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The role of agricultural machinery in improving green grain productivity in China: Towards *trans*-regional operation and low-carbon practices

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ABSTRACT

Agricultural machinery is effective in improving food production and labor productivity, but it also raises environmental concerns. The impacts of agricultural machinery on the green total factor productivity (GTFP) of grain in China are still under debate in the scientific literature. This study proposed an integrated framework for confronting this issue. The findings suggest that both agricultural mechanization and the GTFP of grain demonstrate a consistent upward trend with moderate fluctuations between 2001 and 2019. By expanding the spatial pattern, there is a positive spatial correlation between them. In addition, we compared the results in three grain functional areas by using the spatial Durbin model (SDM). There were significantly positive spatial spillover effects in major grain-producing areas, which were attributed to the *trans*-regional operation of agricultural machinery and its carbon reduction effects on neighboring provinces. Notably, the direct effects in major grain-marketing areas and producing-marketing balance areas were significantly positive because agricultural machinery has played a critical role in filling the gap in local labor shortages in grain production. Accordingly, adaptive strategies including building the "Internet + agricultural machinery operation" platform, implementing the land consolidation suitable for machinery, and developing low-carbon agricultural machinery should be fully considered by Chinese policy-makers to promote mechanized agriculture and a low-carbon economy. The findings of this study can help us better understand the role of agricultural machinery in improving green grain productivity in China and thus have significance for the modern and green transformation of agricultural production systems.

1. Introduction

Agricultural machinery, as an advanced tool of agricultural modernization, plays a critical role in enhancing agricultural labor conditions, promoting agricultural economic output, and adjusting the agricultural industrial structure [1–3]. More importantly, it also has a large effect on food production and agricultural labor productivity, affecting food security and livelihoods of farmers [4].

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However, under the influence of global warming and a rapidly growing population, agricultural machinery is characterized as a significant source of air pollution because of its increasing energy consumption and CO_2 emissions [5–7]. It is increasing the pressures on agricultural production, threatening its ability to supply itself with adequate amounts of food [8,9]. The green transition, which involves the mechanization of agricultural development, aims to achieve resource-saving and environmentally-friendly grain production. This is reflected in the continuous growth of the green total factor productivity (GTFP) of grain [10,11]. Nonetheless, this process varies spatially across the globe, countries, and regions. Therefore, under the uncertainty of global change, whether agricultural machinery can be conducive to improving the green transformation of grain production has been a crucial issue for rural development.

Recently, an argument on the role of agricultural machinery in green grain productivity has attracted the attention of the scientific community. Schulz pointed out that the progress of agricultural technology could help address the global food problem [12]. Hicks stated that the labor shortage of agricultural production can be solved through agricultural mechanization, which could be considered an effective replacement for labor, therefore promoting labor productivity [13]. The environmental and socioeconomic effects of agricultural mechanization have received a great deal of attention. Some scholars have also proposed that the advantages of mechanization options are increases in resource use efficiency, as well as labor and land productivity [14–16]. This is especially the case in countries with more efforts to improve the mechanization of smallholder agriculture. However, environmental problems caused by the rapid popularization of mechanized agriculture and the increase in energy input in agricultural production have caused increasing concern [17–19]. There are some opponents arguing that the agricultural sector did not perform well in terms of energy saving and pollution control [20–22]. Whether advocating or opposing the idea, the environmental and socioeconomic effects of agricultural machinery are a controversial matter for many researchers.

In China, scholars introduced “agricultural mechanization” to characterize the level of agricultural machinery, such as the amount of agricultural machinery, the total power of agricultural machinery, and the operating area of agricultural machinery. It is widely agreed that agricultural mechanization, as a key part of technological advances in agricultural production, is correlated with food security and grain yield increase [23–25]. More particularly, along with the rapid process of urbanization came the labor shortage in agricultural production, and the development of grain production technology showed a trend of replacing labor input with mechanical input, which effectively reduced agricultural production costs as well as improved grain yield and agricultural productivity [26,27]. In addition, the agricultural machinery operation service across the region (i.e., *trans*-regional operation of agricultural machinery) can reduce energy and carbon emissions by generating spatial spillovers of grain production: the *trans*-regional operation of agricultural machinery, on the one hand, can reduce the total power consumption of agricultural machinery; on the other hand, it is conducive to establishing an integrated market for production factor flows, thereby resulting in the reasonable allocation of low-carbon resources. Consequently, the *trans*-regional operation of agricultural machinery is beneficial for promoting low-carbon practices [28,29].

Despite growing research interests in agricultural machinery and grain productivity improvement, studies quantifying agricultural machinery and its impacts on grain productivity from the green transformation perspective have been rare. In this study, we introduced the concept of the GTFP of grain to measure the green grain productivity, and the “agricultural mechanization” to characterize the level of agricultural machinery. Given the regional differentiation in China in terms of geographical conditions, demographic structure, and agricultural activities, we attempted to analyze and compare the spatiotemporal dynamics of agricultural mechanization and the GTFP of grain in different grain functional areas and model the impacts of agricultural mechanization on the GTFP of grain to determine whether agricultural machinery has a substantial role in promoting green grain productivity. Two issues should be addressed: (a) whether agricultural mechanization has favorable effects on the GTFP of grain; and (b) how can this information be used to achieve agricultural modernization and green transformation in the agricultural sector?

2. Theoretical framework

2.1. What is the GTFP of grain?

The implementation of agricultural mechanization inevitably has impacts on grain productivity. Previous studies have often used total factor productivity (TFP) as a measure to assess the technological effects of agricultural mechanization. TFP represents the output that is not accounted for by the input quantity used in production [30,31]. It reflects the efficiency and effectiveness of production efforts. Recently, the concept of green productivity was drawn from the integration of two important developmental strategies—productivity improvement and environmental protection [32,33]. Consequently, the GTFP has been used by scholars to measure green economic growth and determine the long-term sustainability of a region. It incorporates factors such as energy and the environment into the production function, reflecting economic growth based on resource protection and environmental improvements [34].

Grain is not only the basic unit of energy for individuals but also the basis of renewable energy and applied science and technology [35]. Therefore, grain plays a key role in maintaining social stability, military strategy, science and technology, and economic development. During the sowing and harvesting of agricultural products, the use of chemical products and agricultural machinery has negative environmental impacts, including CO_2 emissions [36,37]. As a result, reducing the environmental damage caused by grain production and how to effectively allocate production factors such as arable land, labor force, and water resources have received extensive attention. The GTFP of grain is a measure that assesses the progress of grain production towards green and efficient development [38]. It captures the sustainability and effectiveness of grain production practices.

The GTFP of grain can be further decomposed into technical change (TC) and efficiency change (EC). TC reflects the outward shift of the production frontier, and TC greater than 1 means that the current period has achieved an outward shift of the production possibility frontier compared to the previous period, that is, the “growth effect”. EC reflects the movement of the evaluated production units to the production frontier, and an EC greater than 1 means that the evaluated production unit has achieved an improvement in resource allocation efficiency in the current period, that is, the “catch-up effect” [39]. There are many methods of measuring GTFP, such as the stochastic frontier analysis (SFA) method and the data envelopment analysis (DEA) method. Because the traditional DEA method cannot measure GTFP, which includes unexpected output, many scholars have used the Malmquist–Luenberger (ML) index to measure the agricultural GTFP [40]. However, these models cannot evaluate and rank multiple fully effective decision units effectively. Therefore, Tone [41] proposed a Super SBM model based on the modified relaxation variable. Currently, the Super SBM-ML index has been widely used to study the GTFP of grain [42].

2.2. Relationship between agricultural mechanization and GTFP of grain

In 2020, the comprehensive agricultural mechanization rate reached 71.25% in China, implying that it has entered the advanced development stage. As noted by Zhu et al. [43], a rapid increase in agricultural mechanization could promote the GTFP of grain. As shown in Fig. 1, first, since young laborers have migrated from rural to urban areas, labor shortages have been an urgent issue for agricultural production. Agricultural mechanization, as a consequence, has been an effective replacement to avoid the pressure of technical efficiency decline in grain production. Additionally, the utilization of agricultural machinery has greatly reduced the cost of labor, thus saving the cost of agricultural production. Second, agricultural mechanization can enhance the level of specialization in the grain production chain and improve resource utilization, including land, fertilizers, and pesticides [44,45]. For example, agricultural machinery operations for plowing, loosening, or land preparation in tillage can enhance soil fertility and contribute to the improvement of the GTFP of grain. Additionally, some agricultural machines for precise seeding can save seed, water, and farmland resources. Third, agricultural mechanization is beneficial to large-scale farming, which could improve grain yield but also reduce energy and carbon emissions. This advantage is mainly attributed to the *trans*-regional operation of agricultural machinery. That is, the *trans*-regional operation of agricultural machinery can provide socialized services for neighboring regions. It contributes to the spatial agglomeration of agricultural machinery, which is helpful in generating the effects of carbon emission reduction [46]. Moreover, the *trans*-regional operation is conducive to allocating low-carbon resources by establishing an integrated market for production factor flows [47]. Consequently, it could achieve the reasonable allocation of low-carbon resources.

Conversely, we find opposite arguments about the relationship between agricultural mechanization and the GTFP of grain. Although the *trans*-regional operation could enlarge the socialized service markets for agricultural machinery, its service efficiency was relatively low because of the numerous smallholders with farmland fragmentation in China [48–50]. This may constrain the GTFP of grain in areas with poor farming conditions. The fragmentation of farmland and complex land rights make *trans*-regional operations difficult, disrupting inter-regional resource allocation and reducing the impact on CO_2 reduction. In addition, the rapid increase in agricultural machinery sometimes might cause a substantial rise in energy consumption in the agricultural sector, especially with the enormous growth of carbon emissions and other pollution [51]. Since the 2000s, there has been a magnitude and rapidity characterizing agricultural energy consumption in China (from 42.33 million tons of standard coal in 2000 to 92.63 million tons of standard coal in 2020). Energy and carbon emissions have inevitably increased in the field of agricultural production with the further

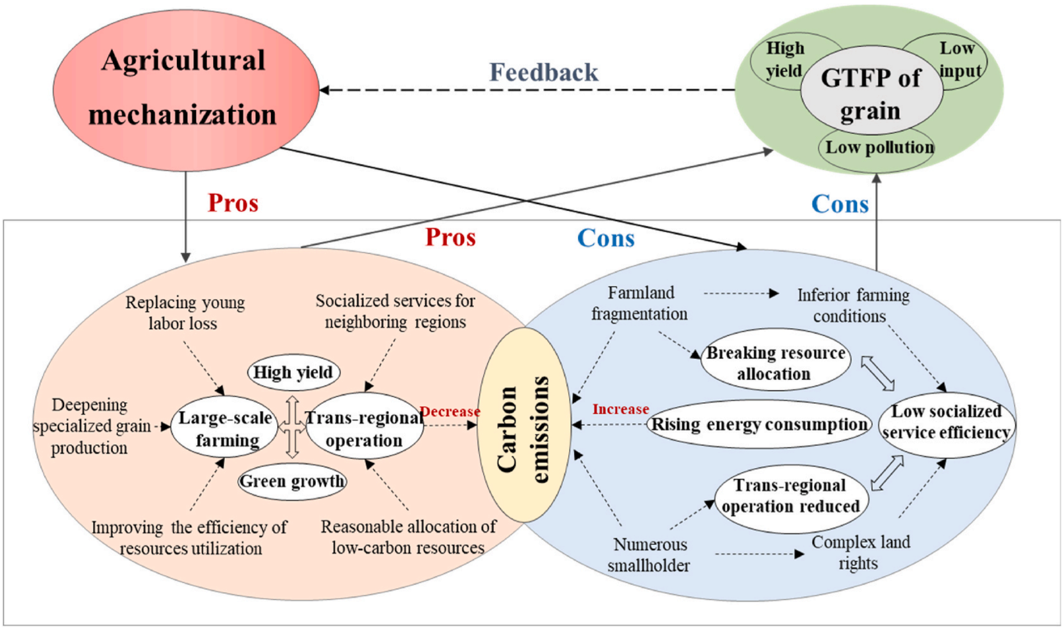

Fig. 1. Theoretical framework of the relationship between agricultural mechanization and GTFP of grain.

improvement of agricultural mechanization levels, which will be a long-term relationship in the future. In addition, several environmental problems have emerged as the outcome of CO_2 emissions.

3. Materials and methods

3.1. Data

This paper focuses on examining the relationship between agricultural mechanization and the GTFP of grain. Considering data availability, we used 2001 to 2019 data from 31 provinces in China (not including Hong Kong, Macao, and Taiwan). To further explore the impact of agricultural mechanization in different regions on the GTFP of grain, we classified the study area into three areas (i.e., the major grain-producing areas, the major grain-marketing areas, and the producing-marketing balance areas) according to the function of grain production (see Fig. 2). Among them, "major grain-producing areas" are areas suitable for growing crops in terms of climate, soil, geographical environment, and technology. They also benefit from favorable agricultural backgrounds, supportive social policies, and other factors that are conducive to grain production. It includes 13 provinces, such as Jilin, Henan, Sichuan, Shandong, Hunan, and Heilongjiang. The "major grain-marking areas" are developed regions with high population density and scarce arable land resources, so the grain self-sufficiency rate in these areas is relatively low. Such areas include seven provinces including Beijing, Shanghai, Zhejiang, Fujian, Hainan, and Guangdong. The "producing-marketing balance areas" primarily exist in the western areas to ensure grain self-sufficiency. These regions also face the need for economic development. There are 11 provinces in these regions, including Guizhou, Guangxi, Yunnan, Gansu, Qinghai, Tibet, Xinjiang, and Chongqing.

The data used in this study can be categorized into grain production data, socioeconomic data, and ecological data. Grain production data include metrics such as total farmland area sown with grain, total grain yield, and other relevant indicators, mainly sourced from the China Statistical Yearbook. Socioeconomic data, such as the number of labors employed in grain production and fixed assets investment for grain production, are mainly sourced from the local statistical yearbooks of 31 provinces, partly from the Statistical Yearbook of Rural Areas of China. Ecological data (e.g., disaster area of farmland, effective irrigation area, utilization of chemical fertilizers, pesticides, agricultural films, diesel fuel, etc.) was mainly obtained from the Chinese Rural Statistical Yearbook (see Tables 1 and 2 for detailed descriptions of variables and their quantification).

Fig. 2. Study area: distribution of three grain functional areas in China.

Table 1
Variable definitions of the GTFP of grain.

Type	Indicators	Explanation
Inputs	Labor (I_1)	I_1=The number of labors employed in grain production × C_A
	Land (I_2)	I_2 = Total farmland area sown with grain
	Capital (I_3)	I_3=Fixed assets investment for grain production × C_A
	Water (I_4)	I_4 = Effective irrigation area × C_B
	Chemical substance (I_5)	I_5= (The use of fertilizer, pesticide, mulching films and diesel for the grain production) × C_B
Desirable output	Total grain production (O_d)	O_d = Total grain yield
Undesirable output	Agricultural carbon emissions (O_u)	See Equation (3)

Table 2
Calculation of agricultural carbon emissions.

Carbon source	Carbon emission coefficient	Data source
Fertilizer	0.8956 kg/kg	Oak Ridge National Laboratory, USA (2009)
Pesticide	4.9341 kg/kg	Oak Ridge National Laboratory, USA (2009)
Mulching films	5.18 kg/kg	Oak Ridge National Laboratory, USA (2009)
Diesel	0.5927 kg/kg	IPCC United Nations Intergovernmental Panel of Experts on Climate Change
Tillage	312.6 kg/hm^2	Zhang et al. (2021)
Irrigation	266.48 kg/hm^2	Zhang et al. (2021)

3.2. Methods

3.2.1. Measuring the GTFP of grain

3.2.1.1. Variable selection. The concept “agriculture” in the existing statistical yearbook mainly refers to general agriculture, i.e., agriculture, forestry, animal husbandry, and fishery [52]. To establish the GTFP of the grain rate indicator, it is necessary to focus on the specific concept of agriculture, which is associated with grain production. Therefore, we use the method of two weighting coefficients (coefficient A and coefficient B), as illustrated in Eqs. (1) and (2).

$$C_A = (O_a / O_t) \times C_B \tag{1}$$

$$C_B = A_g / A_C \tag{2}$$

where C_A represents coefficient A; C_B represents coefficient B; O_a represents the value of agricultural output for a particular agricultural production, and O_t refers to the overall output value of agriculture in general. A_g represents the total area sown with grain, and A_C represents the total area sown with crops. The indicators system used to measure the GTFP of grain includes inputs and outputs in the grain production process (Table 1). Input variables encompass labor, land, capital, water, and chemical substances, including chemical fertilizers and pesticides. Output variables consist of two types: desirable output, such as total grain yield, and undesirable output, such as agricultural carbon emissions. We used the normalized values to calculate the GTFP of grain.

This paper selected agricultural carbon emissions as the undesired output of the GTFP of grain. There are many methods of calculating agricultural carbon emissions. The main sources of carbon emissions in agricultural production are pesticides, agricultural films, fertilizers, diesel, tillage, and irrigation [53]. There are two main sources of carbon emissions for agricultural production: *i)* it damages organic carbon in the soil and generates carbon emissions; *ii)* the electricity used for agricultural irrigation consumes fossil fuels, which can contribute to carbon emissions. In addition, investments are made in chemical-based production methods, as well as the utilization of agricultural machinery that relies on burning chemical fuels like diesel. To summarize, agricultural carbon emissions can be estimated based on Eq. (3):

$$C_e = \sum C_{ei} = T_i \times \sigma_i \tag{3}$$

where C_e represents the total carbon emissions arising from agricultural production, C_{ei} signifies the cumulative carbon emissions encompassing all sources, T_i denotes the specific consumption within agricultural production, encompassing elements like mulch, fertilizer, pesticides, irrigation, and so forth, while σ_i represents the carbon emission coefficient assigned to each individual carbon source (See Table 2).

3.2.1.2. Super SBM model -ML index. In this study, each province was regarded as a DMU of production. Undesirable outputs were almost always a part of the energy consumption process. The Super SBM model, introduced by Tone [41], integrates the calculation of efficiency by incorporating the assessment of the undesirable output, which is closer to the real production process and allows for a better evaluation of the nature of efficiency. The equation for the Super SBM model can be expressed as Eq. (4) and Eq. (5):

$$\rho^* = \frac{\frac{1}{m}\sum_{i=1}^{m}\left(\frac{\overline{x}}{x_{ik}}\right)}{\frac{1}{(s_1+s_2)}\left(\sum_{r=1}^{s_1}\frac{\overline{y}^d}{y_{rk}^d}+\sum_{t=1}^{s_2}\frac{\overline{y}^u}{y_{rk}^u}\right)} \tag{4}$$

$$s.t.\begin{cases} \overline{x} \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j; i = 1, 2, \cdots m \\ \overline{y}^d \leq \sum_{j=1,\neq k}^{n} y_{rj}^d\lambda_j; r = 1, 2, \cdots s_1 \\ \overline{y}^u \geq \sum_{j=1,\neq k}^{n} y_{tj}^u\lambda_j; t = 1, 2, \cdots s_2 \\ \lambda_j \geq 0, j = 1, 2, \cdots n, j \neq 0 \\ \overline{x} \geq x_{ik}; \overline{y}^d \leq y_{rk}^d; \overline{y}^u \geq y_{tk}^u \end{cases} \tag{5}$$

where $\overline{x}, \overline{y}^d$ and $\overline{y}^u$ are inputs, desirable outputs, and undesirable outputs are used as relaxed variables; D is the weight vector; and ρ^* is the optimal solution of the model. The DMU is valid when $\rho^* \geq 1$. The SBM model produces a technical efficiency value for a specified time period, which cannot be used to analyze dynamic changes in energy efficiency. The Malmquist index was used to analyze dynamic productivity changes. Chung et al. [40] renamed the Malmquist index the ML index after they applied the directional distance function containing undesirable output to the Malmquist model. This new index was subdivided into two components: EC and TC index [54,55].

The ML index from t to t+1 is calculated as shown in Eq. (6), Eq. (7), and Eq. (8):

$$ML^{t,t+1} = \left\{\frac{\left[1+\overrightarrow{D}_0^t(x^t, y^t, b^t; y^t, -b^t)\right]}{\left[1+\overrightarrow{D}_0^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})\right]} \times \frac{\left[1+\overrightarrow{D}_0^{t+1}(x^t, y^t, b^t; y^t, -b^t)\right]}{\left[1+\overrightarrow{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})\right]}\right\}^{1/2} \tag{6}$$

$$EC^{t,t+1} = \frac{1+\overrightarrow{D}_0^t(x^t, y^t, b^t; y^t, -b^t)}{1+\overrightarrow{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \tag{7}$$

$$TC^{t,t+1} = \left\{\frac{\left[1+\overrightarrow{D}_0^{t+1}(x^t, y^t, b^t; y^t, -b^t)\right]}{\left[1+\overrightarrow{D}_0^t(x^t, y^t, b^t; y^t, -b^t)\right]}\frac{\left[1+\overrightarrow{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right]\right.}{\left[1+\overrightarrow{D}_0^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})\right.}\right\}^{1/2} \tag{8}$$

where x, y, and b represent input, desirable output, and undesirable output, respectively; $\overrightarrow{D}_0^t(x^t, y^t, b^t; y^t, -b^t)$ and $\overrightarrow{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})$ are the distance functions of periods t and $t+1$, respectively; $\overrightarrow{D}_0^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})$ is the distance function of period $t+1$ under the technical condition of period t; and $\overrightarrow{D}_0^{t+1}(x^t, y^t, b^t; y^t, -b^t)$ is the distance function of period t under the technical condition of period $t+1$. In addition, $ML > 1$, $ML = 1$, and $ML < 1$ indicate an increase, constant, and decrease in total factor energy efficiency, respectively; $EC > 1$, $EC = 1$, and $EC < 1$ indicate an increase, constant, and decrease in technical efficiency, respectively; and $TC > 1$, $TC = 1$ and $TC < 1$ indicate technological progress, constant and decline, respectively [56].

3.2.2. Bivariate spatial correlation test

3.2.2.1. Global spatial correlation. Spatial characteristics mainly refer to the spatial interaction of individuals and include spatial autocorrelation and spatial heterogeneity [57]. Moran's I describe the spatial autocorrelation characteristics between neighboring economic behaviors. In general, spatial autocorrelation describes the characteristics of one variable, either the explanatory or the explained variable, and does not directly study the relationship between the two. The bivariate spatial autocorrelation method, which is better suited for characterizing the correlation between two geographical factors, can be used to tackle this problem. The expression for bivariate global spatial autocorrelation (Bivariate Moran's I) is shown in Eq. (9):

$$I = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(y_i - \overline{y}) \Big/ S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \tag{9}$$

where $S^2 = \frac{1}{n}\sum_{i=1}^{n}(yi - \overline{y})^2, \overline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$, i is the bivariate global spatial autocorrelation coefficient, which represents the similarity in the spatial distribution of the explanatory variables in study area i and the explanatory variables in study area j. Moran's I range from -1 to 1. A positive value indicates positive spatial autocorrelation, meaning regions with similar attributes exhibit noticeable spatial aggregation. A negative value indicates a negative spatial correlation between adjacent spatial units. The magnitude of Moran's I, whether large or small, signifies the strength (or weakness) of the spatial connection. The sample variance is s^2, and the sample count is n. According to Eq. (10), W_{ij} is a spatial weight matrix with a range of 0–1. Its principle is that the value of i and j of two adjacent provinces in space is 1, indicating that there is a common boundary between them. If the two are not adjacent in space, that is, the number of common boundaries is 0, then the value is 0.

$$W_{ij} = \begin{matrix} 1 & i \neq j & \text{and} & \text{neighboring} \\ 0 & i \neq j & \text{and} & \text{not} - \text{neighboring} \\ 0 & i = j & & \end{matrix} \tag{10}$$

3.2.2.2. Local spatial correlation. The bivariate local Moran's I is shown in Eq. (11):

$$I = z_i \sum_{j=1}^{n} w_{ij} z_j \tag{11}$$

where z_i and z_j are the standardized values of the variances of the observed values of i and j in the study area and I represents the local correlation between the explanatory variables in study area i and the explained variables in study area j. There are four types of local correlation: high-high, low-low, low-high, and high-low. In the high-high case, as the independent variable increases, the dependent variable also increases. In the low-low case, both the independent and dependent variables have low values when they are clustered together. The high-low and low-high cases indicate a negative correlation between the variables.

3.2.3. Spatial durbin model (SDM)

3.2.3.1. Variable selection.

(1) Explained variable. The GTFP of grain was selected as the explanatory variable, which reflected the high-quality development of grain production to some extent. The data for this variable were derived from Section 3.2.1.

(2) Core explanatory variables. Agricultural mechanization plays a significant role in the GTFP of grain. In this study, the level of agricultural mechanization was represented by the "total power of agricultural machinery". As noted by Wu [58], the "total power of agricultural machinery for grain production" is consistent with the "total power of agricultural machinery". Considering the importance of availability and validity, the scholars have chosen to measure agricultural mechanization using the variable "the total power of agricultural machinery".

(3) Control variables. We introduced some variables that were not of interest but should be controlled for their potential impacts on the outcomes. We selected 10 control variables based on (i) information collected in the field, (ii) the analysis of the conceptual framework above, and (iii) collaboration with academic experts. Table 3 illustrates the variables in light of drivers influencing the GTFP of grain and selected from the three dimensions, i.e., basic conditions of agricultural production, household characteristics, and the external environment.

3.2.3.2. Basic model. The spatial correlation between variables can be effectively studied using spatial lag models (SLM), and spatial error models (SEM). The SDM is a formula that is an ordinary type of SLM and SEM. The SDM not only reveals the spatial spillover effect of the dependent variable in adjacent regions but also studies the influence of independent variables in adjacent regions on their

Table 3
Variable definitions of the SDM.

Type	Indicators	Explanation
Dependent variable	GTFP of grain	Green total factor productivity of grain
Independent variable	Agricultural mechanization	Total power of agricultural machinery
Control variables		
Basic conditions of agricultural production	Farmland quality (C_1)	C_1=Fertilizer application rate/Total area sown with grain
	Crop damage rate (C_2)	C_2 = Damaged area sown with grain/Total area sown with grain
	Crop planting structure (C_3)	C_3 = Grain sown area/Crop sown area
	Agricultural infrastructure integrity (C_4)	C_4 = Mileage of rural road/Total area of rural areas
Household characteristics	Education level of farmers (C_5)	C_5=Rural population with a high school education or above/Total rural population
	Age of labor (C_6)	C_6=The number of labors aged below 65/Total rural labors
	Household income (C_7)	C_7 = Gross income generated by the household-life expenditures
External environment	Economic structure (C_8)	C_8 = GDP in agriculture/Total GDP
	Urbanization rate (C_9)	C_9=Urban population/Total population
	Agricultural terms of trade (C_{10})	C_{10}=Producer price index for agricultural products/Price index of means of agricultural production

own dependent variables [59,60]. It is a common model for an empirical test of the spatial spillover effect. In later research, tests will provide support by using SDM. Assuming that the general expression of SDM is shown in Eq. (12).

$$LnGTFP_t = a + \beta LnX_t + \theta WLnX_t + \varepsilon \tag{12}$$

where $LnGTFP_t$ represents the natural logarithm of the dependent variable, GTFP which is associated with grain production in a specific province during year *t*. LnX_t is the logarithm of the independent variable and the control variable of the province in year *t*, β is the corresponding parameter, and θ is the spatial regressive coefficient. *W* is the spatial weight matrix, α is the intercept, and ε is a random error term. All variables are presented in logarithmic forms to eliminate possible heteroscedasticity.

If there are spatial lag terms, the regression coefficient of an econometric model cannot directly be used to reflect the marginal effect of explanatory variables. Lesage and Pace [61] proposed a partial derivatives method to decompose the spatial spillover effect into a direct effect and an indirect effect through spatial cross-section data. This approach applies to both spatial cross-section data and spatial panel data. Eq. (13) and Eq. (14) provide a detailed description of the decomposition procedure:

$$LnGTFP_t = (I - \rho W)^{-1}(\beta\, Ln\, X_t + \theta WLnX_t) + (I - \rho W)^{-1}a + (I - \rho W)^{-1}\varepsilon \tag{13}$$

$$\left[\frac{\partial LnGTFP^1}{\partial LnX_{1k}} \cdots \frac{\partial LnGTFP^n}{\partial LnX_{nk}}\right]_t = (I - \rho W)^{-1}\begin{bmatrix} \beta_k^1 & W_{12}\theta_k^1 & \cdots & W_{1n}\theta_k^1 \\ W_{21}\theta_k^2 & \beta_k^2 & \cdots & W_{2n}\theta_k^2 \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1}\theta_k^n & W_{n2}\theta_k^n & \cdots & \beta_k^n \end{bmatrix} \tag{14}$$

4. Results and analysis

4.1. Dynamics of agricultural mechanization and GTFP of grain

4.1.1. Spatiotemporal dynamics of agricultural mechanization

As mentioned earlier, we used the “total power of agricultural machinery” to represent the level of agricultural mechanization. From 2001 to 2019, the agricultural machinery in China changed from 533.84 million kW to 1023.18 million kW, with an increasing rate of 5.09%. The level of agricultural mechanization exhibited a generally increasing trend with moderate fluctuations. As shown in

Fig. 3. Changes of agricultural mechanization in China from 2001 to 2019. (a) Temporal changes of agricultural mechanization in China from 2001 to 2019. (b) Spatial changes of agricultural mechanization in China at the provincial level from 2001 to 2019. Note: AM is the abbreviation for agricultural mechanization.

Fig. 3a, from 2001 to 2015, the level of agricultural mechanization continued to increase remarkably, reaching a peak of 1118.85 million kW in 2015 and decreasing in 2016. From 2016 to 2019, the degree of agricultural mechanization exhibited a consistent growth rate of 1.37% on average. With the rapid urbanization process in 2001, there was a serious shortage of surplus rural labor. As discussed in the Theory of Induced Institutional Innovation, according to Jelle et al. [62], when the elasticity coefficient of labor supply is low or the labor cost exceeds the land cost, continuous labor input reduces land revenue. As a result, agricultural machinery is induced to replace labor input. Since 2004, the Chinese government has offered a subsidy for purchasing agricultural machinery, which has inspired farmers to buy agricultural machinery with enthusiasm. The "golden decade" for the advancement of agricultural mechanization is the decade from 2004 to 2015. In 2015, when the emission standards of agricultural machinery were upgraded from China II to China III, the government discontinued subsidies for purchasing agricultural machinery with China II emission standards [63]. In 2016, there was a decline in the level of agricultural mechanization. Subsequently, the focus of agricultural mechanization shifted from quantitative changes to qualitative changes in its development. Efforts towards high-quality development have led to a reduction in the pace of average yearly growth in agricultural mechanization.

As shown in Fig. 4, we selected 2001, 2010, and 2019 as typical years to illustrate the spatial dynamic characteristics of agricultural mechanization. The trend presented a gradual decrease from the eastern to the western region. The level of agricultural mechanization was relatively high in some provinces in eastern regions, such as Shandong, Henan, and Hebei, where the fertile soil, plain terrain, and abundant farmland provide superior conditions for agricultural production activities as well as machinery operations. In some western provinces, such as Tibet, Qinghai, and Gansu, the level of agricultural mechanization is relatively low, where inferior geographical conditions and farmland resource allocation have constrained agricultural productivity. The level of agricultural mechanization in different areas ranked as follows: major grain-producing areas > producing-marketing balance areas > major grain-marketing areas, which was consistent with the functional orientation of each area. Additionally, Fig. 3b illustrates the annual growth rate of agricultural mechanization, ranking as producing-marketing balance areas > major grain-producing areas > major grain-marketing areas. This result indicates that compared with major grain-producing areas, the producing-marketing balance areas provide significant growth potential for agricultural machinery. Whether there is saturation or idleness of agricultural machinery in major grain-producing areas needs to be further discussed.

4.1.2. Spatiotemporal dynamics of the GTFP of grain

As shown in Fig. 5a, during the study period, the GTFP of grain exhibited an increasing trend, displaying an average yearly growth rate of 3.31%. Before 2004, the GTFP of grain was always less than 1. Since 2004, the introduction of financial subsidies for agriculture, rural areas, and farmers has significantly increased the GTFP of grain, with its value surpassing 1. However, the GTFP of grain declined slightly in 2005 because of the lag in subsidy policy implementation in some provinces. From 2006 to 2009, some policies, such as offering financial subsidies for grain production and protecting grain prices, effectively reduced farmland abandonment. The GTFP of grain rose significantly, with an average yearly growth rate of 3.84%. In 2010, the GTFP of grain decreased again, which can be attributed to the sluggish stage of TC. Next, the GTFP of grain experienced steady growth. In particular, the GTFP of grain entered a period of rapid growth and witnessed a phase of substantial acceleration, with an average annual growth rate of 10.49% between 2016 and 2019 (13th Five-Year Plan).

Fig. 5b illustrates that the GTFP of grain in each province showed an increasing tendency. In terms of spatial distribution, there was a noticeable decline moving from the eastern to central regions, and further to the western region. This spatial pattern closely mirrors the distribution observed in agricultural mechanization, as shown in Fig. 6. Moreover, there was a significant spatial differentiation for each grain functional area. The GTFP of grain and its average annual growth rate ranked as follows: major grain-producing areas > producing-marketing balance areas > major grain-marketing areas. The average annual growth rate of the GTFP of grain in major grain-producing areas was 3.81%. These areas are located in the plains, where the fertile soil and efficient unitization of chemical fertilizers and pesticides are helpful to achieve high-yield and green grain production [64]. In producing-marketing balance areas, such as Tibet and Qinghai, the GTFP of grain exhibited relatively lower levels due to constraints posed by physical conditions and general socioeconomic development. In some provinces in major grain-marketing areas, such as Beijing, Shanghai, and Tianjin, the local economic growth came at the cost of cultivated land and environmental conservation [65–67]. As a result, ineffective grain production methods and resulting environmental pollution have contributed to a decrease in the GTFP of grain. Further exploration of the components of GTFP revealed a consistent relationship between changes in GTFP and TC curves in major grain-producing areas and

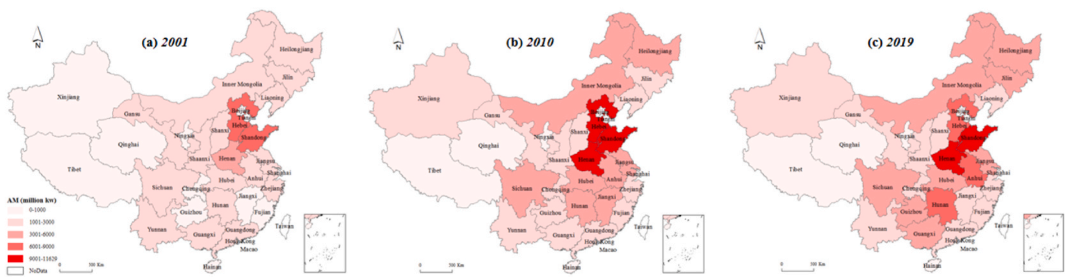

Fig. 4. Spatial distribution of agricultural mechanization in 2001, 2010, and 2019. (a), (b) and (c) represents the spatial distribution of agricultural mechanization in 2001, 2010, and 2019, respectively.

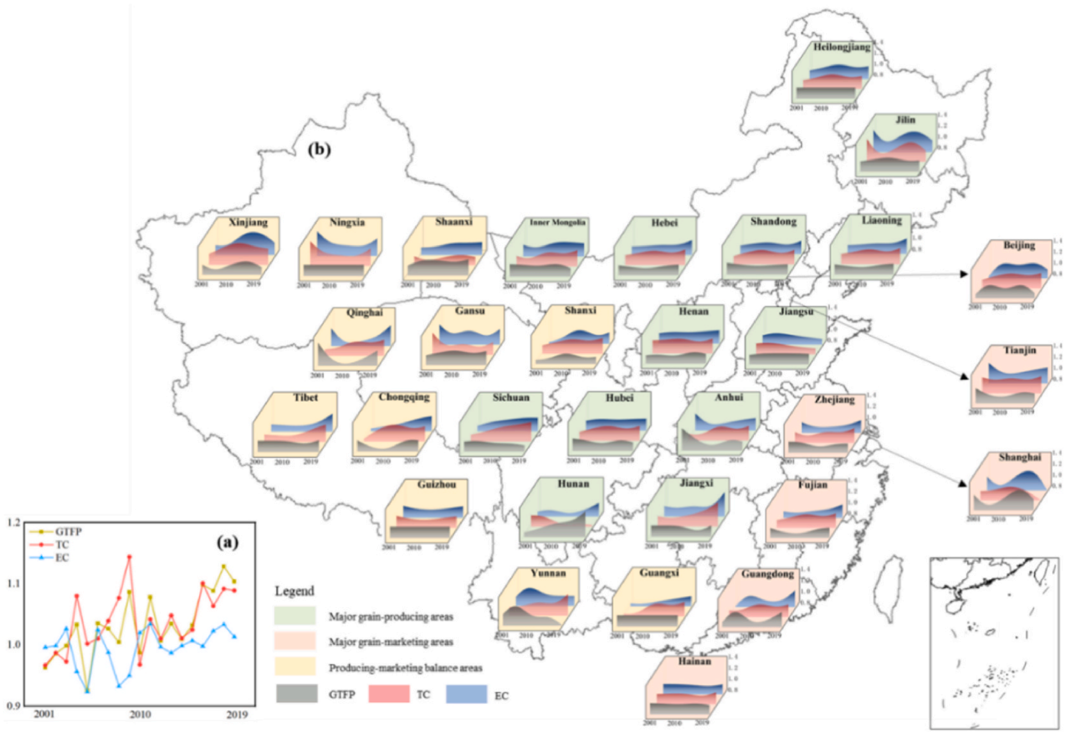

Fig. 5. Changes of GTFP of grain in China from 2001 to 2019. (a) Temporal changes of GTFP of grain in China from 2001 to 2019. (b) Spatial changes of GTFP of grain in China at the provincial level from 2001 to 2019.

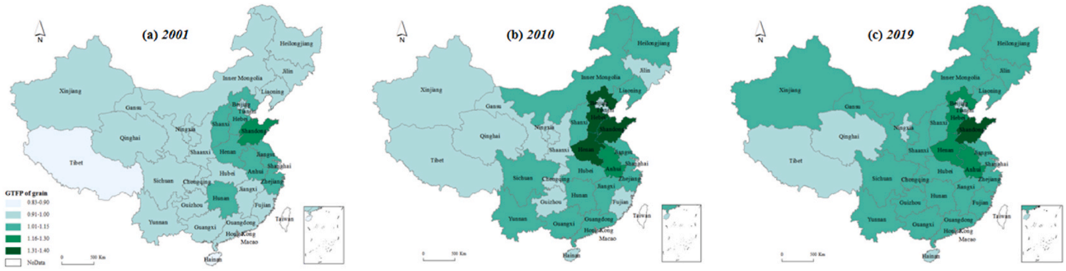

Fig. 6. Spatial distribution of GTFP of grain in 2001, 2010, and 2019. (a), (b) and (c) represents the spatial distribution of GTFP of grain in 2001, 2010, and 2019, respectively.

Fig. 7. Cluster maps for the bivariate spatial autocorrelation analysis of the agricultural mechanization and GTFP of grain in 2001, 2010, and 2019. (a), (b) and (c) represents the cluster maps in 2001, 2010, and 2019, respectively.

grain production-marketing balance areas. This can be attributed to the fact that the GTFP of grain in the major grain-producing areas is mainly influenced by technological progress. Similarly, the GTFP of grain in the major grain-marketing areas is mainly influenced by technical efficiency [68].

4.2. Spatial correlation between agricultural mechanization and GTFP of grain

As mentioned earlier, the agricultural mechanization and GTFP of grain both presented an increasing trend from 2001 to 2019. Next, we introduced a bivariate spatial autocorrelation test to further explore their spatial relationship. The findings indicated that the global bivariate Moran's I ranged between 0.288 and 0.356. This result indicated that throughout the entire period, Moran's I value exhibited a positive and significant correlation at the 1% level, and their spatial correlation intensified over time.

Next, we conducted an examination of three types of spatial autocorrelation (high-high, low-low, low-high, and high-low) using local Moran's I and LISA analysis. Fig. 7 illustrates a substantial spatial variation in clustering across three representative years, as depicted by the cluster maps. We found that provinces demonstrating significant spatial clustering increased from 6 to 13, and the majority of these provinces exhibited a high-high spatial cluster pattern. The distribution of provinces with high-high spatial clusters significantly expanded during the period, including provinces such as Shandong, Henan, Jiangsu, and Anhui, which are major grain-producing areas. The level of agricultural mechanization was higher in these provinces. Simultaneously, farmers exhibited a preference for prioritizing high grain production efficiency while mitigating the negative impact of environmental pollution. The provinces with low-low spatial clusters were concentrated in the western and southern regions of China, including Xinjiang, Tibet, and Hainan. There was no obvious change in this type of spatial clustering. The provinces with low-high spatial outliers experienced a declining tendency and were located in some hilly and mountainous areas (such as Chongqing and Guizhou). This can be attributed to the unfavorable geographical and economic conditions of mountainous areas, which often lack land availability and are unsuitable for mechanical operations, thereby reducing the level of agricultural mechanization. However, the relatively low input-output ratio for grain production as well as the high GTFP of grain can be accounted for by alternative factors such as high socioeconomic level, financial support, urbanization, and driving effects of the industry on agriculture. Both have positive effects on the GTFP of grain. The continuous increase in provinces with high-high spatial clusters and the decrease in provinces with low-high spatial outliers indicate that agricultural mechanization positively influences the GTFP of grain.

4.3. Model estimation results

4.3.1. Overall estimation results of the SDM

The outcomes of the regression analyses of the OLS and SDM models are presented in Table 4. The findings suggested that the spatial model outperforms the OLS model. The Hausman test indicates that fixed effects should be used instead of random effects in the panel data analysis. Both the LR test and Wald test confirm that the SDM model is not characterized by SEA or SAR models, as they do not show significant deviations. Among all the models, the time fixed SDM model was selected for this investigation because it achieved the highest pseudo-R^2 value.

As shown in Table 5, the SDM analysis revealed a significant and positive association between agricultural mechanization and the GTFP of grain ($p < 0.01$). The results also confirmed that the development of agricultural mechanization in neighboring provinces exerts a positive effect on the local GTFP of grain expansion. More specifically, a 1% increase in the neighboring provinces' development level of agricultural mechanization will increase the GTFP of grain in the local province by 0.055% on average.

Table 6 summarizes the direct, spillover, and total effects of agricultural mechanization computed from the estimated SDM. The estimates suggested that agricultural mechanization had a significant impact on the GTFP of grain. At a significant level of 1%, it can be concluded that the direct effect coefficient is 0.078, and the spillover effect coefficient is 0.057; thus, the positive direct effects were greater than the positive spillover effects. Agricultural mechanization can enhance resource utilization efficiency as well as obtain more output with less input, thereby reducing production costs. Agricultural machinery, as a new type of labor input, is more stable than humans and animals, together with stable grain productivity. Agricultural machinery in local provinces transferred to

Table 4
Results of the LM test, LR test, Wald test, and Hausman test.

Test	OLS	SDM		
		Spatial fixed effects	Time fixed effects	Spatial and time fixed effects
LM _ lag	14.94***	6.31**	1.24*	4.14*
LM _ err	24.51***	17.61*	4.01*	9.41**
Robust _ LM _ lag	11.24***	7.33***	1.74**	6.01**
Robust _ LM _ err	30.81***	25.64***	9.46**	11.77**
LR _ lag	–	10.72**	14.02***	12.99**
LR _ err	–	33.02***	49.17***	37.17***
Wald _ lag	–	11.11**	14.87***	13.04**
Wald _ err	–	32.67***	48.77***	37.01***
R^2	0.7432	0.7650	0.8072	0.7911
Hausman = 39.73	–	–	–	–

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Estimation results of the SDM.

Variables	Time fixed effects
Agricultural mechanization	0.076***(0.048)
Farmland quality	0.026***(0.058)
Crop damage rate	−0.024***(0.166)
Crop planting structure	0.013(2.385)
Agricultural infrastructure	0.017***(1.543)
Education level of farmers	0.014**(0.063)
Age of labors	−0.013***(0.436)
Household income	0.031***(0.156)
Economic structure	−0.013(0.256)
Urbanization rate	−0.014(1.345)
Agricultural terms of trade	0.029(2.103)
W*Agricultural mechanization	0.055***(0.012)
W*Farmland quality	−0.006(0.043)
W*Crop damage rate	−0.031***(0.154)
W*Crop planting structure	−0.006(2.017)
W*Agricultural infrastructure	0.015**(1.326)
W*Education level of farmers	0.012**(0.055)
W*Age of labors	−0.005***(0.410)
W*Household income	0.010***(0.133)
W*Economic structure	−0.020(0.223)
W*Urbanization rate	−0.031(1.109)
W*Agricultural terms of trade	0.088(1.947)

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses.

Table 6
Direct effect, spatial spillover effect, and the total effect of agricultural mechanization on GTFP of grain.

Variables	Total effect	Direct effect	Spatial spillover effect
Agricultural mechanization	0.135***(0.453)	0.078***(0.321)	0.057***(0.675)
Farmland quality	0.03***(1.257)	0.036***(0.456)	−0.006(-1.234)
Crop damage rate	−0.075***(-0.430)	−0.033***(-1.011)	−0.042***(-1.566)
Crop planting structure	0.007(2.240)	0.013(2.211)	−0.006(-2.012)
Agricultural infrastructure	0.032***(2.321)	0.017***(2.124)	0.015***(2.001)
Education level of farmers	0.026***(0.787)	0.012***(0.871)	0.014***(0.743)
Age of labors	−0.017***(-0.453)	−0.012***(-0.321)	−0.005***(-0.219)
Household income	0.041***(0.345)	0.031***(0.987)	0.01*(0.147)
Economic structure	−0.033(-0.321)	−0.013(-0.443)	−0.02**(-0.777)
Urbanization rate	−0.044(-0.333)	−0.014(-0.781)	−0.031**(-0.801)
Agricultural terms of trade	−0.117(-0.665)	−0.029(-0.710)	−0.088(-0.862)

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses.

neighboring provinces through *trans*-regional operation could improve the GTFP of the grain of neighboring provinces.

The estimation results of the control variables show that farmland quality and agricultural infrastructure have significantly positive direct effects on the local GTFP of grain. In particular, a 1% increase in farmland quality was associated with a 0.036% increase in the GTFP of grain; moreover, a 1% increase in the agricultural infrastructure level causes the GTFP of grain in the local county to increase by 0.017%. The results suggested that fertile soil and integrated agricultural infrastructure (irrigation, sewage, transportation, etc.) easily improve the physical conditions of agricultural production, thereby achieving green economic growth. The spatial spillover effects of farmland quality were insignificant, whereas agricultural infrastructure showed a positive spillover effect at the 1% significance level; i.e., a 1% increase in the agricultural infrastructure level was associated with a 0.015% increase in the GTFP of grain in neighboring provinces. This relationship reached a significance level of $p < 0.05$. The direct effects and spatial spillover effects from the education level of farmers and household income were positive and significant. The reason was that well-educated farmers and household incomes preferred to choose efficient and green grain production activities with low environmental pollution. Additionally, it was supposed that the agricultural infrastructure, education level of farmers, and household income have shown a positive externality to neighboring regions. The variable crop damage rate and age of laborers have negative direct effects and spatial spillover effects on the GTFP of grain. This can be explained by the fact that labor quality has constrained the use of agricultural machinery. Elderly farmers, who possess limited education and skill sets, display a preference for conventional farming techniques that lack advanced agricultural technology and machinery. As a result, the impact of agricultural mechanization was diminished. These findings are consistent with prior research on grain productivity.

4.3.2. Estimation results of the SDM in different periods

To further study the temporal change in the impacts of agricultural mechanization on the GTFP of grain, we computed the direct

Table 7
Direct effect, spatial spillover effect, and the total effect of agricultural mechanization on GTFP of grain in different periods.

Variables	2001–2005			2006–2010			2011–2015			2016–2019		
	Total effect	Direct effect	Spatial spillover effect	Total effect	Direct effect	Spatial spillover effect	Total effect	Direct effect	Spatial spillover effect	Total effect	Direct effect	Spatial spillover effect
Agricultural mechanization	0.116***	0.117***	−0.001***	0.113***	0.070***	0.043***	0.127***	0.069***	0.058***	0.121***	0.061***	0.060***
Farmland quality	0.002***	0.009***	−0.007***	0.024***	0.012***	0.013***	0.061***	0.024***	0.037***	0.083***	0.031***	0.052***
Crop damage rate	−0.021***	−0.002***	−0.019***	−0.002***	−0.001***	−0.001***	−0.007***	−0.002***	−0.005***	−0.012***	−0.005***	−0.007***
Crop planting structure	−0.090	−0.034	−0.057	0.016	−0.010	0.026	0.021	−0.028**	0.049	0.105	−0.014**	0.119
Agricultural infrastructure	0.037**	0.015**	0.022	0.031**	0.010**	0.021	0.016*	0.011*	0.005**	0.026***	−0.004***	0.030*
Education level of farmers	0.021***	0.011***	0.010***	0.032***	0.015***	0.017***	0.018***	0.024***	0.009***	0.038***	0.024***	0.014***
Age of labors	−0.022***	−0.007***	−0.029***	−0.024***	−0.012***	−0.012***	−0.029***	−0.015***	−0.014***	−0.038***	−0.029***	−0.009***
Household income	0.034***	0.022***	0.120***	0.025***	0.013***	0.0172***	0.022***	0.013***	0.009*	0.021***	0.011***	0.100*
Economic structure	0.003	0.016	−0.013	−0.037	−0.024	−0.014	0.130	−0.011	0.140**	0.031	−0.025	0.056
Urbanization rate	−0.022	−0.004	−0.019	−0.084	−0.013	−0.072	−0.190	−0.076	−0.114	−0.305	−0.128	−0.177
Agricultural terms of trade	0.298	0.067	0.231*	0.168	0.049	0.119	−0.277*	0.068	−0.345*	0.152	0.111*	0.041

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Direct effect, spatial spillover effect, and the total effect of agricultural mechanization on GTFP of grain in different grain function regions.

Variables	Major grain-producing areas			Major grain-marketing areas			Producing-marketing balance areas		
	Total effect	Direct effect	Spatial spillover effect	Total effect	Direct effect	Spatial spillover effect	Total effect	Direct effect	Spatial spillover effect
Agricultural mechanization	0.093***	0.053***	0.040***	0.163***	0.126***	0.037***	0.094***	0.058***	0.036***
Farmland quality	0.090***	0.056***	0.034***	0.550***	0.033***	0.022***	0.076***	0.052***	0.024***
Crop damage rate	−0.112***	−0.074***	−0.038***	−0.036***	−0.030***	−0.006***	−0.058***	−0.043***	−0.015***
Crop planting structure	0.007	0.004**	0.003	0.005	0.003	0.002	0.006	0.003	0.003
Agricultural infrastructure	0.019***	0.011***	0.008***	0.009**	0.005*	0.004*	0.011**	0.007**	0.004**
Education level of farmers	0.067***	0.044***	0.023***	0.076***	0.064***	0.012***	0.058***	0.119***	0.061***
Age of labors	−0.016***	−0.011***	−0.005***	−0.011***	−0.003***	−0.007***	−0.013***	−0.007***	−0.006***
Household income	0.041***	0.012***	0.029***	0.022***	0.015***	0.006***	0.034***	0.023***	0.011***
Economic structure	−0.094	−0.021	−0.073	0.047	0.013	0.034	−0.005	−0.001	−0.004
Urbanization rate	−0.034	−0.004	−0.030	0.024	0.008	0.016*	−0.037	−0.002	0.035
Agricultural terms of trade	0.099	0.048	0.051	0.047	0.021	0.026	0.047	0.026	0.021

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

and spillover effects of agricultural mechanization from the estimated SDM in four periods: 2001–2005, 2006–2010, 2011–2015, and 2016–2019. The estimation results of the direct and spillover effects in different periods are shown in Table 7.

The estimates of the direct effects indicated that agricultural mechanization positively contributes to the GTFP of grain in local provinces. This is in line with the expectations. However, the direct effects tended to decrease as the coefficient varied from 0.117 to 0.061 ($p < 0.01$). Analyzing the estimation results of spillover effects reveals that agricultural mechanization has significant spatial spillover effects. During the period from 2001 to 2005, agricultural mechanization exhibited negative spillover effects on the GTFP of grain. Specifically, the analysis revealed that a 1% increase in the level of agricultural mechanization within the local province corresponded to an average decline of −0.001% in the GTFP of grain in neighboring provinces. This result suggested that agricultural mechanization does not seem to contribute to the adjacent growth of the GTFP of grain in the early period. Next, the spatial spillover effects of agricultural mechanization became positive and significant from 2006 to 2019. Additionally, its coefficient increased from 0.043 to 0.060 ($p < 0.01$). This finding implied that the *trans*-regional operation of agricultural machinery may exert a pull-out effect and impact the GTFP of grain in neighboring provinces. Although the spatial spillover effects showed an increasing tendency during the study period, the positive direct effects are more dominant than the spillover effects of agricultural mechanization. This may be evidence that agricultural mechanization mainly influences the GTFP of grain in local provinces, and the *trans*-regional operation of agricultural machinery has the potential to be strengthened by governments. The estimates of the control variables in each period were consistent with the overall estimation results. In particular, the spatial spillover effects of agricultural infrastructure varied from 0.022 to 0.030, which implied that agricultural infrastructure plays an increasingly important role in promoting the GTFP of grain in neighboring provinces.

4.3.3. Estimation results of the SDM model in three grain functional areas

The direct and spillover effects of agricultural mechanization were computed from the estimated SDM in three grain functional areas: major grain-producing areas, major grain-marketing areas, and producing-marketing balance areas. The estimation results aided in identifying the spatial differentiation of impacts on the GTFP of grain.

Table 8 shows that the direct, spillover, and total effects of agricultural mechanization were positive in these areas. More specifically, the total effects on major grain-marketing areas were greater than those of other areas. Furthermore, the results indicate that the direct effects are greater in major grain-marketing areas, while the spillover effects are greater in major grain-producing areas. More specifically, in terms of major grain-marketing areas, a 1% increase in agricultural mechanization was associated with a 0.126% increase in the GTFP of grain in local provinces; moreover, a 1% increase in the agricultural mechanization level caused the share of GTFP of grain in the neighboring province to increase by 0.04% in major grain-producing areas. Spatial spillover analysis revealed that the adoption of agricultural mechanization enhances efficiency and output in major grain-marketing areas through *trans*-regional operations. When it comes to the outcomes for the control factors, we found that the estimates were consistent with the overall estimates. Interestingly, the spillover effects of the urbanization rate were significantly positive in major grain-producing areas, which suggested that the rapid urbanization process easily caused technological progress, thereby leading to technology spillovers to adjacent regions [69,70].

5. Discussion

5.1. Agricultural machinery, trans-regional operation, and carbon emissions

Based on the findings of the SDM estimation, the spatial spillover effects from agricultural mechanization changed from negative to

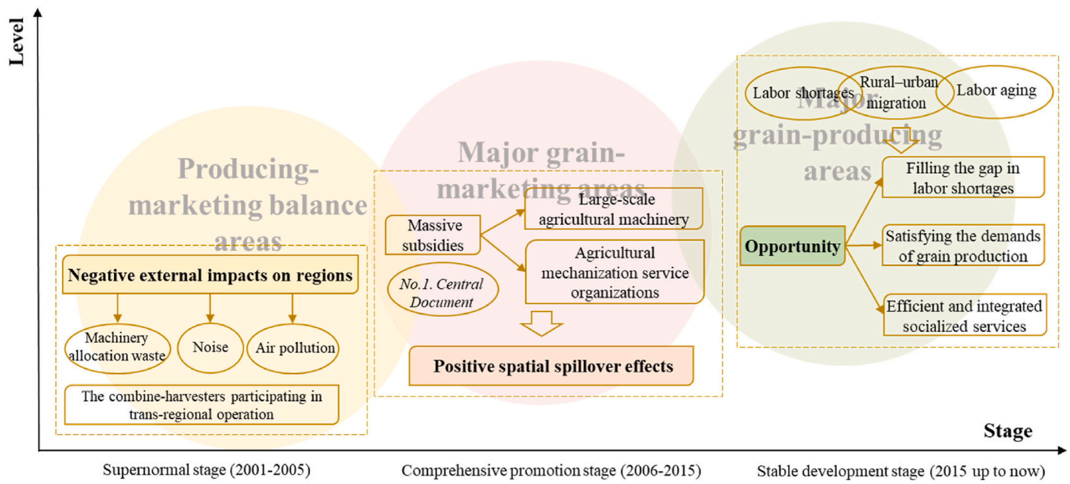

Fig. 8. The Evolving process of *trans*-regional operation of agricultural machinery in China.

positive due to the influence of *trans*-regional operation and carbon emissions during the study period. As shown in Fig. 8, the *trans*-regional operation of agricultural machinery has experienced different stages in China [71]: the first stage (2001–2005), referred to as the "supernormal stage", witnessed a sharp increase in combine harvesters participating in the *trans*-regional operation, driven by initiatives from local agricultural machinery departments. The supply of agricultural machinery exceeded the demand of local farmers. Such agricultural mechanization could have negative externalities to the region, such as noise, air pollution, and machinery configuration waste. Afterward, the significantly positive spatial spillover effects from agricultural mechanization shown in this study are in line with other relevant studies [72,73]. In 2004, the government implemented the *Law on the Promotion of Agricultural Mechanization*; meanwhile, from 2004 to 2017, the Chinese "No. Central Document" focused on the development of agricultural mechanization. Massive subsidies were tilted toward large-scale agricultural machinery and agricultural mechanization service organizations [74]. The *trans*-regional operation entered a stable development stage when operators of agricultural machinery were encouraged to expand their farming scale and promoted the exchanges of grain production activities between different regions, thereby causing a positive spatial spillover effect from agricultural mechanization. Rural-urban migration in China resulted in a labor shortage and an aging agricultural workforce. From 2001 to 2005, the average growth rate of labor aging in China was 1.90%, whereas it increased to 4.72% from 2015 to 2019. In rural areas, agricultural mechanization, particularly *trans*-regional operation, can help alleviate labor shortages. In this stage, the agricultural machinery offered by *trans*-regional operations could satisfy the demands of grain production [75–78]. Our findings suggest that a stable *trans*-regional operation of agricultural machinery has the potential to positively impact grain production activities in its associated areas by enhancing efficiency and promoting integrated services within the region.

Studies have explored the role of agricultural machinery in promoting or inhibiting the energy and environmental performance of agricultural sector of China [79]. To further understand the relationship between agricultural mechanization and carbon emissions, we analyzed their respective trends and compared them. Fig. 9 shows that agricultural mechanization showed a fluctuating increasing trend, whereas the trend for agricultural carbon emissions was inverted U-shaped. The agriculture sector in the early period witnessed a considerable decline in the use of animal and human power, as well as an increase in machinery in agriculture-related activities. This agricultural transformation inevitably resulted in the enormous growth of carbon emissions and fossil energy consumption. Subsequently, the opposite changing pattern between agricultural mechanization and carbon emissions suggested that agricultural mechanization was beneficial to reduce carbon emissions, which could be attributed to large-scale farming together with the *trans*-regional operation of agricultural machinery. This result confirms the fact mentioned in the Theoretical framework that spatial agglomeration effects caused by *trans*-regional operation could achieve the reasonable allocation of low-carbon resources [80,81]. In addition, the engine emission standards of agricultural machinery upgrades (from China II to China III) can be viewed as another reason to limit carbon emissions and other pollution. Facing serious environmental problems in the agricultural sector, the *trans*-regional operation of agricultural machinery may be a feasible alternative to promote energy environment performance.

5.2. *Impacts of agricultural machinery on the GTFP of grain: A comparative analysis*

According to the results obtained from SDM, the positive direct effects were greater than the spillover effects in three grain functional areas. This result indicated that agricultural mechanization has a direct influence on the GTFP of grain within the province. However, it is important to acknowledge the significant spatial spillover effects of agricultural mechanization in neighboring provinces. The positive direct effects in major grain-marketing areas were greater than those in other areas. Being developed areas, the major grain-marketing regions experienced rapid rural-urban migration due to high rates of urbanization. In particular, surplus agricultural labor can be transferred more easily. Therefore, agricultural machinery has been essential in filling the gap in labor shortages in grain production. Agricultural machinery has made a substantial contribution to the growth of the GTFP of grain. In terms of producing-marketing balance areas, the rapid growth of agricultural machinery input (annual 4.5%) has facilitated the GTFP of grain. The direct effects of agricultural mechanization in major grain-producing areas are estimated to be positive but not statistically significant, suggesting that the impact of agricultural machinery input may have reached a saturation point. According to the *Law of Diminishing Returns*, increasing inputs of agricultural machinery could even reduce the GTFP of grain.

In contrast, the spatial spillover effects in the main grain-producing areas were greater than those in other areas. As mentioned above, the magnitude and *trans*-regional operation of agricultural machinery caused significant spatial spillover effects on neighboring provinces. In addition, the severe labor shortage in the major grain-marketing areas has forced technological reforms in agricultural machinery. With the advantage of developed economic conditions, new machinery and technology were easily popularized, thus generating a technological spillover effect [82]. The lack of significant spatial spillover effects in producing-marketing balance areas can be attributed to the absence of locational and technological advantages (Fig. 8).

5.3. *Policy implications for developing mechanized agriculture with low-carbon practices*

Based on the analysis and findings, the effectiveness and feasibility of the proposed policies are evaluated in alignment with the policy objectives of governments. First, the impacts of agricultural mechanization on the GTFP of grain varied across grain functional areas. Therefore, it is important to develop feasible strategies for each grain functional area to promote sustainable and environmentally friendly grain production. i) To prevent local saturation caused by excessive agricultural machinery input, stakeholders should regulate and optimize the utilization of machinery to ensure the maximum benefits of agricultural mechanization on the GTFP of grain. Therefore, greater emphasis should be placed on regulating the aggregate utilization of agricultural machinery and ensuring the effective utilization of the existing agricultural machinery through enhanced efforts. ii) Considering the technology spillover effects in major grain-marketing areas, governments should provide greater funding for the study and development of technology and

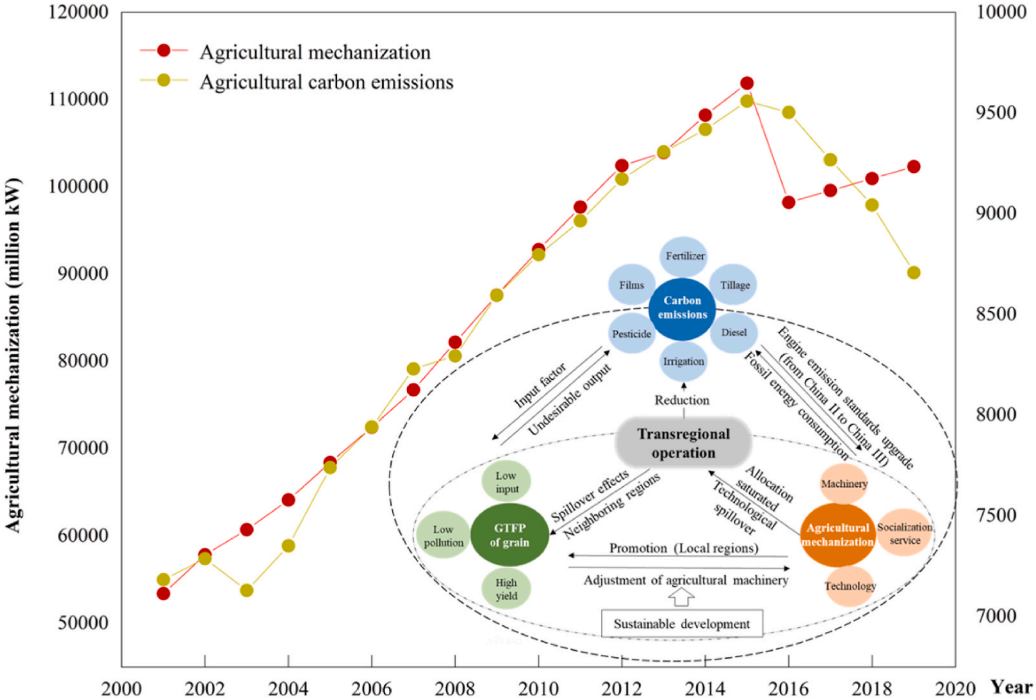

Fig. 9. Interaction of agricultural mechanization, *trans*-regional operation, and carbon emissions.

equipment innovation of agricultural machinery, thereby increasing the innovation externality. iii) Concerning the inferior geographical conditions and economic locations in producing-marketing balance areas, encouraging the use of small-scale agricultural machinery in these areas can enhance grain productivity.

Second, as the *trans*-regional operation of agricultural machinery has positive external effects on the GTFP of grain, a big data platform for the *trans*-regional service of agricultural machinery through “Internet + agricultural machinery operation” could be built to exchange the technology and experience between different regions. Third, inferior geographical conditions have been the major limiting factors for agricultural machinery operation, especially in hilly and mountainous areas. To address this issue, efforts should be made to promote land consolidation suitable for mechanization, which involves enlarging farmland plots, improving road connectivity for cultivation, and ensuring the availability of agricultural machinery operations. Finally, agricultural machinery is usually accompanied by high energy consumption and carbon emissions, which inevitably affects the green development of agriculture. Therefore, it is necessary to provide practical solutions and support for the development of low-carbon agricultural machinery. Such findings have potential implications for agricultural modernization and a low-carbon economy in the future.

6. Conclusions

By applying an integrated framework, this study explored the impacts of agricultural mechanization on the GTFP of grain in China and compared the results at the regional level, and various conclusions can be drawn: From 2001 to 2019, both agricultural mechanization and the GTFP of grain experienced an increasing tendency with an average growth rate of 5.09% and 3.31%, respectively. Its spatial distribution of urbanization showed a pattern of gradual decline from the eastern coastal areas to the central and western areas. Additionally, their distribution was consistent in the three grain functional areas: major grain-producing areas > producing-marketing balance areas > major grain-marketing areas. The global bivariate Moran's *I* exhibited a range of values between 0.288 and 0.356 ($p < 0.01$), implying an increasing spatial correlation between agricultural mechanization and the GTFP of grain in China. Furthermore, the SDM estimation results showed that the direct, spatial spillover, and total effects of agricultural mechanization exhibit a significant positive trend during the study period. However, the direct effects tended to decrease from 0.117 to 0.061, while the spatial spillover effects increased. This can be explained by the fact that labor quality has constrained the use of agricultural machinery in the local province. Additionally, the increasing spatial spillover effects can be attributed to the *trans*-regional operation of agricultural machinery; more importantly, spatial agglomeration effects caused by *trans*-regional operation could even achieve the reasonable allocation of low-carbon resources. Both of them improved the GTFP of grain. This phenomenon was typical in major grain-producing areas. In addition, the direct effects in these areas have been insignificant, which indicated that the excessive input of agricultural machinery has decreased the marginal benefits of agricultural mechanization on the GTFP of grain. In contrast, the direct effects in major grain-marketing areas are significantly positive because agricultural machinery has played a critical role in filling the gap in local labor shortages in grain production.

Given the spatial differentiation of results in these areas, adaptive strategies based on grain functional orientation and local agricultural characteristics should be fully considered by policy-makers. In addition, the *trans*-regional operation of agricultural machinery should be strengthened by building the "Internet + agricultural machinery operation" platform, which is beneficial to exchange technology and experience between different regions. "Land consolidation suitable for mechanization" should be implemented to guarantee the availability of agricultural machinery operation in hilly and mountainous areas. Furthermore, more practical offers should be given to developing low-carbon agricultural machinery, which has great significance to achieve mechanized agriculture and a low-carbon economy in the future.

While this study proposed a new idea and an effective methodology for analyzing the impacts of agricultural mechanization on the GTFP of grain, there were several limitations and uncertainties. First, due to time constraints and the availability of data, the study unit in this study was at the provincial level. To provide significance to detailed analysis, more resources should be directed toward the inclusion of a small level, such as city and county. Second, when calculating the GTFP of grain, the undesirable output only referred to the carbon emissions. In fact, the undesirable outputs in actual grain production activities also include water pollution, soil contamination, and soil erosion. More efforts in further studies should be focused on a more integrated measurement of the GTFP of grain.

Author contribution statement

Wenqiu Ma: Conceived and designed the experiments; Wrote the paper.
Tongxin Liu: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.
Wenqing Li: Conceived and designed the experiments.
Heng Yang: Contributed reagents, materials, analysis tools or data.

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

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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