The Impact of Climate Change on Fertiliser Input in China: Analysis Based on Provincial Panel Data

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Abstract. Climate change directly affects agricultural production by changing temperature and precipitation patterns, and as a key input factor in modern agriculture, the efficiency of fertiliser use is closely related to climate change. Based on panel data of 31 provinces in China from 2012 to 2022, this study uses fixed effects and time trend OLS regression models to explore the direct impact of climate change on fertiliser input and the mediating role of agricultural output. The results showed that: (1) the increase of temperature significantly reduced the use of fertiliser (coefficient -5.159), but the effect of precipitation was not significant; (2) The increase of mechanisation level slightly increased the demand for fertiliser (coefficient 0.006), reflecting that technical input may stimulate the use by expanding the planting scale; (3) The amount of chemical fertiliser decreased year by year after 2013, and the decrease in 2022 was 301.43 million tons, which was related to environmental protection policies or technological progress; (4) The mediating effect of agricultural output has not been verified. The results show that climate change directly affects fertiliser input through temperature change, while policy regulation plays a significant role in reducing fertiliser use. This study provides an empirical basis for coordinating sustainable agricultural development and climate change adaptation in China.

Keywords: fertiliser input, climate change, panel data analysis, agriculture.

1 Introduction

Climate change is one of the most pressing challenges of the 21st century [1], significantly affecting agriculture, a sector inherently dependent on climatic conditions. Climate changes and precipitation patterns disrupt agricultural productivity, compelling farmers to adapt their production strategies.

Fertiliser input, a key determinant of crop yields, is among the critical factors influenced by these climatic variations. Chemical fertiliser is an indispensable input factor in modern agricultural production, also an important material basis for ensuring food security [2]. It can provide necessary nutrient elements for crops, such as N and P, and improve crop yield. Since the widespread application of chemical fertilisers, global food production has increased significantly, making a great contribution to meeting the food demand of the growing population. However, at the same time, greenhouse gas

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emissions during fertiliser production and application affect the climate system. Unreasonable fertilisation increases greenhouse gas emissions and exacerbates global warming [3], affecting crops' growing environment and the demand for fertilisers. Changes in soil fertility caused by climate change can affect farmers' fertiliser input choices. For instance, in some areas with increased precipitation, nutrient loss from the soil is accelerated, and farmers need to increase the amount of fertiliser input to maintain crop growth and yield. On the contrary, in arid regions, insufficient soil moisture may lead to lower fertiliser utilisation, and farmers need to adjust the type of fertiliser used and the amount. Higher temperatures also affect crops' nutrient requirements and fertilisers' decomposition rate.

Third, China is the world's largest consumer of inorganic fertiliser [2]. According to FAO, China's inorganic fertiliser consumption reached 43,223.3 thousand tons in 2022, accounting for 23.36% of the global total (185 million tons), making it once again the world's largest inorganic fertiliser consumer [4].

Therefore, studying the impact of climate change on fertiliser use in China is of dual significance for achieving sustainable agricultural development and formulating rational fertiliser management policies. To build a mathematical model based on the research problem, it is first necessary to clarify the question to be answered: How does climate change affect fertiliser inputs, and do temperature and precipitation directly affect farmers' fertiliser input behaviour. Since nutrient management is the most effective adaptive measure of agricultural yields in response to climate change [5], the second question to be answered is whether there is an intermediary effect between agricultural yield and climate change and fertiliser input, that is, whether yield change is an important channel for climate change to affect fertiliser input. Third, is there an interaction between the effects of climate change on fertiliser inputs, and how does the interaction between temperature, precipitation and agricultural output affect fertiliser inputs.Using the OLS regression model, this study assesses the vulnerability of fertiliser input use in China to possible perturbations from temperature and precipitation, due to climate change - these are the mechanisms of action of climate factors on fertiliser input. The methodology section provides more details of the process of establishing the quantitative model and the analysis method.

2 Literature Review

So far, much progress has been made in the study of the impacts of climate change on agricultural production, especially quantitative studies based on models and data. There are two main research methods: the crop mechanism model based on crop growth theory and experimental data and the econometric model based on climate scenarios and historical data [6]. The former generally overestimates the negative impacts of climate change because it ignores the adaptive behaviour of farmers. In contrast, econometric models can incorporate adaptation behaviour into the analysis, providing more reliable impact assessments. Therefore, this study decided to investigate the impact of climate change on fertiliser inputs using an econometric model. Hou et al. constructed a multi-input-multi-output production function based on agricultural micro input-output data

and meteorological data and estimated the impact of climate change on agriculture in different regions [7]. Concerning the impact of extreme weather on agricultural production, Chen & Gong estimated agricultural TFP through Cobb-Douglas stochastic frontier analysis and found that extreme high-temperature weather had a negative impact on agricultural TFP and agricultural input in the short term by using panel regression analysis, which in turn led to a decline in agricultural output [8].

Few studies have investigated the factors affecting fertiliser inputs from the perspective of agricultural economics. Burrell divided the research methods of fertiliser demand into two categories: one is to study the response of fertiliser demand to price changes through dual cost or profit functions [9]. The other category is a simplified model that examines the impact of changes in fertiliser prices and agricultural commodity prices on fertiliser demand. Denbaly & Vroomen used data from different regions to study the relationship between fertiliser demand and price, land rent and other factors [10]. Most of the existing studies focus on the impact of relative prices on fertiliser demand, while there are few studies on how climate change affects fertiliser inputs, and there are few relevant studies at home and abroad. Cao & Zhu used planting data and meteorological data from various provinces in China to estimate the impact of climate change on fertiliser input in the planting industry [6], but there is a lack of research on the impact of extreme weather.

3 Hypothesis

Some assumptions are made in this paper. Firstly, climate change will directly affect fertiliser inputs, and this effect is likely to be nonlinear. Moderate temperature (e.g., elevated) may increase fertiliser demand (to compensate for crop growth pressure). Too much or too little precipitation can reduce fertiliser efficiency and cause farmers to adjust their use. Based on the agricultural adaptability theory, farmers' short-term response to climate change may manifest as direct input strategies adjustment [8].

Second, agricultural yield is a mediating variable for climate change affecting fertiliser inputs. Climate change indirectly affects fertiliser inputs by affecting agricultural yields. For instance, farmers may increase fertiliser use when yields fall to compensate for the loss. Changes in farm yields partially explain the effects of temperature, precipitation, and extreme weather on fertiliser inputs. This aligns with the production function theory [7], and output, as the core link between input and output, may transmit the economic effects of climate shocks.

Third, there is an interaction between climatic factors and agricultural output. Under the low-yield scenario, farmers are more sensitive to temperature and precipitation, and may significantly adjust fertiliser inputs. Under the high yield scenario, farmers are less sensitive to climate change and adapt fertiliser use less.

4 Methodology

Based on the existing literature, this paper intends to construct a panel data framework with regional and time-fixed effects using China's provincial planting data and

meteorological data. With the help of the Ordinary Least Squares (OLS) regression model, the impact of temperature and precipitation caused by climate change on fertiliser input use was estimated, which provided empirical evidence for the in-depth understanding of the impact of climate change on agricultural development in China. The model is based on econometric methods recommended in the previous literature to explain the adaptive behaviour of farmers, which is often ignored in mechanical crop models.

4.1 OLS Regression Model

A two-way fixed effects model is used, controlling for province and time fixed effects. The baseline specification is an OLS regression in Equation (1).

$$Fertilizer_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 T_{it}^2 + \beta_3 P_{it} + \beta_4 P_{it}^2 + \beta_4 Y_{it} + \beta_5[(T - \overline{T}) \times (Y - \overline{Y})] + \beta_6[(P - \overline{P}) \times (Y - \overline{Y})] + X'_{it}\gamma + \varepsilon_{it} \quad (1)$$

The variables in the regression are explained below.

$Fertiliser_{it}$: Amount of chemical fertiliser input per unit in region i in period t

T_{it}: Annual average temperature in region i in period t.

P_{it}: Average precipitation in region i in period t

Y_{it}: Agricultural output per unit area in region i in period t. Agricultural output may mediate between climate variables and fertiliser input; climate variables affect fertiliser input by affecting agrarian output. For example, farmers may increase fertiliser inputs to maintain high yields when climatic conditions are favourable and agricultural output increases.

X'_{it}: control variable: mechanisation level (MECH) that affect fertiliser input.

ε_{it}: The random error term represents the impact of other random factors not considered in the model on fertiliser input, which cannot be fully explained by the explanatory variables in the model. In an ideal case, its mean is 0, and classical assumptions such as the same square difference are satisfied.

4.2 Data Source

Based on the above background setting, the data required by the model include meteorological data: temperature, precipitation, and agricultural output data (the top 3 major crops in China's consumption: rice, wheat, and corn), fertiliser input data, and some variables to be controlled, including cost of fertiliser, and mechanisation level, were constructed as panel data. The data were processed to supplement the mean value of the missing data of each province and region in the year, eliminate the missing observation points, and interpolate the climate data. Interpolation is often used in many scientific disciplines to complete missing data or to improve resolution [11].

The data of fertiliser input are from the China Academy for Rural Development-Qiyan China Agri-research Database (CCAD), Zhejiang University and the National Bureau of Statistics. Crop yield data, and the total power of agricultural machinery were obtained from the National Bureau of Statistics. Cost of fertiliser and price of

agricultural output are collected from Compilation of Cost and Income Data of Agricultural Products from all over China. The temperature and precipitation data are derived from the annual data set of China Surface Climate Data, the National Meteorological Science Data Sharing Service Platform, some are obtained from climate bulletin and water bulletin of each province.

4.3 Variables

In this paper, the amount of fertiliser input is taken as the explained variable, and Table 1 defines each variable.

The level of mechanisation is an important factor affecting fertiliser application by farmers and is represented by MECH. On the one hand, mechanisation of whole fields and deep sowing can effectively improve soil layer structure, optimise land quality, provide good nutrient absorption space for crop roots, and thus enhance the comprehensive production capacity of crops. On the other hand, agricultural mechanisation can improve the efficiency of fertiliser use to a certain extent, helping to increase the amount of fertiliser used. This paper uses the total power of agricultural machinery to measure this important factor.

Table 1. Variable Definition.

Variable	Notation	Connotation
Temperature	T	Annual average temperature (℃)
Precipitation	P	Average annual cumulative precipitation (mm)
Agriculture Yield	Y	Yield per unit area (kg/ha)
Fertiliser Input	F	Net amount of agricultural chemical fertiliser applied (ten thousand tons)
Mechanisation Level	MECH	Total power of agricultural machinery (10,000 kW)

5 Empirical Results and Analysis

The sample used in this paper have 341 observations, covering 31 provinces, and the time span is from 2012 to 2022. The software used in the empirical analysis is STATA15.

5.1 Descriptive Statistics of Variables

Table 2 shows the descriptive statistics of each variable, and the data show that the mean value is 182.38, and the standard deviation is large (144.22), indicating that there is a significant difference in the usage of each province, among which Henan province has the most fertiliser input, and Xizang has the least. The distribution of climate variables has a large span, with the lowest annual average temperature in Heilongjiang and the highest annual average temperature in Hainan, which is related to the geographical

dimension. The average yield of the three main crops is 16,453.76, and the mechanisation level has a large difference (standard deviation 2,925.02).

Table 2. Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Fertiliser (10,000 tons)	341	182.379	144.217	2.83	716.09
T (℃)	341	13.699	5.503	.609	25.839
T2 (℃2)	341	217.867	149.705	.371	667.653
P (mm)	341	976.086	539.414	125.39	2358.436
P2 (mm2)	341	1242858.2	1221102.7	15722.651	5562221.5
Y (kg/ha)	341	16453.762	3544.996	4996.25	25185.57
MECH (10,000 kW)	341	3370.654	2925.016	93.97	13353.02

5.2 Fixed Effect Model

Table 3. FE Model Regression Results.

F	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
T	-5.159	2.96	-1.74	.092	-11.205	.887	*
T2	.056	.057	1.00	.327	-.059	.172	
P	-.031	.021	-1.52	.139	-.073	.011	
P2	0	0	1.46	.155	0	0	
Y	0	.001	0.17	.867	-.003	.003	
T_Y	.001	.001	0.81	.425	-.001	.003	
P_Y	0	0	1.16	.253	0	0	
MECH	.006	.003	2.04	.05	0	.012	*
2012 (base year)	0	.	.	.	.	.	
2013	3.638	1.648	2.21	.035	.272	7.004	**
2014	6.238	2.318	2.69	.012	1.503	10.972	**
2015	8.149	3.348	2.43	.021	1.311	14.987	**
2016	10.426	4.716	2.21	.035	.795	20.057	**
2017	5.233	4.434	1.18	.247	-3.822	14.287	
2018	-2.2	4.568	-0.48	.633	-11.528	7.128	
2019	-10.749	5.387	-2.00	.055	-21.75	.251	*
2020	-15.607	5.15	-3.03	.005	-26.124	-5.09	***
2021	-16.443	5.686	-2.89	.007	-28.055	-4.832	***
2022	-30.143	8.255	-3.65	.001	-47.001	-13.285	***
Constant	240.881	44.654	5.39	0	149.687	332.076	***
Mean dependent var	182.379		SD dependent var		144.217		
R-squared	0.457		Number of obs		341		
F-test	8.823		Prob > F		0.000		
Akaike crit. (AIC)	2726.332		Bayesian crit. (BIC)		2795.306		

*** $p<.01$, ** $p<.05$, * $p<.1$

Table 3 shows the estimation results of core variables under fixed effects. Firstly, regarding the effect of temperature on fertiliser input, the coefficient of temperature (T) is -5.159 (p=0.092), which is significant at the 10% level, indicating that for every 1℃ increase in temperature, fertiliser use decreases by about 5.16 units. However, the temperature squared term (T^2) is not significant, and the nonlinear effect is not confirmed. The T-Y interaction term was positively significant (β_6=0.001, p=0.425), indicating that high temperature had an inhibitory effect on fertiliser efficiency in high yield areas. Precipitation (P) and its square term (P^2) are not significant, possibly because the effect of precipitation on fertiliser use is offset by other variables (e.g. irrigation). The coefficient of mechanisation level is 0.006 (p=0.05), indicating that for every 1 unit increase in mechanisation, fertiliser use increases by 0.6%, reflecting that technological inputs may stimulate demand by expanding planting scale or improving fertilisation efficiency. The significant decrease in fertiliser use from 2013 to 2022, especially after 2020 (e.g.coefficient in 2022: -30.143, p=0.001), may be related to environmental protection policies or technological progress. The intermediary effect between agricultural yield and climate change and fertiliser input is not evident or does not exist. R2=0.457, the model is significant as a whole (F=8.823, p=0.000), indicating that the variable can explain 45.7% of the variation.

5.3 Time Trend Model

Table 4. Time Model Regression Results.

F	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
T	2.05	1.955	1.05	.303	-1.942	6.042	
T2	.034	.057	0.59	.558	-.083	.15	
P	-.027	.018	-1.51	.141	-.064	.01	
P2	0	0	1.79	.084	0	0	*
Y	-.001	.001	-0.56	.579	-.004	.002	
T_Y	-.001	.001	-1.15	.257	-.004	.001	
P_Y	0	0	-0.34	.735	0	0	
MECH	.004	.002	1.64	.111	-.001	.009	
time	-2.932	.692	-4.23	0	-4.346	-1.518	***
Constant	176.055	32.845	5.36	0	108.976	243.133	***
Mean dependent var		182.379		SD dependent var		144.217	
R-squared		0.367		Number of obs		341	
F-test		7.658		Prob > F		0.000	
Akaike crit. (AIC)		2760.706		Bayesian crit. (BIC)		2795.193	

*** *p*<.01, ** *p*<.05, * *p*<.1

After replacing the year dummy variable with a linear time trend, the results in Table 4 show that the coefficient of time variable (time) is -2.932 (p=0.000), indicating that the annual average reduction of fertiliser use over time is 29,300 tons, which is consistent with the direction of policy regulation. As for the significance of variables under the time model, only P2 is significant at the 10% level (p=0.084), which may absorb part

of the variation due to the time trend. R2=0.367, which is lower than in the FE model, indicating that the year dummy variable captures the time effect better than the linear time trend.

6 Conclusion

Climate change directly affects agricultural production by changing temperature and precipitation patterns, and as a key input factor in modern agriculture, the efficiency of fertiliser use is closely related to climate change. The literature review shows that most of the existing studies focus on the impact of price on fertiliser demand, but less on the direct and indirect effects of climate change. Based on China's provincial panel data of meteorology, agricultural output and mechanization level from 2012 to 2022, this paper uses the econometric OLS regression model to analyze the direct and indirect effects of climate change on fertiliser input with agricultural output as the "intermediary".

Empirical results shows that: (1) the increase of temperature significantly inhibited the use of chemical fertiliser (coefficient -5.159, p=0.092), but the nonlinear effect was not verified; (2) the effect of precipitation on fertiliser input is not significant and may be offset by irrigation and other factors; (3) the increase of mechanization level will slightly increase the use of chemical fertiliser (coefficient 0.006, p=0.05); (4) the use of fertiliser decreased year by year after 2013, with the largest decline in 2022 (coefficient -30.143, p=0.001), which may be related to environmental protection policies; (5) the mediating effect of agricultural output is not significant. It is also found that the time trend model shows that the annual decrease of fertiliser use is 29,300 tons (p=0.000), but the explanatory power of the model is lower than that of the fixed effect model.

Based on the findings, relevant policy-making and management departments should pay attention to climate-adaptive agricultural policies and induce farmers to reduce excessive fertilisation by using subsidies or tax lever. Promote precision fertilisation technology, optimize efficiency based on climate change characteristics, and reduce resource waste. Also, improve agricultural mechanisation and promote the coordinated application of chemical fertiliser use and climate monitoring technology.

This study also has limitations, for example, extreme weather events were not included in the model due to difficulties in obtaining historical data and the specific characteristics of different climate types and crop planting structure are not distinguished. Future research can take these into account, refine the mechanism linking climate change and fertiliser inputs, and conduct regional heterogeneity studies. Differences in response across climate zones can be analyzed in combination with GIS. The potential application of fertiliser substitution technologies such as organic fertiliser can also be explored.

References

1. Tamang, B.: Global Climate Change: Challenges, Opportunities, and Multilateral Strategies for Sustainable Development. NPRC Journal of Multidisciplinary Research 1(4), 65 – 76 (2024).
2. Zhang, Y., Fan, X., Mao, Y., Wei, Y., Xu, J., Wu, L.: The Coupling Relationship and Driving Factors of fertiliser Consumption, Economic Development and Crop Yield in China. Sustainability 15(10), 7851 (2023).
3. Saeed, Q., Zhang, A., Mustafa, A., Sun, B., Zhang, S., Yang, X.: Effect of long-term fertilization on greenhouse gas emissions and carbon footprints in Northwest China: A field scale investigation using wheat-maize-fallow rotation cycles. Journal of Cleaner Production 332, 130075 (2022).
4. FAOSTAT: fertilisers by Nutrient, https://www.fao.org/faostat/en/#data/RFN, last accessed 2025/3/29.
5. Yuan, X., Li, S., Chen, J., Yu, H., Yang, T., Wang, C., Huang, S., Chen, H., Ao, X.: Impacts of global climate change on Agricultural Production: A Comprehensive Review. Agronomy 14(7), 1360 (2024).
6. Cao, D., Zhu, H.: The Impact of Climate Change on fertiliser Input in China's Planting Industry. WEST FORUM 27(1) (2017).
7. Hou, L., Qiu, H., Wang, Y., Sun, laixiang.: The Impact of Climate Change on Agricultural Production in China: An Analysis Based on the Multiple Input Multiple Output Production Function. Agricultural Technology Economy 3, 4 – 14 (2015).
8. Chen, S., Gong, B.: Response and adaptation of agriculture to climate change: Evidence from China. Journal of Development Economics 148, 102557 (2021).
9. Burrell, A.: THE DEMAND FOR FERTILISER IN THE UNITED KINGDOM. Journal of Agricultural Economics 40(1), 1 – 20 (1989).
10. Denbaly, M., Vroomen, H.: Dynamic fertiliser Nutrient Demands for Corn: A Cointegrated and Error - Correcting System.American Journal of Agricultural Economics 75(1), 203 – 209 (1993).
11. Picornell, A., Oteros, J., Ruiz-Mata, R., Recio, M., Trigo, M. M., Martínez-Bracero, M., Lara, B., Serrano-García, A., Galán, C., García-Mozo, H., Alcázar, P., Pérez-Badia, R., Cabezudo, B., Romero-Morte, J., Rojo, J.: Methods for interpolating missing data in aerobiological databases. Environmental Research 200, 111391 (2021).

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