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Dynamic analysis of agricultural green development efficiency in China: Spatiotemporal evolution and influencing factors (Postprint)

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Abstract

Green development of agriculture is important for achieving coordinated and high-quality regional development for China. Using provincial data from 1990 to 2020, this work explored the dynamics of agricultural green development efficiency of 31 provinces in China, its spatiotemporal characteristics, and its driving factors using a super-efficiency slacks-based measure (Super-SBM), the Malmquist productivity index (MPI), spatial autocorrelation, and a geographic detector. Results showed that the overall agricultural green development efficiency showed a U-shaped trend, suggesting a low level of efficiency. Although a gradient difference was visible among eastern, central, and western regions, the efficiency gap narrowed each year. Technological progress and efficiency both promoted agricultural green development efficiency, especially technological progress. Agricultural green development efficiency had significant spatial aggregation characteristics, but Moran' s I result showed a downward trend from 2015 to 2020, indicating a risk of spatial dispersion in the later stage. The provinces with high agricultural green development efficiency were mainly concentrated in the eastern region, while those with low efficiency were concentrated in the central and western regions. Agricultural green development efficiency was influenced by various factors, which showed differences according to time and region. The impact of the labor force' s education level and technological progress increased during the study period, and significantly facilitated agricultural green development efficiency in the eastern region, while the central and western regions were still affected by the scale level and environmental regulation, reflecting the advantages of the eastern region in terms of economy and technology. In the future, strengthening agricultural scientific and technological innovation and deepening interprovincial cooperation can help further improve the level of green agricultural development. In addition, local governments should formulate more precise local agricultural support policies based on macro-level policies and local conditions.

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Full Text

Preamble

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Dynamic Analysis of Agricultural Green Development Efficiency in China: Spatiotemporal Evolution and Influencing Factors

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Abstract: Green development of agriculture is crucial for achieving coordinated and high-quality regional development in China. Using provincial data from 1990 to 2020, this study explored the dynamics of agricultural green development efficiency across 31 Chinese provinces, examining its spatiotemporal characteristics and driving factors through a super-efficiency slacks-based measure (Super-SBM), the Malmquist productivity index (MPI), spatial autocorrelation analysis, and geographic detector methods. Results showed that overall agricultural green development efficiency exhibited a U-shaped trend, indicating a generally low efficiency level. Although gradient differences were evident among eastern, central, and western regions, the efficiency gap narrowed annually. Both technological progress and efficiency improvements promoted agricultural green development efficiency, with technological progress playing a particularly important role. Agricultural green development efficiency displayed significant spatial aggregation characteristics, though Moran' s I showed a downward trend from 2015 to 2020, suggesting a risk of spatial dispersion in later stages. Provinces with high agricultural green development efficiency were concentrated mainly in the eastern region, while low-efficiency provinces were concentrated in the central and western regions. Agricultural green development efficiency was influenced by various factors that showed temporal and regional variations. The impact of labor force education level and technological progress increased during the study period, significantly facilitating agricultural green development efficiency in the eastern region, while the central and western regions remained affected by scale level and environmental regulation, reflecting the eastern region' s advantages in economy and technology. In the future, strengthening agricultural scientific and technological innovation and deepening interprovincial cooperation can help further improve green agricultural development. Additionally, local governments should formulate more precise local agricultural support policies based on macro-level policies and local conditions.

Keywords: regional development; economy; technology; spatial evolution; influencing factors; super-efficiency slacks-based measure

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1 Introduction

Green development represents a paramount objective in China' s contemporary development agenda. Promoting green agricultural development is essential for accelerating agricultural supply-side reform, fostering sustainable agricultural development, and preserving ecological resources. Although China has achieved considerable progress in agricultural technology and development, production continues to face challenges. For instance, increasing pollution levels and non-ecological factors have generated various resource and environmental problems, including food safety issues, nonpoint source pollution, and declining soil fertility (Wang, 2020). Agriculture has replaced industry as China's largest pollution source (Wang and Lin, 2021), making the transformation of agriculture to improve quality and efficiency an urgent priority.

Green development efficiency serves as the primary method for measuring the level of green development. Higher green development efficiency corresponds to higher levels of green development, and improving such efficiency represents an important pathway for promoting society' s transition toward environmental sustainability (Xue et al., 2020; Yang et al., 2022). Researchers have developed green development efficiency based on relevant international theories, primarily stemming from the ecological efficiency theory proposed by Schaltegger and Sturm (1990), which aims to measure the relationship between economic development and the environment. The core mission of green development involves achieving balance between economic growth, social progress, and ecological protection by treating resources and the environment as endogenous growth factors and constructing a common, coordinated, and fair sustainable development model through changes in development mechanisms and modes. Correspondingly, agricultural green development efficiency minimizes pollution and resource excess while ensuring agricultural economic development (Coluccia et al., 2020; Cui et al., 2021; Duan et al., 2021). By constructing an index system to measure agricultural green development, we can reflect the effectiveness of agricultural green development initiatives (Bergius et al., 2017; Firbank, 2020). Agricultural green development efficiency has been widely documented across various production sectors, including dairy, olives, rain-fed farms, and rice (Meul et al., 2007; Basset-Mens et al., 2009; Picazo-Tadeo et al., 2011; Gómez-Limón et al., 2012; Saber et al., 2021). Some scholars have examined promotion mechanisms through specific aspects such as agricultural nitrogen efficiency (Godinot et al., 2016), agricultural water use efficiency (Todorovic et al., 2016; Akram and Mendelsohn, 2017), and agricultural machinery efficiency (Hillesheim and Luxem, 2018). In recent years, research perspectives have diversified; for example, Kanter et al. (2018) studied the relationship between agricultural industrialization and green development efficiency, while Colmenares and Cando (2021) and Song et al. (2022) discussed climate change impacts.

Data envelopment analysis (DEA) and improved DEA models, such as the slacks-based measure (SBM) and Super-SBM, are commonly used to measure agricultural green development efficiency (Pan and Ying, 2013; Bell et al., 2016; Lahouel, 2016; Jia and Xia, 2017). Additional measurement methods include stochastic frontier analysis (Quiroga et al., 2017; Han et al., 2018), life-cycle assessment (LCA) (Rodríguez et al., 2019), analytic hierarchy process (AHP) (Zeng and Yu, 2022), entropy method (Chen et al., 2022), and ecological footprint (Yang and Yang, 2019). These methods have been employed to examine resource utilization, evaluate outcomes, and provide development warnings (Angulo Meza et al., 2019; Richterova et al., 2021).

Research on China' s agricultural green development efficiency has focused on three aspects: regional agricultural resource utilization efficiency, natural and social resource allocation efficiency, and efficiency under resource and environmental constraints. Studies on regional resource utilization efficiency have used national, provincial, and watershed data (Wu and Song, 2018; Fu et al., 2020; Gao and Ge, 2020; Guo et al., 2021), focusing specifically on water and cultivated land resources (Tong et al., 2015; Zhang et al., 2017; Xu, 2018). Research on resource allocation efficiency has examined water, land, and scientific-technological resources (Deng and Yang, 2017; Tang and Wang, 2018; Lu et al., 2022). Studies under environmental and resource constraints have analyzed agricultural technical efficiency, production efficiency, and environmental efficiency (Cui, 2018). Literature topics have primarily addressed efficiency measurement and evaluation (Meng et al., 2017; Tang and Wang, 2018), spatiotemporal evolution (Du and Jiang, 2020), development-oriented prediction (Song et al., 2013), and environmental impact analysis (Zeng et al., 2018).

Several research gaps remain. First, most studies have focused on river basins rather than the national level. In the new era, a "divide-and-rule" development model holds great significance for regional coordinated development and improving green agricultural development efficiency. Given China' s vast territory, strengthening policy formulation and implementation from an interprovincial cooperation perspective is necessary. Additionally, most studies have used cross-sectional data to examine efficiency from single perspectives (e.g., water or cultivated land resource efficiency) and have seldom employed long-period panel data to measure agricultural green development efficiency, resulting in limited analysis of spatiotemporal distribution patterns and evolutionary regulation. Comprehensive measurement of the spatiotemporal process is not only conducive to assessing past and current agricultural development status but also enables future trend prediction through spatial pattern changes. Research must be strengthened from a spatiotemporal evolution perspective, incorporating carbon emissions and environmental pollution as undesirable outputs. Another weakness concerns measurement models; most studies use the SBM model with undesirable outputs but seldom consider further comparison of decision-making units with efficiency values of 1, making the Super-SBM model necessary.

Addressing these gaps, this study offers a diversified perspective by comprehensively utilizing efficiency measurement, spatial analysis, interprovincial geographic detection, and measuring agricultural green development efficiency across China. Based on Super-SBM, we constructed a quantitative evaluation model incorporating economic input, resource input, economic output, and pollution output to measure efficiency in 31 provinces (including autonomous regions and province-level municipalities) from 1990 to 2020. We then used MPI to analyze dynamic change drivers, examined spatial distribution and evolution characteristics through spatial autocorrelation analysis, and employed geographic detector technology to reveal influencing factors. This process addressed three key questions: How does China' s agricultural green development efficiency evolve? What are its spatiotemporal characteristics? What drives its growth at production and factor levels? Addressing these issues can promote green development of China' s agricultural economy and provide macro-level data references for rural revitalization and high-quality agricultural production.

2.1 Index System

Agricultural green development efficiency represents the efficiency value between inputs and outputs, requiring indicator selection from both perspectives. Indicators should be selected based on scientific validity, availability, and systematic principles, referencing established mature research.

Based on previous studies, we selected the number of agricultural employees, crop-sowing area, effective irrigation area, total power of agricultural machinery, and chemical fertilizer application as input factor indicators (Pan, 2014; Wang and Zhang, 2018; Wei et al., 2018; Sun et al., 2019). Expected output indices included the total output value of agriculture, forestry, animal husbandry, and fisheries, converted to constant 1990 prices. Unexpected outputs adversely impact the agricultural production environment. Most scholars have considered agricultural carbon emissions or nonpoint source pollution, which are correlated and should both be treated as unexpected outputs for more accurate green development measurement. Agricultural nonpoint source pollution manifests primarily through excessive use and residual pollution of agricultural chemicals such as fertilizers, pesticides, and agricultural film. Therefore, we used excess nitrogen (phosphorus) from chemical fertilizers and agricultural film residue to characterize pollution levels (Wang and Zhang, 2018; Guo et al., 2021). The indicators are shown in Table 1 .

2.2 Super-SBM Model

The Super-SBM model assessed agricultural green development efficiency, with specific calculations performed using MaxDEA. The first step established a possible production set of inputs and outputs, including factor inputs, economic growth, and emissions output, forming an efficiency analysis framework. Assuming the production system has n decision-making units (DMUs), namely provinces, each DMU contains three input-output vectors: input, expected output, and unexpected output, defined as three matrices **X**, **Y**^d, and **Y**^u, where **X** = [x$_1$, ···, x], **Y**^d = [y$_1$^d, ···, y ^d], and **Y**^u = [y$_1$^u, ···, y ^u].

The possible production set of inputs and outputs can be defined as:

$$P = \{(x, y^d, y^u) \mid x \geq X\lambda, y^d \leq Y^d\lambda, y^u \geq Y^u\lambda, \lambda \geq 0\}$$

where P is the possible production set and λ represents the ideal expected input, economic growth, and emissions output of the frontier.

The second step constructed a Super-SBM model containing unexpected outputs. The specific calculation formula is as follows:

$$\rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 - \frac{1}{s_1+s_2}\left(\sum_{p=1}^{s_1}\frac{s_p^{d+}}{y_{pk}^d} + \sum_{q=1}^{s_2}\frac{s_q^{u+}}{y_{qk}^u}\right)}$$

where is agricultural green development efficiency; m, s_1, and s_2 represent the number of input elements, expected outputs, and unexpected outputs, respectively; j and k denote DMU and DMU , respectively; i, p, and q represent input, expected output, and unexpected output values; **s**$^-$, **s**^d+, and **s**^u+ are slack vectors for input, expected output, and unexpected output, respectively; and λ is a constant vector representing the weight of each DMU.

2.3 MPI

The MPI generally measures production efficiency by decomposing efficiency change into two components: the technical progress change index (TC) and technical efficiency change index (EC) (Guan and Tan, 2014). Since improvements in agricultural total-factor productivity (TFP) represent productivity gains and industrial upgrading conducive to green development efficiency, we used this method to analyze TC and EC contributions. The specific model is as follows:

$$\text{TFP} = \text{TC} \times \text{EC},$$

$$\mathrm{TC} = \left[\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^{t+1}, y^{t+1})} \times \frac{D_0^{t+1}(x^t, y^t)}{D_0^t(x^t, y^t)} \right]^{1/2},$$

$$\mathrm{EC} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}.$$

According to these formulas, the MPI change value equals the agricultural TFP change value, representing productivity changes in a decision-making unit from period t to t+1. When TFP > 1, productivity shows an upward trend; when TFP < 1, productivity declines. TFP can be decomposed into TC and EC, where TC represents the contribution of production frontier movement to productivity, and EC represents the contribution of technical efficiency change from t to t+1. With period t technology as reference, the output distance function of the period t input-output vector is $D_0^t(x^t, y^t)$; with period t technology as reference, the output distance function of the period t+1 input-output vector is $D_0^t(x^{t+1}, y^{t+1})$.

2.4 Exploratory Spatial Data Analysis

Spatial autocorrelation examines the interaction mechanism between element attribute values (Luc, 1995). Using global spatial autocorrelation (GSA) and local indicators of spatial association (LISA), we analyzed the spatial aggregation state of agricultural green development efficiency across 31 provinces, with calculations completed using GeoDA software.

Moran' s I is calculated as:

$$I = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}} \times \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}$$

where n represents the 31 provinces; Y and Y are agricultural green development efficiency values for provinces i and j, respectively; $\bar{Y}$ is the average value; and W is the spatial connection matrix between provinces i and j.

We tested Moran' s I using the Z-statistic:

$$Z = \frac{I - E(I)}{\sqrt{\mathrm{VAR}(I)}}$$

where $E(I)$ is the expected autocorrelation of the observed variable and $\mathrm{VAR}(I)$ represents variance.

Local Moran' s I for region i is:

$$I_i = \frac{Y_i - \bar{Y}}{\sigma^2} \sum_{j=1}^{n} W_{ij}(Y_j - \bar{Y})$$

where positive and negative values indicate the degree of spatial correlation between region i and adjacent regions. Other parameters remain as defined above.

We analyzed LISA using Moran' s I scatterplots. In the scatterplot, the first quadrant represents high efficiency-high spatial (HH) agglomeration areas, where provinces have high agricultural green development efficiency and are surrounded by high-level provinces. These provinces maintain close links and generate frequent technological cooperation, producing significant spatial spillover effects that form high-level agglomeration areas. The second quadrant represents low efficiency-high spatial (LH) agglomeration areas, where provinces have low efficiency but are surrounded by high-level provinces, representing regions where high-level benefits spread outward with large regional spatial differences. The third quadrant represents low efficiency-low spatial (LL) agglomeration areas, where provinces have low efficiency and are surrounded by low-level provinces, forming low-level agglomeration areas. The fourth quadrant represents high efficiency-low spatial (HL) agglomeration areas, where provinces have high efficiency but are surrounded by low-level provinces, creating regional polarization effects.

2.5 Geographical Exploration

To investigate contributions of various factors to spatial differentiation in agricultural green development efficiency, the geographic detector method treats influencing factors as explanatory variables and efficiency values as explained variables (Wang et al., 2010; Wang and Xu, 2017). The formula is:

$$q = 1 - \frac{\sum_{i=1}^{k} n_i \sigma_i^2}{n\sigma^2}$$

where $i = 1, 2, \cdots, k$ represents stratification or partition of independent variable X and dependent variable Y; n and n are the number of units in layer i and the entire region, respectively; σ ^{2} and σ^2 are variances in layer i and the whole region' s Y values, respectively; and q represents the effect of influencing factors on agricultural green development efficiency. The q value ranges between 0 and 1, with larger values indicating stronger factor effects.

3.1 Dynamic Variation of Agricultural Green Development Efficiency

As shown in Figure 1 [Figure 1: see original paper], overall agricultural green development efficiency exhibited a fluctuating downward trend that can be divided into three periods: 1990–2004, 2005–2007, and 2008–2020. From 1990 to 2004, average efficiency values declined rapidly from 0.863 to 0.726, a decrease of 15.87%. During this period, the urban-rural income ratio expanded from 1.8:1.0 in the 1980s to 3.1:1.0 in 2004, making rural income growth the primary challenge for practitioners and policymakers. Difficulties in increasing farmers' income restricted agricultural development levels and reduced production enthusiasm. The 2005–2007 period showed a slight inverted U-shaped trend, as national agricultural policies focused on infrastructure investment to improve productivity and competitiveness. These policies enhanced both production efficiency and resource-environmental efficiency in the short term, but effects were unsustainable. High investment and resource consumption without corresponding environmental pressure created the inverted U-shaped pattern where efficiency first improved then weakened, though this trend also revealed substantial room for resource conservation. From 2008 to 2020, average efficiency showed a fluctuating but slowly rising trend, with an overall increase of 4.02%. During this period, traditional agriculture shifted toward ecological and circular practices, consumer demand structures changed, and science and technology innovation strategies increased investment in agricultural R&D, improving sustainable development capacity and contributing to green development efficiency (Guo et al., 2021).

Based on differences in natural conditions, economic development, transportation, and economic benefits, China is divided into three major economic zones: east, central, and west (Wang and Bai, 2018). Analysis revealed obvious gradient differences in efficiency values across these regions, ranking from high to low moving east to west. The eastern region showed a slightly fluctuating but generally medium efficiency level, indicating high coordination between agricultural production, environmental protection, and resource conservation. The central and western regions exhibited U-shaped changes. After 2014, central region efficiency began rising above the national average, while western region efficiency, though relatively low, also increased significantly after 2014. Contrary to some previous studies concluding that regional efficiency gaps have widened (Xue et al., 2020; Cui et al., 2021), our research demonstrates that over larger temporal and spatial spans, obvious gradient differences exist but show a decreasing trend year by year. Generally, no "Matthew Effect" has emerged in interprovincial agricultural green development efficiency, though fluctuations cannot be ignored. Despite government emphasis on balancing urban-rural development, economic growth, and resource-environmental coordination to narrow regional disparities, China's territory exhibits differences in resource distribution, economic development, and industrial structure that make effectively reversing long-formed regional imbalances difficult in the short term. Moreover, new policy coverage expansion and implementation effect manifestation require time. Therefore, existing research suggests a long road ahead before all regions achieve truly coordinated and balanced development.

3.2 Decomposition of Agricultural Green Development Efficiency

To further analyze temporal trends, we decomposed national agricultural green development efficiency (Table 2 and Figure 2 [Figure 2: see original paper]). Overall, TFP, TC, and EC fluctuations across 31 provinces showed a slow upward trend. TFP improvement is conducive to green development efficiency enhancement. Average TFP from 1990 to 2020 was 1.015, representing a 1.50% increase. The largest TFP fluctuations occurred during 2001-2005 (decreasing 0.83%) and 2011-2020 (decreasing 0.36%).

TFP decreased significantly during 2001-2005 when major agricultural product prices were essentially at or above international market levels. Under these conditions, raising agricultural product prices was unlikely to increase farmers' income, potentially reducing production and investment enthusiasm. Additionally, the traditional small-scale agriculture system based on household contract responsibility lowered commodity rates and productivity while inadequately absorbing rural surplus labor. High illiteracy and semi-illiteracy rates in China' s rural labor force, combined with low education quality, restricted adoption of new agricultural science and technologies, leading to continuous cultivated land reduction and agricultural production environment deterioration.

TFP rose during 2006-2010 as governments increased environmental protection focus (Du and Jiang, 2020). Moreover, China' s 2006 agricultural tax abolition improved producer enthusiasm and enhanced rural access to human, material, and financial resources.

After 2011, TFP stagnated for multiple reasons. Affected by the 2008 global financial crisis and major 2009 weather disasters, downward pressure on domestic grain prices accumulated continuously. In response, China introduced economic stimulus policies, but many zombie enterprises characterized by high energy consumption, high pollution, and low efficiency reemerged, causing excessive investment and low efficiency. Additionally, accelerated industrialization and urbanization created problems including rural population aging, imperfect agricultural infrastructure, weak agricultural materials and technical equipment, and inability to withstand disasters, leading to increasingly serious ecological problems.

This analysis reveals that sharp fluctuations in agricultural green development efficiency were almost always accompanied by macro-level policy adjustments. China has enacted numerous agricultural laws and policies to stabilize and increase grain production, ensure food security, raise farmers' nonagricultural income, and adjust rural economic structure (Li and Qian, 2004; Zhao et al., 2022). However, many agricultural policies promote economic development while aggravating pollution, resulting in excessive investment and low efficiency. Policymakers must therefore find ways to balance agricultural pollution control, food security, and farmers' income.

Regarding factor decomposition, TC' s contribution to TFP and agricultural green development efficiency was significantly greater than EC' s (Figure 2), indicating that agricultural productivity and green development efficiency depend less on resource combination, agricultural skills, and management methods than on advanced production technologies and equipment. Prior to 2001–2010, TC promoted TFP, but after 2010, this promotion weakened significantly, reflecting declining domestic R&D for new agricultural technologies and products. As suggested by some studies (Fang and Zeng, 2021; Mao et al., 2021), future policies should focus on releasing agricultural talent and emerging technologies to promote synchronous improvement in agricultural productivity and green development efficiency through technological innovation.

3.3 Spatial Differences in Agricultural Green Development Efficiency

Table 3 shows Moran' s I values distributed between 0.301–0.539, all greater than 0.000, with Z-values between 2.741–4.853, all passing the Z-test at the 1% significance level. These results indicate strong spatial dependence among adjacent provinces. Temporally, Moran's I showed an upward trend from 1990 to 2015 and a downward trend from 2015 to 2020, suggesting significant aggregation characteristics but with a risk of spatial dispersion in later stages.

Figure 3 [Figure 3: see original paper] summarizes province distributions in Moran' s I scatterplots to clarify local spatial correlations. The three municipalities (Beijing, Tianjin, Shanghai) and eastern coastal provinces (Jiangsu, Zhejiang, Fujian, Hainan) were in the HH aggregation area. With efficiency improvements, Guangdong and Shandong provinces entered the HH quadrant in 1995 and 2010, respectively. Anhui Province was in the HH quadrant except when it entered the LH aggregation area between 1995 and 2005. Hebei and Henan provinces remained stable after entering the LH quadrant from the LL aggregation area in 1995 and 2010, respectively. Jilin, Hunan, and Hubei provinces were in the LH quadrant after experiencing fluctuations. Northwestern inland provinces (Qinghai, Sichuan, Gansu, Ningxia Hui Autonomous Region, Inner Mongolia Autonomous Region, Shaanxi, Shanxi) were in the LL quadrant. Yunnan Province, Guizhou Province, and Xinjiang Uygur Autonomous Region entered the LL quadrant in 1995. Guangxi Zhuang Autonomous Region was in the LL quadrant except when it moved into the HL quadrant between 2010 and 2015. Heilongjiang and Liaoning provinces were in the HL aggregation area from 1990 to 2020, while Tibet Autonomous Region was in the HL quadrant from 1990 to 2005 before slipping into the LL quadrant after 2005, indicating downward efficiency risk. Chongqing Municipality was in the HL quadrant after fluctuating between HL and LL. Overall, only Guangdong, Shandong, and Anhui provinces increased efficiency during the study period, while Guizhou Province and Xinjiang, Tibet, and Guangxi autonomous regions decreased.

Interprovincial spatial autocorrelation analysis revealed that HH areas were mainly distributed in eastern China, characterized by rapid economic development, high-level technological innovation and management capacity, rich agricultural natural resources, and high-level agricultural ecological development (Cao and Zeng, 2019). Modernization raised agricultural green development efficiency to high levels, and these eastern advantages spread to surrounding low-efficiency areas. Leveraging this influence to formulate cross-regional assistance policies and strengthen local government implementation can maintain the "catch-up effect" and continuously narrow interprovincial gaps. Hebei, Henan, Hubei, and Hunan provinces adjacent to HH areas leverage their own regional advantages while benefiting from HH radiation, suggesting potential to rise from LH to HH over time.

LL areas were mainly distributed in central and western regions, which are major grain-producing areas whose important agricultural status contrasts sharply with fragile environments. Agricultural development depends heavily on natural resources, but these regions suffer from lack of scientific planting technologies, labor force loss (Chen et al., 2020), and low green development efficiency, producing negative spatial spillover effects. One response involves strengthening top-level design for coordinated agricultural economy and resource conservation development and improving environmental awareness among agricultural production agents. HL areas were mainly distributed in northeastern China, which, with superior production conditions and strong potential, represents an advantageous grain production region. However, this region faces problems such as low resource recycling rates and excessive water and soil resource consumption, with relatively weak radiation to surrounding areas, indicating a need to explore optimal green development paths based on regional characteristics (Yu and Hao, 2018).

3.4 Influencing Factors of Agricultural Green Development Efficiency

Agricultural green development efficiency is affected by various factors. Referencing literature and considering major agricultural development problems (Pan, 2014; Wang and Zhang, 2018), we selected eight indicators to explore influencing mechanisms: agricultural development level, agricultural scale level, labor force education level, financial policies for supporting agriculture, technological progress, agricultural disaster rate, environmental regulation, and agricultural industrial structure (Figure 4 [Figure 4: see original paper]). As described in

Section 2.5, we used a geographic detector model to detect spatiotemporal factors in efficiency evolution. We first discretized original data, clustered factor values using ArcGIS natural breakpoint method, then calculated clustering data for 2000, 2010, and 2020 using the geographic detector, obtaining q-values for each factor represented in radar charts.

Figure 5 [Figure 5: see original paper] shows that agricultural development level, environmental regulation, and financial policies for supporting agriculture were the main factors affecting efficiency. In 2000, agricultural scale level (q = 0.020) and technological progress (q = 0.075) had small q-values and weakest effects. In 2010, agricultural scale level (q = 0.086) had the weakest effect. In 2020, agricultural scale level (q = 0.055) and agricultural disaster rate (q = 0.098) had the weakest effects. Agricultural development level was the most significant factor, but its influence weakened yearly, with q-values decreasing from 0.640 in 2000 to 0.490 in 2020. Environmental regulation' s effect first increased then decreased, with q-values rising from 0.560 in 2000 to 0.630 in 2010, then falling to 0.580 in 2020. Financial policies' q-value decreased by 0.100 from 2000 to 2010 and by 0.120 from 2010 to 2020, indicating declining influence. Labor force education level' s q-value increased from 0.150 in 2000 to 0.300 in 2020, with continuously rising influence. Technological progress' s q-value increased from 0.070 in 2000 to 0.300 in 2020, showing rapidly increasing influence. Agricultural industrial structure' s q-value decreased from 0.310 in 2000 to 0.250 in 2020, indicating continuously declining influence.

The decreasing influence of agricultural development level suggests it is not positively related to green development efficiency. Improving development level increases farmers' income, but increased income does not significantly improve technical levels; instead, it increases inputs of agricultural materials like chemical fertilizers to improve output, which does not benefit green development efficiency (Zhao et al., 2022). Environmental regulation' s effect showed a trend of first rising then falling. In early agricultural development stages, output and income growth were promoted mainly through natural resource consumption and increased social factor inputs, with relatively extensive growth patterns. At that time, environmental regulation significantly improved agricultural resource environmental efficiency. As economy, technology, and environmental awareness improved, agricultural production increased dependence on advanced management methods, weakening environmental regulation' s role. Although macro-level policy adjustments significantly affected green development efficiency, local financial support policy influence declined, indicating local policy formulation was insufficiently specific or accurate. Lack of information about farmers' preferences for agricultural public goods during policy formulation often caused financial expenditure structures for supporting agriculture to deviate from social demand (Li and Qian, 2004). Agricultural industrial structure' s effect also declined, indicating that agricultural industrial transformation effects have not been significant in recent years, particularly in some central and western regions, though leisure and ecological agriculture development needs further exploration (Hu and Zhong, 2019).

During the study period, labor force education level and technological progress showed increasing influence on green development efficiency. Higher education levels are conducive to agricultural modernization by improving the labor force' s capacity to master advanced science and technology, effectively use market information, and interpret policy. Overall, improving labor force education level promotes large-scale production, optimizes resource allocation, increases employment opportunities, and advances rural development. Technological progress' s influence also increased rapidly. With socioeconomic development, technological progress becomes an inevitable agricultural development demand. Current agricultural development aims not only to reduce back-end industrial chain costs but also to satisfy consumer demands regarding product quality and characteristics, areas where technological progress plays important roles in production, processing, and sales.

By dividing 31 provinces into eastern, central, and western China and analyzing 2020 as an example, we examined regional differences in influencing factors. Spatially (Table 4), agricultural development level, technological progress, and agricultural industrial structure significantly affected green development efficiency in the eastern region. In the central region, agricultural disaster rate and industrial structure had less impact while other factors were more significant. Western China' s green development efficiency was mainly constrained by environmental regulation and agricultural development level. These results support spatial autocorrelation analysis and reflect eastern region advantages in economy, technology, and ideas. Although agriculture is not a leading eastern region industry, regional characteristics such as strong environmental protection advocacy and agricultural science and technology adoption enable rapid efficient development. The secondary industry dominates the central region, providing basic machinery for agricultural production while creating enormous resource and environmental pressure. In western region, most areas have small-scale decentralized operations in arid hilly areas with fragile environments and low labor force education levels, making green development efficiency unable to eliminate environmental regulation impacts.

3.5 Suggestions for Improving Agricultural Green Development Efficiency in China

Based on our findings and current national strategies, we offer the following suggestions:

1. **Strengthen scientific and technological innovation** in agriculture and improve production technical levels. Promote integration of scientific and technological forces and resource sharing, fostering innovative elements such as talent, capital, information, and technology. Transform agricultural development modes through scientific and technological innovation, guiding agriculture toward green, high-quality, well-branded prod-

ucts and processes. These measures will help form a high-quality, efficient, and dynamic modern agricultural industrial system.

2. **Governments at all levels should fully grasp interprovincial spatial correlations** of agricultural green development efficiency. They should consider not only attribute data impacts but also relationship data roles. China' s agricultural green development efficiency shows a pattern of high in the east, low in the west, high in the south, and low in the north. Policies should leverage the pivotal role of network core nodes, strengthening interconnections and interactions between underdeveloped and high-efficiency areas. Create channels to facilitate interprovincial flows of green agricultural production factors, strengthen interprovincial scientific and technological cooperation, and build an agricultural science and technology innovation alliance to improve efficiency through collaborative innovation.

3. **Based on macro-level policies, local governments should formulate more localized agricultural support policies** considering local situations. This involves accurate policy implementation, establishing agricultural development incentive mechanisms, and improving environmental and resource efficiency. Efficient use of agricultural support funds should be promoted to advance grain production technology and avoid rural polarization caused by inefficient policies. For western regions, financial support should enhance not only input factors and infrastructure but also new agricultural technologies, equipment, and management methods. Social factors should also be considered, including ethnic minority culture, tourism, and current agricultural development, to provide better conditions for further agricultural advancement.

3.6 Limitations

This study revealed long-term evolution characteristics and spatial differentiation of green agricultural development, providing macro-level guidance for China. Future research should spatially enrich agricultural green development efficiency evaluations, particularly through special studies on western regions. Moreover, macro-level evaluations should be validated against micro-level assessments. Regarding index selection, ongoing field research development and improved data availability will allow further refinement of input and output element selection. Additionally, in descriptive statistical analysis of 31 provinces, we identified outliers in four provinces/cities: Beijing (1996–1998), Shanghai (2012–2017), Guizhou (1990–1992), and Yunnan (1990–1993). Beijing and Shanghai outliers were lower than other years, while Guizhou and Yunnan outliers were higher. Future research should enhance outlier analysis to yield more accurate understanding of green development efficiency improvement mechanisms.

4 Conclusions

This study measured agricultural green development efficiency across 31 Chinese provinces from 1990 to 2020 using a Super-SBM model, decomposed efficiency through MPI and global Moran’ s I, and examined interprovincial influencing factors. The conclusions are:

1. Overall agricultural green development efficiency was low during the study period, first trending downward then curving upward. Obvious gradient differences existed between eastern, central, and western regions, with the east highest, central intermediate, and west lowest. However, this gap narrowed year by year. MPI analysis showed gradual TFP fluctuation increases. While both technological progress and efficiency improvements promoted green development efficiency, technological progress changes were the main driving force.
2. Agricultural green development efficiency showed significant aggregation characteristics during the study period, though with spatial dispersion risk in later stages. HH areas were mainly distributed in the eastern region with high agricultural technological innovation levels. LL areas were mainly distributed across central and western regions with poor environmental conditions. The spatial distribution structure can be described as high-efficiency and high-radiation in the east, and low-efficiency and low-radiation in the west.
3. Agricultural green development efficiency was affected by various factors. Temporally, agricultural development level, environmental regulation, and financial support for agriculture were consistently main factors, while labor force education level and technological progress influences increased during the study period. Spatially, agricultural development level, technological progress, and industrial structure significantly impacted the east, while central and western regions remained affected by scale level and environmental regulation, reflecting eastern advantages in economy and technology. Thus, interprovincial cooperation is urgently needed to further promote green agriculture development.

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