

## Article

# The Impact of Climate Risk on Agricultural New Quality Productive Forces—Evidence from Panel Data of 31 Provinces in China

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## Abstract

Agricultural new quality productive forces are an important driving force for the transformation of China's agricultural economy and the realization of sustainable development. This study proposes a novel channel to verify the negative effects of climate risk on agricultural new quality productive forces based on the empirical evidence of 31 provinces in China from 2012 to 2022. Specifically, baseline regression results indicate that a 10% increase in climate risk leads to a 1.18% decrease in agricultural new quality productive forces. Moreover, mechanism tests indicate that climate risk negatively affects agricultural new quality productive forces mainly through increasing the severity of natural disasters. Heterogeneity analysis indicates that variances in agricultural digital economy levels, government investment in environmental protections, and the depth of agricultural insurance coverage endowments result in substantial discrepancies in the effects of climate risk on agricultural new quality productive forces. Finally, this study finds that the impact of climate risk varies across provinces with different regional locations and geographical conditions. This study provides useful insights for coping with climate risk and promoting the high-quality development of agricultural new quality productive forces.

**Keywords:** climate risk; agricultural new quality productive forces; natural disasters

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## 1. Introduction

China's economy has shifted from a stage of high-speed growth to a stage of high-quality development. In the agriculture sector, how to achieve high-quality agricultural development has become a topic of concern for governments, academia, and society. As the world's largest agricultural product importer and second largest exporter, China's agricultural sector is steadily gaining prominence on the international stage. In terms of the current stage of agricultural development in China, traditional farming methods have led to slow rural economic growth, which is detrimental to the sustainable development of agriculture [1]. This is primarily manifested in two aspects: on the one hand, China's agricultural development has largely relied on conventional growth drivers such as increased utilization of land, capital, agricultural chemicals, and machinery, which has led to structural surpluses and shortages in agricultural production, resulting in resource waste; on the other hand, traditional agricultural productivity-driven approaches have also caused severe environmental pollution and health issues. Therefore, agriculture sustainability urgently needs to transform from the traditional production pattern that only emphasizes factor contribution and food supply to search for new developments in kinetic energy [2].

In September 2023, Chinese president Xi Jinping first proposed the concept of ‘new quality productive forces’. New quality productive forces refer to the advanced productive forces that are driven by revolutionary technological breakthroughs, innovative allocation of production factors, and industrial upgrading, which require balancing the dual goals of green development and total factor productivity improvements [3]. Agriculture new quality productive forces (ANPFs) refer to the application of new quality productive forces in the agricultural sector, which considers the unique characteristics of agricultural production factors including their composition and utilization [4]. In terms of composition, in addition to the two traditional factors of labor and capital, natural conditions such as sunlight, water, heat, and soil are also important components of agricultural production factors. In terms of utilization, input factors must be applied within a specific agricultural season to be effective for agricultural production. Therefore, agriculture new quality productive forces (ANPFs) can be defined as the improvement of the allocation efficiency between natural inputs and economic inputs, through technological innovation, institutional change, and industrial transformation, in order to achieve sustainable agricultural development [3]. Developing ANPFs can promote the penetration of new technologies and concepts into the agricultural sector, which will contribute to modernization, intellectualization, and greening of agriculture [5], and provide new growth drivers for high-quality agricultural development.

However, the cultivation process of ANPFs is constrained by many factors, among which the attribute of agriculture ‘depending on the weather’ indicates that the negative impact of climate risk on the ANPFs is the most direct and significant factor [4,6]. According to the National Climate Change Adaptation Strategy 2035, sudden extreme events brought by climate change have become an important risk in the process of China’s basic realization of socialist modernization. The 2021 China Climate Change Blue Book shows that extreme heavy rainfall and high-temperature events in China have increased significantly since the mid-1990s. The irregularity and uncertainty of extreme weather events pose serious challenges to economic development and natural ecosystems, particularly for the agricultural sector, which is highly reliant on the natural environment. Therefore, exploring the effects and impact channels of climate risk on ANPFs will help urban policymakers to target policy measures to cope with climate risk, cultivate agricultural new productive forces, and achieve sustainable development of local agriculture.

The existing literature examines the impact of climate risk on agricultural development mainly based on micro and macro aspects. At the micro-level, the extreme weather events have exacerbated the inherent seasonality and instability of the agricultural sector, significantly reducing the working hours that farmers dedicate to agricultural production [7], or forcing farmers to shift to non-productive sectors by lowering their expected income [8–10]. Moreover, some scholars have pointed out that the lack of information and formal agricultural credit are the principal reasons for farmers’ limited capacity to cope with climate risks [11,12]. At the macro-level, previous studies have found that extreme weather significantly reduces regional agricultural economic output [13–15], and it has been shown that this negative impact is more pronounced in areas with a lower income [16,17] or higher temperatures [18]. Additionally, some scholars have examined the damages caused by climate risks to agricultural production factors such as irrigation resources, soil, and farmland [19,20].

Previous studies have mainly focused on four dimensions of new quality productive forces (NPFs): the intrinsic characteristics, influence factors, index construction, and effects. In terms of intrinsic characteristics, existing research has found that NPFs overcome the limitations of traditional production patterns that excessively rely on resource consumption through technical innovation and innovative allocation of production factors, emphasizing

the dual objectives of technical innovation and green development [21]. Gao and Ma [22] further emphasized that the innovative allocation of agricultural production factors and the transformation of agricultural production processes and organizational structures are the main characteristics of ANPFs. As for index construction, existing studies have primarily constructed the NPFs index based on labor objects, laborer material, and labors [23,24]. What has also been found is that the NPFs in the eastern region are higher than in the central and western regions [23]. In terms of influencing factors, existing research has found that factors such as industrial agglomeration [25], digital economic development [25], and new energy policies [26] can promote NPFs. In terms of effects examination, studies have found that NPFs can effectively promote resource allocation efficiency [27], industrial development [28,29], and agricultural modernization [23]. The above research on NPFs provides solid support for the theoretical and empirical analysis in this paper.

Through a review of the relevant literature, this paper found that few studies have focused on the impact of climate risk on ANPFs. Although ANPFs emphasize the application of technical innovation in agricultural production more than traditional agricultural production, it is still necessary to ensure that agricultural production factors can be used effectively for sustainable development. However, the emergence of climate risks may damage irrigation resources, soil, agricultural land [19], and labor factors [7], thereby potentially hindering the development of ANPFs.

Therefore, this paper investigates the impact of climate risk on ANPFs. The potential marginal contributions can be summarized as following four aspects: (1) Despite much literature having focused on the impacts of climate risk on agricultural economic development, there is still a relative lack of literature examining the relationship between climate risk and ANPFs. This paper contributes to clarifying the intrinsic link between climate risk and ANPFs, and provides a theoretical analysis for mitigating climate risk and promoting sustainable development. (2) The heterogeneity analysis in this paper explores the moderating effects of agricultural digital economy development, government environmental protection investment, and the depth of agricultural insurance coverage, which provides a theoretical foundation for policymakers to address climate risk. (3) This study is suitable for developing countries seeking agricultural sustainable development, since it can inspire these countries to explore development patterns that are appropriate to their national conditions.

## 2. Theoretical Analysis and Research Hypotheses

Land, labor, capital, technology, and data are the core production factors for the transformation of agricultural modernization and the development of ANPFs. Cultivating NPFs requires combining innovative factors and technological forces with traditional factor bases, such as land, labor, and capital, in order to promote the transformation of agricultural productivity from ‘old quality’ to ‘new quality’ [30]. According to neoclassical growth theory, climate risk may have a significant negative impact on production factors, increasing the marginal cost of agricultural production and lowering agricultural total factor productivity. For example, climate risk would increase the area of agricultural land affected by disasters [31], along with destroying the irrigation resources for crops, soil quality, and the natural communities on which agricultural production depends [19,32], thereby negatively affecting agricultural production. For the livestock sector, rising climate risk leads to the probability of epidemics occurring and spreading among livestock [33], reduces the quality of livestock feeds [34], and increases the rate of mortality in poultry. Similarly, there is evidence demonstrating that rising climate risk reduces labor hours and efficiency [7]. In summary, climate risk can damage agricultural production factors

and reduce total factor productivity in agriculture, thus impacting ANPFs negatively. Accordingly, this paper proposes Hypothesis 1:

**Hypothesis 1:** *Climate risk will negatively affect ANPFs.*

Natural disasters may be the channel through which climate extremes negatively affect ANPFs. Previous studies have found that climate extremes are positively correlated with the probability of natural disasters [31], and empirical study shows that global warming significantly increases the probability of natural disasters and the extent of losses [35]. According to the neoclassical theory of economic growth, the occurrence of natural disasters significantly reduces the efficiency of land use [19] and the scale of agricultural output that nurtures ANPFs [36]. In addition, according to the opportunity cost theory, the labor migration theory, and the comparative advantage theory, the natural disasters would reduce the expected income from agricultural production, thus creating a disincentive for agricultural production and investment behavior [37]. Therefore, climate risk may be detrimental to ANPFs by increasing the probability and severity of natural disasters, as well as reducing the efficiency of land and labor resource allocation needed to cultivate agricultural new quality productive factors. Accordingly, this paper proposes Hypothesis 2:

**Hypothesis 2:** *Climate risk increases the severity of natural disasters, thereby negatively affecting ANPFs.*

Furthermore, there may be heterogeneity in the impact of climate risk on ANPFs. Improving the allocation efficiency of core production factors and achieving a significant increase in total factor productivity is an important manifestation of fostering ANPFs, while the improvement of the digital economy in agriculture can effectively activate agricultural factor resources and reduce the cost of information searching for farmers, thus rapidly promoting the flow and efficient allocation of agricultural production factors [38]. Moreover, the digital platform enables farmers to monitor crop production, respond to climate risks, and make informed production decisions. Accordingly, this paper proposes Hypothesis 3:

**Hypothesis 3:** *The development of an agricultural digital economy can effectively mitigate the negative impacts of climate risks on agricultural new quality productive forces.*

What is more, variations in climate risk prevention measures across regions result in different impacts of climate risks on agricultural productivity, and local government environmental protection investment is a crucial measure for preventing climate risk. For the agricultural sector, government environmental protection investment can protect agricultural production resources through ecological restoration and the establishment of climate-resilient infrastructure, thereby mitigating the impact of climate risks on agricultural production [39,40]. At the same time, government environmental protection investments related to the agricultural sector can protect natural resources associated with agricultural production, promote the informatization and modernization of agriculture, and effectively reduce the adverse effects of climate risks on ANPFs. Accordingly, this paper proposes Hypothesis 4:

**Hypothesis 4:** *Government investment in environmental protection can effectively mitigate the negative impacts of climate risk on ANPFs.*

According to risk diversity theory, variations in climate risk management levels across regions can also lead to different impacts of climate risks on ANPFs. Agricultural insurance serves the functions of risk diversification and compensation, enabling the dispersion of climate risks both temporally and spatially [41]. Based on the expected utility theory, agricultural insurance can reduce agricultural production risks and stabilize the expected returns from agricultural production. Moreover, agricultural insurance can enhance farmers' confidence in continuing to engage in the agricultural sector in the long term by compensating farmers in the aftermath of natural disasters [42,43], thereby promoting farmers' active adoption of climate adaptation technologies, such as adjusting crop production patterns and diversifying planting [44–46], and mitigating the negative impact of climate risks on agricultural productivity [47]. Accordingly, this paper proposes Hypothesis 5:

**Hypothesis 5:** *Agricultural insurance coverage can effectively mitigate the negative impacts of climate risks on agricultural new quality productive forces.*

### 3. Research Design

#### 3.1. Variables

##### 3.1.1. Dependent Variable

The dependent variable is agricultural new quality productive forces (ANPFs). According to the theoretical connotation and index measure of agriculture new quality productive forces [3,24], this paper adopts the entropy weight method to construct the index system of ANPFs in three dimensions: technological productivity, green productivity, and digital productivity. Specially, we measure technological productivity in terms of technology investment and industrial development. We measure green productivity indicators by green environmental protection, environmental governance, and energy consumption. Finally, we calculate digital productivity based on digitalization levels and digital infrastructure penetration. Further, the calculation of each tertiary indicator is detailed in Table 1.

**Table 1.** Indicator construction of agricultural new quality productive forces.

| Criteria Layer             | Primary Indicator                    | Secondary Indicator                                                          | Attribute |
|----------------------------|--------------------------------------|------------------------------------------------------------------------------|-----------|
| Technological Productivity | Investment in science and technology | Years of schooling per rural labor force                                     | +         |
|                            |                                      | Proportion of adult technical training in agriculture                        | +         |
|                            |                                      | Output per capital in primary sector                                         | +         |
|                            |                                      | Per capital disposable income of rural residents                             | +         |
|                            | Industrial development               | Number of national leading enterprises specializing in agriculture           | +         |
|                            |                                      | Number of professional farmers' cooperatives/employees in primary industry   | +         |
|                            |                                      | Value added of agriculture, forestry, animal husbandry, and fishery services | +         |
|                            |                                      | Output of primary sector/number of employees in primary sector               | +         |

Table 1. Cont.

| Criteria Layer       | Primary Indicator                  | Secondary Indicator                                                                                                          | Attribute |
|----------------------|------------------------------------|------------------------------------------------------------------------------------------------------------------------------|-----------|
| Green Productivity   | Environmental level of greening    | Percentage of forest cover                                                                                                   | +         |
|                      |                                    | Financial expenditure on environmental protection/government public budget expenditure                                       | +         |
|                      | Energy consumption level           | Percentage of COD pollution emissions from agriculture/primary sector output                                                 | +         |
|                      |                                    | Percentage of ammonia emissions from agriculture/primary sector production value                                             | +         |
|                      |                                    | Energy consumption in agriculture, forestry, and fisheries/gross value of production in agriculture, forestry, and fisheries | +         |
|                      |                                    |                                                                                                                              |           |
| Digital Productivity | Digitization level                 | Rural electricity consumption per capita                                                                                     | +         |
|                      |                                    | Rural Digital Financial Inclusion Mobile Payments Index                                                                      | +         |
|                      | Digital infrastructure penetration | Number of rural broadband access subscribers/number of rural households                                                      | +         |
|                      |                                    | Cable line length per square meter                                                                                           | +         |

### 3.1.2. Independent Variable

The independent variable of this paper is the climate risk (Clr). Referring to previous study [48], this paper selects 1973–1992 as the climate reference period, and adopts the method of daily observation of data from meteorological stations and percentile relative thresholds during the reference period to define the extreme thresholds of meteorological indicators in different regions, so as to calculate the number of days of extreme temperature events and extreme precipitation events in each year from 2012 to 2022. Firstly, we extract the daily maximum and minimum temperatures on the same date during the reference period and arrange them in ascending order, defining the mean values of the 90th percentile and the 10th percentile as the thresholds of extreme high temperatures and extreme low temperatures, respectively. Similarly, we ranked daily rainfalls that are above zero during the reference period in ascending order and defined the 95th percentile and the 5th percentile as the thresholds of extreme heavy rainfall and extreme drought, respectively. After that, we compare the daily temperatures at climate observation sites from 2012 to 2022 with the defined extreme thresholds, and if the daily temperature is higher than the defined extreme high temperature or lower than the defined extreme low temperature, then we can conclude that there is an extreme high-temperature event or an extreme low-temperature event. In this way, we can also derive extreme heavy rainfall events and extreme drought events. Finally, we summarize the extreme climate events at a daily level and aggregate to an annual level, so that obtaining the number of extreme high-temperature days, extreme low-temperature days, extreme heavy rainfall days, and extreme drought days for each year. The indicators were standardized as follows:

$$\overline{\text{Index}}_{i,t} = \frac{\text{Index}_{i,t} - \min\{\text{Index}_{k,l}\}}{\max\{\text{Index}_{k,l}\} - \min\{\text{Index}_{k,l}\}}$$

$\overline{\text{Index}}_{i,t}$  refers to the standardized climate risk indices (extreme high temperature, extreme low temperature, extreme heavy rainfall, and extreme drought indices) for province  $i$  in year  $t$ .  $\text{Index}_{i,t}$  refers to the sum of days of each climate extreme in province  $i$  in year  $t$ ,  $\min\{\text{Index}_{k,l}\}$  refers to the minimum value of the number of days of each climate extreme, and  $\max\{\text{Index}_{k,l}\}$  refers to the maximum value of the number of days of each climate extreme. Finally, we weighted and averaged the four sub-indicators to obtain a total climate risk indicator and gave it a weight  $\omega$  of 0.25 as follow:

$$\text{Climate risk}_{i,t} = \sum_{n=1}^4 \omega_n \overline{\text{Index}}_{i,t} / 100$$

### 3.1.3. Control Variables

The control variables include regional economic development (GDP), industrial structure (Ind), government expenditure (Gov), innovation level (Inn), urbanization (Urb), R&D intensity (RD), consumption (Con), and regional industrialization level (Idu). Table 2 presents the definition of the main variables.

**Table 2.** Variable definition.

| Symbol | Definition                                                                                                                                                      | Variable                                  |
|--------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------|
| ANPFs  | Synthesized using the entropy method in three dimensions: scientific productivity and technological productivity, green productivity, and digital productivity. | Agriculture new quality productive forces |
| Clr    | Sum of extreme high-temperature days, extreme low-temperature days, extreme heavy rainfall days and extreme drought days for each year.                         | Climate risk index                        |
| GDP    | Log regional GDP aggregates                                                                                                                                     | Regional economic development level       |
| Ind    | Value added of tertiary industry / value added of secondary industry                                                                                            | Industrial structure                      |
| Gov    | Fiscal expenditure / GDP                                                                                                                                        | Government (provincial) expenditure       |
| Inn    | Log total number of patent applications received                                                                                                                | Regional innovation level                 |
| Urb    | Urban population / total regional population                                                                                                                    | Urbanization                              |
| RD     | Government science and technology expenditures / regional general budget expenditures                                                                           | R&D intensity                             |
| Con    | Total retail sales of consumer goods / GDP                                                                                                                      | Consumption level                         |
| Idu    | Industrial value added / GDP                                                                                                                                    | Regional industrialization level          |

### 3.2. Empirical Model

We verify Hypothesis 1 by conducting Equation (1):

$$\text{ANPF}_{sit} = \beta_0 + \beta_1 \text{Clr}_{it} + \beta_2 \text{Control}_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (1)$$

where  $ANPF_{it}$  is the dependent variable representing the level of agricultural new quality productive forces in province  $i$  in year  $t$ ,  $Clr_{it}$  is the core independent variable representing the composite climate risk index of province  $i$  in year  $t$ ,  $Control_{it}$  is the set of control variables,  $\mu_i$  represents the province fixed effect, which absorbs the influence of urban characteristics that do not change with time and reduces the impact of endogenous problems on the regression results.  $\pi_t$  represents the year fixed effect, which absorbs the effects of regional time trends and fluctuations.  $\varepsilon_{it}$  is the residual term, and  $\beta_0$  is the constant term.  $\beta_1$  is the coefficient of the core independent variable that we are interested in, and  $\beta_1 < 0$  significantly implies that climate risk has significant negative effects on  $ANPF_{it}$ .  $\beta_2$  is the coefficient of the control variables. We use Stata 17.0 software as our tool for all the empirical analysis.

### 3.3. Data Sources and Sample Selection

The data sources of this paper mainly include the following: (1) The data for indicator construction of agricultural new quality productive forces and the provincial panel data come from the China Rural Statistical Yearbook, China Environmental Statistical Yearbook, China Social Statistical Yearbook, China Energy Statistical Yearbook, China Energy Statistical Yearbook, CNRDS database, and Digital Finance Research Centre of Peking University. (2) The indicators used to construct the climate risk index are obtained from the public ETP server of the National Climatic Data Centre (NCDC) of the United States of America, a database that includes data from all meteorological observation stations in mainland China. In this paper, the average temperature and average rainfall of each city are obtained by determining the administrative area that belongs to each station. If there are no stations in the administrative area of a province, the average values of the four nearest stations are taken as the average temperature and average rainfall for that city.

After data collection and indicator construction, we matched the climate risk dataset with provincial panel data, removed data from years with missing key variables, and filled in missing values for individual provinces in certain years by interpolation. Finally, we obtained a balanced panel dataset containing 341 samples with 31 provinces from 2012 to 2022.

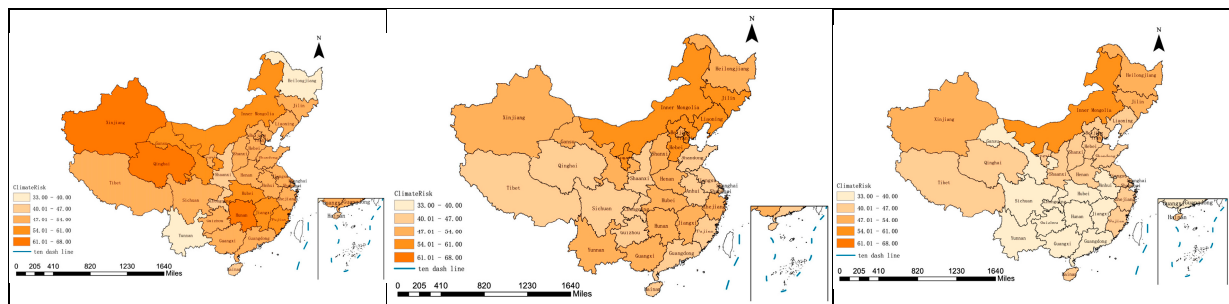
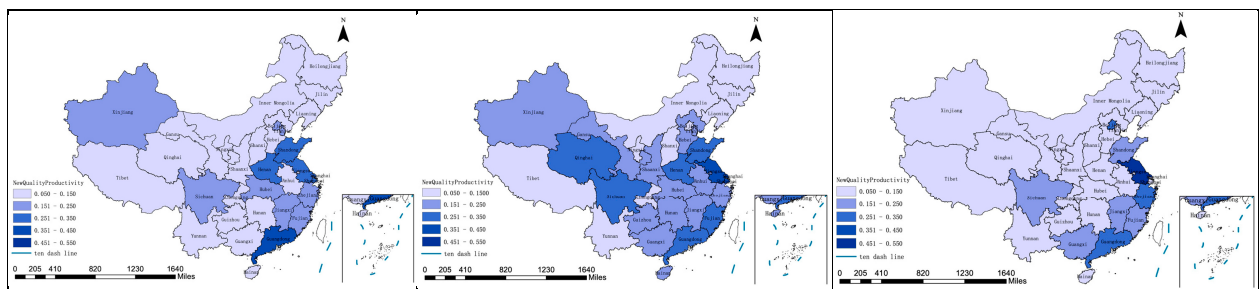
### 3.4. Descriptive Statistics

Table 3 reports the descriptive statistics of the main variables: the mean value of the ANPFs is 0.18 with a standard deviation of 0.09, and the minimum value is 0.05, which occurs in the Tibet Autonomous Region; the maximum value is 0.51, which occurs in Jiangsu Province. The mean value of the climate risk index (Clr) is 0.46, which indicates that the current level of climate change is high overall, and the standard deviation is 0.90, which indicates a large difference in climate risk among provinces. Specially, the minimum value of the climate risk index is 0.26, which occurs in Beijing, and the maximum value is 0.84, which occurs in the Xinjiang Uygur Autonomous Region.

In addition, we use ArcGIS 10.6 software to generate regional distribution maps of climate risks and APNFs in China. Figures 1 and 2 show the dynamic regional changes in climate risk and ANPFs, respectively. Specifically, Figure 1 shows that the western and northwestern regions are facing more severe climate risks, with an upward trend over time, which is consistent with the existing literature [49]. Furthermore, the development of ANPFs shows a distribution of being higher in eastern regions and lower in western regions, implying that the eastern region is developing faster than the central and western regions, which is consistent with the existing literature [3,24], confirming the authenticity and validity of the data in our study.

**Table 3.** Descriptive statistics.

| Variable | N   | Mean  | SD    | Min    | p50    | Max    |
|----------|-----|-------|-------|--------|--------|--------|
| ANPFs    | 341 | 0.180 | 0.090 | 0.0500 | 0.160  | 0.510  |
| Clr      | 341 | 0.460 | 0.090 | 0.260  | 0.460  | 0.840  |
| GDP      | 341 | 9.820 | 1     | 6.570  | 9.960  | 11.770 |
| Ind      | 341 | 1.400 | 0.740 | 0.610  | 1.230  | 5.240  |
| Gov      | 341 | 0.290 | 0.210 | 0.110  | 0.230  | 1.350  |
| Inn      | 341 | 10.78 | 1.530 | 5.140  | 10.940 | 13.81  |
| Urb      | 341 | 0.600 | 0.130 | 0.230  | 0.590  | 0.900  |
| RD       | 341 | 0.020 | 0.020 | 0      | 0.020  | 0.070  |
| Con      | 341 | 0.390 | 0.070 | 0.180  | 0.400  | 0.610  |
| Idu      | 341 | 0.320 | 0.090 | 0.0700 | 0.330  | 0.540  |

**Figure 1.** Dynamic evolution of climate risks in 2012–2022. Note: The samples in the above three figures are taken from 2012, 2017, and 2022, respectively.**Figure 2.** Dynamic evolution of agricultural new quality productive forces in 2012–2022. Note: the samples in the above three figures are taken from 2012, 2017, and 2022, respectively.

## 4. Empirical Results

### 4.1. Benchmark Regression Results

Table 4 presents the baseline regression results of the impact of climate risk on ANPFs. Column (1) presents regression without any control variables and fixed effects, and the results show that climate risk has a significant negative effect on the ANPFs. After the successive inclusion of control variables in Column (2) and the year fixed effect and province fixed effect in Column (3), the coefficient  $\beta_1$  remains significantly negative. Specifically, a 10% increase in climate risk leads to a 1.18% decrease in ANPFs, which suggests that climate risk significantly inhibits ANPFs, and we provide evidence that supports the previous literature, namely that climate risk is detrimental to high-quality agricultural development [14,16]. Thus, Hypothesis 1 is verified.

**Table 4.** Benchmark regression.

| Variable         | (1)<br>ANPFs          | (2)<br>ANPFs         | (3)<br>ANPFs          |
|------------------|-----------------------|----------------------|-----------------------|
| Clr              | −0.287 ***<br>(0.081) | −0.117 **<br>(0.052) | −0.118 ***<br>(0.042) |
| GDP              |                       | 0.058 **<br>(0.023)  | 0.085<br>(0.060)      |
| Ind              |                       | −0.019<br>(0.023)    | −0.018<br>(0.055)     |
| Gov              |                       | 0.075<br>(0.081)     | 0.043<br>(0.114)      |
| Inn              |                       | −0.003<br>(0.015)    | −0.038 **<br>(0.017)  |
| Urb              |                       | 0.034<br>(0.120)     | 0.032<br>(0.554)      |
| RD               |                       | 2.344 **<br>(1.040)  | 1.363<br>(1.035)      |
| Con              |                       | −0.164<br>(0.100)    | −0.018<br>(0.088)     |
| Idu              |                       | −0.110<br>(0.214)    | 0.254<br>(0.284)      |
| Cons             | 0.310 ***<br>(0.045)  | −0.265<br>(0.247)    | −0.307<br>(0.626)     |
| Year–Province FE | YES                   | YES                  | YES                   |
| Obs.             | 341                   | 341                  | 341                   |
| R <sup>2</sup>   | 0.071                 | 0.529                | 0.824                 |

Note: \*, \*\*, and \*\*\* indicate that the test statistics are statistically significant at the 10%, 5%, and 1% levels, respectively; standard errors are reported in parentheses below the coefficients.

#### 4.2. Robustness Test

##### 4.2.1. Endogeneity Test

Our study addresses endogeneity by identifying the cross-multiplication term between the provincial latitude and annual number of extreme weather days as an instrumental variable, following previous research [50,51]. Since the latitude of each province as an objective physical variable is unlikely to have a direct effect on the cultivation of ANPFs, this satisfies the exclusivity of the instrumental variable. Table 4 reports the results of the IV-2 SLS estimation. Column (1) shows that the coefficient in the first stage regression is 0.0002 and is significant at the 1% level, which indicates that the instrument variable is strongly associated with climate risk. The Kleibergen–Paaprk LM statistic rejects the hypothesis that the IV is underidentified at the 1% level. The Kleibergen–Paaprk Wald F statistic is higher than the critical value, indicating that it satisfies the weak instrumental test. Column (2) shows that the coefficient in the second stage regression is significant negative at the 1% level, indicating that climate risk continues to negatively and significantly affect the ANPFs after accounting for endogeneity.

Further, in order to alleviate the interference of omitted variables, we include control variables such as the fiscal support for agriculture (FAS), provincial climate policy uncertainty index (PCP), and agricultural modernization level (AML). The result is shown in Column (3). Finally, considering the two-way causality problem arising from the persistence of climate risk, this paper successively adds the climate risk index with one lag and two lags in the baseline model. The results are shown in Columns (4)–(5) of Table 5, which prove that the baseline regression results are robust.

**Table 5.** Endogeneity analysis.

| Variable                           | (1)<br>Clr            | (2)<br>ANPFs          | (3)<br>ANPFs         | (4)<br>ANPFs         | (5)<br>ANPFs         |
|------------------------------------|-----------------------|-----------------------|----------------------|----------------------|----------------------|
| Clr                                |                       |                       | −0.098 **<br>(0.047) | −0.102 **<br>(0.044) | −0.114 **<br>(0.050) |
| IV                                 | 0.0002 ***<br>(0.000) | −0.120 ***<br>(0.037) |                      |                      |                      |
| Lag 1 Clr                          |                       |                       |                      | −0.069 **<br>(0.031) | −0.063 **<br>(0.033) |
| Lag 2 Clr                          |                       |                       |                      |                      | −0.020<br>(0.051)    |
| Controls                           | YES                   | YES                   | YES                  | YES                  | YES                  |
| Year–Province FE                   | YES                   | YES                   | YES                  | YES                  | YES                  |
| Kleibergen–Paaprk LM statistic     | 68.561                |                       |                      |                      |                      |
| Kleibergen–Paaprk Wald F statistic | 2162.227              |                       |                      |                      |                      |
| Obs                                | 341                   | 341                   | 341                  | 341                  | 341                  |
| R <sup>2</sup>                     | 0.977                 | 0.102                 | 0.828                | 0.834                | 0.827                |

Note: \*, \*\*, and \*\*\* indicate that the test statistics are statistically significant at the 10%, 5%, and 1% levels, respectively; standard errors are reported in parentheses below the coefficients.

#### 4.2.2. Sample Adjust

Firstly, considering that the exogenous effect of the COVID-19 epidemic may bias the experimental results, we shortened the sample period to 2012–2019 and re-evaluated the robustness of our findings. Moreover, considering the specificity of the management system of the four municipalities directly under the central government in China, we re-evaluated the robustness of our findings by excluding the four municipalities directly under the central government. The results in Columns (1)–(2) in Table 6 present the regression analysis results after excluding the relevant samples, indicating that the effect of climate risk on ANPFs remains negative and significant, and the regression results are still verified.

**Table 6.** Adjustment of sample and explanatory variable weight.

| Variable         | (1)<br>ANPFs          | (2)<br>ANPFs         | (3)<br>ANPFs           | (4)<br>ANPFs           | (5)<br>ANPFs           | (6)<br>ANPFs          |
|------------------|-----------------------|----------------------|------------------------|------------------------|------------------------|-----------------------|
| Clr              | −0.080 ***<br>(0.029) | −0.085 **<br>(0.034) | −0.001 ***<br>(0.0002) | −0.001 ***<br>(0.0004) | −0.0009 **<br>(0.0004) | −0.001 **<br>(0.0005) |
| Controls         | YES                   | YES                  | YES                    | YES                    | YES                    | YES                   |
| Year–Province FE | YES                   | YES                  | YES                    | YES                    | YES                    | YES                   |
| Obs              | 248                   | 297                  | 341                    | 341                    | 341                    | 341                   |
| R <sup>2</sup>   | 0.892                 | 0.882                | 0.822                  | 0.823                  | 0.823                  | 0.825                 |

Note: \*, \*\*, and \*\*\* indicate that the test statistics are statistically significant at the 10%, 5%, and 1% levels, respectively; standard errors are reported in parentheses below the coefficients.

#### 4.2.3. Adjusting the Weights of Explanatory Variables

We adjusted the weights of the climate risk index variable. Specifically, we adjusted the weight of the extreme high temperature, extreme low temperature, extreme heavy rainfall, and extreme drought indices to 0.4 and the other extreme weather events to 0.2 (when an event is weighted at 0.4). The results are shown in Columns (3)–(6) of Table 6, indicating that the coefficient of climate risk is still significantly negative at the 1% level.

#### 4.2.4. Other Robustness

We conducted further robustness testing by Propensity score matching and adding the year–province fixed effect.

Propensity score matching (PSM) is a method that matches treatment and control groups by estimating the probability that an individual receives a certain treatment, thereby making the two groups comparable in terms of observable characteristics and simulating

the effects of a randomized experiment, which can effectively alleviate sample selection bias. The specific method is as follows: First, we generate a dummy variable *Clr\_treat* for climate risk (*Clr\_treat* = 1 when the climate risk of a province is higher than the median, and 0 otherwise), and select all control variables as provincial feature variables. Second, we use the Logit model to score the sample provinces. Third, we use the one-to-one nearest neighbor matching method for sample matching (with a caliper value of 0.05). Finally, we perform regression on the treated samples using Equation (1). The result is shown in Column (1) of Table 7, and the coefficient remains significantly negative at the 10% level.

**Table 7.** Other robustness: PSM and including year–province fixed effect.

| Variable.        | (1)<br>ANPFs        | (2)<br>ANPFs          |
|------------------|---------------------|-----------------------|
| Clr              | −0.087 *<br>(0.049) | −0.107 ***<br>(0.044) |
| Controls         | YES                 | YES                   |
| Year–Province FE | YES                 | YES                   |
| Year–Province FE | NO                  | YES                   |
| Obs              | 171                 | 341                   |
| R <sup>2</sup>   | 0.825               | 0.828                 |

Note: \*, \*\*, and \*\*\* indicate that the test statistics are statistically significant at the 10%, 5%, and 1% levels, respectively; standard errors are reported in parentheses below the coefficients.

We further added a year–province fixed effect to control the province-level factors that change over time and enhance the robustness of the experimental results. The result is shown in column (2) of Table 7, and the coefficient remains significantly negative at the 1% level.

## 5. Mechanism and Heterogeneity Analysis

### 5.1. Mechanism Analysis

According to the previous analysis, climate risk may negatively affect ANPFs by increasing the probability and severity of natural disasters. Therefore, we further construct Equation (2) to examine the effect of climate risk on natural disasters as follows:

$$\text{Dis}_{it} = \gamma_0 + \gamma_1 \text{Clr}_{it} + \gamma_2 \text{Control}_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (2)$$

*Dis<sub>it</sub>* indicates the severity of natural disasters in the province *i*. We select the crop-affected area (*Dis1*), area of crop failure (*Dis2*), total disaster-affected area (*Dis3*), and total disaster area (*Dis4*) (The difference between *Dis3* and *Dis4* is that *Dis3* shall not be double-counted, and if the same piece of land has been subjected to several disasters in succession, the affected area shall be counted only on the basis of the one that has resulted in the greatest and most serious damage.) to measure the severity of natural disasters in province *i*, and the meanings of the other variables are consistent with the Equation (1). The results are shown in columns (1) to (4) of Table 8. The coefficients of *Clr* are all significantly positive, indicating that climate extremes significantly increase the severity of natural disasters, confirming that natural disasters are the channel through which climate extremes affect agricultural new quality productive forces.

**Table 8.** Mechanism analysis.

| Variable            | (1)                  | (2)                  | (3)                  | (4)                  |
|---------------------|----------------------|----------------------|----------------------|----------------------|
|                     | DiS1                 | DiS2                 | DiS3                 | DiS4                 |
| Clr                 | 0.185 ***<br>(0.050) | 0.084 ***<br>(0.021) | 2.333 ***<br>(0.682) | 2.048 ***<br>(0.742) |
| GDP                 | 0.026<br>(0.068)     | 0.001<br>(0.029)     | −0.434<br>(0.616)    | −0.517<br>(0.691)    |
| Ind                 | −0.050<br>(0.037)    | −0.023 *<br>(0.014)  | −0.875*<br>(0.455)   | −0.922 **<br>(0.436) |
| Gov                 | −0.074<br>(0.129)    | −0.048<br>(0.051)    | −1.909<br>(1.460)    | −0.989<br>(1.768)    |
| Inn                 | 0.005<br>(0.025)     | 0.006<br>(0.010)     | −0.035<br>(0.188)    | 0.036<br>(0.214)     |
| Urb                 | 0.045<br>(0.397)     | −0.107<br>(0.184)    | −0.072<br>(4.463)    | −1.458<br>(6.354)    |
| RD                  | 0.737<br>(0.852)     | −0.022<br>(0.332)    | 9.820<br>(7.754)     | 2.212<br>(9.817)     |
| Con                 | −0.034<br>(0.074)    | 0.033<br>(0.041)     | −1.720*<br>(0.968)   | −0.823<br>(1.378)    |
| Idu                 | −0.352<br>(0.314)    | −0.157<br>(0.152)    | −6.600 *<br>(3.438)  | −6.426<br>(4.208)    |
| Cons                | −0.143<br>(0.651)    | 0.072<br>(0.266)     | 13.691 **<br>(5.604) | 13.434 **<br>(6.131) |
| Year–Province<br>FE | YES                  | YES                  | YES                  | YES                  |
| Obs.                | 341                  | 341                  | 341                  | 341                  |
| R <sup>2</sup>      | 0.505                | 0.425                | 0.879                | 0.844                |

Note: \*, \*\*, and \*\*\* indicate that the test statistics are statistically significant at the 10%, 5%, and 1% levels, respectively; standard errors are reported in parentheses below the coefficients.

We further analyze the economic implications of our mechanism. Specifically, natural disasters may affect the process of agricultural factor inputs and, ultimately, may have a negative impact on agricultural productivity. According to neoclassical growth theory, in addition to directly causing losses in output, natural disasters can also have adverse effects on the factors that are required for agricultural production (such as land, capital stock, labor quantity, and efficiency), thus increasing the marginal costs of agricultural production, which leads to a reduction in equilibrium agricultural output and is detrimental to the cultivation of ANPFs. For example, natural disasters lead to a reduction in water resources [20] and a decline in land use efficiency [19], negatively impacting agricultural product storage and agricultural production. Additionally, natural disasters directly cause damage to crops and the death of livestock [33]. Furthermore, labor is a crucial element in fostering new agricultural productivity, but there is evidence suggesting that natural disasters can increase external environmental uncertainty, leading farmers who previously engaged in agricultural labor to shift to non-agricultural sectors for employment [9,52], which results in labor outflow from the agricultural sector. Therefore, this paper argued that natural disasters are the mechanism by which climate risk affects ANPFs.

## 5.2. Heterogeneity Analysis

### 5.2.1. Agricultural Digital Economy

An increasing level of agricultural digital economy can effectively activate agricultural factor resources, mitigating the negative impact of climate risk on ANPFs. Therefore, we construct Equation (3) as follows to verify Hypothesis 3:

$$\text{ANPFs}_{it} = \beta_0 + \beta_1 \text{Clr}_{it} + \beta_2 \text{Digital}_{it} + \beta_3 \text{Clr}_{it} * \text{Digital}_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (3)$$

where  $\text{Digital}_{it}$  refers to the agricultural digital economy index of province  $i$  in year  $t$ . Considering the data availability, we synthesized rural digital economy indicators using the entropy method on digital infrastructure and digital technology. Specially,  $\beta_2 > 0$  and  $\beta_3 < 0$  implies that promoting agricultural digital economy can weaken the negative effects of climate risk on ANPFs.

The result in columns (1) of Table 9 shows that the coefficient of the core explanatory variables  $\text{Clr}$  is no longer significant with the inclusion of variable  $\text{Digital}$  and the interaction term  $\text{Clr} * \text{Digital}$ . The coefficient of  $\text{Digital}$  is 0.571 and is significant at the 1% level. Importantly, the coefficient of the interaction term  $\text{Clr} * \text{Digital}$  is  $-0.008$  and is significant at the 10% level, suggesting that agricultural digital economy weakens the reduction effects of climate risk on ANPFs, which verifies our Hypothesis 3.

**Table 9.** Heterogeneity analysis.

| Variable        | (1)<br>ANPFs         | (2)<br>ANPFs         | (3)<br>ANPFs          |
|-----------------|----------------------|----------------------|-----------------------|
| Clr             | −0.018<br>(0.045)    | −0.025<br>(0.055)    | 0.004<br>(0.042)      |
| Digital         | 0.570 ***<br>(0.191) |                      |                       |
| Clr * Digital   | −0.008 *<br>(0.005)  |                      |                       |
| EI              |                      | 2.752 ***<br>(0.864) |                       |
| Clr * EI        |                      | −0.050 **<br>(0.021) |                       |
| CI              |                      |                      | 0.045 **<br>(0.017)   |
| Clr * CI        |                      |                      | −0.001 ***<br>(0.000) |
| Controls        | YES                  | YES                  | YES                   |
| Yea/Province FE | YES                  | YES                  | YES                   |
| Obs.            | 341                  | 341                  | 331                   |
| R <sup>2</sup>  | 0.505                | 0.425                | 0.879                 |

Note: \*, \*\*, and \*\*\* indicate that the test statistics are statistically significant at the 10%, 5%, and 1% levels, respectively; standard errors are reported in parentheses below the coefficients.

### 5.2.2. Government Investment in Environmental Protection

Our study argues that provinces with greater government investment in environmental protection have better agricultural infrastructure and are more resilient to climate extremes, which can reduce the extent of damage to agricultural production. Therefore, we construct Equation (4) as follows to verify Hypothesis 4:

$$\text{ANPFs}_{it} = \beta_0 + \beta_1 \text{Clr}_{it} + \beta_2 \text{EI}_{it} + \beta_3 \text{Clr}_{it} * \text{EI}_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (4)$$

where  $EI_{it}$  is the government investment in environmental protection of province  $i$  in year  $t$ , measured by dividing the general public budget expenditure into environmental protection expenditure. The coefficients  $\beta_2$  and  $\beta_3$  reveal the moderating effect of government investment in environmental protection, indicating that government investment in environmental protection can relieve the negative impact of climate risk on agricultural new quality productive forces.

The result in column (2) of Table 9 shows that the coefficient of the core explanatory variable  $Clr$  is no longer significant with the inclusion of the variable  $EI$  and interaction term  $Clr * EI$ . While the coefficient of  $EI$  is 2.752 and significant at the 1% level, the coefficient of the interaction term  $Clr * EI$  is  $-0.009$  and is significant at the 10% level, which indicates that government investment in environmental protection has a prominent reduction effect on baseline results. This result support our Hypothesis 4.

### 5.2.3. Agricultural Insurance

As we mentioned above, agricultural insurance has a risk diversification and compensation function, by which it is able to diversify climate risk and provide risk compensation for economic consequences. Thus, we specify Equation (5) as follows to examine Hypothesis 5:

$$ANPF_{sit} = \beta_0 + \beta_1 Clr_{it} + \beta_2 CI_{it} + \beta_3 Clr_{it} * CI_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (5)$$

where  $CI_{it}$  is the coverage of agricultural insurance in province  $i$  in year  $t$ , calculated using agricultural insurance revenue divided by agricultural economic output. Similarly, we mainly focus on the coefficients  $\beta_2$  and  $\beta_3$ .  $\beta_2 > 0$  and  $\beta_3 < 0$  significantly indicate that deepening agricultural insurance coverage can sluggishly reduce the negative effects of climate risk on ANPFs.

The result in column (3) of Table 9 implies that the coefficient of the core explanatory variable  $Clr$  is no longer significant with the inclusion of the variable  $CI$  and interaction term  $Clr * CI$ . The coefficient of  $CI$  is 0.045 and is significant at the 5% level. The coefficient of interaction term  $Clr * CI$  is  $-0.001$  and is significant at the 1% level, suggesting that agricultural insurance weakens the negative impacts of climate risk on ANPFs, which supports Hypothesis 5.

## 6. Further Discussion

Geographic variations in agricultural productivity have been found to be differential [53] and resilient in climate change [54], thus we further discuss the heterogeneity effects across regional locations and geographic conditions. Firstly, we consider the regional location by the Yangtze River Economic Belt, which covers 11 provinces and cities along the river and is the most important grain-producing area with high agricultural modernization and obvious infrastructure advantages [55]. At the same time, the Yangzi River Delta is considered to be the pioneer in regional transformation and sustainable development [56,57], so the provinces located in the Yangtze River Economic Belt have natural location and policy advantages in coping with climate risk and fostering ANPFs. Secondly, in terms of terrain conditions, agricultural mechanization is relatively lower in the plateau area than in the plains, due to the undulating terrain, steep slopes, and other features [58], and the prevalence of machinery and equipment usage, as well as operational efficiency, is far less than the plains.

As in our analysis above, this study argues that climate risk has a weaker impact on the ANPFs in provinces located in the Yangtze River Economic Belt, as well as in the higher portions of the plain area. Therefore, we define provinces located in the Yangtze River Economic Belt and plains with more than 30% in an area as  $YR = 1$  and  $PL = 1$ , respectively, and  $YR = 0$  and  $PL = 0$  otherwise, and the results are shown in Table 10.

Columns (1) and (2) show that the negative effects of climate risk are more prominent in provinces located in the non-Yangtze Economic Belt ( $YR = 0$ ). Otherwise, the results in columns (3) and (4) show that the effect of climate risk on the ANPFs in provinces with more plains is not significant. Thus, we verify the heterogeneous impact of climate risk on provinces with different locations and geographic conditions.

**Table 10.** Discussion on locations and geographic conditions.

| Dependent Variable:<br>ANPFs | (1)<br>YR = 1        | (2)<br>YR = 0         | (3)<br>PL = 1         | (4)<br>PL = 0        |
|------------------------------|----------------------|-----------------------|-----------------------|----------------------|
| Clr                          | −0.093<br>(0.113)    | −0.109 ***<br>(0.032) | −0.044<br>(0.034)     | −0.143 **<br>(0.064) |
| GDP                          | −0.040<br>(0.142)    | 0.115<br>(0.068)      | 0.294 ***<br>(0.071)  | 0.033<br>(0.094)     |
| Ind                          | −0.023<br>(0.111)    | −0.003<br>(0.064)     | 0.024<br>(0.032)      | −0.056<br>(0.065)    |
| Gov                          | 1.130 ***<br>(0.257) | −0.015<br>(0.117)     | 0.101<br>(0.205)      | 0.074<br>(0.128)     |
| Inn                          | −0.050 *<br>(0.026)  | −0.012<br>(0.013)     | −0.043<br>(0.026)     | −0.041 *<br>(0.023)  |
| Urb                          | 0.892<br>(0.549)     | −0.237<br>(0.715)     | −0.620<br>(0.649)     | −0.040<br>(0.680)    |
| RD                           | 0.716<br>(0.863)     | 0.084<br>(1.431)      | −2.968 ***<br>(0.799) | 2.481 *<br>(1.355)   |
| Con                          | 0.052<br>(0.112)     | 0.008<br>(0.076)      | 0.244 **<br>(0.104)   | −0.129<br>(0.113)    |
| Idu                          | 1.318<br>(0.870)     | 0.003<br>(0.305)      | 0.259<br>(0.293)      | 0.049<br>(0.340)     |
| Cons                         | 0.002<br>(1.057)     | −0.609<br>(0.812)     | −2.008**<br>(0.772)   | 0.426<br>(0.953)     |
| Year–Province FE             | YES                  | YES                   | YES                   | YES                  |
| Obs.                         | 121                  | 220                   | 132                   | 209                  |
| R <sup>2</sup>               | 0.862                | 0.813                 | 0.910                 | 0.799                |

Note: \*, \*\*, and \*\*\* indicate that the test statistics are statistically significant at the 10%, 5%, and 1% levels, respectively; standard errors are reported in parentheses below the coefficients.

## 7. Conclusions, Implication and Policy Recommendation

### 7.1. Conclusions

Developing ANPFs is crucial in shifting China's agricultural development from increasing quantity to enhancing quality. Therefore, it is necessary to examine the causality between climate risks and ANPFs and take measures to mitigate the negative impact. Accordingly, this study utilized the panel data of 31 provinces in China from 2012 to 2022 to examine the impact of climate risk on ANPFs. The main conclusions are as follows:

(1) A 10% increase in climate risk leads to a significant decrease of 1.18% in ANPFs, and this result remains valid after a set of robustness tests. Our finding supports the previous literature, which suggests that climate risk is detrimental to high-quality agricultural development [14,16]. (2) Mechanism analysis further determines that natural disasters are the main channel through which climate risk restrains ANPFs, which is consistent with previous findings [32,36]. This result suggests that policymakers should take appropriate measures to prevent natural disaster risks for both farmers' expected income and the sustainability of agricultural production. (3) Heterogeneity analysis shows that the negative effects are weaker in those provinces with higher agricultural digital economy, greater government investment in environmental protection, and deeper agricultural insurance coverage [42,43]. (4) Further study finds that provinces located in the Yangtze River

Economic Belt and provinces with a higher proportion of plains would experience a smaller negative impact, which implies that location and geographical conditions should be fully considered when making climate risk policies.

Our findings are limited but significant for theoretical and practical implications. First, this study partially fills the research gap of climate risk and ANPFs, as well as providing theoretical and empirical references for future research. Second, our findings confirm the mutual role of farmers and enterprises that engage in agricultural production and mitigate the adverse effects of climate risks on agricultural production. Third, our findings provide important insights for the sustainable development of agriculture. We emphasized the destructive impact of climate risks on natural resources and the loss of labor resources in the agricultural sector.

As mentioned previously, our study remains limited in some ways. First of all, due to data availability, this study only constructs and calculates ANPFs at a province-level; relative research that extends to a prefecture-level, even an individual-level (such as farmer behavior) is necessary and should be made available in near future. Further, the channels through which climate risk affects ANPFs remain scantily described. In addition to natural disasters, future research on mechanism analyses can expand from other perspectives such as agricultural total factor productivity, industrial agglomeration, human capital, and supply chains. Last but not least, our study is implicated for developing countries since we use provincial observations as the objects of our study, which means that our findings maybe noneffective for countries with different economic levels or institution. This also makes one extension of future research.

## 7.2. Policy Recommendation

Based on the above conclusions, we suggest that policymakers should consider the following:

(1) Establish a natural disaster prevention system under the local conditions. Provinces with different locations and geographical conditions exhibit varied climate risk resilience and capability to resist natural disasters. Therefore, policymakers should improve disaster prevention systems across locations and geographical conditions, enhancing meteorological and agricultural disaster monitoring systems in the pre-disaster era, increasing ecological engineering projects such as farmland water conservancy and wetland restoration, and providing precise relief mechanisms. Additionally, low-carbon agricultural technologies should be promoted in post-disaster reconstruction, putting attention on enhancing agricultural meteorological capabilities of pre-warning and post-disaster recovery. These measures can minimize the extent of damage caused by natural disasters to agricultural production.

(2) Digital infrastructure can provide strong support for the development of ANPFs and promote the reconstruction and recovery of agricultural production. After natural disasters, digital infrastructure is helpful for the recovery and reconstruction of agricultural sectors, which improves the ability of agriculture to cope with multiple climate extremes and enhances the resilience of agricultural economy. Therefore, local government should actively promote agricultural digital infrastructure. First, it is important to increase institutional support for digital infrastructure in the agriculture sector. At the same time, it is also important to accelerate rural digital infrastructure so as to enhance the climate risk resilience of the agricultural sector. Second, governments should increase financing for digital infrastructure and allow private capital or social capital to participate in infrastructure construction. Finally, policymakers should consider the demands across regions and geographical conditions.

(3) Increasing government investment in environmental protection. First, governments should focus their investment on climate-adaptive agricultural technologies, establishing

a technology promotion system for climate-smart agriculture (CSA). Meanwhile, policy-makers can combine the Internet of Things (IoT) and big data technologies to establish an agricultural climate risk warning platform to optimize planting decisions. Second, governments should increase investment in green infrastructure (such as farmland water conservancy, flood control, and windbreak forests). Finally, the lack of formal credit financing channels is the primary reason for the insufficient capacity of farmers to cope with climate risks [11,12]; therefore, governments should encourage financial institutions to develop green financial tools related to agricultural climate insurance so that reduces farmers' income volatility.

(4) Improving the coverage of agricultural insurance. Insurance companies are encouraged to offer multi-tiered insurance and develop specialized weather insurance for high-value agricultural products. Governments should establish a climate risk protection fund jointly with insurance companies and financial institutions, while providing fiscal subsidies for agricultural insurance. Finally, governments should strengthen the promotion and training of agricultural insurance through agricultural technology promotion stations, enhancing farmers' awareness and trust in agricultural insurance.

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