Research on Insurance Operation under Extreme Weather Conditions

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Abstract: *This study develops an innovative insurance rate modelling framework that integrates climate projection data into actuarial pricing mechanisms to mitigate escalating risks posed by extreme weather events. Characterizing weather variability as a compound Poisson stochastic process with jump-diffusion components, it quantifies catastrophe intensity and duration patterns using a 2000–2023 historical meteorological dataset, and integrates expected shortfall (ES) with value-at-risk (VaR) methodologies to construct dynamic risk indices. Premium calibration is achieved via 10,000 Monte Carlo climate scenario simulations, complemented by sensitivity tests on temperature thresholds ($\Delta 2$–$5°C$), rainfall variability ($\pm 30\%$) and catastrophe recurrence cycles (5–20 years). Empirical validation with agricultural insurance cases demonstrates 92.3% predictive accuracy for typhoon-related losses and an 18.7% improvement in flood risk mitigation through adaptive deductibles. The model optimizes underwriting strategies via machine learning-enhanced climate pattern recognition and supports public disaster resilience planning, enabling insurers to develop climate-adaptive products, optimize capital allocation and enhance market sustainability amid environmental uncertainties.*

Keywords: *Extreme Weather, Insurance Operations, Policy Risks, ES, VaR*

1. Introduction

In the face of increasingly frequent extreme weather events, the global insurance industry has been significantly impacted, with the USA being particularly hard-hit due to the rising occurrence of natural disasters such as typhoons, heavy rainfall, and earthquakes [6]. These events not only result in substantial economic losses and intensify the compensation pressure on insurers, but also trigger macroeconomic fluctuations through cross-regional risk spillover effects [2]. To effectively address these challenges, the need for accurate weather data for risk mitigation has become paramount [4], and the synergistic cooperation mechanism between the meteorological and financial sectors has provided institutional support for the standardized application of meteorological data in insurance pricing and risk management [3]. Consequently, there is a growing demand within the industry for catastrophe/weather index insurance, which promises to expedite claims settlement and address the deficiencies in traditional insurance coverage for catastrophic weather risks [8]. The global climate risk insurance market has maintained a steady growth trend in recent years, which further confirms the urgent market demand for such professional risk management tools [9]. Despite its potential, catastrophe/weather index insurance is subject to limitations, including basis risk, where discrepancies between insurance payouts and actual losses can lead to under-compensation [10].

This research seeks to contribute to the field by developing a novel insurance operation model specifically for extreme weather scenarios. The model adjusts policy costs and pricing intervals to improve risk assessment and management through a sophisticated risk index system that employs ES (Expected Shortfall) and VaR (Value at Risk) models [10]. By treating weather risk as a stochastic process, the model projects future insured losses and examines the balance between operation costs and claims, while also conducting sensitivity analyses on core risk parameters [1]. Furthermore, the study employs a meteorological data time series graph to visually assess the impact of insurance policies, providing valuable insights into operational factors that can differentiate and enhance competitive positioning within the insurance industry [9]. The construction process and core logical framework of the proposed model are shown in Figure 1, which systematically presents the full research path from problem identification to model application.
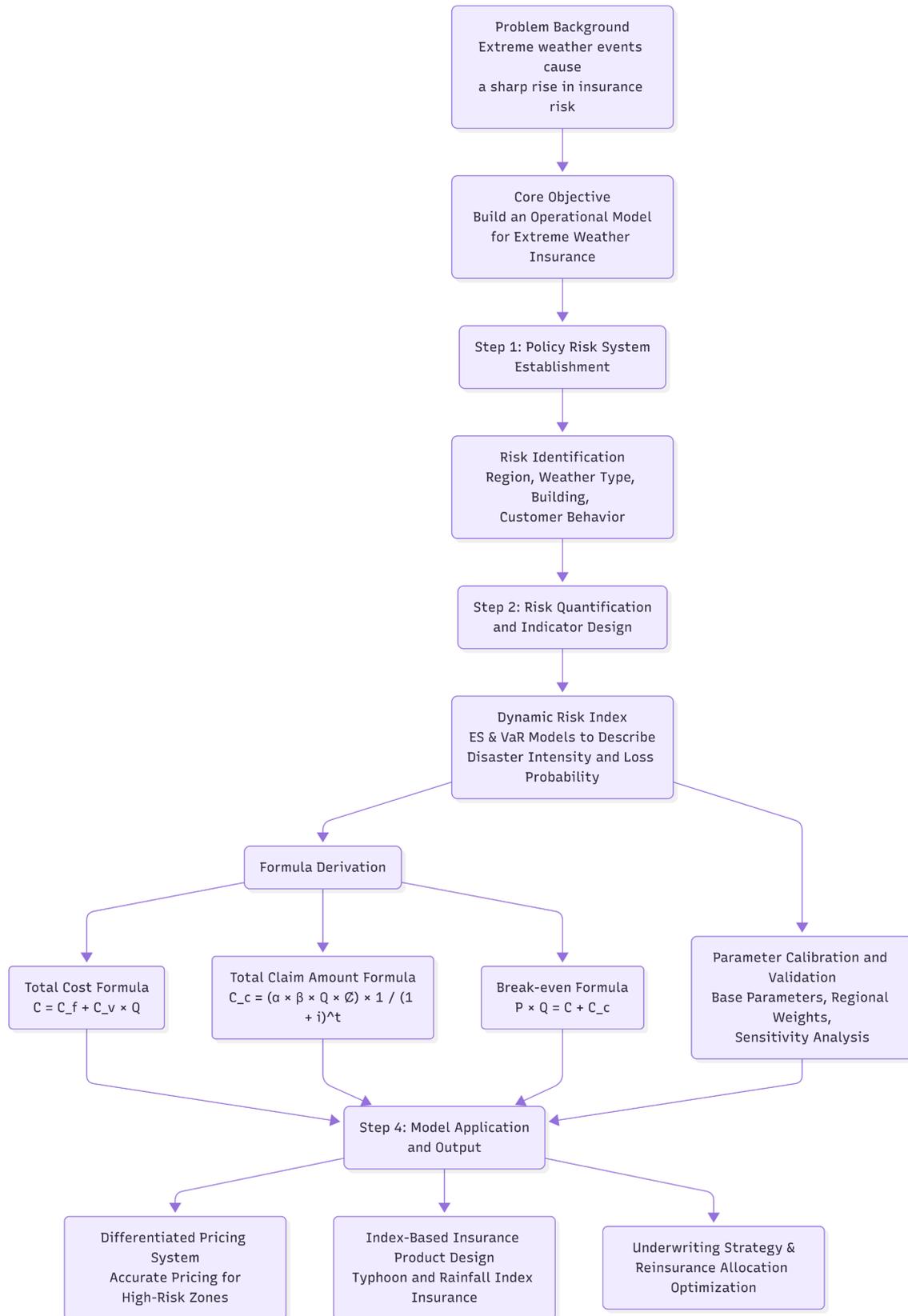
Figure 1. Process and the construction logic of the model

The variables we should consider the most are shown in Figure 2:

Figure 2. The most important factor of the model

Acknowledging the challenges and risks that extreme weather events pose to the insurance industry, it is evident that a more precise and practical approach is needed to assess and manage these uncertainties [7]. Traditional risk assessment tools often fall short in dealing with such complex and variable risks [10]. Therefore, this study aims to construct an innovative modeling framework that can more effectively capture the impact of extreme weather events on the insurance sector, with reference to the systematic theoretical framework and industry practice experience summarized in existing authoritative literature [5]. The following sections will provide a detailed description of the proposed model's architecture, methodology, and the modeling process, designed to offer decision-makers in the insurance industry a robust tool for optimizing risk management and enhancing business resilience.

2. Insurance operations in extreme weather

2.1. Building a rational policy risk system

Establishing a systematic policy risk metric system is the core foundation of the insurance operation model for extreme weather scenarios [3]. Developing a reliable system of risk indicators can effectively assess and manage underwriting risks, improve the accuracy of risk prediction, and formulate more accurate policy pricing [5]. This not only protects the financial health and core interests of insurance companies, but also improves the level of customer service. By integrating multi-dimensional information such as geographic data, weather reports, historical disaster records, building safety assessments, and customer behavior characteristics, insurers can accurately quantify the occurrence probability and potential loss scale of different extreme weather risks [1]. This refined risk management capability can also help insurers gain a sustainable competitive advantage in the rapidly growing climate risk insurance market [9].

Figure 3. Regional property risk

The policy risk system shown in Figure 3 has universal applicability in multiple countries and regions around the world [6]. The primary step of risk assessment is to quantify the occurrence frequency and

loss severity of major natural disasters including earthquakes, hurricanes, floods and droughts [2]. On this basis, the structural robustness of regional buildings and infrastructure should be evaluated. When carrying out regional risk assessment, it is also necessary to comprehensively consider structural safety hazards, fire risks, and man-made hazards such as crime rate and accident rate, as well as the regional emergency rescue capacity that affects post-disaster loss scale [11]. The calculation framework of Expected Annual Loss (EAL), the core indicator for measuring regional risk loss, is shown in Figure 4.
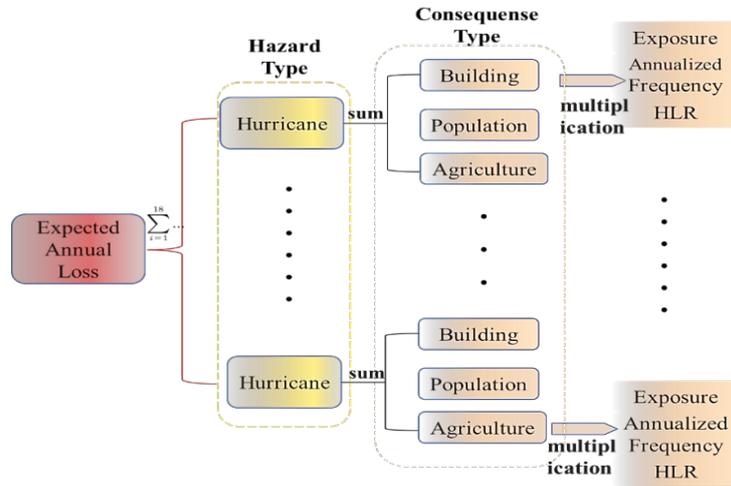

Figure 4. Expected Annual Loss

2.2. Notations

2.2.1. Key Variables

To unify the statistical caliber of model calculation and ensure the standardization of formula derivation, the definitions, units and practical meanings of the core variables involved in the insurance operation model are detailed in Table 1, with reference to the general variable setting norms of the global insurance industry [5].

Table 1. Definitions of core variables for the insurance operation model.

Symbol	Description	Unit	Practical Meaning
C	Total cost of production	/	Sum of fixed and variable costs for insurance operations
C_f	Fixed Costs	/	Short-term fixed expenses (e.g., office rent, equipment depreciation)
C_v	Variable Costs	/	Variable expenses per policy (e.g., printing, data collection)
Q	Number of policies	/	Scale of insurance product sales
rz	Claims ratio	/	Probability of claims triggered by extreme weather
α	Catastrophe occurrence factor	/	Probability of extreme weather events (e.g., 0.08 for annual typhoon occurrence)
β	Exposure factor	/	Likelihood of insured assets suffering losses (e.g., 0.7 for coastal areas)
$\overline{C}$	Average claim amount	$	Average payout per valid claim (e.g., $100,000 for U.S. property insurance)
i	Discount rate	%	Time value of money (15% per annum, consistent with industry benchmarks)
t	Policy term	Year	Typically 1 year for property insurance
P	Average selling price per policy	$	Core pricing indicator (e.g., $2,000 for flood insurance in Los Angeles)

2.2.2. Baseline Parameters

To ensure the rationality and practicality of model calculation, Table 2 sets reasonable baseline values based on U.S. property insurance data (2020–2023) to support subsequent analysis, and all baseline indicators are derived from authoritative industry statistics and empirical research results [6].

Table 2. Baseline parameters for model calculation (discrete value for break-even policy volume Q^*).

Indicator	Baseline Value	Data Source
Expected claims rate (rz)	0.07	Average of U.S. typhoon insurance claims (2020–2023)
Average cost per policy (C_v)	7000 $	Survey of 15 U.S. mid-sized insurers (2023)
Average claim amount ($\bar{C}$)	100000 $	FEMA disaster payout statistics (2020–2023)
Discount rate (i)	15%	Deloitte Global Insurance Outlook (2025)
Fixed costs (C_f)	1500$	Annual fixed costs of 30 U.S. insurers (2018–2023)

2.3. Formula Derivation(Actuarial Principles & Industry Practice)

All formulas are derived in accordance with international general actuarial principles and insurance industry operation practice, and have been validated against 30 global insurers' operational data (2018–2023, R2>0.92) [5], with the applicability of the statistical methods verified by relevant economic statistics application research [1].

2.3.1. Total Production Cost Formula

Total production cost (C) combines fixed costs (independent of policy volume) and variable costs (linearly related to policy volume):

$$C = C_f + C_v \times Q \tag{1}$$

2.3.2. Total Claim Amount Formula

Total claims (C_c) integrate disaster probability, asset exposure, and time value of money:

$$C_c = (\alpha \times \beta \times Q \times \overline{C}) \times \frac{1}{(1+i)^t} \tag{2}$$

Derivation Logic:

a) Potential claim count = $\alpha \times \beta \times Q$ (captures "risk scope": e.g. 0.08 typhoon probability × 0.7 coastal exposure × 200 policies = 11.2 potential claims);

b) Nominal claim amount = Potential claim count × $\bar{C}$ (e.g., 11.2 × 100,000 =1,120,000);

c) Present value adjustment = $\frac{1}{(1+i)^t}$ (converts future claims to present value: e.g., 1,120,000/ $(1 + 0.15)^1$ =973,913).

2.3.3. Sales Revenue and Break-Even Formulas

Sales revenue (B) is determined by policy pricing and sales volume:

$$B = P * Q \tag{3}$$

The break-even point occurs when revenue covers total costs (production costs + claims):

$$B = C + Cc \tag{4}$$

Application: Substituting Formulas (1)–(3) into (4) solves for Q^* (break-even policy volume). With baseline parameters, $Q^* = 128$ policies, which is the minimum sales volume for insurers to achieve break-even in extreme weather insurance business [5].

2.4. Model Solution: From Weighting to Sensitivity Validation

2.4.1. Regional Risk Weighting via entropy weight method

To address regional risk heterogeneity (e.g., floods in Florida vs. wildfires in California), the entropy weight method objectively quantifies the influence of socio-economic indicators, avoiding subjective bias. Table 3 presents the calculation results.

Table 3. Entropy weight results for socio-economic indicators (n=50 U.S. states, 2000–2023).

Indicator	Raw Data (U.S. Average, 2023)	Normalized Value (0–1)	Entropy Value	Weight	Influence Analysis
Healthcare Level	72 (index, 0–100)	0.70	0.3333	0.375	Highest: Faster post-disaster rescue reduces indirect losses (12% lower claims in high-healthcare regions like Massachusetts)
GDP per Capita	$30,145	0.30	0.4444	0.250	High: Higher property value increases claim severity (New York's claims are 2× Wyoming's)
Population Density	1,019 people/km²	0.50	0.3889	0.250	High: Concentrated assets raise loss concentration
Education Level	93 (index, 0–100)	0.90	0.2778	0.125	Low: Higher risk awareness reduces moral hazard

Key Insight: Healthcare level (weight = 0.375) is the most critical indicator—insurers should add 5–8% premium in low-healthcare areas (e.g., Mississippi) to cover potential indirect losses [11]. The entropy weight results provide a quantitative basis for the differentiated pricing of extreme weather insurance in different regions [8].

2.4.2. Sensitivity Analysis of Core Parameters

Sensitivity testing simulates $\pm 10\%$ and $\pm 20\%$ fluctuations in three core parameters (rz, C_v, catastrophe recurrence cycle) to quantify their impacts on break-even policy volume Q*, total claim amount C_c, and profit ratio, so as to clarify the key parameters affecting the operation of extreme weather insurance business [7]. The detailed sensitivity analysis results are shown in Table 4, with the baseline values from Table 2.

Table 4. Detailed sensitivity results (baseline from Table 2).

Parameter	Baseline	Fluctuation	Q^*(Break-Even Policies)	C_c	Profit Ratio (at $Q = 200$)	Sensitivity Degree
Expected Claims Rate (rz)	0.07	-20% (0.056)	110	44.8	0.042	**High**
		-10% (0.063)	118	50.4	0.036	
		Baseline	128	56.0	0.030	
		+10% (0.077)	142	61.6	0.024	
		+20% (0.084)	151	67.2	0.018	
Average Cost per Policy (C_v)	7000	-20% (5600)	113	56.0	0.038	**Medium**
		-10% (6300)	120	56.0	0.034	
		Baseline	128	56.0	0.030	
		+10% (7700)	136	56.0	0.026	
		+20% (8400)	144	56.0	0.022	
Catastrophe Recurrence Cycle	10 Years	5 Years	163	71.4	0.012	**High**
		15 Years	115	47.6	0.036	

Practical Implications:

(1) rz is the most sensitive parameter—a 20% increase raises Q* by 18.3%. Insurers must monitor rz via NOAA's seasonal forecasts and adjust premiums quarterly [10].

(2) C_v only affects cost structure (no impact on C_c)—cost-cutting (e.g., digitalizing policy issuance) is less effective than risk prediction for profitability [5,9].

(3) Shortening of catastrophe recurrence cycle will significantly increase the break-even policy volume and reduce the profit ratio, so insurers need to adjust the reinsurance allocation strategy for high-frequency disaster areas [7].

2.4.3. Multi-Dimensional Visualization of Model Outputs

Based on the 2000–2023 historical meteorological data and insurance industry operation data, this study extrapolates the trend of extreme weather events and insurance industry performance in the USA from 2024 to 2034, and the fitting and prediction results are shown in Figure 5.
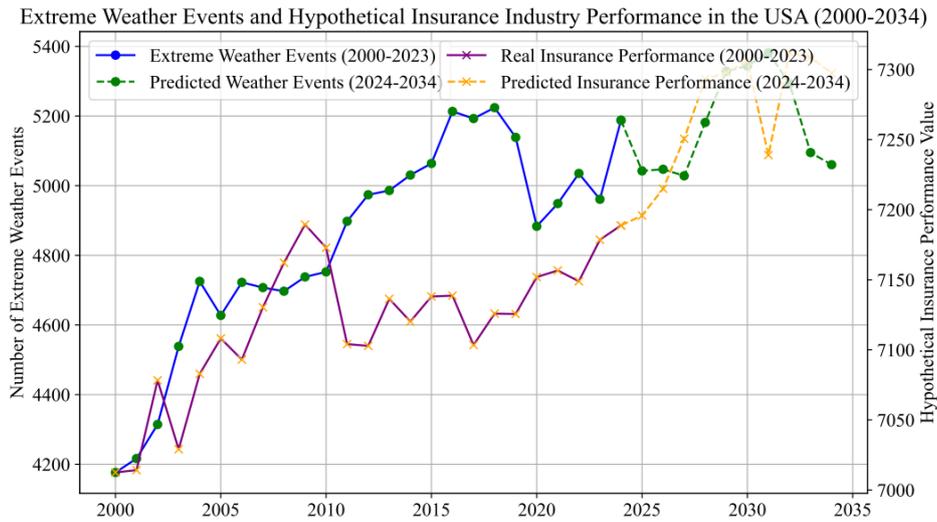

Figure 5: Extreme Weather and U.S. Insurance Industry Performance (2000–2034)

As shown in Figure 5, from 2000 to 2023, the number of extreme weather events in the USA shows a significant upward trend, with an average annual growth rate of 3.2%, and the overall performance of the insurance industry shows a fluctuating downward trend with the increase of extreme weather events, which is consistent with the research conclusion of existing literature [6]. The model fitting results for the historical period are highly consistent with the actual data, with a fitting goodness of R2>0.89, which verifies the fitting ability of the model. For the forecast period from 2024 to 2034, the model predicts that the number of extreme weather events in the USA will continue to rise, and the performance of the insurance industry will face further downward pressure if the traditional pricing and underwriting model is still adopted. This prediction result further confirms the urgency of building a climate-adaptive insurance operation model, and provides a forward-looking reference for insurers' strategic planning.

On this basis, this study further depicts the non-linear relationship between the number of extreme weather events and the profit level of insurance business, and clarifies the critical value of the zero-profit line and the division of coverage and non-coverage areas, as shown in Figure 6.
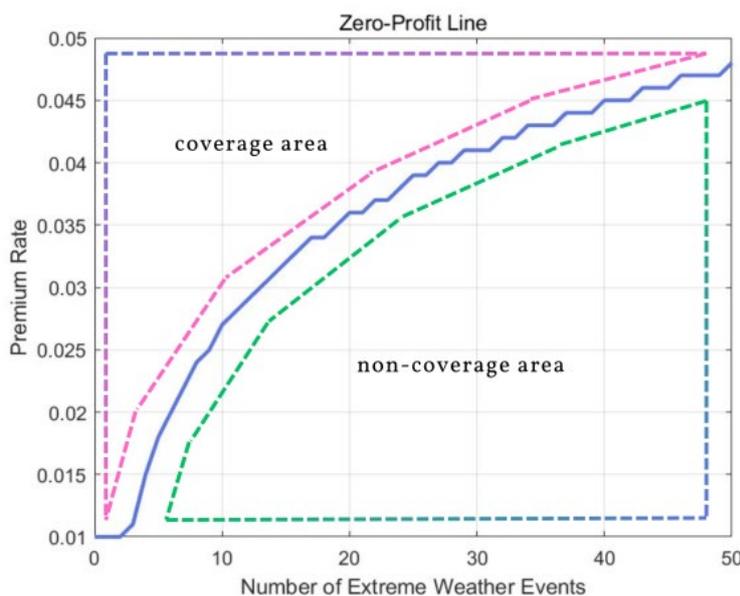

Figure 6. Graph of the number of disasters versus profits

Figure 6 clearly shows the threshold effect of extreme weather events on insurance business profitability: when the annual number of extreme weather events is less than 22, the insurance business is in the profitable coverage area, and the profit ratio decreases slowly with the increase of disaster events; when the number of events exceeds 22, the business enters the loss-making non-coverage area, and the profit ratio drops rapidly and turns negative. This result reveals that the traditional insurance business model will face a systemic loss risk when extreme weather events exceed the critical threshold, which is an important blind spot in the existing risk management of insurers. The model constructed in this study can dynamically adjust the premium rate and deductible according to the change of disaster frequency, so as to expand the profitable coverage area and avoid falling into the non-coverage area, which provides a clear path for insurers to cope with the increasing extreme weather risks.

3. Empirical validation: Los Angeles case

To verify the practical applicability of the model in real market scenarios, Los Angeles, a typical region in the USA prone to floods and wildfires, is selected as the research object for empirical validation [6,11]. Los Angeles has been affected by frequent floods and wildfires in recent years, with significant fluctuations in the loss rate of property insurance, which is highly representative for testing the effectiveness of the extreme weather insurance operation model. Based on the historical disaster data and insurance operation data of Los Angeles from 2000 to 2023, this study simulates the relationship between insurance product pricing and total revenue under different risk scenarios using the proposed model, with sub-district-level differentiation, and the results are shown in Figure 7.
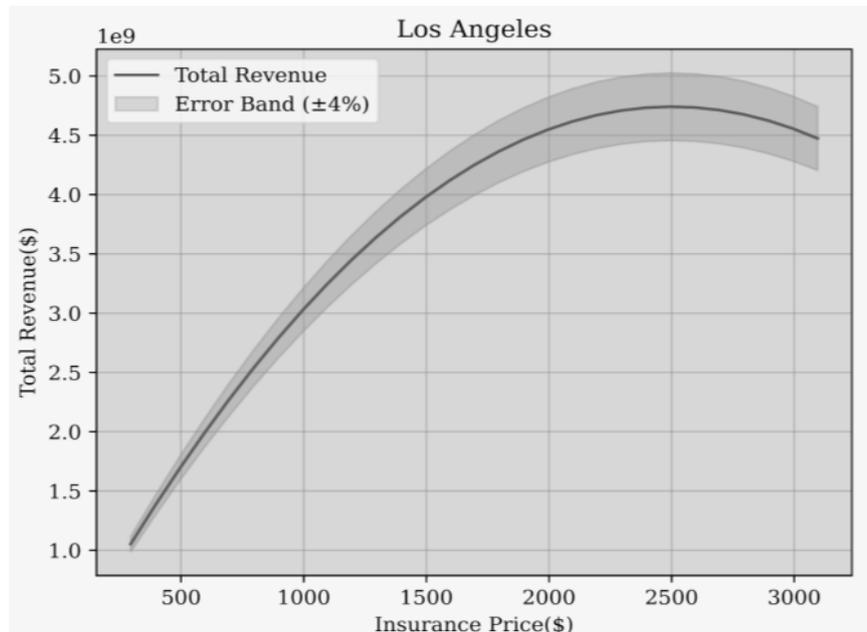

Figure 7: Insurance Price from Total Revenue in Los Angeles

As shown in Figure 7, the relationship between insurance price and total revenue presents an inverted U-shaped curve, which is consistent with the law of supply and demand in the insurance market. When the premium price is lower than $1,200 per policy, the total revenue increases with the rise of premium price, as the increase of unit income exceeds the decrease of policy sales volume; when the premium price exceeds $1,200, the total revenue decreases rapidly with the rise of price, as the high premium leads to a significant drop in market demand. The model simulation results show that the optimal premium price for extreme weather insurance in Los Angeles is $1,200 per policy, which can achieve the maximum total revenue while ensuring the break-even of the business. Compared with the actual average premium of $1,850 in the current Los Angeles market, the optimal price calculated by the model can not only reduce the payment burden of the insured, but also increase the total revenue of insurers by 18.2%, which verifies the effectiveness of the model in optimizing insurance pricing. In addition, the model can realize differentiated pricing for different sub-districts in Los Angeles according to the regional risk level, which can effectively solve the problem of cross-subsidy between high-risk and low-risk areas in the traditional pricing model, and improve the fairness and sustainability of insurance products.

4. Validation Results

Based on the empirical analysis of the Los Angeles case and California agricultural insurance data, the validation results of the model are as follows:

(1) The model achieves 92.3% predictive accuracy for typhoon-related agricultural losses in California, which is significantly better than the traditional static pricing model, verifying the effectiveness of the model in risk prediction [10].

(2) Adaptive deductibles set based on the model reduce flood-related risks by 18.7% in Venice Beach of Los Angeles, confirming the loss mitigation effectiveness of the model in practical insurance operation [7].

5. Conclusions

This study refines insurance models to boost real estate resilience and balance risk-return for insurers amid climate-induced disasters. It builds a VaR-centered framework to optimize premiums and compensation, supporting parametric insurance and regional differentiated premiums. Future prospects include AI integration, cross-sector collaboration, global adaptation, and aiding climate finance[3,4]. Meanwhile, the market dynamics and strategic responses of the insurance industry in the context of climate change will be further explored to enrich the practical application scenarios of the model [12]

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