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Understanding the Impact of Climatic Events on Optimizing Agricultural Production in Northeast China

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Abstract: Climatic events are expected to significantly impact global agricultural production, with China being particularly vulnerable. Research in China emphasizes the urgent need for sustainable agricultural practices that address climate change, implement effective management strategies to mitigate the impacts of climatic events, and ensure food security. Therefore, this study examines the impact of climatic events on agricultural production optimization in Northeast China. To complete this objective, this study uses Method-of-Moments Quantile Regression (MM-QR) and data from 2003 to 2020. The main findings reveal that climatic factors, such as the Standardized Precipitation Index (SPI) and High-Temperature Days (HTDs), have a more pronounced effect on agricultural outcomes at higher production levels, particularly for larger producers. In addition, machinery power (TPAM) enhances productivity. Its role is more focused on risk mitigation than on expanding production. Insurance payouts (AIPE) increase grain production capacity at higher quantiles, while fertilizer use (FEU) has diminishing returns on capacity but encourages planting. Granger causality tests further demonstrate that management factors—such as machinery, irrigation, and insurance—play a more significant role in shaping agricultural outcomes than extreme climatic events. To improve agricultural sustainability in the context of climate change, policy recommendations include promoting climate-resilient crops, investing in smart irrigation systems, expanding affordable agricultural insurance, and encouraging sustainable fertilizer use through incentives and training. These strategies can help mitigate climate risks, enhance productivity, and reduce the environmental impact of agricultural activities.

Keywords: climatic event; food security; agricultural production; Northeast China

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Academic Editor: Gianni Bellocchi

Received: 9 May 2025
Revised: 7 June 2025
Accepted: 9 June 2025
Published: 11 June 2025

Citation: Gao, J.; Faye, B.; Tian, R.; Du, G.; Zhang, R.; Biot, F. Understanding the Impact of Climatic Events on Optimizing Agricultural Production in Northeast China. *Atmosphere* **2025**, *16*, 704. https://doi.org/10.3390/atmos16060704

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1. Introduction

Globally, the deterioration of cultivated land and decline in soil fertility, exacerbated by climate change and its associated disasters, have emerged as significant concerns to food security worldwide [1,2]. Sustainable cultivated land management and addressing climate challenges are crucial for supporting the economy, as global population growth and urbanization are encroaching on agricultural land, thereby threatening food production and food security [3,4]. Climate change results in lower agricultural outputs and disruption of food supply chains [5]. Hence, frequent droughts, compounded by a lack of a universally accepted definition, and population growth pose a significant threat to food

security, highlighting the urgent need for sustainable agricultural practices to mitigate these challenges and ensure long-term food availability [6,7]. Environmental stressors reduce agricultural productivity, exacerbating food insecurity, with the UN's Food and Agriculture Organization (FAO) predicting a 50% increase in global food demand by 2050 [8,9]. Hence, global climate change is increasingly impacting agricultural systems, posing a threat to agricultural production and food demand. In sum, various factors, including climate change, threaten agricultural production, emphasizing the need for more sustainable practices. Therefore, optimizing grain production is a crucial aspect of ensuring food security, particularly in regions that are highly dependent on agriculture.

The impact of climate change on crop production, which is directly linked to global food security, has driven research on its effects on grain production due to climate vulnerability and economic significance [10,11]. In Northeast China, a key agricultural region, climate factors such as temperature fluctuations, rainfall patterns, and extreme weather events have a significant impact on crop production [12]. In recent years, this region has produced over 33% of the national maize, 50% of the soybeans, and 60% of the rice [13]. In contrast, the latter climatic events highlighted can have a major impact on the overall crop yields in the area. Known for its vast and fertile soil, Northeast China is highly productive in terms of grain, particularly corn, soybeans, and wheat [13]. However, changing climatic conditions, including both gradual shifts and extreme events [14,15], have presented both challenges and opportunities for optimizing grain production.

The effect of climatic events on crop production is multifaceted. On the one hand, beneficial climatic conditions, such as timely rainfall and moderate temperatures, can lead to higher crop yields. In essence, warmer temperatures without excessive rainfall decrease maize yields, while extreme cold or wet conditions can boost yields in Northeast China [14]. On the other hand, increasing climate variability, including adverse events such as droughts, floods, and unseasonal frosts, threatens crop production and undermines agricultural sustainability [15,16]. In Northeast China, where agriculture is the backbone of the economy [17], the implications of these climatic events are far-reaching, affecting not only the food supply but also the local economies and the livelihoods of its residents. The strategies to optimize agricultural production in Northeast China involve using maize hybrids with longer growing periods, enhancing agronomic practices such as dense planting and reduced fertilizer use, and adjusting cropping systems by replacing spring maize with winter wheat and summer maize [18,19].

Understanding how to unlock the benefits of favorable climatic events while mitigating the negative impacts of adverse ones is essential for optimizing grain production. The effective management of both positive and negative climatic events can enhance agricultural output. This can be achieved through global agricultural adaptation strategies that mitigate the impacts of climate change, emphasizing sustainable practices, knowledge transfer, and research [20]. The purpose of this study is to investigate how climatic events in Northeast China have influenced the development of agricultural production optimization strategies, particularly in relation to their impact on grain production, providing a novel perspective in this context.

However, based on the existing literature in the study area, several research gaps remain that require further investigation. Some studies have employed modeling approaches to investigate the impact of various climatic extremes on maize grain yield in Northeast China, incorporating annual mean air temperature and accumulated precipitation data [14]. Other research has quantified the climatic suitability of maize and soybeans from 1981 to 2020 using a fuzzy mathematical method to optimize crop planting structures in the Naoli River Basin, considering the impacts of climate change and human activities for sustainable food production [21,22]. Additionally, other studies are examining the

effects of management practices combined with climate change adaptation strategies on future food production, food security, and limited land resources while also assessing the broader impacts of climate change on food production [11,23,24]. Moreover, the frequency of droughts is projected to increase by up to 11.3% (SSP245) and 13.6% (SSP585) [25]. This research highlights the importance of developing sustainable agricultural development plans that incorporate environmental considerations and agricultural infrastructure to ensure food security. In developing regions, it has been observed that the effects of climate change, particularly rainfall variability, discourage farmers from expanding their cultivated areas [26]. Accordingly, research gaps persist in understanding the effects of climatic extremes on grain yields and sown areas. Further investigation is needed to explore the impact of climate change on optimizing agricultural production and the significant role of irrigation and agricultural insurance in mitigating these effects.

Climate change and its induced disaster events have raised public concerns about global food security. Sustainable agricultural practices are crucial for addressing these challenges, particularly in regions heavily reliant on agriculture, such as Northeast China. This region, known for its vast fertile plains, is highly productive in terms of grain, particularly corn, soybeans, and wheat. However, changing climatic conditions, including both gradual shifts and extreme events, have introduced significant challenges for optimizing grain production. This study aims to fill the gap in understanding how climatic events impact agricultural production optimization in Northeast China. The novel contribution of this research lies in providing a comprehensive evaluation of the different quartiles, examining how climate extremes and adaptive strategies affect agricultural productivity, and offering insights for sustainable agricultural development in the region.

2. Research Framework and Theoretical Basis

Global warming alters the climatic suitability of cultivated land, likely shifting the spatial distribution and diversity of global food crop production [27]. Temperature, rainfall, drought, floods, humidity, and evaporation play a crucial role in determining agricultural productivity [28–30]. In other words, these aspects directly influence crop growth, water availability, and the overall health of ecosystems. Therefore, extreme weather events, such as floods and droughts, can severely disrupt farming operations, resulting in significant agricultural production losses. In this context, farmers, with the support of government plans, must continuously adapt to changing climatic conditions, making these climatic aspects vital in assessing long-term agricultural production and ensuring the ability to withstand environmental stressors that affect food production and agricultural output.

Moreover, drought, abnormal temperatures, and natural disasters have put pressure on sustainable agricultural production [31]. In this context, climate resilience is essential for sustaining rural economies and mitigating the adverse effects of environmental changes [32]. Under changing climatic conditions, smallholder farmers are often exposed to environmental shocks, such as extreme weather events [33]. Hence, effective irrigation enables more consistent crop production, especially in arid regions, while agricultural insurance encourages farmers to plant more crops by mitigating financial risk [34,35].

In addition, farmers' organizations are often considered key stakeholders whose participation should be encouraged to achieve effective water governance in agricultural and irrigation programs [36,37]. For instance, NGOs play a pivotal role in raising awareness, conducting research, and promoting the adoption of sustainable water and agricultural practices. Agricultural inputs, including irrigation systems, agricultural machinery power, fertilizer application, and pesticide usage, are essential components for farmers to cope with climatic challenges [34,38]. These inputs are directly linked to the ability to maintain crop yields despite adverse weather conditions. For instance, irrigation systems can help manage

water scarcity during dry spells, while fertilizers and pesticides boost crop productivity and prevent damage from pests. In sum, by optimizing these inputs, farmers can better adapt to climatic conditions and ensure more stable agricultural production. Hence, we hypothesize that climatic factors such as average precipitation and High-Temperature Days significantly influence agricultural outcomes and that management strategies can mitigate these impacts. Hence, this situation underscores the growing threat of extreme climate events to the region and the necessity for adaptive strategies to mitigate their impacts [39].

Higher agricultural labor productivity typically leads to more efficient farming practices, resulting in improved crop management and higher yields [40,41]. So, labor, such as the agricultural workforce and effective irrigation, is foundational to agricultural production. The workforce, often a reflection of human resources, determines the capacity for farm labor. At the same time, the effective irrigated area shows the extent to which land is suitable for agriculture, especially in water-scarce regions [42,43]. These factors highlight the role of both labor and the amount of land area in food production. Increased efficiency in utilizing human resources and land is crucial to sustaining agricultural output, especially in regions facing challenges such as climate change [44]. In a nutshell, adaptation strategies are becoming increasingly important in regions vulnerable to climate change, enabling farmers to maintain productivity and protect their agricultural output from fluctuating environmental conditions. In essence, climatic aspects such as extreme temperatures and drought generally have negative effects. In contrast, technological and infrastructural factors such as irrigation and agricultural assurance tend to have positive effects on both grain production capacity and the total sown area of crops.

3. Materials and Methods

3.1. Study Area

Northeast China, located between 38°43′–53°33′ N and 115°53′–135°5′ E, encompasses the provinces of Heilongjiang, Jilin, and Liaoning, as well as parts of Inner Mongolia, including Chifeng, Tongliao, Hulunbuir, and Xing'an League [17]. This region is one of the world's three major black soil areas, making it highly significant for agriculture. It lies in a temperate humid and semi-humid continental monsoon climate zone, characterized by four distinct seasons. The region experiences cold, dry, and long winters, as well as rainy summers, with annual precipitation ranging from 1000 mm to below 300 mm, concentrated between May and September, as it transitions from a humid to a semi-arid area [45].

In addition, as can be seen in Figure 1, the data represent the Standardized Precipitation Index (SPI) for Heilongjiang, Jilin, and Liaoning provinces from 2003 to 2020. Heilongjiang shows moderate variability, with consistent increases in recent years. Jilin fluctuates, with spikes in 2005 and 2013. Liaoning experiences larger variations, especially in 2009 and 2012, reflecting inconsistent precipitation patterns.

The region's landscape is predominantly characterized by flat plains and mountains, with the Northeast Plain serving as a key agricultural zone that supports large-scale mechanized farming (Figure 2). The Greater Khingan, Lesser Khingan, and Changbai Mountains are rich in forest resources, making them important timber-producing areas. Rivers like the Liao, Songhua, and Nen provide essential irrigation for agriculture. The fertile black soil in this region, rich in organic matter and loose in texture, supports vibrant agricultural ecosystems. As a crucial area for China's food security and ecological stability, grain production reached 17,346.88 tons in 2020, accounting for 25.91% of the total national grain production, and approximately one-third of the grain is transferred out [46]. This study focuses on Heilongjiang, Jilin, and Liaoning. These provinces primarily produce strategic crops, including rice, corn, soybeans, wheat, potatoes, vegetables, and sunflowers [47,48]. Heilongjiang is a major producer of rice and soybeans, while Jilin and Liaoning focus on

corn, wheat, and potatoes. These crops contribute to food security, economic stability, and industrial production in Northeast China.

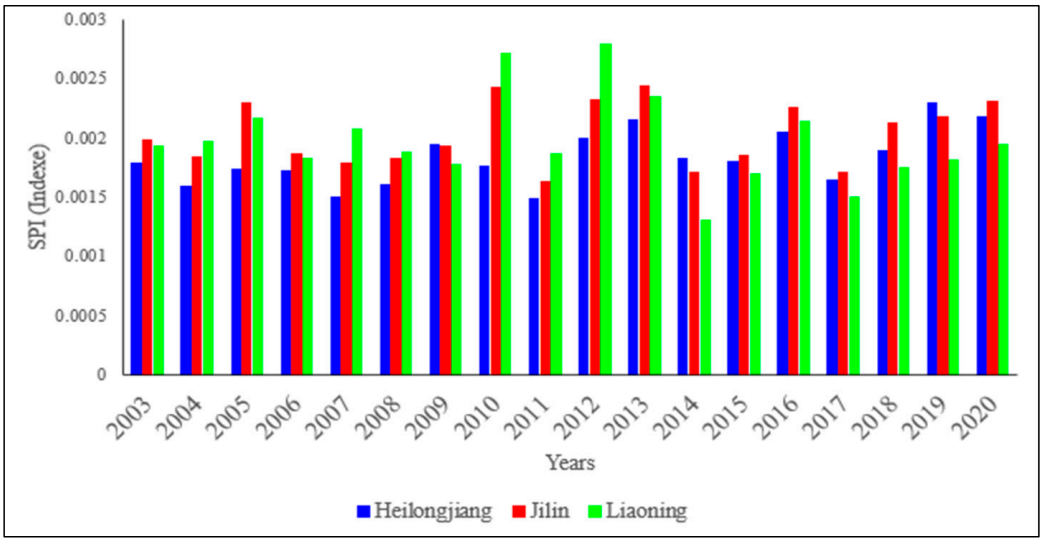


Figure 1. SPI for Heilongjiang, Jilin, and Liaoning provinces from 2003 to 2020.

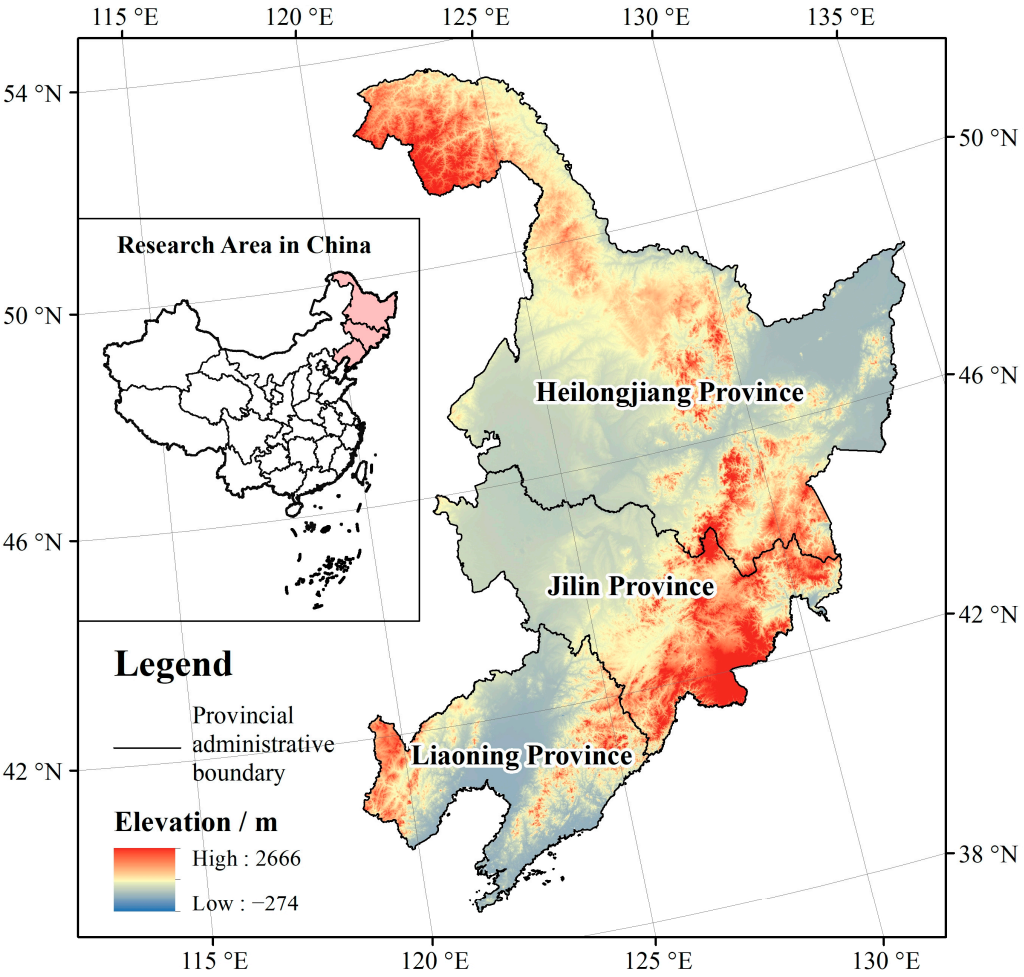


Figure 2. Presentation of the study area.

3.2. Data Sources and Their Overview

This study uses data from a repository detailing sub-national indices for China, covering 31 provinces and 229 cities. The global dataset, spanning from 1993 to 2023, includes four sub-indices—LTDs (Extreme Low-Temperature Days), HTDs (Extreme High-Temperature Days), ERDs (Extreme Rainfall Days), and EDDs (Extreme Drought Days)—which track extreme climate events annually [49,50]. The 1 km monthly precipitation dataset for China (1901–2017) from the National Qinghai–Tibet Plateau Scientific Data Center includes Standardized Precipitation Index (SPI) values calculated using a 1-month accumulation period [51,52]. In addition, data such as the effective irrigation area, agricultural insurance, total power of agricultural machinery per capita, and agricultural labor, among others, are sourced from the city-level Statistical Yearbook. Therefore, due to the unavailability of certain data, such as machinery information for some periods, the study period spans from 2003 to 2020 and encompasses 23 cities in Heilongjiang, Jilin, and Liaoning provinces, resulting in 432 observations.

Concerning the overview of the data, their description reveals key trends and disparities in agricultural factors across the studied region (Table 1). The Comprehensive Grain Production Capacity (CGPC) demonstrates a stable output, with a mean of 9.297 million tons and a low standard deviation of 0.35, indicating consistent production levels. In contrast, extreme weather indicators show high variability, with Extreme Rainfall Days (ERDs) ranging from 0 to 268.75, averaging 28.98, and Extreme Drought Days (EDDs) spanning 0 to 51.7, reflecting fluctuating climatic conditions. The effective irrigation area (EIA) exhibits significant variation, with a mean of 187.875 and a high standard deviation of 184.64, suggesting uneven irrigation infrastructure across the region. Agricultural Insurance Payout Expenditure (AIPE) includes negative values, indicating possible data anomalies (min: −13.57). Fertilizer use (FEU) and machinery power (TPAM) also show considerable disparities, with standard deviations of 24.08 and 5062, respectively. The Standardized Precipitation Index (SPI), averaging near zero (0.004), highlights frequent dry conditions. These findings highlight regional disparities in resource allocation and the varying effects of climate on agricultural practices.

Table 1. The description of the data.

Variable	Unit	Mean	Std. Dev.	Min	Max	Obs
Comprehensive Grain Production Capacity (CGPC)	10,000 tons	9.29	0.35	8.439	10.322	432
Total Sown Area of Crops (TSACs)	Thousand hectares	6.14	0.91	3.93	7.74	432
Extreme Low-Temperature Days (LTDs)	Normalized index	21.45	8.59	0.33	43.24	432
Extreme High-Temperature Days (HTDs)	Normalized index	41.76	8.90	19.82	73.87	432
Extreme Rainfall Days (ERDs)	Normalized index	28.97	27.01	0	268.75	432
Extreme Drought Days (EDDs)	Normalized index	14.39	8.58	0	51.70	432
Standardized Precipitation Index (SPI)	Composite index	0.004	0.048	0.001	1	432
Effective Irrigation Area (EIA)	Thousand hectares	187.87	184.63	1.82	955.47	432

Table 1. *Cont.*

Variable	Unit	Mean	Std. Dev.	Min	Max	Obs
Agricultural Insurance Payout Expenditure (AIPE)	10 thousand RMB	102.10	159.42	−13.57	1235.83	432
Total power of agricultural machinery per capita (TPAM)	10 thousand kilowatts	13,314.42	5062	4684.72	35,830.01	432
Agricultural Labor Productivity (ALP)	RMD per person	2819.62	987.19	1222.23	6794.59	432
Fertilizer Usage (FEU)	10,000 tons	22.56	24.08	0.9	121.88	432

3.3. Methodology

3.3.1. Econometric Specification

To gauge the long-run influence of climatic extremes and farm management factors on agricultural production in Northeast China, we formulate two complementary production functions, one for grain production capacity and one for the cropped area margin, in compact form.

$$\mathrm{CGPC}_{i,t} = f(\mathrm{LTD}_{i,t}, \mathrm{HTD}_{i,t}, \mathrm{ERD}_{i,t}, \mathrm{EDD}_{i,t}, \mathrm{SPI}_{i,t}, \mathrm{EIA}_{i,t}, \mathrm{AIP}_{i,t}, \mathrm{TPAM}_{i,t}, \mathrm{ALP}_{i,t}, \mathrm{FEU}_{i,t}) \quad (1)$$

$$\mathrm{TSAC}_{i,t} = g(\mathrm{LTD}_{i,t}, \mathrm{HTD}_{i,t}, \mathrm{ERD}_{i,t}, \mathrm{EDD}_{i,t}, \mathrm{SPI}_{i,t}, \mathrm{EIA}_{i,t}, \mathrm{AIP}_{i,t}, \mathrm{TPAM}_{i,t}, \mathrm{ALP}_{i,t}, \mathrm{FEU}_{i,t}). \quad (2)$$

$$\ln(\mathrm{CGPC})_{i,t} = \beta_0\mathrm{LTD}_{i,t} + \beta_1\mathrm{HTD}_{i,t} + \beta_2\mathrm{ERD}_{i,t} + \beta_3\mathrm{EDD}_{i,t} + \beta_4\mathrm{SPI}_{i,t} + \beta_5\mathrm{EIA}_{i,t} + \beta_6\mathrm{AIP}_{i,t} + \beta_7\mathrm{TPAM}_{i,t} + \beta_8\mathrm{ALP}_{i,t} + \beta_9\mathrm{FEU}_{i,t} + \in_{i,t} \quad (3)$$

$$\ln(\mathrm{TSAC})_{i,t} = \varphi_0\mathrm{LTD}_{i,t} + \varphi_1\mathrm{HTD}_{i,t} + \varphi_2\mathrm{ERD}_{i,t} + \varphi_3\mathrm{EDD}_{i,t} + \varphi_4\mathrm{SPI}_{i,t} + \varphi_5\mathrm{EIA}_{i,t} + \varphi_6\mathrm{AIP}_{i,t} + \varphi_7\mathrm{TPAM}_{i,t} + \varphi_8\mathrm{ALP}_{i,t} + \varphi_9\mathrm{FEU}_{i,t} + \vartheta_{i,t} \quad (4)$$

where *CGPC* is the Comprehensive Grain Production Capacity (intensive margin), and *TSAC* is the total sown area of crops (extensive margin). *LTD*, *HTD*, *ERD*, *EDD*, *SPI*—counts of extreme low-temperature, high-temperature, rainfall, drought days, and average precipitation (climate shocks). In addition, *EIA*—irrigation and *AIPE* insurance (moderators). Moreover, *TPAM*, *ALP*, *FEU*—machinery power, labor productivity, and fertilizer use are used as control variables.

3.3.2. Method-of-Moments Quantile Regression (MM-QR)

The MM-QR model overcomes the limitations of traditional regression by handling non-parametric data, outliers, uneven distributions, and fixed effects [53]. Diagnostic Q-Q plots and the Shapiro–Francia test indicate pronounced non-normality and thick right tails for several regressors (e.g., ERD, EIA, AIPE). Consequently, mean-based estimators such as OLS or standard fixed effects may blur the influence of extreme-value observations that are precisely the focus of a climate impact study. The MM-QR estimator is chosen because it remains robust to non-Gaussian distributions and heteroscedasticity, allows the entire conditional distribution of the dependent variable to shift with covariates, and accommodates unobserved, quantile-specific fixed effects, capturing latent provincial heterogeneity that varies across the production spectrum [54].

Formally, for province i at time t and quantile $\tau \in \tau \in (0,1)$,

$$Q_{y_i}(\tau|X_i) = (\alpha_i + \delta_i\rho(\tau)) + X_{it}'\beta + Z_{it}'\gamma\rho(\tau) \quad (5)$$

where $Q_{(yi)}(\tau \mid .)$ is the τ-th conditional quantile of either *Ln*(*CGPC*) or *Ln*(*TSAC*); it contains the climate and management variables; $Z_{it} \subseteq X_i$ allows for interaction with the quantile-

shifter ρ(τ); α_i are standard fixed effects; and δ_i $\rho(\tau)$ lets the intercept vary smoothly along the distribution. ρ_τ (u) = $u(\tau - 1_{\{u<0\}})$ is augmented with moment conditions that pin down the scale of unobserved heterogeneity. By construction, MM-QR collapses to the conventional Koenker–Bassett quantile estimator when cross-sectional scale effects δ_i are null, thus nesting simpler models.

3.3.3. Estimation Roadmap

Panel unit root (CADF) and Kao cointegration tests confirm that most series are I(0) or cointegrated; therefore, level equations are admissible. MM-QR is estimated at τ = 0.10, 0.25, 0.50, 0.75, and 0.95 to trace distributional heterogeneity; bootstrapped standard errors (400 replications) ensure finite-sample robustness. Dumitrescu–Hurlin panel Granger tests complement the long-run picture with short-run causality. Collectively, this strategy links tail behavior, long-run equilibrium, and short-run feedback, yielding a nuanced map of how climatic stressors and adaptive capacity interact across the productivity spectrum in Northeast China. The loss function to be minimized is the usual check function.

3.3.4. Matrix of Correlations

Correlation with logCGPC: The variable most strongly correlated with logCGPC is ALP, showing a very strong positive correlation (0.945). This suggests that higher labor productivity is closely associated with greater grain production capacity. Similarly, TPAM also exhibits a strong positive correlation (0.865) with logCGPC, reinforcing the importance of mechanization.

In addition, AIPE and EIA show moderate positive correlations with logCGPC (0.374 and 0.295, respectively), indicating that financial protection and irrigation play supportive roles in boosting productivity. However, FEU shows a negative correlation (−0.187), which may be counterintuitive and worth further investigation, perhaps due to overuse or inefficient application in certain contexts. On the climatic side, correlations are generally weak. For instance, ERD shows a small positive correlation (0.134). At the same time, EDD and SPI both exhibit negative correlations (−0.141 and −0.117), suggesting that droughts and rainfall extremes may have an adverse effect on production, although not a strong one (Table 2).

Correlation with logTSAC: Turning to logTSAC, the most notable correlation is with EIA (0.710), suggesting that areas with more irrigated land tend to have a larger total sown area. AIPE and FEU also show moderate positive correlations (0.396 and 0.549), meaning that insured and fertilized zones tend to be more widely cultivated. Interestingly, TPAM and ALP have weaker correlations with logTSAC (0.220 and 0.255, respectively), implying that while they are crucial for productivity, they may play a more limited role in influencing the extent of land cultivated.

As for climate variables, their correlations with logTSAC are weak and mixed. For example, HTD and EDD both exhibit slight negative associations (−0.108 and −0.058), while ERD displays a mild positive correlation (0.131), indicating that no climatic factor shows a strong standalone relationship with the extent of cultivation. In summary, agricultural labor productivity and machinery are the strongest predictors of grain production capacity, while irrigation and insurance appear to have a more significant influence on the total sown area. Climate variables, although important, appear to exert weaker direct correlations, suggesting potential nonlinear or interaction effects that may require more complex modeling approaches (e.g., GMM, fixed effects, or moderation models).

Table 2. Correlations investigation.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
logCGPC											
(1) logCGPC	1.000										
(2) LTD	−0.041	1.000									
(3) HTD	0.025	−0.092	1.000								
(4) ERD	0.134	−0.069	−0.040	1.000							
(5) EDD	−0.141	−0.207	−0.059	−0.002	1.000						
(6) SPI	−0.117	−0.001	0.022	−0.038	−0.066	1.000					
(7) EIA	0.295	0.017	−0.069	0.090	−0.069	−0.051	1.000				
(8) AIPE	0.374	−0.154	0.036	0.373	−0.009	−0.032	0.452	1.000			
(9) TPAM	0.865	−0.074	0.029	0.126	−0.112	−0.064	0.312	0.314	1.000		
(10) ALP	0.945	−0.033	0.018	0.118	−0.117	−0.079	0.345	0.374	0.915	1.000	
(11) FEU	−0.187	0.033	0.058	0.138	0.194	−0.042	0.485	0.219	−0.147	−0.149	1.000
logTSAC											
(1) logTSAC	1.000										
(2) LTD	0.007	1.000									
(3) HTD	−0.108	−0.092	1.000								
(4) ERD	0.131	−0.069	−0.040	1.000							
(5) EDD	−0.058	−0.207	−0.059	−0.002	1.000						
(6) SPI	−0.121	−0.001	0.022	−0.038	−0.066	1.000					
(7) EIA	0.710	0.017	−0.069	0.090	−0.069	−0.051	1.000				
(8) AIPE	0.396	−0.154	0.036	0.373	−0.009	−0.032	0.452	1.000			
(9) TPAM	0.220	−0.074	0.029	0.126	−0.112	−0.064	0.312	0.314	1.000		
(10) ALP	0.255	−0.033	0.018	0.118	−0.117	−0.079	0.345	0.374	0.915	1.000	
(11) FEU	0.549	0.033	0.058	0.138	0.194	−0.042	0.485	0.219	−0.147	−0.149	1.000

3.3.5. Pesaran's CADF Unit Root Test

Pesaran's CADF test examines whether variables are stationary across panels. Stationarity is crucial for avoiding spurious regression results in panel data analysis. At the level of form, most variables exhibit statistically significant stationarity based on their t-bar statistics and *p*-values.

More specifically, logCGPC and TPAM are strongly stationary at the level, with t-bar values of −6.333 and −7.398, respectively, and *p*-values of 0.000. Other variables such as LTD, EDD, SPI, ALP, and AIPE also appear stationary at the level, given their highly significant *p*-values ($p < 0.05$). This implies that shocks to these variables are likely to be temporary and mean-reverting over time.

However, not all variables pass the stationarity test at this level. For instance, HTD and FEU fail the stationarity test at level (t-bar = 0.324 and 0.357 with *p*-values > 0.6), indicating non-stationarity. However, after first differencing, both become stationary with significant *p*-values (0.000 and 0.003, respectively), confirming that they are integrated of order one (I(1)).

Similarly, logTSAC, ERD, and EIA show moderate t-bar values with *p*-values around 0.01, suggesting weak stationarity. In practical terms, these variables may benefit from further differencing or confirmation through additional unit root tests like IPS or Levin–Lin–Chu (Table 3).

Table 3. CADF unit root test results.

Variable	At Level		At First Difference	
	t-Bar	*p*-Values	t-Bar	*p*-Values
logCGPC	−6.333	0.000		
logTSAC	−2.385	0.009		
LTD	−3.748	0.000		
HTD	0.324	0.627	−7.039	0.000
ERD	−2.215	0.013		
EDD	−4.270	0.000		
SPI	−3.841	0.000		
EIA	−2.333	0.010		
AIPE	−2.700	0.003		
TPAM	−7.398	0.000		
ALP	−5.310	0.000		
FEU	0.357	0.640	−2.756	0.003

3.3.6. Panel Cointegration Test Outcomes

Kao-type cointegration tests were conducted globally to assess the long-term equilibrium relationship between the dependent variables (log-CGPC and logTSAC) and the climatic/explanatory variables. The null hypothesis for each test is no cointegration, with the alternative suggesting that all panels are cointegrated. For logCGPC, most tests at the global level reject the null hypothesis, indicating strong evidence of cointegration. The Dickey–Fuller t and Unadjusted Dickey–Fuller *t*-tests are highly significant ($p = 0.0000$), confirming cointegration. However, the Modified Dickey–Fuller t and Augmented versions are not individually significant ($p > 0.1$), though the unadjusted statistics still support cointegration globally. For logTSAC, the evidence for cointegration is weaker. Only the Augmented DF t (−1.6560, $p = 0.0489$) and Unadjusted versions are significant, while the Modified DF t and DF *t*-tests are not ($p > 0.1$), suggesting limited global cointegration (Table 4).

Table 4. Results of panel cointegration test outcomes.

	Modified Dickey–Fuller t	Dickey–Fuller t	Augmented Dickey–Fuller t	Unadjusted Modified Dickey–Fuller t	Unadjusted Dickey–Fuller t
			logCGPC		
Statistic	−1.2516	−4.7996	−0.7823	−15.4260	−11.7795
p-value	0.1054	0.0000	0.2170	0.0000	0.0000
			logTSAC		
Statistic	−0.3420	−1.2435	−1.6560	−4.0185	−3.4347
p-value	0.3662	0.1068	0.0489	0.0000	0.0003

In general, as shown in Figure 3, the methodology involves data collection, cleaning, and descriptive analysis, followed by stationarity and cointegration tests. It involves MM-QR estimation and Granger causality tests, with the final step focusing on interpreting the results to provide policy recommendations. In brief, this study employs MM-QR to capture heterogeneous effects, handle endogenous variables, and address non-normally

distributed data, thereby surpassing traditional methods [55]. The results of this research are supported by the use of EViews (version 10) for statistical analysis and ArcGIS (version 10.6) for mapping the study area.

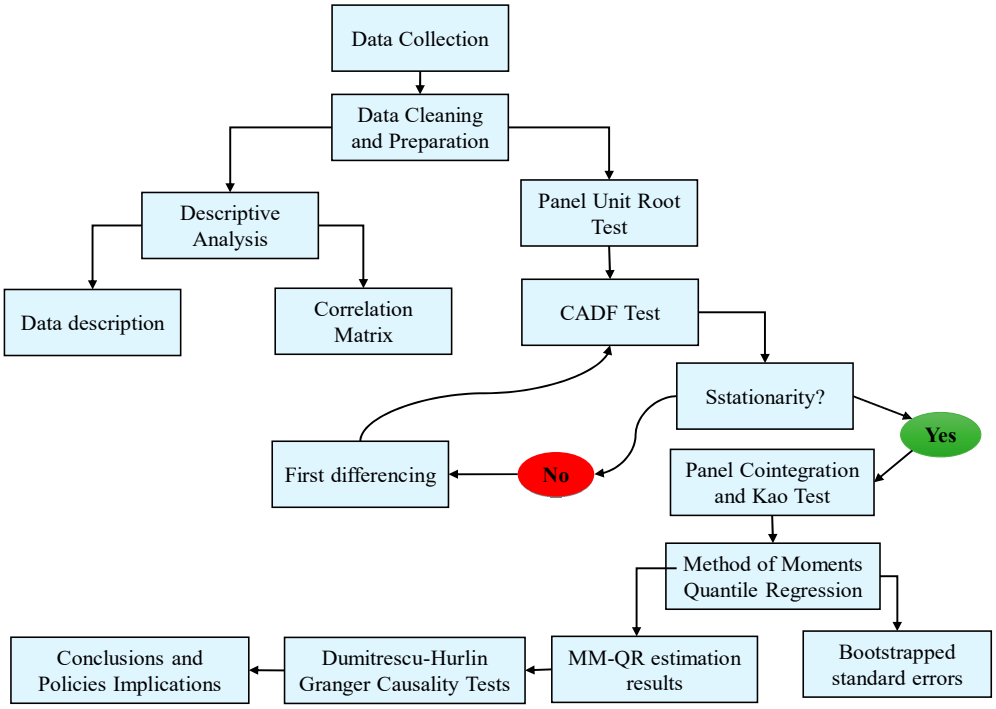


Figure 3. The global flowchart of the methodology.

4. Results and Discussion

4.1. Method-of-Moments Quantile Regression Results

4.1.1. Comprehensive Grain Production Capacity (CGPC)

The Method-of-Moments Quantile Regression (MM-QR) method emphasizes how effects vary across the distribution, rather than being limited to the mean. In essence, by focusing on quantiles, MM-QR provides a more detailed understanding of how extreme climatic events, such as droughts, affect agricultural outcomes at different points in the distribution (e.g., median, lower, or upper quantiles). Table 5 presents the MM-QR results for various variables at different quantiles (10th, 25th, 50th, 75th, and 95th).

Table 5. Method-of-Moments Quantile Regression estimator results.

Variables	Location	Scale	10th	25th	50th	75th	95th
				logCGPC			
LTD	0.002	0.000	0.001	0.001	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
HTD	0.000	−0.000	0.001	0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ERD	−0.000	0.000	−0.000	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
EDD	−0.001	0.000	−0.001	−0.001	−0.001	−0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)

Table 5. *Cont.*

Variables	Location	Scale	10th	25th	50th	75th	95th
SPI	−0.488 ***	−0.126 ***	−0.311 ***	−0.379 ***	−0.482 ***	−0.598 ***	−0.754 ***
	(0.024)	(0.014)	(0.032)	(0.025)	(0.025)	(0.029)	(0.039)
EIA	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AIPE	0.000 ***	0.000	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TPAM	0.000 ***	−0.000 *	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FEU	−0.002 ***	−0.000	−0.001 **	−0.001 ***	−0.002 ***	−0.002 ***	−0.003 ***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	8.530 ***	0.146 ***	8.325 ***	8.405 ***	8.522 ***	8.657 ***	8.836 ***
	(0.057)	(0.034)	(0.072)	(0.061)	(0.057)	(0.067)	(0.095)
logTSAC							
LTD	−0.003	−0.001	−0.001	−0.002	−0.003	−0.003	−0.004
	(0.004)	(0.002)	(0.006)	(0.004)	(0.004)	(0.004)	(0.006)
HTD	−0.011 ***	0.006 **	−0.022 ***	−0.016 ***	−0.011 ***	−0.007 *	0.003
	(0.004)	(0.002)	(0.006)	(0.005)	(0.004)	(0.004)	(0.006)
ERD	−0.000	0.001	−0.002	−0.001	−0.000	0.000	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
EDD	−0.011 ***	0.003	−0.015 **	−0.013 ***	−0.010 ***	−0.009 **	−0.004
	(0.004)	(0.002)	(0.006)	(0.004)	(0.004)	(0.004)	(0.006)
SPI	−1.514 ***	−0.463 ***	−0.682 ***	−1.126 ***	−1.541 ***	−1.828 ***	−2.608 ***
	(0.100)	(0.066)	(0.166)	(0.129)	(0.098)	(0.108)	(0.172)
EIA	0.002 ***	0.000 **	0.002 ***	0.002 ***	0.002 ***	0.003 ***	0.003 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AIPE	0.000 **	−0.000	0.001 *	0.001 **	0.000 **	0.000 **	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TPAM	0.000 **	−0.000 ***	0.000 ***	0.000 ***	0.000 **	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FEU	0.013 ***	−0.004 ***	0.020 ***	0.017 ***	0.013 ***	0.010 ***	0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Constant	5.850 ***	0.315 **	5.284 ***	5.586 ***	5.869 ***	6.064 ***	6.595 ***
	(0.211)	(0.139)	(0.349)	(0.256)	(0.210)	(0.219)	(0.366)
Observations	432	432	432	432	432	432	432

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The SPI variable consistently shows significant negative effects across all quantiles. As SPI increases, the dependent variable decreases, with the impact becoming more pronounced at higher quantiles. This trend aligns with the increasing frequency and severity of droughts, which have been exacerbated by climate change [56]. Drought issues are widespread in China, with Northwestern China facing significant water shortages and a

high risk of drought [57]. This situation suggests that drought conditions, namely low SPI values, negatively impact grain production, especially for larger producers, correlating with increased drought frequency. In essence, low SPI reduces water availability, impacting irrigation and crop yields, particularly for maize and rice, which are the main crops in the study area. In Northeast China, crop yields are projected to decrease by 21.4% for maize and 4.2% for soybeans by 2100 under the SSP585 scenario, compared to 2015 levels [58]. Given these projections, understanding the dynamics of agricultural production is crucial for addressing global food security [59].

Moreover, other key variables, such as AIPE, display a positive and consistent effect across all quantiles, highlighting its role in mitigating the impact of climatic events on grain production. This suggests that financial protection through insurance is crucial for maintaining productivity. Similarly, FEU exhibits a negative effect, particularly at higher quantiles. This highlights the dual role of fertilizers: they improve crop yields on the one hand, but their overuse contributes to a decline in soil fertility, negatively affecting agricultural production [60,61]. Agricultural finance is a crucial factor in agricultural production [62], which confirms the role of AIPE in mitigating the impact of climatic events on agricultural production. The constant term (intercept) remains highly significant, with consistent positive values across all quantiles, indicating a stable baseline effect on the dependent variable. Variables such as EDD, ERD, and EIA do not show significant impacts across quantiles, suggesting weaker or more inconsistent influences. Therefore, increased irrigation may intensify the need to enhance the resilience of irrigated agriculture to drought [63]. Additionally, the influence of topography on the agricultural system [13,64] must be considered as a crucial factor in optimizing agricultural production in Northeast China, alongside climatic events, to ensure comprehensive and sustainable strategies.

Extreme Low-Temperature Days (LTDs), Extreme High-Temperature Days (HTDs), Extreme Rainfall Days (ERDs), and Extreme Drought Days (EDDs) show weaker or inconsistent effects across quantiles, suggesting that their impact on grain production is more variable. Overall, the results indicate that certain variables, particularly SPI, play a more substantial and consistent role in agricultural production, while others exhibit fewer clear patterns. Furthermore, China's diverse terrain and climate, resulting in highly uneven rainfall distribution [65], further complicate agricultural outcomes. The results emphasize sustainable practices, drought resilience, efficient fertilizer use, and investments in insurance and mechanization to boost productivity.

4.1.2. Total Sown Area of Crops (TSACs)

The MM-QR results for the total sown area of crops (TSACs) reveal significant effects of climatic factors and management strategies on land use. China's cultivated land system has evolved through a complex process influenced by numerous challenges [66,67]. Average rainfall is a crucial factor in agricultural production, as it directly influences the expansion and evolution of the sown land area [68]. This highlights the close connection between rainfall and agricultural land use. Key findings from this study align with this. SPI shows a significant negative effect across all quantiles, indicating that drought conditions lead to a reduction in the total sown area. In other words, there is a consistent negative relationship between SPI and agricultural output. This suggests that water availability is a critical factor influencing land use decisions.

Extreme High-Temperature Days (HTDs) negatively impact the sown area, especially for smaller producers. Effective irrigation area (EIA) positively influences sown area expansion across all quantiles. Fertilizer use (FEU) encourages planting and increases sown area, particularly at higher quantiles. Additionally, EDD and HTD exhibit significant nega-

tive effects, particularly at lower quantiles (10th and 25th), indicating that their influence diminishes as the quantile increases.

Liaoning province, a vital agricultural area in Northeast China, has been increasingly affected by frequent droughts in recent years, impacting both agricultural productivity and the environment [69]. Given the wide-ranging and destructive effects of drought, it remains a major concern for researchers worldwide [70]. Moreover, global maize production has shown high sensitivity to climate change, particularly during extreme heat and drought events [71]. In summary, droughts lead to behavioral adaptations, such as reduced sown areas and increased reliance on insurance.

FEU demonstrates significant positive effects, especially at higher quantiles, indicating that its influence grows as conditions worsen. The constant term remains highly significant across all quantiles, with positive values slightly increasing as the quantile rises, suggesting a stable baseline effect. Variables such as ERD, AIPE, and EIA are statistically significant, but they exhibit more varied impacts across the quantiles. In summary, the results highlight that certain variables, notably SPI, have a strong and consistent impact on agricultural production, while others exhibit greater variability. Over the last decade, the frequency and severity of droughts have increased, underscoring growing concerns about the impact of climate change on agriculture [72].

4.2. Dumitrescu & Hurlin (2012) [73] Granger Non-Causality Test and Its Results

Based on Table 6, the results indicate that larger grain production capacity today predicts an increase in future hot day counts, likely through land–atmosphere feedback. Irrigation expansion and cropped area are mutually reinforcing across regions. Insurance payouts have a modest positive effect on production. Machinery power both influences and is influenced by higher yields and larger sown areas. Fertilizer use significantly predicts future yields and acreage overall. The short-term predictive power of extreme event counts is weak, with their impact more evident in longer-term quantile effects (as shown in the MM-QR analysis).

Table 6. Granger causality results: pair and direction.

Pair and Direction	Region
logCGPC → HTD	Yes (p = 0.000)
HTD → logTSAC	No
EIA ↔ logTSAC	Bidirectional ($p \leq 0.05$ both ways)
AIPE ↔ logCGPC/logTSAC	Bidirectional with capacity; one-way logTSAC → AIPE
TPAM ↔ logCGPC/logTSAC	Bidirectional for both margins
FEU → logCGPC/logTSAC	Yes (p = 0.000) on both margins
SPI and extremes (LTD, ERD, EDD)	Mostly no Granger causality either way (high p-values)

In addition, the Dumitrescu–Hurlin Granger causality tests (Table 7) uncover significant short-run dynamics between management factors, climate variables, and agricultural outcomes. Bidirectional relationships are evident between irrigation (EIA) and sown area (logTSAC), insurance (AIPE) and production capacity (logCGPC), and machinery (TPAM) with yields and area, suggesting mutual reinforcement. For example, irrigation infrastructure drives land expansion, while larger cropped areas justify further investments in irrigation. Insurance, in turn, serves as both a result of higher productivity and a catalyst for risk-taking in cultivation. Mechanization enhances efficiency, prompting further investment, while larger operations encourage more mechanization.

Table 7. Results of Dumitrescu & Hurlin (2012) [73] Granger non-causality test.

Direction	W-Bar	Z-Bar	*p*-Value (Z)
	logCGPC		
LTD → logCGPC	0.8034	−0.6809	0.4959
logCGPC → LTD	0.7536	−0.8535	0.3934
HTD → logCGPC	1.1058	0.3666	0.7139
logCGPC → HTD	2.3791	4.7774	0.0000
ERD → logCGPC	1.0607	0.2103	0.8334
logCGPC → ERD	1.4212	1.4592	0.1445
EDD → logCGPC	0.9095	−0.3134	0.7540
logCGPC → EDD	1.0127	0.0440	0.9649
SPI → logCGPC	1.3713	1.2862	0.1984
logCGPC → SPI	2.2568	4.3536	0.0000
EIA → logCGPC	4.4955	12.1087	0.0000
logCGPC → EIA	2.8577	6.4354	0.0000
AIPE → logCGPC	3.4317	8.4235	0.0000
logCGPC → AIPE	5.7230	16.3609	0.0000
TPAM → logCGPC	2.2462	4.3171	0.0000
logCGPC → TPAM	4.5662	12.3537	0.0000
FEU → logCGPC	4.6545	12.6596	0.0000
logCGPC → FEU	1.4447	1.5406	0.1234
	logTSAC		
LTD → logTSAC	0.9352	−0.2245	0.8224
logTSAC → LTD	0.5049	−1.7151	0.0863
HTD → logTSAC	1.1874	0.6492	0.5162
logTSAC → HTD	1.9166	3.1750	0.0015
ERD → logTSAC	1.1153	0.3995	0.6895
logTSAC → ERD	1.5363	1.8579	0.0632
EDD → logTSAC	1.9119	3.1590	0.0016
logTSAC → EDD	0.7246	−0.9542	0.3400
SPI → logTSAC	0.7238	−0.9568	0.3387
logTSAC → SPI	1.2780	0.9632	0.3355
EIA → logTSAC	1.2051	0.7105	0.4774
logTSAC → EIA	3.0453	7.0850	0.0000
AIPE → logTSAC	1.8568	2.9680	0.0030
logTSAC → AIPE	1.9756	3.3797	0.0007
TPAM → logTSAC	1.4828	1.6725	0.0944
logTSAC → TPAM	3.3126	8.0110	0.0000
FEU → logTSAC	1.4275	1.4808	0.1387
logTSAC → FEU	2.5104	5.2321	0.0000

Note: "X → Y" tests whether X Granger causes Y.

Fertilizer (FEU) is identified as a unidirectional driver of short-term productivity and land use, as Granger causality exists between FEU and both CGPC and TSACs, but not vice versa. Grain output also influences climate feedback, with higher production predicting future High-Temperature Days (HTDs), likely through land–atmosphere interactions. Notably, extreme climate events (LTD, ERD, EDD, SPI) exhibit no short-term predictive power on agricultural outcomes, in contrast to their significant long-term effects in MM-QR models. This suggests that climate impacts accumulate over time, such as through multi-season droughts, rather than acting as immediate shocks. Management interventions, such as insurance, irrigation, and machinery, play a critical role in buffering short-term climate risks and enhancing resilience against acute challenges.

In addition, the results highlight a complex relationship between SPI and agricultural productivity, with significant bidirectional effects on grain production and sown areas. Further analysis of SPI's regional impact in Northeast China, focusing on humidity zones, irrigation, crop sensitivity, and behavioral adaptations, would enhance the findings. Additionally, examining the long-term effects of SPI and its interactions with temperature and land–atmosphere dynamics could refine policies and improve drought mitigation strategies, thereby safeguarding food security.

In general, these causality patterns highlight that management factors—not climate extremes—dominate short-run agricultural adjustments. The bidirectional investment–output loops for irrigation, insurance, and machinery emphasize their role as adaptive linchpins. Conversely, the absence of climate-driven causality underscores the need for anticipatory policies, as farmers cannot rapidly adjust to climatic shocks without pre-existing infrastructure or financial tools.

5. Conclusions and Policy Implications

This study examines the impact of increasing climatic events on agricultural production in Northeast China, emphasizing the need for sustainable practices and strategies to optimize agricultural production amid climate change challenges. The results indicate that descriptive and correlation patterns have already pointed to the primacy of labor productivity, machinery power, and irrigation in explaining both grain output and cultivated area. Unit root and Kao tests confirmed that these relationships are cointegrated over time in the study area for sown land.

Method-of-Moment's quantile regressions showed that average precipitation (SPI) has a significant negative effect on both Comprehensive Grain Production Capacity (CGPC) and total sown area of crops (TSACs), particularly at higher quantiles. In contrast, HTD shows a significant negative effect on TSACs at lower quantiles, suggesting that extreme heat events reduce the total sown area, particularly for smaller producers. For the other factors, extreme Low-Temperature Days (LTDs), Extreme Rainfall Days (ERDs), and Extreme Drought Days (EDDs) have weaker or more inconsistent effects on agricultural outcomes. Concerning the mitigation strategies, agricultural insurance payouts (AIPE) positively impact productivity and risk mitigation. Machinery power (TPAM) enhances both productivity and risk management. Fertilizer use (FEU) increases the sown area but can exhibit diminishing returns at higher levels, negatively impacting productivity.

The Granger causality tests reveal bidirectional causality between grain production capacity (logCGPC) and factors such as irrigation area (EIA), agricultural insurance payouts (AIPE), and machinery power (TPAM), indicating strong investment–output relationships. Fertilizer use (FEU) predicts future yields and acreage, whereas extreme climatic events exhibit weaker short-term predictive power.

Specifically, based on the estimation results, the following policy implications can be drawn to improve agricultural sustainability and mitigate climate-related risks and

events. First, policies should enhance the promotion of climate-resilient agriculture. This, for example, offers subsidies for drought-resistant crops and water-efficient technologies while also funding research to develop heat-resistant and drought-tolerant crop varieties to adapt to changing climate patterns. Second, investment should be going into smart irrigation systems and expanding infrastructure in vulnerable regions to optimize water usage and mitigate water scarcity. Third, affordable agricultural insurance should be expanded to make it accessible to all farmers, and climate-indexed insurance linked to specific weather conditions should be developed. Fourth, mechanization needs to be supported through subsidies, loans, and rental services for small- and medium-scale farmers to boost productivity and efficiency. Five, sustainable fertilizer use should be promoted through incentives, training, and precision agriculture to reduce environmental impact and maintain agricultural productivity.

Despite these significant results, new aspects need to be considered in future research. This study is region-specific to Northeast China and focuses on current agricultural practices in the region. Future research should focus on climate change projections, cross-regional comparisons, and the development of long-term adaptive strategies to address these challenges. Previous studies have emphasized that the highest interannual drought severity occurs in May and June [74]. Furthermore, effective drought prediction methods are crucial for mitigating the severe impacts of drought, and it is essential to account for regional differences in agricultural adaptation planning [75,76]. In addition, social surveys are a key tool in scientific research [77], and future studies can use survey data to explore farmers' strategies and behaviors for mitigating the impact of climatic events on agricultural production. In sum, this study calls for a deeper analysis of the heterogeneity of climate events. In essence, there is a requirement to analyze this aspect in detail by region and among farmer households.

Author Contributions: Conceptualization, B.F. and J.G.; methodology, B.F.; software, B.F.; validation, B.F., J.G. and R.T.; formal analysis, B.F.; investigation, B.F.; resources, J.G.; data curation, J.G.; writing—original draft preparation, B.F.; writing—review and editing, G.D., R.Z. and F.B.; visualization, B.F.; supervision, B.F.; project administration, J.G.; funding acquisition, J.G. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by Heilongjiang Province Philosophy and Social Science Research Planning Project 'Research on Security Risk Prevention in Grain Import and Foreign Capital Utilization' (Grant 23JYB284).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

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