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Analysis on the Spatial and Temporal Pattern of China's Grain Production and Its Influencing Factors

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중국 식량 생산의 시공간 분포 탐색 및 생산에 영향을 미치는 요인분석

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Abstract Grain production in China is a significant issue concerning the national economy and people's livelihood. Along with economic development, the pattern of grain production in China has changed dramatically, causing a potential impact on the balance of grain supply and demand and grain security. Based on the grain output of 31 provinces from 2007 to 2019, this study analyzed the changes in grain production distribution in China, tested the spatial autocorrelation of grain output by Moran's I and examined the factors affecting the change of grain production pattern in various provinces of China by Spatial Durbin Model (SDM). There was a clear positive spatial autocorrelation between the grain outputs of different regions. The arable land per capita, agricultural labor, agricultural machine and GDP per capita exerted a significant positive impact on the growth of grain production in China. The spatial spillover effect of agricultural labor, agricultural machine and GDP per capita was significant. These factors are responsible for the change in the grain production layout. This study suggests that agricultural science and technology should be improved, and the arable land in different provinces should be protected to assure grain security.

요 약 식량 안보 문제는 중국 민생에 있어 중요한 문제이다. 경제 발전에 의해 중국 식량 생산 구조가 변화하였다. 이는 식량 수급 균형 및 식량 안보 문제에 잠재적인 영향을 미치고 있다. 본 연구에서는 2007~2019년 중국 31개 성(省)의 식량 생산량을 바탕으로 식량 생산량과 파종면적 두 가지 측면에서 중국 식량 생산 구조의 변화를 분석하고, Moran's I 지수를 활용하여 식량 생산량의 공간상관관계를 검증하였다. 또한 공간더빈모형을 이용하여 중국 각 성의 식량 생산 구조에 미치는 영향요인을 분석하였다. 분석결과 중국의 각 성(省)의 식량 생산량은 공간자기상관성이 있는 것으로 나타났다. 또한 인당 경지면적, 노동력, 농기계 투입 및 1인당 GDP 등의 변수가 중국 식량 생산량에 정의 영향을 미치는 것으로 나타났다. 그중 노동력, 농기계 투입 및 1인당 GDP 등 변수가 유의한 결과가 나타나, 공간 파급효과가 있는 것으로 나타났으며, 중국 식량 생산 구조의 변화를 촉진하는 것으로 판단된다. 이로 인하여 중국 농업 과학기술 수준을 제고해야 하며, 농업 생산 인프라의 완비, 농경지 보호 등을 통하여 중국의 식량 안보를 위해 노력해야 한다.

Keywords : Grain Production, Moran's I, Spatial Durbin Model, Influencing Factors, Spatial-Temporal Pattern

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1. Introduction

Grain is the basis of human existence and provides basic living materials for the whole society. Grain production also affects and restricts the development of other industrial sectors[1]. At the same time, China is also a big grain consumer, and grain security is a major issue related to China's national economy and people's livelihood. Ensuring grain production and stabilizing grain security is of great significance to ensuring China's social-economic development. Ensuring stable grain production and effective supply has always been China's agricultural policy[2]. With the rapid development of urbanization, China's grain production has changed significantly. From the perspective of temporal pattern, China's grain output has shown continuous growth since 2004, but the inter-annual fluctuations of grain production are relatively large[3]. From the perspective of spatial pattern, China's grain production varies significantly among provinces, and grain output in coastal areas decreases year by year[4]. There are apparent temporal and spatial characteristics of grain production. Studying the spatial-temporal pattern of grain production in China will help to better grasp the grain security issues and discuss its influencing factors to put forward targeted policy suggestions.

The spatial layout of China's grain production attracted widespread attention from the Chinese government and scholars. To adjust the production structure of grain and establish the grain security system, the Ministry of Agricultural and Rural Affairs (MARA) of China has successively formulated a series of policy plans. And in recent years, scholars have researched the issue of grain production layout. Since 1978, the regional pattern of grain production in China has undergone significant changes. Generally speaking, grain production in various regions has increased at different levels. The status of major grain-producing areas has risen significantly, while major sales areas have declined considerably. The focus of grain production continues to move northward and is gradually concentrated in plain areas, and the main grain varieties are gradually concentrated in advantageous production areas[5,6]. Specifically, from the perspective of grain yield pattern, the change of grain yield in China can be divided into 1990-1998, 1998-2003, and since 2003. From the perspective of spatial pattern, the grain production position of eastern provinces decreased significantly. And the grain production status of central areas has been weakened, and the western regions have been improved. The grain production position of northeast provinces was relatively stable for a long time. The total grain output of the whole country fluctuated and increased, and the grain production increase of northern areas was more significant than that of southern regions[7]. Moreover, under the influence of various factors such as the rapid development of urbanization in the southeast coastal areas, the widening of the income cap between agriculture and non-agriculture, the expansion of arable land in northern China, and the adjustment of planting structure, China's grain production center has shifted to the north[8,9]. In terms of spatial layout, the research on the pattern of grain production based on different scales will also obtain different results. According to the corresponding literature, relevant studies have studied grain production from multiple perspectives: provinces, cities, and counties[10]. Based on the research of different scales, the basic research methods include the Cobb-Douglas production function model[11], Principal components analysis[12], multiple regression model[13], Mediation model[14], and other methods. There are few studies on the relationship between the changing factors of China's grain production and the spatial pattern of grain production throughout the literature. In the literature discussing the spatial pattern of grain production, although it has been found that there are obvious changes in the spatial layout of grain production in China, it also depicts the characteristics of spatial changes at the regional level. However, it is limited to simple descriptive statistical analysis. Few empirical tests have been conducted from the perspective of spatial effects, nor have they used spatial econometrics to empirically analyze the causes of changes in the spatial distribution of grain production.

Based on the previous studies, this study conducted descriptive statistics from the two aspects of output and sown area for the distribution of grain production in China from 2007 to 2019. It analyzed the changing trends over the years. Then, the spatial autocorrelation of grain output of each province was calculated to reveal the imbalance of grain output patterns in China. The spatial Durbin model (SDM) was used to calculate the direct, indirect, and total effects of various influencing factors on grain production pattern change. By grasping the characteristics of China's grain production layout changes and clarifying its internal laws, this study explores the specific factors that affect it, which is conducive to giving play to the advantages of different regions in China. At the same time, it is conducive to improving the comparative benefits of grain production in China, and it is of great significance for adjusting the location of agricultural resources in China's grain distribution and ensuring grain security.

2. Theoretical analysis and data

2.1 Theoretical analysis

According to the theory of agricultural production economics, grain production is an organic combination of natural and economic reproduction[15]. In the process of natural reproduction, grain production is bound by natural resources[16]. In the process of economic reproduction, grain production is subject to levels of economic and social development, the resource environment, and the inputs of agricultural production[17]. Therefore, based on the three factors of resource environment, the inputs of agricultural production, and economic environment, this study combined the actual situation of China's grain production development and data accessibility and empirically analyzed the influencing factors of China's grain production layout.

1) Resource endowment environment. Among the natural resource conditions, the main influence on grain production is climatic conditions. Climate change directly leads to agricultural climate disasters and agricultural pests and diseases in some areas. Under the impact of climate change, China's grain production structure and regional layout will undergo corresponding changes, leading to fluctuations in China's grain output and even affecting grain security[1]. Water resources are also an essential factor affecting agricultural production among natural resources. Whether water resource is sufficient or not directly affects the irrigated area[5]. Therefore, this study selects the ratio of disaster (Proportion of area affected by agricultural disasters) and irrigated area indicators to examine the natural endowment condition of grain production.

2) Inputs of agricultural production. The inputs mainly include land, labor, fertilizer, and agricultural machine. The land factor is to points to arable land area, which significantly impacts grain production. The previous studies show that the decrease of the arable land area will lead to the decrease of grain sown area, and the decrease of grain sown area will also lead to the reduction of grain output[18]. The labor factor

mainly includes the number of laborers and the educational level of the labor force. There are two views on the outflow of agricultural labor: One view is that the outflow of agricultural labor will increase grain supply, and the other view will reduce grain supply[19]. Studies have shown that the education level of the labor force has a significant positive impact on the improvement of grain production efficiency[20], and the number of fertilizers and agricultural machinery input also has a significant positive effect on grain production[21]. Therefore, this study selects the factors such as arable land area per capita, agricultural labor, fertilizer application, and agricultural machine to investigate the impact of agricultural production input on grain production.

3) Economic environment. The regions with higher GDP per capita usually invest more in manufacturing and service industries but still less in agricultural production. Generally speaking, developing secondary and tertiary sectors by occupying the arable land area will affect grain production[7]. At the same time, with the development of urbanization, the size of arable land will gradually decrease, which will adversely affect grain production[8]. Therefore, this study selects the factors such as the urbanization ratio and GDP per capita to investigate the impact of the economic environment on grain production.

Table 1. Variable description and its expected effect

Variable	Sign	Expected impact
Grain output	y	
Ratio of disaster	x_1	-
Irrigated area	x_2	+
Arable land per capita	x_3	+
Agricultural labor	x_4	?
Agricultural machine	x_5	+
Fertilizer application	x_6	+
Urbanization ratio	x_7	-
GDP per capita	x_8	-

2.2 Variable selection and data source

According to the above analysis, variables of natural endowment, agricultural production input, and economic environment are taken as control variables in this study. The specific description and expected impact of each variable are shown in Table 1.

In the absence of farm-level panel data, aggregate data are often used for analyzing the factors influencing China's grain production layout. Evaluations relying on aggregate data can reveal China's grain layout aggregation characteristics at the regional or national levels. The data selected in this study are from the panel data for China's grain output from 2007 to 2019, derived from the China Rural Statistical Yearbook (2008-2020), China Statistical Yearbook (2008-2020), and statistical yearbooks of various provinces. The data set covered 31 provinces in China and included thirteen consecutive years (2007-2019), with 403 observations. And we used the multiple indexes with 2007 as the base year as the deflator for all variables included.

3. Methods

3.1 Spatial autocorrelation analysis

Tobler pointed the first law of geography in 1970. He proposed that everything is related o everything else, but near things are more connected than distant things[22]. The first law is the foundation of the fundamental concepts of spatial dependence and spatial autocorrelation. The spatial autocorrelation analysis reveals the interaction mechanism between spatial agglomeration and spatial heterogeneity. Meantime, it measures the agglomeration degree in the spatial domain. In this study, spatial autocorrelation is used to test whether the grain output in a certain province is significantly correlated with the areas of grain production in neighboring provinces. According to the size of the spatial analysis range, spatial autocorrelation can be divided into global and local spatial autocorrelation[23]. The global Moran's I statistic for spatial autocorrelation is given as:

$$global\ Moran's\ I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{1}$$

Where n equals the observations, $w_{i,j}$ is the spatial weight matrix between i and j, x_i and x_j indicate the grain output of the provinces i and j, $(i,\ j=1,2,\cdots\ n,\ n=31)$, $\bar{x}$ is the average value of grain output in all observations. As for spatial weight matrix $w_{i,j}$, the premise of spatial analysis is to measure the spatial distance between regions, so based on the previous studies of Ping et al. (2004), Xie er al. (2020), Zhan et al. (2021), we used the geographic distance spatial weight matrix. It can better reflect the spatial correlation of different areas[2,24,25]. And The global Moran's I $\in[-1,1]$, the specific implication of global Moran's I in this study is shown in Table 2. The local Moran's I statistic of spatial association is given as:

$$local\ Moran's\ I = \frac{n(x_i-\bar{x})\sum_{j=1}^{n} w_{i,j}(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{2}$$

Where n, x_i, x_j, $\bar{x}$, $w_{i,j}$ have the same meaning as in Eq 1. The local Moran's I has similar meaning to the global Moran's I. the specific implication of local Moran's I in this study is shown in Table 2. The local spatial autocorrelation can embody the local differences in grain production patterns through Moran scatter plots and local spatial autocorrelation clustering maps (LISA maps)[24]. In this study, we used the Moran scatter plots to divide the local spatial units into four types for the high-high cluster, high-low outlier, low-high outlier, and low-low cluster[26]. The four types of Moran scatter in this study are shown in Fig. 1.

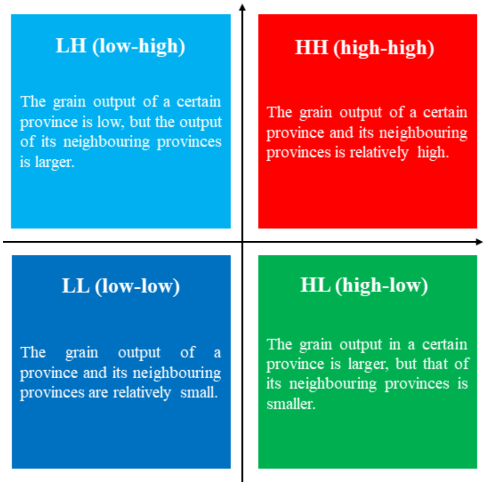

Fig. 1. The four types of Moran scatter

Table 2. The range and implication of global Moran's I

Type	Range	Implication
Global Moran's I $[-1,1]$	Moran's I>0	Positive spatial autocorrelation in the spatial distribution of grain output in neighbouring provinces
	Moran's I<0	Negative spatial autocorrelation in the spatial distribution of grain output in neighbouring provinces
	Moran's I$=0$	No spatial autocorrelation, it's spatially random
Local Moran's I	-	Positive local Moran's I indicates that the high (low) value of a area is surrounded by high (low) values
		Negative local Moran's I indicates that the high (low) value of a area is surrounded by low (high) values

3.2 Spatial econometric model

When the data has spatial correlation, OLS estimation cannot solve the problem of spatial dependence of the data, so a spatial econometric model needs to be adopted. The spatial econometric model includes the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM). The general spatial econometric model is as follows:

$$y_{it} = \beta x_{it} + \rho \sum_{j=1}^{n} w_{i,j} y_{jt} + \theta \sum_{j=1}^{n} w_{i,j} x_{jt} + \mu_{it} \qquad (3)$$
$$\mu_{it} = \lambda w_{i,j} \mu_{it-1} + e_{it}$$

Where y is the dependent variable, x is the independent variable. μ_i denote the random error vector, ρ is the spatial lag coefficient of the dependent variable, β is the coefficient of independent variable, θ is spatial lag coefficient of the independent variable, $w_{i,j}$ is the spatial weight matrix, λ is the spatial error term factor and μ_i is the error term, $\mu_i, e_i \sim (0, \delta^2 I)$. The spatial Durbin model (SDM) contains endogenous and exogenous variables with a spatial lag and wider application space than the spatial lag model and the spatial error model. We used the model in different conditions, as shown in Table 3.

Table 3. The types of spatial econometric model

Type	Condition	Model form
SLM	$\rho \neq 0$ $\theta = 0$	$y_{it} = \beta x_{it} + \rho \sum_{j=1}^{n} w_{i,j} y_{jt} + \mu_{it}$
SEM	$\lambda \neq 0$ $\rho = 0$	$y_{it} = \beta x_{it} + \mu_{it}$ $\mu_{it} = \lambda w_{i,j} \mu_{jt-1} + e_{it}$
SDM	$\rho \neq 0$ $\theta \neq 0$ $\lambda = 0$	$y_{it} = \beta x_{it} + \rho \sum_{j=1}^{n} w_{i,j} y_{jt} + \theta \sum_{j=1}^{n} w_{i,j} x_{jt} + e_{it}$

4. Empirical study

4.1 Temporal dynamics of grain production

The grain output and sown area in China, as shown in Fig. 2, shows that the overall change trend of China's grain production during 2007-2019 is increasing, but with some fluctuations. In terms of grain output, it grew from 504.14 million tons in 2007 to 663.84 million tons in 2019. During these 12 years, there has been an increase of approximately 159.7 million tons, an increase of 31.68%, with an average annual growth rate of 2.32%, which is a relatively fast growth rate. From the perspective of grain sown area, it has the same trend with the grain output in a period. From 2007 to 2019, the grain sown area increased from 105,999 thousand hectares to 116,064 thousand hectares, an increase of 9.50%, with an annual growth rate of 0.76%, lower than the increase in grain output.

(unit: Ten thousand tons, 1000 Ha)

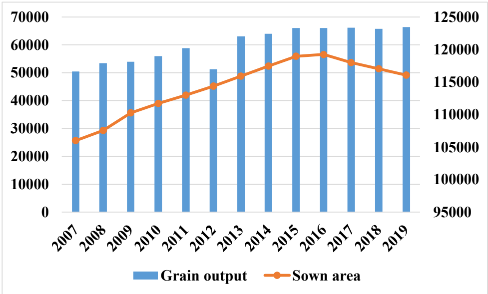

Fig. 2. Grain output and sown area from 2007 to 2019

4.2 Spatial autocorrelation of grain output in China

Based on the grain output's data during 2007-2019 and the geographic distance spatial weight matrix, the global Moran's I of the grain output in China was calculated using Geoda software, as shown in Table 4.

Table 4. Global Moran's I test result of China's grain production during 2007-2019

Year	Global Moran's I	Z-statistic	P-value
2007	0.259**	2.467	0.017
2008	0.275**	2.607	0.013
2009	0.233**	2.244	0.025
2010	0.248**	2.369	0.021
2011	0.255**	2.430	0.017
2012	0.266**	2.516	0.016
2013	0.274**	2.588	0.011
2014	0.262**	2.499	0.016
2015	0.272**	2.581	0.012
2016	0.269**	2.549	0.011
2017	0.313***	2.928	0.007
2018	0.296***	2.797	0.008
2019	0.308***	2.892	0.007

Note: *represents significance at 10%, **5%, and ***1%, respectively.

According to Table 4, Moran's I is greater than 0. In 2007-2016, the Moran's I was significant at the 5% level. From 2017 to 2019, the Moran's I was significant at the 1% level. The results indicate a positive spatial autocorrelation in the grain output from 2007 to 2019, which means that provinces with high output are clustered together, and regions with low output are clustered together. The areas with similar levels of grain output tend to be concentrated. Thus, when analyzing the characteristics of grain output in China and its influencing factors, a spatial panel model needs to be constructed for research.

The global spatial autocorrelation cannot reflect the correlation between the grain production of each province and its neighboring areas. Therefore, Geoda software is used to calculate the local Moran's I for each region. Based on the previous studies[25], the years are selected with 2007 as the base period and 5-year intervals to significantly express the evolution trend of the local correlation of grain production in various provinces. The results are shown in Table 5. The high-high cluster and low-low spatial cluster effects of grain output in China are relatively obvious.

Table 5. Spatial distribution characteristics of grain output

Year	HH	HL	LH	LL
2007	Henan, Shandong, Anhui, Hubei	Sichuan	Shanxi	Xinjiang
2013	Jilin, Henan, Shandong, Anhui	Sichuan	-	Xinjiang
2019	Jilin, Henan, Shandong, Anhui	Sichuan	Shanxi	Xinjiang

4.3 Regression Results of the Spatial Durbin Model

The selection of a spatial lag model (SLM) and spatial error model (SEM) is tested by two LM statistics and robust LM[25]. The results of the two LM tests, as shown in Table 6. The results show that the spatial lag effect and spatial error effect by the Lagrange multiplier test and robust Lagrange multiplier test are statistically significant. The Lagrange multiplier test and robust Lagrange multiplier test show that dependent variable space autocorrelation and error term space autocorrelation exist simultaneously. Anselin proposed that if the two effects are significant or are not significant, the study needs to use the spatial Durbin model (SDM). In the meantime, the LR test and Wald test check whether the SDM can be simplified into SLM and SEM. As shown in Table 6, the spatial Durbin model cannot be reduced to a spatial lag model or a spatial error model by likelihood ratio and Wald test from a spatial fixed Durbin model. Results from the Hausman test show that random effects are rejected, and the fitting degree of the spatial Durbin model under the fixed form is superior to other forms by the logarithmic likelihood value test.

Table 6. Testing results of LM and robust LM, LR test and Wald test

Test		Statistic	p-value
Spatial error	LM	5.174***	0.001
	Robust LM	3.129***	0.002
Spatial lag	LM	44.173***	0.000
	Robust LM	42.129***	0.000
Wald spatial lag test		96.46***	0.000
LR spatial lag test		116.12***	0.000
Wald spatial error test		96.60***	0.000
LR spatial error test		128.01***	0.000
Hausman test		71.15***	0.000

Note: *represents significance at 10%, **5%, and ***1%, respectively.

The spatial Hausman test shows that the fixed effects spatial Durbin model should be used. Fixed effect models include the time fixed effect, individual fixed effect, both individual and time effects.

Table 7. Spatial individual fixed effect and time fixed effect joint significance test

Type	LR statistic	P-value
Individual fixed effect	40.40	0.0000
Time fixed effect	536.02	0.0000

It can be seen from the results in Table 7. The likelihood ratio tests of individual fixed effect and time fixed effect are significant at 1% level, so both individual and time effect is more suitable for analysis. Thus, the spatial Durbin model (both individual and time effects) is more persuasive. Therefore, it was used in this study for empirical analysis and discussion.

Table 7. Regressions results of spatial Durbin model

Variable	Coefficient
Ratio of disaster	-0.001 (0.001)
Irrigated area	0.722*** (0.162)
Arable land area per capita	0.046*** (0.013)
Agricultural labor	0.639*** (0.068)
Agricultural machine	0.076** (0.039)
Fertilizer application	0.229*** (0.061)
Urbanization ratio	-0.008 (0.056)
GDP per capita	0.340*** (0.078)
W*Ratio of disaster	0.001 (0.001)
W*Irrigated area	-0.024 (0.079)
W*Arable land area per capita	-0.511** (0.007)
W*Agricultural labor	-0.006 (0.016)
W*Agricultural machine	0.359*** (0.127)
W*Fertilizer application	0.331*** (0.077)
W*Urbanization ratio	-0.408*** (0.090)
W*GDP per capita	0.568*** (0.104)
ρ	0.351***

Note: *represents significance at 10%, **5%, and ***1%, respectively, Standard errors in parentheses.

As shown in Table 7, The spatial autoregressive parameter ($\rho=0.351$) is significantly positive, indicating that the grain output in China has a significant positive spatial dependence and spatial cluster effect. In the results, preliminary analysis of the estimated coefficients of independent variables found that the ratio of disasters and urbanization were negative. And other independent variables, indicating that they have a significant impact on the changes in the grain production pattern between provinces. From the perspective of the spatial lag of independent variables, the coefficients of arable land area per capita, agricultural machine, fertilizer input, urbanization ratio, and GDP per capita have also passed the significance test, indicating that these variables can affect the change of grain production pattern through spatial spillover effects.

LeSages and Pace's (2009) interpretation of the parameter is given in the form of a partial derivative matrix in the Durbin econometric model. The concepts of the total, direct and indirect effects are proposed[27]. Therefore, the partial differential of the spatial Durbin model is used to calculate the direct and indirect effects of the impact of each independent variable on grain output in China, the results as shown in Table 8. The direct effect shows the influence of the independent variable on grain output in the region, and the indirect effect shows the influence of the independent variable in the other provinces on grain output in the region.

Table 8. Effect analysis of influencing factors on the change of grain production pattern

Variable	Both individual and time effects		
	Direct effect	Indirect effect	Total effect
Ratio of disaster	-0.001***	-0.001	-0.001***
Irrigated area	0.728***	-0.548**	0.180
Arable land per capita	0.047***	-0.011	0.037***
Agricultural labor	0.633***	0.266**	0.899***
Agricultural machine	0.069*	0.304***	0.372***
Fertilizer application	0.237***	-0.232**	0.005
Urbanization ratio	-0.002	-0.377***	-0.379***
GDP per capita	0.327***	0.499***	0.826***

Note: *represents significance at 10%, **5%, and ***1%, respectively.

(1) Direct effects: the direct effects coefficients of the ratio of disaster, irrigated area, arable land area per capita, agricultural labor, fertilizer application, and GDP per capita are significant at the significant level of 1%. The direct effects

of the irrigated area, arable land area per capita, agricultural labor, fertilizer application, and GDP per capita are significantly positive. The coefficients of the ratio of disaster are significantly negative. The direct effects coefficients of the agricultural machine are significant at the significant level of 10%, the coefficient of the direct effects of the agricultural machine is positive.

(2) Indirect effects (spillover effect): The indirect effects coefficients of irrigated area, agricultural labor, agricultural machine, fertilizer application, urbanization ratio, GDP per capita are significant at the significant level of 5%. The indirect effect coefficients of irrigated area, fertilizer application, and urbanization ratio are significantly negative, indicating that the three variables have a negative spatial spillover effect. The irrigated area, fertilizer application, and urbanization ratio will negatively affect grain production in neighboring provinces. The indirect effect coefficients of agricultural labor, machine, and GDP per capita are significant, indicating that the three variable has positive spatial spillover effects. The Agricultural labor, Agricultural machine, and GDP per capita in neighboring provinces will be positively associated with grain production.

According to the spatial Durbin model results, the total effects coefficients of the disaster ratio, the arable land per capita, agricultural labor, agricultural machine, and GDP per capita are significant at the significant level of 1%. The coefficients of the total effects of the urbanization ratio are significantly negative. The coefficients of the total effects of the disaster ratio are significantly negative. However, the variables of the irrigated area and fertilizer application are not significant. To sum up, the more arable land per capita, and the more agricultural labor, besides better agrarian machinery inputs, the lesser natural disasters in the region, the better grain production will be in the area, and as such, the focus on grain production will gradually shift to such areas.

5. Conclusions and policy implications

This study is based on the provincial panel data of 31 provinces in China from 2007 to 2019, analyzes the changes in grain production distribution in China, tests the spatial autocorrelation of grain output, and analyzes the factors affecting the change of grain production pattern in various provinces of China. The conclusions showed the following. (1) The overall change trend of China's grain production during 2007-2019 increases, but with some fluctuations. The Moran's I results indicate an apparent positive spatial autocorrelation in China's grain production, and there is a spatial spillover effect in the grain production pattern of various provinces. Moran's I is rising yearly from the overall trend, indicating that the spatial effect between regions gradually increases. (2) The arable land per capita, agricultural labor, agricultural machine, and GDP per capita have a significant positive impact on the change of grain production in China. Still, the disaster ratio and urbanization ratio have a significant negative effect on the change of grain production. The disaster ratio is associated with the grain output mainly through direct effects, and the urbanization ratio is associated with the grain output mainly through indirect effects, the other variables have different spatial effects.

Based on the conclusions, this study suggests that when adjusting China s overall grain production pattern and formulating grain development policies, the government needs to pay extra attention to geospatial factors, exploring the linkages of the spatial distribution of grain production among China s different provinces. At the same time, pay attention to differences in natural resource endowments in various regions, adopt local conditions, formulate support policies for grain development in line with local characteristics. The following suggestions are proposed: (1) Develop agricultural mechanization, improve agricultural science and technology, improve agricultural infrastructure construction. In order to improve grain production capacity, from the perspective of agricultural machinery, give full play to the potential of agricultural machinery for grain production, subsidize the purchase of agricultural machinery, and increase the popularization of agricultural mechanization. Meantime, establish disaster prevention early warning for grain production. Through advanced agricultural technology, combined with meteorological monitoring and forecasting technologies, real-time monitoring of natural factors such as climate and precipitation are carried out, and water conservancy and irrigation facilities are used to prevent droughts and floods. And through the real-time dynamic monitoring of grain crops to control pests and diseases. Moreover, renovate water conservancy facilities through reconstruction and construction of reservoirs, and improve agricultural irrigation technology by promoting water-saving irrigation technology. (2) Strengthen the management of arable land and monitor arable land quality to preserve the quantity and quality of arable land. In the process of urbanization development, all regions must make relevant land use plans to minimize the occupation of arable land resources. Regarding the phenomenon of abandoned farmland in rural areas, strengthen the improvement and full use of abandoned farmland. Moreover, ensure the number of agricultural labor and stimulate the enthusiasm of rural grain production by increasing the income of grain production in the short term. At the same time, we should promote intensive and large-scale benefits, effectively improving land use and grain income efficiency.

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