sustainability

MDPI

Article

Impact of Climate Change on Agricultural Total Factor Productivity Based on Spatial Panel Data Model: Evidence from China

Zhangqi Zhong, Yiqin Hu * and Lei Jiang

School of Economics, Zhejiang University of Finance & Economics, Hangzhou 310018, China; zzhongz@zufe.edu.cn (Z.Z.); lei_jiang@zufe.edu.cn (L.J.)

* Correspondence: hyq@zufe.edu.cn

Received: 30 January 2019; Accepted: 11 March 2019; Published: 13 March 2019

Abstract: To respond to the adverse impact of climate change on agricultural total factor productivity, the question of how to adopt actively appropriate strategies is particularly critical for the stakeholders. However, the previous researchers have paid more attention to investigating the measure methods, regional differences, and determinants of Chinese agricultural total factor productivity, but the possible impact of climate change factors like rainfall, temperature, and evaporation on regional agricultural total factor productivity in China have not yet received the attention that they deserve. Furthermore, more importantly, the study on how to take active measures to reduce and mitigate the negative effects from climate change is relatively small. Therefore, in allusion to the above-mentioned problems, using the data envelopment analysis and building a spatial panel data model embedded with climate change factors, this paper calculated Chinese agricultural total factor productivity and then explored the possible impact of climate change on regional agricultural total factor productivity at a provincial level in China. Results mainly show that the impact of some factors, like annual total precipitation, average temperature in the growing season, and evaporation intensity on regional agricultural total factor productivity, are all very significant and negative, which suggests that the more precipitation, the higher the temperature is, and the higher evaporation intensity would lower agricultural total factor productivity in China. Furthermore, in order to response to mitigate the adverse effects from climate change on agricultural total factor productivity, local governments should continue to increase financial support for the local agricultural economic development, because this action could be beneficial for the related stakeholders in improving agricultural total factor productivity. Summing up, our evidence study would provide an important basic theory basis in terms of increasing agricultural total factor productivity and promoting regional agricultural economic development in China.

Keywords: agricultural total factor productivity; regional difference; spatial panel data model; adaptive strategy; China

1. Introduction

As the research concerning global climate change has moved along in recent years, a number of prior studies have found that climate change was expected to affect agriculture production in various regions [1–5]. Thus, investigating the impacts of climate change on agricultural production in various countries or regions and exploring the corresponding adaptive strategies to respond to the adverse effects from climate change has already become a research hotspot for several decades all over the world [6,7]. Actually, being a fundamental issue of agricultural production, agricultural total factor productivity (ATFP) is not only a significant factor affecting agricultural economic growth, but it also plays a crucial role in promoting the steady expansion of food production and sustaining increases in rural incomes [8,9]. Additionally, numerous studies have shown that the most effective way to drive agricultural economic development is to improve ATFP growth in various regions [10,11], and thus, there is growing concern from academia about studying regional agricultural total factor productivity and the corresponding policy issues. Especially with continuous worsening for the problems of global warming, the negative effects from global climate change on Chinese ATFP have already emerged [12–14]. Therefore, to mitigate and adapt to the impacts of climate change, for the related stakeholders in China, how to actively adopt the appropriate strategies, like adjusting funding in agricultural research and development from all levels of government, has gradually drawn widespread attention.

At present, the related studies regarding Chinese ATFP can be divided into two primary types. The first type focuses on exploring the related measure method of the ATFP, and thus evaluating and analyzing the source for the realization of Chinese ATFP growth [15–20]. Remarkably, through studying the relationship between agricultural economic reform and ATFP growth in China, Lin [15] found that the reform of the rural economic system played a more important role in promoting Chinese ATFP growth from 1978 to 1984 than that from 1984 to 1987. Also, Chen et al. [18] investigated that the major factor affecting Chinese ATFP growth was technical progress between 1990 and 2003, and it is noted that the significant role of technology efficiency played in driving up ATFP growth cannot be ignored.

The second type of study focuses on the characteristics of regional difference and the corresponding causes of formation for various provincial ATFP in China [21–23]. Generally, these previous studies have shown that regional difference, in terms of technical progress and technology efficiency in agricultural production, varies among regions in China. Notably, Wang et al. [21] thought that the influence of geographic environment on Chinese ATFP growth is likely to be significant, and similar geographical environments in the adjacent regions would promote the spread and development of agricultural technology and benefit the people in sharing the new production technique. Thus, it would lead to a convergence phenomenon of Chinese ATFP growth in the neighboring provinces.

Although previous studies have provided an important theoretical basis for the policy-makers to know the source of ATFP growth, guide agricultural production, and promote the development of provincial agricultural economy by calculating and analyzing ATFP and the corresponding regional difference characteristics and affecting factors in China, the following two aspects have yet to receive the attention that they deserve.

Firstly, the possible impact of climate change from natural factors like rainfall, temperature, and evaporation on regional ATFP has not yet been carried out. Actually, with the sudden warming of the global climate since the 1980s [24,25], recent warming in China has taken a serious, growing trend, and shows a significant regional and seasonal trend [26,27], which could lead to remarkable changes of precipitation, temperature, and evaporation in a region. Moreover, agricultural production itself is very dependent, sensitive, and has been vulnerable to climate change for a long time, and the impact of climate change on ATFP growth affects the various crops and yields of farmers [28–30]. In this context, on the one hand, the agricultural sector has become the most vulnerable to climate change [31,32]. On the other hand, the previous studies have shown that climate change would lower the aggregate TFP in agriculture, and thus curtail farm profits [33]. From a side perspective of some case studies, Pardey et al. [34] found that unfavorable weather conditions might lower ATFP in Minnesota. Furthermore, ABARE [35] also investigated that climate change in the future could bring unfavorable influences to global food production through lessening regional ATFP. Cornall et al. [30] explored the effects of the temperature and precipitation fluctuations on ATFP between 2020 and 2050, relative to those between 1970 and 2000 on a global scale. Moreover, taking the rice crop, for example, and using panel data from 1979 to 2009 in Japan, Kunimitsu et al. [36] investigated climate change influences on ATFP. Therefore, for the related stakeholders in China, in this context, to mitigate possible adverse effects of climate change on agricultural profits, taking effective measures to deal with it is of great essence and significance.

Secondly, being one of the important main participants who will deal with climate change, governments always play a key role in adaptation to climate change and affect both the provision of agricultural production factors and the research and development of new production technologies [37,38]. Therefore, more and more researchers are paying attention to exploring what measures governments should take in recent years. For instance, Smit et al. [39] thought that adaptive measures taken by governments, such as increasing government investment in agricultural research and development, could slow down the impacts of extreme weather events on agricultural ecosystems, and thus benefit farmers' adaptation to climate change. This conclusion had also been verified by Villavicencio et al. [40], in the case of Israel. However, by referring to adaptation as a reaction to climate change, few studies have focused on the influences of public budget investment in agricultural research and development from government at different levels, like federal and state government in the USA, or central and provincial government in China, which may lead to less valuable insights for the policy makers. Especially for China, in order to guarantee each region's agricultural production proceeds smoothly, investment in agricultural research and development for different provinces are usually mainly from financial appropriation from the central government and provincial government, respectively [41]. Notably, however, facing adverse effects of climate change, do differences between the benefits of financial appropriation from the central government or the provincial government exist? Namely, for different provinces in China, which kind of financial appropriation would be more favorable for tackling the negative impacts of climate change? Obviously, understanding this issue may contribute to enabling the related stakeholders to effectively implement future climate adaption policies.

Regrettably, however, there is little research concerning the aforementioned two issues. Given this, by applying the data envelopment analysis (DEA) method to calculate provincial ATFP in China and establishing a spatial econometric model embedded with some important climatic change factors, such as rainfall, temperature, and evaporation, this paper contributes to filling the above gap by discussing the following two major issues. It could not only provide an important theoretical foundation for researchers to deeply understand how climate change would alter ATFP growth in China but could also enable stakeholders to draw appropriate policy conclusions with regards to agricultural adaptation to climate change. Firstly, in the context of global climate change, how climatic factors (temperature, evaporation, and various aspects of precipitation) have affected ATFP in China fitting a spatial econometric model? Secondly, to curtail the unfavorable impacts of climate change on regional ATFP growth in China, which kinds of effective adaptive strategies should be adopted by governments? Furthermore, for various provinces in China, which kind of investments in agricultural research and development (namely, financial appropriation from the central government or from provincial governments) will be more beneficial to curbing the negative influences of climate change?

The rest of this chapter is organized as follows. The methodology and data are presented in the following section. Section 3 discusses the results of the economic modeling analysis. Finally, the conclusions of this research are presented in Section 4.

2. Methods and Data

2.1. Methods

Huffman et al. [42] thought that *ATFP* was the output of crop products produced by farmers per unit input, and that it was established by dividing an index of aggregate output by an index of the inputs employed by farmers in agricultural production, e.g., land, labor, and capital (especially for public agricultural research and development capital). Therefore, we can assume a provincial production function with disembodied technical change, where Y is the total of all types of agricultural production outputs from agricultural production within a provincial aggregated into one output index, and the production function could be described as follows:

$$Y = A(GN, OV)F(L, K, M) \tag{1}$$

where $A(GN, OV)$ is the related technology parameter, and it is hypothesized to be the financial appropriation from the government (GN) used in terms of the investment in agricultural research and development and other factors (OV). K is the provincial physical capital input, L is the provincial labor input, and M is the provincial materials input, mainly consisting of agricultural acreage.

According to the Equation (1), we further define *ATFP* as

$$ATFP = Y/F(L, K, M) = A(GN, OV) \tag{2}$$

Then, we take natural logarithms of both sides of the above Equation (2), and, thus, a random disturbance term μ would be added here. Therefore, we can obtain the preliminary econometric model of agricultural total factor productivity, which is given as follows:

$$lnATFP = lnAGN, OV + \mu \tag{3}$$

For this study, we aim to investigate the impacts of climate change on *ATFP*. Therefore, based on the model conducted by Huffman et al. [42], we will further incorporate climatic conditions to modify it. Namely, we add the three repressors such as temperature, rainfall, and intensity of precipitation here, which can be described as follows:

$$lnATFP_{it} = \beta_1 lnGN_{it} + \beta_2 lnT_{it} + \beta_3 lnP_{it} + \beta_4 lnE_{it} + \mu_{it} \tag{4}$$

where i, t denotes provinces and year, respectively. GN is financial appropriation from the government. T, P, and E represent exogenous climate conditions such as rainfall, temperature, and evaporation, respectively. Next, we will highlight these four factors affecting *ATFP*.

(1) Financial appropriation from the government (*GN*). Public budget investment in agricultural research and development from the government can effectively improve an agricultural environment and promote agricultural technical innovations and progresses in the process of agricultural production [43,44], and thus it seems that agricultural research and development from the government had played a vital role in boosting agricultural productivity growth for a long time. As previously mentioned, for Chinese provincial agricultural production, investment in agricultural research and development are primarily from financial appropriation from the central government (*GC*) and provincial government (*LC*), respectively. Therefore, this paper will explore the impacts of the two R&D investments in adaptation to climate change and hypothesize that financial appropriation from the government at the two levels both have a positive impact on increasing *ATFP* in the local region.

(2) Temperature (*T*). Because it not only affects the growth and development of agricultural crops, but also the arrangement of farming activities and farm machines [45–47]. Therefore, temperature is of prime importance to agricultural production. Actually, although the effects of temperature on agricultural productivity have already attracted widespread concern, this climatic variable is usually measured as the average value in degrees observed over the entire month/quarter/year in previous studies [48,49], and fails to investigate differential effects of temperature during the growing season and the non-growing season, which would inevitably lead to the bias of research results [40]. Therefore, this paper uses the average value in degrees observed over the growing season to analyze the influences of temperature on *ATFP*, and hence hypothesizes that the higher the average temperature is, the lower the *ATFP* is.

(3) Precipitation (*P*). The growth and development of agricultural crops needs a certain amount of moisture to survive, and along with the increasing global warming, precipitation has become one of the important factors affecting regional agricultural production [50–52]. To accurately evaluate

the possible effects of precipitation on *ATFP*, two indexes are required, like the total precipitation over the entire year (PRE) and the intensity of precipitation (namely, this value is established as the ratio between the maximal monthly precipitation and annual precipitation, $INTP$). Notably, however, Villavicencio et al. [40] found that the increase in the intensity of precipitation could significantly lower *ATFP* in various states of the USA. We also hypothesize that the total precipitation and the intensity of precipitation has a negative impact on regional *ATFP*.

(4) Evaporation (E). In addition to the impact of precipitation, the water use efficiency of crops is directly related to evaporation, so it also has a significant influence on regional agricultural production [47,52,53]. The previous studies have shown that the greater the evaporation is, the lower the agricultural activities, including food production, can access, and thus such circumstance would lead to a severe adverse outcome for regional *ATFP* [54]. Likewise, prior studies usually use the average precipitation observed over the entire month/quarter/year to represent a region's evapotranspiration. However, the intensity of evaporation (namely, this value is established as the ratio between the maximal monthly evaporation and annual evaporation, $INTE$) are adopted here to describe a region's evaporation capacity. Also, we hypothesize that this index has a negative impact on regional ATFP.

Furthermore, according to the above analysis, Equation (4) can be expressed as follows:

$$\begin{aligned} lnATFP_{it} = \beta_1 lnGC_{it} + \beta_2 lnLC_{it} + \beta_3 lnTEM_{it} + \beta_4 lnPRE_{it} + \beta_5 lnINTP_{it} + \beta_6 lnEVA_{it} \\ + \beta_7 lnINTE_{it} + \mu_{it} \end{aligned} \tag{5}$$

According to Equation (5), in order to investigate climate change influences on agricultural productivity, we first need to obtain ATFP for 30 provinces in China. According to the study by Coelli et al. [55,56], there are four main types of the measure method of the *ATFP*, namely, production function method, growth accounting index method, the stochastic frontier approach, and the Malmquist productivity index method based on DEA, respectively. Although the last approach cannot separate the measurement error from other sources of statistical noise, and thus there exists technical retrogression due to measurement errors [57], the use of DEA in measuring agricultural productivity primarily has the following two advantages [56]. Firstly, it does not need to make any of the assumptions, and, more importantly, it is a linear programming method which employs data on the input and output quantities of a group of regions to build a piece-wise linear surface over the data points. Secondly, it does not require any market price data to explore the factors influencing agricultural productivity growth measures. Therefore, the analysis here has employed the DEA technique to calculate the *ATFP* index numbers for 30 Chinese provinces. A description of this method can be given as follows:

Assume that k ($k \in 1, 2, 3, \ldots, K$) represents decision making units, t ($t \in 1, 2, 3, \ldots, T$) denotes time periods. There exists the nth kind of inputs ($n \in 1, 2, 3, \ldots, N$) and the mth kind of outputs ($m \in 1, 2, 3, \ldots, M$) in the kth decision-making units, respectively. Under certain conditions, like constant returns to scale (CRS) and strong disposability of inputs (SDI), a reference technique in the kth decision-making units in time t can be defined as follows:

$$L^t\left(y^t \middle| \mathrm{CRS}, \mathrm{SDI}\right) = \begin{cases} \left(x_1^t, \ldots, x_N^t, y_{k,m}^t \leq \sum\limits_{k=1}^{K} z_k^t y_{k,m}^t\right) \\ \sum\limits_{k=1}^{K} z_k^t x_{k,m}^t, n = 1, \ldots, N, z_k^t \geq 0, k = 1, \ldots, K \end{cases} \tag{6}$$

Thus, the technical efficiency function, based on certain conditions like CRS and SDI in the kth decision-making units in time t can be given as:

$$F^t\left(y^t, x^t \middle| \mathrm{CRS}, \mathrm{SDI}\right) = min\left\{\theta : \theta x^t \in L^t\left(y^t \middle| \mathrm{CRS}, \mathrm{SDI}\right)\right\} \tag{7}$$

According to the reciprocal relationship between the distance function and the efficiency function, we thereby can obtain as follows:

$$D_0^t\left(y^t, x^t\right) = \frac{1}{F_0^t(y^t,\, x^t|\mathrm{CRS}, \mathrm{SDI})} \quad (8)$$

Next, the Malmquist productivity index can be obtained as follows:

$$M_0^t = \frac{D_0^t\left(x^t, y^t\right)}{D_0^t\left(x^{t+1}, y^{t+1}\right)} \quad (9)$$

Taking technology conditions in time t as reference, where M_0^t denotes technical efficiency variation from time t to time $t+1$. Similarly, taking technology conditions in time $t+1$ as reference, the Malmquist productivity index from time t to time $t+1$ can be obtained as follows:

$$M_0^{t+1} = \frac{D_0^{t+1}\left(x^t, y^t\right)}{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)} \quad (10)$$

According to Equations (9) and (10), the Malmquist (output-orientated) *ATFP* change index between time t and time $t+1$ could be expressed as follows:

$$M_0\left(x^t, y^t; x^{t+1}, y^{t+1}\right) = \left(\frac{D_0^t\left(x^t, y^t\right)}{D_0^t\left(x^{t+1}, y^{t+1}\right)} \cdot \frac{D_0^{t+1}\left(x^t, y^t\right)}{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)^{0.5} \quad (11)$$

where x, y represents the set of all input vectors and output vectors, respectively. Also, the input vectors in this paper contains labor (L), capital stock (K), and agricultural acreage (M), and the output vectors consists of the corresponding agricultural production (Y). The descriptive statistics of these variables can be found in Table 1. $D_0^t\left(y^t, x^t\right)$ denotes a technical efficiency level in time t compared with the technology conditions in time t, $D_0^t\left(x^{t+1}, y^{t+1}\right)$ means a technical efficiency level in time $t+1$ compared with the technology conditions in time t. $D_0^{t+1}\left(x^t, y^t\right)$ represents a technical efficiency level in time t compared with the technology conditions in time $t+1$. $D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)$ is a technical efficiency level in time $t+1$ compared with the technology conditions in time $t+1$.

Then, based on the above equations, we could obtain 30 provinces' *ATFP* in China. Additionally, according to Equation (5), we also could investigate the impacts of climate change on *ATFP* in China in more detail.

2.2. Data

To exploring the effects of exogenous climate conditions, the data sets between 1993 and 2012 are used here, the related reasons primarily are two-folds. Firstly, as the available monitoring data regarding climatic variables, such as rainfall, temperature, and evaporation covering China's 30 regions did not update frequently, and the most recent and complete data sets are only from 1993 to 2012. Moreover, other data sets employed here such as agricultural labor force, farm output, and agricultural capital stock are concentrated during this period. Therefore, to retain uniformity and consistency of all kinds of data sets, the data sets between 1993 and 2012 are selected in this paper. Secondly, for climatic change factors like rainfall and temperature, these variables usually remained stable in the short-term, and thus it would lead to a minor impact on regional agricultural production [47,52]. Therefore, although the latest data is not available, the existing data are enough to analyze the influences of climate change on ATFP.

For each province, other data sets, such as agricultural output value, financial appropriation from the central government, and financial appropriation from the provincial government, all are from the China Statistical Yearbook (1993–2013). Agriculture labor force and land database can be obtained from the China Labor Statistical Year Book (1993–2013) and the China agricultural yearbook (1993–2013), respectively. Also, as for agricultural capital stock, due to the lack of public statistics, according to the study by prior researchers like Wang et al. [21], it can be estimated by multiplying the original value of productive fixed assets and the corresponding numbers of rural households. The related data sets are from the China agricultural yearbook (1993–2013).

Additionally, the climate variables were derived from data sets provided by the National Meteorological Information Center attached to the China Meteorological Administration. These data sets eliminated the corresponding missing and abnormal data containing all daily ground meteorological data from 824 ground observation station between 1993 and 2012, which has gradually been used by researchers [21]. Preliminary data processing were supported by software such as SQL server and ArcGIS. Table 1 presents the above variables, their names, and descriptive statistics (mean, standard error (S.D.), average (AVG), minimum (Min), and maximum (Max)).

Table 1. Descriptive statistics of the related variables in this paper.

Names	Unit	Obs	AVG	S.D.	Min	Max
ATFP	Dimensionless unit	510	0.9582	0.1046	0.4924	2.1497
GC	Billion Yuan	510	3.2683	3.3930	0.0680	19.6398
LC	Billion Yuan	510	47.5585	60.4635	0.9770	456.1412
PRE	Millimeter	510	8889.1876	5182.2946	990.3939	22,401.5000
INTP	Dimensionless unit	510	0.2439	0.0585	0.1197	0.4392
TEM	Degree centigrade	510	12.8541	5.7818	1.2000	25.9000
INTE	Dimensionless unit	510	0.1447	0.0234	0.0751	0.2379
L	Ten thousand people	510	1052.4159	862.4626	36.3500	4039.6000
K	Billion Yuan	510	224.9121	191.5688	3.9600	926.7100
M	Thousands of hectares	510	3940.5482	2744.4690	222.1000	11,838.3700
Y	Billion Yuan	510	922.4524	739.0078	23.0600	3467.1800

3. Results and Discussions

3.1. Regional Differences

Based on Equation (11), 30 provinces' ATFP in China are calculated here, and the detail value has been given in Appendix A. Due to space limitations, the overall characteristics (Figure 1 and Table 2) and the corresponding spatial evolution features (Figure 2) for Chinese provincial ATFP are highlighted as follows.

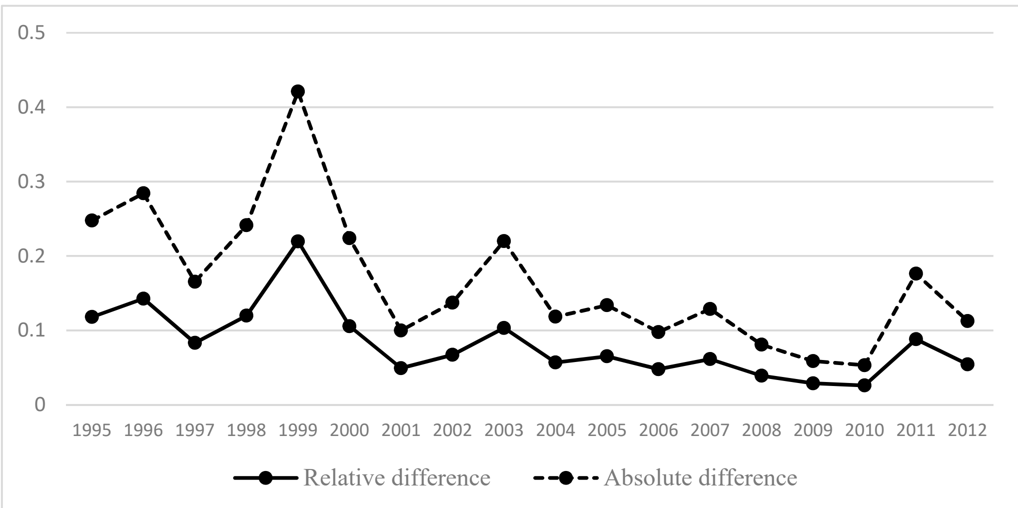
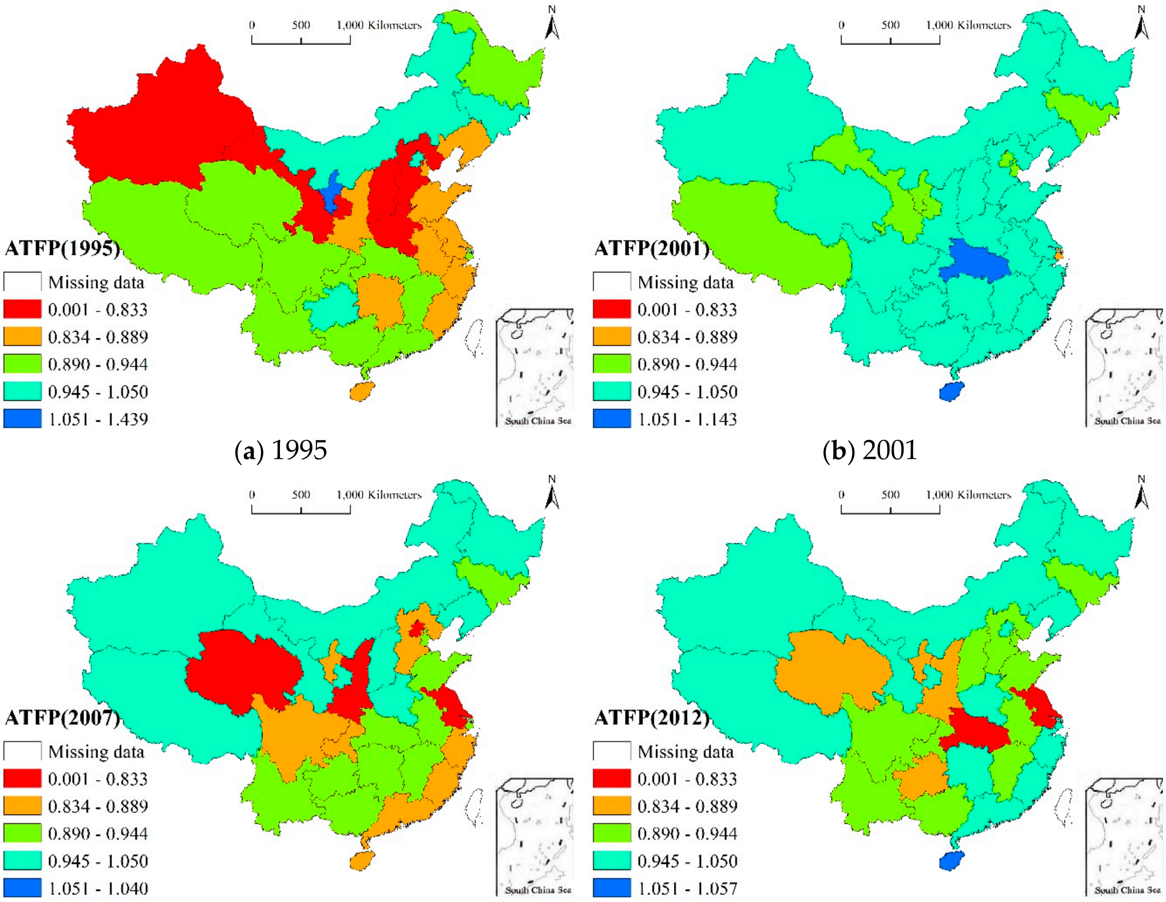


Figure 1. Overall characteristics of agricultural total factor productivity (ATFP) at a provincial level in China.

Table 2. Agricultural TFP by regions from 1995 to 2012.

Regions	1995	1997	1999	2001	2003	2005	2007	2009	2011	2012
The national average	0.911	1.012	1.091	0.971	0.884	0.950	0.910	0.965	1.001	0.934
The eastern average	0.884	1.013	1.064	0.966	0.897	0.925	0.874	0.971	1.022	0.942
The central average	0.854	1.011	1.037	0.991	0.906	0.975	0.929	0.958	1.023	0.923
The western average	0.910	1.020	1.182	0.979	0.828	0.970	0.909	0.974	0.984	0.934
The northeastern average	0.941	1.009	1.039	0.942	0.957	0.914	0.988	0.959	0.933	0.955



(**a**) 1995 (**b**) 2001
(**c**) 2007 (**d**) 2012

Figure 2. Spatial evolution of ATFP at provincial level in China.

As displayed in Figure 1, for the overall characteristics of ATFP at a provincial level in China, the absolute difference presents a downward trend, and the relative difference also declined. Moreover, the overall evolution of these two differences shows a significant fluctuation. Specifically, standard deviation reflecting the relative difference of 30 provinces' ATFP declined by more than 217% in 2012 (0.054), compared to that in 1995 (0.118), with an average annual drop rate of 12.06% between 2002 and 2010. Furthermore, the coefficient of variation reflecting the relative difference had a tendency to drop from 1995 (0.130) to 2010 (0.058).

Notably, however, for provincial ATFP during this period, it shows an increasing trend from 1997–1999, 2001–2003, and 2010–2011, respectively. Investigating the reason, it is related to some special event, such as a severe flood disaster that struck in south China in 1998, the SARS crisis that wreaked havoc across China at the end of 2002, the Yushu Earthquake in Qinghai province, and climate-related disasters in Gansu province. Actually, a number of studies have observed that the unexpected natural disaster or emergency incidents may affect regional agricultural production, and thus results in the decline of its ATFP [58,59]. However, it should be pointed out that with the increase in the financial appropriation from the government in recent years, the impact of natural disasters on regional ATFP tended to be lower. In other words, this may be a positive result owing to appropriate measures taken by the government in adaptation to climate change. The results from our study clearly show that the fluctuation range of provincial ATFP in 1999, in 2003, and in 2011 diminish gradually.

Furthermore, from the perspective of the national level (Figure 2), ATFP increased year by year in the Chinese northern area. For ATFP in most southern regions, particularly for the central region, north China plain, and Sichuan basin in China, it had a tendency to decline. One possible reason for this result is that the climate change factors like temperature and rainfall had played a significant role in affecting regional ATFP. Because according to the study by Zhong et al. [47], they found that along with the increasing global warming, the falling temperature and rainfall shortage in Chinese Sichuan basin and north China plain shown some relatively obvious trends, which had become the leading cause for the ATFP downward. In addition, they also found that climate change may have a significant negative effect on food production in Chinese south regions, and on the contrary, the Chinese northern area would be characterized by increasing agricultural productivity in the future. Based on the above results, it is not difficult for us to perceive that there is a strong relationship between regional ATFP and climate change.

Also, as displayed in Table 2, from the perspective of the regional level (The division of four regions here are as follows, the eastern region contains 10 provinces and municipalities such as Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region consists of 6 municipalities such as Shanxi, Anhui, Jiangxi, Hunan, and Hubei. The western regions include 12 provinces and municipalities such as Chongqing, Sichuan, Guizhou, Yunan, Tibet, Shananxi, Gansu, Qinghai, Ningxia, Xinjiang, Inner Mongolia, and Guangxi. The northeastern regions contain 3 provinces such as Liaoning, Heilongjiang, and Jilin), namely, the eastern region, the central region, the western region and the northeastern region, the evolution of these four regions' ATFP is in a fluctuating trend, and more importantly, Chinese ATFP did not present a convergence effect. In general, four sub-regional results also indicate that regional ATFP in China is rising in the undulation.

3.2. Estimated Results Based on Panel Data Model

According to the calculation results, this paper will explore climate change influences on provincial ATFP and the related policy issues. Considering a big difference existing in the regression results from different econometric models, in order to choose a more optimal model here to estimate the impacts of climate change, the related estimated results based on six econometric models are given in Table 3.

Firstly, an estimated result based on pooled least squares (PLS) is displayed in Table 3, column 2. For some variables, such as *LnINTE* and *Constant*, the null hypothesis cannot be rejected at the 1% and 5%, respectively. Moreover, clearly, two important variables such as LC and GC can be rejected at the 1%, 5%, and 10% significant level. One alternative reason is that section fixed effects is not considered in the PLS model. Actually, for various provinces, there exists a significant gap of financial appropriation between the central and local government, and the previous studies have shown that a remarkable difference existed here that required us to take section-fixed effects that do not change with time, into account with the econometric model [60,61]. Thus, another estimated method, such as the least square dummy variable (LSDV) considering section fixed effects, is introduced here. From the perspective of results in Table 3, column 3, two important variables such as LC and GC cannot be rejected at the 1% significance level. Also, an estimated result considering random effects (RE) is given in Table 3, column 7. According to the Hausman test, the hypothesis of random effects model is strongly rejected. To sum up, we controlled for fixed effects in the following spatial regression models.

Secondly, considering that a lag effect might exist for the impact of financial appropriation from all levels of government on agricultural production, this paper also adds a time-lag term here to analyze the coefficient of regression of lag 1, 2, and 3, which is shown in Table 3, column 4, 5, and 6, respectively. The estimated result indicates that for the variables like LC and GC of lag 1 and 2, both are found to be significant. However, a lag effect for lag 3 has not passed a significant test, which suggests that the effect from the LC and GC of lag 3 on ATFP is not statistically significant. Also, based on the regressions results, we can find that these values, in terms of the coefficients of LC and GC of lag 1 and 2, are relatively close, which shows that the effect of financial appropriation from governments on agricultural productivity is likely to present in the first year and the year following, and a lag effect is not obvious. Thus, in view of agricultural policy, our results may mean that research and development investment in regional agricultural development should not rely too much on the past financial inputs, and for the policy-makers, they should continue to increase investments in agricultural research and development in adaptation as a reaction to climate change to promote agricultural economic development.

Table 3. Results of panel data models without spatial effects.

Variable	PLS	FE	FE (Lag 1)	FE (Lag 2)	FE (Lag 3)	RE
LnLC	−0.0033 (0.0071)	0.0481 *** (0.0138)				−0.0033 (0.0071)
L1.LnLC			0.0354 *** (0.0146)			
L2.LnLC				0.0534 *** (0.0155)		
L3.LnLC					−0.0110 (0.0166)	
LnGC	−0.0187 (0.0118)	−0.1447 *** (0.0299)				−0.0187 (0.0118)
L1.LnGC			−0.1155 *** (0.0302)			
L2.LnGC				−0.1396 *** (0.0309)		
L3.LnGC					−0.0158 (0.0321)	
*LnLC*GC*	0.0037 (0.0030)	0.0058 * (0.0035)				0.0037 (0.0030)
*L1.LnLC*GC*			0.0068 (0.0038)			
*L2.LnLC*GC*				0.0078 * (0.0042)		
*L3.LnLC*GC*					0.0078 * (0.0047)	
LnPRE	0.0045 (0.0098)	−0.0683 ** (0.0291)	−0.0913 (0.0294)	−0.0762 ** (0.0315)	−0.0528 (0.0331)	0.0045 (0.0098)
LnINTP	0.0062 (0.0199)	0.0318 (0.0253)	0.0344 (0.0257)	0.0409 (0.0270)	0.0422 (0.0270)	0.0062 (0.0199)
LnTEM	−0.0020 (0.0106)	−0.1130 * (0.0610)	−0.1207 (0.0621)	−0.1059 (0.0715)	−0.0740 (0.0738)	−0.0020 (0.0106)
LnINTE	−0.0705 *** (0.0272)	−0.1437 *** (0.0370)	−0.1573 (0.0383)	−0.1383 *** (0.0388)	−0.0846 ** (0.0394)	−0.0705 *** (0.0272)
Constant	−0.1956 ** (0.0884)	0.5249 * (0.3219)	0.7409 (0.3160)	0.5687 * (0.3533)	0.5140 (0.3711)	−0.1956 ** (0.0884)
R^2	0.0254	0.1049	0.0830	0.0838	0.0332	0.0360
F-statistic	1.87	7.92	5.73	5.40	1.88	
p-Value	0.0730	0.0000	0.0000	0.0000	0.0722	
AIC	−889.46	−946.63	−904.28	−846.02	−818.41	
BIC	−855.58	−912.76	−870.89	−813.14	−786.09	

Notes: t statistics in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Lastly, although spatial regression models considering the fixed effects could be suitable for estimating the climate change influences on ATFP, traditional panel data models all assumed that the dependent and explanatory variables among regions are independent of each other, which might violate the first law of geography to some extent [62,63]. Namely, in this paper, there is some kind of connection for ATFP among provinces, and it is particularly noteworthy that in order to formulate the effective adaptation policies, regional spillover effects among factors should be seriously taken into account in agricultural production, which has also been confirmed by some scholars [64,65]. Hence, regional spillover effects in spatial regression models appears to be particularly critical here. Notably, however, these kind of spatial econometric regression models usually contain the spatial lag model (namely, it usually incorporates the spatially lagged dependent variable) and the spatial error model (namely, this model assumes that the dependent variable is dependent on a set of observed explanatory variables, and the spatially autocorrelated error term).

To choose an appropriate model here, we performed the Lagrange multiplier test and its equivalent, the robust Lagrange multiplier test. Both were conducted to study if spatially auto-correlated error terms or spatially lagged dependent variables should be considered in the econometric regression models to decide which one was the better-fitted model. A series of statistics are given in Table 4. When using the robust Lagrange multiplier (LM) test, the null hypothesis of the spatial error model can be rejected at the significance level, which means that we should choose the spatial lag model (SLM) here. The related analysis results are displayed in Table 5.

Table 4. Results of spatial dependence tests.

Null Hypothesis	Statistic	*p*-Value
LM test no spatial lag, probability	22.651	0.000
robust LM test no spatial lag, probability	4.360	0.050
LM test no spatial error, probability	19.154	0.000
robust LM test no spatial error, probability	0.863	0.428

Table 5. Results of spatial lag panel models considering fixed effects.

	SLM(1)			SLM(2)		
Variable	**Coefficient**	**t Statistics**	***p*-Value**	**Coefficient**	**t Statistics**	***p*-Value**
LnLC	0.0364	2.7745	0.0055	0.0381	2.9153	0.0036
LnGC	−0.1103	−3.8451	0.0001	−0.1149	−4.0296	0.0001
*LnLC*GC*	0.0043	1.3261	0.1848	0.0047	1.4320	0.1521
LnPRE	−0.0570	−2.0926	0.0364	−0.0537	−1.9796	0.0478
LnINTP	0.0280	1.1842	0.2364			
LnTEM	−0.1152	−2.0149	0.0439	−0.1152	−2.0128	0.0441
LnINTE	−0.1267	−3.6526	0.0003	−0.1222	−3.5412	0.0004
ρ	0.2610	4.7106	0.0000	0.2590	4.6665	0.0000
R^2	0.1770			0.1745		
log−likelihood	491.3909			490.6868		

Table 5 reports spatial lag panel model results. From the third column in Table 5, we find out that all variables are statistically significant, at least at the 10% significance level, except *LnLC*GC* and *LnINTP*. The two variables are insignificant. Further, this paper uses a stepwise regression method to remove insignificant variables. Because the *p* value of *LnINTP* is the highest, it would be removed firstly, and the estimated results after removing the variable are given in the seventh column in Table 5. Obviously, all variables are statistically significant, at least at the 5% significance level, except *LnLC*GC.* Hence, we turn to the model analysis.

As shown in the fifth column in Table 5, the estimated coefficient for the *LnLC* is positive and significant, indicating that an increase in financial appropriation from local government drives up provincial ATFP. Therefore, as for the policy implication, to mitigate adverse effects of climate change on agricultural production, various provincial governments still need to continue to increase research and development inputs for regional agricultural economic development. However, unexpectedly, the effect of *LnGC* is found to be negative and significant coefficient, indicating that financial appropriation from central government has a negative impact on ATFP. One possible interpretation is that because the central government is not familiar with provincial agricultural development and lots of finances fail to flow into places that need them urgently, these inputs did not effectively improve the local agricultural productivity. Also, the inverse relationship between subsidies from central government and ATFP might imply that, due to the heterogeneity of agricultural production among Chinese provinces, the financial input in agriculture should consider the state of climatic environment and the characteristics of rural economic development in the region. Not all the financial appropriation would be beneficial for the related stakeholders in the context of global climate change.

Also, to further investigate the combined influence of financial appropriation from local and central government on regional ATFP, the interaction terms of *LnLC*GC* is added here. As exhibited in the fifth and seventh columns in Table 5, although this variable is not significant at the 1%, 5%, and 10% significant level, the estimated coefficient value for *LnLC*GC* is 0.0047, which indicates that a combination of the two, rather than a single influence from the financial appropriation from central government, could promote ATFP growth to some extent. Hence, as for the policy recommendation, our results have shown that provincial government would be better acquainted with the present situation and characteristics of agricultural productivity than that of the central government, so funding inputs on improving ATFP for each province from the central government in China should be combined with financial appropriation from local governments to adapt to climate change.

Finally, the total precipitation over the entire year (*LnPRE*) was found to have a significant and negative impact on provincial ATFP in China. One possible interpretation is that excessive precipitation can trigger extreme floods, and thus seriously restrict agricultural production in all regions and curtail regional ATFP [66]. Actually, Kaminski et al. [53] had come to a similar conclusion for Israel. Moreover, the average value in degrees observed over the growing season (*LnTEM*) is negative and statistically significant, indicating that the higher the temperature, the less the regional ATFP. One alternative reason is that, due to an environment with too high a temperature, this not only hinders the production and development of crops, but also affects productivity of personnel engaged in agricultural reconstruction and agricultural technology extension. Concerned with this issue, many scholars have carried out the relevant research works and also support the issue [67,68]. Additionally, as expected, the intensity of evaporation (*LnINTE*) is negative and statistically significant, indicating that an increase in the intensity of evaporation lowers regional ATFP. The reason might be explained as follows. The faster the regional ATFP evaporates, the lower the availability coefficient of water (namely, the ratio of precipitation and evaporation), which thus would lead to a reduction of agricultural productivity [47]. To sum up, for adaptive strategies taken by the policy-makers to actively address climate change, on one hand, we should pay more attention to the impacts from high temperatures and rainy weather. On the other hand, a specific focus needs to be the effect of regional evaporation on regional ATFP in China, owing to the availability coefficient of water.

4. Conclusions

The aim of this study is to enhance a more systemic and comprehensive understanding of the possible impact of climate change on regional agricultural total factor productivity. To this end, applying the DEA method to calculate provincial ATFP in China, this paper first analyzed overall characteristics and the corresponding spatial evolution features for Chinese provincial ATFP. In the second stage, this paper established a spatial econometric model embedded some important climatic change factors, such as rainfall, temperature, and evaporation, which were applied to investigate climate change influences on agricultural productivity. In addition, we articulated the corresponding adaptive strategies in regard to agricultural adaptation to climate change. Our main conclusions and policy implications are as follows.

Firstly, for provincial ATFP in China, the overall characteristics reflecting absolute difference and relative difference both present a downward trend. Furthermore, from the perspective of a national level, Chinese northern area's ATFP increased year by year. However, as for ATFP in most southern regions, particularly for the central region, north China plain, and the Sichuan basin in China, it had a tendency to decline. Also, from the perspective of the regional level, the evolution of these four regions' ATFP is in a fluctuating trend, and more importantly, Chinese ATFP did not present a convergence effect. In general, four sub-regional results also indicate that regional ATFP in China is rising in the undulation.

Secondly, for the estimated results based on panel data models, no matter what financial appropriation came from provincial or central governments, a time lag effect of research and development investment in regional agricultural development is not obvious. In the context of adaption strategies in adaptation to climate change, continuing to increase investments in agricultural research and development would be more beneficial to promoting agricultural productivity. Also, the estimated coefficient for the *LnLC* is positive and significant, indicating that an increase in financial appropriation from local government drives up provincial ATFP. Unexpectedly, the effect of *LnGC* was found to be a negative and significant coefficient, indicating that financial appropriation from central government has a negative impact on ATFP. Moreover, the impacts of other climate change factors, such as the total precipitation over the entire year, the average value in degrees observed over the growing season, and the intensity of evaporation on provincial ATFP all are negative and statistically significant.

Lastly, for our policy implications, on one hand, climate change may have a significant negative effect on food production in southern Chinese regions, and on the other hand, the Chinese northern area would be characterized by increasing agricultural productivity in the future. Therefore, for the related stakeholders in southern Chinese regions, considering the existing significant relationship between regional ATFP and global climate warming, to take proactive measures to adapt to climate change, all level governments should increase finance inputs to develop new agricultural technologies or switch crops. In addition, according to our results, the effect of research and development from provincial and central governments on ATFP is not the same, and to overcome the adverse effects of climate change on agricultural productivity, the amount of research investment from provincial government is needed more than that from central government. Furthermore, as far as exogenous climate factors, more attention should be paid to the effect of regional evaporation on regional ATFP in China, owing to the availability coefficient of water, expect for high temperatures and rainy weather.

Author Contributions: Conceptualization, Z.Z.; methodology, Z.Z. and L.J.; software, Z.Z.; validation, Z.Z., Y.H. and L.J.; formal analysis, Z.Z. and Y.H.; investigation, Y.H.; resources, Z.Z.; data curation, Z.Z. and L.J.; Writing—Original Draft preparation, Z.Z. and Y.H.; Writing—Review and Editing, Z.Z. and Y.H.; visualization, Z.Z.; supervision, Y.H.; project administration, Z.Z., Y.H. and L.J.; funding acquisition, Z.Z. and Y.H.

Funding: The authors are grateful for the financial support provided by the Ministry of Education of Humanities and Social Science project of China under Grant No. 17YJA790029, No. 18YJC790237, and the National Natural Science Foundation of China under Grant No. 41801118.

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

Appendix A

Table A1. 30 provinces' ATFP in China.

Year	Beijing	Tianjin	Hebei	Shanxi	Inner Mongolia	Liaoning	Jining	Heilongjiang	Shanghai	Jiangsu	Zhejiang	Anhui	Fujian	Jiangxi	Shandong
1994–1995	0.97	0.86	0.83	0.75	1.05	0.85	1.04	0.93	0.92	0.88	0.89	0.87	0.86	0.91	0.86
1995–1996	1.03	0.92	1.23	1.09	0.84	0.96	0.84	0.88	0.92	1.01	0.93	0.90	0.89	1.04	1.05
1996–1997	1.02	0.95	0.93	1.16	1.05	1.02	1.03	0.98	1.27	1.08	0.98	0.97	1.00	1.00	1.06
1997–1998	0.95	0.86	0.99	1.08	0.91	0.97	0.91	1.16	1.04	0.95	0.96	0.94	0.92	1.11	1.13
1998–1999	0.99	1.02	0.99	1.21	0.99	1.01	1.05	1.05	1.01	0.99	1.22	1.02	1.11	0.98	1.09
1999–2000	0.78	0.93	0.92	0.81	0.97	1.02	1.06	1.00	0.82	0.94	0.95	0.97	0.92	0.75	0.96
2000–2001	0.94	0.94	0.95	0.95	0.97	0.95	0.93	0.95	0.89	0.96	0.97	0.97	0.96	1.04	0.96
2001–2002	0.85	0.94	0.95	0.87	0.98	0.94	0.87	0.93	1.02	0.96	0.99	0.96	0.97	1.02	0.99
2002–2003	0.85	0.94	0.94	0.86	0.92	0.94	0.94	0.99	0.84	0.97	0.96	1.06	0.96	0.94	0.95
2003–2004	0.98	0.95	0.93	0.89	0.88	0.94	0.94	0.81	1.06	0.91	0.95	0.91	0.98	0.88	0.94
2004–2005	1.02	0.94	0.93	0.99	0.92	0.94	0.90	0.90	0.67	0.95	0.94	1.00	0.96	0.98	0.94
2005–2006	1.06	0.99	0.96	0.96	0.93	0.91	0.96	0.87	1.11	1.00	1.00	0.96	0.96	0.94	0.98
2006–2007	0.81	0.94	0.87	0.99	0.98	0.99	0.93	1.04	0.90	0.78	0.88	0.93	0.88	0.90	0.91
2007–2008	1.02	0.97	0.95	0.92	0.91	0.93	0.90	0.92	0.78	0.92	0.93	0.94	0.97	0.97	0.96
2008–2009	0.90	0.96	0.97	0.95	0.98	0.96	0.96	0.96	1.01	0.94	1.00	0.94	0.96	0.98	0.96
2009–2010	1.03	0.95	0.96	0.95	0.96	0.95	0.98	0.94	1.00	0.95	0.97	0.94	0.97	0.96	0.97
2010–2011	1.01	1.01	1.04	1.01	0.92	0.92	0.97	0.91	1.20	1.23	0.99	1.03	0.94	1.00	1.04
2011–2012	0.96	0.93	0.90	0.93	0.96	0.97	0.93	0.97	0.97	0.77	0.96	0.93	0.98	0.94	0.91

Year	Henan	Hubei	Hunan	Guangdong	Guangxi	Hainan	Sichuang	Guizhou	Yunan	Tibet	Shaanxi	Gansu	Qinghai	Ningxia	Xinjiang
1994–1995	0.80	0.92	0.88	0.90	0.90	0.88	0.92	0.97	0.94	0.92	0.87	0.82	0.89	1.44	0.81
1995–1996	0.88	1.11	1.09	0.94	1.07	0.96	0.97	0.95	0.94	0.98	1.04	1.20	1.52	0.84	1.19
1996–1997	0.95	1.02	0.96	0.94	0.92	0.91	1.05	1.02	0.97	0.95	1.16	1.15	0.96	0.97	0.93
1997–1998	1.01	1.04	1.10	0.96	1.07	0.93	0.95	1.12	0.94	0.49	1.06	1.01	1.01	0.99	1.01
1998–1999	0.98	0.99	1.05	1.29	1.04	0.94	1.30	0.99	1.01	2.15	1.10	0.99	1.11	1.05	1.02
1999–2000	0.92	0.73	0.84	0.94	0.76	0.73	0.90	0.86	0.73	0.97	0.72	1.11	0.84	0.99	0.95
2000-2001	0.96	1.06	0.97	0.96	0.97	1.14	0.97	1.03	1.04	0.94	1.00	0.94	0.95	0.92	0.97
2001–2002	0.95	1.09	0.98	0.93	1.00	0.73	0.93	1.06	0.92	0.96	0.99	1.03	0.98	0.93	0.96
2002–2003	1.02	0.78	0.78	0.94	0.78	0.62	0.78	0.68	0.85	0.94	0.91	0.94	0.71	0.91	0.82
2003–2004	0.87	0.84	0.88	0.96	0.91	1.02	0.90	0.99	0.83	0.94	0.87	0.93	0.95	0.91	1.01
2004–2005	0.92	1.01	0.96	0.91	1.01	0.99	0.95	0.99	1.06	0.98	0.91	1.01	0.93	0.93	0.96
2005–2006	0.93	0.98	0.96	0.94	0.92	0.92	0.99	0.95	0.92	1.00	0.97	0.90	0.98	0.94	0.90
2006–2007	0.96	0.89	0.90	0.88	0.89	0.89	0.86	0.92	0.91	0.95	0.83	0.98	0.81	0.89	1.01
2007–2008	0.93	0.93	0.94	0.97	0.95	0.92	0.97	0.94	0.94	0.94	0.92	0.91	0.96	0.89	0.95
2008–2009	0.97	0.93	0.97	0.99	0.99	1.02	1.00	0.96	0.95	0.99	0.96	0.95	0.96	0.89	0.96
2009–2010	0.94	0.93	0.95	0.97	0.96	0.92	0.96	0.94	0.97	0.97	0.93	0.94	0.91	0.91	0.98
2010–2011	0.98	1.14	0.98	0.91	1.00	0.84	1.03	1.08	0.98	0.93	1.02	0.94	1.04	1.08	0.85
2011–2012	0.95	0.82	0.96	0.98	0.94	1.06	0.94	0.87	0.93	0.99	0.89	0.95	0.89	0.87	0.99

References

1. Penalba, O.C.; Vargas, W.M. Inter-decadal and inter-annual variations of annual and extreme precipitation over central-northeastern Argentina. *Int. J. Climatol.* **2004**, *24*, 1565–1580. [CrossRef]
2. Nelson, G.C.; Valin, H.; Sands, R.D.; Havlík, P.; Ahammad, H.; Deryng, D.; Kyle, P. Climate change effects on agriculture: Economic responses to biophysical shocks. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, 3274–3279. [CrossRef] [PubMed]
3. Burke, M.; Emerick, K. Adaptation to climate change: Evidence from US agriculture. *Am. Econ. J. Econ. Policy* **2016**, *8*, 106–140. [CrossRef]
4. Altieri, M.A.; Nicholls, C.I. The adaptation and mitigation potential of traditional agriculture in a changing climate. *Clim. Change* **2017**, *140*, 33–45. [CrossRef]
5. Ding, S. A novel discrete grey multivariable model and its application in forecasting the output value of China's high-tech industries. *Comput. Ind. Eng.* **2019**, *127*, 749–760. [CrossRef]
6. Pan, D.; Ying, R.Y. Agricultural total factor productivity growth in China under the binding of resource and environment. *Res. Sci.* **2013**, *35*, 1329–1338.
7. Capalbo, S.M.; Vo, T.T. A review of the evidence on agricultural productivity. *Agric. Product. Meas. Explan.* **2015**, *4*, 96–129.
8. Baldos, U.L.; Hertel, T.W. Global food security in 2050: The role of agricultural productivity and climate change. *Austr. Agric. Res. Econ.* **2014**, *58*, 554–570. [CrossRef]
9. Yao, Z.F.; Liu, X. Research on decomposition and spatial optimization differences of total factor productivity of modern agricultural industry-based on area farmers case in southern region and VRS-DEA model empirically test. *Econ. Geog.* **2016**, *12*, 119–125.
10. Awokuse, T.O.; Xie, R. Does agriculture really matter for economic growth in developing countries. *Can. J. Agric. Econ.* **2015**, *63*, 77–99. [CrossRef]
11. Ding, S.; Dang, Y.G.; Xu, N.; Wang, J.J.; Xu, Z.D. A novel grey model based on the trends of driving factors and its application. *J. Grey Syst.* **2018**, *30*, 105–126.
12. Bai, X.G.; Chen, X.N.; Huo, X.X. Study on the effect of climate change on the productivity growth of single and total factor productivity in main producing areas of apple. *J. Agric. Econ.* **2015**, *8*, 98–111.
13. Yin, C.J.; Li, G.C.; Fan, L.X. Climate change, the stocks of sci-tech resources, and agricultural productivity growth. *Chin. Rural Econ.* **2016**, *5*, 16–28.
14. Wang, Y.Z.; Liu, D.W. Spatial and temporal changes of total factor productivity in agriculture of Chongqing under constraints of climatic factors. *Sci. Geogr. Sin.* **2017**, *37*, 1942–1952.
15. Lin, J.Y. Rural reforms and agricultural growth in China. *Am. Econ. Rev.* **1992**, *82*, 34–51.
16. Mao, W.; Koo, W.W. Productivity growth, technological progress, and efficiency change in Chinese agriculture after rural economic reforms: A DEA approach. *China Econ. Rev.* **1997**, *8*, 157–174. [CrossRef]
17. Jin, S.; Huang, J.; Hu, R.; Rozelle, S. The creation and spread of technology and total factor productivity in China's agriculture. *Am. J. Agric. Econ.* **2002**, *84*, 916–930. [CrossRef]
18. Chen, P.C.; Yu, M.M.; Chang, C.C.; Hsu, S.H. Total factor productivity growth in China's agricultural sector. *China Econ. Rev.* **2008**, *19*, 580–593. [CrossRef]
19. Cao, K.H.; Birchenall, J.A. Agricultural productivity, structural change, and economic growth in post-reform China. *J. Dev. Econ.* **2013**, *104*, 165–180. [CrossRef]
20. Luo, H.X. The triple shock of Chinese agricultural economic growth and the governance of economic deceleration under the new normal. *Shanghai Econ. Res.* **2017**, *2*, 24–33.
21. Wang, Y.; Song, W.F.; Han, X.F. Space econometric analysis on agricultural total factor productivity and its influencing factors in China: Based on the statistic data from 1992 to 2007. *Chin. Rural Econ.* **2010**, *8*, 24–35. [CrossRef]
22. Shi, H.; Wu, F.W. Industrialization, urbanization and the productivity progress of agriculture. *World Econ. Pap.* **2011**, *3*, 59–73.
23. Shi, C.L.; Zhu, J.F.; Jie, C.L. Regional difference and convergence analysis of agricultural total factor productivity growth in China. *Inq. Econ. ISS* **2016**, *4*, 134–141.
24. Mitchell, J.F. The greenhouse effect and climate change. *Rev. Geophys.* **1989**, *27*, 115–139. [CrossRef]
25. Yi, Y.H.; Wang, S.W. The global climate is suddenly warming in 1980s. *Chin. Sci. Bull.* **1992**, *37*, 528–531.
26. Ding, Y.H.; Dai, X.S. China's temperature has changed over the past 100 years. *Atmos* **1994**, *20*, 19–26.

27. Sha, W.Y.; Shao, X.M.; Huang, M. China's warming and its impact on the natural boundaries since 1980s. *Sci. China Ser. D* **2002**, *32*, 317–326.
28. Holden, N.M.; Brereton, A.J. Adaptation of water and nitrogen management of spring barley and potato as a response to possible climate change in Ireland. *Agric. Water Manag.* **2006**, *82*, 297–317. [CrossRef]
29. IPCC. *Climate Change 2007: Fourth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2007.
30. Gornall, J.; Betts, R.; Burke, E.; Clark, R.; Camp, J.; Willett, K.; Wiltshire, A. Implications of climate change for agricultural productivity in the early twenty-first century. *Philos. Trans. R. Soc. B-Biol. Sci.* **2010**, *365*, 2973–2989. [CrossRef]
31. Reilly, J. Climate change and global agriculture: Recent findings and issues. *Am. J. Agric. Econ.* **1995**, *77*, 727–733. [CrossRef]
32. Wang, J.; Mendelsohn, R.; Dinar, A.; Huang, J.; Rozelle, S.; Zhang, L. The impact of climate change on China's agriculture. *Agric. Econ.* **2009**, *40*, 323–337. [CrossRef]
33. Xie, L.Y.; Li, Y.; Xu, Y.X. Updated understanding on the impacts of climate change on food production and food security. *Prog. Clim. Chan. Res.* **2014**, *10*, 235–239.
34. Pardey, P.G.; James, J.; Alston, J.; Wood, S.; Koo, B.; Binenbaum, E.; Hurley, T.; Glewwe, P. *Science, Technology and Skills. Background Paper for the World Bank's World Development Report. 2008l*; University of Minnesota: St. Paul, MN, USA; CGIAR Science Council: Rome, Italy; World Bank: Washington, DC, USA, 2007.
35. ABARE. Statistical tables. In *Australian Commodities*; Quarter: Hong Kong, China, 2007; pp. 541–577.
36. Kunimitsu, Y.; Iizumi, T.; Yokozawa, M. Is long-term climate change beneficial or harmful for rice total factor productivity in Japan: Evidence from a panel data analysis. *Paddy Water Environ.* **2014**, *12*, 213–225. [CrossRef]
37. Iglesias, A.; Garrote, L. Adaptation strategies for agricultural water management under climate change in Europe. *Agric. Water Manag.* **2015**, *155*, 113–124. [CrossRef]
38. Ashofteh, P.S.; Bozorg-Haddad, O.; Loáiciga, H.A. Development of adaptive strategies for irrigation water demand management under climate change. *J. Irrig. Drain. Eng.* **2017**, *143*, 04016077. [CrossRef]
39. Smit, B.; Skinner, M.W. Adaptation options in agriculture to climate change: A typology. *Mitig. Adapt. Strateg. Glob. Chang.* **2002**, *7*, 85–114. [CrossRef]
40. Villavicencio, X.; McCarl, B.A.; Wu, X. Climate change influences on agricultural research productivity. *Clim. Chang.* **2013**, *119*, 815–824. [CrossRef]
41. NBSC. National bureau of statistics of the People's Republic of China. In *China Statistical Yearbook (1994–2014)*; China Statistical Publishing House: Beijing, China, 2015.
42. Huffman, W.E.; Evenson, R.E. Do formula or competitive grant funds have greater impacts on state agricultural productivity. *Am. J. Agric. Econ.* **2006**, *88*, 783–798. [CrossRef]
43. Alston, J.M.; Beddow, J.M.; Pardey, P.G. Agricultural research, productivity, and food prices in the long run. *Science* **2009**, *325*, 1209–1210. [CrossRef]
44. Mao, S.P.; Cao, Z.W.; Liu, Y.T. Research on science and technology input of Chinese agricultural research institutes. *ISS Agric. Econ.* **2013**, *1*, 49–56.
45. Smoyer-Tomic, K.E.; Kuhn, R.; Hudson, A. Heat wave hazards: An overview of heat wave impacts in Canada. *Nat. Hazards* **2003**, *28*, 465–486. [CrossRef]
46. Smith, P.; Olesen, J.E. Synergies between the mitigation of, and adaptation to, climate change in agriculture. *J. Agric. Sci.* **2010**, *148*, 543–552. [CrossRef]
47. Zhong, Z.Q.; Wang, Z.; Xia, H.H.; Sun, Y. Temporal and spatial variation of the potential agricultural productivity of China under global climate change. *J. Nat. Res.* **2015**, *30*, 2018–2032.
48. Asseng, S.; Foster, I.A.; Turner, N.C. The impact of temperature variability on wheat yields. *Glob. Change Biol.* **2011**, *17*, 997–1012. [CrossRef]
49. Lobell, D.B.; Hammer, G.L.; McLean, G.; Messina, C.; Roberts, M.J.; Schlenker, W. The critical role of extreme heat for maize production in the United States. *Nat. Clim. Chang.* **2013**, *3*, 497. [CrossRef]
50. Zhou, H.; Wan, J.; Jia, H. Resilience to natural hazards: A geographic perspective. *Nat. Hazards* **2010**, *53*, 21–41. [CrossRef]
51. Rosenzweig, M.R.; Udry, C. Rainfall forecasts, weather, and wages over the agricultural production cycle. *Am. Econ. Rev.* **2014**, *104*, 278–283. [CrossRef]

52. Wang, Z.; Yue, Q.; Xia, H.B.; Zhong, Z.Q.; Sun, Y. China in 2050: Climate scenarios and the stability of the HU line. *Chin. Sci. Earth Sci.* **2016**, *46*, 1505–1516.
53. Kaminski, J.; Kan, I.; Fleischer, A. A structural land-use analysis of agricultural adaptation to climate change: A proactive approach. *Am. J. Agric. Econ.* **2012**, *95*, 70–93. [CrossRef]
54. Ji, S.; Unger, P.W. Soil water accumulation under different precipitation, potential evaporation, and straw mulch conditions. *Soil Sci. Soc. Am. J.* **2001**, *65*, 442–448. [CrossRef]
55. Coelli, T.J.; Rao, D.; Battese, G.E. *An Introduction to Efficiency and Productivity Analysis*; Kluwer Academic Publishers: Boston, MA, USA, 1998.
56. Coelli, T.J.; Rao, D. Total factor productivity growth in agriculture: A Malmquist index analysis of 93 countries, 1980–2000. *Agric. Econ.* **2005**, *32*, 115–134. [CrossRef]
57. Lambert, D.K.; Parker, E. Productivity in Chinese provincial agriculture. *J. Agric. Econ.* **1998**, *49*, 378–392. [CrossRef]
58. Mercer, J. Disaster risk reduction or climate change adaptation: Are we reinventing the wheel. *J. Intern Dev.* **2010**, *22*, 247–264. [CrossRef]
59. Gentle, P.; Maraseni, T.N. Climate change, poverty and livelihoods: Adaptation practices by rural mountain communities in Nepal. *Environ. Sci. Policy* **2012**, *21*, 24–34. [CrossRef]
60. Lee, L.; Yu, J. Estimation of spatial autoregressive panel data models with fixed effects. *J. Econom.* **2010**, *154*, 165–185. [CrossRef]
61. Bester, C.A.; Hansen, C.B. Grouped effects estimators in fixed effects models. *J. Econom.* **2016**, *190*, 197–208. [CrossRef]
62. Jiang, L.; Folmer, H.; Ji, M. The drivers of energy intensity in China: A spatial panel data approach. *China Econ. Rev.* **2014**, *31*, 351–360. [CrossRef]
63. Zhong, Z.Q.; Jiang, L.; Zhou, P. Transnational transfer of the emissions embodied in trade: Characteristics and determinants from a spatial perspective. *Energy* **2018**, *147*, 858–875. [CrossRef]
64. Yang, G.; Yang, M.Y. The empirical analysis of correlative effect among China's agricultural total factor productivity-Based on static and dynamic spatial panel model. *Econ. Geogr.* **2013**, *33*, 122–129.
65. He, Y.Y.; Li, G.C. The space associated spillover effects of Chinese agricultural TFP growth. *For. Sci. Tech. China* **2016**, *1*, 130–136.
66. Kundzewicz, Z.W.; Schellnhuber, H.J. Floods in the IPCC TAR perspective. *Nat. Hazards* **2004**, *31*, 111–128. [CrossRef]
67. Luo, Q. Temperature thresholds and crop production: A review. *Clim. Chang.* **2011**, *109*, 583–598. [CrossRef]
68. Sánchez, B.; Rasmussen, A.; Porter, J.R. Temperatures and the growth and development of maize and rice: A review. *Glob. Change Biol.* **2014**, *20*, 408–417. [CrossRef] [PubMed]