Fusing multi-model climate risk assessment and insurance profitability prediction: a machine learning-based cross-country comparative analysis

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Abstract. Climate change-induced increases in the frequency and intensity of extreme weather events year after year pose a significant challenge to the profitability of the global insurance industry. Traditional risk assessment models have limitations in predicting insurance profitability due to the difficulty in coping with the nonlinearity and complexity of climate risk. To this end, this study proposes a multi-model fusion approach that combines fuzzy assessment models, entropy weighting, linear regression, and machine learning models (LightGBM & XGBoost) to assess the impact of climate risk on the profitability of the insurance industry. By analyzing cross-country empirical data from the U.S. and U.K. insurance markets, this study reveals the differences and challenges in coping with climate risk in different countries. The findings show that climate risk significantly affects the profitability of insurance companies and that machine learning models exhibit higher accuracy and reliability in risk prediction compared to traditional methods. This paper provides an empirical basis for insurers and policymakers to address the economic impacts of climate change and makes recommendations for optimizing insurance risk management.

Keywords: Climate Risk, Insurance Profitability, Machine Learning, LightGBM, XGBoost, Cross-Country Comparison, Entropy Weighting Method, Fuzzy Assessment.

1. Introduction

The impacts of climate change are gradually intensifying, with extreme weather events (e.g., hurricanes, floods, droughts and wildfires) becoming more frequent and intense globally. These disasters are not only a shock to the global economic system, but also pose unprecedented challenges to the insurance industry. Insurance companies are an important part of the economic system for risk management and transfer, and while they provide coverage for financial losses, they are also under pressure to pay out large amounts of money due to the frequency of natural disasters [8]. As climate risks become more complex and unpredictable, traditional risk assessment models relying on historical data are facing significant limitations to cope with the high level of uncertainty about future climate risks [5].

The profitability of the insurance industry depends on accurate risk assessment models. However, as climate change intensifies, traditional actuarial models and statistical methods (e.g., linear regression and loss distribution analysis) perform poorly when dealing with complex, nonlinear risks [1]. These models typically assume that future risk patterns are consistent with historical trends, but climate change-induced weather extremes are often highly uncertain and difficult to accurately predict with traditional linear models. Machine learning models, especially gradient boosting models (e.g., LightGBM and XGBoost), have been gradually gaining attention from the insurance industry in recent years due to their advantages in handling complex nonlinear data [7]. These models are able to automatically learn complex patterns from massive climate and insurance data and continuously optimize the accuracy of risk prediction.

Climate change is also widening the global “insurance protection gap”, where many individuals and businesses face uninsured coverage in high-risk areas due to increased insurance costs or reduced insurance coverage because of excessive risk [2]. This protection gap not only increases the economic risk to society, but also weakens the financial capacity of insurers in responding to disasters.

Therefore, insurers are in urgent need of more effective tools to assess and predict future climate risks and thus design more forward-looking risk management strategies.

In view of this, this study proposes an approach that incorporates multiple models, combining fuzzy assessment models, entropy weighting, multiple linear regression, and advanced machine learning models (e.g., LightGBM and XGBoost) to assess the impact of climate change on insurance profitability. Through cross-country empirical data analysis, the U.S. and the U.K. are selected as representative countries to explore the variability of different economies and insurance markets in responding to climate risks. This study not only proposes a more accurate climate risk prediction framework, but also provides important practical guidance for insurance companies and policy makers.

The core questions of the study include (1) How does climate risk affect the profitability of insurance companies? (2) How do traditional risk assessment methods and machine learning models perform in climate risk prediction? (3) What are the significant differences between U.S. and U.K. insurers in addressing climate risk? By addressing these questions, this study not only provides insurers with scientific risk management tools, but also offers constructive suggestions for addressing the economic challenges posed by global climate change.

The contributions of this study are: (1) it proposes a fusion model that combines traditional statistical methods and machine learning, which makes up for the shortcomings of traditional models in dealing with complex climate risks; (2) it demonstrates the potential of machine learning techniques in nonlinear risk prediction; (3) through cross-country comparative analyses, it reveals the similarities and differences in coping with climate risks in different countries and provides a reference basis for the global insurance market in dealing with the climate change challenges.

2. Literature of Review

The impact of climate change-induced extreme weather events on the global economy is becoming increasingly significant. In particular, the insurance industry, as an important tool for risk management and transfer, is facing increasing financial pressure and management challenges. The existing literature has extensively explored the impact of climate change on the insurance industry, the limitations of traditional risk assessment models, and the application of machine learning techniques in the insurance industry.

2.1. Economic impact of climate change on the insurance industry

Increased climate change has led to a high frequency of extreme weather events, which has had a significant impact on the stability and profitability of the insurance industry. According to a report by Swiss Re Institute (2021), insurance payouts due to natural disasters have risen significantly globally in 2020 and 2021. Particularly in regions such as North America, Europe and Asia, where the frequency of natural disasters triggered by climate change has increased, insurers are facing increasing pressure to pay out claims. Research suggests that climate change not only increases financial risk for insurers, but also further exacerbates the “insurance protection gap” (Botzen, Deschenes, & Sanders, 2019) on a global scale. This “insurance protection gap” refers to a gradual decline in insurance coverage or a sharp increase in insurance costs in some high-risk areas, resulting in many people and businesses being unable to obtain adequate insurance coverage.

Stern (2016) notes that climate change-induced extreme weather events have cost the global economy trillions of dollars, with the insurance industry bearing the brunt. While insurers have responded to these risks through measures such as raising premiums and limiting benefit coverage, these measures are still insufficient to deal with more frequent and severe climate disasters in the future. Insurers need more advanced risk assessment tools to accurately predict future climate risks and optimize their risk management strategies.

2.2. Limitations of traditional risk assessment models

The insurance industry has long relied on traditional risk assessment models such as linear regression models and loss distribution models. These models perform better in stable risk environments, but with the increased nonlinearity and uncertainty associated with climate change, traditional models have revealed significant limitations in predicting future risk (Berliner, 2017). Traditional models rely on historical data and assume that future risk patterns are consistent with historical trends. However, extreme weather events due to climate change are highly unpredictable and linear models struggle to capture such complex changes.

Friedman, Hastie, and Tibshirani (2001) point out that traditional statistical models have difficulty in dealing with the nonlinear features of climate risk. For example, the interaction of multiple climatic factors may trigger compound hazard events, and traditional linear regression models cannot effectively capture these complex interrelationships. In addition, the inability of traditional models to adapt to the "long-tail risks" (i.e., catastrophic events that occur very infrequently but with large losses) induced by climate change further restricts their use in insurance risk prediction.

2.3. Machine Learning in Insurance Risk Management

In order to cope with the inadequacy of traditional models in complex climate risk prediction, machine learning technology has gradually been widely used in the insurance industry in recent years. Unlike traditional models, machine learning models are able to automatically learn complex patterns from a large amount of high-dimensional data and have strong nonlinear data processing capabilities, thus showing significant advantages in climate risk prediction (Ke et al., 2017). In particular, gradient boosting decision tree models such as LightGBM and XGBoost have become popular tools in insurance risk management due to their efficient training speed and excellent prediction accuracy (Chen & Guestrin, 2016).

Henckaerts et al. (2020) found through their study that machine learning-based climate risk prediction models exhibit higher prediction accuracy than traditional linear models when dealing with weather-related insurance claim risks. The study also showed that machine learning models are better able to capture nonlinear risk patterns under complex climatic conditions, thus providing insurers with more reliable risk management tools. The introduction of machine learning technology provides the insurance industry with a completely new approach to climate change risk, which can help improve insurers' ability to cope with future climate risks.

3. Research Method

This study aims to assess the impact of climate change on insurance profitability by combining traditional statistical models with machine learning algorithms to construct an integrated framework for multi-model integration. In order to ensure the robustness and interpretability of the results, this paper uses fuzzy assessment models, entropy weighting, multiple linear regression and machine learning algorithms (LightGBM & XGBoost) for the analysis, as well as cross-country comparative analyses of empirical data from the U.S. and U.K. insurance markets. The specific methodology of this study is described below.

3.1. Data sources and processing

The primary data sources for this study include financial data (e.g., premium income, claims ratio, profitability, etc.) for U.S. and U.K. insurance companies, which are derived from publicly available financial reports and industry databases. Climate risk data, including data on temperature anomalies, precipitation, hurricane frequency, and other extreme weather events, which are obtained from the National Climatic Data Center (NCDC) and the UK Met Office (Met Office).

In order to ensure the comparability and consistency of the data, the data were cleaned and standardized in this study. First, samples with missing data and outliers were excluded. Secondly, different variables were standardized to eliminate possible bias due to differences in magnitude. In addition, taking into account the differences in the economic volume of different regions, this study also applies some smoothing to the data to ensure the accuracy of the analysis results.

3.2. Fuzzy assessment modeling and entropy weighting approach

In order to quantify the comprehensive impact of climate risk on the profitability of insurance companies, this study adopts the fuzzy assessment model [10] combined with the entropy weight method [16]. The fuzzy assessment model is able to deal with complex and uncertain systems and is particularly suitable for the assessment of multidimensional indicators; while the entropy weight method is used to determine the objective weights of each assessment indicator and reduce the influence of subjective bias.

3.2.1. Calculation of weights for the entropy weighting method

The entropy weight method determines the weight of each indicator by calculating its information entropy with the following formula:

$$H_j = -\frac{1}{\ln n}\sum_{i=1}^{n} P_{ij} \ln P_{ij}$$

Where H_j denotes the entropy value of the j indicator, P_{ij} is the standardized value of the i sample on the j indicator, and n is the number of samples. The entropy value can be derived from the weight of each indicator, and the greater the weight, the greater the influence of the indicator on the profitability of the insurance company.

3.2.2. Application of fuzzy assessment models

After the entropy weighting method determines the weights of each index, the fuzzy assessment model is used to provide a comprehensive score for the profitability of insurance companies. Specifically, this paper constructs a fuzzy relationship matrix R, which is combined with the weight vector A to finally obtain the comprehensive evaluation result B of the insurance company's profitability:

$$B=A\cdot R$$

Where B represents the combined profitability score of insurance companies under different climate risk conditions.

3.3. Multiple linear regression analysis

In order to further analyze the specific impact of each climate risk factor on the profitability of insurance companies, a multiple linear regression model was used in this study. The model was used to analyze the linear relationship between independent variables (e.g., temperature anomalies, precipitation, hurricane frequency, etc.) and dependent variables (profitability of insurance companies).

The basic form of the multiple regression model is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon$$

Where y denotes the profitability of the insurance company, x_1, x_2,...,x_n denotes each climate factor, β_1, β_2,..., β_n denotes the error term, and denotes the regression coefficient of each climate factor. In this study, the regression coefficients are used to measure the effect of each climatic factor on the profitability of insurance companies and the significance test (p-value) is used to assess the effect of the regression model.

3.4. Machine Learning Models (LightGBM & XGBoost)

In order to solve the problem that traditional regression models cannot capture complex nonlinear relationships, two advanced machine learning algorithms-LightGBM and XGBoost-are introduced in this study.They are able to perform well in dealing with high-dimensional data, nonlinear relationships, and complex interaction effects.

3.4.1. LightGBM model

LightGBM (Light Gradient Boosting Machine) is an efficient machine learning algorithm based on Gradient Boosting Decision Tree (GBDT), which is characterized by high computational speed and low memory consumption. Its advantage is to reduce the prediction error by generating the decision tree step by step. In this study, the LightGBM model is used to predict the profitability of insurance companies, and the input variables include climate risk data and insurance financial data.

The objective function of LightGBM is:

$$L(y,\hat{y})=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2+\lambda\|\theta\|$$

Where y_i is the true profitability, $\hat{y}_i$ is the forecast, λ is the regularization term, and θ is the model parameter.

3.4.2. XGBoost model

XGBoost [14,15] is another machine learning algorithm based on gradient boosting with good regularization effect, which can improve the prediction accuracy while preventing overfitting (Chen & Guestrin, 2016). XGBoost is able to efficiently deal with complex climate risk data by constructing multiple weak learners and progressively optimizing the loss function.

The objective function of XGBoost is:

$$Obj=\sum_{i=1}^{n}L(y_i+\hat{y}_i)+\sum_{k=1}^{K}\Omega(f_k)$$

Where $L(y_i+\hat{y}_i)$ is the loss function, $\Omega(f_k)$ is the complexity of the k tree, and K is the number of decision trees.

3.5. Cross-country comparative analysis

For the purpose of in-depth analysis of the impact of climate risk on the insurance markets of different countries, the United States and the United Kingdom are selected as the subjects of empirical analysis in this study. The insurance markets of these two countries are highly representative with significant differences in climate risk exposure, economic development level and policy environment. This study explores the coping strategies of different economies in the context of climate change by comparing the differences in profitability of insurance companies in the US and the UK in the face of climate risk.

4. Results and analysis

This study empirically analyzes climate risk and profitability in the U.S. and U.K. insurance markets through fuzzy valuation modeling, entropy weighting, multiple linear regression analysis, and machine learning models (LightGBM & XGBoost). This section presents the results from these analytical methods in detail, with optimization interpretations and discussions.

4.1. Results of entropy weighting method and fuzzy assessment modeling

The results of the entropy weighting methodology are calculated to establish weights for each climate risk factor, reflecting the relative importance of these factors to insurer profitability. Claims ratios, temperature anomalies and hurricane frequency were calculated to have the greatest impact on insurance profitability, particularly in the US market, where hurricane frequency was weighted more heavily. Table 1 illustrates the weights of different climate risk factors in the US and UK markets.

Table 1. Entropy weights for climate risk factors in the US and UK insurance markets

Climate risk factors	US weights	UK weights
Claims ratio	0.35	0.40
Temperature anomaly	0.25	0.20
Precipitation	0.15	0.18
Hurricane frequency	0.20	0.10
Economic resilience	0.05	0.12

Based on this weighting, the results of the fuzzy assessment model show that the higher the climate risk, the lower the profitability of insurance companies. In particular, the profitability of US insurers is more affected due to their exposure to a high frequency of hurricanes and extreme weather events. In contrast, UK insurance companies, although also facing the challenge of climate change, are relatively less negatively affected by climate risk due to their relatively stable economic environment and stronger policy support.

4.2. Results of multiple linear regression analysis

In order to further quantify the specific impact of each climate factor on insurance company profitability, multiple linear regression analysis was used in this study. Table 2 demonstrates the regression results for the U.S. and U.K. markets, analyzing the relationship between factors such as temperature anomalies, precipitation, and hurricane frequency and insurance profitability.

Table 2. Results of Multiple Regression Analysis (US vs. UK)

Variable	Regression coefficient (US)	p-value (US)	Regression coefficient (UK)	p-value (UK)
Temperature anomaly	-0.12	0.004**	-0.10	0.015*
Precipitation	-0.08	0.030*	-0.06	0.045*
Hurricane Frequency	-0.18	0.001**	-0.09	0.022*
Economic resilience	0,10	0.010**	0.14	0.008**

Significance level: $*p < 0.05$, $**p < 0.01$

The regression analysis shows that temperature anomalies, precipitation and hurricane frequency have a significant negative impact on the profitability of US insurers, particularly hurricane frequency, which has a particularly significant impact on the US market. In contrast, while the UK market is also affected by these climate risks, its economic resilience mitigates the negative shocks to some extent, resulting in a smaller decline in profitability for UK insurers in the face of climate risk.

4.3. Results of the machine learning model

In order to better capture the complexity and nonlinear relationship of climate risk, this study uses two machine learning models, LightGBM and XGBoost, for predictive analysis. The results show that the machine learning models outperform traditional linear regression models in predicting the impact of climate risk on insurance profitability. Tables 3 and 4 demonstrate the predictive effectiveness of LightGBM and XGBoost models in the US and UK markets, respectively.

Table 3. Predictive effects of the LightGBM model

Indicator	United States (LightGBM)	United Kingdom (LightGBM)
Mean Squared Error (MSE)	0.015	0.022
R^2	0.88	0.82

Table 4. Predictive effect of XGBoost model

Indicator	United States (LightGBM)	United Kingdom (LightGBM)
Mean Squared Error (MSE)	0.012	0.020
R^2	0.89	0.84

As can be seen from the results, the XGBoost model has a slightly higher forecasting accuracy than LightGBM in the US and UK markets, especially in terms of reducing the forecasting error (MSE). The high R^2 values of the two models indicate that they are well able to explain the complex impact of climate risk on insurer profitability. Compared to the traditional linear regression model, the machine learning model significantly improves the prediction accuracy and is able to handle the nonlinear relationship between climate risk and insurance profitability more effectively.

4.4. Cross-country comparative analysis

A cross-country comparative analysis of the U.S. and U.K. insurance markets reveals significant differences between the two countries in their response to climate risk. The U.S. market suffers a greater impact on profitability due to its high frequency of hurricanes and other extreme weather events, with the regression coefficients and weights for hurricane frequency being significantly higher in the U.S. than in the U.K. This suggests that US insurers face greater financial pressures in response to high frequency extreme weather events. In contrast, UK insurers are also affected by climate change, but profitability is less affected by climate change due to their market stability and policy support.

In addition, the UK insurance market has shown greater resilience, which is linked to its policy environment and the structure of the insurance market. UK insurers have been able to mitigate the negative impact of climate risk to some extent through stricter regulation and more robust risk diversification strategies. The US insurance market, on the other hand, relies more on market capacity and financial flexibility to cope with climate risk. Therefore, this study suggests that insurers in different countries need to develop different coping strategies in response to climate change based on their respective market conditions and policy environments.

5. Discussion

5.1. Main Research Findings

This study finds that climate change significantly affects the profitability of insurance companies, especially the impact of climate factors such as temperature anomalies, precipitation and hurricane frequency on the insurance market. Through entropy weighting and fuzzy assessment modeling, this study reveals the variability of the impact of climate risk in the insurance markets of different countries. This is in line with the existing literature, for example, Stern (2016) and Botzen et al. (2019), both of which point out that the financial pressures faced by insurance companies are gradually increasing as the number of extreme weather events due to climate change increases.

Multiple linear regression analysis shows that climate factors have a particularly significant negative impact on the U.S. insurance market, with hurricane frequency in particular having the largest impact on profitability. This reflects the current state of the US market facing frequent extreme weather events. In contrast, the UK insurance market, although also affected by climate change, has seen relatively little volatility in profitability due to its more resilient economy and more robust policy support.

In addition, machine learning models (LightGBM and XGBoost) perform well in predicting the impact of climate risk on insurers' profitability, especially when dealing with complex nonlinear relationships, with higher prediction accuracy and lower error (MSE) compared to traditional linear regression models. This result is consistent with the studies of Chen and Guestrin (2016) and Ke et al. (2017), further demonstrating the potential of machine learning techniques in climate risk management.

5.2. Implications for the insurance industry

The findings suggest several important practical recommendations for the insurance industry to address climate change. First, as climate risks become increasingly complex, insurers need to adopt more flexible and intelligent risk management tools. While traditional linear models are difficult to capture the nonlinearity and complexity of climate risks, machine learning models (e.g., LightGBM and XGBoost) provide effective tools for predicting complex climate risks and help insurers optimize premium pricing and payout strategies.

Second, cross-country comparative analysis shows that insurers in different countries should develop differentiated response strategies based on their respective market conditions and climate risk characteristics. For the U.S. market, insurers need to strengthen reinsurance mechanisms and risk diversification strategies due to its higher exposure to extreme weather risks such as hurricanes. In contrast, the U.K. market can further optimize insurance product design and climate risk management measures by relying on its economic resilience and strict regulatory policies.

5.3. Advantages of multi-model fusion

This study demonstrates the advantages of multi-model fusion by combining traditional statistical methods and modern machine learning techniques. Entropy weighting and fuzzy assessment models provide powerful tools for comprehensive quantification of multidimensional risk impacts, while multiple linear regression and machine learning models provide more accurate predictions of climate risk-specific impacts. Compared to single models, the multi-model fusion approach better captures the complexity of climate risk and improves the accuracy of predicting changes in insurer profitability under different scenarios.

In particular, machine learning models show significant advantages in handling large-scale and complex climate data. lightGBM and XGBoost not only improve the predictive ability of the models through improved gradient boosting algorithms, but also effectively deal with nonlinear relationships, which is particularly suitable for climate risk assessment. Machine learning models show the potential to surpass traditional models when dealing with multidimensional risks induced by climate change.

5.4. Research Limitations

Despite the multi-model fusion approach and cross-country comparative analysis in this study, there are still some limitations. First, the study relies on historical data, whereas future scenarios of climate change may differ significantly from the historical record, and the frequency and intensity of extreme weather events may be further exacerbated, resulting in model projections based on historical data underestimating the actual impacts of future climate risks. Second, the study was limited to the United States and the United Kingdom, which may limit the broad applicability of the conclusions, especially in regions where the impacts of climate change are more severe, such as small island states or developing countries. Therefore, future research should be extended to more countries to ensure the generalizability of the results.

5.5. Directions for future research

Future research can be expanded in the following areas. First, as the impact of climate change on the global economy and society becomes more pronounced, integrating real-time data such as Internet of Things (IoT) devices, satellite monitoring, etc. will improve the accuracy of climate risk assessment and help insurers respond to risks more flexibly. Second, research should further incorporate socio-economic factors such as population migration, economic development levels and policy changes into the risk assessment framework, so as to build a more comprehensive climate risk prediction model, which will provide a more forward-looking management tool for the insurance industry and policy makers. Finally, hybrid models should be developed, combining traditional actuarial models with machine learning algorithms to provide more explanatory and accurate risk assessment tools, enhancing the interpretability and practicality of the models, and facilitating the application of the models by insurance companies and regulators in actual operations.

6. Summary

This study delves into the impact of climate change on the profitability of insurance companies through multi-model integration and reveals the differences in climate risk response between the US and the UK. Despite the strong theoretical and practical value of this study, there are some limitations, and future research can further expand the data sources and research objects to improve the generalizability and prediction accuracy of the model. Meanwhile, the integration of real-time data, the introduction of socio-economic factors, and the development of more interpretable hybrid models will provide new directions for further research in the field of climate risk management.

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