Impact of climate change on agricultural productivity: a combination of spatial Durbin model and entropy approaches

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Abstract

Purpose – Global climate change characterized by an increase in temperature has become the focus of attention all over the world. China is a sensitive and significant area of global climate change. This paper specifically aims to examine the association between agricultural productivity and the climate change by using China's provincial agricultural input–output data from 2000 to 2019 and the climatic data of the ground meteorological stations.

Design/methodology/approach – The authors used the three-stage spatial Durbin model (SDM) model and entropy method for analysis of collected data; further, the authors also empirically tested the climate change marginal effect on agricultural productivity by using ordinary least square and SDM approaches.

Findings – The results revealed that climate change has a significant negative effect on agricultural productivity, which showed significance in robustness tests, including index replacement, quantile regression and tail reduction. The results of this study also indicated that by subdividing the climatic factors, annual precipitation had no significant impact on the growth of agricultural productivity; further, other climatic variables, including wind speed and temperature, had a substantial adverse effect on agricultural productivity. The heterogeneity test showed that climatic changes ominously hinder agricultural productivity growth only in the western region of China, and in the eastern and central regions, climate change had no effect.

Practical implications – The findings of this study highlight the importance of various social connections of farm households in designing policies to improve their responses to climate change and expand land productivity in different regions. The study also provides a hypothetical approach to prioritize developing regions that need proper attention to improve crop productivity.

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Retraction notice: The publishers of the *International Journal of Climate Change Strategies and Management* wish to retract the article by Dongbei Bai, Lei Ye, ZhengYuan Yang, and Gang Wang (2022), "Impact of climate change on agricultural productivity: a combination of spatial Durbin model and entropy approaches", published in the *International Journal of Climate Change Strategies and Management* as part of a special issue, Vol. ahead-of-print, No. ahead-of-print, https://doi.org/10.1108/IJCCSM-02-2022-0016e. It has come to our attention that the peer review process has been compromised; there are also concerns relating to the authorship of the paper, as well as to the identity of the author 'Gang Wang'; as a result, the findings cannot be relied upon. These concerns have not been addressed by the authors. The publisher of the journal sincerely apologises to the readers.

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Originality/value – The paper explores the impact of climate change on agricultural productivity by using the climatic data of China. Empirical evidence previously missing in the body of knowledge will support governments and researchers to establish a mechanism to improve climate change mitigation tools in China.

Keywords Climate change, Agricultural productivity, Three-stage SDM, OLS approach, Spatial spillover effects

Paper type Research paper

1. Introduction

Global climate change regularly causes a series of environmental, social, ecological and economic issues that are threatening human development and survival. Human society has experienced several adverse consequences caused by climatic changes such as glacier melting, sea level rise and the increase of natural calamities (such as severe tropical storms, heat waves and irregular precipitations). Several studies showed that the impacts of climate change are multidimensional, such as climate change and national income (Dell *et al.*, 2009; Nordhaus, 2006), economic growth (Barrios *et al.*, 2010; Burke *et al.*, 2015; Hsiang and Solow, 2010), nonagricultural sector output (Dell *et al.*, 2012; Sun *et al.*, 2019), international trade (Jones and Olken, 2010; Li *et al.*, 2015) and human health (Deschenes, 2014). Political conflict (Maystadt and Ecker, 2014), population migration (Gray and Mueller, 2012) and energy demand (Maximilian and Erin, 2014) are closely associated.

The annual average surface temperature is rising at the degree of 0.23°C every 10 years, and this trend will continue for a long in the future (Brown and Caldeira, 2017; Huang *et al.*, 2017). Agricultural production is related to the world's human food rations and the livelihood of families in most developing regions. Because agricultural productivity is extremely dependent on climate and meteorological conditions, this vulnerability makes agriculture the most significant and susceptible sector influenced by climate change. At present, the academic community has conducted extensive research on the facts and climate change impacts. Previous studies (Su *et al.*, 2021; Fahad *et al.*, 2022a), show that the impact of extreme weather, such as floods and droughts caused by climate change, on agricultural production in developing countries and low-income countries is much higher than in developed and high-income countries. The risk of food shortage and security still exists and with every 1°C increase in temperature, global grain production will decrease by about 10% (Yi *et al.*, 2018; Fahad *et al.*, 2022b; Hossain *et al.*, 2022).

Under the traditional extensive economic development model, relying on the agricultural development model of high investment and high pollution, China has achieved the achievement of feeding 22% of the world's population with only 8% of the world's land, but it has also paid a huge cost of resources and environment (Chen and Gong, 2021). In the future, China's agriculture needs to change to be a more efficient, resource-saving and environmentally friendly sustainable development model. Ensuring national food security, especially absolute ration security, has always been one of the core objectives of China's agricultural policy. At the same time, China is a large geographical country and the north and south regions almost span the tropical, subtropical, temperate and sub-cold zones, and the east and west roughly cover humid, semi-humid, semi-arid and arid areas. There are obvious differences in climatic and meteorological conditions and agricultural production modes, and there are also great differences affected by climate change (MA *et al.*, 2018). Therefore, keeping in view the climate change severity, studying the association between agricultural production and climate change is of great significance to stabilize China's future grain production and supply security (Fisher *et al.*, 2012).

Relevant elements of climate change (such as sunshine duration, precipitation and temperature) are important indicators of agricultural production input, which will have different effects on agricultural output. Therefore, it is worth considering whether there will be a deviation in the estimation of traditional agricultural productivity without considering climate factors. Is agricultural productivity reduced or increased under climate change? To answer the above questions, there is a need to conduct empirical research on the basis of combining relevant theories with China's realistic background. Therefore, the marginal contribution of this paper lies in the following:

- From the research perspective, using the existing literature for reference, this paper makes a more comprehensive measurement of climate change and agricultural productivity, and deeply explores the development mechanism and specific utility between climate change and agricultural productivity without separating the relationship between them.
- In the empirical aspect, this paper manually collected a microclimate data set (including temperature, precipitation, duration of sunshine, wind speed and air pressure) from 2000 to 2019 from 30 provinces in China. Compared to traditional research data, it can more accurately measure its specific impact on agricultural productivity.

The empirical test is carried out on the basis of data from the 30 Chinese provinces from 2000 to 2019. Through the robustness test of three-stage spatial Durbin model (SDM) model, based on geographic matrix, economic matrix and economic geographic nested matrix, index replacement and quantile regression, the specific effects and action mechanism of climate change and agricultural productivity are comprehensively discussed. It is conducive to the in-depth study of the topic of improving agricultural productivity under climate change.

2. Literature review

The climatic changes impact on agricultural productivity is essentially both an ecological development and food security issue. For the majority of developing countries, agricultural production is not only related to farmers' livelihood but also closely associated with the long-term necessities of all mankind for nutrition and food. Currently, there are several studies focusing on the impact of climate change on agricultural production. An extensive literature focuses on the climatic changes effects on crop yield, but there is no unified study available on the climate change impact on agricultural productivity (Song *et al.*, 2010).

The general view is that climate change tends to have an adverse effect on agricultural production. First, because climate warming affects the growth period of crops, such as shortening the growth time of double-cropping rice, spring wheat and soybean, its per unit yield may decline. It is estimated that under the premise that crop varieties and production levels remain unchanged, by 2050, climate warming will likely turn most of China's two cropping areas into three cropping areas. In addition, extreme high temperature and drought accelerate the evaporation of soil water, the decomposition of organic matter and the loss of nutrients, thus reducing land productivity; high-temperature weather increases the risk of farmers suffering from heat-related traumatic injury and chronic diseases, which may reduce farmers' labor supply and labor capacity, and then reduce labor productivity. Overall, the decline of land and labor productivity may eventually lead to the decline of agricultural output. In addition, the input of production factors such as chemical fertilizer, pesticides and cultivated land is the core factor affecting agricultural total factor productivity. Climate change leads to increase in diseases and pests and the breeding of weeds, thereby increasing the application of pesticides and herbicides. Second, current climate change has a major adverse effect on global crop productivity (Dasgupta *et al.*, 2018;

Pranuthi and Tripathi, 2018; Rahman *et al.*, 2018). In terms of specific crop production, Ratnasiri *et al.* (2019) used Sri Lankan data and showed that the negative impact of temperature increase on rice production is much greater than the change in rainfall (Ratnasiri *et al.*, 2019). Meanwhile, studies based in central China show that climate change is not conducive to rice production in central China. Even considering the effect of CO_2 fertilizer, the unit yield of single cropping rice in central China will decrease by 10%–11% by the middle of this century compared to the first 10 years of this century (Lv *et al.*, 2018). Research based on Sichuan, China, shows that rice yield per unit is likely to decrease by 17%–43% under the influence of future climatic changes (Xu *et al.*, 2018).

The second view is that climatic changes will have a positive influence on agriculture. Studies have confirmed that farmers will actively take a series of adaptation measures, such as adjusting agricultural input factors. To make full use of heat resources, for example, farmers will breed excellent crop varieties and adjust the agricultural structure to ensure agricultural output. For example, farmers will choose to expand the use of fertilizers and other chemicals, increase irrigation and adopt conservation tillage to maintain soil production capacity and water storage capacity. In terms of natural conditions, the increase of temperature can increase the efficient accumulated temperature during the crop development period, expand the suitable planting area and multiple cropping index of crops and move the north boundary of thermophilic crop planting and multi-crop system to the north and west. Based on research on rice production in Northeast China, climate warming is obviously beneficial to the unit yield level and total yield of particular rice cropping in Chinese cold regions (Tao *et al.*, 2008; Xiong *et al.*, 2014; Wang *et al.*, 2014), and predicted results show that this trend of increase in yields will continue till 2030, but it is not clear after 2030 (Masutomi *et al.*, 2009). Similarly, studies based on the lower and middle ranges of the Yangtze River in China show that climate change reduces the unit yield of single cropping rice and increases the unit yield of late rice, and the direction of the change in the unit yield of early rice is uncertain (Tao *et al.*, 2013). From foreign studies on wheat and maize production, a few studies based in central Asia, Canada, Russia and Ukraine show that climate warming is beneficial to wheat production (Belyaeva and Bokusheva, 2018; Sommer *et al.*, 2013). Like rice and wheat, studies have shown that climatic changes have a positive effect on maize yield (Butler *et al.*, 2018; Roberts *et al.*, 2013).

The third view is that climatic changes have an uncertain impact on agricultural productivity. In terms of specific crop production, Chen *et al.* (2016) used Chinese provincial data from 1961 to 2010 to find that climate warming increased the yield of single cropping rice by about 11%, but the yield of double cropping rice decreased by 1.9% under the same warming conditions (Chen *et al.*, 2016). Other scholars focus their research on other crops such as soybeans and rape. By using Chinese panel data of 2,256 counties from 2000 to 2009, Chen *et al.* (2016) found that there is a non-linear inverted "U" association between soybean yield and climate factors. If climate warming continues, China's soybean production will be reduced by the end of this century (Chen *et al.*, 2016). Cui (2020) investigated the relationship between the change of crop planting area and long-term weather change in various regions of the USA. In some originally dry and cold regions, the planting area has increased on a large scale because climate change is gradually suitable for the growth of corn and soybeans (Cui, 2020). In terms of agricultural productivity, Villavicencio and others studied the climate change impact on agricultural total factor productivity in the USA. The findings show that precipitation next year has a substantial positive impact on agricultural total factor productivity, but precipitation density has a significant negative impact on agricultural total factor productivity, while temperature change has no significant impact on agricultural total factor productivity in most areas (Villavicencio *et al.*, 2013). Besides temperature and rainfall, other weather factors, such as relative wind speed, humidity, sunshine duration and evaporation rate, may also affect agricultural output. Zhang *et al.* (2018) found that ignoring the positive contribution of relative humidity will lead to climate change (warming), in which the impact on rice yield is overestimated by 12.5% and the impact on wheat yield is overestimated by 29.6% (Zhang *et al.*, 2017; Zhang *et al.*, 2018).

Current research on the climatic changes impact on crop yield has more discussion on the three global staple food crops of wheat, corn and rice, while the relevant research on other crops is still insufficient. Although most studies tend to believe that climate change has an adverse effect on yield of crop, the academic community has not yet discussed the climate change impact on agricultural production.

Consequently, following the existing research findings, this study uses the three-stage SDM approach reflecting the unexpected output to estimate agricultural productivity on the basis of eliminating external environment and random errors, to offer recommendations for agricultural development. Therefore, compared to previous studies, this paper is innovative in the agricultural productivity measurement method. Combining three-stage DEA modeling considering environmental factors and random interference, a three-stage SDM approach reflecting unexpected output is constructed to optimize the accuracy of agricultural ecological efficiency measurement; on the other hand, agricultural ecological efficiency measured on the basis of eradicating the influence of ecological factors and random interference more accurately reflects the local agricultural ecological environment. Based on this, the policy recommendations for the growth of green agriculture are put forward.

3. Material and methods

3.1 Calculation of agricultural production efficiency based on three-stage spatial Durbin model

We use the entropy method to comprehensively measure the regional weather index, and use the three-stage SDM model considering unexpected output to measure agricultural production. This paper focuses on the three-stage SDM model considering unexpected output.

The first stage calculates the initial agricultural ecological efficiency and the relaxation of the index by using the unexpected output SDM model.

Tone (2001, 2002) proposed an SDM model considering the unexpected output, as shown in equation (1). In equation (1), $x = (x_{ij}) \in R^{m\times n}$, $y = (y_{ij})\ R^{s\times n}$, $y = (y_{ij})\ R^{s\times n}$ n departments, m inputs and s outputs, including good outputs s_1 and bad outputs S_2. S^- and S^b represent excess input and unexpected output (redundancy), while S_g represents the insufficient expected output; ρ is the efficiency value:

$$\rho = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i}{x_{i0}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{i=1}^{m}\frac{s_r^b}{y_{r0}^b}\right)} \tag{1}$$

$$\begin{aligned} &subject\quad tox_0 = X\lambda + S^- \\ &y_0^g = Y^g\lambda - S^g \\ &y_0^b = Y^b\lambda - S^b \\ &S^- \geq 0, S^g \geq 0, S^b \geq 0 \end{aligned} \tag{2}$$

In equation. (1), ρ is the efficiency value, m represents the inputs number, s_1 is the expected outputs number and s_2 is unexpected outputs number. S_i^- and X_t, respectively, represent the input redundancy, S_r^g and Y_r^g represent the input variables of the decision-making unit, S_k^b and Y_k^b, respectively, represent the expected output deficiency and λ is the expected output variables of the decision-making unit, and, respectively, represent the undesired output excess and undesired output variables of the decision-making unit; and λ represents the weight vector.

The second stage denotes the exercise of existing scholars (Freid *et al.*, 2002), the stochastic frontier model is used to measure the redundancy value and environmental variables and the input–output data of agricultural ecological efficiency are adjusted according to the measurement results. The equation used is:

$$\begin{aligned} s_{ij}^- &= f^i(zj;\beta_i^-) + v_{ij}^- + \mu_{ij}^- \\ s_{ij}^g &= f^i(zj;\beta_i^g) + v_{ij}^g + \mu_{ij}^g \\ s_{ij}^b &= f^i\left(zj;\beta_i^b\right) + v_{ij}^b + \mu_{ij}^b \end{aligned} \tag{3}$$

In equation (3), s_{ij}^- represents the relaxation of input or output indicators of s_{ij}^g agricultural productivity in j region in i year, s_{ij}^b is the relaxation of undesired output indicators of agricultural productivity in j province and city in i year; $f^2(Z_j, \beta_i)$ refers to the influence of environmental variables on relaxation. Assuming that zj = $[z_{1j}, z_{2j}, \ldots, z_{kj}]$, $j = 1,2,\ldots, n$ agricultural productivity is affected by k factors, then, β_i is the parameter to be estimated. In equation (3), $v_{ij} + \mu_{ij}$ is the comprehensive error term in the v_{ij} measurement of agricultural ecological efficiency, $v_{ij \sim iidN}{}^{+}(0, \sigma^2)$, σ^2 reflects the statistical noise v_{ij} affecting agricultural productivity, where μ_{ij} is the variance that represents the role of management inefficiency in the measurement of agricultural productivity, where $\mu_{ij} \sim iidN^+\left(\mu^i, \sigma_\mu^2\right)$, μ^i is the mean value represents the variance. Assumptions σ_μ^2 and μ_{ij} are independent of each other, and v_{ij} are μ_{ij} independent of environmental variables. By definition of $\gamma = \sigma_\mu^2/\left(\sigma_\mu^2 + \sigma_v^2\right)$, when γ approaching 1, the management inefficiency rate accounts for the main influence position, and when γ approaching 0, the random factors account for the main influence position. In this paper, the maximum likelihood estimation of unknown parameters is used to adjust the input–output data. The formula is as follows:

$$\begin{aligned} X_{ij}^A = X_{ij} &+ \left[\max\left(f(z_j;\beta_{ij}^-) - f(z_j;\beta_{ij}^-)\right)\right] + \left[\max(v_{ij}^-) - v_{ij}^-\right], i = 1,2,\cdots,m; j \\ &= 1,2,\cdots,n \end{aligned} \tag{4}$$

$$\begin{aligned} y_{ij}^A = Y_{ij}^g &+ \left[\max\left(f\left(z_j;\beta_{ij}^g\right) - f\left(z_j;\beta_{ij}^g\right)\right)\right] + \left[\max\left(v_{ij}^g\right) - v_{ij}^g\right], i = 1,2,\cdots,s_1; j \\ &= 1,2,\cdots,n \end{aligned} \tag{5}$$

$$\begin{aligned} y_{ij}^{bA} = Y_{ij}^b &+ \left[\max\left(f\left(z_j;\beta_{ij}^b\right) - f\left(z_j;\beta_{ij}^b\right)\right)\right] + \left[\max\left(v_{ij}^b\right) - v_{ij}^b\right], i = 1,2,\cdots,s_2; j \\ &= 1,2,\cdots,n \end{aligned} \tag{6}$$

X_{ij}^A, y_{ij}^A and y_{ij}^{bA} represent the adjusted agricultural productivity input indicators, expected and unexpected output indicators, respectively. x_{if} represents the input variable before adjustment, y_{ij}^{g} is the expected output variable before adjustment and y_{ij}^{b} is the unexpected output variable before adjustment. [max $(f(z_i;\ \beta_{ij}))$] shows that all decision-making units in the agricultural productivity measurement are adjusted in the same external environment, and [max$(v_{ij}) - v_{ij}$] means that the statistical noise in the agricultural productivity measurement is removed. In the second stage of analysis, the formula is as follows:

$$E(\mu|\varepsilon) = \sigma^* \times \left[\frac{\phi\left(\lambda \frac{\varepsilon}{\sigma}\right)}{\phi\left(\frac{\lambda\varepsilon}{\sigma}\right)} + \frac{\lambda\varepsilon}{\sigma} \right] \tag{7}$$

In equation (7), ε is the joint error term, $\sigma^* = (\sigma_\mu\ \sigma_v)/\sigma$, $\sigma = \sqrt{\sigma_\mu^2 + \sigma_v^2}$, $\lambda = \sigma_\mu/\sigma_v$, ϕ and φ are the density normal distribution functions of standard normal distribution, respectively. The third stage is to use the adjusted data in the second stage and use the unexpected SDM model to calculate the efficiency again.

Combined with the characteristics of China's agricultural productivity, three indicators such as economic development level, government policy support for industrial development and technical support are selected as environmental variables. On the basis of considering the availability of relevant indicators and the selection requirements of environmental indicators, the output value of regional primary industry is selected as the proxy variable of regional macroeconomic development level, and the local financial expenditure on agriculture is selected as the proxy variable to reflect the government's support for agricultural development, taking into account the reality of multi-technical support for agricultural development; Science and technology expenditure is selected as the proxy variable of technology investment in the current year.

3.2 Calculation of the climate index based on the entropy method

- Indicator description: assuming that the year span is d, the number of provinces is N and the number of indicators is M, X_{LKH} is expressed as the H indicator of city K in the L-th year.
- Determination of index entropy:

$$A_j = -b\sum_{L=1}^{d}\sum_{K=1}^{N}\left[Y_{LKH} L \ln Y_{LKH}\right] \tag{8}$$

Among $b = \frac{1}{\ln(dN)}$, $Y_{LKH} = \dfrac{X'_{LKH}}{\sum_{L=1}^{d}\sum_{K=1}^{N} X'_{LKH}}$

- Determination of utility value and weight of indicator information:

$$G_j = 1 - A_j;\ W_j = \frac{G_j}{\sum_{j=1}^{M} G_j} \tag{9}$$

- Determination of index score:

$$Z_{LK} = \sum_{j=1}^{M}\left(W_j X'_{LKH}\right) \tag{10}$$

Through the above formula, the climate index of each province can be calculated.

3.3 Establishment of regression model

Following the previous research studies (Song *et al.*, 2022), considering the reality of China's agricultural development and the availability of data, this paper intends to build the following model to measure the climate change impact on agricultural productivity:

$$\ln agrp_{it} = \alpha_0 + \alpha_1 \text{climate}_{it} + \alpha_2 x_{it} + v_t + \omega_i + \mu_{it} \tag{11}$$

In equation (8), $agrp_{it}$ represents the agricultural total factor productivity of i province in the t year, $climate_i$ is the climate variable of the i province in the t year, including annual rainfall, annual average temperature, sunshine duration, average air pressure and average wind speed. x_{it} refers to the annual socio-economic variables of each province, including per capita GDP, Engel coefficient, actually used foreign capital, industrial productivity (gross industrial output value above designated size/total regional area) and capital productivity (total fixed asset investment/expenditure in the general budget of local finance). α is the parameter to be estimated, v_t and ω_i represent the fixed effect of time and provinces and μ_{it} is a random error term.

3.4 Spatial model construction

3.4.1 Construction of spatial weight matrix. For testing the robustness of the research results, three weight matrices are used for spatial econometric analysis. The constructed weight matrix is as follows:

- *Geographic distance matrix (W)*. Based on the geography first law, everything is connected to other things, but things that are closer are closely associated than things that are far away. Therefore, the geographical distance matrix is proposed based on the communal distance (geographical) between the two regions. The closer the (geographical) distance between the two regions, the greater the weight given. The specific estimation equation is as follows:

$$W_{ij} = 1/d_{ij} \tag{12}$$

$$d_{ij} = ar\cos\left[\left(\sin\phi_i \times \sin\phi_j\right) + \left(\cos\phi_i \times \cos\phi_j \times \cos \triangle \tau\right)\right] \times R \tag{13}$$

  where W_{ij} is the matrix of geographical distance, d_{ij} is the provinces geographical distance, ϕ_i and ϕ_j represent the longitude and latitude of the city. $\Delta\tau$ is the longitude difference between two cities and R is the ball radius:

- *Economic distance matrix (M)*. Using common exercises, the matrix of economic distance on the index of GDP per capita is proposed:

$$M_{ij} = 1/\left|\left(PGDP_j - PGDP_i\right)/\left(PGDP_j + PGDP_i\right)\right| \tag{14}$$

  where M_{ij} is the matrix of economic distance, and $PGDP_i$ and $PGDP_j$ signify the per capita gross domestic product of i provinces and j cities, respectively:

- *Economic geography nested matrix (C)*. Referring to the common practice in academic circles (Fingleton and Gallo, 2008), the geographic distance weight and economic distance weight are combined to construct the economic geography nested matrix, which broadly reflects the descriptions of spatial distance (geographic) and economic-related characteristics:

$$C_{ij} = \left(1/|PGDP_j - PGDP_i + 1|\right) \times e^{-d} \tag{15}$$

where C_{ij} is the matrix of spatial economic distance, $PGDP_i$ and $PGDP_j$ represent the per capita gross domestic product of i provinces and j cities, respectively, and d_{ij} is the geographical distance.

3.4.2 Construction of spatial Durbin model. The SDM, the spatial autocorrelation model, the spatial autoregressive model and the spatial error model are commonly used econometric models. By comparing the goodness of fit of the model and comparing the maximum likelihood log likelihood and information criteria akaike information criterion, bayesian information criterion and other indicators, this study selects the SDM to estimate the spatial effect of human capital and constructs different SDMs as follows:

$$\begin{aligned}\ln agrp_{it} = {} & \alpha_0 + \alpha_1 \sum_j W_{ij} \ln agrp_{it} + \alpha_2 \ln \text{climate}_{it} + \alpha_3 \sum_j W_{ij} \ln \text{climate}_{it} + \alpha_4 x_{it} \\ & + \alpha_5 \sum_j W_{ij} x_{it} + v_t + \omega_i + \mu_{it}\end{aligned} \tag{16}$$

$$\begin{aligned}\ln agrp_{it} = {} & \alpha_0 + \alpha_1 \sum_j M_{ij} \ln agrp_{it} + \alpha_2 \ln \text{climate}_{it} + \alpha_3 \sum_j M_{ij} \ln \text{climate}_{it} + \alpha_4 x_{it} \\ & + \alpha_5 \sum_j M_{ij} x_{it} + v_t + \omega_i + \mu_{it}\end{aligned} \tag{17}$$

$$\begin{aligned}\ln agrp_{it} = {} & \alpha_0 + \alpha_1 \sum_j C_{ij} \ln agrp_{it} + \alpha_2 \ln \text{climate}_{it} + \alpha_3 \sum_j C_{ij} \ln \text{climate}_{it} + \alpha_4 x_{it} \\ & + \alpha_5 \sum_j C_{ij} x_{it} + v_t + \omega_i + \mu_{it}\end{aligned} \tag{18}$$

where α_0 denotes the constant term and μ_{it} is the disturbance term; i shows the space and t is the time; v_t and ω_i are the space effects and time effects, respectively; W_{ij}, M_{ij} and C_{ij} are the weight matrix; α_1 is the spatial autoregressive coefficient that shows the effect of the adjacent unit variables on the explained variables of this spatial unit; α_2 represents the climate change coefficient; α_3 and α_5 show the influence coefficient of independent variables from other regions; and α_4 is the control variable coefficient.

3.5 Data sources and descriptive analysis

The relevant data of agricultural productivity was obtained from Statistical Yearbook of China and China Agricultural Yearbook. Weather data are compiled and provided by the data service room of the National Meteorological Information Center of the China Meteorological Administration. We use the geographic information system spatial analysis software (ArcGIS) to add the China grid's ground-level average temperature, rainfall, average wind speed and sunshine duration and average air pressure to the provincial level. Finally, we obtained a balanced panel data set composed of 30 provincial climate data. The economic and social statistics in this study were obtained from the China statistical data application support system. The database covers a series of statistical indicators of China's provincial land resources and basic information, national economic accounting, population, employment, wages and income, investment, finance, agriculture, domestic trade, telecommunications, industry, education, health and social welfare. Some missing values in the data set are filled by interpolation (Table 1).

Figure 1 shows the average temperature, precipitation, duration of sunshine, average wind speed and average air pressure in 30 provinces of China from 2000 to 2019. From the specific time evolution, the sunshine duration, air pressure, wind speed and precipitation basically show a stable trend. The temperature showed a small growth trend of fluctuation.

As it can be seen from Figure 2, because China spans multiple natural zones and has different geographical locations and climatic conditions, the agricultural productivity of its 30 provinces shows significant differences. Specifically, the agricultural productivity of Shanghai, Hainan Province and Jilin Province is significantly greater than that of other provinces, while the agricultural productivity of Gansu, Anhui and Shaanxi is in the downstream position.

Table 1.
Descriptive statistics

Variable	Obs	Mean	SD	Min	Max
LSZC	600	1,761.77	1,485.45	28.76	7,506.80
AGOT	600	1,224.05	1,104.88	24.90	5,408.59
PGM	600	2,809.36	2,683.92	93.97	13,353.02
EIA	600	2,003.08	1,514.57	109.24	6,177.59
FAR	600	175.13	137.60	6.17	716.09
SAFC	600	3,634.72	2,737.49	46.52	14,338.10
REC	600	212.19	337.30	1.50	1,949.11
NAE	600	944.42	702.64	30.27	3,569.00
APFU	600	199.69	1,118.65	0.06	14,338.10
ADND	600	1,198.16	1,085.19	1.10	7,394.00
CDRS	600	14,872.05	12,524.73	470.25	55,870.00
AFL	600	585,085.97	510,385.99	9254.90	2,759,312.00
Precipitation	600	948.3373	449.6422	200.8411	883.4588
Temperature	600	13.8990	5.3419	2.5495	15.1509
Windspeed	600	2.1509	0.4183	1.1162	2.1721
Air pressure	600	953.9564	70.8204	707.3806	989.8101
Sunshine duration	600	2,052.0621	486.8779	932.9999	2,042.3585

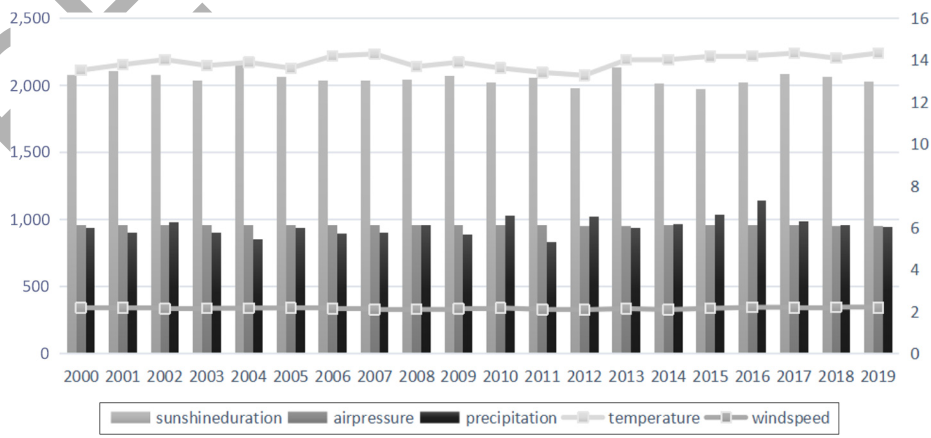

Figure 1.
Time variation diagram of climatic variables (2000–2019)

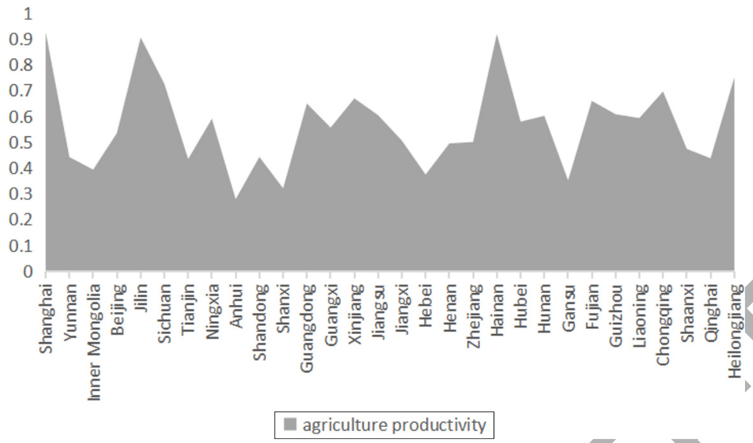

Figure 2.
Change in the chart of agricultural productivity in 30 provinces of China (average value from 2000 to 2019)

4. Results and discussion

4.1 Benchmark regression results

Table 2 presents the benchmark regression results. In Model (I)–Model (VI), the estimation coefficient of the independent variable climate is always significantly negative, indicating that climate change has a negative impact on agricultural productivity. This conclusion is consistent with the research results of many authoritative literatures and verifies the research hypothesis. After gradually adding the control variables, it is found that the regression coefficient shows a fluctuating upward trend. Furthermore, per capita GDP and actual foreign capital utilization showed a positive but insignificant effect on the growth of agricultural production. Engel coefficient, industrial productivity and capital productivity showed a substantial negative effect on agricultural productivity (Table 3).

With regard to the decomposition of climate variables and the regression of various factors, the impact of annual precipitation and air pressure on the growth of agricultural total factor productivity is not significant. The increase of temperature and wind speed has a significant negative impact on agricultural productivity, both at the level of 1%. The sunshine duration has a significant negative impact on agricultural productivity, but it is only significant at the level of 10%.

4.2 Analysis of spatial spillover effect

Before formal analysis, it is essential to assess whether the research object has spatial effects, that is, to assess the spatial autocorrelation of agricultural productivity and climate change. In this research, the Moran'i index method is used to estimate the spatial effect of each year under the geographical distance matrix:

$$I = \frac{\sum_{i=1}^{n} \sum_{i=1}^{n} w_{ij} \left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{\sum_{i=1}^{n} w_{ij} \left(xi - \overline{x}\right)^2}$$

Moran's I index ranges from [−1.1]. Higher than 0 represents positive autocorrelation, while lower than 0 shows autocorrelation autocorrelation. If Moran's I index approaches 0, then the spatial distribution is random, representing that there is no spatial correlation between regions.

Table 2. Benchmark regression results

Variables	(I)	(II)	(III)	(IV)	(V)	(VI)
Climate	−0.2152* (0.0655)	−0.2170* (0.0638)	−0.2455** (0.0342)	−0.2410** (0.0370)	−0.2310** (0.0455)	−0.2535** (0.0221)
PGDP		−0.0156 (0.7030)	−0.0752* (0.0821)	−0.0968** (0.0286)	−0.0761* (0.0987)	0.0013*** (0.0000)
ECT			−0.1973*** (0.0001)	−0.2041*** (0.0001)	−0.2904*** (0.0001)	−0.2952*** (0.0000)
AUFC				0.0243** (0.0278)	0.0231** (0.0372)	0.0298*** (0.0050)
INP					−0.0387 (0.1197)	−0.0174 (0.4739)
CLP						−0.0018 (0.9540)
_Cons	2.2081** (0.0139)	2.3793** (0.0179)	2.9638*** (0.0032)	3.0451*** (0.0024)	2.7206*** (0.0078)	1.8793** (0.0314)
Fixed provinces	YES	YES	YES	YES	YES	YES
Fixed years	YES	YES	YES	YES	YES	YES
N	600	600	600	600	600	600
Adj. R^2	0.7387	0.7383	0.7447	0.7465	0.7471	0.7687

Notes: p-values in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; provincial level robust clustering standard error in brackets

Table 3. Impact of weather factors on agricultural productivity

Variables	(I)	(II)	(III)	(IV)	(V)
Precipitation	0.1350 (0.1527)				
Temperature		−0.0544*** (0.6733)			
Windspeed			−0.2426*** (0.0045)		
Air pressure				0.8360 (0.5734)	
Sunshine duration					−0.2121* (0.0602)
PGDP	−0.0637 (0.2157)	−0.0630 (0.2231)	−0.0622 (0.2240)	−0.0612 (0.2390)	−0.0680 (0.1863)
ECT	−0.2896*** (0.0001)	−0.2897*** (0.0001)	−0.2662*** (0.0005)	−0.2893*** (0.0001)	−0.2889*** (0.0001)
AUFC	0.0236** (0.0351)	0.0233** (0.0381)	0.0236** (0.0340)	0.0228** (0.0434)	0.0235** (0.0356)
INP	−0.0380 (0.1361)	−0.0407 (0.1105)	−0.0216 (0.4089)	−0.0397 (0.1200)	−0.0366 (0.1512)
CLP	−0.0100 (0.7821)	−0.0078 (0.8288)	−0.0076 (0.8320)	−0.0087 (0.8097)	−0.0129 (0.7215)
_cons	0.6897 (0.3261)	0.7245 (0.3075)	0.8628 (0.2158)	0.0629 (0.9651)	0.8751 (0.2122)
Fixed provinces	YES	YES	YES	YES	YES
Fixed years	YES	YES	YES	YES	YES
N	600	600	600	600	600
Adj. R^2	0.7458	0.7449	0.7486	0.7450	0.7465

Notes: Values in the parentheses indicate p-values; *,** and *** represent $p < 0.1$, $p < 0.05$, $p < 0.01$ accordingly

It can be seen from Table 4 that the Moran's I index of agricultural productivity and climate change under the weight of geographical distance from 2011 to 2019 is significant, indicating that there is a significant spatial autocorrelation between climate change and agricultural productivity in 30 provinces of China from 2011 to 2019, that is, the two appear agglomeration in spatial distribution.

Referring to the testing ideas of the authoritative literature (Elhorst, 2014; Hunneman *et al.*, 2021), we tested the spatial econometric model in four steps. First, lagrange multiplier (LM) test results show that the structural equation modelling (SEM) model and the SAR model are applicable (LM lag test, r-lm lag test, LM err test and r-lm err test all pass the 1% significance level test); second, LR test significantly rejected the original hypothesis, indicating that the SDM model will not be simplified into SEM model. Third, the results of the Hausman test support the fixed effect; finally, the joint significance test did not accept the original hypothesis, indicating that the SDM model with double fixation of time and individual is more appropriate.

Table 5 reports the results of static space panel measurement estimates. Considering the robustness of regression results, the estimation results of the dual fixed-effect SEM model and the SDM model are listed under three matrices, and the decomposition results of direct effects, indirect effects and total effects of the dual fixed-effect SEM model and SDM model based on the partial differential method are followed. The results reveal that the climate coefficient in the SDM model is significantly negative, indicating that the sample provinces have a significant negative impact on agricultural productivity in space. However, the regression coefficient value of the spatial interaction term cannot be directly used to discuss the marginal impact of climate change on agricultural productivity because it will lead to incorrect estimation when analyzing the spatial spillover effect between regions through simple point regression results. It is necessary to use a partial differential interpretation of variable change, that is, to use a direct and indirect effect to explain the influence of independent variables in a region on dependent variables in this region and other regions. We conclude that the indirect effect of climate change on agricultural productivity is significant. It can be seen from the above that climate change negatively affects agricultural productivity, which is reliable with earlier research findings and enhances the robustness of the results.

4.3 Robustness test

4.3.1 Index replacement assessment. For further testing of the results, the robustness analysis is used for measurement errors in this part; Table 6 shows the regression results. In

Year	AGRP	*z*-value	Climate	*z*-value
2011	−0.065**	−0.860	−0.044**	−0.250
2012	−0.064**	−0.827	−0.032**	0.056
2013	−0.078**	−1.220	−0.037**	−0.079
2014	−0.047**	−0.359	−0.036**	−0.034
2015	−0.100**	−1.829	−0.039**	−0.130
2016	−0.089**	−1.537	−0.047**	−0.350
2017	−0.063**	−0.785	−0.045**	−0.288
2018	−0.051**	−0.481	−0.041**	−0.169
2019	−0.043**	−0.236	−0.042**	−0.215

Notes: Values in the parentheses indicate p-values; *,** and *** represent $p < 0.1$, $p < 0.05$, $p < 0.01$ accordingly

Table 4.
Moran's I index of three matrices

Table 5. Spatial model regression results

Variables	SDM (I) Geographical distance	(II) Economic distance	(III) Spatial weight	SEM (IV) Geographical distance	(V) Economic distance	(VI) Spatial weight
Climate	−0.1917* (0.0844)	−0.2128** (0.0493)	−0.2625** (0.0172)	−0.2122* (0.0515)	−0.2359** (0.0325)	−0.2453** (0.0262)
PGDP	−0.0597 (0.2344)	−0.0357 (0.4734)	−0.0300 (0.5356)	−0.0710 (0.1418)	−0.0596 (0.2335)	−0.0469 (0.3440)
ECT	−0.3191*** (0.0000)	−0.3170*** (0.0000)	−0.2160** (0.0146)	−0.2840*** (0.0001)	−0.2986*** (0.0000)	−0.2759*** (0.0002)
AUFC	0.0170 (0.1188)	0.0131 (0.2151)	0.0234** (0.0240)	0.0220** (0.0379)	0.0232** (0.0295)	0.0246** (0.0190)
INP	−0.0729*** (0.0096)	−0.0232 (0.3414)	−0.0144 (0.5788)	−0.0485* (0.0517)	−0.0387 (0.1121)	−0.0314 (0.1967)
W*DIGE	0.7214 (0.3792)	−0.1647 (0.5789)	−0.4557 (0.1806)	−0.2122* (0.0515)	−0.2359** (0.0325)	−0.2453** (0.0262)
Direct effect	−0.2136* (0.0559)	−0.2067* (0.0622)	−0.2472** (0.0272)	−0.2840*** (0.0001)	−0.2986*** (0.0000)	−0.2759*** (0.0002)
Indirect effect	−0.5299 (0.3065)	−0.1333 (0.6466)	−0.3234 (0.2654)	−0.0145*** (0.0000)	−0.0154*** (0.0000)	−0.0152*** (0.0000)
Total effect	0.3163 (0.5515)	−0.3399 (0.2914)	−0.5707* (0.0757)	−0.0485* (0.0517)	−0.0387 (0.1121)	−0.0314 (0.1967)
N	600	600	600	600	600	600
Adj. R^2	0.3855	0.3604	0.3262	0.3039	0.4041	0.4037

Notes: Values in the parentheses indicate p-values; *,** and *** represent $p < 0.1$, $p < 0.05$, $p < 0.01$ accordingly

Variables	(I)	(II)	(III)	(IV)
Climate	−0.0827* (0.8176)	−0.1961** (0.5837)		
Climate2			−0.2354*** (0.0000)	−0.1212** (0.0378)
PGDP		0.0462 (0.7713)		0.0058 (0.7966)
ECT		0.2990 (0.2012)		0.0538 (0.4483)
AUFC		−0.0326 (0.3455)		0.0163* (0.0805)
INP		0.2478*** (0.0017)		−0.0005 (0.9776)
CLP		−0.1416 (0.2054)		−0.0880***(0.0067)
_Cons	2.3389 (0.3957)	1.6989 (0.6266)	2.0660*** (0.0000)	0.5663 (0.3030)
N	600	600	600	600
Adj. R^2	0.8795	0.8816	0.3081	0.3760

Notes: Values in the parentheses indicate *p*-values; *,** and *** represent $p < 0.1$, $p < 0.05$, $p < 0.01$ accordingly

Table 6. Robustness analysis of measurement errors

the benchmark regression, the number of agricultural production refers to the practice of Gollin *et al.* (2014) and Tombe (2015) and takes the added value per labor as the measurement index of productivity, which is specifically obtained by dividing the agricultural added value in each year (calculated at the constant US dollar price in 2010) by the number of agricultural employed population. At the same time, the climate change index is also changed from entropy method to principal component analysis method. The test results of Models (I) and (II) show that climate has a significant negative impact on agricultural productivity when changing the measurement method of agricultural productivity. Validation of Models (III) and (IV) shows that climate still has a significant negative impact on agricultural productivity when climate is measured by the principal component method. Therefore, different methods of measuring agricultural productivity and climate do not affect the core conclusions of this paper. The effect of climate on agricultural productivity has certain credibility, which verifies the research hypothesis again (Table 7).

4.3.2 Quantile regression. To further verify the robustness of the results, we used quantile regression for further comparison. In all quantiles, the estimated climate coefficient is negative at the level of 1%. After adding the control variable, the absolute value of the coefficient fluctuates and increases. It shows that the impact of climate change on agricultural productivity is always significantly negative, which again verifies the research hypothesis. The higher the quantile, the greater the absolute value of the estimated coefficient of climate. The absolute value of the estimated coefficient of climate decreased from 0.3577 in the 0.25 quantile to 0.4729 in the 0.75 quantile, and the negative influence increased by about 1/3. The main reason is that with the increase of the severity of climate change, crops cannot adapt to the extreme weather impacts, including global warming, floods and droughts, resulting in the decline of agricultural productivity. Second, from the results of the control variables, the impact of per capita GDP on agricultural productivity is always significantly positive in all quantiles, that is, it can promote agricultural productivity. Engel coefficient, foreign capital utilization rate, industrial productivity and capital productivity are significantly negative in two quantiles and not significant in the other quantile. At the same time, we use the tail reduction processing for correlation robustness analysis, and uniformly replace the values less than 2.5% in the data set with the values of 2.5%, and the values greater than 97.5% with the values of 97.5%. The results of

Table 7. Quantile regression and tail reduction

Variables	$Q = 0.25$		$Q = 0.5$		$Q = 0.75$		Tail-shrinking treatment	
Climate	−0.3573*** (0.0000)	−0.3577*** (0.0000)	−0.4122*** (0.0000)	−0.4143*** (0.0000)	−0.4618*** (0.0000)	−0.4729*** (0.0000)		
ClimateW							−0.2648** (0.0256)	−0.3073*** (0.0061)
PGDP		0.1392*** (0.0000)		0.1841*** (0.0000)		0.2233*** (0.0000)		−0.0647 (0.1963)
ECT		−0.1163** (0.0268)		−0.2815*** (0.0000)		−0.1987 (0.2011)		−0.2910*** (0.0001)
AUFC		−0.0135* (0.0736)		−0.0063 (0.2342)		−0.0456*** (0.0028)		0.0263** (0.0157)
INP		−0.0466*** (0.0006)		−0.0841*** (0.0000)		−0.0600 (0.1241)		−0.0363 (0.1441)
CLP		−0.0323 (0.1858)		−0.0735*** (0.0049)		−0.0206 (0.8365)		−0.0163 (0.6431)
_cons		1.4868*** (0.0002)		1.0313*** (0.0034)		1.7892 (0.1580)		2.8355** (0.0108)
Fixed province	YES	YES	YES	YES	YES	YES	YES	YES
Fixed year	YES	YES	YES	YES	YES	YES	YES	YES
N	600	600	600	600	600	600	600	600
Adj. R^2	0.7387	0.7383	0.7447	0.7465	0.7471	0.7687	0.7412	0.7733

Notes: Values in the parentheses indicate p-values; *,** and *** represent $p < 0.1$, $p < 0.05$, $p < 0.01$ accordingly

tail shrinking treatment showed that the impact of climate change on agricultural productivity was significantly negative, which again verified the research hypothesis.

4.4 Heterogeneity test

Table 8 reports the empirical test of climate on the heterogeneity of agricultural productivity in different regions and different rice planting modes. The results show that there are regional differences in the impact of climate on agricultural productivity under different geographical conditions, and the research hypothesis is confirmed. From the existence of climate on agricultural productivity in different regions, the estimated coefficients of climate in the central eastern regions are not significant, indicating that the inhibitory effect of climate on agricultural productivity in these two regions is not obvious. In general, the change in climate in the western region can significantly reduce the agricultural productivity of the region. At the same time, as China is mainly planted with rice, an empirical analysis is carried out according to the different harvest times of rice planting (one season rice, two season rice and three season rice). The results showed that the climate of the rice planting areas of one season, two seasons and three seasons had an adverse effect on agricultural productivity, but only the rice planting area of one season was significant at the level of 5%, and the results of two seasons rice and three seasons rice were not significant.

5. Conclusions and policy recommendations

China's long-term sustainable development is mainly dependent on the stable development of better agricultural policies in China. To achieve sustainable development, China's agriculture must depend on technological progress to drive the growth rate of total factor agriculture growth. Using the three-stage SDM model, this paper calculates the provincial agricultural productivity from 2000 to 2019. At the same time, temperature, precipitation, sunshine duration, average wind speed and average air pressure are selected by the entropy method to calculate the climate index. The impact of climate change on agricultural productivity is discussed. The following conclusions are drawn: climate has a significant negative impact on agricultural productivity. This conclusion passed the robustness test of index replacement, quantile regression and tail reduction. Further, during the subdivision of climatic factors, although annual precipitation has no significant impact on the growth of agricultural total factor productivity, temperature and wind speed have a significant negative impact on agricultural productivity. The heterogeneity test indicates that climatic changes significantly hinder the growth of agricultural productivity in the western region, and the climate in rice planting areas in one season has a significant negative impact on agricultural productivity.

5.1 Policy implications

First, governments at all levels should strive to establish and improve the construction and service of the meteorological forecast and early warning system, improve agricultural infrastructure, build farmland and water conservancy and strengthen the prevention of meteorological disasters.

Second, the government should promote the systematic research on the climate change impact on agriculture, reduce the uncertainty of agricultural production, further change the mode of agricultural development, change from mainly relying on traditional agricultural factor investment in the past to depending on technical advancement and improving technological efficacy, further strengthen the R & D and promotion of agricultural technological progress and enhance the support of agricultural technological growth to agricultural productivity. Third, the

Table 8. Heterogeneity test results

Variables	East (I)	Middle (II)	West (III)	One (IV)	Two (V)	Three (VI)
Climate	−0.1596 (0.4107)	−0.2299 (0.3793)	−0.5029** (0.0148)	−0.3878** (0.0215)	−0.1019 (0.6098)	−0.6291 (0.4615)
PGDP	0.0537 (0.6465)	0.0702 (0.5980)	0.1434* (0.0791)	−0.1192* (0.0805)	0.1417 (0.1867)	0.0268 (0.9214)
ECT	−0.2887* (0.0687)	0.1498 (0.5567)	0.3873** (0.0455)	−0.3363*** (0.0015)	−0.2390* (0.0960)	−0.9297 (0.5566)
AUFC	0.0164 (0.4714)	0.0366 (0.1517)	0.0280* (0.0530)	0.0363** (0.0214)	−0.0155 (0.4036)	−0.0279 (0.6848)
INP	−0.0071 (0.8975)	0.0006 (0.9961)	−0.1289** (0.0147)	−0.0348 (0.2977)	−0.1383** (0.0257)	−0.1138 (0.7096)
CLP	−0.1176** (0.0435)	−0.0164 (0.8733)	0.2602*** (0.0001)	−0.0287 (0.5783)	−0.0044 (0.9358)	−0.2177 (0.7633)
_cons	−0.0228 (0.9918)	1.5398 (0.5741)	5.7776*** (0.0016)	4.0319*** (0.0082)	−0.1709 (0.9355)	2.8691 (0.7804)
N	220	160	220	340	240	20
Adj. R^2	0.7902	0.7569	0.7532	0.7496	0.6812	−0.2039

Notes: Values in the parentheses indicate p-values; *,** and *** represent $p < 0.1$, $p < 0.05$, $p < 0.01$ accordingly

government should promote the "quality and efficiency" of agriculture, and increase the education and technical cultivation of rural labor force, cultivate new agricultural business entities and develop agriculture with high efficiency and moderate scale.

Fourth, we should strengthen the meteorological information transmission service and build a new agricultural meteorological information platform with the new mode of internet plus, providing timely meteorological information for farmers and other subjects, and providing countermeasures at the same time, reducing the impact of extreme climate on agricultural production and achieving sustainable agricultural development.

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