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Spatial double dividend from China's main grain-producing areas policy: total factor productivity and the net carbon effect

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Because of the reductions in China's cultivated land area and the significant impact on the agricultural market, the main grain-producing areas (MGPA) policy has become vitally important for ensuring China's food security. However, guaranteed food security and sustainability require ecological security, which raises the question of whether food production should come at the expense of the environment. This study used 1998–2020 panel data from 30 Chinese provinces and a spatial difference-in-differences model (SDID) to explore the MGPA policy effects and mechanism paths on agricultural total factor productivity (ATFP) and the net carbon effect (NCS). It was found that economically, the MGPA policy promoted local ATFP improvements and had positive spillover effects on surrounding provinces through factor diffusion, and environmentally, the MGPA policy had a positive effect in the MGPA policy implementation areas but inhibited the NCS in surrounding provinces. Further explorations of the environmental performances revealed that the MGPA policy promoted growth in agricultural carbon sinks and agricultural carbon emissions, with the environmental performances being primarily reflected in an increase in carbon sinks and a decline in the carbon emissions density. The mechanism test showed that the MGPA policy's local environmental performance was achieved through economic performance. The ATFP was refined into technical innovation (TI), technology adoption (TA), and business scale (OS), with the mechanistic roles of these three refining paths being OS > TI > TA. A further mechanism test revealed that the MGPA policy effects on the ATFP were influenced by the various adjustment of production support, government support, and collaborative support. Based on the above analysis, this study gives policy recommendations to ensure food security and the realization of China's dual carbon target.

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Introduction

Even though China has one-fifth of the world's population, it only has around 8% of the world's cultivated land, making it 126th in the world for per capita cultivated land area (Zhang et al., 2021a). Over time, China's agricultural production land has been converted to functional land to deal with urban expansion, which had further decreased the supply of cultivated land (Hovhannisyan and Devadoss, 2020; Tian and Wan, 2000). Since China acceded to the WTO, its agricultural production costs, fragmented farmlands, and other production issues have meant that its agricultural products have had no comparative advantages. Further, rises in domestic grain prices have led to a significant increase in grain imports (Diao et al., 2003). Given the significant impact of China's limited supply of cultivated land on the agricultural market, ensuring food security has become of utmost importance (Hovhannisyan and Bozic, 2017; Huang et al., 2017; Tan et al., 2005). The Chinese government has implemented several policies to address this challenge, such as direct grain subsidies, agricultural machinery purchase subsidies, and minimum grain purchase price policies. At the end of 2003, China's 13 provinces, which together account for 64% of China's total cultivated land area and contribute 75% of its total grain output (Zhang et al., 2019b), were identified as China's main grain-producing areas, and received policy support and investment to achieve China's agricultural production targets (Luo et al., 2017).

Since the MGPA policy was established, China's grain output has increased from 43,000 tonnes in 2003 to 680 million tonnes in 2021. However, due to the short-lived scale effects in the main grain-producing areas, ensuring the total national grain harvest and the supply of other essential agricultural products has been challenging. Therefore, improving ATFP is crucial to ensuring food security, protecting scarce resources, and enhancing social sustainability (Jin and Huffman, 2016; Laborde and Piñeiro, 2018; Zhang et al., 2021b). Previous MGPA policy studies have mainly focused on assessing production efficiencies and the influences of natural and unnatural factors on agricultural production in main grain-producing areas, but have only provided indirect assessments of the MGPA policy effectiveness (Chou et al., 2019a; Deng et al., 2022; Shuang-yu et al., 2021; Sui et al., 2018; Xie et al., 2018). Similarly, studies on the ATFP policy drivers have tended to focus on single policies such as taxation (Fulginiti and Perrin, 1997; Headey et al., 2010; Hu et al., 2021), with few studies treating the MGPA policy as a one-time policy intervention to explore its local policy effects (Luo et al., 2020; Wu et al., 2022). Unfortunately, as previous studies have failed to assess the ATFP, which plays a crucial role in the development of main grain-producing areas, as well as the potential MGPA policy spatial spillover effects. Therefore, it is necessary to determine the direct influence the policy has had on ATFP and the indirect spillover effects.

Ecological security guarantees food security and sustainability. Therefore, it is vital to assess whether or not food is being produced at the expense of the environment. Climate change is now the most serious global environmental problem facing life on Earth (IPCC, 2014; Xiong et al., 2021). As a major carbon emitter, China has committed to reaching its carbon emissions peak by 2030 and achieving carbon neutrality by 2060 (Xiong et al., 2021; Yu and Zhang, 2021b). Agriculture emits about 17% of China's total carbon emissions, which is higher than in the United States (7%) and globally (11%) (Guan et al., 2008; Huang et al., 2019; Xiong et al., 2017). Unlike the industrial sector, the agricultural sector emits carbon and also has a significant carbon sink function (Cui et al., 2022b, 2022a). Due to these positive and negative externalities, agriculture has a significant role in helping achieve China's 2060 carbon neutrality goal (Cui et al., 2022a). Many studies have explored the factors associated with agricultural carbon reductions and the carbon sink capacities of different crops (Ahmed and Sarkar, 2018; Liu et al., 2022d; Poore and Nemecek, 2018; van Kessel et al., 2013). However, only a minority of studies have directly examined the net carbon effect policy drivers for both carbon emissions and carbon sinks. The planting area expansions in the main grain-producing areas will inevitably increase the agricultural carbon emissions, but will also result in expanded carbon sinks. However, the agglomeration economies in these provinces can improve ATFP through technological progress, the optimal allocation of resources, and scale effects, which can reduce the use of carbon sources such as agricultural materials. Previous environmental MGPA policy performance assessments have mainly focused on single negative environmental issues such as surface source pollution (Luo et al., 2020; Wu et al., 2022). Therefore, on the basis of assessing the MGPA policy's economic performance, it is necessary to more fully understand the environmental performance, and explore the possible dual dividends of the MGPA policy's ability to guarantee China's national food security strategy while benefiting the environment.

Therefore, this study makes three main contributions. First, it adopts a unique approach by treating the MGPA policy as a quasi-natural experiment and directly examining its impact on agricultural production from local and spatial perspectives. This approach deviates from existing studies that indirectly explored the policy effects by focusing on the main grain-producing areas. By expanding the analysis scope, this paper provides a more comprehensive understanding of the MGPA policy impacts on agricultural production. Second, while previous agricultural environmental studies have primarily focused on single negative environmental factors, such as carbon emissions and surface source pollution, this paper takes a more holistic approach by integrating the negative and positive agricultural production environmental impacts, specifically focusing on the net carbon effects, and developing a comprehensive MGPA policy environmental performance index that considers both the carbon emissions and the carbon sinks. Third, the study innovatively explores the logical links between economic performance and environmental performance to examine the possible double MGPA policy dividends.

Literature review

To date, there have been three main research directions: MGPA policy, agricultural economic issues, and agricultural environment issues. Therefore, to highlight the contributions of this paper's study, this section summarizes and compares research in these three areas.

MGPA policy. Because main grain-producing areas are critical to national food security (Chou et al., 2019b), previous studies have mainly taken global or local perspectives to examine these areas. First, some studies have focused on evolutionary and feature layouts to examine productivity measures, such as grain production efficiencies (Shuang-yu et al., 2021; Zhang et al., 2021b), cultivated land utilization efficiencies (Xie et al., 2018), and ecological security issues associated with cultivated land (Zou et al., 2022). Other studies have examined all or a few main grain-producing areas to analyze the time evolution and spatial distribution of data and determine the heterogeneity of agricultural production conditions and efficiency in China. To examine the amplification effects of the MGPA policy on China's food security, some studies have further explored influencing factors, such as the grain yield per unit area change characteristics and the main influencing factors (Cheng et al., 2007), farmland water conservation performances, and identify the performance determinants (Luo et al., 2017).

Second, some studies have taken a natural environment perspective to explore the factors influencing agricultural production, such as climate change impacts. Based on the analysis of the distribution characteristics and change rules of climate change in the main grain-producing areas, the impact degree of climate change on agricultural production was further discussed (Chou et al., 2019a; Sun et al., 2020). Due to the particularity of agricultural production, its interaction with the natural environment, such as agricultural economic growth, energy consumption, water resources, and perceptions of climate change, has also been widely concerned (Song et al., 2019a; Wang et al., 2020c; Zhang et al., 2019b). Third, with a focus on optimizing the external agricultural production environment in the main grain-producing areas to promote efficient agricultural production, other studies have taken unnatural environmental perspectives to determine the direct influencing factors, such as resource allocation efficiencies, land operation scales, and technological innovations (Deng et al., 2022; Qin et al., 2022, 2020), and the indirect influencing factors, such as rural financial service efficiency improvements, urbanization quality, traffic advantages, and internet development (Geng et al., 2022; Shuang et al., 2021; Tian and Ma, 2022b).

Agricultural policy and agricultural economy. As agricultural producers are primarily profit-oriented, they often adopt production models that are economically advantageous and easy to operate (Guo et al., 2021; Peshin, 2013). Therefore, agricultural policies have mainly been based on subsidies and assistance. Many studies focused on agricultural policies have specifically examined the impacts on the agricultural economy; for example, the agricultural subsidy policy, which provided direct grain subsidy, improved seed, agricultural machinery, and minimum purchase price subsidies (Huang et al., 2013), was found to have a significant incentive effect on agricultural production (Chen et al., 2017; Garnett et al., 2013). With a focus on ensuring agricultural producers' economic benefits, other studies have examined the effects of subsidies on food production (Khonje et al., 2022; Liang et al., 2019; Wang et al., 2020a), production welfare (Daniel and Kilkenny, 2009), rural employment (Bollman and Ferguson, 2019), agricultural production scales (Azzam et al., 2021), and family dietary structures (Matita et al., 2022). Agricultural insurance policies, which have been found to reduce the natural and unnatural risks associated with agricultural production (Birthal et al., 2022; Smith and Goodwin, 1996; Tang and Luo, 2021), have motivated agricultural producers, increased risk factor inputs (Quiggin, 1992; Ramaswami, 1993; Tang and Luo, 2021), and encouraged producers to expand their business scales (Burns and Prager, 2018), all of which have had flow-on effects on the supply of different crops (Goodwin and Smith, 2003; Walters et al., 2015; Yu et al., 2018) and increased agricultural GDP (Liu et al., 2022b). Other studies have found that different agricultural support policies contribute differently to the agricultural economy (Ivanov, 2020).

As agricultural production efficiency is an essential driver of agricultural economic development, this has attracted significant research. Production efficiency can be measured using either single-factor or total-factor productivity (TFP). As single-factor productivity is only one input and ignores contributions from other production factors, the measurement results have generally been biased (Filippini and Hunt, 2015; Shao and Wang, 2023; Tang and Li, 2019). However, as TFP considers inputs from all factors, it more comprehensively and accurately measures the agricultural production driving forces (Gong, 2020). The TFP economic production sources include technological progress and technical efficiency; however, TFP changes are also reflected in input and output factor changes (Huang et al., 2022). Two main methods have been used to measure TFP; data envelopment analysis (DEA) based on nonparametric linear programming, and stochastic frontier analysis (SFA) based on parametric methods (Auci and Coromaldi, 2021; Chen and Gong, 2021b; Yu, 2021a; Zhu et al., 2022). Because these methods calculate efficiency by tracking the production frontier (Wang et al., 2018; Xia and Xu, 2020), they have been widely used in ATFP research (Auci and Coromaldi, 2021; Brümmer et al., 2006; Chen and Gong, 2021b; Coelli and Rao, 2005; Guo et al., 2022; Liu et al., 2021a). Significant research has also examined the ATFP driving factors, such as agricultural R&D expenditure, and economic openness, and labor, land, and policy factors, such as institutional changes, tax policies, and inclusive finance (Dandan et al., 2015; Fulginiti and Perrin, 1997; Headey et al., 2010; Hu et al., 2021; Looga et al., 2018).

Agricultural policy and agricultural environment. Subsidies and other incentive policies have the potential to provide loss compensation (Luo et al., 2014) and promote sustainable global agricultural development (Garnett et al., 2013; Mohring et al., 2020). Government subsidies and insurance, such as crop insurance, are closely associated with pesticide consumption, which can facilitate greater technological adoption (Fang et al., 2021; Luo et al., 2014; Visser et al., 2020), encourage farmers to use greener alternatives such as organic fertilizers and biological pesticides (Tang and Luo, 2021; Tur-Cardona et al., 2018; Wang et al., 2014) and reduce their use of agricultural pollutants (Norton et al., 2016), which in turn reduces the negative agricultural production externalities and promotes green, sustainable agricultural development (Garnett et al., 2013). Environmental policies, such as carbon taxes and trading, can also impact the agricultural environment (Dumortier and Elobeid, 2021; Yu et al., 2022a).

Environmental agricultural production problems are mainly associated with non-point source pollution and carbon emissions. As carbon emissions increase and aggravate climate change effects, there is a two-way constraint relationship between agricultural production and carbon emissions. Agricultural carbon emissions have heterogeneous distribution characteristics because of geography, climate, soil quality differences, and other factors (Moucheng and Lun, 2021). Agricultural carbon emissions influencing factors and emissions reduction paths have been internally examined, such as farming mode, management mode, and organic agriculture (Blanco-Canqui, 2021; Maria Gamboa and Galicia, 2011; Poore and Nemecek, 2018; van Kessel et al., 2013; Yu et al., 2022b), and externally examined, such as environmental policies, economic levels, resource allocations, technical abilities, and industrial agglomeration (Abdul-Salam et al., 2019; Ahmed and Sarkar, 2018; Dumortier and Elobeid, 2021; Liu et al., 2022d; Long and Tang, 2021; Maraseni et al., 2021; Myint et al., 2021; Srivastava et al., 2021; Zhang et al., 2019a). Because of the need to globally reduce carbon emissions, the emissions reduction potential of agriculture's carbon sink function has also been studied, from which it was found that the carbon sink capacities of crops have spatiotemporal heterogeneity because of different factors such as crop type, planting region, and production behavior (Chen et al., 2020; Cui et al., 2022b; She et al., 2017).

The literature review revealed that there have been extensive studies on agricultural policies and the agricultural environment. However, from the perspective of research subjects, most studies have focused on the impact of a single subsidy or insurance policy on decision-making or agricultural production. Because these policies have usually been implemented across China, they are characterized by universality. From the perspective of research, most previous studies have generally only explored the agricultural production drivers in China's main grain-producing areas, with few employing a DID model to evaluate the MGPA policy intervention effects at a national level. From the perspective of research conclusions, previous studies have been limited to the economic or environmental policy impacts rather than exploring the logical relationships between these impacts.

Research hypothesis

After the MGPA policy was implemented, some particular economically focused grain production policies were introduced in the main grain-producing areas, such as high-quality grain industrial policies, commodity grain-based policies, grain production core area policies, and county grain production incentives, to play an economic role mainly in the form of increasing special fund expenditures and providing production incentives.

First, increasing the expenditure of special funds. The perfect competition model was developed under the assumption that land endowments would remain unchanged, the agricultural producer production function form for which was the Cobb–Douglas form (Chen and Gong, 2021b):

$$Y = AK^{\alpha}L^{\beta}M^{\gamma} \tag{1}$$

where Y is total agricultural production output, L is labor factor inputs, K is capital input, M is land input, A is agricultural sector technological progress, and α, β, and γ respectively represent the output capital, labor, and land elasticities. It was assumed that the labor, capital, and land input returns to scale for the independent producers were constant, that is, $\alpha+\beta+\gamma=1$. When there is an earmarked expenditure, the production function can be changed to

$$Y = AK^{\alpha}L^{\beta}M^{\gamma}H^{\theta} \tag{2}$$

where H is the special capital input and θ is the special capital input output elasticity. As the government provides more public asset inputs for agricultural producers in the main grain-producing areas to improve the agricultural production conditions, the returns to scale increase, that is, $\alpha+\beta+\gamma+\theta>1$.

Taking the logarithm of Eq. (2), the output-based TFP is then equal to the actual output divided by the factor inputs; therefore, Eq. (2) is transformed into:

$$atfp = y - \alpha k - \beta l - \gamma m = a + \theta h \tag{3}$$

where $atfp, y, k, l, m, h$ are, respectively, the logarithms for the corresponding uppercase letters. The equation indicates that ATFP is proportional to special government assets, that is, as government special assets investment increases in the main grain-producing areas, natural geographical advantages, standard land construction, modern agricultural machinery upgrading, plant diseases, and insect pest prevention and control technology upgrading, and particular policy driven production management models gradually improve agricultural production conditions and ATFP.

Second, with a focus on increased production incentives. On the one hand, dynamic asset poverty theory was used to analyze the behavior of agricultural producers constrained by asset poverty (Gao et al., 2017). When the agricultural producers' time preferences and policy constraints are consistent, producers with different productive assets have different production curves, as shown in Fig. 1, where F1 represents a low-productivity production curve, and F2 represents a high-productivity production curve. At static equilibrium, A_0 is the asset poverty equilibrium point. In dynamic equilibrium, if the agricultural producer's assets are to the left of equilibrium point A_0, the producer uses the time effect to accumulate assets to obtain high-yield rewards, which involves preparing better quality seeds, machinery, and agricultural materials for the next production cycle to increase the ATFP and yield in future production cycles.

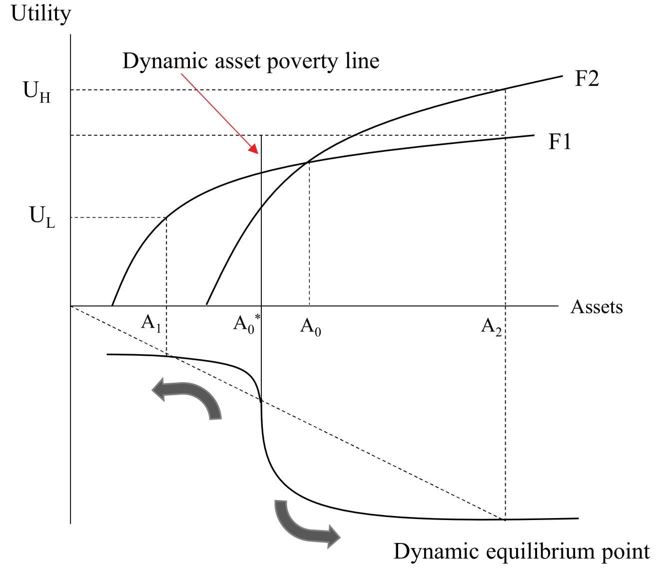


Fig. 1 Agricultural producer dynamic asset poverty analysis. When agricultural producers have different asset levels, different productivity rates are chosen.

On the other hand, for agricultural producers not constrained by asset poverty, the analysis is performed by constructing a profit maximization function. In Eq. (1), the labor price is P_L, the asset price is P_K, the grain price is P, and ω is all other agricultural production expenditure. The agricultural producers' profit maximization function is, therefore:

$$\max \quad YP - P_L L - P_K K - \omega \tag{4}$$

Substituting this into Eq. (1), we get:

$$\max \quad AK^{\alpha}L^{\beta}M^{\gamma}H^{\theta}P - P_L L - P_K K - \omega \tag{5}$$

Taking the derivative of L and K in Eq. (5), we get:

$$Y'_L = \frac{1}{A\beta} \cdot \frac{P_L}{P} \tag{6}$$

$$Y'_K = \frac{1}{A\alpha} \cdot \frac{P_K}{P} \tag{7}$$

Equations (6) and (7) indicate that for agricultural producers unconstrained by asset poverty, after obtaining financial incentives, producers with higher asset allocation freedom tend to continue to expand production scales. Therefore, because of scale and agglomeration effects, the production factor input costs reduce, P_L and P_K reduce, technological progress A improves, production elasticity α and β increases, and there is only a small price fluctuation in necessary daily agricultural products. Finally, Y'_L and Y'_K reduce, which means that because the producers' dynamic equilibrium point moves to the right again, the agricultural producers choose a higher factor productivity level to obtain greater output (Zhang et al., 2022b), which improves the social ATFP aggregate.

Based on the quantitative analysis of the two influence forms, this paper proposes the following hypothesis:

Hypothesis 1: *The MGPA policy improves ATFP and achieves economic policy performance.*

Given the dual asset support and high-yield incentives background, agricultural producers in the main grain-producing areas are motivated (Picard and Zeng, 2005), which positively stimulates agricultural production and increases carbon sinks. Because the consequent demand for agricultural production materials increases as the scale expands, total carbon emissions increase. However, concentrated scale production does not increase the use of materials. Convergent grain production implies an increased homogeneity of the grain production factors, that is, scale production agglomeration can ensure food production growth through production methods such as technology sharing and management model sharing, which improves the carbon source material use efficiencies (Zhang et al., 2017) and reduces carbon emissions, which leads to a decline in the NCS. Therefore, this paper proposes the following hypothesis:

Hypothesis 2: *The MGPA policy improves the local NCS and realizes the policy's environmental goals.*

First, when there is asset accumulation and high-yield production incentives, agricultural producers expand production scales, and industrial agglomeration drives the formation of a grain production polarization center. Because of the homogeneity of essential production equipment and materials for grain and other agricultural planting industry products, the production factors spread to the tangible markets in neighboring provinces (Liu et al., 2022a). Second, China's base population characteristics mean there is an overwhelming basic demand for food and other agricultural products (Cheng et al., 2007). The main grain-producing areas primarily fulfill the bottom line of the national food demand, and the non-main grain-producing areas fulfill the demand for all other agricultural products. These activities in the polarized centers give neighboring provinces knowledge elements (Liu et al., 2022c); therefore, the spillover and absorption effects promote an orderly factor circulation channel between the main grain-producing areas and the non-main grain-producing areas, which accelerates the ATFP in the adjacent areas. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 3: *The MGPA policy improves ATFP in the neighboring provinces to the main grain-producing areas, resulting in spatial economic performance spillovers.*

Since the MGPA policy was implemented, the grain production market share in China's grain market from the main grain-producing areas has gradually increased and started to grasp dynamic moves. However, the decline in grain profits has dampened the enthusiasm of agricultural producers in the non-main grain-producing areas and reduced their grain production. Because the carbon sink calculations in this study were mainly related to grain planting, the total carbon sink in the non-main grain-producing areas has had a downward trend. This grain planting decline in the non-main grain-producing areas does not mean a decline in non-grain planting; rather, it presents additional market opportunities. Because of the spillover effects from the polarized center (Dong et al., 2020), the non-main grain-producing areas have absorbed quality production factors and expanded their non-grain cultivation areas. However, as there is greater heterogeneity in non-grain product cultivation, the absorbed production factors play a less robust role, which leads to an increase in carbon source material consumption and the associated carbon emissions. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 4: *The MGPA policy has a negative spatial spillover effect on the NCS in the neighboring provinces to the main grain-producing areas.*

Hypothesis 2 assumes that the resource allocation efficiency has been improved during the process of achieving environmental performance, which improves the ATFP in the main grain-producing areas. On the one hand, the increase of ATFP results in higher producer incomes and motivates production expansion, and carbon sink increases. On the other hand, the ATFP growth rate has two components; technological progress and technical efficiency, which comprises agricultural production technology innovation, technological adoption, and business scale. The technological innovation promotion and application achievements and abstract theoretical knowledge are transformed into natural productive forces, with this agricultural production scale agglomeration further amplifying technological progress and reducing agricultural materials consumption, thereby achieving win-win economic growth and carbon emissions reductions (Zhang et al., 2019b). Based on the above analysis, the following hypothesis is proposed:

Hypothesis 5: *From the local perspective, the ATFP is a positive impact mechanism in the process of the MGPA policy promoting NCS.*

The logical relationships between the MGPA policy, ATFP, and NCS are illustrated in Fig. 2.

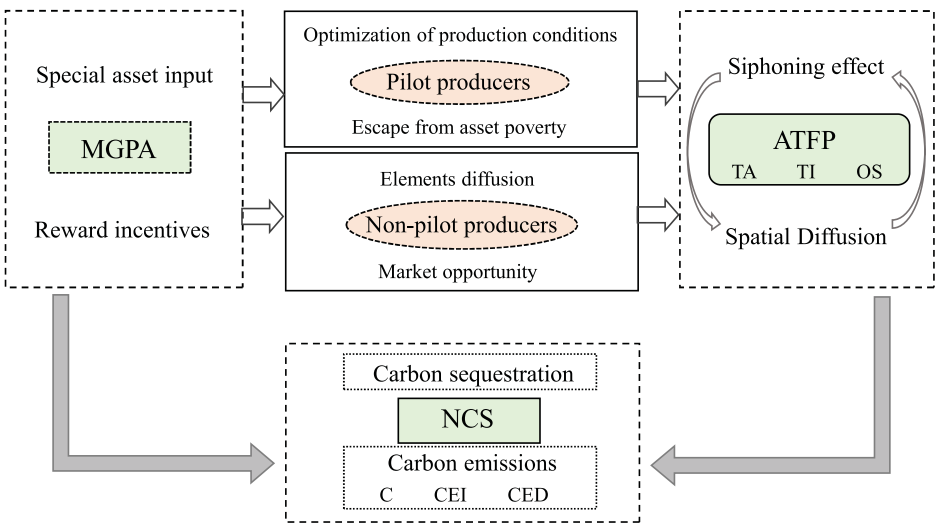


Fig. 2 MGPA, ATFP, and NCS theoretical logic. Based on the theoretical analysis in this paper, this figure shows the MGPA policy path influencing ATFP and NCS.

Table 1 ATFP inputs and outputs.

	Factor	Indicator
Output	Crop yield	Yields for cereal, oil plants, cotton, bast fiber plants, and tobacco
Input	Labor	Plant industry labor force
	Land	Sown crop area
	Agricultural machinery	Total planting machinery power
	Fertilizer	Chemical fertilizer purity
	Pesticide	Pesticide quantity
	Agricultural film	Film quantity

Model, methodology, and data

Research variables and data sources

Explained variables

Agricultural total factor productivity (ATFP): DEA and SFA models have commonly been used to measure TFP. Compared with the parametric SFA method, DEA, a non-parametric method, does not need specific production functions or invalid items to be set in advance, which avoids any subjective influences (Chen et al., 2021). Therefore, the DEA method was used to calculate the ATFP. To avoid the shortcomings associated with radial and non-radial distance functions and the sequencing of effective production units, the super efficiency SBM model was employed, which is described in the following:

$$\begin{aligned} &\rho = \min \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{x_{i0}}}{\frac{1}{s}\sum_{k=1}^{s}\frac{\bar{y}_k}{y_{k0}}} \\ &\text{s.t. } \overline{x_i} \geq \sum_{j=1,\neq 0}^{n}\lambda_j x_j, \forall i; \\ &\quad \overline{y_i} \geq \sum_{j=1,\neq 0}^{n}\lambda_j x_j, \forall k; \\ &\overline{x_i} \geq x_{i0}, 0 \leq \bar{y}_k \leq y_{k0}, \lambda_j \geq 0 \end{aligned} \tag{8}$$

where ρ is the objective function and its efficiency value, m and s are the number of input and output variables, and x, y are the model inputs and outputs. This study did not consider undesirable outputs. The selected input and output indicators are shown in Table 1.

Agricultural net carbon sink effect (NCS): The agricultural NCS effect refers to the net carbon absorption after the carbon emissions are eliminated, that is, the agricultural carbon sequestration minus the agricultural carbon emissions. There are six primary planting carbon emissions sources: pesticides, agricultural film, chemical fertilizers, agricultural diesel, land tillage, and agricultural irrigation electricity consumption (Huang et al., 2019; Wang et al., 2020). The specific calculation formula is as follows:

$$C = \sum C_i = \sum T_i \times \varphi_i \tag{9}$$

where C is the total agricultural production carbon emissions, C_i is the carbon emissions for i carbon source, and T_i and φ_i are the carbon source consumption and carbon emission coefficients. The carbon emissions coefficient and carbon sources are shown in Table 2.

The planting industry's carbon sinks are related to the carbon absorption that takes place during the plant growth cycle, that is, the amount of carbon absorbed by crops during photosynthesis. The calculation formula is as follows:

$$Q = \sum Q_i = \sum e_i \times P_i(1 - r)/H_i \tag{10}$$

where Q is the total planting industry carbon sink, Q_i is the total carbon sink for the ith crop, P_i is the economic yield for the crop, e_i is the carbon required for the photosynthesis of this crop, r is the water content, and H_i is the economic coefficient, the values for which are shown in Table 3 (Qiao et al., 2022).

Table 2 Carbon resource emissions factors.

Carbon resource	Carbon emissions factor	Reference
Fertilizer	0.8956 kg C/kg	ORNL[a]
Pesticide	4.934 kg C/kg	ORNL[a]
Agricultural film	5.18 kg C/kg	IREEA[b]
Agricultural diesel	0.5927 kg C/kg	Wener (2009)
Irrigation electricity	25 kg C/hm^2	Dubey[c]
Ploughing carbon	31260 kg C/hm^2	IABCAU[d]

[a]Indicates data from Oak Ridge National Experiment.
[b]Indicates data from the Institute of Agricultural Resources Ecology and Environment.
[c]Indicates data from Dubey Laboratory, U.S. Department of Agriculture.
[d]Indicates data from the Institute of Agriculture and Biotechnology, China Agricultural University.

Mechanism variables

Adjustment variables: Government support (GS), which can affect MGPA policy effectiveness, provides a favorable external environment for agricultural production. The core GS financial input reduces agricultural production's natural and market risks and boosts production efficiency and economic benefits (Shanshan and Bingle, 2021). However, the effectiveness of the GS measure depends on regional agricultural planning. Therefore, the measurement is the ratio of the gross plantation product to the gross agricultural product multiplied by the regional financial agricultural support.

Production support (PS) indicates the agricultural development stage, which can impact MGPA policy effectiveness. As the agglomeration degree in agricultural industries varies, there are different scale effects and production conditions in different areas and industries. Effective industrial agglomeration can result in resource sharing and technology spillovers (Wu et al., 2020; Zhang et al., 2022). Therefore, the measurement equation is $IA_{ij} = \sum_{i=1}^{30}\left[\left(x_{ij}/\sum_{i=1}^{n}x_{ij}\right)/\left(x_i/\sum_{i=1}^{n}x_i\right)\right]$, where IA_{ij} is the locational entropy of industry i in province j, x_{ij} is the output value of industry $i(i = 1, 2, 3....)$ in province j, and x_i is the output value of industry $i(i = 1, 2, 3....)$ nationwide. The regional entropy for the planting industries in each province was calculated in this study.

Collaborative support (CS) is the combined government support and production support effect, which is measured as the product of GS and PS.

Mediating variables: Technological innovation (TI) is the planting industry's technological progress and the technical support given to low-carbon agriculture and is measured by the number of planting industry patents.

Technology adoption (TA) is the total mechanical power per unit sowing area. Mechanized production is the core requirement for agricultural modernization and indicates the agricultural technology adoption degree.

Operation scale (OS) is the ratio of cultivated land area to planting population. The scale effect can improve factor utilization and crop yield.

Control variables. Regional economic development level (RED) is measured by per capita GDP; the higher the regional economic development, the greater the regional finance and manufacturing strength to support agricultural development.

Agricultural planting structure (APS) is the ratio of sown grain area to sown crop area; the higher the proportion of sown grain area, the higher the grain output.

Agricultural scale operations (AS) is the agricultural machinery power of a unit of cultivated land area; the higher the operations scale, the more likely an agglomeration economy.

Table 3 Carbon sink crop parameters.

Crops	Rice	Wheat	Corn	Legume	Tuber crops	Peanut	oilseed rape	Sugar cane	Cotton
Carbon absorption rate	0.41	0.49	0.47	0.45	0.42	0.45	0.45	0.45	0.45
Water content	0.12	0.12	0.13	0.13	0.70	0.10	0.10	0.50	0.08
Economic coefficient	0.45	0.40	0.40	0.34	0.70	0.43	0.25	0.50	0.10

Table 4 Descriptive statistical analysis.

	Full sample					MGPA			Non-MGPA		
	Obs.	Mean	SD	Min	Max	Obs.	Mean	SD	Obs.	Mean	SD
ATFP	690	0.619	0.290	0.142	2.653	299	0.712	0.264	391	0.548	0.288
NCS	690	1966	1608	28.65	7551	299	3186	1376	391	1034	1052
GS	690	150.5	165.2	1.970	767.4	299	183.8	182.9	391	125.1	145.5
PS	690	1.188	0.620	0.0420	4.164	299	1.267	0.429	391	1.128	0.728
CS	690	201.8	313.8	0.753	2392	299	243.8	319.5	391	169.7	306.0
TI	690	485.5	862.0	0	5055	299	559.4	1004	391	429.0	731.4
TA	690	0.532	0.267	0.109	1.416	299	0.523	0.252	391	0.539	0.278
OS	690	11.59	5.571	4.110	44.12	299	14.06	6.785	391	9.702	3.379
RED	690	33958	28651	2342	164,889	299	30947	23,367	391	36260	31949
APS	690	0.658	0.131	0.328	1.143	299	0.723	0.108	391	0.609	0.125
AS	690	0.532	0.267	0.109	1.416	299	0.523	0.252	391	0.539	0.278
DD	690	0.237	0.162	0	0.936	299	0.240	0.155	391	0.234	0.168
AIS	690	0.530	0.0891	0.338	0.777	299	0.517	0.0622	391	0.541	0.104
AED	690	1.636	1.276	0.162	10.43	299	1.692	1.231	391	1.592	1.310

Disaster degree (DD) is the ratio of the affected area to the total crop planting area; the more significant the disaster area, the less conducive to agricultural production sustainability.

Agricultural industrial structure (AIS) is measured by the proportion of the planting industry output value and the total agricultural output value; the higher the planting industry output value, the stronger the carbon reduction potential for the agglomeration economy.

The agricultural economic development level (AED) is measured by the ratio of the planting, forestry, animal husbandry, and fishery increment in output value to the number of people engaged in the sector; the higher the agricultural economic development, the higher the agricultural modernization, and the stronger the possibility of green agricultural production.

Data sources. The GDP per capita, crop output, number of employees, agricultural output value, agriculture financial support, and other data were extracted from the China Statistical Yearbooks. The agricultural machinery power, fertilizer use, pesticide use, agricultural film use, regional cultivated land area, irrigation area, and other data were extracted from the China Rural Statistical Yearbooks, and the number of planting patents was extracted from the CNKI patent database. All data were logarithmically processed to eliminate any dimensional effects. The descriptive statistics for each variable are shown in Table 4. The mean values for the main grain-producing area variables were generally higher than those in the non-main grain-producing areas, especially for ATFP, NCS, and OS, which suggests that there were good agricultural production conditions and positive externalities in the main grain-producing areas. However, whether the effects were because of the MGPA policy requires further empirical investigation.

Research methods

DID method. The classic difference-in-differences (DID) model has been widely used to evaluate policy effects (Li et al., 2022a; Yang and Wang, 2021; Zhang et al., 2021b). Based on the policy implementation time and place, the sample data were divided into an experimental group and a control group to analyze the net policy implementation effects. The model was as follows:

$$\begin{aligned}\mathrm{ATFP}_{it} &= a_0 + a_1\mathrm{TEST}_{i,t} + a_2\mathrm{RED}_{i,t} + a_3\mathrm{APS}_{i,t} \\ &\quad + a_4\mathrm{AS}_{i,t} + a_5\mathrm{DD}_{i,t} + u_i + v_t + \varepsilon_{it}\end{aligned} \tag{11}$$

$$\begin{aligned}\mathrm{NCS}_{it} &= \sigma_0 + \sigma_1\mathrm{TEST}_{i,t} + \sigma_2\mathrm{RED}_{i,t} + \sigma_3\mathrm{DD}_{i,t} \\ &\quad + \sigma_4\mathrm{AIS}_{i,t} + \sigma_5\mathrm{AED}_{i,t} + u_i + v_t + \varepsilon_{it}\end{aligned} \tag{12}$$

where ATFP and NCS are the explained variables, i is the province, t is the year, and TEST is the policy dummy, which comprises time dummy and place dummy variables; that is, $\mathrm{TEST}_{it} = \mathrm{treat}_{it} \times \mathrm{time}_{it}$. If the data were from the main grain-producing areas, $\mathrm{treat}_{it} = 1$; otherwise, $\mathrm{treat}_{it} = 0$. If the data were from the year after the policy release, then $\mathrm{time}_{it} = 1$; otherwise $\mathrm{time}_{it} = 0$. u_i is the region fixed effect, v_t is the year fixed effect, and ε_{it} is the error term. Other variables were as previously described.

SDID method. Because of the close economic connections between the different provinces, the agricultural provincial production efficiencies, and agricultural carbon sink effects were inevitably affected by adjacent areas (Meng et al., 2017). Therefore, the adjacent area impacts were considered by constructing a spatial weight matrix (Li et al., 2022b). However, if spatial weight matrices are only constructed based on geographical distance, the spatial correlations over time cannot be distinguished. Therefore, based on the spatial weight matrix, a spatiotemporal weight matrix (Liu et al., 2022c) with time dimensions and a spatial DID (SDID) model was constructed to analyze the impacts of the MGPA policy on ATFP and NCS and the associated spatial spillovers (Jia et al., 2021b; Wang et al., 2022b; Yang et al., 2022; Zhu and Lee, 2022). The model was as follows:

$$\begin{aligned}\mathrm{ATFP}_{it} &= \beta_0 + \rho\mathrm{TW\,ATFP}_{i,t} + \beta_1\mathrm{TEST}_{i,t} + \beta_2\mathrm{RED}_{i,t} + \beta_3\mathrm{APS}_{i,t} + \beta_4\mathrm{AS}_{i,t} + \beta_5\mathrm{DD} \\ &\quad + \beta_1^*\mathrm{TW\,TEST}_{i,t} + \beta_2^*\mathrm{TW\,RED}_{i,t} + \beta_3^*\mathrm{TW\,APS}_{i,t} + \beta_4^*\mathrm{TW\,AS}_{i,t} + \\ &\quad \beta_5^*\mathrm{TW\,DD}_{i,t} + u_i + v_t + \varepsilon_{it}\end{aligned} \tag{13}$$

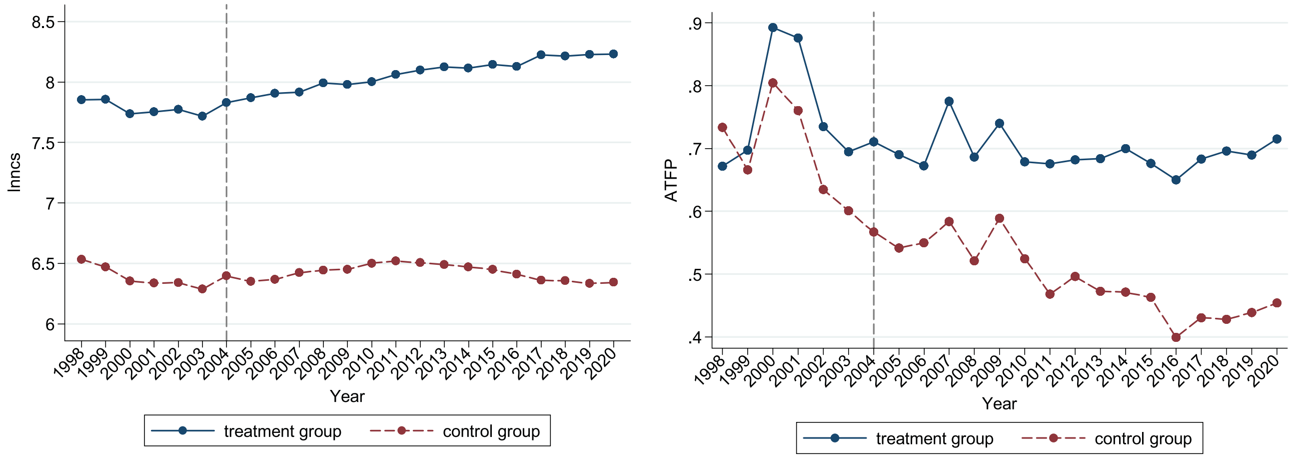


Fig. 3 Parallel trend test. This figure presents the ATFP and NCS trends after dividing the sample into the main and non-main grain-producing areas.

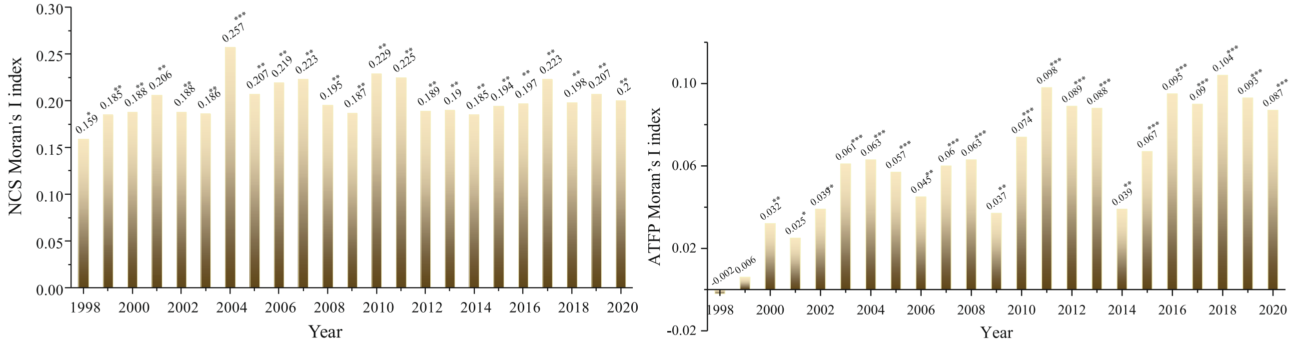


Fig. 4 Moran index. This figure presents the respective ATFP and NCS global autocorrelations.

$$\begin{aligned}\mathrm{NCS}_{it} = {} & \varepsilon_0 + \rho \mathrm{TW\,NCS}_{i,t} + \varepsilon_1 \mathrm{TEST}_{i,t} + \varepsilon_2 \mathrm{RED}_{i,t} + \varepsilon_3 \mathrm{DD}_{i,t} \\ & + \varepsilon_4 \mathrm{AIS}_{i,t} + \varepsilon_5 \mathrm{AED}_{i,t} + \varepsilon_1^{*} \mathrm{TW\,TEST}_{i,t} + \varepsilon_2^{*} \mathrm{TW\,RED}_{i,t} \\ & + \varepsilon_3^{*} \mathrm{TW\,DD}_{i,t} + \varepsilon_4^{*} \mathrm{TW\,AIS}_{i,t} + \varepsilon_5^{*} \mathrm{TW\,AED}_{i,t} + u_i + v_t + \varepsilon_{it}\end{aligned} \tag{14}$$

where i is the province, t is the year, ρ is the spatial autocorrelation coefficient used to explain the spatial interactions between ATFP and NCS, TW is the spatiotemporal weight matrix, β^*, ε^* is the spatial regression coefficient, u_i is the region fixed effect, v_t is the year fixed effect, and ε_{it} is the error term. The other variables were as previously described.

Results and discussion

Spatiotemporal ATFP and NCS characteristics

Time trend feature. The use of the DID and SDID models was motivated by the need to meet the parallel trend assumption (Acemoglu and Angrist, 2001; Jia et al., 2021a). This assumption ensures that the estimated policy effects in the main grain-producing areas are accurately represented. Therefore, an ATFP and NCS change trend chart was developed for the sample period. Figure 3 shows that before 2004, the ATFP and NCS in the main and non-main grain-producing areas exhibited similar change trends. The gap between the ATFPs in the two regions was small, with an initial increase followed by a decline, while the NCS was relatively stable. However, after 2004, the ATFP in the non-main grain-producing areas continued to decline, whereas the NCS in the main grain-producing areas steadily increased. This indicated that the ATFP and NCS change trends in the two regions started to diverge after 2004; therefore, the ATFP and NCS in the 13 main grain-producing areas before the policy intervention satisfied the common trend assumption. It is worth noting that since 2000, China's overall ATFP has had a downward trend, which has been primarily reflected in the non-main grain-producing areas since 2004. One possible reason for this is that after China acceded to the WTO in 2001 and was exposed to an open market environment, Chinese agricultural products faced technological, talent, and resource limitation challenges (Diao et al., 2003). Statistical analyses revealed a significant decrease in the sown areas for grain and other crops, which inevitably inhibited the ATFP and agricultural economic growth. To ensure national food security, China implemented its MGPA policy in 2004 to stabilize its agricultural factor production efficiencies (Yang et al., 2010) and promote greener economies of scale. As the comparative advantage of agricultural products in the non-main grain-producing areas declined, the ATFP gradually decreased.

Spatial features

Global spatial correlation features: Moran's I index in spatial statistics was used to assess the NCS and ATFP spatial agglomeration and dispersion characteristics. To examine the NCS and ATFP spatial relationships, local and global spatial correlation tests were conducted based on the adjacency matrix. Figure 4 shows that from 1998 to 2020, the Moran NCS index was positive and significant at a 10% level, and the Moran ATFP index was significantly positive from 2000 to 2020, which indicated that China's provincial NCS and ATFP had strong spatial agglomeration within the spatial scope. The spatial NCS correlation degree was relatively stable, and the spatial ATFP correlation degree had significant fluctuations and an upward trend.

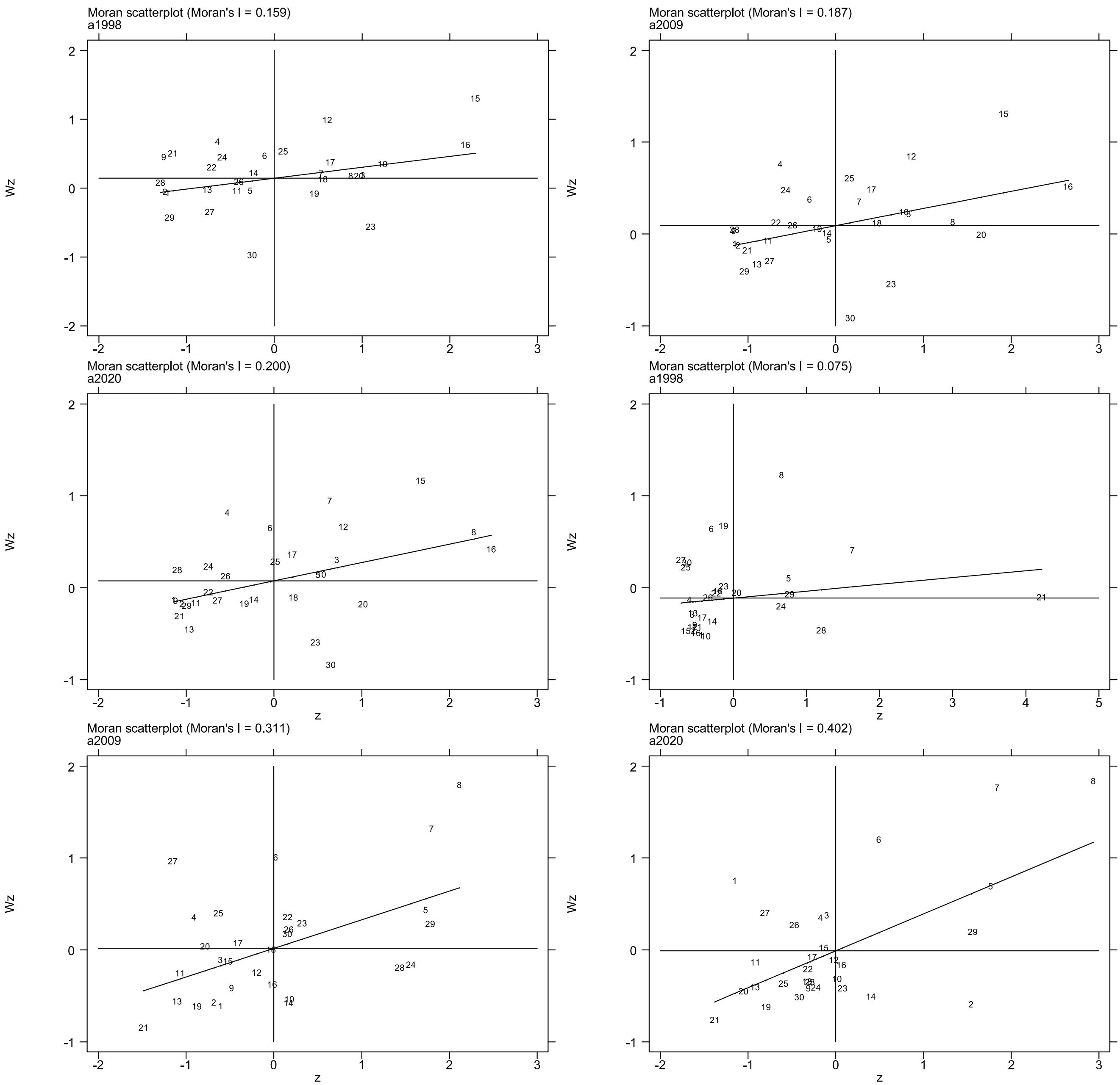


Fig. 5 Moran scatter plots. This figure presents the respective local ATFP and NCS spatial correlations.

Because local Moran index scatter plots accurately reflect local spatial correlations, local Moran index scatter plots for 1998, 2009, and 2020 were drawn. The solid line in Fig. 5 represents the Moran I global test regression line, the slope represents the test statistics, and each point represents the provincial NCS or ATFP. The first and third quadrants respectively represent the high–high (HH) and low–low (LL) aggregation NCS and ATFP characteristics, and the second and fourth quadrants respectively represent the low–high (LH) and high–low (HL) aggregation characteristics. The NCS and ATFP Moran scatterplots show that from 1998 to 2020 most provinces were in quadrants 1 and 3, with few in quadrants 2 and 4, which further indicated that the NCS and ATFP had prominent spatial agglomeration characteristics and that provinces at similar levels were more likely to form clusters.

Regional spatial distribution features: To more deeply explore the ATFP and NCS spatial distributions and compare the main and non-main grain-producing areas differences after the MGPA policy pilot was implemented, based on the Moran index, ArcGIS software was used to illustrate the regional ATFP and NCS distribution characteristics and the size differences between the main and non-main grain-producing areas. Figure 6 shows that the ATFP in the main grain-producing areas and their neighboring provinces was mostly high. The NCS in the MGPA policy implementation provinces was much higher than in their neighboring provinces, which indicated that the main grain-producing areas were playing a lead role.

To further explore whether the agricultural production in the main grain-producing areas was playing a lead role and to elucidate the driving factors for the ATFP and NCS flow direction, a Gravity model was used to capture the spatial associations between the ATFP and NCS in each province, and social network visualization was employed to show the ATFP and NCS association networks. The arrow represents the driving

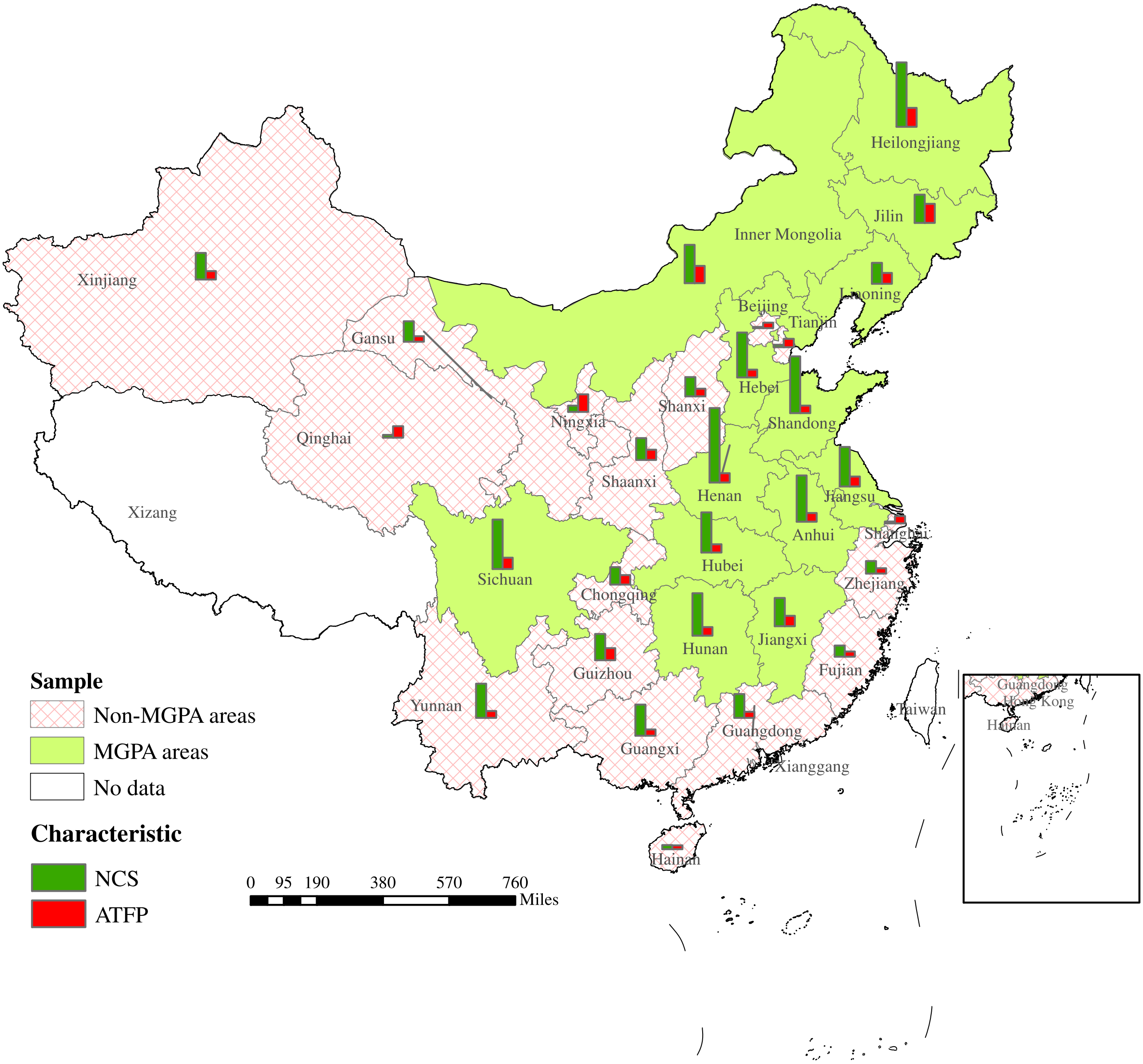
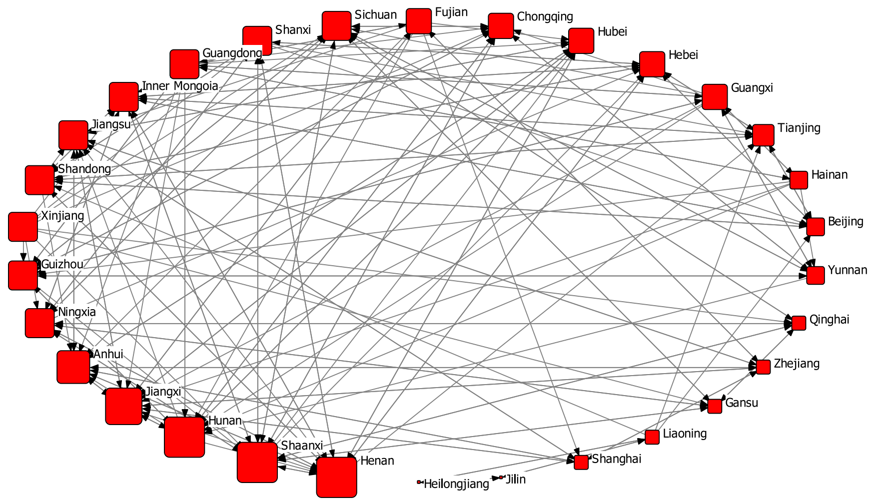


Fig. 6 Spatial distribution feature. The spatial ATFP and NCS distribution characteristics.

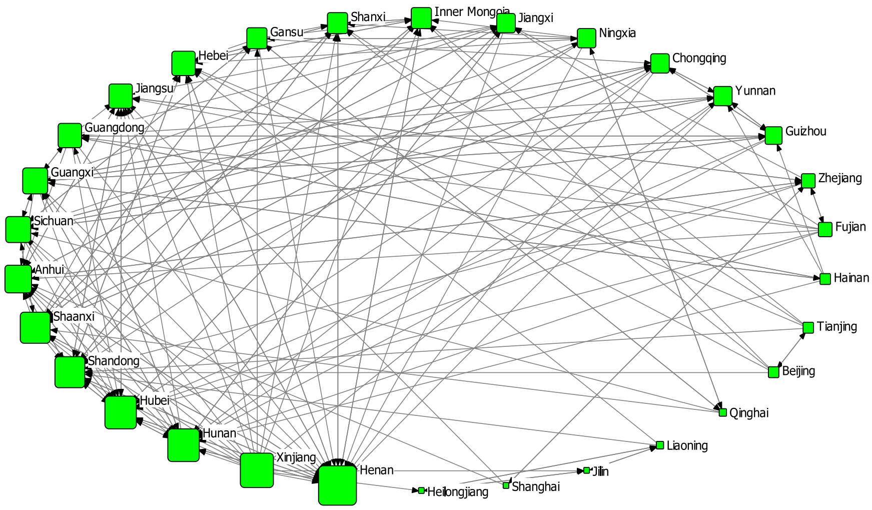
factor spillover directions and shows the ATFP and NCS polarization and diffusion effects (Liu et al., 2022c). Figure 7a shows that Henan, Hunan, Jiangxi, Anhui, and the other main grain-producing areas had comparative agricultural production advantages because of MGPA policy-related projects and funding preferences. They were found to have a strong correlation with the other provinces, which revealed the siphoning effects of the ATFP driving factors and the communication channels between the neighboring provinces. There were also some MGPA policy spillover effects in the non-main grain-producing areas, which indicated that the production agglomerations in the main grain-producing areas were gradually moving from a primary to a development stage. As shown in Fig. 7b, the NCS in Henan, Hunan, Hebei, Shandong, and the other main grain-producing areas were polarized and closely related to the other provinces, which further indicated the NCS driving factor siphoning effects. There were also some spillover effects in the main grain-producing areas. Unlike the ATFP, the NCS driving factor spillover direction was concentrated within the internal provinces in the main grain-producing areas.

MGPA policy performance test. To test whether the MGPA policy had resulted in economic and environmental dividends in the main grain-producing areas, had been an effective driving force for agricultural productivity, and had elevated China's double carbon peak and carbon neutral goals, the classical DID and SDID models were used to conduct a regression analysis on the MGPA policy effects on the NCS and ATFP. The MGPA policy effect evaluation category was then extended from the local areas to the neighboring areas. The estimation results are shown in Table 5.

Dual economic and environmental performance inspection. Based on the direct effect perspective, traditional DID model estimation found that the ATFP policy dummy variable regression coefficient (0.115) was significantly positive at a 1% level, which indicated that when compared with the non-main grain-producing areas, the MGPA policy had significantly improved the agricultural production efficiencies and the agricultural economic growth driving forces in the main grain-producing areas. On the one hand, to increase grain production, agricultural producers in the main grain-producing areas received a higher share of government funds for



(a) ATFP association network



(b) NCS association network

Fig. 7 ATFP and NCS social network association structure. The strength of the correlations between each region.

Table 5 MGPA effects on the NCS and ATFP.

Variables	ATFP		NCS	
	DID	SDID	DID	SDID
did	0.115***(3.35)	0.325***(4.011)	0.232***(5.91)	2.160***(9.584)
lnAPS	1.361***(13.59)	0.524***(6.103)		
lnAS	−0.414***(−8.79)	0.307***(9.039)		
lnRED	0.101*(1.88)	−0.009(−0.349)	0.028(0.40)	−0.693***(−7.046)
lnDD	−0.014(−1.29)	−0.001***(−0.120)	0.031**(2.35)	−0.071(−1.549)
lnAIS			−0.089(−0.60)	3.103***(13.679)
lnAED			0.119**(2.05)	1.365***(12.007)
TW*did		0.660***(3.371)		−1.020*(−1.703)
TW*lnAPS		1.611***(6.755)		
TW*lnAS		−0.453***(−5.985)		
TW*lnRED		0.158***(2.776)		−0.838***(−3.543)
TW*lnDD		0.356***(5.056)		0.714***(4.043)
TW*lnAIS				−4.833***(−9.668)
TW*lnAED				−0.658***(−2.779)
Constant	−1.465***(−3.01)	−1.666***(−3.927)	6.943***(11.18)	14.317***(6.208)
W*dep.var.		−0.537***(−4.306)		0.907***(49.945)
N	690	690	690	690
R-squared	0.573	0.549	0.218	0.508
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

*, **, ***, respectively, represent significance at 10%, 5%, and 1%.

regional planning and industrial and commercial grain construction. Therefore, even though there had been fund allocation differences in the various industry chains, the process objectives were the same: developing superior seeds, standard grain field construction, farmland water conservancy technological improvements, pest and disease prevention and control, and the upgrading of farm machinery and equipment, grain processing technology, and planting technology. To motivate higher production efficiency, producers were given guidance on optimizing their production environments and mastering the upgraded equipment, which gradually resulted in a scale effect. On the other hand, agricultural producers in the main grain-producing areas also received production incentives, which assisted the asset poverty-constrained agricultural producers to improve their technical efficiency for the existing production conditions and assist the non-asset poverty-constrained agricultural producers to upgrade their technology and gain scale benefits. Therefore, to enhance the overall ATFP, the policy had different technological progress, technical efficiency, and scale efficiency driving effects. This was similar to research in other industries, where technology, energy, urban land, and other factor production efficiencies were all improved to varying degrees in the context of urban scale development and manufacturing and service agglomeration (Cheng and Jin, 2020; Tanaka and Managi, 2021; Widodo et al., 2015; Zhang et al., 2022a). However, the conclusion may not be validated considering the actual situation in some regions.

The regression coefficient (0.232) for the NCS policy dummy variable was significantly positive at 1%, which indicated that compared with the non-main grain-producing areas, the MGPA policy had significantly improved the agricultural net carbon sink effect in the main grain-producing areas and had achieved the agricultural goal of reducing emissions, increasing carbon sinks, and improving economic performances. The key focus of the MGPA policy was to encourage agricultural production agglomeration and scale effects through targeted incentive policies: an extensive grain-producing county policy, a significant commodity grain base policy, a grain industry policy, a grain production core area policy, and some other measures. Therefore, on the one hand, the MGPA policy improved the planting industry's scale and standardization and enhanced its ability to absorb carbon emissions based on natural crop growth characteristics (Cui et al., 2021). On the other hand, the MGPA environmental policy effect was mainly related to the producers' internal and external economies of scale in the agglomeration areas. Because of production specialization, more efficient factor inputs, information technology sharing, and other advantages from the scale effect, previously fragmented planting in the main grain-producing areas significantly improved (Ding et al., 2022). Firstly, Industrial agglomeration generally leads to an increase in crop cultivation, which often leads to an increase in agricultural carbon emissions. However, after agricultural production efficiency improvements, carbon emissions per unit area generally decline. Secondly, proper scale planting can also promote the efficient use of agricultural materials and reduce the use of chemical fertilizers and pesticides, which can lead to a decrease in agricultural materials input carbon emissions. Therefore, the carbon emission density reduced while the output increased, as was also found by Peng et al. (2020), Wang et al. (2020b), and Liu and Zhang (2021b).

When examined from a spatial effects perspective, first, the SDID model estimation results revealed that the direct ATFP and NCS policy effect coefficients (0.325 and 2.160, respectively) were significantly positive at 1%, which was consistent with the DID model estimation results and confirmed the robustness of the regression results and the reliability of the SDID model results. Second, the spatial ATFP autoregressive coefficient (−0.537) was significantly negative, which indicated that there was a significant mutual ATFP inhibition between the provinces, that is, as provinces with high ATFPs had a stronger attraction to the agricultural production factors in adjacent regions, the ATFP growth was inhibited in these adjacent regions. The spatial NCS autoregressive coefficient (0.907) was significantly positive, which indicated that the NCS had a significant spatial spillover effect and that local NCS improvements promoted NCS improvements in adjacent regions. Third, the ATFP policy space item coefficient (0.660) was significantly positive at 1%, which indicated that the MGPA policy had had a positive spillover effect on the ATFP in neighboring provinces. Because the main grain-producing areas were agricultural production demonstration areas, there had been imitation and learning effects in neighboring provinces (Chen and Zhang, 2022). On the one hand, intangible knowledge elements such as technical experience, management experience, and governance system experience in the main grain-producing areas have smoothly overflowed through channels such as media experience reports, training sessions, and experience exchange meetings (Bai et al., 2017). After absorbing and applying this knowledge, producers in neighboring provinces improved their management efficiency and reduced the ineffective use of input factors, which was ultimately reflected in ATFP enhancement. On the other hand, agricultural producers in neighboring provinces also gained tangible material factors from the main grain-producing areas, such as new production equipment, and high-quality materials, which when adopted, improved their efficiencies and enhanced their ATFP (Aldieri et al., 2021). This policy space effect has also been observed in previous studies (Chen et al., 2021a; Yu and Li, 2021).

However, the NCS spatial term coefficient (−1.020) was significantly negative at 10%, which indicated that the MGPA environmental policy effects had not been carried over to surrounding provinces. Because ensuring national food quantity and quality security was a key reason for the MGPA policy, the lack of comparative advantage in the non-main grain-producing areas led to grain planting scale declines, which reduced carbon sinks and had no effect on the relatively high carbon emissions. These findings were in contrast to previous studies on the environmental performance spillover effects of environmental regulatory policies (Jia et al., 2021a; Yu and Zhang, 2021b), but were similar to the conclusions of Feng et al. (2020). However, it should be noted that the MGPA policy was not intended to be an environmental regulatory policy. Therefore, the NCS inhibition in the adjacent areas was not related to the pollution paradise hypothesis; rather, it was because of the policy-driven economic agglomeration.

The estimated APS coefficients regression results were significantly positive, which indicated that grain-oriented agricultural planting structures could improve local ATFP, promote agricultural production in adjacent areas, and benefit from scale efficiency. The direct AS effect was significantly positive, and the spatial item coefficient was significantly negative; the higher the agricultural machinery coverage, the more conducive to improving agricultural production efficiency (Li et al., 2021). However, due to terrain, agricultural machinery replacement costs, and other conditions, areas with low AS were more likely to lose high-quality elements. Although the direct effect RED coefficient in the SDID model was insignificant, the estimated RED coefficient in the DID model was significantly positive, which indicated that RED can be fed back to the primary industry through improved infrastructure, such as roads and information platforms. The spatial terms coefficient indicated that the effect had a spatial spillover effect on the surrounding provinces. The DD direct effect was significantly negative, and the spatial coefficient was significantly positive. As agricultural production is dependent on the weather, natural disasters can seriously affect agricultural inputs and outputs; therefore, as agricultural production in the surrounding areas is critical to food security, the market and the government must employ external means to

Table 6 Further effect of the MGPA policy on the NCS.

Variables	(1) CS	(2) CE	(3) CEI	(4) CED
did	2.158*** (9.592)	1.980*** (9.903)	0.532*** (7.302)	−0.008*** (−6.983)
TW*did	−1.020* (−1.707)	−1.092** (−2.100)	0.383* (1.866)	−0.012*** (−3.548)
Control variables	Control	Control	Control	Control
Constant	14.312*** (6.217)	14.144*** (7.005)	6.546*** (6.105)	0.431*** (6.896)
W*dep.var.	0.907*** (50.076)	0.915*** (54.327)	0.440*** (5.741)	0.534*** (8.622)
N	690	690	690	690
R-squared	0.509	0.5422	0.760	0.635
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

*, **, ***, respectively, represent significance at 10%, 5%, and 1%.

promote ATFP. Among the regression results of NCS, the RED regression results were significantly negative because the higher the urbanization in regions with high per capita GDP, the greater the secondary and tertiary economic development. While agricultural production gains external benefits from economic development, land management scales shrink with urban expansion. The spatial DD coefficient term was significantly positive, which was consistent with the ATFP conclusion, that is, the market and the government need to use external forces to promote production increases in surrounding areas. The direct AIS effect was significantly positive, and the spatial term coefficient was significantly negative. The more significant the AIS is under a scale economy, the higher the planting industry proportion, the lower the emissions, and the higher the carbon sinks. However, the more efficiently the adjacent area production factors flow out, the lower the possibility of scale expansion. The AED direct effect was significantly positive, and the spatial term coefficient was significantly negative, which indicated that economic development depended on agricultural production, which could lead to increases in agriculture's NCS effects. Because China's agriculture is in its primary modernization stage (Fei and Lin, 2017), regions with high AED are still polarized, which restrains the NCS in the surrounding areas.

Further environmental performance testing. The results confirmed that the MGPA policy had significantly improved the agricultural NCS in the main grain-producing areas, and was in line with China's double carbon goals. However, as it was not possible to determine whether the MGPA policy's path to NCS improvements was related to carbon reductions or carbon sink increases, it was necessary to further explore the impact of the MGPA policy on the agricultural carbon sinks (CS) and the agricultural carbon emissions (CE).

The results in column (1) in Table 6 show that the direct effect coefficient for the policy dummy variable was significantly positive, and the spatial effect coefficient was significantly negative, indicating that the increase in carbon sinks was one of the MGPA policy paths to NCS improvement in the main grain-producing areas. The MGPA policy has resulted in many advantages for the main grain-producing areas, such as rewards for large grain-producing counties, accelerated planting industry concentration scales, and improved carbon sink capacities. Given this pattern, the planting industry production factors in the surrounding provinces flowed to the main grain-producing areas, which reduced the scale and CS levels. The results in column (2) in Table 6 show that the MGPA policy did not reduce the total carbon planting industry emissions in the main grain-producing areas; however, this did not prove that the MGPA policy had not played an environmental role as the expanded planting scale inevitably led to an increase in total carbon emissions, that is, the MGPA policy's carbon reduction effect may not have been as significant as the growth in carbon emissions from the expanded production scale. Therefore, to ensure the authenticity of the environmental performance evaluation, the MGPA policy's carbon reduction effect was further explored using carbon emissions per unit output and unit area.

Columns (3) and (4) in Table 6, respectively, show the agricultural carbon intensity (CEI) and agricultural carbon density (CED) regression results, the direct effect coefficients for which were opposite. The CEI regression result was significantly positive, and the CED regression result was significantly negative, that is, the MGPA policy had significantly promoted the carbon emissions per unit output value in the main grain-producing areas and significantly reduced the carbon emissions per unit area. In this case, we still believe that the MGPA policy does play a part in carbon reduction performance. As the planting output value changes trends is difficult to reflect the planting scale change trends. The MGPA policy has led to grain-oriented planting structures, with a downward trend in cash crop scale. However, as the cash crop market income is higher than for food crops, the current grain-oriented production situation still resulted in small output value increases or decreases when business scales were expanded. Therefore, both the CE and CEI rose. As the CED excluded the planting scale change impacts, it was possible to determine whether the MGPA policy economies of scale had contributed to the carbon reductions per unit area. The direct CED effect was significantly negative, indicating that the large-scale production in the main grain-producing areas had led to a use reduction in or an abandonment of traditional agricultural materials, had reduced the carbon emissions per unit area, and had achieved carbon reductions through management innovations, optimized resource allocations, and technological innovation. The results comparison in column (2) indicates that the MGPA policy carbon reduction effect did not completely offset the emissions increment from the scale operation increases and that it takes longer for carbon density reductions to affect total carbon emissions reductions.

Robustness test

Replacing the spatiotemporal weight matrix. Weight matrices are cornerstones of spatial econometric modeling. The endogenous spatiotemporal weight matrix constructed in this paper meant that the impact of the initial spatial weight matrix setting was eliminated by the global Moran index proportion in different years, which was endogenous to the model data. Therefore, to further verify the stability of the research conclusions, a transformation space weight matrix was employed to assess whether the relationship between the same group of variables in the same period under the same research framework could be interpreted in the same way (Fan and Hudson, 2018). The adjacency matrix was replaced by a geographic distance matrix and an endogenous space-time weight matrix was

Table 7 Robustness test.

Variables	(1)		(2)		(3)	
	ATFP	NCS	ATFP	NCS	ATFP	NCS
did	0.414*** (5.344)	2.202*** (8.745)	−0.069 (−0.455)	0.857 (1.968)	0.391*** (3.982)	0.416** (2.533)
TW*did	2.835*** (6.907)	−1.122 (−0.848)	−0.139 (−0.252)	−1.257 (−0.405)	0.880*** (4.205)	−1.544*** (−4.423)
Control variables	Control	Control	Control	Control	Control	Control
Constant	−4.947*** (−4.722)	46.044*** (5.387)	1.789* (1.954)	66.163*** (4.648)	−2.415*** (−5.268)	10.538*** (6.190)
W*dep.var.	−0.999*** (−2.740)	0.164 (0.637)	0.369*** (3.561)	0.192 (0.655)	−0.410*** (−3.041)	0.984*** (384.529)
N	690	690	180	180	690	690
R-squared	0.594	0.434	0.409	0.461	0.587	0.876
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*, **, ***, respectively, represent significance at the 10%, 5%, and 1%.

constructed containing the variable time effects and geographical and economic dependencies between the regions, after which the SDID regression was conducted, the results for which are shown in Column (1) in Table 7. The ATFP direct and spatial effect coefficients were significantly positive, which verified the direct promotion and spatial spillover effects of the MGPA policy on the ATFP. The direct effect NCS coefficient was significantly positive; however, the spatial term coefficient was negative and insignificant. The possible explanation for these results was that because adjacent regions tend to have similar natural conditions, such as topography, climate, and crop type, the geographical distance matrix could have weakened these similarities. Because of the differences in social needs and natural conditions, the MGPA policy's spatial polarization would have been weakened; therefore, the benchmark regression results were still considered robust.

Falsification test. The MGPA policy was proposed in 2003 and formally implemented in 2004. To prioritize policy support and investment preferences, the main grain-producing areas' agricultural producers adjusted their agricultural production structures and integrated land management scale requirements (Zhang et al., 2021a). The ATFP and NCS changes in the main grain-producing areas may also have led to technological and management mode changes. Therefore, to exclude the impact of these unobservable factors on the benchmark regression results, a counterfactual test was conducted to determine whether the benchmark regression results included the expected MGPA policy effects (Gao et al., 2020). The MGPA policy implementation was advanced to 2002, and the sample was taken from 1998 to 2003 to test whether the MGPA policy affected the ATFP and NCS. If the coefficient was insignificant, it indicated that the ATFP and NCS improvements were the result of the MGPA policy rather than any other factors. The results in Table 7, Column (2) show that the direct and spatial effects of the ATFP and NCS coefficients were insignificant; that is, the double dividend resulted from the MGPA policy, which again confirmed the robustness of the results.

Endogeneity test. Both the DID and SDID models have been widely used to identify the effectiveness of pilot policies (Heckman and Robb Jr, 1985; Jia et al., 2021a; Li et al., 2017) as they allow for the establishment of quasi-natural random experiments, eliminate extraneous unobservable factors, and establish control and experimental groups. However, policy implementation is not random and is closely related to regional economic development levels, primary agricultural conditions, geographical locations, and other factors. Therefore, as the initial differences between the provinces could have impacted the ATFP and NCS differently, there may have been estimation deviations. To control for the influence of these factors, the cross terms for these benchmark factors and linear time trends were added to the regression (Edmonds et al., 2010; Lu et al., 2017; Song et al., 2019b) using the following equation:

$$Y_{it} = \alpha + \rho \mathrm{TW}\, Y_{i,t} + \beta \mathrm{TEST}_{i,t} + \varphi X'_{i,t} + \varepsilon Z'_{i,t} \times \mathrm{time} + \beta^{*} \mathrm{TW\ TEST}_{i,t} + \varphi^{*} \mathrm{TW}\, X' + \varepsilon^{*} \mathrm{TW}\, Z'_{i,t} \times time + u_i + v_t + \varepsilon_{it} \quad (15)$$

where $Z'_{i,t}$ represents the geographical locations and the agricultural production conditions in the province, and specifically indicated whether it was an eastern province, whether the land management scale from 1998 to 2003 was higher than the national average, and whether the agricultural machinery level from 1998 to 2003 was higher than the national average. time represented the linear time trend, with $Z'_{i,t} \times$ time controlling the influences of the inherent linear ATFP and NCS characteristic differences between the provinces before the MGPA policy implementation to avoid any possible estimation deviations resulting from the non-random selection of the main grain-producing areas. Column (3) in Table 7 reports the estimation results after controlling for these inherent characteristics. The direct and the spatial effect ATFP and NCS coefficients were consistent with the benchmark regression results, which again verified the benchmark regression results and resolved any possible endogeneity problems.

Table 8 Changing the standard error.

Variables	(1) ATFP		(2) NCS	
	DID	SDID	DID	SDID
did	0.115*** (3.35)	0.161*** (4.47)	0.230** (2.25)	0.066** (2.26)
TW*did		0.361*** (5.33)		−0.072* (−1.68)
Control variables	Control	Control	Control	Control
N	690	690	682	680
R-squared	0.573	0.286	0.222	0.972
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Values in the parentheses are the clustering standard errors at the provincial level; *, **, ***, respectively, represent significance at 10%, 5%, and 1%.

Changing the standard error. To mitigate the potential impact of different initial economic development levels across provinces, this study used standard clustering errors for regressions at the provincial level. The results in Table 8 show that the ATFP and NCS regression results were consistent with the benchmark regression results; therefore, the benchmark regression results were robust.

Mechanism identification

Mechanism identification of environmental performance. The above analysis only confirmed the double dividend of the MGPA policy from a local perspective. Because the MGPA policy was initially established to enhance economic performance, it was not clear whether the environmental performance depended on economic performance achievements. Therefore, the ATFP was introduced into the MGPA policy influencing process on the NCS to further explore the logical associations between the dual dividends. Because the ATFP could be decomposed into three separated indices; technical progress, scale efficiency, and pure technical efficiency (Li et al., 2019); to explore the refinement role path, technological innovation (TI) (Chen et al., 2008), operational scale (OS) and technology adoption (TA) were used to respectively measure the ATFP decomposition terms.

The mechanism variables (from now on referred to as M) were then added to the benchmark regression to assess whether they had played mediating roles in the transmission direction, which was accomplished by observing the changes in the policy dummy variable (did) coefficients (Alesina and Zhuravskaya, 2011; Persico et al., 2004). As shown in Fig. 8, path 1, if the did coefficient decreased after M was added to the benchmark regression, this variable was considered a positive MGPA policy mechanism affecting NCS, that is, when the MGPA positively (or negatively) affected M, M also positively (or negatively) affected NCS. As shown in Fig. 8, path 2, if the did coefficient increased after M was added to the benchmark regression, it indicated that this variable was a negative MGPA policy mechanism affecting NCS, that is, when the MGPA positively (or negatively) affected M, M negatively (or positively) affected NCS. The results when the mediating variables were included in the benchmark regression are shown in Table 9.

Compared with column (1), column (2) shows that the did coefficient decreased by 0.145, and the ATFP coefficient was significantly positive, that is, the ATFP was a positive MGPA policy mechanism to improve NCS. Therefore, the detailed conduction direction of ATFP was further explored.

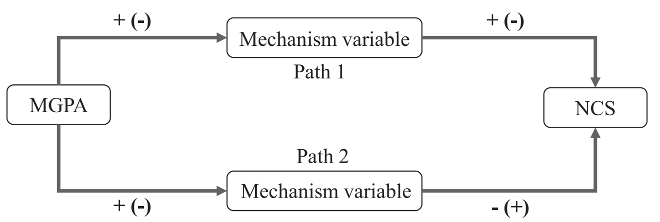


Fig. 8 Forward mechanism. Possible action paths for the mechanism variables for the MGPA policy effects on NCS.

First, the technological innovation transmission mechanism was explored. Compared with column (1), column (3) shows a 0.142 decrease in the did coefficient and a significantly positive TI coefficient, indicating that TI was a positive MGPA policy mechanism promoting NCS and verifying that TI was one of the directions in which the ATFP played a mechanism role. Therefore, the production technology research and development potential in the main grain-producing areas improved because of the national funding and associated projects. On the one hand, producers were willing to use new technologies when guaranteed income (Aldieri et al., 2021), and on the other hand, the continuous improvements in the market demand and scientific and technological research and development institutions accelerated agricultural science and technology research. Cost minimization drove agricultural technological innovation, which reduced carbon source material consumption, increased grain yields, reduced carbon densities, and increased planting scales.

Second, the technology adoption transmission mechanism was explored. Compared with column (1), the did coefficient in column (4) decreased by 0.145, and the TA coefficient was significantly positive, indicating that TA was a positive MGPA policy mechanism for environmental performance improvements and verifying that TA was one of the directions in which ATFP played a mechanism role. This may have been because the MGPA policy's agricultural machinery subsidies increased the producers' modern agricultural production technology adoption through cost sharing and the associated economic benefits demonstration, and the MGPA policy's technology promotion encouraged producers to substitute new agricultural technologies for inefficient technologies (Wu and Ding, 2021) to increase their TA. On the one hand, substituting agricultural machinery for labor improved production efficiency, with the higher economic returns stimulating producers to expand their planting scales, which in turn, improved the carbon sink capacities. On the other hand, the increased use of agricultural machinery also reduced the need for extensive treatment methods, such as straw burning, and the associated carbon emissions (Capaz et al., 2013). While some studies have found that the environmental efficiency of agricultural mechanization was significantly negative and had a downward trend (Jiang et al., 2020), this may have been because mechanical production needs a coordinated scale to improve factor productivity and the NCS. For example, Northeast China, an important grain-producing area in China, has high mechanization and, in recent years, has significantly improved its cultivated land intensification (Zhong et al., 2022), which has

Table 9 Mechanism identification for environmental performance.

Variables	NCS (1)	NCS (2)	NCS (3)	NCS (4)	NCS (5)
did	2.160*** (9.584)	2.015*** (8.830)	2.018*** (10.780)	2.015*** (8.976)	1.518*** (10.214)
ATFP		0.319*** (3.409)			
TI			0.555*** (18.846)		
TA				0.380*** (3.947)	
OS					0.574*** (8.873)
Control variables	Control	Control	Control	Control	Control
Constant	14.317*** (6.208)	10.401*** (3.459)	18.878*** (7.804)	16.370*** (5.619)	17.278*** (8.968)
N	690	690	690	690	690
R-squared	0.508	0.518	0.673	0.521	0.833
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*** represents significance at 1%.

improved efficiency and significantly reduced its carbon densities (Tian et al., 2021).

Third, the transmission mechanism based on scale operations was explored. Compared with column (1), the benchmark regression coefficient in column (5) decreased by 0.642, and was significantly positive, indicating that OS was a positive MGPA policy mechanism to improve NCS and verified that OS was one of the directions in which ATFP played a mechanism role. This indicated that the high-yield rewards and financial support provided through the MGPA policy accelerated land transfers, strengthened the protection of cultivated land, and encouraged producers to expand their operating scales and develop more effective carbon sinks. Further, because large-scale operations require that production facilities and agricultural technologies be shared, production costs fall, there are fewer carbon sources and materials used, and therefore, there is a reduction in carbon emissions.

In summary, the three ATFP variables were all found to play mediating roles. The comparison of the effects of the three variables shown in Fig. 9 revealed that OS played the most prominent role in the refining mechanism, followed by TI and TA. This indicated that the MGPA policy improved NCS through ATFP, the ATFP mechanism was mainly reflected in the operating scale expansions, and there was room for TI and TA improvements. Therefore, this analysis revealed that the environmental performances resulting from the MGPA policy had been mainly driven by scale expansions and that technological promotion and innovation had played small driving roles, which was not conducive to sustainable NCS improvements. Therefore, the policy preferences in the main grain-producing areas should be consciously biased toward improved agricultural technology.

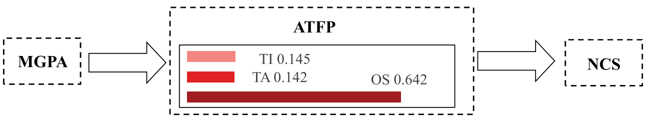


Fig. 9 Comparison of three mechanisms. Comparison of the MGPA policy effects for three refinement mechanisms that affect NCS.

Further analysis. The above analysis confirmed that environmental performances depended on their economic performances. Therefore, it was necessary to explore the action paths affecting economic performance to ensure the double dividend. The economic MGPA policy performance effect was influenced by the local governments' focus on agricultural production and the agricultural development stage. Therefore, moderating variables; government support (GS), production support (PS), and collaborative support (CS); were introduced to identify the MGPA policy mechanism path to improved economic performance, the results for which are shown in Table 10.

GS analysis. As shown in Table 10, the direct effect of GS was significantly negative, which indicated that government financial support had not yet improved agricultural production efficiency and had inhibited agricultural economic growth, which was counter to the original intentions. On the one hand, these results indicated that China's government support tended to focus on distribution rather than effect and there was an inefficient use of funds. There was a serious lag in fund circulation for projects such as the external construction of public products and for the allocation of the agricultural material purchase subsidies needed for agricultural growth, which hampered increases in agricultural production and quality. Agricultural production was also constrained by both natural and market risks. In a mature market when supply exceeds demand, unreasonable government support can hinder marketization, disrupt market order, send negative market prediction signals to agricultural producers, adversely affect technology promotion and scale effect realization, and ultimately inhibit agricultural production efficiency improvements (Tan et al., 2013; Zhang et al., 2021b). On the other hand, while this paper measured agricultural economic output quantity, most rational agricultural producers tend to plan agricultural production from a cost-benefit perspective and then seek to maximize their economic benefits by improving quality. Therefore, because of the production conditions provided by the MGPA policy, the producers may have sought to cultivate superior agricultural products rather than increasing output,

Table 10 Further analysis of the economic performance mechanism.

Variables	ATFP	G-support	P-support	C-support
	(1)	(2)	(3)	(4)
did	0.325***(4.011)	1.953***(3.387)	1.371***(5.352)	0.441***(4.716)
GS		−0.068***(−1.812)		
did*GS		0.531***(2.916)		
PS			−0.150***(−4.546)	
did*PS			0.961***(5.537)	
GS*PS				0.001(0.034)
did*CS				0.151*(1.944)
TW*did	0.660***(3.371)	10.153***(2.689)	2.963***(4.750)	0.448*(1.667)
TW*GS		−0.408**(−2.149)		
TW* did*GS		2.851**(2.387)		
TW*PS			−0.745***(−9.818)	
TW*did*PS			2.105***(4.425)	
TW*CS				0.074**(2.017)
TW*did*CS				−0.750***(−3.014)
Control variables	Control	Control	Control	Control
Constant	−1.666***(−3.927)	−2.167***(−3.912)	−0.685*(−1.648)	−1.695***(−3.505)
W*dep.var.	−0.537***(−4.306)	−0.496***(−3.922)	0.068(0.702)	−0.425***(−3.334)
N	690	690	690	690
R-squared	0.549	0.568	0.371	0.563
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

*, **, *** respectively, represent significance at 10%, 5%, and 1%.

which means that the GS support effect may not yet be reflected in the ATFP. Interestingly, the direct effect of the did*GS was significantly positive, which was opposite to the direct GS effect and indicated that in the main grain-producing areas, the original food security intention of the policy played a guiding and optimization role for the government's financial support, that is, it highlighted the social and political effects and emphasized the economic effects. Therefore, the growth in agricultural support funds and the reasonable arrangements enhanced the role of the MGPA policy in promoting ATFP.

The indirect GS effect was significantly negative, indicating that the government's financial support for agriculture negatively impacted the ATFP in neighboring provinces. This may have been because the agricultural financial expenditure improved the external agricultural production environment (Boyle et al., 2014) and reduced total producer costs. While agricultural enterprises tend to follow the interest orientations and production investment distributions from provinces with good public facilities and more capital subsidies, there is competition for similar agricultural products in neighboring provinces. Because the MGPA policy subsidies put farmers in the neighboring provinces at a price competition disadvantage, weaker farmers may have allocated their income sources to factors such as migrant workers to avoid competition, which would have reduced their production scales and any centralized production advantages, which would have adversely affected AFTP improvements. However, the indirect effect of did*GS was significantly positive, which indicated that the agricultural expenditure based on the MGPA policy could improve the ATFP in neighboring provinces. The possible explanation is that under MGPA policy guidance, the provinces in the main grain-producing areas increased their local food crop shares to ensure food production security, which could have motivated neighboring provinces to expand their cash crop scales, which could have improved their ATFP through economies of scale. Further, to improve productivity, after the main grain-producing areas increased their agricultural technology research and development investments, the surrounding provinces also adopted advanced agricultural production technologies and business models, which would have led to ATFP improvements.

PS analysis. The direct PS effect was significantly negative, indicating that any agricultural industry agglomeration improvements would inhibit the ATFP, that is, the ATFP was not shown to continuously improve with the PS level. The possible explanation for this was that the producer concentration resulted in innovation inertia because of the competition intensification and the restricted environmental resources, that is, innovation may have become a high-risk behavior to be avoided (Peng et al., 2022). In this situation, conservative producers would have sought to increase their income by expanding their scale rather than by increasing their unit outputs. The increases in factor prices associated with industrial agglomeration are often more detrimental to factor selection optimization and overall industry configuration, which could hinder the adoption of innovations and ATFP improvements. The did*PS was significantly positive, which indicated that any increase in PS in the main grain-producing areas promoted increases in their ATFP. This result was possible because the main production areas took the lead in implementing the government-led advanced production technology and operating system pilot projects. Because of the intensive producer distributions, the economic benefits from the advanced production modes could have had a better driving effect (Zeng and Yu, 2022), which could have improved the willingness of producers to adopt new production technologies, which then promoted ATFP improvements.

The indirect PS effect was significantly negative, which indicated that agricultural industry clusters could inhibit ATFP increases in neighboring provinces. This may have been because there was an increase in product output in the industrial clusters (Garcia et al., 2020; Wang et al., 2022a), which resulted in a decrease in production scale and R&D investments in the neighboring provinces because of the increased competition, which inhibited ATFP. The indirect effect of PS*did was significantly positive, which proved that the PS in the main grain-producing areas improved the ATFP in the neighboring provinces possibly because the main grain-producing areas industrially agglomerated to focus on mechanization and land intensification; for example, the mechanical corn harvest rate reached more than 75% in 2018 (Xie et al., 2022), which increased the surplus of rural labor in the main grain-producing areas, which gave the neighboring provinces additional agricultural labor sources and improved their ATFP.

CS analysis. The direct effect of CS was not significant. Based on the above analysis, there may be two reasons for this result. First, the PS could have prevented producers from technologically innovating because of the risks, which would have inhibited the ATFP. However, as GS can spread producer costs, reduce risks (Gao et al., 2021), and encourage technological progress, the CS inhibited the negative PS mechanism on ATFP. Second, the PS guides agricultural public infrastructure construction, which reduces financial agriculture support waste, improves facilities and economic benefit utilization rates due to the producer concentration, and promotes the GS role in improving ATFP. Therefore, PS and GS coordination reduces any adverse effects on ATFP. The direct effect of did*CS was significantly positive, which indicated that the CS in the main grain-producing areas could have improved the ATFP. Financial support could have led to improved local public facilities, and industrial agglomeration could have promoted producer information sharing and improved the local ATFP.

The indirect effect of CS was significantly positive, which indicated that CS had had a positive effect on the ATFP in neighboring provinces. This could have been because of increased collaborative agricultural investment and producer support in the local agricultural agglomeration areas. Modern agricultural construction may have had a driving and demonstration effect on neighboring provinces and improved their ATFP. However, although the indirect effects of GS and PS in the main grain-producing areas were significantly positive, the indirect effects of did*CS were significantly negative. The possible explanation is that the simultaneous implementation of GS and PS under the MGPA policy attracted key modern production factors that were in short supply, such as technical personnel and agricultural investment, which consequently restrained the ATFP in the neighboring provinces.

Conclusion

Based on 1998 to 2020 panel data from 30 provincial regions in China, this paper used DID and SDID models with spatio-temporal weight matrices to test the direct and spatial spillover effects of China's MGPA policy on ATFP and NCS and analyze the specific MGPA policy paths affecting ATFP and NCS, from which the following conclusions were drawn.

(1) The MGPA policy improved the ATFP through special financial support and production incentives. The results were validated through a series of robustness tests. The spatial autoregressive ATFP coefficient was significantly negative, and the spatial MGPA policy spillover on ATFP was significantly positive, which indicated that the main

grain-producing areas played a demonstration role in promoting increased ATFP in the neighboring provinces through the intangible and tangible spillover factors.

(2) The MGPA policy significantly improved the NCS in the main grain-producing areas. Further analysis revealed that increased CS and reduced CE per unit area were the main environmental MGPA policy performance improvements. Although the spatial autoregressive NCS coefficient indicated that the agricultural NCS between the provinces was mutually promoting, the spatial spillover effect of the MGPA policy on NCS was significantly negative, which suppressed the agricultural production NCS in neighboring provinces was objectively suppressed due to the production agglomeration in the main grain-producing areas.

(3) The environmental performance mechanism analysis revealed that the MGPA policy had double dividends and positively impacted environmental performance through economic performance. The detailed ATFP mechanism analysis revealed that TI, TA, and OS were all positive MGPA policy mechanisms for NCS improvements. OS was found to have the most significant impact, which indicated that land fragmentation in China's main grain-producing areas was still widespread.

(4) The MGPA policy economic performance mechanism analysis indicated that GS, PS, and CS all positively contributed to enhanced economic performances and increased the ATFP in the main grain-producing areas. PS was found to play the most prominent role, indicating that industrial agglomeration was more efficient in generating positive MGPA policy effects. Spatially, both GS and PS positively contributed to MGPA policy economic performance spatial spillovers due to market changes, factor flows, and labor spillovers. Due to the combined GS and PS effect, the main grain-producing areas were able to attract critical factors, leading to an opposite CS result.

Future studies should consider regional differences when investigating the MGPA policy impact on ATFP and NCS. To more fully understand the MGPA policy implementation effects, it is also necessary to evaluate the MGPA policy differences between the economic and environmental performances using more detailed local categories.

Policy implications

The following policy recommendations were formulated from the above conclusions.

(1) Continue to implement support policies in the main grain-producing areas. Because the MGPA policy double dividend was verified in the main grain-producing areas, the policy should continue to be promoted. To improve the fund utilization rate of special subsidies and production incentives and further enhance the MGPA policy performance, two steps could be taken. First, the fund flow monitoring platform needs to be re-established or upgraded to ensure that local measures such as factor subsidies and public facility construction are implemented. Second, to ensure real-time agricultural data network ranking system for agricultural production needs to be constructed that assesses food production, arable land utilization, and producer situations in main grain-producing areas.

(2) Promote land transfers and develop moderate-scale operations to encourage intensive production. First, relevant agriculture and rural departments should establish efficient land transfer mechanisms and arable land protection methods to promote agricultural production clustering and regional production specialization and improve information sharing and infrastructure sharing to enhance regional agricultural production output efficiency. Second, to further improve the ATFP in the main grain-producing areas, financial support for agriculture must be strengthened to accelerate public facility construction in agricultural agglomeration areas and stimulate the scale effects.

(3) To promote both economic and environmental performances, greater attention needs to be paid to policy-derived performances. Positive MGPA policy environmental performance was verified, which indicated that the policy was able to simultaneously address national food security and environmental protection issues. However, current environmental performances are still limited. Therefore, focusing on measures such as technological upgrading and rational production layout planning can enhance MGPA policy environmental benefits, such as reductions in surface source pollution and carbon emissions.

(4) A spatial network of agricultural factors centered on the main grain-producing areas needs to be developed. First, establishing a technological R & D cooperative mechanism between provinces led by the main grain-producing areas and involving neighboring provinces could promote cost-sharing, results-sharing, and an overall improvement in agricultural production efficiency. Second, strengthening agricultural production planning communication between provinces, which would also obviate any negative competition.

Data availability

All data generated or analyzed during this study is submitted as a supplementary file.

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Author contributions

The authors confirm their contribution to the paper as follows: DY: conceptualization, methodology, software, writing, and formatting; SZ: data curation, writing—original draft; WW: writing—review & editing, visualization; YL: research idea and design, participation in related article writing. All authors agree to be held accountable for the accuracy and integrity of this research.

Competing interests

The authors declare no competing interests.

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