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Climate Change, Farm Irrigation Facilities, and Agriculture Total Factor Productivity: Evidence from China

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Abstract: Due to the trend of global warming, individuals from all walks of life have paid close attention to how climate change affects food security. China is a sizable nation with a rich climate and a diverse range of food crops that are of interest to researchers. Additionally, there is little mention of agricultural technology and farm irrigation facilities in academic research on climate change and agricultural economic growth in China. As a result, this study uses the SBM model, panel fixed effect model, and SYS-GMM model to examine the development trend of climate change and food security based on the panel data of Chinese provinces from 2000 to 2020. The study found that China has maintained an average annual growth rate of 4.3% in agricultural total factor productivity (TFP) in recent years, despite the impact of extreme weather. The average annual precipitation has a depressing influence on the TFP in agriculture, while the average annual temperature has the opposite effect. The farm irrigation facilities and agricultural technology's moderating impact is mostly shown in how well they attenuate the impact of climate change on the TFP in agriculture. Food crops have thereby improved their ability to survive natural risks and attain higher yields as a result of advancements in agricultural technology and increasing investment in contemporary farm irrigation facilities. The study's conclusions are used in the article to make the suggestion that strengthening climate change adaptation is necessary to ensure food security. The strategic policy of "storing grain in technology and storing grain in the soil" and the advancement of contemporary agricultural technology must be put into reality while the management system for grain reserves is being improved.

Keywords: climate change; farm irrigation facilities; agriculture total factor productivity (TFP); technical advancement

Citation: Li, H.; Liu, H. Climate Change, Farm Irrigation Facilities, and Agriculture Total Factor Productivity: Evidence from China. *Sustainability* **2023**, *15*, 2889. https://doi.org/10.3390/su15042889

Academic Editor: Aaron K. Hoshide

Received: 16 December 2022
Revised: 31 January 2023
Accepted: 2 February 2023
Published: 6 February 2023

1. Introduction

The sustainability of agricultural development, which is essential for human survival, has been severely threatened by climate change [1]. The average annual surface temperature in China is increasing due to global warming at a rate of 0.23 °C every ten years. The distribution of temperature and precipitation over space and time will continue to vary due to climate change, which will also increase the frequency and severity of extreme events, including torrential rainstorms, floods, droughts, and insect outbreaks [2]. China has been able to feed 22% of the world's people on only 8% of the planet's territory while using a high-input, high-pollution agricultural growth model, but at a significant cost to resources and the environment. China's agriculture will need to adapt to a more effective, resource-efficient, and environmentally friendly development model in the future against the backdrop of high-quality and sustainable agricultural development as agricultural modernization progresses. Increasing agriculture's total factor productivity (TFP), which is often calculated as the ratio of the total agricultural output to total factor input, is the key to maintaining agricultural economic growth [3]. However, because of how it affects agricultural production and input levels, climate change, particularly extreme weather, has raised a great deal of uncertainty regarding the improvement of the agricultural TFP, making it necessary to find a solution [4]. Smallholder farmers can adopt a variety of adaptive strategies in response to climate change, including crop restructuring, more irrigation, and variety selection. However, it is insufficient to rely solely on farmers to take adaptive action [5]. Therefore, it is only possible to make up for the shortcomings of smallholder farmers in adapting to climate change by properly understanding the policy perspective.

Academics have conducted a great deal of research on agricultural TFP, farm irrigation systems, and climate change. First off, there are numerous studies on the effects of climate change on agricultural output in the body of existing literature, and this literature holds a dominant position [6–9]. Additionally, the effects of climate change on agricultural output are mainly detrimental [10]. There is still no agreement among academics regarding the effects of climate change on agricultural productivity due to the significant geographical differences in these effects. In addition, the model that uses unit yield as the explanatory variable allows researchers to examine how climate change affects various crop yields, but it falls short in its understanding of input-output efficiency [11,12].

Based on the difference in climate change indicators, Villavicencio et al. [13] examined the impacts of climate change on the TFP in U.S. agriculture from two perspectives: temperature and precipitation. The results show that annual precipitation had a significant positive effect on the TFP, but the precipitation density had a significant negative effect on the TFP, and temperature change did not have a significant impact on the TFP in most regions. Liang et al. [14] analyzed the effects of climate change on the TFP in agriculture at the seasonal and regional levels, showing that temperature and precipitation in different agricultural regions and seasons accounted for 70% of the TFP changes in U.S. agriculture from 1981 to 2010.

Based on the agricultural TFP of different industries, crops, or cash crops, further research on the effects of climate change on rice yield per plant (TFP) in Japan by Kunimitsu et al. [15] revealed that climate change has different influences on the TFP in different regions. According to Chen and Gong [16], in the short term, extremely high temperatures will negatively affect China's planting industry's TFP, leading to a greater loss in land output. The usual growth cycle of food crops is shortened by a rise in temperature, which also concerns the food supply and consumption due to aberrant precipitation and incalculable harm to grain production per unit area [17,18]. Due to changes in rainfall, evaporation, runoff, and other water-related processes, as well as the subsequent redistribution of water resources over time and geography and subsequent changes in soil moisture, food production is impacted by inadequate water supplies [19,20].

Second, many techniques are now available to measure the change in the agricultural TFP at various phases. The measurement results differ slightly as a result of the different input–output indicators and periods chosen, although the TFP is infrequently considered in studies of farm irrigation facilities. Numerous studies have been conducted on farm irrigation facilities, the majority of which are performance-focused and use the economic growth model as their theoretical framework. These studies examine the contribution of farm irrigation facilities to agricultural output with a focus on the associations between these facilities and economic growth, grain production, farmers' income, and the environment [21]. Scholars build performance evaluation index systems of governance and assess their direct performance, indirect performance, and total performance using the DEA model and network analysis following pertinent evaluation criteria such as the 3E, 4E, and IOO models [22]. The DEA Tobit two-step approach, S-SBM model, Malmquist–Luenberger index, three-stage DEA model, and UHSBM model were derived to provide an empirical analysis of infrastructure supply and investment performance from both static and dynamic perspectives, respectively. These models address the shortcomings of unintended outputs, environmental factors, and random factors.

Additionally, the impacts of farm irrigation infrastructure on agricultural production are mostly seen in four areas: agricultural growth, lowering production costs, fostering structural adjustment in the agricultural business, and fostering agricultural technology advancement [23,24]. The Cobb–Douglas production function model typically includes variables representing infrastructure investment for assessing the marginal effects of farm irrigation facilities on agricultural development [25]. Some academics have recently concentrated on the ecological and production value of agricultural production-related farm irrigation facilities [26]. We can assess the value of ecosystem services in terms of controlling greenhouse gas emissions and controlling the climate as well as conserving water, soil, biodiversity, and the environment to further investigate the effects of farm irrigation facilities on agricultural environmental efficiency [27–29].

The results of the literature search revealed that the majority of academics have also talked about how climate extremes affect food production. Furthermore, it has been established that boosting the building of farm irrigation facilities can significantly raise the quantity and quality of food produced. The relationship between climate change, farm irrigation facilities, and TFP in agriculture, however, has not received much attention from researchers. In addition, many academics have overlooked the impacts of both undesirable outputs and climate change when measuring the TFP in Chinese agriculture. Few academics have concentrated on the effect of farm irrigation facilities on the TFP in agriculture, notably the significance of agricultural technology, when researching the growth processes of China's agricultural economy.

The input structure varies greatly across China's huge territory and wealth of resources, climatic change, and farm irrigation facilities. Additionally, "living off the sky" continues to be the norm in most places. It is clear that two factors need to be prioritized to improve the agricultural TFP. To start, there are differences in the initial factor input for farm irrigation facilities, the structure of endowments, and the rate at which various regions develop agricultural technology. The second is the fluctuation of climatic conditions. The production structure of agricultural economic development changes with the environment. Thus, we need to precisely study how investments in farm irrigation facilities and climate change affect the trajectory of the agricultural TFP.

In light of this, using inter-provincial panel data and a theoretical model of economic growth, this study undertakes an empirical test. The SBM model is utilized in this work to assess the influence of undesirable production on China's agricultural TFP. In addition, the panel fixed-effect model and SYS-GMM model are suggested to precisely investigate the relationship between climate change, farm irrigation facilities, and China's agricultural TFP. On the one hand, we examine the crucial part that farm irrigation facilities play in the process of how harsh climate impacts food production. On the other hand, in order to supplement the already-present data on the variables impacting TFP in agriculture, the crucial component of technological advancement is introduced. It offers practical policy recommendations for managing the shocks brought on by climate change and guaranteeing food security.

This study looks at the effects of climate change, agricultural technology, and farm irrigation facilities on agricultural TFP and aims to innovate in the following areas:

(1) The impact of extreme weather on agricultural production. With global warming, extreme meteorological disaster events such as heavy rainfall, floods as well as droughts are frequent. The annual average surface temperature in China is rising at a rate of 0.26 °C/decade, bringing unpredictable changes to the spatial and temporal distribution of temperature and precipitation and increasing challenges to sustainable agricultural development. Therefore, this paper chooses the average annual precipitation and average temperature as the indicators of climate change, which is different from some scholars.

(2) The impact of non-desired output, i.e., agricultural carbon emissions, is taken into account when measuring TFP in agriculture. In addition, this method is different from other studies, such as DEA.

(3) Introducing two intermediary variables—farm irrigation facilities and agricultural technology—to broaden the scope of the research.

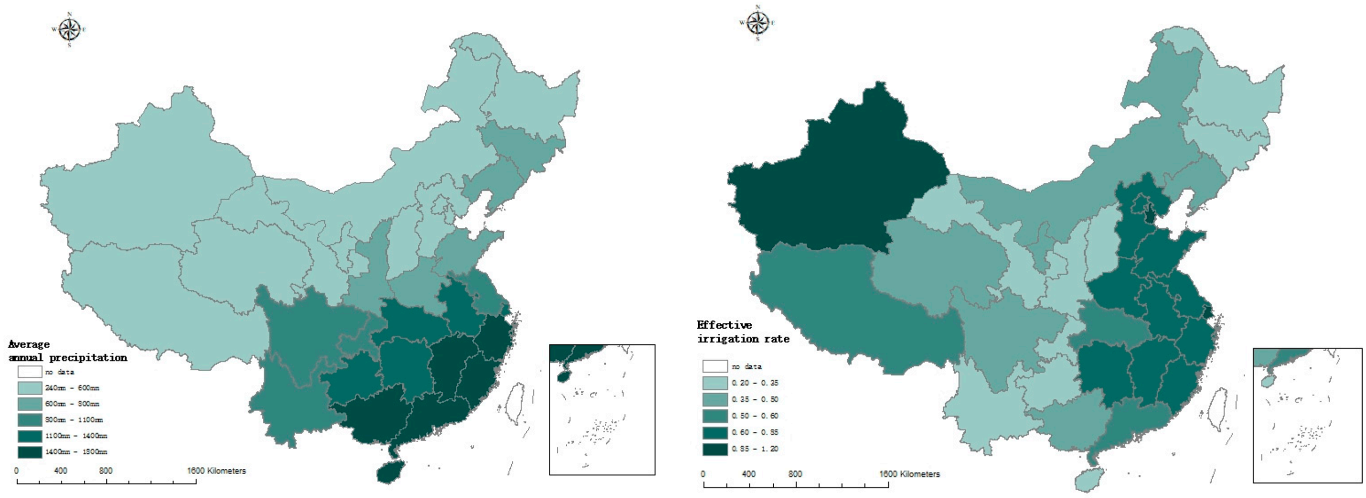
(4) Using the most recent years of data from 2000 to 2020 for the agricultural TFP measurement. Furthermore, this paper provides a scientific foundation and policy suggestions for future food security.

To this end, this paper is organized as follows: Section 2 illustrates the study area, methodology, models, indicator selection, and data sources used in this study. Section 3 discusses theoretical analysis and analyzes the impact of climate change and farm irrigation facilities on the total factor productivity growth in agriculture using an econometric model. Section 4 contains research conclusions and policy implications.

2. Materials and Methods

2.1. Study Area

The study area of the article is located in the eastern part of Asia and the west coast of the Pacific Ocean. At present, there are 34 provincial administrative regions in China, including 23 provinces, 5 autonomous regions, 4 municipalities directly under the central government, and 2 special administrative regions. Due to the limitation of data availability, this part of the empirical sample data mainly comes from relevant statistics for 31 provinces in China. The study area is shown in Figure 1.



(**a**) (**b**)

Figure 1. Digital elevation model of the study area. (**a**) Average annual precipitation in China from 2000 to 2020. (**b**) Prevalence of irrigation in China from 2000 to 2020; the ratio of the effective irrigated area to the cultivated area is known as the prevalence of irrigation. The figure includes the provincial boundaries (gray line). The files used to create the map are licensed under GS (2019) 1822 available at: http://www.gov.cn (accessed on 1 December 2022). The data on annual precipitation are taken from the National Weather Data Network (http://data.cma.cn, accessed on 1 December 2022). The data on the effective irrigated area to the cultivated area are taken from the EPS database (https://www.epsnet.com.cn, accessed on 1 December 2022), the *China Statistical Yearbook*, and the *China Rural Statistical Yearbook* (http://www.stats.gov.cn, accessed on 1 December 2022).

There are five different types of terrain in China's general topography: mountains, plateaus, basins, plains, and hills. The country is high in the west and low in the east. This offers a range of possibilities and settings for the growth of China's industry and agriculture. In China, the north and south experience significantly different wintertime temperatures, and summertime highs are typical across the board. Furthermore, the distribution of yearly precipitation is more southerly than northern, with more rain falling in the summer and autumn and less in the winter and spring. Agricultural productivity and other things are intimately tied to rainfall conditions.

Due to its size and the huge variations in its temperature and precipitation patterns, China has a complex and varied climate. This makes China a good location for growing the majority of the world's crops. China's climate has several elements that are helpful for the growth of agricultural production, but it also has some disadvantages. Droughts, floods, cold waves, and typhoons are the most common severe weather phenomena that have a significant influence on China. These disasters frequently have a negative impact on agricultural productivity and farmers' lives.

2.2. Methods

The impact of undesirable outputs is not taken into account when measuring efficiency using the conventional data envelopment analysis (DEA), which only considers economic benefits. This ignores the issue of input–output slackness and is at odds with the actual agricultural production process. This study employs an over-efficient SBM model with non-desired outcomes, which explicitly incorporates the slack variables of each input and output into the objective function. The impact of the slack variables on the measured values is discussed as the total factor productivity (TFP) of each province in the nation is measured using the Max DEA program from 2000 to 2020. The model expressions are as follows:

$$\begin{gathered}\rho^* = min\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{i0}}}{1+\frac{1}{S_1+S_2}\left(\sum_{j=1}^{S_1}\frac{S_j^g}{y_{j0}^g}+\sum_{k=1}^{S_2}\frac{S_k^b}{z_{k0}^b}\right)}\\ \text{s.t.}\begin{cases}x_0 = X\lambda + S^-, y_0^g = Y^g\lambda - S^g, z_0^b = Z^b\lambda + S^b\\ S^- \geq 0, S^g \geq 0, S^b \geq 0, \lambda \geq 0\end{cases}\end{gathered} \quad (1)$$

where, in the formula, ρ^* is the agricultural TFP, where $0 < \rho^* \leq 1$; S^-, S^g, and S^b are the slack vectors of inputs, desired outputs, and undesired outputs, respectively. x_i, y_j^g, and z_k^b are the input of i, the desired output of j, and the non-desired output vector of k, respectively. "0" is the evaluated unit. m, S_1, and S_2 are the number of input, desired output, and non-desired output elements. X, Y^g, and Z^b are matrices consisting of inputs, desired outputs, and undesired outputs. λ is the weight vector. When $S^- = S^g = S^b = 0$, $\rho^* = 1$, signifying that the decision unit is totally legitimate; otherwise, it denotes a loss and necessitates adjusting the input and output quantities.

Malmquist's proposal for the Malmquist Index was merged with the DEA theory to create the intertemporally variable TFP in 1953, and the equation is as follows:

$$TFP = \left[\frac{D_0^{t+1}(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_t, y_t)} \times \frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^t(x_t, y_t)}\right]^{1/2} = EC \times TC \quad (2)$$

where the technical efficiency change index and the technical progress change index, respectively, are denoted by the letters EC and TC. The expressions for each of these two are as follows:

$$\begin{gathered}EC = SEC \times PEC = \frac{S_0^t(x_t,y_t)}{S_0^t(x_{t+1},y_{t+1})} \times \frac{D_0^t(x_{t+1},y_{t+1})}{D_0^t(x_t,y_t)}\\ TC = \left[\frac{D_0^t(x_{t+1},y_{t+1})}{D_0^{t+1}(x_{t+1},y_{t+1})} \times \frac{D_0^t(x_t,y_t)}{D_0^{t+1}(x_t,y_t)}\right]^{1/2}\end{gathered} \quad (3)$$

where, in the formula, SEC and PEC are the scale efficiency change index and pure technical efficiency change index, respectively. The criteria for determining EC, TC, SEC, and PEC are the same. TFP > 1 denotes that the total factor productivity increases, TFP < 1 denotes that the total factor productivity decreases, and TFP = 1 denotes that the total factor productivity does not cause changes.

2.3. Model Specification

The article analyzes the data by constructing an adjustment model and mediation model using the panel fixed effect method and the SYS-GMM method. The text that follows displays the model's precise form.

2.3.1. Adjustment Model

The agricultural TFP is influenced by climate change and farm irrigation facilities. In order to study the adjustment effect of agricultural technology, the interaction term was set separately for precipitation and temperature using it. And, build the following model.

$$\begin{aligned} TFP_{i,t} &= \alpha_0 + \alpha_1 pre_{i,t} + \alpha_2 tem_{i,t} + \alpha_3 fru_{i,t} + \alpha_4 x_{i,t} + \mu_i + \varepsilon_{i,t} \\ TFP_{i,t} &= \alpha_0 + \alpha_1 pre_{i,t} + \alpha_2 tem_{i,t} + \alpha_3 fru_{i,t} + \alpha_4 tc_{i,t} + \alpha_5 tc_{i,t} * pre_{i,t} \\ &+ \alpha_6 tc_{i,t} * tem_{i,t} + \alpha_7 x_{i,t} + \mu_i + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

2.3.2. Mediation Model

A dynamic process affecting the agricultural TFP is influenced by beginning conditions as well as current factors affecting the agricultural TFP, among other things. In order to determine how climate change and farm irrigation facilities affect the agricultural TFP, this study attempts to control the initial conditions, incorporate the lagging term of the agricultural TFP ($TFP_{i,t-1}$) into the regression model, and build the following model.

$$\begin{aligned} TFP_{i,t} &= \alpha_0 + \alpha_1 pre_{i,t} + \alpha_2 tem_{i,t} + \alpha_3 fru_{i,t} + \alpha_4 x_{i,t} + \mu_i + \varepsilon_{i,t} \\ TC_{i,t} &= \alpha_0 + \alpha_1 pre_{i,t} + \alpha_2 tem_{i,t} + \alpha_3 fru_{i,t} + \alpha_4 x_{i,t} + \mu_i + \varepsilon_{i,t} \\ TFP_{i,t} &= \alpha_0 + \alpha_1 pre_{i,t} + \alpha_2 tem_{i,t} + \alpha_3 fru_{i,t} + \alpha_4 tc_{i,t} + \alpha_5 x_{i,t} + \mu_i + \varepsilon_{i,t} \\ TFP_{i,t} &= \alpha_0 + \alpha_1 TFP_{i,t-1} + \alpha_2 cli_{i,t} + \alpha_3 tem_{i,t} + \alpha_4 fru_{i,t} + \alpha_5 tc_{i,t} + \alpha_6 x_{i,t} + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{5}$$

In Formulas (4) and (5), TFP_{it} is the agricultural TFP of province i in year t; pre_{it} represents the climate variable of province i in year t, that is, the yearly precipitation; tem_{it} is the average temperature; fru_{it} is the input of farm irrigation facilities in year t in province i, that is, the effective irrigation area per capita; tc_{it} is the input variable for the Malmquist–Luenberger index in year t in province i; x_{it} is a control variable, including the rural road density, agricultural structure, population density, and fiscal decentralization; α is the parameter to be estimated; μ_i represents the fixed effect of each province; and $\varepsilon_{i,t}$ is the random error term. All variables are logged to avoid heteroskedasticity in the model.

2.4. Variables

2.4.1. The Agricultural TFP

Output variables: Including the expected output and undesired output, the expected output makes use of the grain output, whereas undesired output typically refers to non-point-source pollutants such as chemical oxygen demand (COD), nitrogen (N), or phosphorus (P), as well as other pollutants or agricultural carbon emissions. This paper intends to use agricultural carbon emissions as the undesired output.

The sources of agricultural carbon emissions have diverse characteristics. The sources of agricultural carbon emissions have been comprehensively identified as chemical fertilizers, pesticides, agricultural diesel, agricultural film, land plowing, and irrigation power consumption [30,31]. A method for calculating agricultural carbon emissions is built based on the sources of carbon in agriculture that have been recognized:

$$E = \sum E_i = \sum T_i \times \delta_i \tag{6}$$

where, in the formula, E is the total amount of agricultural carbon emissions, i is the type of agricultural carbon sources, T_i is the consumption of each carbon source, and δ_i is the carbon emission coefficient of each carbon source. The coefficient is 0.8956 kgC/kg, the carbon emission coefficient of pesticides is 4.9341 kgC/kg, the carbon emission coefficient of the agricultural film is 5.18 kgC/kg, the carbon emission coefficient of diesel is 0.5972 kgC/kg, the carbon emission coefficient of tillage is 312.6 kgC/hm^2, and the carbon emission coefficient of agricultural irrigation should be 25 kgC/hm^2 [32,33].

Input variables: This paper only chooses seven indicators as input variables—labor, machinery, fertilizer, pesticide, agricultural film, diesel oil, and land—in order to comply with the empirical rule of the decision-making unit (DMU) and the number of input variables in DEA analysis [34–36]. The mechanical power input, for example, refers to the total power index of various agricultural machines, including tractors, balers, and seeders used in agricultural output, etc. [37]. The labor force input is based on the number of rural residents per unit area in each region [38]. The amount of agricultural chemical fertilizers applied in each region (in pure volume), pesticide input (the amount of pesticides per unit area in each region), agricultural film input (the amount of agricultural plastic film per unit area in each region), diesel input (the amount of agricultural diesel per unit area in each region), and land input (the effective irrigated area at the end of each region) are used because considering that the article measures the TFP of agriculture, combined with the common phenomenon of agricultural replanting, fallow, and abandonment in China, the ratio of effective irrigated area to cultivated land area and crop sown area are used instead. Agricultural land input is more accurate.

2.4.2. Climate Variables

The influence of climate change on agricultural production is mostly evident in temperature and precipitation [39]. Since this paper focuses on the agricultural TFP of food crop production, annual precipitation is used to measure the impact of climate change on agriculture. The accumulated temperature variable, which is frequently used in agronomy, reflects the impact of temperature on the growth and development of food crops from two aspects: temperature and time [40]. The TFP's impact is comparatively more consistent. In order to quantify the impact of climate change on the agricultural TFP, this research constructs the relationship between annual precipitation and the average temperature and TFP [41].

2.4.3. Farm Irrigation Facilities

At present, scholars usually utilize two types of indicators, monetary and physical, for measurement. However, monetary indicators tend to depart from the true worth of infrastructure since they are usually direct sums of investment volumes, while physical indicators are similarly incorrect due to variances in units of measurement. Usually, the more accurate way is to utilize the perpetual inventory method to estimate agricultural irrigation facilities, but the selection of the depreciation rate and initial capital stock has a significant impact on the inventory results [42,43]. Therefore, experts have varying estimations of farm irrigation facilities. Therefore, based on synthesizing the available research literature, this work selects the effective irrigated area as an index to measure the input of farm irrigation infrastructure.

2.4.4. Control Variables

Several factors affect grain output, farmers' income, and economic development level. In order to objectively evaluate the impact of climate change and farm irrigation facilities on the agricultural TFP, combined with previous research and actual conditions, the model also selected the agricultural structure, and seven disaster factors that have a significant impact on the agricultural TFP are used as control variables (see Table 1).

Table 1. Index system for evaluation of agricultural infrastructure governance efficiency.

First-Level Indicator	Secondary Indicators	Specific Description
Explained variable	*tfp*	Agricultural total factor productivity
Explanatory variables	*pre*	Average annual precipitation
	tem	Average temperature
Moderator	*fru*	Effective irrigation area per capita
	tc	Malmquist index
Control variable	*aff*	Affected area/crop sown area
	cap	Water conservancy investment
	eng	Food consumption expenditure/rural household consumption expenditure
	fer	Fertilizer application per unit area by region
	fil	Usage of agricultural plastic film per unit area by region
	inv	Water conservancy investment
	wat	Waterlogging area per capita

Note: The table is organized by the author.

2.5. Data Sources and Statistical Analysis

The time range of the above variables is from 2000 to 2020. The source data are primarily taken from the EPS database (https://www.epsnet.com.cn, accessed on 1 December 2022), the *China Statistical Yearbook*, and the *China Rural Statistical Yearbook* (http://www.stats.gov.cn, accessed on 1 December 2022).

The economic data of agricultural inputs and outputs as well as climate data for each province from 2000 to 2020 were compiled into a table in accordance with pertinent databases and statistical yearbooks. A descriptive statistical analysis was then carried out for each indicator's data, and the results are shown in Table 2.

Table 2. Descriptive statistics of different variables in China from 2000 to 2020.

Variables	Mean	Standard Deviation	Minimum Value	Maximum Value
tfp	1.01682	0. 0936045	0. 7184745	1.30906
pre	1384.856	2262.111	167	15,574.63
tem	13.84364	5.379699	2.998849	24.80421
fru	1062.781	775.7506	217.1962	4066.159
tc	1.012202	0.1122717	0.6795132	1.363629
aff	0.2085708	0.145902	0	0.6460758
cap	407.8922	308.2451	38.0959	1598.9
eng	0.3802011	0.0760678	0.259	0.56
fer	579.413	264.1651	170.0166	1396.03
fil	31.38759	30.8204	4.710912	148.1515
inv	1218.027	1278.347	52.809	5638.867
wat	3644.95	4690.888	24.46483	21,561.78

Note: Data compiled by the authors.

3. Results

3.1. Trend and Regional Analysis of Agricultural Total Factor Productivity (TFP)

The agricultural TFP for the entire country is calculated in this research using the Max DEA software and the super-efficiency SBM model, incorporating unexpected production. The dynamic trajectory of the agricultural TFP in various grain-producing regions is considerably diverse from 2000 to 2020, as illustrated in Figure 2. The primary regions for producing grain have an upward tendency overall. The agricultural TFP in this region has been in a good and steady state for a long time, and the agricultural output has resulted in some economic gains, except in 2003, when the governance efficiency was lower than 0.5; the agricultural TFP in the main grain-selling locations varies substantially.

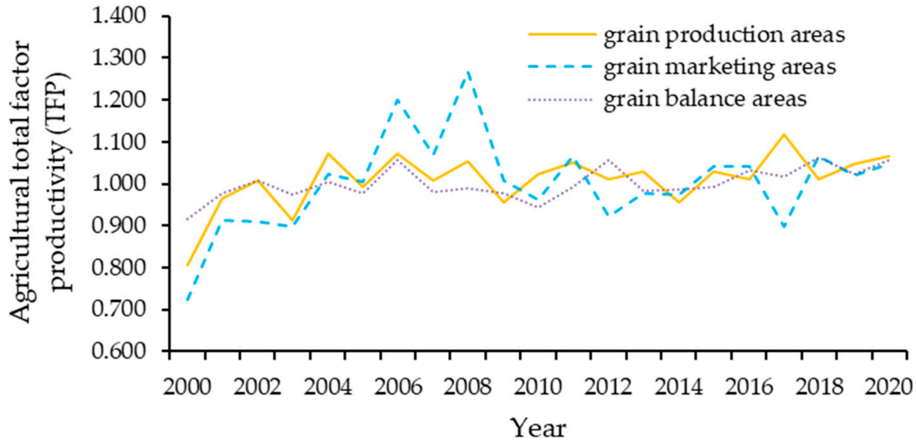


Figure 2. Internal mechanism of farm irrigation facilities affecting the agricultural TFP operation diagram. (China can be divided into three categories, including grain production areas, grain marketing areas, and grain balance areas. Of these, there are 13 grain production areas, including Heilongjiang, Jilin, Liaoning, Inner Mongolia, Hebei, Henan, Shandong, Jiangsu, Anhui, Jiangxi, Hubei, Hunan, and Sichuan; 7 grain marketing areas, including Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan; and 11 grain balance areas, including Shanxi, Ningxia, Qinghai, Gansu, Tibet, Yunnan, Guizhou, Chongqing, Guangxi, Shaanxi, and Xinjiang).

The other 25 Chinese provinces increased positively between 2000 and 2020, as indicated in Table 3, except for Guangdong, Hainan, Guizhou, and Shaanxi, where the TFP was less than 1. The fact that it was larger than 0.970 and that Jilin Province had the highest score and Guizhou Province had the lowest index among them showed that TFP in China was still progressing well. Additionally, the average annual growth rate of the agricultural TFP in the 29 provinces was 4.3%, slightly higher than the findings of the other scholar. The ability to tolerate natural risks has increased grain production in recent years, despite the impact of harsh weather. This is because investments in modern irrigation and water conservation facilities have increased due to technological advancement. However, the precise causes demand further investigation.

Ningxia and Shanghai had the lowest indexes, both of which were not high, showing that further advancement in agricultural technology is needed to accelerate the development of modern agriculture. Less than half of the provinces reached above 1 on the technological progress and change index (TC) from 2000 to 2020, with the lowest indexes being low values in both cases. Only four provinces had an index of technical efficiency change (EC) below 1, which was consistent with the TFP comparison result and showed that China's agricultural technological level was in good shape. There are 11 provinces in which all three major indexes are larger than 1, and EC is primarily responsible for the rise in TFP, according to the three major indexes. It is clear that in order to raise the local TFP, each province in the nation should concentrate on raising its technological level and increasing its investment in agricultural production.

The national agricultural total factor productivity (TFP) value, which accounts for inputs from farmland and water facilities, can be seen in Figure 3. It fluctuated from 0.821 in 2000 to 1.040 in 2004 and then from 2005 to 2020, except in 2005, 2009, 2010, and 2014, wherein the TFP remained above 1. The average TFP showed an upward trend from 2000 to 2004 and an upward trend from 2005 to 2020, with the smaller fluctuations being brought on by the varying trend of the technological progress change index (TC). The technical efficiency index (EC) is influenced by both the scale efficiency change index (SEC) and the pure technical efficiency change index (PEC), with the mean value of the pure technical efficiency change index (PEC) trending more similarly while the scale efficiency change index has a different trend. Additionally, the mean value of total factor productivity (TFP) and mean value of the technical efficiency index (EC) are relatively similar (SEC). This suggests that the technical efficiency index (EC) and the pure technical efficiency index of change have a significant impact on the total factor productivity (TFP) in agriculture (PEC).

Table 3. TFP of agriculture in China from 2000 to 2020.

Province	TFP	EC	TC
Hebei Province	1.028	1.030	0.997
The Nei Monggol Autonomous Region	1.012	1.004	1.007
Liaoning Province	1.056	1.063	0.993
Jilin Province	1.328	1.326	1.001
Heilongjiang Province	1.014	1.016	0.998
Jiangsu Province	1.230	1.225	1.004
Anhui Province	1.019	1.021	0.999
Jiangxi Province	1.008	1.003	1.005
Shandong Province	1.064	1.067	0.998
Henan Province	1.034	1.033	1.001
Hubei province	1.025	1.024	1.001
Hunan Province	1.026	1.025	1.001
Sichuan Province	1.025	1.023	1.002
Beijing	1.071	1.046	1.024
Tianjin	1.116	1.127	0.990
Shanghai	1.006	1.023	0.984
Zhejiang Province	1.112	1.108	1.003
Fujian Province	1.000	0.990	1.010
Guangdong Province	0.998	1.012	0.987
Hainan	0.980	0.962	1.019
Shanxi Province	1.041	1.048	0.994
The Guangxi Zhuang Autonomous Region	1.015	1.017	0.998
Guizhou Province	0.978	0.991	0.987
Yunnan Province	1.017	1.023	0.994
Shaanxi Province	0.998	0.932	1.071
Gansu Province	1.010	1.018	0.992
Qinghai Province	1.028	1.033	0.995
The Ningxia Hui Autonomous Region	1.023	1.040	0.984
The Xinjiang Uygur Autonomous Region	1.009	1.002	1.007

Note: Data are calculated by Max DEA software. TFP = EC × TC = PEC × SEC × TC.

3.2. Analysis of the Impact of Climate Change on the Agricultural TFP

The Hausman test findings for model (1) in Table 4 indicate that the panel fixed effect model is preferable to the mixed regression and random effect models. In terms of the regression results of the explanatory variables, while precipitation has played a negative, but not significant, role on the agricultural TFP, temperature has a significant positive effect on the agricultural TFP. The reason is that precipitation irregularity increases the likelihood of geological disasters such as floods and damage to food production, transportation, and other links, endangering food supply and utilization. The annual precipitation varies greatly across the entire nation and exhibits an upward trend, with four peaks occurring in 2010, 2012, 2016, and 2020, so it is not significant. In comparison to other years, 2016 had much more precipitation, whereas the highest amount of precipitation in 2011 was very low (as shown in Figure 4). Data analysis demonstrates that China's average annual accumulated temperature of 13 to 15 °C in the range of floating, in general, is rising. In 2007, 2017, and 2019, there were three relatively obvious annual accumulated temperature peaks, and in 2012, there were the most resources; climate change is the most direct characteristic of climate warming. For crops well north, the winter cold brings beneficial effects, resulting in increased grain production [44].

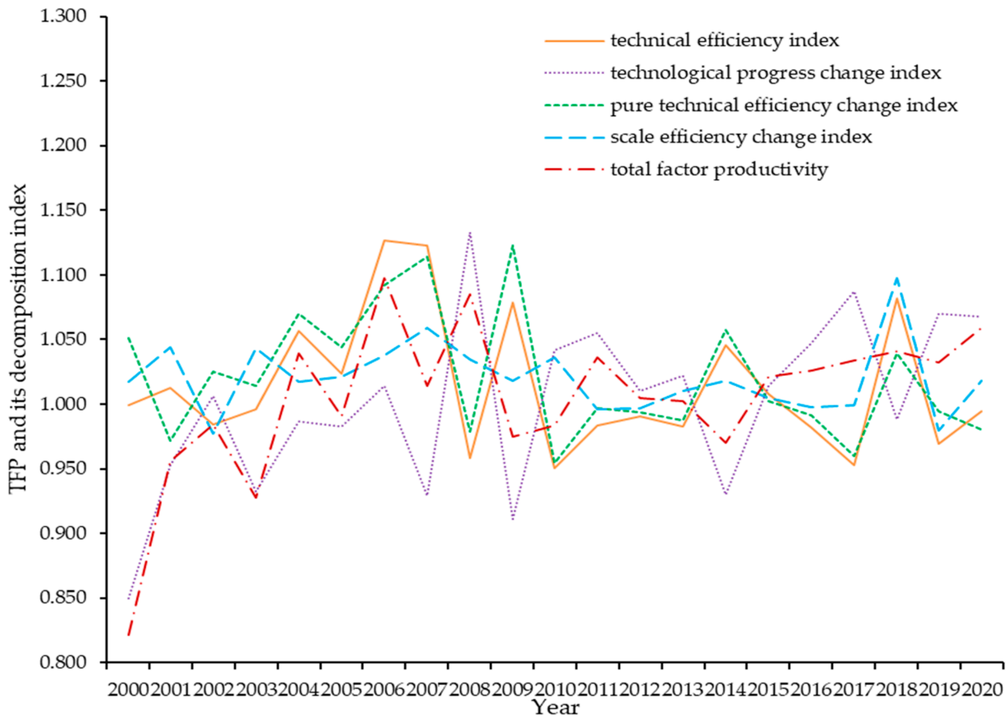


Figure 3. Trend chart of the agricultural total factor productivity (TFP) and its decomposition indicators from 2000 to 2020. (TFP = EC × TC = PEC × SEC × TC, TFP is agricultural total factor productivity, EC is the technical efficiency index, TC is the technological progress change index, PEC is the pure technical efficiency change index, and SEC is the scale efficiency change index).

The moderating factors were decentralized to prevent multicollinearity, and the moderating effect was examined using the panel fixed-effect model. The panel fixed-effect model outperformed the random-effect model, according to the Hausman test. According to model (2)'s findings, the temperature had a positive main effect coefficient on the agricultural TFP, whereas precipitation had a negative main effect coefficient. Agricultural technology served as a moderating factor that attenuated some of the negative effects of rising precipitation on the agricultural TFP. The coefficient of the interaction term between agricultural technology and precipitation was positive but insignificant. With the advancement of science and technology, factors such as breeding technology, greenhouses, and the widespread use of agricultural technology have significantly reduced the impact of natural disasters on food production and improved the security of grain production [45–47]. These factors, along with climate change brought on by a lack of resources such as water, heat, and other resources, have contributed to global warming [48]. The negligible coefficient of the interaction term between agricultural technology and precipitation, however, may have two causes. On the one hand, there is an irregular tendency in the current precipitation situation in China. According to research, a 20% decrease in rainfall will render useless any technology used to boost the productivity of food crops. Agricultural technology has a limited ability to reduce precipitation. On the other hand, the regulation effect of irrigation technology on precipitation instability may be weakened due to the early construction and heavy damage of farm irrigation facilities and the serious abandonment of mechanical wells caused by the beginning of the groundwater protection plan, which is consistent with the small regression coefficient of the interaction term between climate change and the input of farm irrigation facilities mentioned above [49].

Table 4. Estimation results of climate change on the agricultural TFP.

Variables	**(1)**	**(2)**
lnpre	−0.0160 * (−1.80)	−0.00997 (−1.17)
tem	0.0264 ** (2.16)	0.0289 ** (2.52)
lnfru	0.108 *** (3.05)	0.0818 ** (2.47)
lncap	0.0331 (1.33)	0.0452 * (1.93)
lnaff	−0.370 *** (−6.47)	−0.266 *** (−4.74)
lneng	0.0563 (1.10)	0.0275 (0.57)
lnfer	−0.0756 ** (−2.06)	−0.0661 * (−1.92)
lninv	−0.0177 * (−1.68)	−0.0124 (−1.25)
lnfil	−0.0115 (−1.10)	−0.0143 (−1.44)
lnwat	0.0120 (0.39)	0.0150 (0.52)
tc		0.324 *** (7.80)
c_lncli_tc		0.0315 (0.55)
c_tem_tc		−0.0401 *** (−3.95)
_cons	−0.504 (−1.20)	−0.954 (−2.38)
N	522	522
adj. R2	0.0658	0.1825

Note: ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively, with standard errors in parentheses; the same below.

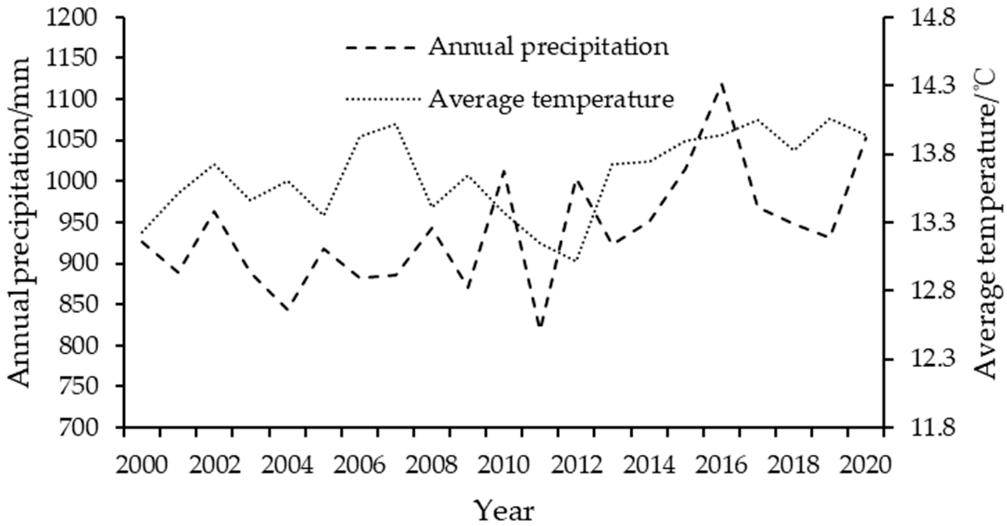


Figure 4. Trend chart of the average annual precipitation and the average temperature in China from 2000 to 2020 (http://data.cma.cn, accessed on 1 December 2022).

Agricultural technology, as a moderator variable, significantly reduces the temperature rise's positive influence on the agricultural TFP due to the sharp rise in temperature and aggravation of drought, plant diseases, and insect pests; it also affects the crop quality, causes an increase in extreme weather, and poses a threat to agricultural production [50]. Agricultural technology and a temperature interaction coefficient under the 1% level are significantly negative.

The paper offers a simple theoretical model to explain the influence of climate change on the agricultural TFP and the function of farm irrigation facilities based on the aforementioned literature review. Agriculture is considered to conform to the standard C-D production function form:

$$Y = AF\ (K, L) \tag{7}$$

where Y stands for the agricultural output; A stands for the agricultural TFP; and K and L stand for the capital and labor inputs for agricultural production, respectively.

In addition, A = θT, that is, A is a function of factor allocation (θ) and agricultural technological progress (T). Farm irrigation facilities do, however, have a ceiling effect ($\theta \leq 1$) that reduces the efficiency with which agricultural output elements are distributed. Therefore, T' (f) = 0, θ'(f) $\geq$ 0, θ''(f) $\leq$ 0, and f stands for farm irrigation facilities.

This paper analyses the impact of climate factors on the agricultural TFP, which is denoted by *cli*. The formula is as follows:

$$\frac{dA}{dcli} = \frac{\partial A}{\partial cli} + \frac{\partial A}{\partial \theta(f) T(f)} \cdot \frac{\partial \theta(f)}{\partial cli} \cdot \frac{\partial T(f)}{\partial cli} = \frac{\partial A}{\partial cli} + \frac{\partial A}{\partial f} \cdot \frac{\partial f}{\partial cli}, \tag{8}$$

The influence of climate change on the agricultural TFP is dependent on two factors: the direct effect of climate on the TFP and the indirect effect of climate change on the TFP, which is the input of farm irrigation facilities on the effectiveness of factor allocation θ and technical advancement.

Conclusion 1: Technological progress plays a regulatory role.

3.3. Analysis of the Impact of Farm Irrigation Facilities on the Agricultural TFP

The panel fixed effect model is used in this study to investigate the relationship between farm irrigation facilities, technological advancement, and the agricultural TFP based on the intermediary effect. The first-order lagged TFP is used as the instrumental variable in the systematic GMM estimate approach to show how climate change affects TFP, and the data passed the robustness test. Table 5 displays the findings, which demonstrate that model (6) passed the test for instrumental variables. The residual terms only possessed a first-order serial correlation, according to the findings of the AR (1) and AR (2) tests, and there was no second-order autocorrelation. All of the Hansen statistics' P-values were higher than 0.1, proving the validity of the instrumental variables.

According to the results of model (5)'s estimation, the agricultural TFP with one lag period passed the positive significance test at the 10% level in all models, suggesting that capital accumulation in the early stages may not have a positive impact on agricultural economic growth in the later stages and that there may be a phenomenon known as diminishing marginal utility. It has been demonstrated, however, that TFP does exhibit "inertia" in time series. A continuous accumulation adjustment process is being used to improve the agricultural TFP.

The coefficient of farm irrigation facilities in model (3) is significantly positive based on the regression results, indicating that these facilities have a positive spillover effect on grain production growth and that accelerating infrastructure investment is a key strategy for enhancing the agricultural TFP. The accumulation of farm irrigation facilities is the primary internal component of technical advancement, which is consistent with model (4)'s finding that the coefficient of farm irrigation facilities is significantly positive. Model (5) shows that agricultural technology and farm irrigation facilities have a significant positive impact on the agricultural TFP, suggesting that technological advancement has a mediating effect. Model (6) shows that accelerated technical innovation and progress can boost the improvement of the agricultural TFP. These results are consistent with the estimated results of the fixed effects.

Table 5. Estimation results of farm irrigation facilities on the agricultural TFP.

Variables	(3) *lntfp*	(4) *tc*	(5) *lntfp*	(6) *lntfp*
lnpre	−0.0160 *	−0.00108	−0.0157 *	−0.0189
	(−1.80)	(−0.12)	(−1.85)	(−1.47)
tem	0.0264 **	−0.0000847	0.0264 **	0.0116 **
	(2.16)	(−0.01)	(2.27)	(2.20)
lnfru	0.108 ***	0.0879 *	0.0818 **	0.0884
	(3.05)	(2.39)	(2.42)	(1.52)
lncap	0.0331	−0.0171	0.0381	0.0405
	(1.33)	(−0.66)	(1.60)	(1.44)
lnaff	−0.370 ***	−0.150 *	−0.326 ***	−0.346 **
	(−6.47)	(−2.52)	(−5.94)	(−2.73)
lneng	0.0563	0.110 *	0.0239	−0.122 *
	(1.10)	(2.06)	(0.49)	(−1.77)
lnfer	−0.0756 **	0.00322	−0.0765 **	−0.103 *
	(−2.06)	(0.08)	(−2.19)	(−2.74)
lninv	−0.0177 *	−0.00704	−0.0156	−0.0390 **
	(−1.68)	(−0.64)	(−1.56)	(−2.12)
lnfil	−0.0115	0.0266 *	−0.0193 *	0.0000478
	(−1.10)	(2.44)	(−1.92)	(0.00)
lnwat	0.0120	0.0338	0.00206	−0.0343
	(0.39)	(1.05)	(0.07)	(−1.20)
tc			0.293 ***	0.248 *
			(7.06)	(1.85)
L.lntfp				−0.153 *
				(−2.02)
_cons	−0.504	0.355	−0.608	
	(−1.20)	(0.81)	(−1.52)	
N	522	522	522	493
adj. R^2	0.0658	0.0290	0.1516	
AR(1)				−2.84
AR(1) p-value				0.005
AR(2)				−0.14
AR(2) p-value				0.888
Sargan-test				23.03
Sargan-test p-value				0.113

Note: L.TFP is the agricultural TFP of the lag period. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively, with standard errors in parentheses.

This research also investigates the underlying mechanisms through which the investment in farm irrigation facilities impacts the agricultural TFP. To find the solution to this question, we can simultaneously derive the input of agricultural irrigation facilities on both sides of Equation (8):

$$\frac{d^2A}{dclidf} = \frac{\partial^2 A}{\partial cli \partial f} + \frac{\partial^2 A}{\partial^2 f} \cdot \frac{\partial f}{\partial cli}, \tag{9}$$

The left side of Equation (9), which can be broken down into direct impacts and indirect effects of farm irrigation facility investment, shows how farm irrigation facility investments are used to deal with the consequences of climate change on the agricultural TFP.

The technical effects of farm irrigation facilities primarily consist of two aspects, as depicted in the figure: (1) horizontal effect: assuming that the agricultural technical conditions of T1 do not change, the increase in the stock level of farmland water conservancy facilities (as shown in Figure 5, from f1 to f2) will increase the allocation efficiency of agricultural production factors, and the agricultural TFP will also gradually rise; (2) growth effect: based on the assumption that exogenous agricultural technical circumstances exist, the agricultural TFP will steadily rise from T1 to T2, while the marginal utility will fall. This means that a higher level of farmland and farm irrigation facilities will correlate to a lower θ' and A′.

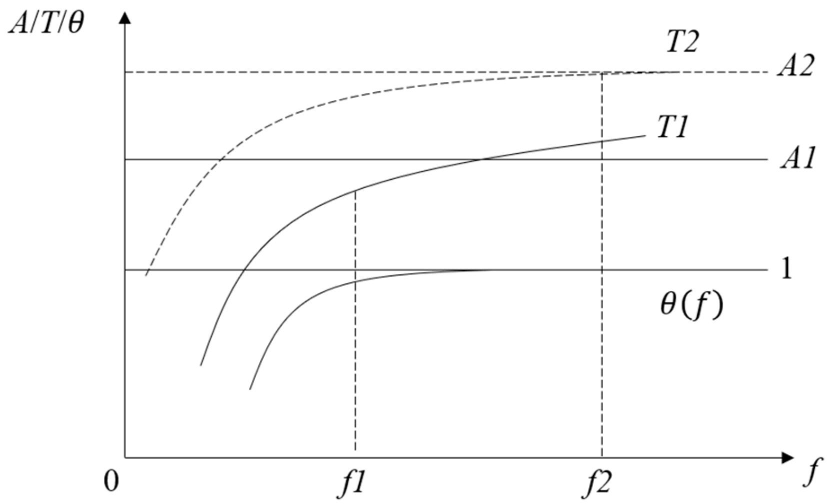


Figure 5. Diagram of internal mechanisms of farm irrigation facilities affecting agricultural TFP operations.

Conclusion 2: Technological progress plays an intermediary role in the process of TFP affected by farm irrigation facilities.

3.4. Limitations and Implications

Climate change is one of the shifts the world is going through. According to this paper's analysis of climate change in China from 2000 to 2020, which is also in line with the conclusions of Li et al. [51], China is currently undergoing extreme warming. Alexander et al. [52] conducted research on extreme climate change, and the results showed that 70% of the world's land area exhibits a growing trend toward a continuous decline in the number of cold night days and a continuous increase in the number of warm night days. As a result, the Chinese region fits with the trend of global climate change. The results of earlier investigations are more compatible with the finding that the intensity of precipitation increases with some variations in precipitation variability [53].

Precipitation was shown to be the principal growth factor impacting grain output and to have a suppressive effect on grain production when the effects of temperature and precipitation on the TFP in agriculture were compared, which was in line with the findings of Yang et al. [54]. The data analysis results revealed that, in contrast to the findings of other studies, the rise in temperature was accompanied by an increase in the agricultural TFP. Combining the research findings of Liu et al. and Haider et al. [55,56] on the impact of temperature change on grain production in a particular country, it is possible to conclude that, despite China's ongoing warming trend, the country's warming climate has advanced the start of the warmer season in spring and postponed the start of the cooler season in autumn. Crops have more time to grow, absorb sunlight, photosynthesize, and change matter as a result. This theoretically increases their production capacity and may, in part, result in larger grain yields.

To sum up, the analysis of this work still has numerous limitations.

Firstly, there are other elements besides climate change that have an impact on the TFP in agriculture. Human factors are also crucial. In theory, investing in farm irrigation facilities can increase the TFP [57]. The policymakers of farm irrigation facility investment are unable to determine the degree of farm irrigation facility investment that is most appropriate for all types of climate change challenges in all places due to factors such as food security [58,59]. How to open the "last mile" of agricultural technology promotion, which is related to the development of digital platforms for agricultural technology services, as well as how to allow the most cutting-edge and advanced agricultural science and technology achievements to permeate the village, home, and field, is critical. It is essential to obtain local government spending at this time. As a result, future research will continue to focus more on the processes of harsh climate and the effects of anthropogenic variables on the food supply.

Second, this study measures the effect of climatic extremes on agricultural production using average temperature and precipitation density rather than measuring climate extremes directly. According to preliminary findings, temperature change has a large positive impact on the agricultural output increase, while extreme precipitation weather has a negative impact. The measurement and evaluation of extreme weather events as well as the processes by which they affect the productivity of all factors in agriculture, however, require more in-depth study.

Third, due to the size of the research region, there are also significant variations in hydrothermal conditions, particularly for the many food crops that have distinct spatial distribution patterns. Regions or types of changes affected directly by climate change vary greatly [60]. For instance, whereas precipitation increases in South China may increase the likelihood of agricultural disasters, precipitation increases in Northwest China will greatly enhance agricultural output [61,62]. Therefore, future research will concentrate on how extreme climatic change affects the agricultural TFP in various regions of China and for various food crops.

4. Conclusions

In this study, we examined the mechanism underlying the impact of climate change on the agricultural total factor productivity (TFP), developed a model of the moderating effect, examined the moderating impact of farm irrigation facilities and agricultural technology, and empirically tested the model using panel data from all provinces. The result is the same as that used by Li et al., Alexander et al., and Yang et al. The present paper confirms their findings using the most recent data, different methods, and more scientific indicators of agricultural TFP measurement. The main conclusions are as follows:

(1) Similar to the findings of other studies, this paper finds that climate extremes and farm water facilities have an impact on food output. Agriculture's technological advancements also have a moderating and mediating effect;

(2) In contrast to the findings of other studies, the paper discovers that China's average agricultural TFP between 2000 and 2020 is 4.3%, with a TFP above 1 in 25 provinces, at a somewhat faster rate than other research. Furthermore, this paper makes the case that the average annual cumulative temperature in China varies between 13 and 15 degrees with a general upward trend, and the warming is beneficial for crop growth and preventing freezing calamities, which has a large and positive impact on the agricultural TFP.

The article does, however, have certain shortcomings. Instead of relying solely on data that are available to the public, we must do additional field research for micro-subjects in future studies. Additionally, we must broaden our choice of indicators, particularly for extreme climate change.

The aforementioned findings have significant policy ramifications for combating climate change and guaranteeing domestic food security: (1) in order to handle the food crisis in the short term while strengthening the ability to foresee meteorological disasters, the method for managing grain reserves should be strengthened in light of the constricting effect of climate change on the agricultural TFP; (2) we must aim at the moderating influence of agricultural technology and farm irrigation systems in the process of climate change on the agricultural TFP. On the one hand, we must firmly implement the "storing grain in technology, storing grain in the land" strategy, "short board" swallow the infrastructure, adjust measures to local conditions to adjust the structure of grain cropping systems and planting, and achieve cultivation optimization of new varieties of crops, taking the comprehensive technology to improve the ability to withstand natural disasters and improve crops' adaptability to environmental changes. On the other hand, although agricultural technology has controlled the precipitation process, its influence has not been substantial, indicating that China's response to climate change and the overall rate of the agricultural technology extension mechanism transformation still need to be improved.

Author Contributions: H.L. (Hai Li) generated the conceptualization, methodology, software, and validation; carried out formal analysis, investigation, resources, and data curation; and wrote the original draft, including preparation, review, visualization, supervision, and editing. H.L. (Hui Liu) provided statistical assistance and read, revised, and shaped the manuscript to the present form. H.L. (Hai Li) and H.L. (Hui Liu) co-provided project administration and funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Key Science Fund Project of Hunan Provincial Department of Education, grant number 18A085; Hunan Provincial Philosophy and Social Science Fund Project, grant number 21YBA079; and Hunan Postgraduate Scientific Research Innovation Project, grant number CX2018B403.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: This is not applicable to this article since no datasets were generated.

Conflicts of Interest: The authors declare that they have no conflict of interest.

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