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Research article

Grain industrial agglomeration and grain green total factor productivity in China: A dynamic spatial durbin econometric analysis

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ABSTRACT

Appropriate industrial agglomeration has several benefits, including reducing environmental pollution, promoting innovation and enhancing grain green total factor productivity (GTFP). It is an effective strategy for promoting high-quality and sustainable development in the grain industry. In this study, the slacks-based measure of the global Malmquist–Luenberger (SBM-GML) model is used to estimate China's grain GTFP using the panel data of 31 provinces from 2001 to 2020. Furthermore, a dynamic spatial econometric model is employed to empirically investigate the impact of grain industry agglomeration on grain GTFP and its regional heterogeneity. The results show that GTFP exhibits a fluctuating growth tendency, with advancements in green technology serving as the primary engine of that expansion. (2) The deepening of grain industrial agglomeration has a long-term promoting effect on the grain GTFP of local and neighbouring areas, with the long-term effect being more significant than the short-term effect, as revealed by the dynamic spatial Durbin model. (3) According to the heterogeneity analysis, industrial agglomeration's impact on grain GTFP is most noticeable in the production and sales balance. Therefore, encouraging regional cooperation and communication while raising the grain industrial agglomeration standard is crucial. The degree of regional economic growth, the state of the agricultural infrastructure and the conditions of the natural resources should all be considered by policymakers when developing distinct and focused policy assistance for each region.

1. Introduction

The security of grains in emerging nations has been a global focus [1]. As the largest developing country, China attaches significant importance to grain security by continuously improving its grain production capacity, transforming its grain industrial development mode and achieving the milestone of 'basic self-sufficiency of grain and absolute safety of grain rationing'. However, relying on factor inputs to drive grain production, the long-standing growth pattern has led to excessive resource consumption and severe agricultural non-point source pollution. As a result, several obstacles are in the way of the grain industry's sustainable development [2,3]. In addition to the constant input of production elements like land, labour, capital and other factors, the sustainable development of the grain industry also necessitates constant improvement in the effectiveness of their usage, namely, the productivity of the whole factor

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in the production of grains. However, the traditional calculation method for the grain total factor productivity fails to consider the damage caused by grain production to resources and the environment, rendering it unable to reflect the actual performance of the grain industry's development. Therefore, incorporating resources and natural environment variables into the calculation of green total factor productivity (GTFP) during the stage of economic green transformation can fairly and objectively reflect the success of the grain industry's green development [4,5].

With resource constraints and environmental deterioration in mind, the factor-driven grain increase model is unsustainable, and industrial cluster and intensive development are crucial for enhancing resource utilisation efficiency, enhancing GTFP and encouraging the grain industry's wholesome and sustainable growth [6]. Industrial agglomeration generally relates to the closeness of comparable operations in an identical sector within a specific geographic area [7]. With tightening resource and environmental constraints, traditional grain production methods can no longer maximise land utilisation in the grain industry. Large-scale production methods have emerged, further evolving into agglomeration of the grain industry [8].

Therefore, it is imperative to study the role of industrial agglomeration in the grain industry's sustainable development from the grain GTFP perspective to promote the high-quality development of the grain industry and ensure grain security in developing countries. Based on the research gaps, this study employs the SBM-GML model to estimate grain GTFP in 31 Chinese provinces from 2001 to 2020. Additionally, considering regional heterogeneity, we use a dynamic spatial econometric model to systematically examine the influence of grain industrial agglomeration on grain GTFP.

This study aims to contribute in several aspects. First, it incorporates grain non-point source pollution and carbon emissions as additional measures of undesired outputs in grain GTFP assessment. Second, the empirical research framework includes spatial components to investigate the direct effects of industrial agglomeration on grain GTFP and its geographical spillover effects. Third, considering the disparities in economic foundation and resource endowment among different grain production functional zones, the study analyses the varying effects of grain industry agglomeration in the primary grain-producing area, the production and sales balance area and the primary grain-sales area.

2. Theoretical analysis

Grain industry agglomeration refers to the economic phenomenon that all kinds of grain production and operation subjects gather in a specific area to form a certain scale. The organic combination of all kinds of grain production and operation subjects can better play a comparative advantage and enhance the comprehensive production capacity of grain [9]. With the gradual development of grain production in the direction of scale and intensification, industrial agglomeration has become an effective way to improve GTFP and promote the grain industry's high-quality development [10]. On the one hand, grain industry agglomeration can produce a scale economy effect, competition effect and knowledge spillover effect to improve GTFP. On the other hand, industry agglomeration can also inhibit the improvement of GTFP through crowding and confinement effects [11]. Based on this, this study constructs a theoretical analysis framework (Fig. 1). Furthermore, based on the specific role of the above effects in the grain production process, this work demonstrates the impact of grain industry agglomeration on the GTFP in three aspects: direct impact, spatial spillover effect and heterogeneity analysis.

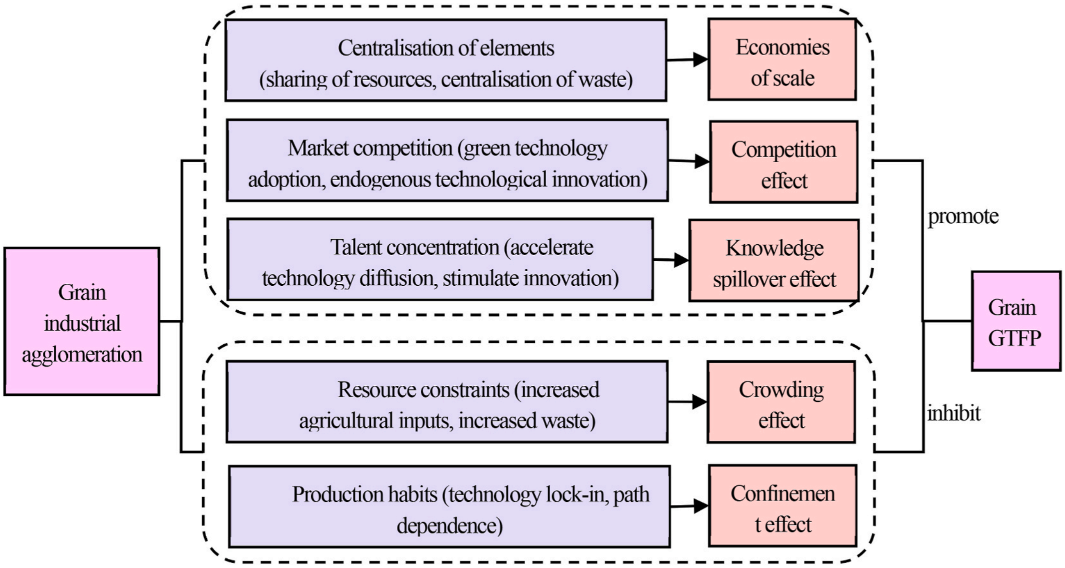

Fig. 1. Mechanisms of grain industrial agglomeration on grain GTFP.

2.1. Direct effect of industrial agglomeration on grain GTFP

The scale effect generated by grain industry agglomeration can promote the overall productivity of grain production by optimising resource allocation efficiency and improving production methods [12]. On the one hand, moderate industrial agglomeration facilitates large-scale grain production by sharing labour, machinery and other production factor resources. This situation allows multiple production and management entities to share infrastructure and utility costs, leading to intensified grain production, scientific management and efficient resource allocation [13,14]. Additionally, moderate industrial agglomeration enables centralised treatment of production waste, reducing pollution control costs and minimising surface pollution and carbon emissions, thus enhancing the overall productivity of environmentally friendly grain production [15].

On the other hand, industrial agglomeration intensifies competition in the grain market, compelling grain production and management entities to continuously improve their production technology [16]. Such entities adopt green agricultural inputs instead of polluting and residue-laden products, thereby enhancing the quality of grain and grain products through environmentally friendly production practices to improve market competitiveness and promote the overall productivity of green grain production. Furthermore, industrial agglomeration stimulates endogenous innovation within the grain production and management entities. Excellent entities serve as benchmarks for other farmers to learn from, driving continuous improvements in grain production efficiency, technological innovation and management capacity, further enhancing the grain industry's green development level [17].

Nonetheless, the impact of industrial agglomeration on the GTFP is not always favourable, and grain industry agglomeration may also generate negative externalities. Conversely, along with industrial agglomeration, the scale of grain production is expanding; however, China has limited high-quality arable land, water and other production resources. Producers can only increase the use of pesticides, chemical fertilisers and other abundant factor inputs to ensure yields, which triggers the congestion effect, affects grain production and leads to increased waste and cumulative damage to local water resources, arable land and the surrounding ecological environment [18]. These factors hinder the improvement of GTFP. In contrast, the risk and learning costs of adopting new technologies and methods are increasing due to the significant input of certain production factors and infrastructure in the early stages. As a result, some production and management entities find it challenging to change their production modes easily. Excessive industrial agglomeration can create a confinement effect that hinders the adoption and development of new technologies. This situation is not conducive to improving the GTFP.

H1. The effect of industrial agglomeration on grain GTFP is uncertain.

2.2. Spatial effect of industrial agglomeration on grain GTFP

Grain industrial agglomeration can enhance the GTFP in the neighbouring regions through spillover effects, which include both physical knowledge, such as high-quality seeds, biopesticides, organic fertilisers and advanced machinery and equipment, as well as non-physical knowledge, including new technologies and methods of grain production and green management and operation concepts [19]. Unlike other industries, grain production decisions depend directly on individual farmers, who generally have strong 'imitation ability' and herd mentality. Therefore, in the case of a very transparent grain production process, grain industry agglomeration can promote the integration and innovation of agricultural green knowledge and technology by increasing the opportunities for exchange and learning among grain production and management subjects and promoting the integration and innovation of advanced grain production and management. Integration and innovation promote the diffusion of advanced grain production management experience and technology, accelerate the continuous spillover of new knowledge and technology, and thus enhance the GTFP in the neighbouring regions [20,21]. Furthermore, the agglomeration of the grain industry in a specific region will also produce a siphon effect, attracting grain production resources from neighbouring regions to gather in that region, which is not conducive to enhancing GTFP in neighbouring regions. In conclusion, through spatial spillover effects, grain industry agglomeration affects neighbouring regions' local GTFP and GTFP.

Significant differences exist between the economic base, scientific and technological strength, resource endowment and other factors between different regions of China. Therefore, the role played by grain industry agglomeration in different regions and the effect of the role are not fixed; thus, regional heterogeneity may exist. Accordingly, this study proposes the following research hypothesis.

H2. There is a spatial spillover effect of the effect of industrial agglomeration on GTFP, and the effect is regionally heterogeneous.

3. Materials and methods

3.1. Measurement of grain GTFP

3.1.1. Calculation method of grain GTFP

This study calculates the grain GTFP using data envelopment analysis (DEA). This approach was first put forth by Charnes et al. [22], and developed by Banker et al. [23] to create several models for efficiency evaluation. Early literature used the angle and radial DEA model to evaluate the efficiency. It is necessary to select the input and output angles, and the input or output is required to change proportionally, which is not in line with the actual production situation [24]. Considering the DEA model's non-angular and non-radial features, Tone [25] proposed the SBM standard efficiency model; however, when more than two effective units exist in a given period, the SBM standard efficiency model cannot rank them. As a result, Tone [26] advanced the SBM super-efficiency model, although it did not consider unexpected outputs. Based on these shortcomings, this study refers to Tone's [27] research and selects the SBM super-efficiency model that includes unexpected outputs to measure the agricultural GTFP. Assuming that the kth decision-making unit (j = 1, 2, …n) has input vector $x \in R^M$, expected output vector $y^g \in R^{s_1}$ and unexpected output vector $y^g \in R^{s_2}$, respectively. At the same time, matrix $X = [x_1, x_2, \cdots, x_n] \in R^m \times n$, $Y^g = [y_1^g, \cdots, y_n^g] \in R^{s_1} \times n$, and $Y^b = [y_1^b, \cdots, y_n^b] \in R^{s_2} \times n$ are defined. For the measured decision-making unit k, Equation (1) is

$$
\begin{aligned}
&\min \rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{ik}}}{1 - \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} s_g^r / y_{rk}^g + \sum_{t=1}^{s_2} s_t^b / y_{tk}^b\right)} \\
&s.t. \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik} \\
&\sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j + s_r^g \geq y_{rk}^g \\
&\sum_{j=1, j\neq k}^{n} y_{tj}\lambda_j - s_t^b \leq y_{tk}^b \\
&\lambda \geq 0, s^g \geq 0, s^b \geq 0, s^- \geq 0
\end{aligned}
\tag{1}
$$

λ is the weight vector; s_i^-, s_r^g and s_t^b comprise the slack variable. $\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}$ represents the average inefficiency level of inputs, and $\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} s_r^g / y_{rk}^g + \sum_{t=1}^{s_2} s_t^b / y_{tk}^b\right)$ represents the average inefficiency level of outputs. ρ is the efficiency value of the decision-making unit, which can be greater than 1, allowing for the distinction between effective and ineffective decision-making units. Equation (1) can be used to determine each evaluated unit's efficiency level under certain technological circumstances; however, this static analysis of technology efficiency does not adequately capture the impact of productivity changes on agricultural production and development. Therefore, some scholars have referred to the Malmquist productivity index proposed by Diewert et al. [28]and Fare et al. [29], and formed the ML index [30]and GML index [31], which consider resource consumption and environmental pollution. The GML index can address the issue of linear programming's impossibility of solutions better than the ML index. The GML index is explained herein, as shown in Equation (2).

$$
GML^{t,t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; x^t, y^t, b^t\right) = \frac{1 + D_G^T(x^t, y^t, b^t)}{1 + D_G^T\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \tag{2}
$$

If $L^{t,t+1} < 1$, the expected output decreases, the undesired output increases and the agricultural green total factor productivity is lower than the previous level. Otherwise, it indicates an improvement in GTFP. The GML index can be divided into green technology progress (GTC) and green technology efficiency (GEC) [32].

$$
\begin{aligned}
&GML^{t,t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; x^t, y^t, b^t\right) \\
&= \frac{1 + D_C^t(x^t, y^t, b^t)}{1 + D_C^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \times \left[\frac{\left(1 + D_G^T(x^t, y^t, b^t)\right)/\left(1 + D_C^t(x^t, y^t, b^t)\right)}{\left(1 + D_G^T\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right)/\left(1 + D_C^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right)}\right] \\
&= \frac{TE^{t+1}}{TE^t} \times \left[\frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}}\right] \\
&= GEC^{t,t+1} \times GTC^{t,t+1}
\end{aligned}
\tag{3}
$$

In Equation (3), the values of $L^{t,t+1}$, $GEC^{t,t+1}$ and $GTC^{t,t+1}$ are all greater than 0. When their values are greater than 1, they indicate an improvement in grain GTFP, an improvement in GEC and the occurrence of GTC, respectively. Otherwise, it indicates a reduction in grain GTFP, a deterioration in GEC and green technology backwardness.

3.1.2. Selection and treatment of indicators

This study uses the grain GTFP index for 31 Chinese provinces between 2001 and 2020 as its research subject. The input variables include indicators like arable land resources, water resources, labour and agricultural materials. Since China has no separate indicators to measure grain inputs in current macro data, the study separates the relevant grain input data from general agricultural input using the weight coefficient method. Among them, weight coefficient A = grain sowing area/crop sowing area, weight coefficient B = (Output value of agriculture/total value of forestry, animal husbandry and fishing) × A. Specifically, (1) the grain sowing area of each province in previous years serves as the input indicator for cultivated land resources. (2) The effective irrigation area, which serves as the input indicator for water resources, is calculated by multiplying the effective irrigation area of agriculture in each province in previous years by the weight coefficient A. (3) The labour input indicator is represented by the labour force for grain production, which is the number of employees in agriculture, forestry, animal husbandry and fishing in each province over time multiplied by the weight coefficient B. (4) Examples of agricultural material input indicators include the amount of pure fertiliser used in grain production, the amount of pesticide used, the amount of film used, the amount of diesel utilised and the overall power of machines. These indicators are derived by multiplying the total output of agricultural machinery, the total output of pure agricultural fertiliser, the total output of pesticides, the total output of film and the total output of diesel by the weight coefficient B for each province.

The output variables include expected output and unexpected output [33]. Expected output is represented by the grain yield of each province in previous years. In contrast, unexpected output is represented by carbon emissions and non-point source pollution generated during grain production. Carbon emissions are calculated by summing six carbon emission sources, including the effective irrigation area, total grain sowing area, diesel fuel consumption for grain production, the pure amount of fertiliser used for grain production, pesticide use and film use, multiplied by their respective emission coefficients. The calculation is shown in Equation (4).

$$E = \sum E_i = \sum T_i \times \delta_i \tag{4}$$

Here, E represents the total carbon emissions generated in grain production in each province (city), and E_i represents the emissions of different carbon sources in grain production in each region. T_i represents the total amount of carbon sources in grain production, and δ_i represents the emission coefficient of each carbon source in grain production.

Agricultural non-point source pollution indicators include TN, TP and COD; however, organic matter in farmland drainage has little impact on water pollution. The results of two pollution source surveys in China also show that COD emissions from planting account for less than 5% of the total COD emissions from agricultural sources; therefore, this study only considers TN and TP as measuring indicators of non-point source pollution and adopts the unit survey and evaluation method for calculation. The calculation is shown in Equation (5).

$$E_{ij} = \sum_{i=1}^{I} G_{ij} \times \mu_{ij} = \sum_{i=1}^{I} EU_i \times \rho_{ij} \times \mu_{ij}, j = 1, 2 \tag{5}$$

Here, E_{ij} represents the emissions of pollutants from units i and j, which is the emission of TN and TP in grain production. G_{ij} represents the generation of pollutants from unit i and j, while μ_{ij} is the loss rate of pollutants from unit i and j. EU_i represents the total number of units i, which refers to the total number of units that generate pollution. This study specifically refers to the applied amounts of chemical fertilisers and the total output of various grain crops. ρ_{ij} is the pollution coefficient of units i and j. The relevant data for ρ_{ij} and μ_{ij} are obtained from the 'Handbook of Agricultural Source Coefficients for the First National Pollution Source Census and other materials. The relevant data are sourced from the 'National Agricultural Cost–Benefit Data Compilation', 'China Statistical Yearbook' and 'China Rural Statistical Yearbook'. Missing data are completed using provincial statistical yearbooks and the linear interpolation method.

3.2. Spatial influence effect of industrial agglomeration on grain GTFP

3.2.1. Space-panel model construction

This study examines the spatial impacts of industrial agglomeration on grain GTFP using a spatial econometric model. The geographical auto-correlation of industrial agglomeration and grain GTFP is first assessed using the global $Moran's\ I$ index, as shown in Equation (6), before undertaking spatial econometric analysis.

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{6}$$

Among them, $S^2 = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \overline{Y})^2$; $\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$. Y_i represents the observed value of region i, n is the total number of regions, and W_{ij} is the spatial weight matrix. The $Moran's\ I$ index's absolute value is below 1. If the $Moran's\ I$ index is higher than 0, there is spatial spillover and a positive spatial auto-correlation in the observed variable. If the $Moran's\ I$ index is less than 0, negative spatial auto-correlation arises in the observed variable, meaning that spatial agglomeration exists. If the $Moran's\ I$ index equals 0, the observed variables are independent and have no spatial correlation. This study intends to create an adjacency spatial weight matrix whose matrix elements represent whether there is a common boundary between provinces. If a common boundary exists, the value is 1; otherwise, the value is 0.

After running a geographic auto-correlation test on the two variables, a spatial panel model is created to see if industrial agglomeration has a spatial spillover effect on grain GTFP. This study uses the spatial Durbin model (SDM) to calculate the regional spillover impact of industrial agglomeration on grain GTFP. The fundamental form of the model is displayed in Equation (7):

$$\ln GTFP_{it} = \alpha + \rho W \ln GTFP_{it} + \beta \ln Agg_{it} + \beta_1 X_{it} + \delta W \ln Agg_{it} + \delta_1 W X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{7}$$

A dynamic spatial panel model is further constructed to avoid endogeneity issues, with explanatory variables lagged by one period. The model effectively controls for individual differences and time dynamics, allowing for better identification of the impact of industrial agglomeration on grain GTFP. The fundamental form of the model is displayed in Equation (8):

$$\ln GTFP_{it} = \alpha + \tau \ln GTFP_{i(t-1)} + \rho W \ln GTFP_{it} + \beta \ln Agg_{it} + \beta_1 X_{it} + \delta W \ln Agg_{it} + \delta_1 W X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{8}$$

Here, $\ln GTFP_{it}$ is GTFP, $\ln Agg_{it}$ is the concentration degree of grain production and X_{it} represents the control variable. Furthermore, α is a constant term, β comprises the spatial estimated coefficients, W represents the Critical-space weight matrix, μ_i represents the year effect, φ_t represents the spatial effect, and ε_{it} is the error term.

3.2.2. Variable selection

1) Explained variable. The GTFP index was chosen as the dependent variable because it represents China's high-quality development in the grain economy. The data for this variable are taken from Section 2.1.
2) Core explanatory variable. Academic scholars often measure grain industrial agglomeration (*Agg*) using the HHI index, spatial Gini coefficient and location entropy methods. This study utilises the location entropy index to assess the degree of agglomeration in the grain sector to account for significant scale disparities between Chinese provinces, eliminate regional scale discrepancies and reflect the genuine spatial concentration of geographical elements. The calculation is shown in Equation (9).

$$Agg_{it} = \frac{grainoutput_{it}}{\sum_{i=1}^{n} grainoutput_{it}} \Big/ \frac{Agriculturaloutput_{it}}{\sum_{i=1}^{n} Agriculturaloutput_{it}} \tag{9}$$

Here, i represents the region, t represents the period and grain output represents the region's grain production. Agricultural output represents the total agricultural output value of the region, n represents the number of regions and Agg represents the agglomeration level of grain production. The degree of agglomeration increases with increasing Agg value.

3) Control explanatory variables. The following control variables are chosen in consideration of the research focus. (1) Rural economic development level (*PCIF*) represents the overall economic development status of rural areas in various provinces and cities and is determined by rural populations' per capita disposable income. (2) Agricultural industry structure (*AIS*) is the ratio of the area used for sowing grains to all other crops in each province and city. (3) Labour productivity (*PCA*) is calculated by dividing each province's and city's grain production labour force by the total grain planting area. Generally, the larger the per capita operational scale, the easier it is to boost automated production efficiency. (4) Mechanisation level (*ML*) reflects the substitutability of machinery for human resources and is measured by the overall power of machinery utilised in grain production. (5) The disaster-affected rate (*DAR*) reflects the effects of natural disasters and is calculated as the ratio of the grain disaster area to the sowing area of grain crops in each province and city. (6) Irrigation facilities level (*IFL*), which assesses the level of excellence of farmland water conservancy infrastructure, is calculated as the ratio of the effective irrigation area to the area used for planting crops in each province and city. (7) Human capital (*HC*), which weights and sums the labour force by different levels of education. (8) The proportion of agricultural expenditure to general public budget expenditure represents financial support for agriculture (*AFI*).

3.2.3. Data sources

This study uses panel data from 31 provinces in China (excluding Hong Kong, Macao and Taiwan) from 2001 to 2020 as research samples. The data mainly come from the 'China Statistical Yearbook', 'China Rural Statistical Yearbook', 'Yearbook of Agricultural Cost–Benefit Data', provincial statistical yearbooks and the EPS database. Individual missing data is supplemented using the moving average method. The descriptive statistics for each variable are shown in Table 1.

Table 1
Definitions and descriptive statistics of variables used in the study.

	Variable	Description	Mean	Std.
Explained variable	GTFP	SBM-GML	1.015	0.140
Core explanatory variable	Agg	Location entropy	0.998	0.501
Control explanatory variables	PCIF	Rural per capita disposable income	8256.247	5960.057
	AIS	Grain sowing area/total crop sowing area	0.652	0.129
	PCA	Grain sowing area/grain labour force	12.185	5.723
	ML	Total mechanical power used in grain production	7.035	4.340
	DAR	Area of grain crops affected by disasters/total grain sowing area	0.217	0.154
	IFL	Effective irrigation rate	1971.204	1544.884
	HC	Education duration law	7.330	0.913
	AFI	Financial expenditure for agriculture/general public budget expenditure	0.103	0.036

4. Results

4.1. Calculation results of grain GTFP

The present research uses the SBM super-efficiency model and the GML index to compute China's grain GTFP using input–output data from 31 provincial-level units on the mainland from 2001 to 2020. The results are shown in Fig. 2. Overall, from 2001 to 2020, the grain GTFP of the 31 provinces in China demonstrated a shifting rising pattern, with an average of 1.011 and an annual growth rate of 2.66%. This outcome proves that China's grain GTFP has generally improved and that the grain business is going towards development that is environmentally friendly, effective and of high quality.

Regarding stages, during the 'Tenth Five-Year Plan' period, China's grain GTFP decreased by an average of 0.37% per year. This decline was mostly caused by natural calamities, such as floods, droughts and freezing temperatures at the beginning of the 21st century, which seriously damaged grain production. During the 'Eleventh Five-Year Plan' period, the grain GTFP fluctuated significantly due to the concurrent consequences of the financial crisis and environmental regulations. During the 'Twelfth Five-Year Plan' period, with China's economy entering a new normal, the government continuously encouraged innovation, promoted green production technologies for grain and issued an array of environmental protection measures, resulting in good overall development momentum for grain GTFP. During the 'Thirteenth Five-Year Plan' period, due to the emphasis on green development concepts and promotion of green technological progress, the grain GTFP steadily improved. Decomposing the grain GTFP shows that both technological progress and efficiency showed a fluctuating upward trend, with technological progress and grain GTFP showing similar trends but efficiency fluctuating more frequently and with smaller increases. This outcome shows that advancements in green technology were primarily responsible for China's grain GTFP improvement during the study period. It is worth noting that during the 'Thirteenth Five-Year Plan' period, China's grain technical efficiency slightly increased, becoming a key driver of grain GTFP. This result indicates that China's grain production has gradually transitioned from focusing on input elements and neglecting efficiency improvement to an intensive and high-quality development stage. The grain industry has continued to improve in resource element efficient allocation, production organisation management and institutional arrangements. A resource-efficient and green growth model driven by both wheels is now within reach for grain GTFP.

Fig. 3 shows the comparison of regional grain GTFP. From a regional perspective, the grain GTFP in the main grain-producing areas was generally higher than the national average level during the investigation period. The grain GTFP in the main grain-sales areas showed stable growth, while the grain GTFP in the production-sales balanced areas was significantly lower than the other two areas during the 'Eleventh Five-Year Plan' period but has grown most rapidly in recent years. Possible reasons are that the terrain in the main grain-producing areas is mostly plains, with better resource endowment. In the development of green production technology for grains, the promotion and application of agricultural green production technology that is beneficial to the growth of grain crops is receiving growing attention. Additionally, the region's overall output value includes a disproportionately high amount of grain crops; as a result, the production process places more emphasis on environmental conservation to ensure long-term advantages. The main grain sales areas are generally economically more developed and focus more on improving technological efficiency; however, agricultural production and its ecological environment are often sacrificed, resulting in insignificant growth in grain GTFP. At the same time, the plateau mountainous regions of central and western China are where production-sales balances are most prevalent. Here, the natural environment is harsher, and grain production depends more on chemical inputs such as fertilisers and pesticides, leading to more severe pollution and carbon emissions. Nonetheless, with the government's increased financial support for grain production and the rapid expansion of central and western China in recent years, their grain GTFP has substantially improved.

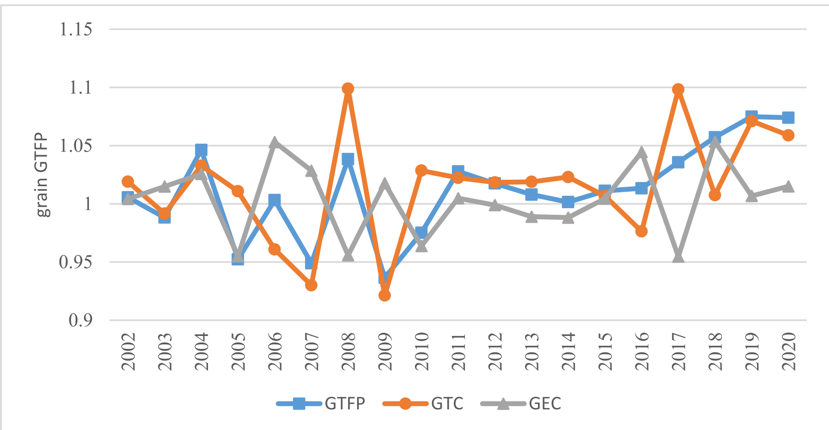

Fig. 2. China provincial grain GTFP in 2001–2018.

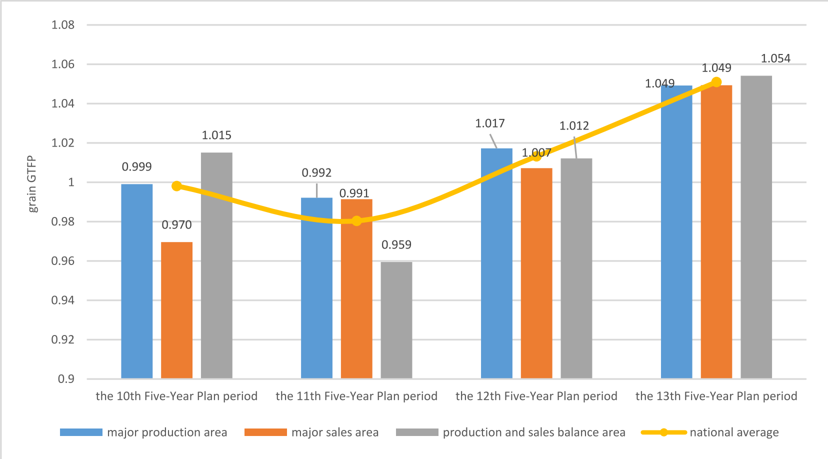

Fig. 3. Comparison of subregional grain GTFP.

Table 2
Global Moran's I of grain GTFP and grain industrial agglomeration.

Year	AGG	GTFP	Year	AGG	GTFP
2001	0.408***	–	2011	0.442***	0.501***
2002	0.436***	0.376***	2012	0.407***	−0.041
2003	0.440***	0.350***	2013	0.390***	−0.230**
2004	0.446***	0.034	2014	0.360***	−0.185*
2005	0.416***	0.035	2015	0.421***	0.066
2006	0.394***	0.189**	2016	0.407***	−0.029
2007	0.370***	0.051	2017	0.402***	0.381***
2008	0.426***	0.204**	2018	0.457***	0.253***
2009	0.390***	0.142**	2019	0.459***	0.142*
2010	0.423***	0.325***	2020	0.487***	0.062

4.2. Spatial correlation analysis

The research period in China's provinces was used in this work to investigate the worldwide spatial auto-correlation of industrial agglomeration and grain GTFP using Moran's I (Table 2). The grain industrial agglomeration Moran's I index is significantly positive at the 1% level, while the grain GTFP Moran's I index is typically more than 0 and significant at least at the 10% level. This shows that in most years in China, industrial agglomeration at the province level and grain GTFP are strongly spatially correlated, supporting further research into the spatial impacts of industrial agglomeration on grain GTFP.

4.3. Empirical results of spatial analysis

4.3.1. Statistical tests for model form selection

Before conducting empirical analysis using spatial econometric models, this study verifies the applicability of the models through various tests, including the LM test, Wald test and LR test (Table 3) [34]. First, the LM test is significant at the 1% level, demonstrating that the model contains both a spatial error component and a spatial lag term. By further adopting the Wald test and LR test, the null hypothesis is significantly rejected, indicating that the SDM cannot be degraded into the spatial autoregressive model (SAR) or spatial error model (SEM). Therefore, the SDM model should be selected for regressing the dependent variable. Second, the Hausman test determines whether to select a random or fixed effects model, and the LR test determines whether to select time-fixed effects, spatial fixed effects or time and spatial double fixed effects model. The final result shows that the time and spatial double fixed SDM model

Table 3
Results of the suitability test of the spatial measurement model.

Test	Statistical value	P-value	Test	Statistical value	P-value
LM-lag	76.434***	0.000	Wald-lag	16.20*	0.063
Robust LM-lag	10.620***	0.001	LR-lag	32.17***	0.000
LM-error	69.952***	0.000	Wald-error	18.41**	0.031
Robust LM-error	4.138**	0.042	LR-error	36.07***	0.000

Table 4
Baseline regression model.

Variable	SAR	SEM	SDM		DSDM	
	Main	Main	Main	W*x	Main	W*x
L.GTFP					0.217***	−0.054
					(4.49)	(−0.55)
Agg	0.152***	0.141***	0.155***	0.195**	0.152***	0.163*
	(3.37)	(3.07)	(4.43)	(2.29)	(4.14)	(1.75)
PCIF	0.097	0.095	0.192**	−0.064	0.168*	−0.014
	(1.17)	(1.07)	(2.21)	(−0.52)	(1.87)	(−0.10)
AIS	−0.333***	−0.276***	−0.356***	−0.697***	−0.339***	−0.646**
	(−3.32)	(−2.67)	(−4.03)	(−2.62)	(−3.56)	(−2.26)
PCA	0.174***	0.169***	0.171***	−0.029	0.156***	0.014
	(3.88)	(3.63)	(3.83)	(−0.40)	(3.45)	(0.20)
ML	−0.091**	−0.097**	−0.073**	0.056	−0.065*	0.022
	(−2.42)	(−2.52)	(−2.10)	(0.81)	(−1.89)	(0.32)
DAR	−0.013*	−0.012*	−0.013**	−0.007	−0.014**	−0.008
	(−1.89)	(−1.84)	(−2.00)	(−0.44)	(−2.11)	(−0.53)
IFL	−0.077	−0.061	−0.113**	−0.287***	−0.109**	−0.269***
	(−1.35)	(−1.04)	(−2.11)	(−3.58)	(−2.03)	(−3.38)
HC	0.088	0.108	0.023	−0.394	0.050	−0.369
	(0.47)	(0.58)	(0.13)	(−0.79)	(0.29)	(−0.69)
AFI	0.033	0.032	0.041	0.024	0.029	0.040
	(1.01)	(0.91)	(1.27)	(0.55)	(0.82)	(0.83)
ρ	0.308***	0.301***	0.282***	–	0.278***	–
	(5.46)	(5.20)	(4.86)	–	(4.70)	–
R^2	0.141	0.145	0.169	–	0.196	–
sigma2_e	0.011***	0.011***	0.011***	–	0.012***	–
	(8.17)	(8.09)	(8.51)	–	(8.54)	–
Log-likelihood	385.8310	385.8310	385.8310	–	403.0728	–

should be selected. Third, considering the possibility of a time lag effect on grain GTFP, i.e. the previous GTFP may positively or negatively impact the current GTFP, this study uses the dynamic spatial Durbin model (DSDM) for regression analysis.

4.3.2. Spatial panel model regression analysis

The estimation outcomes for the SAR, SEM, SDM and DSDM models are presented in Table 4. The SAR, SEM and SDM models are employed among them to validate the efficacy and reliability of the estimation results. The estimation outcomes of the DSDM model are primarily covered herein.

First, turning to the results, the growth of GTFP in different regions has significant time lag effects and spatial spillover effects. The coefficient of the time lag term of GTFP is significantly positive at the level of 1 %, indicating that the development level of GTFP in the previous period has a positive effect on the development of GTFP in the current period. That is, there is an ‘inertial effect’ on the growth of GTFP. The GTFP spatial lag term coefficient is also significantly positive at the 1% level, indicating that the GTFP of a province will be positively affected by the GTFP of neighbouring provinces. GTFP has a ‘siphon effect’ in China’s inter-provincial grain production.

Second, industrial agglomeration significantly affects grain GTFP both directly and indirectly. The correlation between industrial agglomeration and grain GTFP is significant and positive at the 1% level, according to the regression coefficient of industrial agglomeration. Moderate industrial agglomeration can leverage economies of scale and achieve the intensive and scientific management of grain production by sharing production factors, sharing infrastructure costs and centralised waste disposal and enhancing the efficient allocation of resources. The higher the degree of industrial agglomeration is, the more concentrated the innovative elements such as knowledge, technology and talent are in the province, which is conducive to the integration and innovation of advanced production experience and emerging technologies, thus promoting the improvement of grain GTFP. The spatial lag term coefficient of industrial agglomeration is also significantly positive, indicating a positive effect on the grain GTFP level of adjacent provinces due to technology spillover and knowledge dissemination.

Finally, among all the control variables, the rural economic development level has a significantly positive estimated coefficient, indicating that rural areas with high levels of economic development have a higher degree of marketisation of agricultural factors and agricultural organisation, which is conducive to guiding farmers to rationally allocate production factors and effectively achieve centralised treatment of pollution, thus improving grain GTFP. The coefficients of agricultural industry structure and lag term are both significantly negative, indicating that an increase in the proportion of non-grain crops in this region will inhibit the growth of grain GTFP in this region and neighbouring regions. The estimated coefficient of per capital labour management scale is significantly positive, indicating that large-scale operation can optimise the allocation of production factors such as labour, reduce production costs and transaction costs and achieve intensive and scientific management of grain production and efficient allocation of resources. The estimated coefficient of the mechanisation level is significantly negative because the improvement in the mechanisation level leads to a significant increase in complementary consumption goods such as fuel power (agricultural diesel) and agricultural film usage, resulting in over-investment of resources or increased pollution emissions. The estimated coefficient of disaster degree is significantly negative because natural disasters will seriously affect grain output, and farmers may have to increase chemical inputs to ensure yield, thereby suppressing the improvement of grain GTFP. The coefficient and lag term coefficient of irrigation facilities level are both significantly negative, indicating that the level of irrigation facilities has an inhibitory effect on the improvement of grain GTFP in this region and neighbouring regions, possibly due to problems such as 'overuse' and 'crowding effects' caused by the imperfect construction of farmland irrigation facilities.

4.3.3. Spatial spillover effect decomposition

LeSage et al. [35] contend that drawing inferences about the effect of industrial agglomeration on GTFP exclusively from the point estimate results of the DSDM may be incorrect. Therefore, this study uses partial differentiation to calculate industrial agglomeration's direct, indirect and total effects on grain GTFP. The DSDM model adds time lag variables and their spatial lag terms as explanatory variables to the SDM model, allowing for effect decomposition divided into short-term and long-term effects. Table 5 reports the estimates of the short-term direct effect, short-term indirect effect, short-term total effect, long-term direct effect, long-term indirect effect and long-term total effect of the DSDM model.

The direct, indirect and overall effects of industrial agglomeration on grain GTFP are significantly positive in the spatial effect decomposition across the short and long terms. This result indicates that provincial industrial agglomeration can positively impact local grain GTFP while generating positive spillover effects on neighbouring provinces or regions through demonstration, technology spillover and other positive spatial spillover effects. This situation promotes the healthy and sustainable development of the grain industry in surrounding provinces. Specifically, the coefficient of industrial agglomeration shows that in the short term, when the level of industrial agglomeration in a province increases by one percentage point, the grain GTFP increases by 0.170%. This promotion effect is further increased to 0.218% in the long term. The indirect effect is similar. In the short term, when the level of industrial agglomeration in a province increases by one percentage point, the grain GTFP in neighbouring provinces will increase by 0.277%; in the long term, it will increase to 0.362%. Industrial agglomeration can positively impact grain GTFP by improving resource allocation efficiency, improving grain production methods, saving operating management costs and accelerating knowledge and technology spillover effects. Furthermore, this positive impact is stable and sustainable in the long term.

Overall, the effect of each control variable on grain GTFP is consistent with the results analysed earlier. Additionally, long-term effects are significantly greater than short-term effects, indicating that including explanatory variables such as industrial agglomeration significantly impacts grain GTFP in the long run.

4.3.4. Robustness test

This study tested the robustness of the benchmark regression results using three techniques: changing the spatial weight matrix, using truncation treatment and reducing the sample size. The estimation results are shown in Table 6.

This study conducted tests from four aspects to test the robustness of the core conclusions. First, the geographically adjacent spatial weight matrix is replaced with a binary spatial weight matrix. Second, we replace the geographic adjacent spatial weight matrix with an economic geography weight matrix. Third, each variable was truncated by 1% to avoid the influence of extreme values on the results. Finally, sample data from the 'Fifteen-Year Plan' period were deleted to shorten the time and reduce the amount of data. The impact of grain industrial agglomeration on grain GTFP was re-examined using the DSDM. The estimation results in Table 6 show that the outcomes of the above three robustness tests were not significantly different from the core conclusions of this study. This result indicates that industrial agglomeration has a significant direct promotion effect and spatial spillover effect on grain GTFP, and the results of the benchmark regression are robust.

Table 5
Dynamic space Durbin model effect decomposition.

Variable	Short term			Long term		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Agg	0.170***	0.277**	0.447***	0.218***	0.362**	0.580***
	(4.37)	(2.14)	(2.97)	(4.33)	(2.11)	(2.90)
PCIF	0.168*	0.045	0.213	0.215*	0.060	0.275
	(1.92)	(0.26)	(1.14)	(1.92)	(0.27)	(1.13)
AIS	−0.395***	−0.986**	−1.382***	−0.508***	−1.284**	−1.793***
	(−3.80)	(−2.41)	(−3.01)	(−3.78)	(−2.35)	(−2.92)
PCA	0.163***	0.084	0.247*	0.208***	0.113	0.322*
	(3.41)	(0.74)	(1.69)	(3.40)	(0.74)	(1.66)
ML	−0.067*	0.002	−0.064	−0.085*	0.001	−0.084
	(−1.83)	(0.02)	(−0.60)	(−1.83)	(0.01)	(−0.60)
DAR	−0.015**	−0.014	−0.029	−0.019**	−0.018	−0.038
	(−2.17)	(−0.68)	(−1.23)	(−2.16)	(−0.69)	(−1.23)
IFL	−0.126**	−0.408***	−0.534***	−0.162***	−0.531***	−0.693***
	(−2.54)	(−3.50)	(-4.34)	(−2.58)	(−3.33)	(−4.16)
HC	0.038	−0.407	−0.369	0.048	−0.523	−0.475
	(0.20)	(−0.57)	(−0.45)	(0.20)	(−0.57)	(−0.45)
AFI	0.031	0.062	0.093	0.039	0.081	0.120
	(0.95)	(1.01)	(1.41)	(0.95)	(1.01)	(1.40)

Table 6
Robustness.

Variable	Effect type	(1)	(2)	(3)	(4)
Agg	Short-term direct effect	0.171***	0.195***	0.170***	0.270***
		(3.30)	(4.28)	(4.37)	(4.70)
	Short-term indirect effect	0.349**	0.756**	0.277**	0.572***
		(1.68)	(2.14)	(2.14)	(3.83)
	Short-term total effect	0.520***	0.951***	0.447***	0.842***
		(2.38)	(2.65)	(2.97)	(4.57)
	Long-term direct effect	0.229***	0.260***	0.218***	0.304***
		(3.37)	(4.40)	(4.33)	(4.56)
	Long-term indirect effects	0.619	1.251**	0.362**	0.564***
		(1.64)	(2.08)	(2.11)	(3.63)
	Long-term total effect	0.848***	1.511**	0.580***	0.869***
		(2.11)	(2.45)	(2.90)	(4.54)
	Year effect	Yes	Yes	Yes	Yes
	Individual effect	Yes	Yes	Yes	Yes
Observations		589	589	589	310

Table 7
Results of the grain production functional area heterogeneity test.

	Grain production functional area		
Variable	main producing area	main sales area	Production and sales balance area
Agg	0.279***	0.015	0.238***
	(4.33)	(0.17)	(3.60)
W*Agg	−0.115	0.134	−0.021
	(−1.14)	(0.92)	(−0.15)
L. GTFP	0.195**	0.424***	0.272***
	(2.13)	(3.17)	(3.95)
W*L. GTFP	−0.140	0.144	0.480***
	(−0.96)	(0.68)	(3.23)
Short-term direct effect	0.196**	0.441***	0.246***
	(2.12)	(3.38)	(3.78)
Short-term indirect effect	−0.088	0.172	0.386***
	(−0.45)	(0.78)	(2.84)
Short-term total effect	0.108	0.613**	0.632***
	(0.45)	(2.18)	(4.30)
Long-term direct effect	0.273**	0.472***	0.308***
	(2.13)	(3.33)	(3.50)
Long-term indirect effects	−0.127	0.252	0.462***
	(−0.48)	(1.03)	(2.66)
Long-term total effect	0.146	0.724**	0.770***
	(0.44)	(2.17)	(4.27)
Year effect	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes
ρ	0.345***	0.023	0.220**
	(4.94)	(0.27)	(2.35)
R^2	0.0587	0.1823	0.2806
sigma2_e	0.010***	0.016***	0.011***
	(11.53)	(8.58)	(10.65)
Log-likelihood	−240.9831	−203.3961	97.5833
N	247	133	209

4.3.5. Regional heterogeneity analysis

Due to the influence of terrain, natural resources, economic development level and other factors, there are apparent differences in the grain industry's development mode and agglomeration level in different regions. This variation somewhat affects the relationship between industrial agglomeration and grain GTFP. Following the research methodology outlined in Section 3.3, we established the DSDM model of industrial agglomeration on grain GTFP in the primary grain-producing area, the primary sales area and the production and sales balance area to further investigate the direct impact of industrial agglomeration on grain GTFP and the spatial heterogeneity of spatial spillover effects. The empirical results are shown in Table 7.

First, the time lag coefficient of grain GTFP is significantly positive in the three groups of regression, indicating that the current grain GTFP level of the three types of grain production functional areas has a promoting effect on the development of grain GTFP in the future. From the perspective of spatial lag term, the spatial lag term coefficient of grain GTFP in the main grain-producing areas and the production and marketing balance areas is significantly positive. This result indicates that the grain GTFP level in these areas has a positive spatial spillover effect on the grain GTFP in the adjacent areas. Then, by comparing the coefficient values, it can be found that the spatial spillover effect of GTFP in the main grain-producing areas is the largest. Compared with the production and marketing balance area, the regional integration development of the main grain-producing areas is more in-depth, and the green production and management technology has been more widely promoted and applied, thus forming a higher positive spatial spillover effect in the main grain-producing areas. Regional integration development in the main grain-producing area is more in-depth than in the production and sales balancing area, and green production and management technology is more widely promoted and applied, thus forming a higher positive spatial spillover effect in the main grain-producing area.

Second, depending on the regression results in Table 7, different industrial agglomeration effects on grain GTFP in the three regions can be observed. (1) The direct effect of industrial agglomeration on grain GTFP in major grain-producing areas is significantly positive, but the short-term and long-term spatial spillover effects are insignificant. (2) The direct effect, spatial spillover effect, and the total effect of industrial agglomeration on grain GTFP in the production and sales balancing area are all significantly positive in the short and long term. (3) The direct and total effects of industrial agglomeration on GTFP in the main grain-sales area are significantly positive, but the short-term and long-term spatial spillover effects are insignificant. The main reason may lie in the inverted U-shaped relationship between industrial agglomeration and grain GTFP. Among them, the grain industrial agglomeration degree in the main grain-producing area is relatively high and has approached the inflexion point of the inverted U-shaped curve. In contrast, the industrial agglomeration degree in the primary sales and production and sales balancing areas is relatively low and has not yet reached the inflexion point of the inverted U-shaped curve. Therefore, boosting the industrial agglomeration degree in the primary sales region and production and sales balancing area offers a sizeable spatial scope for modifying China's grain production structure and improving grain GTFP.

Finally, looking at regional division, the direct and spillover effects of industrial agglomeration on grain GTFP in both the short and long term are still broadly consistent, and the effect of long-term effects is typically more significant than that of short-term effects, which is consistent with the findings of the overall sample analysis.

5. Discussion

This study employs spatial econometrics to analyse the impact of industrial agglomeration on GTFP. The results shed light on the relationship between industrial agglomeration and the high-quality development of the grain industry.

This study's findings share some similarities and differences with those of other studies on GTFP. For example, Li et al. [4] demonstrated that agglomeration in the agricultural service industry has a non-linear positive effect on the total factor productivity of grain, using unit capital planting scale as a critical variable. Gao [36] found an 'inverted U-shaped' relationship between industrial agglomeration and GTFP based on the dual perspective of industrial and spatial economics. As demonstrated in their study, grain industry agglomeration can significantly increase the level of GTFP. This view aligns with the findings of this study.

Based on their study, we also find that grain industry agglomeration significantly enhances the local GTFP level and produces positive spillover effects on the GTFP of neighbouring regions [37,38]. On the one hand, agglomeration in the grain industry promotes the agglomeration of knowledge, technology and talent, among other innovation factors [39]. It enhances communication and learning opportunities between grain production and business entities and facilitates the integration of advanced production experiences, emerging technologies and innovations [40]. On the other hand, agglomerations in the grain industry can promote the diffusion of advanced grain production and management experience and technology by increasing communication and learning opportunities between grain producers and businesses [41]. This situation accelerates the continuous spillover of new knowledge and technology, ultimately improving the GTFP in neighbouring areas. Industrial agglomeration promotes the green transformation and upgrading of the grain industry and its high-quality development.

Furthermore, it has been argued that various factors influence grain production, including economic development, agricultural infrastructure and natural resource conditions [42]. Therefore, this study further develops the analysis of regional heterogeneity, and the results show that the impact of industrial agglomeration on grain GTFP may vary according to geographic regions, i.e. there are significant differences in the role played by industrial agglomeration in different grain production functional areas.

Our study provides empirical evidence that industrial agglomeration can enhance the level of GTFP in local and neighbouring areas; however, this research has some limitations. First, there is a lack of regional data, and the use of provincial panel data for empirical evidence has limitations. Second, China's macro data do not have a distinct indicator for measuring grain inputs. Therefore, the study employs the weight coefficient method to distinguish relevant grain input data from general agricultural inputs. This approach may result in statistically biased outcomes. Additionally, it is crucial to explore how industrial agglomeration affects the level of GTFP; therefore, future research could investigate the impact of industrial agglomeration on grain GTFP from a micro perspective, such as by utilising data at the city or firm level.

6. Conclusions and policy implications

This study examines the spatial characteristics of China's grain GTFP and investigates the influence of industrial agglomeration on grain GTFP. The study reveals that from 2011 to 2020, green technological progress primarily drives the overall fluctuating upward trend of grain GTFP in China's 31 provinces. China's grain technology efficiency has steadily improved in recent years, and the intensive green growth model of 'two-wheel-drive' of grain GTFP is promising. The DSDM analysis indicates that the expansion of regional industrial agglomeration enhances grain GTFP in the local area and neighbouring regions. Furthermore, the long-term impact of this promotion is more substantial than the short-term effect. The heterogeneity analysis indicates that industrial agglomeration has a significantly positive direct effect on grain GTFP in the main grain production area. In the production and marketing balance area, the direct effect, spatial spillover effect and total effect of industrial agglomeration on grain GTFP are significantly positive in the short and long term. Industrial agglomeration's direct and total effects on grain GTFP are also significantly positive in the main grain marketing area.

The conclusions herein have significant policy implications for improving the level of GTFP and promoting its high-quality development. First, high-quality economic development has set new goals and requirements for developing the grain industry. The government should encourage the adoption of key technologies and promote green technological innovation. In addition, it should improve the cooperation mechanism between industry, academia, research and the environmental monitoring system of grain production management. Moreover, the government should strengthen the promotion, application and supervision of new technologies to improve the overall growth of green productivity as the main driving force and support the high-quality development of grain production. Second, the government should pay more attention to the long-term effects of grain industry agglomeration. On the one hand, it should actively build advantageous characteristics of the grain industry agglomeration heights and constantly improve the regional exchange and cooperation mechanism to form the scale effect and cluster advantages, enhancing the efficiency of grain economic development. On the other hand, the government should establish an inter-regional factor relief mechanism through scientific and reasonable spatial planning and appropriately guide surplus elements to low-level agglomeration provinces to overcome the adverse effects of transfer and closure on the green development of the grain industry. Finally, the government should consider the level of regional economic development, agricultural infrastructure, natural resource conditions and other relevant factors when providing differentiated and precise policy support for different regions.

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Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Jinzhi Wang: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation. **Fang Long:** Writing – review & editing, Supervision, Resources, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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