The Impact of Climate Risk on the Insurance Decisions of Agricultural Enterprises

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Abstract. Against the backdrop of escalating global climate change, climate risk has increasingly affected agricultural production. This study analyzes how climate risk influences insurance decisions of agricultural firms, using data from 304 Chinese agricultural enterprises between 2011 and 2022.The empirical findings indicate that climate risk significantly influences agricultural enterprises' insurance decisions, with varying impacts observed across different types of extreme climate events. This study suggests policy recommendations to enhance risk early-warning systems, optimize agricultural insurance product design, and increase government support, aiming to advance the insurance system and promote sustainable agricultural development.

Keywords: Climate risk, Agricultural insurance, Heterogeneity

1 Introduction

The intensification of global climate change has heightened the frequency and severity of climate risks. The Global Risks Report (World Economic Forum, 2021) identifies climate risk as the most probable global threat in the coming decade, posing serious challenges to agricultural production and increasing demands on enterprise risk management (Sun et al., 2024) [1]. The increasing frequency of extreme weather events directly undermines agricultural stability, threatens food security, and endangers rural livelihoods, highlighting the critical urgency of addressing agricultural climate risks. As a key market-based tool for mitigating natural disasters, agricultural insurance enables risk transfer and provides essential financial protection, particularly in high-risk regions (Chen et al., 2024) [2]. Yet, whether enterprises display heterogeneous insurance behaviors under different extreme climate events remains unclear. This study addresses this gap by examining firm-level heterogeneity in insurance decisions, thereby deepening understanding of how agricultural enterprises respond to climate risks and informing improvements in agricultural insurance systems and enterprise risk strategies.

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Previous research has initially explored the link between climate risk and agricultural insurance demand. Gao et al. (2022), based on background risk theory, found that higher levels of risk and uncertainty are closely associated with increased insurance demand [3]. Similarly, An et al. (2022) demonstrated that the growing frequency of climate change and extreme weather events exacerbates climate risks, widens the insurance gap, and stimulates the demand for climate risk management products [4]. At the micro level, Chen et al. (2024) and Robinson (2021) found that climate risks trigger farmers' loss aversion, heighten public risk perception and awareness, and translate into stronger insurance purchasing intentions. Productive farmers, being more directly affected by climate risks, tend to exhibit higher willingness to insure [5,6]. Farmers, constrained by cognitive, temporal, and resource limitations, align their insurance purchase decisions with perceived risk levels to mitigate production losses (R.Peng et al.,2021) [7]. On a macro scale, physical risks like extreme weather events directly impact agricultural assets and materials, affecting the structure and pricing of property insurance products (Massa et al.,2020) [8]. Wei et al. (2021) further revealed that extreme climate events, by expanding the area of affected farmland, lead to direct agricultural economic losses, which in turn heighten the demand for insurance coverage [9]. However, previous studies have largely concentrated on regional disparities, with limited attention paid to how different types of extreme climate events exert differentiated effects on corporate insurance decisions. Peters et al. (2023), for instance, proposed that the mechanism of climate risk transmission and the extent of disaster losses are closely linked to the level of insurance coverage in affected regions [10].

This study offers two main innovations. First, it disaggregates climate risk into four types—heat, cold, rainfall, and drought—and extends analysis from households to enterprises to uncover heterogeneous effects of these events on agricultural insurance decisions. Second, it develops an Agricultural Enterprise Insurance Purchase Intention Index by integrating text mining with the entropy method, offering a novel framework to quantify insurance behavior. The remainder of the paper outlines the empirical design (Section 2), presents results and robustness tests (Section 3), and concludes with key findings and policy implications (Section 4).

2 Empirical Research Design

2.1 Data Sources

Data on 304 listed agricultural firms in China, spanning from 2011 to 2022, were sourced from the CSMAR and Wind databases, yielding 3,648 valid observations across 100 cities in 26 provinces. Climate data were sourced from the annual China Climate Change Blue Book, while agricultural economic data were obtained from the *China Rural Statistical Yearbook*, municipal statistical yearbooks, and the official publications of the National Bureau of Statistics and the Ministry of Agriculture and Rural Affairs. To ensure data quality, the following criteria were applied: (1) Exclusion of listed companies marked as ST or *ST during the observation period; (2) Removal of firms with over 30% missing key data; (3) Inclusion of only agricultural enterprises with at least three years of continuous observations;(4) Elimination of firms with missing key variables for three or more consecutive years. To address data gaps, the study utilized the multiple imputation method, conducting five rounds of imputation to create a complete dataset for empirical analysis.

2.2 Variable Definition

2.2.1 Dependent Variable. The dependent variable in this paper is the insurance decision of agricultural enterprises (*Insurance*), measured through the construction of an Agricultural Enterprise Insurance Purchase Intention Index. Referring to the keyword clustering framework for insurance purchasing behavior proposed by Thamtarana et al [11]. The research focus on'purchase intention 'includes terms like Internet and tax incentives. Utilizing policy documents such as the *Guiding Opinions on Accelerating the High-Quality Development of Agricultural Insurance* and the *Regulations of the People's Republic of China on Agricultural Insurance*, this study applies natural language processing (NLP)to identify high-frequency feature words related to'purchase intention. 'Six keyword categories emerged: economic factors (e.g., loan interest rates), policy incentives (e.g., tax benefits), products and services (e.g., claims processing, product innovation), awareness and trust (e.g., customer satisfaction), technology and innovation (e.g., online insurance, digital consultation), and purchasing barriers (e.g., information asymmetry). The annual search volume for these keywords was then retrieved from the Baidu Index. The entropy weighting method was applied to assign objective weights: for each keyword category, we calculated the entropy value based on the variability across firms and years, with lower entropy indicating higher discriminative power and thus a higher weight. The final index was computed as the weighted sum of normalized search volumes, rescaled by dividing by 100 to ensure comparability. This method reduces subjective bias in index construction and captures multidimensional aspects of insurance purchase intentions.

2.2.2 Independent Variable. Building on the Global Climate Physical Risk Index(*GCPRI*) developed by the Chinese Academy of Sciences and Southwestern University of Finance and Economics—covering 170 countries worldwide—the index has been localized and expanded to provincial and sub-provincial levels in China, resulting in the China Provincial and Municipal Climate Risk Index(*CCPRI*).The CCPRI encompasses data from 1993 to 2023 across 31 provinces(a total of 962 provincial-level samples)and 229 prefecture-level cities(6,950 samples).Each set of CPRI data consists of four sub-indices: LTD(extreme low-temperature days), HTD(extreme high-temperature days), ERD(extreme rainfall days),and EED(extreme drought days), providing a valuable data foundation for climate change empirical research. Drawing on this dataset, this study adopts the CCPRI values for Chinese provinces and cities from 2011 to 2022 as the independent variable to measure the level of climate risk.

2.2.3 Control Variables. This study includes control variables at both the firm and regional levels to account for other factors influencing the dependent variable. At the firm level, firm size (*Size*), calculated as the natural logarithm of year-end total assets, indicates the enterprise's risk-buffering capacity. Leverage (*Lev*), measured by the asset–liability ratio, reflects financial health, while board size (*Bsize*), represented by the natural logarithm of board members, suggests enhanced strategic decision-making potential through cognitive diversity. At the regional level, the value added of the primary industry (*Agdp*), sourced from the China Rural Statistical Yearbook, indicates agricultural factor allocation efficiency. The per capita disposable income of rural residents (*Dpi*), derived from the comprehensive tracking survey by the *Rural Social and Economic Survey Department of the National Bureau of Statistics*, signifies the level of agricultural economic development and the purchasing power of insurance. The relief degree of land surface (*Rdls*) is obtained from the kilometer-grid dataset on China's topographic relief developed by Tian et al. (2024) [12], characterizes the natural environmental features of each region.

Table 1 presents the descriptive statistics of all variables. To verify the validity of the model specification, this study employs the Variance Inflation Factor (VIF) to diagnose potential multicollinearity. The results indicate that all variables exhibit VIF values significantly below the critical threshold of 10, suggesting that the selected control variables do not suffer from severe multicollinearity issues. This finding ensures a sound data foundation for the subsequent empirical analysis.

Table 1. Descriptive Statistics Results.

Variable Category	Variable Name	Symbol	Observations	Mean	Std. Dev.	Min	Max
Dependent Variable	Insurance Decision	Insurance	3648	1130.5602	1315.654	13.7600	16000.00
Explanatory Variable	Climate Risk Index	CPRI	3648	33.5140	10.723	1.6995	86.53
Regional-Level Control Variables	Agricultural Value Added	Agdp	3648	246.4904	172.702	0.0062	2012.10
	Per Capita Disposable Income	Dpi	3648	2.11e+04	9024.846	2621.0000	46276.00
	Terrain Relief	Rdls	3648	0.3643	0.555	0.0200	5.84
Firm-Level Control Variables	Firm Size	Size	3648	21.6979	1.258	17.9186	24.94
	Board Size	Bsize	3648	2.2027	0.400	0.3447	3.04
	Leverage	Lev	3648	0.4113	0.203	0.0559	1.20

2.3 Model Specification

This study employs a two-way fixed effects regression model to analyze how climate risk influences the insurance decisions of agricultural enterprises, accounting for both individual and time effects. Firm-level clustered robust standard errors are used to ensure the reliability of the estimation results. The model is defined as follows:

$$Insurance_{i,t} = \alpha_0 + \alpha_1 CPRI_{i,r,t} + \alpha_2 X_{1it} + \alpha_3 X_{2rt} + \mu_i + \lambda_t + \varepsilon_{i,t}$$

Where X_{1it} and X_{2rt} represent control variables at the enterprise and regional levels, respectively. The model further incorporates firm fixed effects μ_i and time fixed effects λ_t to control for unobservable heterogeneity across firms and over time. $\varepsilon_{i,t}$ denotes the random error term.

3 Empirical Results Analysis

3.1 Baseline Regression Results

Table 2 presents findings from the two-way fixed effects model analyzing how climate risk influences agricultural enterprises' insurance decisions. Column (1) displays the regression outcomes of the CPRI on insurance decisions without control variables. Columns (2)–(4) present the results with the sequential addition of firm-level and regional-level control variables. Model comparisons reveal that the positive correlation between climate risk and agricultural insurance decisions remains statistically significant at the 1% level, even after accounting for these factors. This finding suggests that higher climate risk significantly promotes insurance participation among agricultural enterprises.

Table 2. Baseline Regression Results.

Variable	(1) Insurance	(2) Insurance	(3) Insurance	(4) Insurance
CPRI	0.656 (0.56)	0.580 (0.49)	3.610*** (3.54)	3.651*** (3.59)
Firm-level control variables	Not controlled	Controlled	Not controlled	Controlled
Regional-level control variables	Not controlled	Not controlled	Controlled	Controlled
Firm fixed effects	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled
Observations	3,648	3,648	3,648	3,648
R^2	0.673	0.679	0.683	0.688

Note: Values in parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

3.2 Robustness Tests

3.2.1 Adjusting the Sample Range. The global public health emergency of the COVID-19 pandemic may have intersected with climate risk events, collectively affecting enterprises' insurance decisions and potentially skewing the generalizability of the findings. To mitigate the impact of the pandemic, this study omits data from 2020 onwards and recalculates the regression model. As indicated in Column (1) of Table 3, the coefficient for climate risk on the insurance decisions of agricultural enterprises remains positive and statistically significant at the 1% level, aligning with the baseline regression results in both direction and magnitude. This indicates that even after excluding the potential confounding influence of the pandemic, climate risk continues to exert a significant positive impact on agricultural insurance decisions, thereby confirming the stability of the empirical findings.

Table 3. Robustness Test Results.

Variable	(1) Insurance	(2) Insurance	(3) Insurance
CPRI	5.648*** (4.90)	3.651* (1.77)	3.729*** (3.61)
Control variables	Controlled	Controlled	Controlled
Firm fixed effects	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled
Observations	2,736	3,648	3,648
R^2	0.829	0.688	0.910

Note: Values in parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

3.2.2 Changing the Clustering Standard Errors. Following the approach of Fan et al. (2024) [13], this study further tests the robustness of the results by altering the clustering level of standard errors. Specifically, the clustering dimension is expanded from the firm level to the provincial level, and province-level clustered robust standard errors are employed to correct for potential heteroscedasticity. As presented in Column (2) of Table 3, the coefficient of the explanatory variable remains consistent in sign and significance with that of the baseline regression. This finding shows that the results are not materially affected by the change in clustering level, demonstrating that the conclusions are robust and applicable across different hierarchical structures.

3.2.3 Winsorization Treatment. To mitigate the potential influence of outliers, this study refers to the methodology of Fan et al. (2022) [14] and Wang et al. (2025) [15] by applying a winsorization procedure to all variables. Specifically, after arranging the sample data in ascending order, values below the 1st percentile and above the 99th percentile were replaced with the 1%and 99%quantile values, respectively. The regression analysis was re-estimated using the adjusted dataset. As indicated in Column (3) of Table 3, the regression coefficients maintain their sign and significance, consistent with the baseline regression. The impact of climate risk on the insurance decisions of agricultural enterprises continues to be significant at the 1% level. These findings confirm that the study's conclusions are robust and not driven by extreme values.

3.3 Heterogeneity Analysis

This study examines the varied impacts of extreme climate events on agricultural enterprises' insurance decisions by using regressions with four sub-indices: LTD (extreme low-temperature days), HTD (extreme high-temperature days), ERD (extreme rainfall days), and EED (extreme drought days) as explanatory variables. Table 4 reveals that extreme rainfall days (ERD) significantly positively influence insurance decisions at the 5% level, whereas extreme high- temperature days (HTD) have a significantly negative impact at the 10%level. In contrast, the effects of extreme low temperature (LTD) and extreme drought (EED)are statistically insignificant. The underlying mechanisms can be interpreted as follows. First, from the perspective of risk perception, floods caused by extreme rainfall are highly visible and destructive, intensifying firms' risk awareness and thereby positively stimulating insurance purchasing behavior. In contrast, drought evolves gradually and accumulatively; during its early stages, enterprises can often mitigate its impact through large-scale irrigation, resulting in weaker linkage with insurance decisions. Second, extreme heat substantially increases operating costs and revenue volatility, weakening enterprises' financial capacity and thus negatively affecting their insurance demand. Third, the adaptability and effectiveness of agricultural technologies vary under different extreme climate conditions. Under extreme cold, modern agricultural technologies—such as greenhouse cultivation and cold- resistan crop varieties—help mitigate adverse impacts (Li et al., 2024) [16], reducing the need for insurance. Conversely, extreme rainfall-induced floods can cause farmland waterlogging, accelerate soil nutrient loss, and damage key agricultural infrastructure, thereby diminishing the disaster resistance of new agricultural productivity and heightening enterprises' dependence on insurance.

Table 4. Heterogeneity Analysis Results.

Variable	(1) Insurance	(2) Insurance	(3) Insurance	(4) Insurance
LTD	-4.830 (-1.22)	—	—	—
HTD	—	-1.753* (-1.94)	—	—
ERD	—	—	3.592** (2.23)	—
EED	—	—	—	0.723 (0.79)
Control variables	Controlled	Controlled	Controlled	Controlled
Firm fixed effects	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled
Observations	3,648	3,648	3,648	3,648
R^2	0.689	0.688	0.690	0.688

Note: Values in parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4 Research Conclusions and Policy Implications

Utilizing panel data from 304 listed agricultural enterprises in China from 2011 to 2022, this study examines how climate risk shapes insurance decisions and how effects vary across extreme climate events. Results show that climate risk significantly drives insurance uptake as firms seek to mitigate potential losses. Heterogeneity analysis indicates that extreme rainfall markedly promotes insurance participation due to heightened flood risk sensitivity, whereas extreme heat dampens demand by constraining firms' payment capacity. Extreme drought and cold events show no significant influence. Robustness tests—excluding pandemic years, adjusting clustered errors, and applying winsorization—confirm the consistency and reliability of these findings. This study suggests enhancing climate risk monitoring and early-warning systems based on the aforementioned conclusions. By optimizing monitoring networks and early-warning mechanisms, authorities should ensure the rapid and accurate detection of dynamic changes in extreme climate conditions and timely dissemination of relevant information to the public and enterprises. This would enhance firms' capacity for risk identification and assessment in response to extreme climate events, thereby supporting the formulation of more scientific and effective adaptation strategies. Second, promote product innovation among insurance institutions. Insurance providers should accelerate the development of diversified, market- oriented, and practical agricultural insurance products that better align with the varied needs of farmers and agricultural enterprises under different climate risk scenarios. Such innovation would help improve insurance accessibility and effectiveness. Finally, increase government subsidies for agricultural insurance. By expanding fiscal input and raising both the scope and level of insurance subsidies, policymakers can effectively enhance the coverage of agricultural insurance. This would enhance agricultural producers' resilience to climate risks and support the sector's stability and sustainable development. Despite these insights, the study faces two limitations. The sample of listed enterprises may not capture the behavior of smaller firms or individual farmers, and the insurance intention index—based on text mining and entropy methods using Baidu data—may not fully reflect internal decision-making. Future research should broaden sample scope, integrate multi-source data, and conduct cross-country analyses to enhance external validity.

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