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ARTICLE

MEASURING THE MARGINAL EFFECTS OF CLIMATE WARMING ON WHEAT IN CHINA'S HUANG-HUAI-HAI REGION AND RESPONSIVE MEASURES

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ABSTRACT

Climate is the precondition for agricultural production. Climate warming is the most striking characteristic of changes in global climate and has an important effect on grain production. Based on wheat production and meteorological data in the Huang-Huai-Hai region spanning from 2000 to 2020, we apply the MO-OLS model to examine the spatiotemporal heterogeneous effects of climate warming on regional wheat yield per unit area; then, using the spatiotemporal heterogeneous effects of climate warming as the explained variable, we utilized a series of explanatory variables to regress the influencing factors. This research shows: 1) the marginal effects of climate warming on wheat yield per unit area is generally negative and exhibits spatiotemporal differences, that is, higher latitude regions are less negatively affected by climate warming; 2) the development in crop diversity and industrialization exacerbate the marginal effects of climate warming, while improvements in urbanization, construction of irrigation and water conservancy infrastructure and intensity of fertilizer application weaken the marginal effects of climate warming. Based on empirical results, we propose policy suggestions like enhancing guidance on agroecological technologies, increasing the level of mechanization of agricultural production and stepping up the construction of agricultural infrastructure.

KEYWORDS

Climate warming, wheat yield per unit area, Huang-Huai-Hai region, MO-OLS, spatiotemporal heterogeneity

1. INTRODUCTION

Wheat is the second largest grain crop in China only next to rice and plays a fundamental role in stabilizing the operation of national economy. Total wheat production in China rose to 134.3 million tons in 2020 from 53.84 million tons in 1978. In particular, China achieved a growth in wheat production for 15 consecutive years from 2003 to 2017. Continuous growth in wheat production laid a solid foundation for the steady development of China's socio-economy. Grain yield enhancement depends on an increase in sown area and yield per unit area. However, with advancement of urbanization in China, it is difficult to further increase the inputs of agricultural land and agricultural labor force; in addition, the volatility in relative prices of agricultural products has induced a change in the structure of agricultural products, making it inevitable that the production area of economic crops will squeeze out that for grain crops. Hence, the room for increasing the sown area of grain in China is rather limited even in the future. China needs to feed 20% of the world's population with only about 7% of the world's total arable land and still faces heavy pressure to ensure grain supply and security. It is already unrealistic to increase grain output simply by increasing the amount of factor input.

To enhance grain yield and ensure China's grain security in the future, the key is to increase grain yield per unit area. Current studies addressing influencing factors of China's grain output mostly focus on four aspects: management measures, agricultural science and technology, agricultural policy and climate. Wu et al. (2020) argue that grain crops' environmental adaptability can be improved by implementing appropriate management measures and reducing redundant input factors [1]. Xu (2012) and Tang et al. (2017) found that large-scale operation play an important role in improving overall grain production capacity and risk resistance capacity [2, 3]. Zhang et al. (2016) pointed out that scientific and technological advancement has become the primary force driving grain production and ensuring grain security [4]; studies conducted by Zhou et al. (2013) & Zhou et al. (2016) respectively show that improvement in agricultural varieties and popularization and application of advanced agricultural production tools play a crucial role in improving grain yield per unit area[5, 6]. In terms of agricultural policies, Chen et al. (2010) and Hua et al. (2017) asserted that advancement in grain price subsidy policy and improvement in agricultural production subsidies significantly increase grain production capacity and grain yield per unit area [7, 8].

Agriculture is an overlapping area of economic and natural reproduction, where climate acts as the precondition. Tan et al. (2015) stated that climate change exerts all-round and multi-layer influences on agricultural production and potentially threatens China's grain security, causing instability of grain supply and systematic grain risks [9]. Meteorological disasters have a significantly negative effect on agricultural production, but advancement in the construction of agricultural infrastructure helps reduce adverse climatic impact and improve agricultural resistance to risks, thereby alleviating to a certain extent the negative effects of climate change [10-12].

With respect to wheat, Liu et al. (2015), Luy (2017), Zhang et al. (2017) and Li et al. (2018) revealed the great potential of wheat production in China and the huge gaps between real total output and potentially maximum output and between real yield per unit area and potentially maximum yield partly due to the effect of the climate factor [13-16]. Studies by Han (2014) and Zhao et al. (2020) suggested that compared with other grain crops, wheat is more susceptible to climatic effects due to a longer growth cycle and high requirement on climatic conditions [17, 18]. In the meantime, the climatic effect on wheat across different regions may vary due to latitudinal differences that result in varying climatic effects on wheat production. Specifically, high latitude regions are more likely to be positively affected by climate warming [19], and climatic conditions may fluctuate at different time points. Hence, spatiotemporal heterogeneity and other factors should be considered when estimating the marginal effects of climate warming on grain production.

Since 1978, total wheat production in China has been growing at an annal rate of 2.2%, and the percentage of wheat against total grain production has risen to 20.05% in 2020 from 17.67% in 1978. In opposition to this trend, the total sown area of wheat has been continuously dropping to 23.38 million hectares in 2020 from 29.183 million hectare in 1978, representing an annual decrease rate of 0.46%. The proportion of sown area of wheat to total sown area of grain has also dropped to 20.02% from 24.2% in 1978. The increase in wheat yield per unit area has become a crucial driver of wheat production growth in China. From a perspective of spatiotemporal distribution, the main wheat growing areas in China has shown a trend of continual concentration. Presently, a wheat-dominated main growing area has arisen from the Huang-Huai-Hai plain, and with relevant production factors streaming in, wheat production in the region has been increasingly concentrated. As of 2020, the total sown area of wheat in the region has reached 13.87 million hectares, accounting for 59.32% of the total sown area of wheat nationwide; the ratio of wheat production in the region to total national production has also grown to 63.4% in 2020. Therefore, researching the effect of climatic change in the region on wheat yield per unit area, as well as the adaptive adjustment effect of human factors on climate, will be of a great value.

Presently, climate warming is the major characteristic of global climate change and has a significant effect on wheat production. Existing studies indicate that climate warming has become the major factor restricting further growth of wheat production, and for every 1°C of temperature rise, the wheat production drops by about 6% [19]. Against the background of global warming, overcoming or mitigating the negative effects of climate warming through a series of artificial measures is the key to further stimulating the potential of grain production, fulfilling continual growth of wheat production and ensuring the grain security of China. As such, this research has the following contributions: ① considering regional heterogeneous differences and volatility of climate warming, we incorporated regional and temporal heterogeneities into the estimation of the marginal effects of climate warming on wheat yield per unit area, followed by an analysis of heterogeneous marginal effects of climate warming across different regions at different time points. ② We conducted a regression analysis of the marginal effects of climate warming using a series of socioeconomic factors to examine the roles that human management measures, socioeconomic development and agricultural production inputs play in addressing the impact of climate warming, with a view to providing sensible policy suggestions for mitigating the negative effects of climate warming.

2. MODELS, VARIABLES AND DATA

2.1 MO-OLS model

In this research, the mean observation ordinary least squares (MO-OLS) model proposed by Keane & Neal (2020) is applied to examining the effect of climate warming on wheat yield per unit area [20]. The MO-OLS model implements interactions between explanatory variables and time and individual characteristics to obtain estimation coefficients of different individuals at different time points, followed by multiple iterations to continuously reduce estimation bias and eventually obtain consistent coefficient estimates. Conventional OLS model can also estimate it β_{it} through interactions between explanatory variables and dummy variables of time and individuals. but the calculation may have no solution. This is because (N+T)*(K+1) explanatory variables are included in the equation, and hence infeasible solutions may occur when obtaining the inverse of $x_{it}^T x_{it}$. The general form of the MO-OLS model is shown in Equation (1), where i=1,…, N denotes the number of individuals, t=1,…, T denotes period. x_{it} is a (K+1)*1-dimensional independent variable which contains a constant term and its vector form is $(1, x_{1it}, x_{2it}, \ldots, x_{kit})^T$, $x_{1it} x_{2it} x_{kit}$, y_{it} is dependent variable, β_{it} is estimation coefficient of a dependent variable individual across different time points on the (K+1)*1, $\beta_{it} = (\beta_{0it}, \beta_{1it}, \ldots, \beta_{kit})$, and u_{it} is a disturbance term.

$$y_{it} = \beta_{it}^T x_{it} + u_{it} \tag{1}$$

The MO-OLS model comprises four hypotheses: , the disturbance term of ①, is independent and identically distributed; the explanatory variable of ② is weakly exogenous: $E(x_{it}u_{it}) = 0$; ③ $E(u_{it}^2 | x_{it}) < \infty$; β_{it}, the estimation coefficient of ④, is additively divisible, $\beta_{it} = \beta + \gamma_i + \mu_i$; where γ_i is individual effect and μ_i is temporal effect.

To address the appearance of infeasible solutions in conventional OLS regressions, the MO-OLS model estimates β_{it} through mixed regression and regressions at individual and temporal levels. First, Equation (1) is rewritten as:

$$y_{it} = x_{it}^T \beta_{it} + v_{it} \tag{2}$$

$$v_{it} = x_{it}^T \gamma_{it} + x_{it}^T \mu_{it} + u_{it} \tag{3}$$

β under OLS is mixed according to the estimates of Equation (2)

$$\hat{\beta} = (\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} x_{it} x_{it}^T)^{-1} (\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} x_{it} y_{it}) \tag{4}$$

Substituting into Equation (4), we obtain:

$$\hat{\beta} = \beta + Q_{xx,NT}^{-1} (\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} x_{it} x_{it}^T \gamma_i)$$

$$+ Q_{xx,NT}^{-1} (\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} x_{it} x_{it}^T \mu_t) + Q_{xx,NT}^{-1} (\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} x_{it} u_{it}) \tag{5}$$

Where, $Q_{xx,NT}^{-1} = (\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} x_{it} x_{it}^T)^{-1}$ Next, the interaction between individuals and explanatory variables in Equation (3) is incorporated into Equation (2) to estimate the $\hat{\beta}_i$ on the individual level.

$$y_{it} = x_{it}^T (\beta + y_i) + v_{it} \tag{6}$$

$$v_{it} = x_{it}^T \mu_t + u_{it} \tag{7}$$

Similarly, OLS is used to estimate $\hat{\beta}_i$

$$\hat{\beta}_i = \beta + \gamma_i + Q_{xx,T}^{-1} (\frac{1}{T} \sum_{t=1}^{T} x_{it} x_{it}^T \mu_t) + Q_{xx,T}^{-1} (\frac{1}{T} \sum_{t=1}^{T} x_{it} x_{it} u_{it}) \tag{8}$$

Where, $Q_{xx,T}^{-1} = (\frac{1}{T} \sum_{t=1}^{T} x_{it} x_{it}^T)^{-1}$. Next, $\hat{\beta}_i$ is estimated on the temporal level:

$$y_{it} = x_{it}^T (\beta + \mu_t) + v_{it} \tag{9}$$

$$v_{it} = x_{it}^T \gamma_i + u_{it} \tag{10}$$

$$\hat{\beta}_i = \beta + \mu_t + Q_{xx,T}^{-1} (\frac{1}{T} \sum_{t=1}^{T} x_{it} x_{it}^T \gamma_i) + Q_{xx,T}^{-1} (\frac{1}{T} \sum_{t=1}^{T} x_{it} u_{it}) \tag{11}$$

Where, $Q_{xx,T}^{-1} = (\frac{1}{N} \sum_{t=1}^{N} x_{it} x_{it}^T)^{-1}$. Based on the estimates of $\hat{\beta}$, $\hat{\beta}_i$ and $\hat{\beta}_t$, the estimate of $\hat{\beta}_{it}$ can be initially constructed. However, the initial estimate of $\hat{\beta}_{it}$ is biased, and is thus denoted here as $\hat{\beta}_{it}^{pro}$

Where $R_N = Q_{xx,N}^{-1} (\frac{1}{N} \sum_{i=1}^{N} x_{it} x_{it}^T \gamma_i)$, $R_{t,NT} = Q_{xx,NT}^{-1} (\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} x_{it} x_{it}^T \mu_t)$, $Q_{xu,N} = Q_{xx,N}^{-1} (\frac{1}{N} \sum_{i=1}^{N} x_{it} u_{it})$, R_N, $R_{i,NT}$, $Q_{xu,T}$, and $Q_{xu,NT}$ are similarly defined as stated above.

$(\beta + \gamma_i + \mu_t)$ is the true value part in Equation (12), $(R_N - R_{i,NT}) + (R_T - R_{t,NT})$ is the estimation bias caused by the correlation bias between explanatory variables and heterogeneity, $Q_{xu,N} + Q_{xu,N} - Q_{xu,NT}$ is the error part caused by the correlation between x_{it} and u_{it}, which can be eliminated via multiple iterations.

The bias term $(R_N - R_{i,NT}) + (R_T - R_{t,NT})$ in Equation (12) can be eliminated through accurate calculation. In $(R_N - R_{i,NT})$, $\hat{\beta}_i$ is used to

$$\hat{\beta}_{it}^{pro} = \beta_i + \beta_t - \beta = (\beta + \gamma_i + \mu_t) + (R_N - R_{i,NT}) + (R_N - R_{t,NT}) + (Q_{xu,N} + Q_{xu,T} - Q_{xu,NT}) \tag{12}$$

$$\begin{aligned}(\hat{R}_N - R_{i,NT}) + (R_T - R_{t,NT}) &= (R_N - R_{i,NT}) + (R_T - R_{t,NT}) + Q_{xx,N}^{-1} \frac{1}{N} \sum_{i=1}^{N} (x_{it} x_{it}^T R_T + x_{it} x_{it}^T Q_{xu,N}) \\ &+ Q_{xx,T} \frac{1}{T} \sum_{i=1}^{N} (x_{it} x_{it}^T R_N + x_{it} x_{it}^T Q_{xu,N}) - Q_{xx,NT}^{-1} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} x_{it}^T R_T + x_{it} x_{it}^T R_N + x_{it} x_{it}^T Q_{xu,N} + x_{it} x_{it}^T Q_{xu,T})\end{aligned} \tag{13}$$

$$\hat{\beta}_{it} = \beta_i + \beta_t - \beta + \sum_{l=0}^{L} (-1)^{l+1} (Q_{xx,N}^{-1} \frac{1}{N} \sum_{i=1}^{N} x_{it} x_{it}^T \Gamma_{1,l} + Q_{xx,N}^{-1} \frac{1}{T} \sum_{i=1}^{N} x_{it} x_{it}^T \Gamma_{2,l} - Q_{xx,NT}^{-1} \frac{1}{NT} \sum_{i=1}^{N} \sum_{i=1}^{T} x_{it} x_{it}^T \Gamma_{1,l} + x_{it} x_{it}^T \Gamma_{2,l}) \tag{14}$$

$$\ln y_{it} = \beta_{0,it} + \beta_{1,it} \ln rain_{it} + \beta_{2,it} (\ln rain_{it})^2 + \beta_{3,it} \ln temp_{it} + \beta_{4,it} (\ln temp_{it})^2 + \beta_{warmth,it} \ln warmth_{it} + \alpha_i + \theta_t + \varepsilon_{it} \tag{15}$$

$$\hat{\beta}_{warmth,it} = \beta_0 + \beta_1 zw_{it} + \beta_2 irr_{it} + \beta_3 mach_{it} + \beta_4 fert_{it} + \beta_5 ind2_{it} + \beta_6 rgdp_{it} + \beta_7 cit_{it} + \beta_8 pro_i + \beta_9 year_t + \varepsilon_{it} \tag{16}$$

approximately estimate γ_i, thereby deriving $\hat{R}_N$ and $\hat{R}_{i,NT}$. Similarly, we can also obtain $\hat{R}_T$ and $\hat{R}_{t,NT}$. The substitution process is shown as follows:

Subtracting Equation (12) by Equation (13) can eliminate the original bias but it also incorporates another bias. Using estimated $\hat{R}_N$, $\hat{R}_{i,NT}$, $\hat{R}_T$ and $\hat{R}_{t,NT}$ to approximately estimate the new bias in Equation (13) and repeating the subtraction process stated above L times, we eventually make the bias arbitrarily small. The iterative equation is:

Where when $l>0$, $\Gamma_{1,l} = Q_{xx,T}^{-1} (\frac{1}{T} \sum_{t=1}^{T} x_{it} x_{it}^T \Gamma_{2,l-1})$, $\Gamma_{2,l} = Q_{xx,N}^{-1} (\frac{1}{N} \sum_{t=1}^{N} x_{it} x_{it}^T \Gamma_{1,l-1})$; and $\Gamma_{1,l=0} = \hat{\beta}_i$, $\Gamma_{2,l=0} = \hat{\beta}_t$ Equation (14) is an easily constructed estimator because it is only relevant to initial estimates ($\hat{\beta}_i, \beta_t$ *and* β) and x_{it}.

In this research, the MO-OLS model is applied to quantify the marginal effects of climate warming on wheat yield per unit area. The MO-OLS is relatively more objective when estimating climatic effects on agricultural production due to the consideration of their spatiotemporal heterogeneity, that is, it allows for different marginal effects of climate on agricultural production across different regions at different time points. With a relatively large researched area and long research period, climate change produces heterogeneous effects across different regions and in the meantime, climate itself experiences fluctuations at different time points. In addition, differences in economic development mode, popularization of agricultural machinery and irrigation and water conservancy infrastructure across different regions are all factors making the adaptability of agricultural production in a region exhibit spatiotemporally differentiated characteristics, and regions with relatively sophisticated irrigation and water conservancy infrastructure are in a better position to cope with negative climatic impacts. The sole estimation coefficient under the conventional OLS model fails to reflect the spatiotemporal heterogeneity in the effect of climate change on agricultural production in the researched area. Hence, we applied the MO-OLS model to estimate the spatiotemporal heterogeneous effects of climate on wheat yield per unit area. The specific form of the model is as follows:

Equation (15), the dependent variable is wheat yield per unit area which is obtained taking the natural log of the result of the division of total wheat production by its sown area; among the independent variables, climate warming is the core explanatory variables which is expressed by the annual range of temperature of wheat growing period. Annual range of temperature is an important indicator reflecting the trend of climate warming [21] and a crucial factor influencing the growth of agricultural crops [22]. The variable is calculated as the difference between the maximum 1-day temperature and the minimum 1-day temperature in a year. Here, the difference between the maximum and minimum 1-day temperatures during the wheat growing period of each year is used as a proxy variable of climate warming. The control variable covers factors potentially affect not only the annual range of temperature but also wheat yield per unit area, including total precipitation and its quadratic term during wheat growing period, as well as mean temperature and its quadratic term in the growing period. Furthermore, to validate the robustness of model estimation, the explanatory variable is replaced: the annual range of temperature is the difference between maximum and minimum 1-day temperatures, which is highly susceptible to the effect of extreme values and may not accurately depict the trend of climate warming; to ensure the robustness of estimation results, the calculation of the annual range of temperature is appropriately modified. The difference between daily mean maximum and minimum temperatures during wheat growing period is used as a substitution variable in order to eliminate the potential effect of extreme values. In terms of the substitution of control variables: the number of precipitation days of wheat growing period and its quadratic term are used to substitute total precipitation of the growing period and its quadratic term; the total duration of sunshine of wheat growing period and its quadratic term are used to replace mean temperature and its quadratic term; α_i and θ_t spectively denote individual fixed effect and time fixed effect. Logarithms of all the above independent variables except individual and time fixed effects are taken.

2.2 Analysis of the influencing factors of $\widehat{\beta_{warmth,it}}$

Climate warming has been the most noticeable trend of climate change over the past few decades. Existing studies confirm that climate warming has restricted further growth in wheat production in most regions worldwide [19]. In the meantime, however, humans have adopted a variety of measures to adapt to the effects of climatic change. Existing research indicates that scientific and technological advancement, variety improvement and enhancement in agricultural and rural infrastructure and the level of agricultural production mechanization have positive impacts on grain productivity; apart from enhancing agricultural resistance to natural disasters, human management measures also play a moderating effect on the influence of natural environment on grain production [23]. Based on the estimation results of the MO-OLS model, this research adopts $\hat{\beta}_{warmth,it}$, the estimation coefficient of climate warming, as the explained variable,and agricultural crop diversity, construction of irrigation and water conservancy infrastructure, level of agricultural mechanization, intensity of fertilizer application, industrialization, urbanization and economic development as explained variables and uses the panel Tobit model to quantify the effect of human management measures on moderating climate warming. The panel Tobit model is a random effects model where the controlling for the individual effect introduces multiple individual dummy variables, leading to an impossibility of model estimation. Therefore, we draw on the practices of Fang et al. (2014) to adopt the higher-level individual fixed-effects in the model [24]. Here, the individual characteristics are controlled at the provincial level. The model setting is as follows:

2.3 Variable selection and descriptive statistics of data

The Huang-Huai-Hai region comprises Shandong, Anhui, Henan, Jiangsu and north Hubei. Wheat data in Equation (15) are from the statistical yearbooks of different provinces from 2001 to 2021, including Statistical Yearbook of Henan, Statistical Yearbook of Shandong, Statistical Yearbook of Anhui and Rural Statistical Yearbook of Hubei. Wheat yield per unit area is calculated by dividing the total wheat production by wheat sown area. Sown area of wheat at the prefectural level is not included in the Statistical Yearbook of Jiangsu and thus is omitted; year-to-year monthly meteorological data are from the National Meteorological Information Center; studies of Luo et al. (2021) are drawn upon to define the wheat growing period as October to May of the following year [25]. On this basis, data of climatic indicators across the wheat growing period, including total precipitation, mean temperature, mean relative air humidity and mean, maximum and minimum of daily temperatures, are obtained.

Table 1. Descriptive statistics prefectural wheat and climate data

Category of variable	Name of variable	Meaning of variable	Unit	Mean	Standard deviation	Minimum value	Maximum value
Dependent variable	Total wheat production	Total wheat production	Ton	1413885	1252592	10810	5504900
	Sown area of wheat	Sown area of wheat	Hectare	249206.9	190230.9	3404	787150
	Wheat yield per unit area	Total production/ sown area	-	5.085	1.471	1.532	7.755
Independent variables	Precipitation	Total precipitation during growing period	mm	366.793	221.015	24.9	1389.12
	Mean temperature	Monthly mean temperature during growing period	℃	10.3	1.7	5.7	14.4
	Relative air humidity	Relative air humidity during growing period	%	62.886	7.603	38.15	78.7
	Mean maximum temperature	Monthly mean maximum temperature during growing period	℃	15.2	1.777	8.2	19.8
	Mean minimum temperature	Monthly mean minimum temperature during growing period	℃	5.1	2.178	-0.1	10.6
	1-day maximum temperature	1-day maximum temperature during growing period	℃	26.5	2.4	17.1	32.1
	1-day minimum temperature	1-day minimum temperature during growing period	℃	-3.4	2.9	-10.6	3.3

Data spanning 21 years across 39 prefectural cities, as well as 819 samples, were obtained by matching meteorological data and data of statistical yearbook. The researched area covers the most parts of Shandong and Henan, as well as the northwest of Anhui and northeast of Hubei. Descriptive statistics of variables in Equation (12) are shown in Table 1: during 2000-2020, regional wheat yield per unit area experienced a process from year-to-year growth to range-bound fluctuations. Generally, regional wheat yield per unit area grew to 5.678 tons per hectare in 2020 from 4.175 tons per hectare in 2000; from time-period perspective, wheat yield per unit area exhibited a steady linear growth trend from 2000 to 2008, gradually increasing to 5.356 tons/hectare from 4.175 tons/hectare, which was followed by a range-bound fluctuation at [5.356, 5.678] between 2008 and 2020.

The independent variables of total precipitation and relative air humidity showed no regular changes over the researched period, and the trend of mean temperature is shown in Figure 1. During the researched period, mean minimum temperature showed a minor fluctuation range and thus a stable trend; in comparison, mean maximum temperature exhibited a relatively larger fluctuation range and a slightly upward trend. The trends of mean temperature and mean maximum temperature exhibited similar fluctuation trends, which may be attributed to the effects of the fluctuation in maximum temperature.

Data of independent variable in Equation (13) are from statistical yearbooks at provincial and prefectural levels, the descriptive statistics of which are shown in Table 2. The indicator of agricultural crop diversity is denoted by the proportion of the sown area of non-grain crops to total sown area; effective irrigation area is applied as the indicator of the construction of irrigation and water conservancy infrastructure, which showed a linear upward trend, growing to 347,280.5 hectares in 2020 from 280,174.4 in 2000, pointing to a continuous improvement in the coverage of irrigation and water conservancy infrastructure; the division of total agricultural machinery power by cultivated area denotes the level of agricultural mechanization, which exhibited a continuously growing trend to 1.322 kWh per hectare in 2020 from 0.852 kWh per hectare in 2000; the intensity of fertilizer application is expressed by pure volume of fertilizer applied divided by the total sown area, which showed a continuous growth trend from 1.928 tons per hectare in 2000 to 2.525 tons per hectare in 2006 but fluctuated within the range of [1.961, 2.108] tons/hectare between 2007 and 2020 with no significant trend of growth. The proportion of the output of the secondary industry to regional GDP is used to denote the level of industrialization; while the proportion of urban population to registered residential population is used to denote the level of urbanization.

3. EMPIRICAL RESULTS

3.1 Effects of climate warming on wheat yield per unit area

Estimation results of Equation (12) are shown in Table 3. Results of Models (1) and (2) are regression outcomes after the warmth variable is substituted by mean maximum and mean minimum temperatures; results of Models (3) and (4) are estimates of climate warming, in which Model (3) employs annual range of temperature as the proxy variable of climate warming, and Model (4) uses monthly range of mean temperature as the proxy temperature of climate warming; Model (5) involves substitution of control variables as discussed earlier, specifically, total precipitation

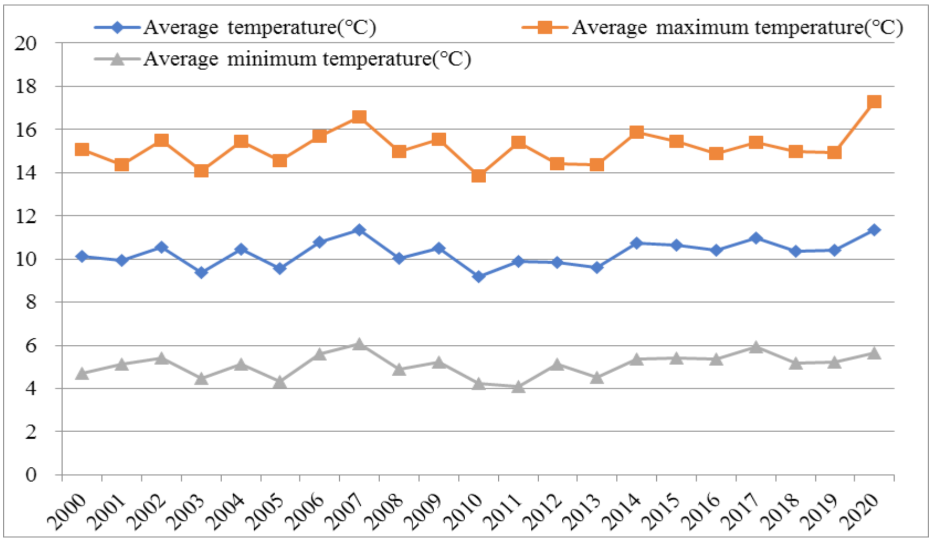

Figure 1. Trends of temperature change

Data source: National Meteorological Information Center (http://data.cma.cn/)

Table 2. Descriptive statistics of data of influencing factors

Category of variable	Name of variable	Meaning of variable	Unit	Mean	Standard deviation	Minimum value	Maximum value
Independent variable	Agricultural crop diversity	Sown area of non-grain/total sown area	-	0.332	0.106	0.100	0.615
	Irrigation and water conservancy infrastructure	Effective irrigation area	Hectare	303563.3	160523.4	30400	646470
	Level of agricultural mechanization	Total agricultural machinery power/ cultivated area	-	1.259	0.446	0.320	2.837
	Fertilizer application intensity	Pure volume of fertilizer applied/total sown area	-	2.202	2.447	0.457	19.934
	Industrialization	Output value of secondary industry/ regional GDP	-	0.478	0.090	0.239	0.717
	Urbanization	Urban population/ registered	-	0.419	0.161	0.099	0.823

and mean temperature variables are substituted by the number of days during growing period and duration of sunshine hours, and the core explanatory variable is annual range of temperature. Models (3), (4) and (5) are robustness tests for one another.

The regression results of Model (1) show that a rise in mean maximum temperature causes a generally significant decrease in wheat yield per unit area, for every 1% rise in maximum temperature, the average wheat yield per unit area decreases by 1.076%; estimates of Model (2) indicate that a rise in minimum temperature has a significantly positive effect on wheat yield per unit area, for every 1% rise in minimum temperature, wheat yield per unit area grows by 0.397%. Regression results of Model (3) show that climate warming decreases wheat yield per unit area, for every 1% growth of annual range of temperature during wheat growing period, wheat yield per unit area decreases by 0.211%; regression results of Model (4) indicate that for every 1% growth in monthly range of mean temperature, wheat yield per unit area decreases by 0.305%; with control variables being substituted, Model (5) shows that a rise in annual range of temperature still has a negative effect on wheat. Although estimates of Model (3) and Model (5) are not statistically significant, the signs of their estimation coefficients are consistently negative as those of Model (4), confirming that climate warming generally has a negative effect on wheat yield per unit area in the region. According to regression results of Models (3) through (5), the level of effect of climate warming on regional wheat yield per unit area falls between -0.2% and -0.3%.

3.2 Data visualization analysis of $\hat{\beta}_{warmth,it}$

Figure 2 shows the temporal scatterplots about the marginal effects of climate warming on wheat yield per unit area, where the left graph is the estimation coefficient of climate warming in Model (3) and the right graph is the estimation coefficient of climate warming in Model (4). As can be seen from the figure, the estimated coefficients of $\hat{\beta}_{warmth,it}$ are largely smaller than 0 regardless of whether annual range of temperature or monthly range of mean temperature is used. The estimates of $\hat{\beta}_{\ln sdtemp,it}$ fall in [-3.597, 1.963] when annual range of temperature is used, while the value of estimation coefficient of $\hat{\beta}_{\ln dtemp,it}$ in Model (4) falls in [-2.044, 1.121]. Further, the estimation coefficients of these models both exhibit a larger number of negative scatter points than those above 0 each year, indicating that the marginal effects of

Table 3. MO-OLS estimation of effects of climate on wheat yield per unit area

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	Wheat yield per unit area	Wheat yield per unit area	Wheat yield per unit area	Wheat yield per unit area	Wheat yield per unit area
lnrain	1.553**	1.952***	1.500**	1.729***	4.680*
	(0.661)	(0.690)	(0.696)	(0.669)	(2.437)
(lnrain)^2	-0.133**	-0.165***	-0.130**	-0.148***	-0.554**
	(0.056)	(0.058)	(0.060)	(0.056)	(0.274)
lntemp	15.594**	20.913***	12.171**	20.150***	-29.187**
	(7.355)	(6.954)	(6.110)	(7.383)	(14.169)
(lntemp)^2	-2.930**	-4.544**	-2.516**	-4.068***	2.050**
	(1.473)	(1.409)	(1.236)	(1.481)	(0.977)
lnhtemp	-1.076***	-	-	-	-
	(0.277)	-	-	-	-
lnltemp	-	0.423***	-	-	-
	-	(0.165)	-	-	-
lnsdtemp	-	-	-0.211	-	-0.202
	-	-	(0.135)	-	(0.143)
lndtemp	-	-	-	-0.305*** (0.089)	-
cons	-20.576** (9.524)	-29.235*** (9.081)	-16.874** (7.783)	-27.800** (9.689)	96.268* (9.222)
Number of observed values	819	818	819	819	819
Wald test	39.50	52.40	24.63	48.56	21.97
P-value	0.000	0.000	0.000	0.000	0.001
Iteration	370	512	379	385	1500

Note: Numbers in brackets shown in the above models are standard deviations of the estimates; *, ** and *** respectively denote significance levels of 10%, 5% and 1%.

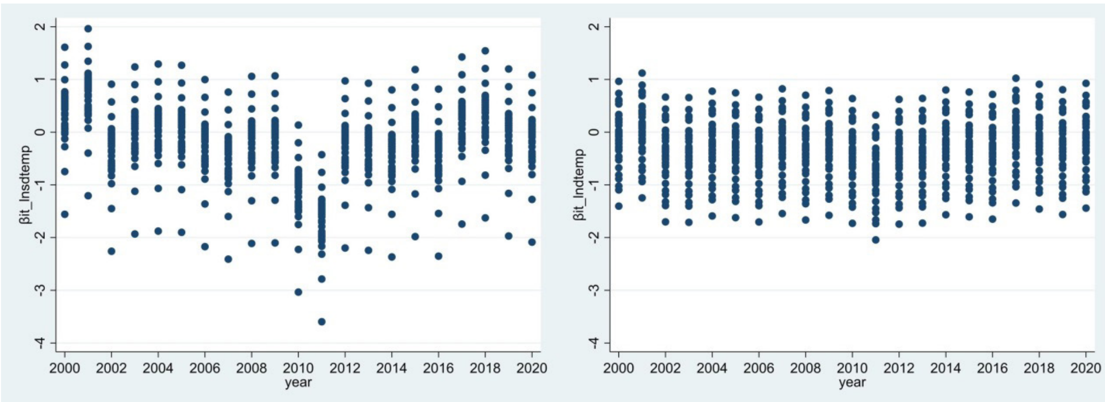

Figure 2. Temporal scatterplots of $\hat{\beta}_{warmth,it}$

climate warming on wheat yield per unit area are basically negative across different years in most regions. In terms of the temporal trend, the negative effects of climate warming on wheat yield per unit area gradually deepened before 2011, followed by a slight mitigation.

In addition, the distribution of scatter points of estimates of $\hat{\beta}_{warmth,it}$ of both models, as shown in Figure 2, are rather concentrated, where the scatter points of $\hat{\beta}_{\ln sdtemp,it}$, that is, estimation coefficient of annual range of temperature, mostly fall between (-2, 2), while the value of $\hat{\beta}_{\ln dtemp,it}$ is concentrated within (-1,1) and the distribution of its scatter points is more concentrated. The above shows the limited values of dependent variables, which is also why Tobit estimation is adopted in Equation (13).

Figures 3 and 4 show the regional distribution of $\hat{\beta}_{warmth,it}$ across different years, that is, the spatiotemporal distribution of marginal effects of climate warming on wheat yield per unit area. Specifically, Figure 3 shows the spatiotemporal distribution of $\hat{\beta}_{\ln sdtemp,it}$ and Figure 4 shows the spatiotemporal distribution of $\hat{\beta}_{\ln dtemp,it}$. The white area is the data missing area.The light orange parts in the above two figures denote regions with $\hat{\beta}_{warmth,it}$ smaller or equal to 0, that is, the marginal effect of climate warming on wheat yield per unit area in the area is monotonically non-increasing; the deep orange parts are regions with marginal effect larger than 0, which are positive effect region of climate warming on wheat yield per unit area. In terms of temporal trend, Figures 3 and 4 both show that marginal effects of climate warming on wheat yield per unit area within the negative effect area continuously expand then gradually decrease, a trend that is especially pronounced in Figure 3. Before 2011, the light orange parts exhibited a growing trend followed by a decrease. From the perspective of distributional regions, north of Henan and the majority part of Shandong, that is, high latitude regions in the figures, showed positive marginal effects of climate warming across the majority of years; while north of Hubei, west

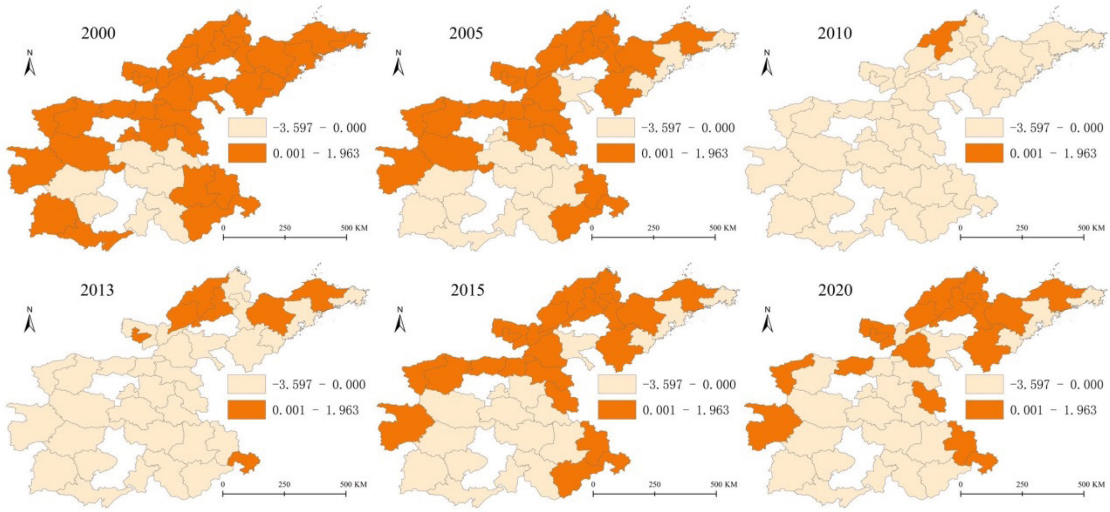

Figure 3. Spatiotemporal distribution of $\hat{\beta}_{\ln sdtemp,it}$

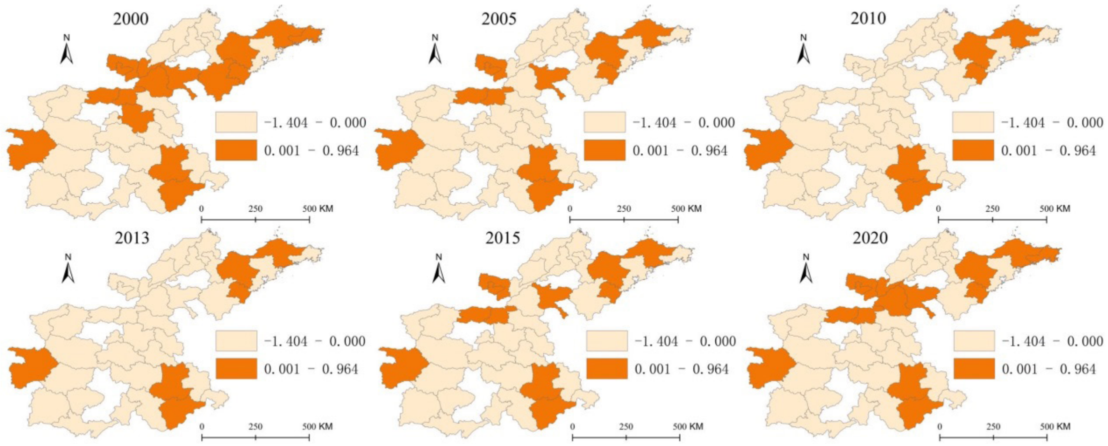

Figure 4. Spatiotemporal distribution of $\hat{\beta}_{\ln dtemp,it}$

of Anhui, west and southeast of Henan exhibited negative marginal effects across the majority of years.

The estimation coefficient $\hat{\beta}_{warmth,it}$ not only reflects the direct effect of climate warming on wheat yield per unit area but also the outcome of influence after climate change is moderated by various socioeconomic factors. The rapid economic growth of China from 2000 to 2020 was accompanied by the country rising to be the second largest economy in the world and fast industrialization, urbanization and development of the market-oriented economy. Do these socioeconomic factors exert a facilitating or siphonic effect on agricultural production? In addition, do factors like popularization and enhancement of agricultural mechanization, more advanced agricultural production tools and acceleration in the construction of irrigation and water conservancy infrastructure, play a role in adapting agricultural production to climate warming? The question whether the above-mentioned socioeconomic factors strengthen or weaken the spatiotemporal heterogeneous effects of climate warming on wheat yield per unit area is another focus of this research. Table 4 shows the regression results of Equation (13), which reflect the adaptability of socioeconomic factors to climate warming.

3.3 Analysis of influencing factors of $\hat{\beta}_{warmth,it}$

Table 4 shows the regression estimates of Equation (13), where the explained variable of Model (6) is the estimation coefficient of climate warming in Model (3), the explained variable of Model (7) is the estimation coefficient of climate warming in Model (4). The two models are robustness test for each other. The test results of LR reject the original hypothesis of the mixed Tobit regression, indicating that the panel Tobit model with random effects should be used. As can be known from Equation (13) and Table 2, the explanatory variables include agricultural crop diversity, irrigation and water conservancy infrastructure, level of agricultural mechanization, fertilizer application intensity, industrialization, urbanization, level of regional economic development and fixed effects at individual and temporal levels. Specifically, a rise in the indicator of agricultural crop diversity, namely, the growth in the proportion of non-grain sown area, significantly exacerbates the spatiotemporal heterogeneous effects of climate warming and enhances the marginal effects of climate warming on wheat production. This may be attributed to the fact that relatively low grain prices facilitate farmers to shift their priority towards more rewarding economic crops, causing decreased attention to staple crops like wheat and thus contributing to the negative effects of climate warming. Furthermore, producers' adjustment of their production adaptability may also be a cause of the spatiotemporal heterogeneous effect in the region. Therefore, improving the purchase prices of staple grain, enhancing grain production subsidies and improving the returns of grain production and thus increasing farmers' motivation constitutes another policy measure potentially mitigating the negative effects of climate warming. An improvement in the level of construction of irrigation and water conservancy infrastructure significantly decreases the marginal effects of climate warming on wheat production, as well as its heterogeneous effect, as manifested by the positive role that irrigation and water conservancy infrastructure plays in moderating even seasonal precipitation. However, the level of agricultural mechanization has little effect on coping with climate warming. Furthermore, increasing fertilizer application intensity also significantly decreases the marginal effects of climate warming and eliminates the heterogeneous differences of the variable. Hence, enhancing the construction of irrigation and water conservancy infrastructure and further improving the level of agricultural modernization serve as another effective measure to mitigate the negative effects of climate warming. Advancement in urbanization significantly decreases the negative effects of climate warming. Progress in economic development and urbanization plays an important role in absorbing excessive labor forces in rural areas, improving the living standards of rural residents and enhancing infrastructural construction in rural areas all have a driving effect on agricultural productivity [26, 27]; industrialization, however, exacerbates the negative effect of climate warming and constitutes

Table 4. Regression analysis the influencing factors of $\hat{\beta}_{warmth,it}$

	Model (6)	Model (7)
	$\hat{\beta}_{\ln sdtemp,it}$	$\hat{\beta}_{\ln dtemp,it}$
zw	0.050^{***}	0.001
	(0.001)	(0.001)
irr	-0.133^{***}	-0.016^{***}
	(0.001)	(0.000)
mach	0.001	0.001^{***}
	(0.002)	(0.000)
fert	-0.013^{***}	-0.002^{***}
	(0.001)	(0.000)
ind2	0.148^{***}	0.013^{***}
	(0.009)	(0.000)
cit	-0.037^{***}	-0.003^{***}
	(0.005)	(0.000)
cons	1.831^{***}	0.130^{***}
	(0.017)	(0.001)
Individual	Control	Control
Time	Control	Control
Number of observed values	819	819
Log likelihood	2183.237	3949.618
Wald test	1329561.38^{***}	$2.83e+07^{***}$
LR-chi^2	5135.21^{***}	8868.57^{***}

Note: Numbers in brackets shown in the above models are standard deviations of the estimates; *, ** and *** respectively denote significance levels of 10%, 5% and 1%.

one of the causes of regional heterogeneous effects. Yang et al. (2020) argued that China's industrialization in the past 20 years has progressed rapidly at the cost of absorbing agricultural resources, and although China has entered its early stage of industry nurturing agriculture, such back-feeding is still carried out in an extensive way [28]. Therefore, accelerating the pace of, and fulfilling the intensive and accurate way of, industry nurturing agriculture plays a crucial role in speeding up the construction of agricultural infrastructure and supporting agricultural modernization.

4. CONCLUSION AND POLICY IMPLICATIONS

4.1 Conclusion

The MO-OLS model is applied to quantify the marginal effects of climate warming on wheat yield per unit area during 2000-2020, followed by an analysis of the adaptability of socioeconomic factors to climate warming using panel Tobit model based on the regression estimates of the MO-OLS model. The following empirical conclusions are drawn: ① climate warming has a significant effect on wheat yield per unit area, for every 1% increase in regional climate warming, wheat yield per unit area decreases by 0.2%-0.3%. ② As can be known from the temporal scatterplots, the effects of climate warming in the majority part of the researched area are negative and the distribution of scatter points is rather concentrated, indicating that the marginal effects of climate warming on the majority of prefectural cities are negative. In addition, according to spatiotemporal distributions shown in Figures 3 and 4, the marginal effects of climate warming on wheat yield per unit area are positive in high-latitude regions and negative in most other regions. ③ Socioeconomic factors play a significant role in coping with the effects of climate warming on wheat yield per unit area. Regression results, as shown in Table 4, indicate that the development in crop diversity and industrialization exacerbate the marginal effect of climate warming, while improvements in urbanization, construction of irrigation and water conservancy infrastructure and intensity of fertilizer application weaken the spatiotemporal heterogeneous effects of climate warming, thereby playing a positive effect on containing the negative effects of climate warming. Improvement in agricultural mechanization does little to mitigate the marginal effects of climate warming.

4.2 Policy implications

The following policies are proposed:

① Climate warming is a general trend of the ongoing global climate change. In agricultural production, relevant authorities should step up their abilities related to weather prediction, forecast and pre-warning, enhance guidance on agricultural climatic technologies and thus appropriately adjust production periods based on climatic conditions. In addition, inputs in wheat breeding should be enhanced to provide fundamental technological support for improving wheat yield per unit area. Presently, China has achieved substantial progress in wheat breeding technologies [23]. Further promoting the popularization and application of superior varieties and improving crops' adaptability to climate warming serves as an important step towards advancing steady growth in wheat yield. ② The intensity of grain subsidy should be strengthened. The development in agricultural crop diversity will exacerbate the spatiotemporal heterogeneous effects of climate warming in a region and add to the negative effects of climate warming. Stepping up wheat production subsidy and improving returns on grain production help mitigate the negative effects of climate warming. ③ As can be known from the empirical results, construction of irrigation and water conservancy infrastructure helps reduce the negative effects of climate warming. Therefore, regional geographic advantages, such as superior water conservancy conditions in the Yellow River and Yangtze River basins should be exploited to improve the level of farmland water conservancy infrastructure as effective tools to regulate regional droughts and floods and thus reduce random exogenous shock of climate. ④ The pace of industry nurturing agriculture should be accelerated. Reducing fertilizer prices and improving subsidy to Home Appliances Going to the Countryside program goes a long way to help. By exploiting China's strengths as the largest manufacturer in the world, the costs of agricultural production can be reduced. Further reducing fertilizer costs and improving the popularization of agricultural mechanization helps lighten farmers' production burdens, scale up agricultural production and mechanization, thereby fulfilling a modernized transformation of agriculture nurtured by industry in an intensive and accurate way.

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