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Article

The Impact of Climate Change Perception on Agricultural Insurance Adoption Among Food Legumes Farmers: A Case Study from Baicheng City in Jilin Province of China

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Abstract

Like other agricultural products, food legumes production faces uncertainty risks stemming from climate change, which may affect yields and consequently impact farmers' livelihoods. Agricultural insurance serves as one of the climate change adaptation measures available to farmers, helping mitigate the impacts of climate change on agricultural production and livelihoods. Based on a survey of 460 food legumes farmers in Baicheng City, Jilin Province of China, this study employs a binary probit regression model to analyze how perceptions of climate change influence farmers' adoption of agricultural insurance as an adaptation measure. Robustness tests are conducted by using a replacement econometric model and altering the climate change perception variable. Results indicate that food legumes farmers' perceptions of climate change significantly influence their agricultural insurance purchasing behavior. Farmers who perceive lower temperatures and more severe frosts are more inclined to purchase agricultural insurance. Participation in food legumes production cooperatives and prior experience with yield reductions exert significant positive effects on insurance purchase decisions. Therefore, enhancing climate change awareness campaigns, establishing meteorological risk defense mechanisms, and leveraging the driving role of cooperative organizations hold positive implications for reducing farmers' exposure to climate change risks.

Keywords: climate change; perception; food legumes; agricultural insurance; adaptation measures

1. Introduction

Food legumes refer to various leguminous crops, excluding soybeans and peanuts, primarily cultivated for harvesting dry or fresh seeds. They are mainly grown in impoverished regions of Northeast, North, Northwest, and Southwest China characterized by harsh ecological environments and scarce water resources. Due to their exceptional adaptability, unique nutritional value, health benefits, and effective nitrogen-fixing capabilities, they align with the agricultural production principle of "one control, two reductions, and three fundamentals". They are ideal crops for developing grain-legume rotation systems and promoting organic dryland farming tailored to local conditions. They play a vital role in addressing food security in remote, underdeveloped, and ethnic minority regions, ensuring income growth for farmers and herders in remote areas, improving dietary structures for the general population, and preserving agricultural diversity (Chen et al. 2021). The 2019 Central Document No. 1 emphasized accelerating the development of distinctive rural

industries, promoting diverse specialty industries tailored to local conditions, advocating for “one village, one product” and “one county, one industry,” and actively developing the coarse grain and pulse sector. The China Food and Nutrition Development Outline (2021–2035) encourages residents to improve their nutritional intake by consuming more grains and legumes. Rising living standards and consumption levels have driven new demand for plant-based proteins and healthy foods, fueling sustained growth in food legumes production and consumption. This trend is powerfully propelling the development of minor grain and bean industries, with promising prospects for the food legumes sector.

However, agriculture is a vulnerable sector, and the catastrophic impacts of climate change and its associated meteorological risks are occurring with increasing intensity and frequency. China's National Climate Change Adaptation Strategy to 2035 states that agricultural production is profoundly affected by climate change. Existing agricultural resource endowments and the nation's large population amplify natural risks to agricultural production while causing climate risks to exhibit distinct clustering characteristics and chain reactions. This deepens the contradiction between the severe climate change situation and the objective need for stable and high agricultural yields. Therefore, enhancing farmers' climate change adaptation capacity holds significant importance for consolidating poverty alleviation achievements and comprehensively advancing rural revitalization. The IPCC Sixth Assessment Report identifies agricultural insurance as a key adaptation strategy. According to the China Regulations on Agricultural Insurance, this insurance involves insurers providing compensation for property losses incurred by policyholders during agricultural production due to specified natural disasters, accidents, epidemics, or diseases covered under the policy. Current agricultural insurance products primarily include yield insurance, price insurance, income insurance, and index insurance. As a market-based risk management tool, agricultural insurance plays a vital role in mitigating agricultural disaster risks, safeguarding producers' interests, and promoting the sustainable development of modern agriculture.

The practice of agricultural insurance in China in the modern sense began with the introduction of Western insurance concepts in the early 20th century, marked by initiatives such as the oxen mutual cooperative insurance in He County, Anhui Province in 1934 and the Beibei Livestock Insurance Society in Chongqing in 1939. However, for a considerable period, agricultural insurance developed slowly due to high operating costs, significant risks, and a lack of fiscal support. A historic turning point occurred in 2004 when China explicitly called for “accelerating the establishment of the policy-based agricultural insurance system.” In 2007, the central government formally launched a pilot program for agricultural insurance premium subsidies, targeting five crop varieties including corn and rice in six provinces and regions such as Jilin, Inner Mongolia, and Xinjiang. This marked China's entry into a phase of rapid policy-driven development characterized by government guidance and fiscal subsidies. Subsequently, each year's Central Document No. 1 has outlined plans for agricultural insurance development, driving continuous improvements to its institutional framework. In 2013, the implementation of the Regulations on Agricultural Insurance placed the sector on a standardized, law-based development track. In 2019, the Guiding Opinions on Accelerating High-Quality Development of Agricultural Insurance were issued, further clarifying its direction toward enhancing quality and efficiency while serving modern agriculture. After years of expanding coverage, increasing product types, and raising standards, a comprehensive protection network has now been established. This network centers on the three major grain crops (rice, wheat, corn) and has gradually extended to important agricultural products such as soybeans and oilseeds. While solidifying the foundation of food security, the scope of agricultural insurance services is accelerating its expansion from traditional bulk agricultural products to locally advantageous specialty crops, driven by the establishment of a broader food security perspective and the depth of agricultural supply-side structural reforms. This represents not only an inherent requirement for expanding coverage, increasing product offerings, and raising coverage standards, but also a key measure for boosting farmers' incomes and serving the revitalization of rural industries. The development history of China's agricultural insurance is summarized in Table 1.

Table 1. The Development of Agricultural Insurance in China.

Year	Event	Significance
1930s	the oxen mutual cooperative insurance in He County, Anhui Province in 1934 and the Beibei Livestock Insurance Society in Chongqing in 1939	the earliest practice of agricultural insurance in China
2004	the Central Document No. 1 explicitly called for the first time to “accelerate the establishment of a policy-based agricultural insurance system”	address the slow development of agricultural insurance
2007	the central government officially launched a pilot program for agricultural insurance premium subsidies	enter a phase of rapid policy-driven development
2013	implementation of the Regulations on Agricultural Insurance	enter the path of standardized and law-based development
2019	issuance of the “Guiding Opinions on Accelerating the High-Quality Development of Agricultural Insurance”	clarify the direction for high-quality development of agricultural insurance

As a major mung bean production area in China, Jilin Province accounts for approximately 10-33% of the national output (see Figure 1). Baicheng mung beans from Jilin Province are characterized by large, plump seeds, bright color, and high protein content. They are recognized as a national geographical indication product in China. Mung bean cultivation has become a significant source of income for farmers in Baicheng City and a primary means of poverty alleviation and prosperity (Zhang et al. 2012). From 2012 to 2024, Baicheng City in Jilin Province exhibited a slight upward trend in annual average temperature (see Figure 2), while annual precipitation showed significant fluctuations (see Figure 3). Reviewing Jilin's history of severe droughts and the increasingly prominent flood risks in recent years (see Table 2), it is evident that these factors directly impact mung bean yield stability and farmers' income. To better address climate risks and safeguard agricultural production, the critical value of agricultural insurance has become increasingly prominent. However, there is currently no unified mandatory policy for food legumes insurance nationwide. Instead, local governments independently explore such programs. Insurance for mung beans and other minor grains and pulses falls under the category of locally advantageous specialty agricultural product insurance and is not included in central government premium subsidies. Jilin's bean insurance centers on soybeans as the core insured crop, extending coverage to mung beans and other minor grains and pulses. It incorporates nationally unified policies like comprehensive cost insurance, while some regions also adopt innovative insurance-plus-futures models. Farmers contribute 25% of the premium, with the government providing a 75% subsidy. As one of Jilin Province's first pilot cities for policy-based agricultural insurance, Baicheng City has insured corn, rice, soybeans, sunflower seeds, and peanuts since 2007. However, farmers bear the risk for food legumes like mung beans they cultivate. In 2017, Baicheng City first included coarse grains and pulses in its local specialty insurance subsidy program. The provincial government adopted a subsidy-replacement approach, covering up to 60% of the actual burden borne by county governments in impoverished counties and 50% in non-impoverished counties. Food legumes like mung beans were explicitly designated as key support targets. That same year, Anhua Agricultural Insurance Company insured 920,000 mu (approximately 61,333 hectares) of specialty coarse grain and pulse crops. Therefore, this study examines whether climate change perception influences the adoption of agricultural insurance adaptation measures among 460 food legumes farmers in Baicheng City, Jilin Province, and investigates the response relationship between the two. The findings aim to provide policy insights for addressing climate change risks and promoting agricultural insurance.

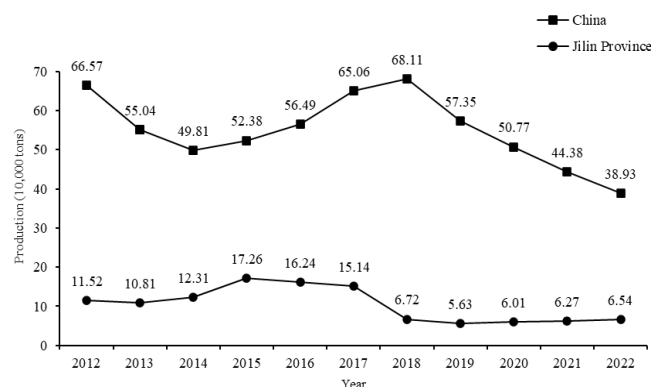


Figure 1. Mung Bean Production in Jilin Province, 2012–2022. Source: Annual Data from the National Bureau of Statistics of China, <https://data.stats.gov.cn/easyquery.htm?cn=E0103>.

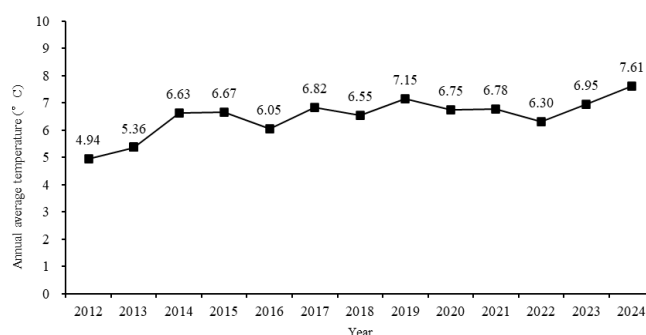


Figure 2. Annual Average Temperature in Baicheng City, Jilin Province, 2012–2024. Source: National Environmental Information Center, National Oceanic and Atmospheric Administration, <https://www.ncei.noaa.gov/data/global-summary-of-the-day/archive/>.

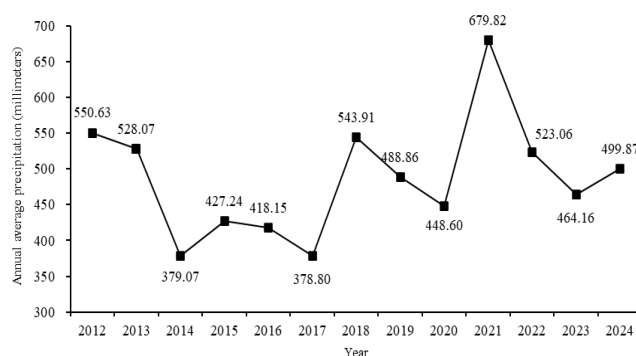


Figure 3. Annual Average Precipitation in Baicheng City, Jilin Province, 2012–2024. Source: Peng Shouzhang. (2020). China 1km Resolution Monthly Precipitation Dataset (1901–2024). National Qinghai-Tibet Plateau Science Data Center, <https://doi.org/10.5281/zenodo.3114194>.

Table 2. Agricultural Natural Disaster Situation in Jilin Province, 2012–2023.

Year	Drought (10,000 hectares)	Flooding (10,000 hectares)	hail damage (10,000 hectares)
2023	0.0	22.8	3.3
2022	0.0	16.7	2.6
2021	4.4	11.6	8.4
2020	12.7	4.0	7.0

2019	-	28.6	12.5
2018	109.9	1.7	16.3
2017	62.5	44.9	13.3
2016	52.4	7.1	6.1
2015	70.0	2.4	12.2
2014	182.7	2.4	8.9
2013	-	47.2	19.8
2012	30.4	7.0	5.2

Source: Jilin Province Statistical Yearbooks for 2015, 2018, 2021, and 2024.

2. Literature Review

2.1. The Concept and Measurement of Farmers' Perception on Climate Change

Farmers' perception on climate change refers to their understanding, cognition and intuitive judgement of climate change (Lü and Chen 2010). In China, most rural populations perceive climate change through three channels: daily activities, production activities, and observation of natural phenomena. This perception plays a crucial role in adjusting agricultural production and enhancing economic efficiency (Yun et al. 2009). Accurate perception of climate change by farmers translates into adaptive decision-making for farm households. This may involve effectively leveraging climate-related benefits for agricultural production, timely mitigation of climate-induced risks, or reducing adverse impacts of natural disasters on farming, thereby promoting sustainable agricultural production and household livelihoods (Zhao and Xue 2016). However, due to individual objective influences, the outcomes of such perceptions carry inherent uncertainty. Cui et al. (2012) found through empirical surveys that most agricultural practitioners exhibit significant deficiencies in perceiving climate evolution patterns, with their subjective judgments often diverging markedly from statistical results derived from meteorological observations. Yun et al. (2009) further noted that while public perceptions of temperature changes generally align with measured data, discrepancies still exist. When precipitation exhibits large short-term fluctuations, the average perceived intensity of temperature changes tends to exceed that of precipitation. Chang et al. (2012) also noted that while awareness of climate change adaptation has been preliminarily established among policymakers and grassroots communities, the public's perception framework remains characterized by weak foundations and insufficient scientific basis. Rahman et al. (2023) specifically highlighted that agricultural populations' understanding of climate variability mechanisms often remains superficial.

Perceptions of climate change encompass two distinct dimensions: awareness of general climate variations such as temperature and precipitation, and recognition of extreme climate events like droughts and frosts. General climate changes are gradual in nature (Schlenker and Roberts 2009). They directly impact crop physiological activities and phenological development, manifesting through long-term cumulative effects such as adjustments in crop planting structures, changes in water resource utilization, and increased pest and disease incidence (Liu et al. 2025). Farmers can mitigate risks by adjusting production factors such as adopting drought-tolerant varieties, improving irrigation techniques, and optimizing fertilizer and labor inputs, which may lead to underestimating their severity (Deressa et al. 2009). Extreme climate events, however, occur rapidly and are characterized by unpredictability and suddenness (Liu 2023). They directly impact crop growth and yields, causing agricultural economic losses (Fu et al. 2023). Jose and Ruben (2023) highlighted that extreme events like droughts are sudden and unpredictable, leading to abrupt yield declines or total crop failure. Farmers struggle to mitigate such risks through preemptive measures, making insurance demand more pronounced in these scenarios.

There are primarily three methods for measuring climate change perceptions: questionnaire surveys and scales, participatory rural appraisals, and behavioral inference. First, questionnaire surveys and scales are divided into direct perception measurement and Likert scale quantification. Direct perception measurement involves structured questionnaires asking farmers for their intuitive

judgments on climate change, such as “Has rainfall decreased over the past decade?” or “Has the frequency of extreme weather events increased?” (Chu 2024). Likert scale quantification employs 5-point or 7-point scales to assess the intensity of farmers' perceptions regarding the severity of climate change. For instance, in their Bangladesh study, Kabir et al. (2017) asked farmers to rate “frequency of droughts” and “risk of market price fluctuations” on a 1-5 scale, constructing a risk matrix to visualize different risk scenarios. Second, participatory rural appraisal involves group interviews. In studies of agro-pastoral transition zones, Bian and Song (2014) facilitated collective discussions among farmers through core group interviews to rank the perceived impacts of climate change phenomena. They found that farmers in Yanchi County, Ningxia, ranked precipitation and temperature changes in alignment with meteorological observation trends. Third, behavioral inference methods, which reverse-engineer perceptions from adaptive behaviors. By examining farmers' adopted adaptation measures such as altering planting times or adopting drought-tolerant varieties, researchers can indirectly infer the intensity of their climate risk perceptions (Feng 2017). Based on this, this study adopts Chu's (2024) measurement method for climate change perception. A structured questionnaire asks farmers about their intuitive judgments on climate change, such as “Has the local average temperature/precipitation changed over the past five years?” and “Has the severity of local droughts/frosts changed over the past five years?” The response options are set as “1 = increased; 2 = unchanged; 3 = decreased” and “1 = worsened; 2=unchanged; 3=lessened,” thereby measuring farmers' climate change perceptions.

2.2. Climate Change Adaptation Measures

Climate change adaptation measures refer to the various adjustments and behavioral choices adopted by farmers to cope with extreme weather and climate events and their associated risks in the background of climate change (Wang et al. 2022). Hou et al. (2018) categorized farmers' adaptation measures into three types. The first is productive adaptation measures, which involve strategies to increase agricultural inputs and protective measures based on existing practices. Examples include adjusting crop planting times, increasing fertilizer and pesticide application rates, changing crop varieties, enhancing irrigation, actively utilizing fallow land after harvest, and adopting new technologies (Below et al. 2010; Hou et al. 2018), and implementing water conservation measures like plastic mulching, straw mulching, and artificial grass planting (Feng et al. 2017; Wang 2022; Gao et al. 2025). Second, livelihood adaptation measures involve supplementing existing land income through alternative income sources, such as off-season labor, expanding crop cultivation scale, acquiring relevant agricultural skills (Hou et al. 2018), and diversifying income streams (Smit and Skinner 2002). Third, protective adaptation measures aim to enhance resilience against agricultural losses caused by climate variability, such as accessing agricultural loans or purchasing crop insurance (Smit and Skinner 2002; Wang 2022; Feng et al. 2024). Wheeler et al. (2013) further categorized farmer adaptation measures into expansionary measures (e.g., acquiring land or water rights, increasing irrigated areas), adjustment measures (e.g., improving irrigation facilities and management systems, planting water-efficient crops), and contractionary measures (e.g., selling land, reducing irrigated areas, selling water rights). Lü and Chen (2010) found that farmers in Dezhou City of Shandong Province of China, primarily adopted passive adaptation measures such as adjusting farming schedules, increasing inputs, and irrigation, supplemented by active adaptation measures like crop variety adjustment, infrastructure construction, new technology adoption, and improvement of the ecological environment around farmland.

Farmers are influenced by various factors when selecting adaptation measures. Derssa et al. (2009) noted that education level, gender, age, household head health status, climate information, and social capital all affect farmers' choice of climate change adaptation measures. Lack of adaptation information and financial constraints are two major barriers hindering adaptation efforts. Wu (2015) found that factors such as household head gender, years of education, income structure, cropping scale, meteorological information, and agricultural technical services significantly influence farmers' climate change adaptation behaviors. Bryan et al. (2009) identified farmers' agricultural experience,

socioeconomic status, availability of technology extension services, and access to credit services as primary influencing factors. Liu et al. (2018) examined factors influencing farmers' willingness to pay for agricultural insurance. They concluded that individual or household characteristics such as gender, education level, household income, and number of dependents, along with factors like the amount of cultivated land and disaster experience, significantly affect farmers' willingness to purchase agricultural insurance. Among farmers in Wuhu and Tongling, Anhui Province of China, the more severe the disaster losses, the greater the likelihood of purchasing weather index insurance (Meng 2018). Furthermore, climate change perception is considered a key factor influencing farmers' adaptation decisions. Grothmann and Patt (2005) proposed a social cognitive model of individual proactive adaptation to climate change from a cognitive perspective, indicating that climate change perception is a crucial determinant of whether farmers take adaptation actions. Chen and Hu (2023) similarly argued that climate change perceptions, combined with farmer education levels, farming experience, farm size, and household income, collectively influence adaptation decisions. Sérès (2010) observed that Zambian farmers' selection of extreme climate adaptation measures correlates with their perceived intensity of climate change. Wheeler et al. (2021) found that farmers in the southern Murray-Darling Basin who were more likely to perceive climate change risks tended to make lower-risk agricultural production decisions and engage in more climate adaptation behaviors. Shang et al. (2020) further indicated that higher levels of climate risk perception among farmers correlate positively with their willingness to adopt risk management tools.

2.3. The Impact of Climate Change Perception on Farmers' Adoption of Adaptation Measures

Existing research suggests that farmers' perceptions of climate change, serving as the foundation for adaptive behaviors, will drive climate change adaptation actions. Most scholars typically employ empirical models such as binary logit models, binary probit models, and multinomial logit models to validate and analyze the relationship between these two factors. For instance, Li et al. (2013) used a probit model to analyze that the stronger the perceptions of extreme climate impacts among farmers and herders, the more inclined they are to adopt adaptive behaviors. Kurukulasuriya (2007) employed a multinomial logit model to examine farmers' crop selection responses to climate change, revealing that crop choice behavior is highly sensitive to climate variability. Wang et al. (2016) used a multinomial logit regression model to quantitatively analyze factors influencing farmers' adaptation strategy selection, finding that deeper perceptions of extreme climate impacts correlate with greater adoption of adaptation behaviors such as livestock sales, intensive farming, and seasonal migration. Zhao et al. (2016) employed a binary logit model to investigate that perceptions of climate change exert a significant positive influence on farmers' adoption of variety improvement and out-migration measures. Moreover, farmers' climate change perceptions exhibit notably differential impacts on their adoption of various adaptive behaviors. Feng et al. (2016) employed logit and mlogit models to examine factors influencing apple growers' adaptation to drought. Results indicated that growers' perception of drought severity and household participation in cooperatives positively influence the adoption of preventive adaptation strategies. Gao et al. (2025) analyzed factors influencing climate adaptation behaviors among apple growers using a binary logit model. They found that both perceptions of climate change conditions and perceptions of its impacts negatively affect the adoption of technology-oriented adaptation behaviors. Regarding adaptive measures like purchasing agricultural insurance, Wang et al. (2022) employed a probit model to analyze how climate change perceptions among food legumes farmers in Shanxi and Jiangsu influenced their willingness to buy weather index insurance. They found that stronger perceptions of abnormal average temperatures, rainfall, and drought disasters correlate with higher insurance purchase probabilities. Chen and Hu (2023) employed a logit model to reveal that peach growers perceiving increased frequency of extreme weather events exhibit higher probability of purchasing crop insurance. Du (2011) utilized a binary logit model to demonstrate a significant positive correlation between farmers' perception of agricultural risks and their demand for agricultural insurance. Li et al. (2017) analyzed factors influencing farmers' demand for weather index insurance through logit

regression models, indicating that Heilongjiang farmers exhibit stronger insurance willingness when they perceive clearer correlations between weather events and crop yields. McCarthy (2003) employed a probit model to compare payment willingness for rainfall index insurance across four regions in Morocco, revealing that farmers exhibit greater willingness to purchase insurance as the risks they face increase.

In summary, Numerous scholars have investigated farmers' perceptions of climate change and their adaptive behaviors. Key areas of focus include farmers' understanding of climate change, the adaptive actions they undertake and their influencing factors, as well as the impact of climate change perceptions on the adoption of adaptive measures. However, most studies have concentrated on adaptive measures related to production practices, with limited quantitative research on how climate change perceptions influence farmers' adoption of adaptive measures such as purchasing agricultural insurance. Additionally, studies at the micro-level have rarely examined food legumes farmers. Therefore, based on a survey of food legumes farmers in Baicheng City, Jilin Province, this paper examines the impact of climate change perceptions on the adoption of agricultural insurance as an adaptation measure among food legumes farmers.

3. Data Source and Sample Description

3.1. Description of Baicheng City's Climate Characteristics

Baicheng City is located in the heart of the Songnen Plain, with soil composed of Quaternary Tao'er River alluvial deposits. The topsoil predominantly consists of chestnut calcareous soil and sandy loam, making it exceptionally suitable for mung bean production and cultivation. The region boasts abundant light and heat resources, with a frost-free period of 125–140 days, annual sunshine hours of 2,960, and effective accumulated temperature $\geq 10^{\circ}\text{C}$ reaching 2,900–3,100 $^{\circ}\text{C}$. The daily temperature variation of 14–15 $^{\circ}\text{C}$ during August and September facilitates nutrient accumulation in crops. The dry autumn climate further enhances mung bean drying and color development, improving overall quality.

Research by Yu et al. (2019) indicates that Baicheng City has experienced significant climate change over the past two decades, with markedly rising temperatures and an increasing trend in high-temperature days. Precipitation shows a linear decrease, while the maximum consecutive rainfall duration has extended. Baicheng Station recorded the highest number of frost days, decreasing from northwest to southeast. Localized torrential rains frequently occur across all regions.

3.2. Data Source

This study employed stratified random sampling in 2018 and 2019 to select survey participants from food legumes farmers in Baicheng City, Jilin Province of China. Field surveys were conducted across 19 townships in five counties within Baicheng City. To mitigate potential data biases arising from farmers' comprehension or illiteracy, the survey utilized one-on-one, face-to-face interviews with adult food legumes farmers possessing full cognitive and behavioral capacity. The questionnaire comprised four main sections: basic information on food legumes farmers, land management practices, food legumes cultivation techniques, market access services, and climate change issues. A total of 460 completed questionnaires were collected.

3.3. Sample Description

From the sample area distribution (Table 3), Da'an City has 30 households, accounting for 6.52% of the total sample; Taobei District has 41 households, accounting for 8.91% of the total sample; Taonan District has 146 households, accounting for 31.74% of the total sample; Tongyu County has 178 households, accounting for 38.7% of the total sample; and Zhenlai County has 65 households, accounting for 14.13% of the total sample.

Table 3. Sample Distribution.

County	Town	Sample	Percentage
Da'an City	Chagan Town	3	6.52
	Shaoguo Town	27	
Taobei District	Daobao Town	14	8.91
	Lingxia Town	27	
Taonan District	Dongsheng Village	37	31.74
	Anding Town	23	
	Wafang Town	22	
	Treasure Village	8	
	Najin Town	54	
	Wild Horse Village	2	
Tongyu County	Wulanhua Town	58	38.7
	Shuanggang Town	3	
	Xinxing Village	61	
	Xinhua Town	20	
	Zhanyu Town	26	
	Hongxing Town	10	
Zhenlai County	Jianping Town	25	14.13
	Zhenlai Town	12	
	Heiyupao Town	28	
Total		460	100

From the sample characteristics (Table 4), male heads of households dominate food legumes cultivation, accounting for 98.48%. Among food legumes farmers, 367 individuals aged 35–59 constitute the primary age group, accounting for 79.78%. Educational attainment primarily consists of primary and junior high school levels, comprising 38.48% and 47.17% respectively. Household size predominantly ranges from 1 to 3 members, accounting for 58.26%. A significant proportion of households have annual incomes of 90,000 yuan or higher, representing 38.73%. The 2018 survey collects data from 233 households, while the 2019 survey collects data from 227 households.

Table 4. Sample Description.

Characteristics	Category	Sample	Percentage
Household Head Gender	Male	453	98.48
	Female	7	1.52
Age	15–34 years old	43	9.35
	35–59 years old	367	79.78
	60 years old and above	50	10.87
Education	Illiterate	12	2.61
	Elementary School	177	38.48
	Junior high school	217	47.17
	High school and above	54	11.74
Number of household members	1–3 person	268	58.26
	4–6 person	189	41.09
	7–9 person	3	0.65
Total household income	0–30,000 yuan	97	21.23
	30,000–60,000 yuan	96	21.00
	60,000–90,000 yuan	87	19.04
	90,000 yuan and above	177	38.73
Year	2018	233	50.65
	2019	227	49.35

4. Empirical Analysis

4.1. Model Specification

Whether food legumes farmers purchase agricultural insurance (Y) is influenced by factors such as their perception of climate change (X_1), individual characteristics (X_2), household characteristics (X_3), land management characteristics (X_4), and external environment (X_5). Since the dependent variable is a binary choice variable, a binary probit model is employed for analysis. The empirical model is:

$$\text{Prob}(Y_i = 1|X, \beta) = \Phi(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5) \quad (1)$$

Where β_i represents the regress coefficient for each variable, X_i denotes variables influencing food legumes farmers' agricultural insurance purchase decisions, and X_1 is the core independent variable in this study. $\text{Prob}(Y_i=1)$ represents the probability of observing agricultural insurance purchase, and Φ denotes the cumulative distribution function of the standard normal distribution. Note that the coefficients from probit regression differ from those in OLS regression; marginal effects must be further calculated to determine the impact of X on Y .

4.2. Variable Definition and Description

Explained variable. Whether agricultural insurance is purchased.

Explanatory variable. Food legumes farmers' perception of climate change refers to their perception of four categories: changes in the average annual temperature over the past five years, changes in the average annual precipitation, the severity of drought, and the severity of frost.

Control variables. These encompass four categories: individual characteristics (age, education level), household characteristics (household size, total household income), operational characteristics (proportion of food legumes planting area relative to total cultivated land), and external environment (membership in food legumes production cooperatives, experience of yield reduction).

Specific variable definitions and descriptions are provided in Table 5. As shown in Table 5, 39% of food legumes farmers have purchased agricultural insurance. They perceive that the average annual temperature has risen over the past five years, average annual precipitation has decreased, and the severity of droughts and frosts has increased. Regarding individual characteristics, the average age of food legumes farmers is approximately 48.27 years, with an average education level of 7.96 years—equivalent to the second year of junior high school. For household characteristics, the average household size is 3 persons, and the average log of total household income is 11.09. In terms of operational characteristics, food legumes account for about 41% of cultivated land area. Regarding external conditions, 32% of food legumes farmers participate in production cooperatives, while 74% have experienced adverse weather during critical growing periods, resulting in reduced agricultural yields. The final column of Table 5 displays the variance inflation factor (VIF) values for each variable. All VIF values were below 10, with an average of 1.33, indicating no multicollinearity issues among the variables.

Table 5. Variable Definition and Descriptive Statistical Analysis.

Variable Name	Variable Definition	Variable Characteristics	Mean	SD	Min	Max	VIF
Insurance	Whether to purchase agricultural insurance	Categorical variable, 1=Yes, 0=No	0.39	0.488	0.00	1.00	—
Temperature	Perception of average annual temperature changes over the past five years	Categorical variable, -1 = decrease; 0 = unchanged; 1 = increase	0.41	0.840	-1.00	1.00	1.17

Precipitation	Perception of average annual precipitation changes over the past five years	Categorical variable, -1 = decrease; 0 = unchanged; 1 = increase	-0.27	0.895	-1.00	1.00	1.94
Drought	Perception of drought severity over the past five years	Categorical variable, -1 = alleviated; 0 = unchanged; 1 = aggravated	0.43	0.836	-1.00	1.00	1.98
Frost	Perception of frost severity over the past five years	Categorical variable, -1 = alleviated; 0 = unchanged; 1 = aggravated	0.05	0.878	-1.00	1.00	1.32
Age	age	Actual variable, actual age (unit: years)	48.27	9.574	21.00	74.00	1.30
Education	Level of education	Actual variable, 0 = illiterate, 6 = elementary school, 9 = junior high school, 12 = high school and above (unit: years)	7.96	2.360	0.00	12.00	1.06
Population	Number of family members	Actual variable, actual number of people (unit: persons)	3.46	1.138	1.00	8.00	1.25
Income	Total household income	Actual variable, the logarithm of total household income	11.09	1.158	7.40	15.42	1.30
Proportion	The proportion of cultivated land used for planting food legumes	Actual variable, actual proportion (unit: %)	0.41	0.603	0.01	11.25	1.06
Cooperative	Whether to join the food legumes production cooperative	Categorical variable, 1=Yes, 0=No	0.32	0.466	0.00	1.00	1.23
Experience	Whether to experience a yield reduction	Categorical variable, 1=Yes, 0=No	0.74	0.441	0.00	1.00	1.05

Note: Mean VIF = 1.33.

4.3. Empirical Results

This study employs STATA 17.0 statistical software to perform probit model regression. The mean variance inflation factor (VIF) is 1.33, indicating no multicollinearity issues among variables. The likelihood ratio test assesses model validity, yielding a p-value below 0.001 and an adjusted R-squared (R^2) ranging from 0.258 to 0.416, confirming the constructed model's satisfactory fit. Since the regression coefficients of a binary probit model do not reflect the marginal effects of influencing factors, it is more reasonable to use the marginal probability dy/dx to represent the marginal impact of marginal changes in each explanatory variable on food legumes farmers' purchase of agricultural insurance. The probit model regression results are shown in Table 6. Columns (1) to (3) display the results of progressively adding more control variables, while Column (4) shows the marginal effects corresponding to the regression in Column (3).

Perception of Climate Change. Using column (3) as the baseline regression result, empirical evidence indicates that two climate change perception variables—Temperature and Frost, significantly influence food legumes farmers' purchase of agricultural insurance. The coefficient for perceived annual average temperature change is negatively significant at the 10% level. When food legumes farmers perceive a decrease in temperature, their probability of purchasing agricultural insurance increases by 5.8%. The coefficient for perceived frost severity is positively significant at the 1% level. When farmers perceive an increase in frost severity, their probability of purchasing agricultural insurance rises by 18.2%. Perceptions of annual average precipitation changes and

drought severity do not significantly influence food legumes farmers' agricultural insurance purchases.

Individual Characteristics. Empirical results indicate that farmers' age and education level do not significantly affect insurance purchase decisions, likely because agricultural insurance is mandated by local industrial poverty alleviation policies.

Household Characteristics. Column (2) results indicate that the number of family members has a significant positive effect on food legumes farmers' insurance purchase, while total household income has no significant impact.

Operational Characteristics. The proportion of food legumes planting area relative to total cultivated land has a negative but insignificant effect on insurance purchase.

External Factors. Participation in food legumes production cooperatives and experiencing yield reductions significantly and positively influence food legumes farmers' purchase of agricultural insurance, both passing the 1% significance level test. When food legumes farmers join production cooperatives, their probability of purchasing agricultural insurance increases by 40.1%. If food legumes farmers experienced climate-induced yield reductions during critical growing periods in the past five years, their probability of purchasing agricultural insurance increases by 11.8%.

Table 6. Baseline Regression Results.

	(1) Insurance	(2) Insurance	(3) Insurance	(4) Marginal Effect
Temperature	-0.3260*** (0.0810)	-0.2922*** (0.0815)	-0.2178** (0.0899)	-0.0578** (0.0237)
Precipitation	0.0717 (0.1016)	0.0226 (0.1031)	0.1581 (0.1150)	0.0436 (0.0313)
Drought	0.0298 (0.1139)	0.0051 (0.1169)	0.0169 (0.1266)	0.0142 (0.0333)
Frost	0.8211*** (0.0849)	0.8137*** (0.0872)	0.6894*** (0.0937)	0.182*** (0.0239)
Age		-0.0057 (0.0077)	-0.0052 (0.0082)	-0.00163 (0.00173)
Education		-0.0088 (0.0327)	-0.0207 (0.0319)	-0.00525 (0.00801)
Population		0.1859*** (0.0676)	0.1070 (0.0694)	0.0321** (0.0156)
Income		0.0476 (0.0642)	0.0144 (0.0729)	-0.000495 (0.0149)
Proportion			-0.2763 (0.3251)	-0.00719 (0.0119)
Cooperative			1.3179*** (0.1650)	0.401*** (0.0495)
Experience			0.5026*** (0.1665)	0.118*** (0.0357)
Constant	-0.2964*** (0.0875)	-1.1474 (0.9990)	-1.1566 (1.0900)	
N	460	457	457	
chi ²	132.2149	138.5215	179.2103	
r ² _p	0.2582	0.2835	0.4158	

Note: T statistics in parentheses *p<0.1, **p<0.05, ***p<0.01.

4.4. Robustness Test

Robustness test results are shown in Table 7. Column (5) presents the results of the probit model. Columns (6) and (7) replace the probit model with logit and OLS regression models, respectively, to test the robustness of the estimation results. Column (8) replaces the two perception variables—perceived drought severity(Drought) and perceived frost severity(Frost)—with the number of drought occurrences(Drought_2) and the number of frost occurrences(Frost_2), respectively. The logit and OLS models indicate that farmers' perceptions of annual average temperature changes and frost severity still significantly influence their agricultural insurance purchasing behavior, consistent with the probit model results. After replacing the two perception variables, perceptions of annual average temperature changes and frost occurrence frequency maintain consistent effects with the probit model. Results for other variables also align with the probit model findings. In summary, the empirical results of this study are relatively robust.

Table 7. Robustness Test Results.

Perception of	(5) Probit Model	(6) Logit Model	(7) OLS Model	(8) Replace Explanatory Variables
Temperature	-0.2178** (0.0899)	-0.3928** (0.1592)	-0.0578** (0.0237)	-0.2136** (0.0895)
Precipitation	0.1581 (0.1150)	0.2707 (0.2074)	0.0436 (0.0313)	0.1870* (0.1111)
Drought	0.0169 (0.1266)	0.0388 (0.2287)	0.0142 (0.0333)	
Frost	0.6894*** (0.0937)	1.2145*** (0.1703)	0.1815*** (0.0239)	
Drought_2				0.0931 (0.1232)
Frost_2				0.6424*** (0.0952)
Age	-0.0052 (0.0082)	-0.0127 (0.0145)	-0.0016 (0.0017)	-0.0045 (0.0082)
Education	-0.0207 (0.0319)	-0.0345 (0.0579)	-0.0053 (0.0080)	-0.0253 (0.0320)
Population	0.1070 (0.0694)	0.1973 (0.1240)	0.0321** (0.0156)	0.1079 (0.0692)
Income	0.0144 (0.0729)	-0.0141 (0.1315)	-0.0005 (0.0149)	0.0278 (0.0739)
Proportion	-0.2763 (0.3251)	-0.5101 (0.5772)	-0.0072 (0.0119)	-0.2561 (0.3156)
Cooperative	1.3179*** (0.1650)	2.2701*** (0.3009)	0.4006*** (0.0495)	1.3212*** (0.1650)
Experience	0.5026*** (0.1665)	0.8295*** (0.2993)	0.1183*** (0.0357)	0.4917*** (0.1654)
Constant	-1.1566 (1.0900)	-1.3904 (1.9410)	0.2145 (0.2177)	-1.2876 (1.1130)
N	457	457	457	457
chi ²	179.2103	139.4261		170.3134
r ² _p	0.4158	0.4148		0.4076

Note: T statistics in parentheses *p<0.1, **p<0.05, ***p<0.01.

5. Conclusions and Discussion

5.1. Conclusions

This study employs a binary probit model to examine how food legumes farmers' perceptions of climate change influence their adoption of agricultural insurance as an adaptation measure. The analysis is based on questionnaire data collected from 460 food legumes farming households in Baicheng City, Jilin Province of China. Results indicate that farmers' perception on climate change significantly influence their agricultural insurance purchase behavior. Those perceiving lower temperatures and more severe frosts are more inclined to purchase insurance, while perceptions of precipitation changes and drought severity show no significant effect. Additionally, household size, membership in food legumes production cooperatives, and prior experience with yield losses exert significant positive effects on insurance purchase. Conversely, factors such as age, education level, total household income, and the proportion of food legumes acreage relative to total cultivated land show no significant influence on insurance adoption, potentially due to the policy-driven nature of agricultural insurance.

5.2. Discussion

Although this study empirically reveals the impact of climate change perceptions on the adoption of agricultural insurance by food legumes farmers, certain limitations exist in the research process. First, the sample is restricted to 460 food legumes farming households in Baicheng City, Jilin Province of China, representing a relatively limited coverage that may not fully reflect farmer behavior in other food legumes producing regions of China or under different climatic conditions. Second, the cross-sectional data approach makes it difficult to capture the dynamic evolution between farmers' perceptions and insurance purchasing behavior. Third, the measurement of climate change perceptions primarily relies on farmers' subjective perceptions, potentially introducing recall bias or social desirability bias. Fourth, although the model controlled for multiple variables, it may still have omitted certain potential influencing factors, such as farmers' risk attitudes, insurance product knowledge, and credit accessibility. Furthermore, agricultural insurance purchasing behavior may be influenced by external factors like local policy incentives and insurer promotion efforts, which are not fully incorporated into this study's analytical framework. Future research could expand the sample to include farmers from additional provinces, diverse climatic zones, and different crop types, conducting regional comparative analyses to test the generalizability of findings. Simultaneously, constructing panel data through multi-year tracking surveys would better identify the causal relationships and dynamic mechanisms linking climate change perceptions to insurance adoption behavior.

5.3. Recommendations

Through multi-channel and multi-format outreach and education, enhance food legumes farmers' awareness of climate change. Governments at all levels, rural communities, and public welfare organizations can utilize diverse methods (public service announcements, educational training, etc.) and channels (online/offline platforms, internet TV/mobile devices, books/brochures, etc.) to disseminate knowledge about the impacts of meteorological disasters and corresponding response measures. This will improve farmers' understanding of climate change, strengthen their risk management awareness, and optimize their adaptive behaviors in purchasing agricultural insurance.

Build a multi-stakeholder meteorological risk defense mechanism involving government, enterprises, and farmers to enhance food legumes farmers' capacity to respond to climate change. Strengthen communication and cooperation among farmers, communities, and regions to establish robust meteorological disaster early warning systems and weather forecasting networks. Improve the accuracy of meteorological services to meet the needs of food legumes farmers.

Encourage food legumes farmers to join economic cooperatives and deepen the driving role of cooperative organizations. Leverage the advantages of food legumes cooperatives in information gathering, knowledge dissemination, technology diffusion, and scale organization to provide farmers with technical guidance on climate change adaptation. This will enhance farmers' awareness and capacity for prevention, helping them respond scientifically and accurately to climate change risks.

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