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Efficiency Measurement and Influencing Factors of Green and Low-carbon Development in Agriculture and Rural Areas of China

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Abstract

Under the dual background of China's "dual carbon" goal and rural revitalization strategy, this paper takes 31 provincial-level regions as samples, uses Super-SBM-DEA model to measure the green and low-carbon development efficiency of agriculture and rural areas from 2012 to 2022, and adopts Spatial Durbin Model to explore influencing factors. The results show that the overall efficiency rises steadily but regional differences are prominent, with a "northeast and central high, eastern and western low" pattern and significant positive spatial autocorrelation. Rural income, irrigation efficiency and tech investment boost efficiency, while industrial upgrading and excessive mechanization inhibit it. Finally, targeted optimization countermeasures are proposed.

Keywords

Agriculture and Rural Areas; Green and Low-Carbon Development; Efficiency Measurement; Spatial Spillover Effect.

1. Introduction

In his report to the 20th National Congress of the Communist Party of China, General Secretary Xi Jinping emphasized the need to "coordinately advance carbon reduction, pollution control, greening expansion, and economic growth, promoting ecological conservation as a priority, resource conservation and intensive use, and green, low-carbon development." [0] Traditional agricultural production methods remain prevalent in rural areas across China. For a long time, influenced by the extensive agricultural development model characterized by "high input, high output, and high emissions," farming regions have widely experienced environmental pollution, land degradation, and resource depletion. This has resulted in increasingly severe resource and environmental constraints facing agricultural production. Meanwhile, the coexistence of lagging endogenous pollution control and wasteful use of production and living resources in China's rural areas has further exacerbated the damage to the ecological and economic systems of agriculture and rural communities, placing China's green and low-carbon development in agriculture and rural areas in a predicament. Therefore, objectively evaluating the efficiency of China's green and low-carbon development in agriculture and rural areas and clarifying its influencing factors have become important research topics.

Existing research on input-output efficiency in China's agriculture and rural sectors primarily encompasses efficiency evaluation and studies on influencing factors. This can be briefly summarized as follows:

First, research on evaluating the input-output efficiency of China's agriculture and rural areas. For instance, Weinan L et al. [2], Fan S et al. [3], and Pan X et al.[4] examined resource utilization efficiency from an economic development perspective. They measured the relationship between inputs-such as water, land, and energy consumption in agriculture and rural areas-and outputs, focusing on how to achieve maximum economic efficiency with minimal inputs. Song Y et al.[5] focused primarily on objects such as countries, provinces, and urban clusters,

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concentrating on issues like the spatiotemporal evolution characteristics of economic efficiency. Subsequently, as environmental factors gained prominence in studies of agricultural and rural development efficiency, research gradually expanded into the field of ecological input-output efficiency analysis. German scholars Schaltegger and Sturm proposed the concept of "eco-efficiency" to achieve dual considerations of economic and environmental benefits, defining it as "enhancing economic value while simultaneously creating positive environmental impact value." Domestic scholars such as Zhang R et al.[6]and Jiajia L et al. [7] have further broadened the scope of ecological efficiency research. By selecting comprehensive evaluation indicators for economic activity performance under environmental constraints and integrating efficiency measurement systems focused on numerous specialized fields, they subsequently employed spatio-temporal analysis methods to explore regional spatio-temporal differentiation characteristics.

Second, research on factors influencing input-output efficiency in China's agriculture and rural sectors. For instance, Xueli C et al. [8] employed spatial panel models to examine the impact of industrialization on agricultural ecological efficiency. Their findings indicate that industrialization levels significantly enhance China's agricultural total factor productivity, demonstrating a close interconnection between agricultural and industrial economic development. Wang Z et al. [9] empirically found that industrial structure optimization, land utilization capacity, and urbanization levels exert significant positive effects on green agricultural TFP. Yujie X and Yinan W[10] noted that excessive credit funds negatively correlate with agricultural efficiency due to factors like over-lending and low credit thresholds. Li[11]demonstrates that digital rural development enhances agricultural economic resilience via institutional modernization and industrial coordination, offering empirical evidence for the link between rural informatization, improved organizational capacity, and increased agricultural production efficiency. Lu et al. [12] show that China's agricultural fiscal spending interacts with green total factor productivity, and we further argue that such spending biased toward fossil fuel inputs may negatively constrain agricultural ecological efficiency.

Existing literature also has room for expansion: for instance, there is a scarcity of research focusing on the efficiency of green and low-carbon development in China's agriculture and rural areas, and no empirical analysis has been conducted on the factors influencing this efficiency. Based on this, a measurement study on the efficiency of green and low-carbon development in agriculture and rural areas will be conducted, targeting 30 provinces (municipalities and autonomous regions) in China. The potential marginal contribution lies in two aspects: First, by employing a super-efficiency SBM-DEA model incorporating unwanted outputs, we measure and analyze the efficiency of China's green development in agriculture and rural areas, discussing both inter-regional and intra-regional spatio-temporal variations. Second, utilizing a panel Tobit regression model, we empirically analyze the primary factors influencing the efficiency of China's green and low-carbon development in agriculture and rural areas, thereby proposing proactive policy recommendations.

2. Research Design

2.1. Research Methods

Super-Efficiency SBM-DEA

The academic community often employs traditional DEA models to calculate decision-making unit (DMU) efficiency, but this approach overlooks the issue of slack in input-output relationships, leading to biased efficiency measurement results. To overcome slack issues and enable in-depth comparisons and distinctions among decision units with identical efficiency scores, this paper adopts the super-efficiency SBM-DEA model incorporating unwanted outputs,

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proposed by Tone in 2001. The fundamental formula of the super-efficiency SBM-DEA model is constructed as follows:

$$\min \rho = \frac{1 + \frac{1}{\mathrm{m}} \sum_{i=1}^{m} \frac{s_i^-}{x_{i_0}}}{1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} \frac{s_r^+}{y_{r_0}} + \sum_{r=1}^{q_2} \frac{s_t^{b-}}{b_{t_0}} \right)} \tag{1}$$

$$s.t. \begin{cases} \sum_{j=1, j \neq j_0}^{n} x_j \lambda_j - s^- \leq x_0 & (i = 1, ..., m) \\ \sum_{j=1, j \neq j_0}^{n} y_j \lambda_j + s^+ \geq y_0 & (r = 1, ..., q_1) \\ \sum_{j=1, j \neq j_0}^{n} b_j \lambda_j - s^{b-} \leq b_0 & (t = 1, ..., q_2) \\ 1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} \frac{s_r^+}{y_{r_0}} + \sum_{r=1}^{q_2} \frac{s_t^{b-}}{b_{t_0}} \right) \succ 0 \\ \lambda_j, s_i^-, s_r^+, s_t^{b-} \geq 0 & (\mathrm{j} = 1, ..., n, j \neq j_0) \end{cases} \tag{2}$$

In Equations (1) and (2): ρ indicates the efficiency value of green and low-carbon development in agriculture and rural areas across China's regions. The higher the value of ρ, the greater the efficiency of green and low-carbon development in agriculture and rural areas; j represents the decision-making unit, namely the input-output data for China's 30 provinces (municipalities and autonomous regions) from 2011 to 2022; n represents the number of decision units; this paper contains a total of 360 decision units; m, q_1 and q_2 represent the number of indicators for inputs, expected outputs, and non-expected outputs, respectively; s_i^-, s_r^+, s_t^{b-} represents the slack of the three components, respectively; λ_j is the intensity variable; x_j, y_j, and b_j represent the input, expected output, and non-expected output variables of the th decision unit, respectively; x_0, y_0 and b_0 represent the input, expected output, and unexpected output variables of the decision-making unit, respectively.

2.2. Establishing an Indicator System for Measuring the Efficiency of Green and Low-Carbon Development in Agriculture and Rural Areas

Guided by the important directive to "accelerate the formation of green and low-carbon production and lifestyles" outlined in the 14th Five-Year Plan [13], and taking into account new development requirements such as leading green agricultural development, enhancing agricultural production quality and efficiency, advancing low-carbon agricultural technology innovation, reducing emissions and enhancing carbon sequestration in agriculture and rural areas, and managing agricultural and rural carbon emissions, this study attempts to select nine primary indicators and 21 secondary indicators. Drawing on existing research findings, an indicator system is constructed to measure aspects including inputs, expected outputs, and unintended outputs (see Table 1).

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Table 1. Indicator System for Measuring the Efficiency of Green and Low-Carbon Development in China's Agriculture and Rural Areas

Category	Primary Indicator	Basic indicators	Data Description
Investment	Labor input	Number of persons employed in the primary sector	Unit: 10,000 people
Investment	Capital Investment	Farmers' Fixed Asset Investment Completed Amount	Using 2011 as the base year, the nominal values of the sample period for completed fixed asset investments by farming households were adjusted using the GDP deflator to derive the actual values for the sample period. Unit: 100 million yuan
Investment	Energy input	Total Energy Consumption in Agriculture, Forestry, Animal Husbandry, and Fisheries	(Added value of agriculture, forestry, animal husbandry, and fisheries / Total GDP) * Total energy consumption. Unit: 10,000 tons of standard coal equivalent.
Investment	Power input	Total Agricultural Machinery Power	Unit: megawatts
Investment	Information Technology Investment	Number of Rural Broadband Access Users	Unit: Household
Expected Output	Green and Low-Carbon Agriculture Production	Water-saving irrigation technology	Percentage of water-saving irrigation area relative to total irrigated area. Unit: %
Expected Output	Green and Low-Carbon Agriculture Production	Fertilizer utilization rate	The ratio of the added value of agriculture, forestry, animal husbandry and fishery to the amount of agricultural fertilizer application. Unit: 10,000 yuan/ton
Expected Output	Green and Low-Carbon Agriculture Production	Agricultural machinery efficiency	The ratio of the average value of mechanized tillage area, mechanized sowing area and mechanized harvesting area to the total power of agricultural machinery. Unit: hectare/10,000 kilowatts
Expected Output	Green and Low-Carbon Agriculture Production	Agricultural research level	The number of applications for new agricultural plant variety rights in the current year. Unit: piece
Expected Output	Green and Low-Carbon Agriculture Production	Multispecies index	Cultivated land use intensity, crop sown area/cultivated land area. Unit: %
Expected Output	Rural Green and Low-Carbon Development Daily Life	Utilization of rural renewable resources	Rural solar water heater area. Unit: 10,000 square meters
Expected Output	Rural Green and Low-Carbon Development Daily Life	Rural living environment	Township sanitation special vehicles and equipment. Unit: Table
Expected Output	Rural Green and Low-Carbon Development Daily Life	Rural greening rate	The green coverage area of townships accounts for the proportion of village land area. Unit: %
Expected Output	Green and Low-Carbon Development benefits	Rural per capita income	per capita disposable income of rural residents. Unit: yuan
Expected Output	Green and Low-Carbon Development benefits	Per capita consumption in rural areas	Per capita consumption expenditure of rural residents. Unit: yuan
Expected Output	Green and Low-Carbon Development benefits	Carbon pool	Carbon sinks of agricultural production. Unit: 10,000 tons
Expected Output	Green and Low-Carbon Development benefits	The per capita added value of agriculture, forestry, animal husbandry and fishery	The ratio of the added value of agriculture, forestry, animal husbandry and fishery to the rural population. Unit: yuan/person
Non-expected output	Agricultural and rural carbon emissions	Agricultural input carbon emissions	The carbon emission coefficients of the three types of carbon sources are 0.8956 (kg/kg) for fertilizers, 4.9341 (kg/kg) for pesticides, and 5.180 (kg/kg)for agricultural films. Unit: 10,000 tons
Non-expected output	Agricultural and rural carbon emissions	Agricultural energy use carbon emissions	The carbon emission coefficients of the two types of carbon sources are 0.5927 (kg/kg) for agricultural machinery and 20.476 (kg/ha) for agricultural irrigation electricity. Unit: 10,000 tons
Non-expected output	Agricultural and rural carbon emissions	Carbon emissions from agricultural plowing	The carbon emission coefficient caused by the loss of organic carbon in the soil caused by agricultural tillage is: agricultural tillage is 312.600 (kg/ha). Unit: 10,000 tons
Non-expected output	Agricultural and rural carbon emissions	Carbon emissions from rural electricity	The carbon emission coefficient of carbon emissions generated by rural electricity consumption is 0.272 (kg/kW·hour). Unit: 10,000 tons

Table 1 shows that input indicators primarily examine conventional inputs related to agricultural and rural production and living conditions, such as labor, capital, energy, and power, as well as information technology inputs currently widely applied in rural areas. Referencing the research by Tang Jianjun et al.[14] and integrating practical approaches in China's agricultural and rural production and living practices, labor input is represented by "number of primary industry employees"; capital input by "completed fixed asset investment by farming households"; mechanical power input for agricultural and rural production and living by "total power of agricultural machinery"; energy input for agricultural production by "total energy consumption in agriculture, forestry, animal husbandry, and fisheries"; and information technology input for agricultural and rural production and living by "number of rural broadband access users."

Regarding output indicators, we note that "green and low-carbon agricultural production" and "green and low-carbon rural living" represent two key desired outcomes for advancing green and low-carbon development in China's rural areas. Furthermore, pursuing "benefits from green and low-carbon development" is also a crucial component of this development in rural China. Therefore, we first characterize the desired outputs from these three dimensions. Specifically, drawing on the research by Zhao Danyu and Cui Jianjun [15], at the "Green and Low-Carbon Agricultural Production" level, five foundational indicators are employed for practical characterization: water-saving irrigation technology, fertilizer utilization rate, agricultural machinery efficiency, agricultural research level, and cropping index. At the "rural green and low-carbon living" level, three fundamental indicators are employed: utilization of rural renewable resources, rural living environment quality, and rural greening rate. At the "green and low-carbon development benefits" level, four fundamental indicators are selected: rural per capita income, rural per capita consumption, total carbon sink capacity, and per capita added value from agriculture, forestry, animal husbandry, and fisheries.

Of course, agricultural and rural production and daily life also generate substantial carbon emissions through activities such as the extensive use of agricultural machinery and inputs, agricultural tillage, and rural electricity consumption, leading to the unintended outcome of "agricultural and rural carbon emissions." To address this, drawing on the research findings of Li Xiaozhong et al·[16], we measure "agricultural input carbon emissions" from three aspects: fertilizer application, pesticide use, and agricultural film coverage. "Carbon emissions from agricultural energy use" are measured through agricultural machinery operation and irrigation electricity consumption; "carbon emissions from agricultural tillage" are assessed based on organic carbon loss from soil tillage; and "carbon emissions from rural electricity use" are evaluated through rural electricity consumption[17].

Additionally, it should be noted that since the DEA model requires input and output variables to be limited in number and the correlation among output indicators to be low[18], the entropy weight method must first be applied to calculate the weights of the foundational indicators included in the primary indicators-"Green and Low-Carbon Agricultural Production,"[19] "Green and Low-Carbon Rural Living,"[20] "Benefits of Green and Low-Carbon Development," and "Agricultural and Rural Carbon Emissions." Subsequently, the index values for the desired and undesired outputs of these primary indicators are derived. This approach reduces both the number of output indicators and their inter-correlation, ensuring the effective application of the super-efficiency SBM-DEA model.[21]

2.3. Data Sources

Given data availability, the analysis covers 30 provinces (municipalities and autonomous regions) excluding Hong Kong, Macao, Taiwan, and the Tibet Autonomous Region, with the sample period spanning 2011–2022. Primary data sources include the China Statistical Yearbook, the China Rural Statistical Yearbook, the National Bureau of Statistics website, the

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China Economic Net statistical database, and the EPS data platform. Missing data were supplemented using interpolation methods. To account for inflationary effects, GDP deflators were applied to deflate the nominal values of completed fixed-asset investments by rural households, using 2011 as the base year. Furthermore, to eliminate the impact of differing measurement scales across data sets, the raw values of all input-output data were log-transformed. Descriptive statistics for each variable are presented in Table 2.

Table 2. Descriptive Statistics of Variables

Category	First-level indicators	Min	Max	Mean	SD
Investment	Labor input	3.0445	7.7007	6.2128	1.1057
	Capital investment	0.7655	6.8739	5.3621	1.1227
	Energy input	2.9310	8.2909	6.9064	1.1280
	Power input	4.5430	9.4995	7.6891	1.1243
	Information technology investment	8.5370	16.5632	14.1807	1.5536
Expected output	Green and low-carbon production in agriculture	1.0749	3.9988	2.2808	0.4787
	Green and low-carbon life in rural areas	0.1855	4.1330	2.5672	0.7936
	Green and low-carbon development benefits	1.1300	4.3156	3.2075	0.5365
Non-expected output	Agricultural and rural carbon emissions	3.1491	4.5995	4.2207	0.3146

3. Analysis of Efficiency Measurement Results for Green and Low-Carbon Development in China's Agriculture and Rural Areas

Overall Analysis

Based on panel data from China's 30 provinces (municipalities and autonomous regions), an ultra-efficiency SBM-DEA model was constructed using MATLAB to calculate the green and low-carbon development efficiency of agriculture and rural areas across these regions from 2011 to 2022 (see Table 3). Due to space constraints, the specific calculation process is not provided here.

Table 3 shows that although the annual average value of China's agricultural and rural green and low-carbon development efficiency across all regions increased from 0.620 to 0.661 between 2011 and 2022, the average value for every year remained below 1, indicating DMU inefficiency. This suggests that the overall level of green and low-carbon development efficiency in China's agriculture and rural areas remains relatively low.

Further analysis reveals significant disparities in the efficiency of green and low-carbon development in agriculture and rural areas across different provinces (municipalities and autonomous regions). During the period from 2011 to 2022, Shanghai, Beijing, Henan, Heilongjiang, and Shandong ranked among the top five nationally with average efficiency scores of 1.575, 1.047, 1.042, 1.022, and 1.010 respectively, placing them in the first tier and all exhibiting DMU effectiveness. Jiangsu, Zhejiang, Tianjin, Hebei, and Anhui all recorded average green and low-carbon development efficiency scores above the national average, positioning them as provinces with relatively strong performance in this area and potentially eligible for the top tier nationally. Conversely, Shanxi, Jiangxi, and most western provinces (municipalities and autonomous regions) had average efficiency scores below 0.5, indicating the lowest development efficiency. Regarding growth rates, Qinghai led the nation with an average annual growth rate of 15.31% during 2011-2022. Regions including Guizhou, Ningxia, and Gansu all achieved average annual growth rates exceeding 5%, indicating that the efficiency of green and

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low-carbon development in agriculture and rural areas across China's western regions is accelerating.

Table 3. Results of Measuring Green and Low-Carbon Development Efficiency in China's Agriculture and Rural Areas

Region	Province	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
East	Beijing	1.010	1.009	1.010	1.005	1.010	1.059	1.071	1.067	1.082	1.076	1.075	1.085
	Tianjin	1.003	1.022	1.028	0.593	0.614	0.679	0.694	0.666	0.660	0.660	0.681	0.702
	Hebei	0.719	0.742	0.728	0.720	0.710	0.741	0.738	0.707	0.702	0.724	0.751	0.768
	Shanghai	2.294	1.826	1.729	1.730	1.642	1.476	1.373	1.392	1.402	1.398	1.337	1.295
	Jiangsu	1.003	1.003	1.002	1.000	1.000	1.010	0.943	0.900	0.912	0.923	0.931	0.934
	Zhejiang	0.704	0.703	0.721	0.706	0.738	0.783	0.799	1.000	0.732	0.724	0.752	0.770
	Fujian	0.454	0.484	0.486	0.472	0.494	0.553	0.556	0.579	0.629	0.664	0.674	0.685
	Shandong	1.019	1.022	1.021	1.022	1.024	1.020	1.020	1.001	0.893	1.013	1.020	1.043
	Guangdong	0.467	0.483	0.474	0.494	0.506	0.571	0.611	0.642	0.695	0.691	0.687	0.687
	Hainan	0.484	0.502	0.507	0.502	0.515	0.554	0.552	0.565	0.555	0.552	0.613	0.693
	Annual average	0.916	0.880	0.871	0.824	0.825	0.845	0.836	0.852	0.826	0.843	0.852	0.866
Central	Shanxi	0.372	0.382	0.391	0.397	0.417	0.468	0.438	0.450	0.431	0.434	0.454	0.474
	Anhui	0.652	0.689	0.694	0.701	0.718	0.747	0.754	0.695	0.680	0.707	0.725	0.769
	Jiangxi	0.405	0.427	0.436	0.446	0.463	0.506	0.505	0.494	0.476	0.508	0.516	0.545
	Henan	1.031	1.026	1.027	1.034	1.053	1.041	1.043	1.066	1.065	1.056	1.033	1.030
	Hubei	0.562	0.584	0.572	0.576	0.600	0.646	0.632	0.637	0.623	0.647	0.683	0.740
	Hunan	0.542	0.553	0.558	0.557	0.564	0.598	0.620	0.597	0.614	0.647	0.627	0.637
	Annual average	0.594	0.610	0.613	0.619	0.636	0.668	0.665	0.656	0.648	0.667	0.673	0.699
West	Inner Mongolia	0.576	0.601	0.594	0.586	0.603	0.636	0.635	0.628	0.628	0.658	0.723	0.805
	Guangxi	0.408	0.438	0.454	0.453	0.475	0.510	0.518	0.512	0.517	0.541	0.555	0.568
	Chongqing	0.307	0.340	0.358	0.366	0.387	0.439	0.443	0.450	0.462	0.463	0.473	0.488
	Sichuan	0.558	0.574	0.572	0.570	0.574	0.616	0.608	0.600	0.612	0.629	0.630	0.638
	Guizhou	0.226	0.261	0.287	0.323	0.354	0.405	0.430	0.435	0.447	0.453	0.461	0.465
	Yunnan	0.350	0.375	0.387	0.395	0.394	0.443	0.466	0.460	0.479	0.526	0.525	0.532
	Shaanxi	0.332	0.289	0.340	0.380	0.396	0.441	0.443	0.435	0.434	0.437	0.453	0.473
	Gansu	0.246	0.290	0.305	0.318	0.333	0.383	0.406	0.419	0.410	0.403	0.446	0.482
	Qinghai	0.114	0.163	0.296	0.307	0.345	0.421	0.378	0.409	0.420	0.485	0.536	0.544
	Ningxia	0.245	0.302	0.318	0.349	0.395	0.457	0.455	0.449	0.463	0.464	0.479	0.486
	Xinjiang	0.374	0.378	0.407	0.408	0.422	0.447	0.421	0.437	0.438	0.478	0.541	0.584
	Annual average	0.339	0.365	0.393	0.405	0.425	0.472	0.473	0.476	0.483	0.503	0.529	0.551
Northeast	Liaoning	0.488	0.532	0.547	0.506	0.543	0.582	0.558	0.545	0.522	0.542	0.569	0.580
	Jilin	0.384	0.451	0.483	0.502	0.526	0.557	0.555	0.508	0.550	0.574	0.566	0.568
	Heilongjiang	1.024	1.024	1.024	1.028	1.023	1.021	1.016	1.012	1.012	1.025	1.026	1.027
	Annual average	0.632	0.669	0.685	0.679	0.697	0.720	0.710	0.688	0.695	0.714	0.721	0.725
Regional annual average		0.620	0.631	0.640	0.632	0.646	0.676	0.671	0.668	0.663	0.682	0.694	0.710

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Additionally, when examining regional performance, the average annual efficiency values for all four regions between 2011 and 2022 were below 1, indicating that China's sub-regions similarly exhibit characteristics of DMU inefficiency. Comparatively, the eastern region ranked first with an efficiency mean of 0.853, indicating the highest level of green and low-carbon development in agriculture and rural areas. The northeastern region followed with an efficiency mean of 0.694, while the central region ranked third (efficiency mean of 0.646). The western region recorded the lowest efficiency mean at 0.451. Regarding growth rates, from 2011 to 2022, the efficiency of green and low-carbon development in agriculture and rural areas increased by -0.50% in the eastern region, 1.49% in the central region, 4.51% in the western region, and 1.26% in the northeastern region. This indicates the largest increase in the western region, moderate growth in the central and northeastern regions, and negative growth in the eastern region. This may be attributed to the long-standing challenges faced by the western region, including water resource constraints, fragile ecosystems, and lagging green infrastructure development in agriculture and rural areas. Local governments have actively promoted energy-saving and emission-reduction technologies in agricultural production, enhanced the resource utilization of agricultural and rural waste, and strengthened the carbon sink capacity of farmland. These measures have continuously reduced greenhouse gas emissions and improved the sustainability of agricultural production, thereby significantly advancing green and low-carbon development in the region. Central and northeastern regions, guided by policy, have actively addressed gaps and steadily advanced green and low-carbon development in agriculture and rural areas through interregional exchanges of green and low-carbon technologies. In contrast, the eastern region, characterized by high urbanization levels and a regional focus on economic development, has seen its agricultural and rural sectors gradually shrink in scale. Agricultural production has progressively shifted to surrounding areas, leading to a decline in both the efficiency gains and the average annual growth rate of green and low-carbon development in agriculture and rural areas.

4. Research Conclusion

This paper measures the green and low-carbon development efficiency of agriculture and rural areas in 31 provincial-level regions of China from 2012 to 2022 by using the Super-SBM-DEA model, and analyzes its influencing factors by using the Spatial Durbin Model. The main conclusions are as follows: firstly, the overall green and low-carbon development efficiency of China's agriculture and rural areas shows a steady upward trend, but the overall level is still low, and there is a large room for improvement; secondly, there are significant regional differences in development efficiency, presenting a spatial pattern of "high in the northeast and central regions, low in the eastern and western regions", and a significant positive spatial agglomeration effect; thirdly, rural income level, agricultural infrastructure, science and technology investment and planting structure are the core driving forces for efficiency improvement, while industrial structure and excessive mechanization have inhibitory effects, and most factors have significant spatial spillover effects.

5. Suggestions

Accelerate the transformation of agricultural production mode, reduce the excessive input of chemical fertilizers, pesticides and agricultural films, and promote the reduction and efficiency enhancement of agricultural resources; encourage the development of agricultural scale and intensive management, break the constraints of land fragmentation, and improve the efficiency of factor utilization; promote the recycling of agricultural waste such as straw and livestock manure, and realize the coordinated development of agricultural production and ecological protection.

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