) principle serves as a widely recognized benchmark in risk assessment, persistently employed in the delineation of tolerable risks [8].

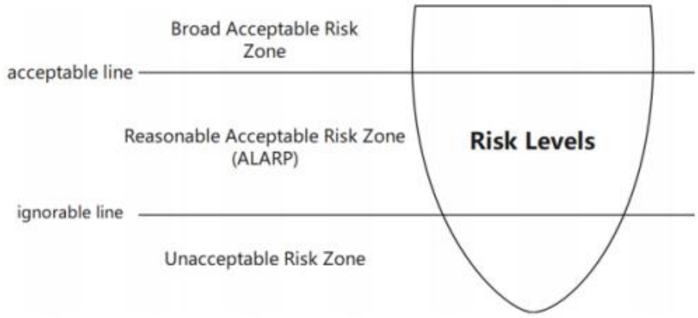

Figure 1: Risk level diagram

The ALARP criterion divides risks into three zones: unacceptable, reasonably acceptable, and widely acceptable, as shown in Figure 1 above.

In the above model, extreme weather brings positive impacts and a series negative impacts. And the paper defines the risk factor related to the positive impacts and negative impacts of extreme weather. The paper defines the risk factor Ω as:

$$\Omega = \frac{Q_{positive}}{Q_{negative}} \quad (11)$$

Based on the risk assessment criterion ALARP and risk factor **Ω**, the paper obtains the risk assessment standards as follows:

$$\Omega = \begin{cases} 0\sim0.35 & Broad\ Acceptable\ Risk \\ 0.35\sim0.9 & Reasonable\ Acceptable\ Risk \\ > 0.9 & Unacceptable\ Risk \end{cases} \quad (12)$$

When the risk level is in Unacceptable Risk, the insurance companies will not choose to take the risk to underwrite policies; Under other risk levels, the companies could choose to underwrite polices.

Multi-scale Geographically Weighted Regression(MGWR) model

Multi-scale Geographically Weighted Regression (MGWR) [9] is an advanced spatial analysis technique that extends the traditional **Geographically Weighted Regression (GWR)** framework. Unlike GWR, which assumes a uniform bandwidth for all covariates, MGWR allows each covariate to have a distinct spatial scale (bandwidth), thereby capturing spatial heterogeneity with greater precision. This adaptability makes MGWR particularly well-suited for analyzing complex spatial datasets where relationships exhibit variations across different locations and scales. The MGWR model can be mathematically expressed as follows:

$$y_i = \beta_0(\mu_i, v_i) + \sum_{k=1}^{K} \beta_k(\mu_i, v_i) X_{ik} + \varepsilon_i \quad (13)$$

Here, y_i represents the dependent variable for the *i*-th location, (μ_i, v_i) are the geographic coordinates, X_{ik} are the independent variables, $\beta_k(\mu_i, v_i)$ are the location-specific coefficients for the *k*-th covariate, and ε_i is the error term.

In the area of climate change, community administrators should implement specific strategies to enhance the level of protective measures. Therefore, the paper introduces the protection factor of community administrators into the MGWR model, expanding its form as follows:

$$y_i = \beta_0(\mu_i, v_i) + \sum_{k=1}^{K} \beta_k(\mu_i, v_i) X_{ik} + \beta_P(\mu_i, v_i) P_i + \varepsilon_i \tag{14}$$

where P_i is the level of protective measures for location *i*, our goal is to minimize risk D_i and Cost C_i. Risk can be defined as :

$$D_i = 1 - \frac{R_i}{R_{\max}} \tag{15}$$

where R_i is the community's capacity to withstand risk at location *i*, and R_{max} is the maximum capacity to withstand risk.

The cost C_i is defined as follows:

$$C_i = C_{base} + g \bullet P_i \bullet C_{protect} \tag{16}$$

where C_{base} is the base cost, g is an adjustment coefficient, $C_{protect}$ is the cost per unit of protective measure.

Our goal is to minimize the following loss function:

$$L = \sum_i (D_i + \lambda \bullet C_i) \tag{17}$$

where λ represents the trade-off coefficient between risk and cost.

This protection model enables community leaders to determine the appropriate level of protective measures based on their specific circumstances and requirements. By adjusting P_i, communities can make informed decisions that balance risk mitigation with economic considerations. Therefore, community leaders could choose the appropriate measures to adapt to risks posed by climate change in specific locations.

3. Results

3.1. The result and analysis of risk level evaluation model

The model is to determine whether the companies should underwrite the insurance in extreme weather conditions and the paper also uses this model to compare the simulation result for two regions in different continents.

In the model, the paper uses "Entropy Weight Method" to determine the weights of second-level negative indicators, which is shown in Figure 2.

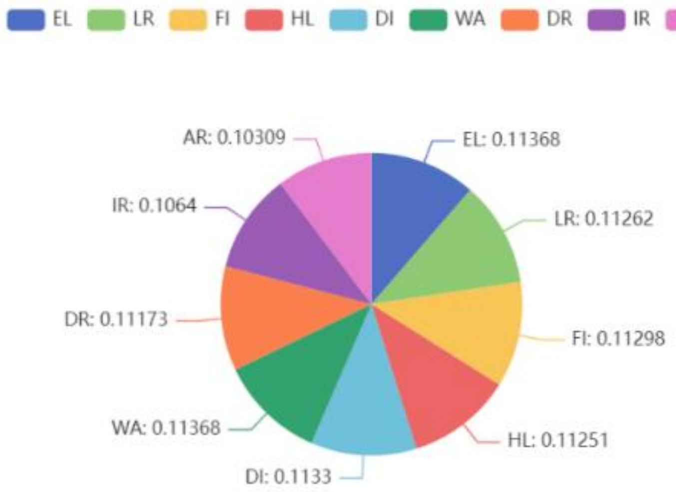

Figure 2: Weights of second-level negative indicators

The paper uses the risk factor Ω to determine whether the companies should underwrite the insurance. The paper chooses China and the USA as the continents for the model demonstration because natural disasters frequently occur in both countries, and the paper can find a lot of data on extreme weather events in these two nations. Finally, the paper analyzes the result of China and USA in 2018.

Through using our risk level evaluation model and ALARP criterion, the value obtained for the four first-level indicators of $Score_{Human}$, $Score_{Environment}$, $Score_{Economy}$ and $Score_{Insurance}$ of China and USA are shown in Figure 3.

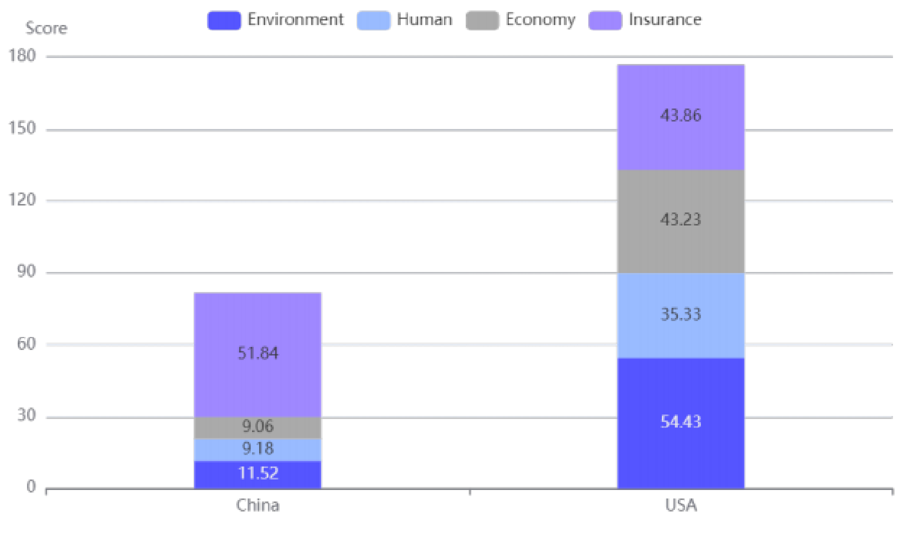

Figure 3: Negative score of first-level indicator in China and USA

Then, the paper calculates the risk factor value Ω about China and USA in 2018 and get that the Ω in China is 0.64 and in USA is 1.13. Therefore, the paper knows the risk level of China is “Reasonable Acceptable Risk” and the risk level of USA is “Unacceptable Risk”. The paper conclude that the insurance companies will choose to underwrite polices to take the risk in most locations of China and will not to do it in most locations of USA.

Subsequent to the initial analysis, the negative scores for China and the USA were computed for the years 2019 and 2020, in addition to those previously calculated for 2018. The results are in Figure 4 below.

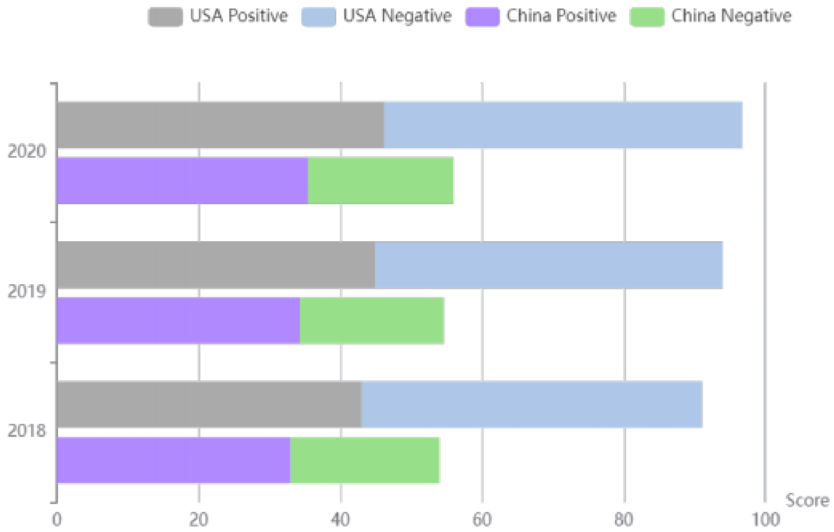

Figure 4: Results of negative score in China and USA

Therefore, for property owner, they can select areas with normal weather conditions, reinforce building constructions, enhance the capability to withstand extreme weather events such as floods and wildfires, and reduce the population and economic losses caused by natural disasters. Based on this, the value of the risk factor will decrease, which will affect the insurance company's strategy on whether to underwrite insurance.

3.2. The result and analysis of MGWR model

The model is to minimize the loss in specific locations to make community developers develop the strategies to adapt to the climate change. As mentioned earlier, the strategies adopted by the community essentially constitute a multi-objective optimization problem involving the level of protective measures, denoted as P_i, risk denoted as D_i, and cost denoted as C_i. The paper solved these three parameters in North America and Asia, and show the results in Figure 5 and Figure 6.

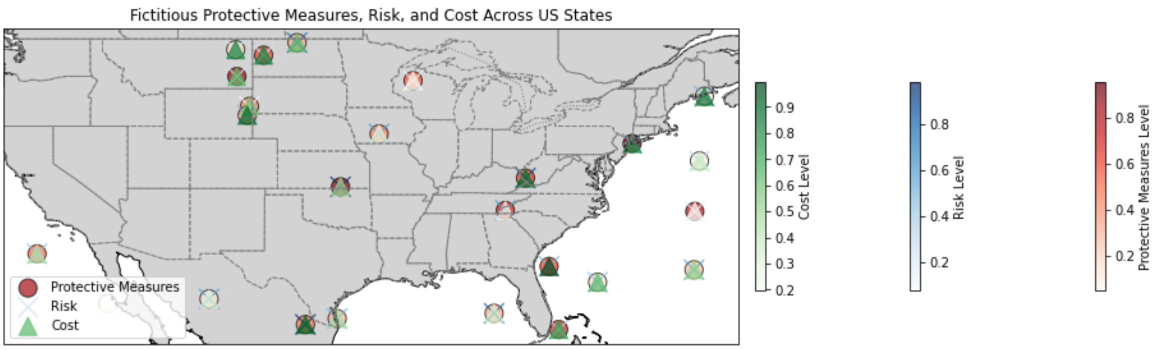

Figure 5: Community Protective level, Risk level and Cost in North America

Figure 5 shows the results in North America. The paper found that in extreme weather conditions, the greater the potential loss may arise from risks, the higher the cost should be for the community's investment in protective measures. An approximate protective level of 70% is required in relation to the losses, with costs around 50%.

The results in Asia are shown in Figure 6 below which describes the protective level, risk level, and cost in Asia.

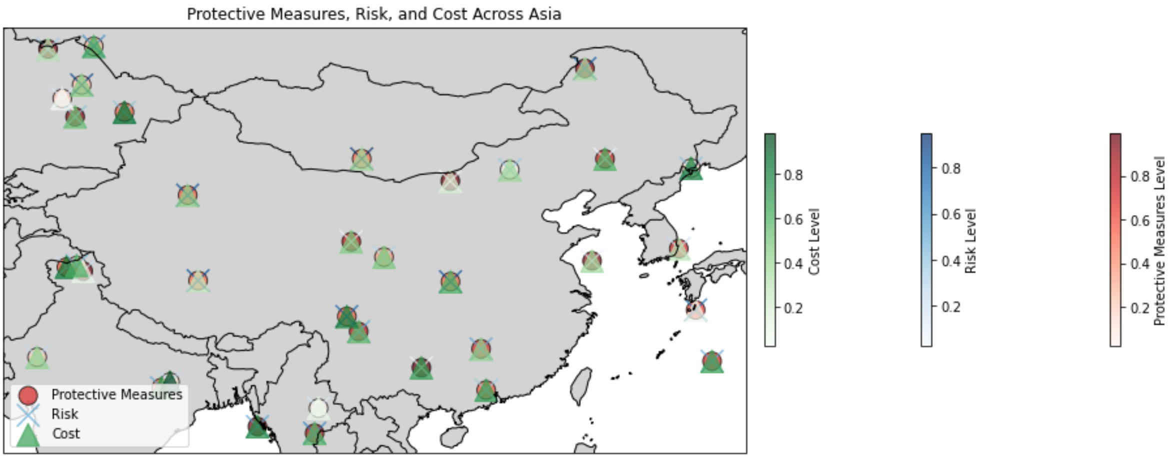

Figure 6: Community protective level,Risk level and Cost in Asia

In Asia, An approximate protective level of 50% is required in relation to the losses, with costs around 50%.

The figure in Figure 7 below presents property loss scenarios in North America and Asia under different intervention measures from 2024 to 2034. These interventions include “No Intervention” and “Community Intervention”.

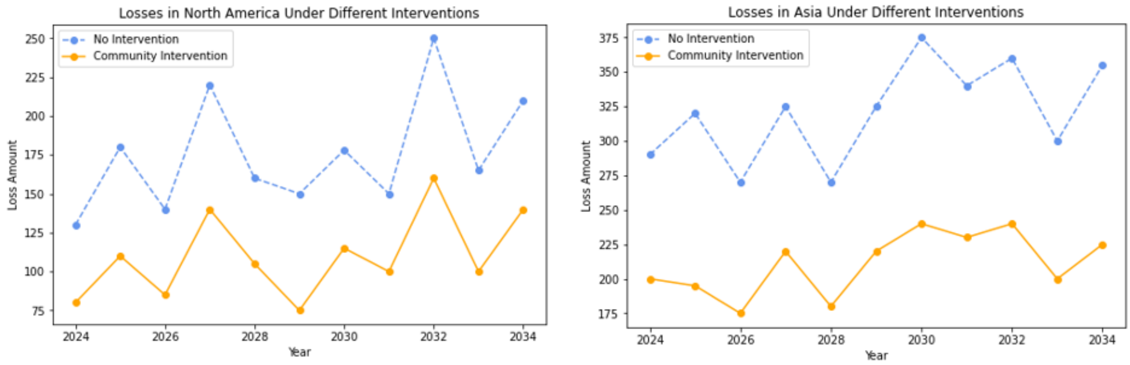

Figure 7: Losses in North America and Asia under different interventions

In North America, the impact of two different intervention levels on property losses is analyzed. Under the "No Intervention" scenario, property losses increase from 125 units in 2024 to 215 units in 2034. This trend indicates that, in the absence of mitigation measures, extreme weather events may result in a substantial escalation in property losses over time. With the implementation of "Community Intervention," property losses increase from 75 units in 2024 to 140 units in 2034. This suggests that community-level intervention measures, including infrastructure development, emergency preparedness, and public education, can mitigate the rate of increase in property losses over time. To further reduce losses, community administrators should continue to strengthen community and property owner intervention measures, especially in improving building weather resistance and risk management strategies.

In Asia, property losses under "No Intervention" rise from 285 units in 2024 to 355 units in 2034. With the implementation of "Community Intervention," property losses increase from 200 units in 2024 to 225 units in 2034. This suggests that community-level intervention strategies, including infrastructure development, emergency preparedness, and public education, can mitigate the rate of increase in property losses over time. To further reduce losses, community administrators

should give prioritize community-level interventions while encouraging property owners to adopt more proactive disaster mitigation measures [10].

Over time, whether in North America or Asia, regions implementing intervention measures demonstrate a deceleration in the rate of loss growth, emphasizing the importance of long-term planning and sustained efforts [11].

4. Conclusions

The risk level evaluation model deals with the problem of whether the companies should underwrite policies is fundamentally rooted in the uncertainty brought about by natural extreme weather events. The model uses the Entropy Weight Method to determine the weights of indicators and then calculate the risk factor Ω, and uses the ALARP criterion to determine the level of risk. The model possesses high flexibility, allowing adjustments based on specific problems and requirements. Additionally, its results are typically straightforward to interpret, facilitating understanding and acceptance by decision-makers; The MGWR model with protection factor is to minimize the loss and community administrators could decide the best strategies to develop the community corresponding to the calculated loss. The model with risk-based insurance pricing strategies and multi-objective optimization techniques has demonstrated the potential to provide insurance companies with a more nuanced understanding of spatial risk patterns and to inform strategic decision-making. The model's ability to balance humanitarian considerations with economic efficiency is a significant advancement in the field of insurance risk assessment.

Despite these two model's strengths, risk level evaluation model's accuracy is highly dependent on the quality and completeness of the input data, which could be affected by biases or incompleteness; The MGWR model and associated multi-objective optimization algorithms are complex, requiring specialized knowledge and skills, potentially increasing the difficulty and cost of implementation. Future research and development should focus on refining the model to enhance its predictive accuracy and simplify its implementation, making it more accessible to a broader range of stakeholders. Additionally, the model's application extends beyond the insurance industry, offering valuable insights for urban planners, policymakers, and communities in preparing for and mitigating the impacts of climate change. By leveraging this framework, society can take proactive steps towards building a more resilient future in the face of increasing environmental uncertainties.

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