Spatiotemporal Heterogeneity of Agricultural Carbon Emission Efficiency in Xinjiang and Its Determinants: Postprint

Authors: Liu Haijun, Zhang Haihong, Yan Junjie, Li Xiang, Li Gaofeng

Date: 2025-05-14T13:23:25+00:00

Abstract

In the process of promoting low-carbon agricultural development, in-depth research on the spatio-temporal heterogeneity of agricultural carbon emission efficiency and its influencing factors is of great significance for accelerating Xinjiang' s agricultural economic development and driving the green transformation of agricultural production. Taking 14 prefecture-level cities in Xinjiang from 2000 to 2020 as the research object, this study evaluates agricultural carbon emission efficiency using the SBM model with undesirable outputs and the Malmquist index model, employs a spatial autocorrelation model to analyze the spatial correlation characteristics of agricultural carbon emission efficiency, and finally utilizes a Tobit model to explore the influencing factors of agricultural carbon emission efficiency in Xinjiang. The results show that: (1) From 2000 to 2020, the agricultural carbon emission efficiency of various prefecture-level cities in Xinjiang generally reflects a "slow-fast-slow" development trajectory, with significant regional differences. (2) In 2000, the agricultural carbon emission efficiency in Tacheng region exhibited low-high clustering characteristics; in 2007, Changji Hui Autonomous Prefecture was in high-high clustering, and by 2014, Turpan City and Changji Hui Autonomous Prefecture were located in high-high clustering; in 2020, Bayingolin Mongol Autonomous Prefecture, Hami City, and Changji Hui Autonomous Prefecture were in low-high clustering. Overall, high-high clustering regions show a decreasing trend, while low-high clustering regions demonstrate an increasing trend. (3) The degree of cultivated land scale and the overall development level of agricultural economy have positive impacts on agricultural carbon emission efficiency; agricultural industrial structure, crop planting structure, and effective irrigation rate have negative impacts on agricultural carbon emission efficiency. Through the study on the spatio-temporal heterogeneity and influencing factors of agricultural carbon emission efficiency in Xinjiang, this research aims to provide theoretical support and empirical evidence for sustainable agricultural development in arid regions.

Full Text

Preamble

ARID LAND GEOGRAPHY
Vol. 48 No. 5 May 2025

Spatiotemporal Heterogeneity and Influencing Factors of Agricultural Carbon Emission Efficiency in Xinjiang

LIU Haijun[1,2,3], ZHANG Haihong[2], YAN Junjie[2], LI Xiang[2], LI Gaofeng[2]
(1. Key Laboratory of Microbial Resources Protection, Development and Utilization, Yili Normal University, Yining 835000, Xinjiang, China;
2. School of Resources and Environment, Yili Normal University, Yining 835000, Xinjiang, China;
3. School of Geographical Sciences, Southwest University, Chongqing 400715, China)

Abstract: In the process of promoting low-carbon agricultural development, in-depth research on the spatiotemporal heterogeneity of agricultural carbon emission efficiency and its influencing factors is of great significance for accelerating Xinjiang' s agricultural economic development and driving the green transformation of agricultural production. This study takes 14 prefectures and cities in Xinjiang as the research objects, evaluates agricultural carbon emission efficiency using the non-expected output SBM model, employs the Malmquist index to analyze dynamic evolution trends, uses a spatial autocorrelation model to examine spatial correlation characteristics, and finally applies the Tobit model to explore influencing factors. The results show: (1) From 2000 to 2020, the agricultural carbon emission efficiency in Xinjiang' s prefectures and cities generally followed a "slow-fast-slow" development trajectory, with significant regional differences. (2) In 2000, Tacheng Prefecture showed low-high agglomeration; by 2007, Changji Hui Autonomous Prefecture was in high-high agglomeration; by 2014, Turpan City and Changji Hui Autonomous Prefecture were in high-high agglomeration; and by 2020, Bayingol Mongolian Autonomous Prefecture, Hami City, and Changji Hui Autonomous Prefecture were in low-high agglomeration. Overall, high-high agglomeration regions showed a decreasing trend, while low-high agglomeration regions showed an increasing trend. (3) The degree of arable land scale and overall agricultural economic development level positively influence agricultural carbon emission efficiency, while agricultural industry structure, crop planting structure, and effective irrigation rate negatively affect it. Through research on the spatiotemporal heterogeneity and influencing factors of Xinjiang' s agricultural carbon emission efficiency, this study aims to provide theoretical support and empirical evidence for sustainable agricultural development in arid regions.

Keywords: agricultural carbon emission efficiency; non-expected output SBM model; spatial correlation; influencing factors; Xinjiang

Introduction

Climate change has become a severe global environmental issue attracting widespread attention, primarily driven by large-scale greenhouse gas emissions from human activities. The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report indicates that industrial activities are the main factor driving global warming. However, the primary, secondary, and tertiary industries also emit substantial greenhouse gases, with agricultural activities becoming a non-negligible source of global carbon emissions. Therefore, developing low-carbon agriculture and researching the spatiotemporal evolution characteristics and influencing factors of Xinjiang' s agricultural carbon emission efficiency are crucial for reducing agricultural carbon emissions, alleviating environmental pressure, and hold important practical significance.

Currently, academic circles have extensively discussed low-carbon agriculture, with main research directions focusing on: (1) carbon emission sources, and (2) influencing factors of agricultural carbon emission efficiency. Early studies focused on farmland carbon emissions, believing that cultivation led to soil organic carbon loss. Subsequent research indicated that ruminant animal breeding and rice paddy methane emissions, pesticide and fertilizer application, and tillage are also important carbon sources. Therefore, constructing a more precise and detailed agricultural carbon emission measurement system requires starting from agricultural material management, rice cultivation, and livestock breeding management. In the initial research stage, scholars focused on decomposing agricultural carbon emission efficiency and found that improving carbon emission efficiency mainly resulted from technological innovation and progress rather than fundamental improvements in carbon emission efficiency. As research deepened, scholars discovered that influencing factors are complex and diverse, including rural economic development level, agricultural industry structure, crop planting structure, occurrence and intensity of natural disasters, and agricultural fiscal policy support, all playing key roles in guiding agricultural low-carbon transformation.

Although existing research has enriched the study of agricultural carbon emission efficiency and laid a foundation for exploring its current characteristics, spatial interactions, and influence mechanisms, certain limitations remain. First, livestock and other land resource uses were ignored when constructing indicator systems. Second, the diversity, heterogeneity, and driving mechanisms of spatial differences were not thoroughly explored when studying spatial distribution characteristics. Based on this, this paper takes 14 prefectures and cities in Xinjiang from 2000 to 2020 as the research area, constructs measurement indicator systems from four dimensions: fertilizer input, irrigation, machinery input, and livestock input, quantitatively analyzes the spatiotemporal evolution characteristics of agricultural carbon emission efficiency in Xinjiang based on the non-expected output SBM model, explores spatial heterogeneity among regions using the Malmquist index, and finally uses the Tobit model to explore influencing factors, providing theoretical support and empirical evidence for Xinjiang' s agricultural transformation, upgrading, and modernization.

1.1 Study Area Overview

Xinjiang is located in the hinterland of the Eurasian continent, with abundant sunshine and large diurnal temperature differences, making it a golden zone for crop cultivation and livestock breeding. However, the region also faces challenges such as water resource shortages and land resource degradation, leading to a complex situation where internal and external factors intertwine in Xinjiang' s agricultural carbon emission efficiency. As an important commercial grain production base in China, its development status plays a crucial role in national food security and regional economic development. However, planting and animal husbandry generate substantial carbon emissions, especially greenhouse gases from livestock production that cannot be ignored. Therefore, studying the spatiotemporal heterogeneity and influencing factors of Xinjiang' s agricultural carbon emission efficiency lays a theoretical foundation for regional agricultural sustainable development and is significant for accelerating Xinjiang' s agricultural economic development and promoting green development model transformation.

1.2 Indicator System and Data Sources

Agricultural carbon emission efficiency refers to the CO generated per unit of agricultural product during production, representing an important indicator for measuring environmental impacts of agricultural production activities. In Xinjiang' s agricultural carbon emission accounting system, forestry and fisheries account for relatively small proportions, while livestock breeding scale is substantial. Therefore, this study focuses on carbon emissions within the narrow agricultural scope. Accordingly, fertilizer input, irrigation, machinery input, and livestock input are used as input indicators, while agricultural total output value and agricultural carbon emissions are used as output indicators to construct the indicator system for evaluating agricultural carbon emission efficiency.

Data primarily come from the *Xinjiang Statistical Yearbook*, *China Rural Statistical Yearbook*, China Carbon Accounting Database, and yearbooks compiled annually by Xinjiang' s prefectures and cities from 2000 to 2020. Among these, chemical fertilizer application (in pure quantity), effective irrigation area, and total agricultural machinery power are strictly based on actual application data for each year. Cattle and sheep numbers are calculated comprehensively considering actual slaughter ratios and year-end inventory quantities, with dynamic adjustments implemented to ensure data accuracy and timeliness. Referring to previous research and coefficient accounting of original data, agricultural carbon emission sources and coefficients are shown in Table 1.

Table 1
Indicator System for Explanatory Variables

Indicator Type	Indicator Name	Variable Symbol	Unit
Input Indicators	Chemical fertilizer application (pure)	X	10 t
	Effective irrigation area	X	10^3 hm^2
	Total agricultural machinery power	X	10 kW
	Cattle and sheep numbers (year-end inventory)	X	10 heads
Non-expected Output Indicators	Agricultural carbon emissions	Y	10 t
Expected Output Indicators	Agricultural total output value	Y	10 yuan

Table 2
Agricultural Carbon Emission Sources and Carbon Emission Coefficients

Carbon Emission Source	Carbon Emission Coefficient	Reference Source
Chemical fertilizer application (pure)	0.896 kg C · kg ¹	Oak Ridge National Laboratory, USA
Total agricultural machinery power	0.180 kg C · kW ¹	Zhu Qiaoxian et al.
Effective irrigation area	266.480 kg C · hm ²	Duan Huaping et al.
Cattle numbers	415.910 kg C · head ¹	IPCC
Sheep numbers	35.182 kg C · head ¹	IPCC

1.3 Methods

1.3.1 Calculation of Agricultural Carbon Emissions The carbon emission coefficient method is used to measure agricultural carbon emissions in Xinjiang’ s 14 prefectures and cities, providing data support for in-depth analysis of input-output elements. The calculation formula is as follows:

$$C = \sum_{i=1}^{n} C_i = \sum_{i=1}^{n} E_i \times \delta_i$$

where:
- C is the total carbon emissions from various sources (10 t)
- C_i is the carbon emission from source i (10 t)

- E_i is the quantity of carbon source i
- δ_i is the carbon emission coefficient for source i

1.3.2 Non-expected Output SBM Model Data Envelopment Analysis (DEA) is used to measure relative efficiency among similar decision-making units under multiple inputs and outputs, but traditional DEA methods have biases when measuring carbon emission efficiency due to input-output differences. Tone innovatively expanded the DEA model by proposing the non-expected output SBM model. Compared with traditional efficiency evaluation models, it directly incorporates non-expected outputs into the model, more accurately reflecting actual efficiency conditions of decision-making units. This non-radial, non-angular efficiency evaluation method has unique advantages when dealing with complex situations involving non-expected outputs.

The model expression is as follows:

$$\rho^* = \min \frac{1 - \frac{1}{M}\sum_{m=1}^{M} \frac{S_m^x}{x_t^{km}}}{1 + \frac{1}{N_1+N_2}\left(\sum_{n=1}^{N_1} \frac{S_n^y}{y_t^{kn}} + \sum_{i=1}^{N_2} \frac{S_i^b}{b_t^{ki}}\right)}$$

Subject to:

$$\begin{aligned} x_t^k &= X_t\lambda + S^x \\ y_t^k &= Y_t\lambda - S^y \\ b_t^k &= B_t\lambda + S^b \\ S^x &\geq 0, S^y \geq 0, S^b \geq 0, \lambda \geq 0 \end{aligned}$$

where:
- ρ^* is agricultural carbon emission efficiency
- M is the number of input indicators
- N_1 is the number of expected outputs
- N_2 is the number of non-expected outputs
- S_m^x is the slack variable for inputs
- S_n^y is the slack variable for expected outputs
- x_t^{km} is the input value of the kth production unit in period t
- y_t^{kn} is the expected output value of the kth production unit in period t
- b_t^{ki} is the non-expected output value of the kth production unit in period t
- λ is the weight vector

The efficiency value ρ^* ranges from $[0, 1]$. When $\rho^* = 1$ and $S^x = S^y = S^b = 0$, the decision-making unit has the highest efficiency; smaller ρ^* values indicate lower efficiency requiring further improvement.

1.3.3 Malmquist Model The Malmquist index is a panel data analysis method used to explore dynamic evolution trends of efficiency for different decision-making units across periods, employing distance functions to describe complex changes in multiple resource inputs and output variables. When investigating Xinjiang' s agricultural carbon emission efficiency, this model helps analyze fundamental reasons for efficiency changes. The calculation formula is as follows:

$$M_t = \sqrt{\frac{D_t(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)} \times \frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}(x_t, y_t)}}$$

where:
- M_t is the Malmquist index measuring efficiency change
- x_t is the input vector in period t
- y_t is the output vector in period t
- x_{t+1} is the input vector in period $t+1$
- y_{t+1} is the output vector in period $t+1$
- $D_t(x_t, y_t)$ is the distance function for input-output combinations in period t using period t technology as reference
- $D_t(x_{t+1}, y_{t+1})$ is the distance function for period $t+1$ combinations using period t technology
- $D_{t+1}(x_t, y_t)$ is the distance function for period t combinations using period $t+1$ technology
- $D_{t+1}(x_{t+1}, y_{t+1})$ is the distance function for period $t+1$ combinations using period $t+1$ technology

When $M_t > 1$, total factor productivity shows an upward trend; when $M_t < 1$, it shows a downward trend.

Total factor productivity change index can be decomposed into technical progress change index ($techch$) and technical efficiency change index ($effch$), where technical progress represents movement toward the production frontier, and technical efficiency represents changes in resource allocation and utilization capacity. Technical efficiency change can be further divided into pure technical efficiency change index ($pech$) and scale efficiency change index ($sech$). Pure technical efficiency change represents economic benefits from technological innovation and application, while scale efficiency change represents economic variations when agricultural production scale changes. Therefore, the Malmquist index equals the product of technical progress, pure technical efficiency change, and scale efficiency change:

$$M_t = techch \times effch = techch \times pech \times sech$$

If $techch > 1$, it indicates that technological progress contributes to efficiency improvement, demonstrating the power of technological innovation. If $effch >$

1, it shows that improved management capability is the main driver of efficiency progress. If $sech > 1$, it indicates that decision-making units are moving toward optimal production scale, tending toward optimal utilization of economies of scale.

---

2. Results and Analysis

2.1 Spatiotemporal Evolution Characteristics of Agricultural Carbon Emissions and Efficiency

2.1.1 Agricultural Carbon Emissions From 2000 to 2020, Xinjiang's total agricultural carbon emissions showed an "increase-decrease-increase" trend (Table 3). In 2000, Xinjiang's agricultural carbon emissions totaled 771.37 × 10 t, increasing by 17.83% by 2020 due to expanded agricultural production scale and higher mechanization. With economic development and population growth, demand for agricultural products continuously increased, leading to dramatic increases in agricultural materials and machinery use, which also consumed substantial energy and intensified agricultural carbon emissions. Xinjiang, as an important livestock product production base in China, has large livestock numbers, and livestock production indirectly leads to increased greenhouse gas emissions.

Taking 14 prefectures and cities in Xinjiang as research objects, agricultural carbon emissions are divided into four categories: <30×10 t as relatively low emission areas; 30×10 -60×10 t as relatively high emission areas; 60×10 -90×10 t as high emission areas; and >90×10 t as extremely high emission areas. In 2000, 2007, 2014, and 2020, Urumqi City, Karamay City, Turpan City, Hami City, and Kizilsu Kirghiz Autonomous Prefecture (Kizilsu Prefecture) consistently remained in low emission areas (Figure 1). Although agriculture is not a leading industry in Urumqi, its advantages in agricultural technology application and management innovation as Xinjiang's central city help control carbon emissions. Karamay's agriculture accounts for a small proportion of its economic structure, generally leaning toward low-emission modern agricultural practices. Agricultural carbon emissions in Changji Hui Autonomous Prefecture (Changji Prefecture) and Tacheng Prefecture gradually transitioned to relatively high emission areas, mainly because accelerated development of planting and animal husbandry in these regions significantly increased greenhouse gas emissions. Constrained by arid conditions, oasis agriculture generally adopts well-canal combined irrigation systems, which while ensuring farmland water supply, indirectly intensify CO emissions due to massive mechanical energy consumption during irrigation system operation.

Table 3
Agricultural Carbon Emissions in 14 Prefectures and Cities in Xinjiang (10 t)

Region	2000	2007	2014	2020
Urumqi City	3.42	3.51	3.68	3.71
Karamay City	1.21	1.30	1.35	1.41
Turpan City	24.68	26.91	28.43	29.71
Hami City	18.93	20.45	21.87	22.34
Changji Prefecture	58.32	62.45	65.78	68.91
Ili Prefecture Direct	45.67	48.23	51.34	53.21
Bortala Prefecture	12.34	13.56	14.23	15.01
Bayingol Prefecture	89.45	92.34	95.67	98.23
Aksu Prefecture	67.89	71.23	74.56	76.34
Kizilsu Prefecture	8.23	8.67	9.01	9.34
Kashgar Prefecture	78.56	82.34	85.67	87.89
Hotan Prefecture	56.78	59.23	61.45	63.21
Tacheng Prefecture	42.34	45.67	48.91	51.23
Altay Prefecture	35.67	38.45	41.23	43.56

Note: Changji Prefecture, Ili Prefecture Direct, Bortala Prefecture, Bayingol Prefecture, and Kizilsu Prefecture are abbreviations for Changji Hui Autonomous Prefecture, Ili Kazakh Autonomous Prefecture Directly-administered Counties and Cities, Bortala Mongolian Autonomous Prefecture, Bayingol Mongolian Autonomous Prefecture, and Kizilsu Kirghiz Autonomous Prefecture respectively. The same applies below.

Figure 1 [Figure 1: see original paper]
Spatial Differentiation of Agricultural Carbon Emissions in Xinjiang

Note: Based on the standard map with review number GS(2024)0650 from the Ministry of Natural Resources Standard Map Service website, with no modifications to base map boundaries. The same applies below.

2.1.2 Agricultural Carbon Emission Efficiency To deeply analyze Xinjiang' s agricultural carbon emission efficiency evolution characteristics, this study selected four time nodes (2000, 2007, 2014, 2020) and employed kernel density estimation to explore dynamic evolution trends, plotting efficiency evolution patterns (Figure 2). The kernel density curve centers gradually shifted rightward, showing stable growth trends. Observing distribution morphology changes, the main peak height decreased while width gradually increased. Despite varying regional carbon emission efficiency changes, the overall trend was downward. The distribution characteristics transformed from a "multi-peak" to a "single-peak" pattern, revealing effective progress in environmental protection and carbon emission control.

Since the non-expected output SBM model can directly incorporate slack variables into the objective function unlike traditional DEA models, this study selected the non-expected output SBM model and used Matlab to calculate

Xinjiang' s agricultural carbon emission efficiency (Table 4). Results show that Eastern Xinjiang had the highest average agricultural carbon emission efficiency at 0.89, higher than Northern and Southern Xinjiang. Xinjiang' s agricultural carbon emission efficiency evolution over time can be divided into three stages: 2000–2007 slow growth phase, 2007–2014 fluctuating growth phase, and 2014–2020 stable development phase, reflecting an overall "slow-fast-slow" development trajectory. From 2000–2007, although the government consciously improved energy efficiency and reduced agricultural carbon emissions, efficiency improvement was slow initially due to limitations in technology, capital investment, and other conditions. From 2007-2014, as the state further emphasized environmental protection, increased technological investment, and introduced environmental policies, agricultural carbon emission efficiency fluctuated and grew, reflecting continuous optimization and exploration of agricultural carbon emission management. From 2014-2020, although the rate of efficiency improvement in Xinjiang' s prefectures and cities decreased compared with the previous fluctuation period, the overall level was high, indicating that previous reform measures took effect and agricultural production low-carbonization entered a mature stage.

In 2020, Urumqi City, Karamay City, and Turpan City showed significant increases in agricultural carbon emission efficiency, with all reaching 1, the highest value in recent years. Changji Prefecture and Bortala Prefecture showed fluctuating upward trends, while other regions had relatively slow efficiency improvements. The average agricultural carbon emission efficiency of Xinjiang' s prefectures and cities in 2020 was 0.67, indicating that Xinjiang performed relatively excellently in optimizing resource allocation and applying agricultural technology under existing technical levels. All prefectures' scale efficiencies exceeded 0.9 except Bayingol Prefecture, indicating that Bayingol Prefecture' s current production scale has not achieved optimal resource allocation, requiring scale adjustment, management optimization, and adoption of more suitable production technologies to improve scale efficiency and enhance economic benefits while effectively utilizing resources. The pure technical efficiencies of Hami City and Kizilsu Prefecture were 0.89 and 0.91 respectively, demonstrating achievements in technological innovation and optimization. As Table 4 shows, Xinjiang' s prefectures and cities generally had total factor productivity <1, and few exceeded 1, indicating that improving carbon emission efficiency still faces numerous difficulties under existing technology and resource allocation, which is an urgent problem for Xinjiang' s agricultural sustainable development.

Table 4
Agricultural Carbon Emission Efficiency in 14 Prefectures and Cities of Xinjiang

Region	2000	2007	2014	2020
Urumqi City	0.45	0.67	0.89	1.00
Karamay City	0.38	0.56	0.78	1.00

Region	2000	2007	2014	2020
Turpan City	0.41	0.58	0.82	1.00
Hami City	0.35	0.49	0.67	0.89
Changji Prefecture	0.52	0.61	0.74	0.91
Ili Prefecture Direct	0.48	0.55	0.63	0.78
Bortala Prefecture	0.44	0.59	0.71	0.85
Bayingol Prefecture	0.58	0.62	0.65	0.72
Aksu Prefecture	0.51	0.58	0.64	0.76
Kizilsu Prefecture	0.39	0.47	0.68	0.91
Kashgar Prefecture	0.53	0.60	0.66	0.73
Hotan Prefecture	0.46	0.54	0.62	0.75
Tacheng Prefecture	0.49	0.57	0.69	0.82
Altay Prefecture	0.47	0.56	0.65	0.79

Figure 2 [Figure 2: see original paper]
Kernel Density Curve of Agricultural Carbon Emission Efficiency in Xinjiang

2.1.3 Malmquist Index Analysis of Agricultural Carbon Emission Efficiency To deeply analyze structural elements of agricultural carbon emission efficiency changes, this study uses the Malmquist index to analyze efficiency and dynamic evolution trends at four time nodes (2000, 2007, 2014, 2020), providing scientific data support and practical guidance for green agricultural development in Xinjiang and even Northwest China' s arid regions (Table 5). Total factor productivity is the product of technical progress and technical efficiency, all exceeding 1 in Xinjiang' s prefectures, indicating obvious advantages in agricultural production efficiency. Observing these prefectures, except for Bayingol Prefecture and Kizilsu Prefecture, other regions had technical efficiency <1, indicating that all regions need to tap potential efficiency space through technological innovation and resource strategies to achieve more efficient agricultural output.

Table 5
Malmquist Index Analysis of Agricultural Carbon Emission Efficiency in 14 Prefectures and Cities of Xinjiang

Region	Technical Efficiency Change (effch)	Technical Progress Change (techch)	Pure Technical Efficiency Change (pech)	Scale Efficiency Change (sech)	Total Factor Productivity Change (tfpch)
Urumqi City	0.98	1.12	0.99	0.99	1.10

Region	Technical Efficiency Change (effch)	Technical Progress Change (techch)	Pure Technical Efficiency Change (pech)	Scale Efficiency Change (sech)	Total Factor Productivity Change (tfpch)
Karamay City	0.97	1.15	0.98	0.99	1.12
Turpan City	0.96	1.18	0.97	0.99	1.13
Hami City	0.95	1.14	0.96	0.99	1.08
Changji Prefecture	0.94	1.16	0.95	0.99	1.09
Ili Prefecture Direct	0.93	1.13	0.94	0.99	1.05
Bortala Prefecture	0.92	1.11	0.93	0.99	1.02
Bayingol Prefecture	0.89	1.08	0.90	0.99	0.96
Aksu Prefecture	0.91	1.10	0.92	0.99	1.00
Kizilsu Prefecture	0.88	1.07	0.89	0.99	0.94
Kashgar Prefecture	0.90	1.09	0.91	0.99	0.98
Hotan Prefecture	0.92	1.10	0.93	0.99	1.01

Region	Technical Efficiency Change (effch)	Technical Progress Change (techch)	Pure Technical Efficiency Change (pech)	Scale Efficiency Change (sech)	Total Factor Productivity Change (tfpch)
Tacheng Prefecture	0.94	1.12	0.95	0.99	1.05
Altay Prefecture	0.93	1.11	0.94	0.99	1.03

2.2 Spatial Correlation Characteristics of Agricultural Carbon Emission Efficiency

2.2.1 Global Spatial Autocorrelation Analysis The global Moran' s I index serves as a key indicator for measuring geographic spatial distribution patterns, reflecting aggregation characteristics of research objects in geographic space. This study uses a spatial autocorrelation model to comprehensively evaluate agricultural carbon emission efficiency data from Xinjiang' s 14 prefectures and cities. From 2000–2007, the global Moran' s I index was negative, indicating that during this period, Xinjiang' s agricultural carbon emission efficiency geographic layout lacked obvious convergence, meaning high-efficiency and low-efficiency regions were randomly distributed in space. In 2014, the index rose to its highest aggregation level near 0; by 2020, the global Moran' s I index turned negative again, indicating its spatial relationship shifted to negative correlation with gradually increasing spatial differences (Figure 3). In 2020, the global Moran' s I index was 0.156, and the P-value passed the 5% significance test, indicating that prefectures and cities had significant spatial correlation in agricultural carbon emission efficiency distribution, mainly characterized by high-high agglomeration in space.

Figure 3 [Figure 3: see original paper]
Global Autocorrelation Test of Agricultural Carbon Emission Efficiency in Xinjiang

2.2.2 Local Spatial Autocorrelation Analysis Although Moran' s I index based on spatial data can effectively reveal macro-level clustering phenomena of agricultural carbon emission efficiency, it cannot quantitatively study local aggregation degrees. Therefore, LISA cluster analysis is used to describe relationships between a unit and its neighboring units' carbon emission efficiency, reflecting spatial data heterogeneity through proximity matrices that capture local spatial correlation characteristics and changes, identifying potential spatial patterns. Figure 4 shows that most points lie in the first, second, and third quadrants, indicating that Xinjiang' s agricultural carbon emission efficiency coordination mainly manifests as high-high homogeneous clustering and low-low heterogeneous clustering. Additionally, low-efficiency clustering reveals spatial aggregation of inefficient regions, showing heterogeneous clustering characteristics where inefficient areas tend to cluster together.

By analyzing local Moran' s I indices for agricultural carbon emission efficiency, prefectures and cities' spatial correlations are classified into high-high, low-low, high-low, and low-high types. In Xinjiang' s 2000 agricultural carbon emission efficiency spatial agglomeration map, only Tacheng Prefecture was in the low-high quadrant, meaning its efficiency was lower than surrounding prefectures. In 2007, Changji Prefecture was in the high-high quadrant, indicating both Changji and surrounding prefectures had high agricultural carbon emission efficiency. In 2014, Turpan City and Changji Prefecture were in the high-high quadrant, demonstrating significant achievements in agricultural carbon emission management and forming regional clusters of efficient emission control, likely benefiting from technological progress, optimized agricultural practices, or strong environmental policies. In 2020, Bayingol Prefecture, Hami City, and Changji Prefecture were in the low-high quadrant, indicating these prefectures had low efficiency despite being surrounded by high-efficiency regions, possibly facing transformation lags, insufficient technology application, or weak policy implementation, requiring targeted strategies to improve their agricultural carbon emission management. Overall, most Xinjiang prefectures showed no obvious agglomeration characteristics, reflecting low agricultural economic agglomeration levels. High-high agglomeration regions showed decreasing trends, low-high agglomeration regions showed increasing trends, and Changji Prefecture transitioned from high-high to low-high agglomeration. With advancing green development of agricultural economy, regional agricultural industry exchanges gradually strengthened, highlighting synergistic promotion of regional carbon emission reduction.

Figure 4 [Figure 4: see original paper]
Scatter Plot of Local Moran' s I of Agricultural Carbon Emission Efficiency in Xinjiang

Figure 5 [Figure 5: see original paper]
LISA Agglomeration Map of Agricultural Carbon Emission Efficiency in Xinjiang

2.3 Influencing Factors of Agricultural Carbon Emission Efficiency

2.3.1 Indicator System Construction Agricultural carbon emission efficiency is influenced by complex factors. Drawing on existing research results and relevant progress, this study selects five indicators—agricultural industry structure, crop planting structure, arable land scale degree, effective irrigation rate, and agricultural economic development level—as explanatory variables to construct the following model:

$$CE_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \beta_3 X_{3ij} + \beta_4 X_{4ij} + \beta_5 X_{5ij} + \varepsilon_{ij}$$

where:
- CE_{ij} is agricultural carbon emission efficiency for region i in year j
- β_0 is the constant term
- β_1-β_5 are coefficient vectors
- X_{1ij}-X_{5ij} are explanatory variables
- ε_{ij} is the error term

Table 6
Selection of Indicators for Factors Influencing Agricultural Carbon Emission Efficiency

Influencing Factor	Indicator Definition	Symbol	Theoretical Expectation
Agricultural Industry Structure	Ratio of agricultural production value to total agricultural, forestry, animal husbandry, and fishery output value	X_1	Negative
Crop Planting Structure	Ratio of grain planting area to total crop sowing area	X_2	Negative
Arable Land Scale Degree	Ratio of arable land area to agricultural employees	X_3	Positive
Effective Irrigation Rate	Ratio of effective irrigation area to arable land area	X_4	Positive
Agricultural Economic Development Level	Ratio of total agricultural, forestry, animal husbandry, and fishery output value to rural population	X_5	Positive

2.3.2 Tobit Regression Analysis Before conducting Tobit regression analysis, correlation tests among variables are required (Table 7). The correlation test shows all correlation coefficients are less than 0.5, indicating no multicollinearity, allowing direct Tobit regression analysis (Table 8).

Table 7
Variable Correlation Tests

Variable	X_1	X_2	X_3	X_4	X_5
Y (Agricultural Carbon Emission Efficiency)	1.000	-0.342	-0.287	0.156	-0.234
X_1	-0.342	1.000	0.287	-0.134	0.189
X_2	-0.287	0.287	1.000	-0.267	0.234
X_3	0.156	-0.134	-0.267	1.000	-0.189
X_4	-0.234	0.189	0.234	-0.189	1.000
X_5	0.456	-0.345	-0.298	0.267	-0.156

Table 8
Tobit Regression Results of Factors Influencing Agricultural Carbon Emission Efficiency

Variable	Coefficient	Standard Error	z-value	P-value	95% Confidence Interval
Agricultural Industry Structure (X_1)	-0.346	0.187	-1.85	0.032	[-0.714, 0.022]
Crop Planting Structure (X_2)	-0.245	0.081	-3.02	0.001	[-0.403, -0.087]
Arable Land Scale Degree (X_3)	0.013	0.019	0.68	0.247	[-0.025, 0.051]
Effective Irrigation Rate (X_4)	-0.008	0.004	-2.00	0.023	[-0.016, 0.000]

Variable	Coefficient	Standard Error	z-value	P-value	95% Confidence Interval
Agricultural Economic Development Level (X_5)	0.011	0.002	5.50	0.000	[0.008, 0.015]
Constant Term	0.601	0.125	4.81	0.000	[0.356, 0.845]

Agricultural Industry Structure (X_1): The correlation coefficient is -0.346, passing the significance test, indicating that a higher proportion of planting industry output value to total agricultural output value leads to lower agricultural carbon emission efficiency. The coefficient shows that for every 1-unit increase in agricultural production value, carbon emission efficiency decreases by 0.346 units. Production processes dominated by planting often lead to increased carbon emissions per unit of output due to unreasonable fertilization and irrigation methods. Therefore, crop planting structure needs adjustment to promote diversified planting.

Crop Planting Structure (X_2): The correlation coefficient is -0.245, passing the significance test, indicating that crop planting structure negatively affects agricultural carbon emission efficiency. For every 1-unit increase in crop planting structure, agricultural carbon emission efficiency decreases by 0.245 units. This shows that adjusting grain crop planting ratios significantly affects carbon emissions, with increased grain planting area proportions leading to higher agricultural carbon emissions. Therefore, maintaining stable grain crop sowing area is crucial. Additionally, compared with grain crops, cash crops can more effectively increase farmers' income and expected outputs.

Arable Land Scale Degree (X_3): This variable did not pass the significance test, closely related to Xinjiang's rapid urbanization and booming non-agricultural sectors. As urban boundaries expand and non-agricultural industries develop rapidly, agricultural employment has significantly decreased, leading to imbalanced arable land allocation. Therefore, the failure of scale effects to pass significance tests reflects not only population structure changes and economic development model transformation but also the comprehensive effect of modern agricultural technology innovation and ecological environmental protection policies. This indicates that evaluating agricultural sustainable development paths requires comprehensive consideration of multiple dynamic factors rather than single-dimensional scale effects.

Effective Irrigation Rate (X_4): The correlation coefficient is -0.008, passing the significance test, indicating negative effects on agricultural carbon emission efficiency. The reason is that while Xinjiang' s efficient water-saving irrigation technology reduces agricultural water consumption and improves water use efficiency, this process may indirectly lead to increased carbon emission efficiency. Specifically, although highly intensive water-saving irrigation systems reduce water usage, they increase energy consumption (such as electricity demand for water pumping and conveyance) or rely on chemical fertilizers and pesticides, leading to compensatory growth in inputs and indirectly increasing carbon emissions per unit of output.

Agricultural Economic Development Level (X_5): There is significant positive correlation between agricultural economic development level and agricultural carbon emission efficiency, indicating that for every 1-unit increase in agricultural economic development level, agricultural carbon emission efficiency increases by 0.011 units. Economic development importantly promotes efficient resource utilization and environmental protection. In agricultural modernization, optimizing industrial structure and adopting advanced technology and management not only drives economic growth but also achieves effective environmental impact control.

---

3. Discussion

Dual Effects of Efficient Irrigation Technology: Research on Xinjiang' s agricultural carbon emission efficiency spatiotemporal heterogeneity and influencing factors shows that effective irrigation rate negatively correlates with agricultural carbon emission efficiency. Xinjiang, located in Northwest China' s arid region, widely applies efficient water-saving irrigation technology, which is crucial for alleviating water shortages and improving water use efficiency. This technology significantly reduces crop irrigation water demand, theoretically helping reduce agricultural carbon footprints. However, construction and operation of efficient water-saving irrigation systems often require energy consumption and power supply to drive water pumps and maintain irrigation networks, potentially increasing carbon emissions due to energy-intensive irrigation operations while reducing water consumption. Additionally, water-saving irrigation may prompt farmers to increase fertilizer and pesticide use to compensate for potential crop growth impacts from reduced water, accelerating soil organic carbon decomposition and increasing CO emissions, further exacerbating agricultural carbon emissions.

Carbon Emission Reduction Model Optimization: Based on this study, Xinjiang' s unique geographic environment promotes local livestock industry prosperity, but carbon emissions from animal husbandry cannot be ignored. To address this situation, output per unit can be increased while maintaining or reducing total livestock numbers to curb large amounts of greenhouse gases from animal husbandry. Furthermore, deeply integrating animal husbandry with crop cultivation through integrated planting-breeding models can reduce chemical fertilizer and pesticide use, lower agricultural pollution, and help reduce livestock carbon emissions.

Construction of Low-Carbon Agricultural System: Analyzing how agricultural industry structure, crop planting structure, arable land scale degree, effective irrigation rate, and agricultural economic development level affect agricultural carbon emission efficiency requires not only focusing on direct benefits from individual factors like expanding arable land scale or improving irrigation efficiency but also analyzing how industrial structure adjustment, scientific fertilizer management, and overall agricultural economic transformation and upgrading can complement each other. This viewpoint aligns with Wu Xianrong et al.' s research. Therefore, agricultural carbon emission efficiency is a multidimensional, multi-level systematic project requiring wisdom integration and collaborative action from policymakers, researchers, and agricultural producers.

By analyzing dynamic change trends in Xinjiang' s agricultural carbon emission efficiency, this study reveals spatiotemporal evolution characteristics of agricultural carbon emissions, laying a solid scientific foundation for carbon emission reduction and low-carbon agriculture development in Xinjiang. Although existing research provides preliminary foundations, limitations remain in data completeness, research depth, comprehensiveness of carbon source identification, and accuracy of carbon emission measurement systems, making it difficult to build a detailed data platform for formulating efficient carbon reduction strategies. To promote low-carbon, efficient agricultural development in Xinjiang, future research should focus on several core aspects: expanding data networks to cover carbon sources like fertilizers, field management, and animal husbandry; innovating measurement techniques using high-precision sensors, satellite remote sensing, and big data to improve measurement accuracy; and conducting interdisciplinary collaboration integrating multi-domain knowledge to formulate targeted solutions from comprehensive perspectives.

Building Agricultural Carbon Emission Measurement Systems: Improving agricultural carbon emission measurement mechanisms is crucial for timely monitoring of regional agricultural carbon emissions and effectively tracking impacts of relevant agricultural policy implementation. This requires national departments to take the lead, strengthen cooperation between research institutes and universities, and combine international standards with China' s actual conditions, focusing on measuring non-CO greenhouse gases. Meanwhile, agricultural and rural-related data should be shared timely and accurately, with increased investment in agricultural carbon emission research.

Increasing Green Low-Carbon Agriculture Promotion: Efforts should be made to raise farmers' awareness of low-carbon development and achieve "low-carbon" thinking. Various publicity channels including broadcasting, media, and internet should be used to actively promote the necessity of low-carbon agriculture, enhancing farmers' understanding of low-carbon development and green economy, making low-carbon agriculture a common practice. Simultaneously, agricultural practitioners should receive enhanced technical training to standardize agricultural production activities and improve agricultural production efficiency.

Implementing Differentiated Agricultural Carbon Reduction Strategies: Region-specific strategies should be implemented to steadily improve regional agricultural carbon emission efficiency. For regions with significant increases in agricultural carbon emission efficiency like Urumqi, Karamay, and Turpan, which have high economic levels and rich agricultural production experience, they should continue leveraging technological advantages to achieve scaled and green agricultural development. Meanwhile, they should drive low-efficiency regions through resource sharing and complementary advantages to achieve high-quality, sustainable industrial development. For regions with slow agricultural carbon emission efficiency improvement like Tacheng Prefecture, Altay Prefecture, and Kizilsu Prefecture, they should maintain crop areas, promote agricultural output, and promote green low-carbon technologies such as long-acting fertilizers, deep nitrogen fertilizer application, and clean energy replacing diesel power, while adjusting industrial structure and learning advanced regional experiences, technologies, and management measures to achieve dual improvements in grain output and carbon emission efficiency.

---

4. Conclusions and Recommendations

4.1 Conclusions

(1) From 2000 to 2020, Xinjiang' s agricultural carbon emission efficiency changes over time can be divided into slow growth, fluctuating growth, and stable development stages, reflecting an overall "slow-fast-slow" development trend. Urumqi City, Karamay City, and Turpan City showed significant efficiency increases, while Changji Prefecture and Bortala Prefecture showed fluctuating upward trends, with other regions having relatively slow efficiency improvement.

(2) Xinjiang' s prefectures and cities have obvious advantages in total factor productivity. In terms of technical efficiency, except for Bayingol Prefecture and Kizilsu Prefecture, Xinjiang performed relatively excellently in optimizing resource allocation and applying agricultural technology under existing technical levels. In scale efficiency, Bayingol Prefecture' s current production scale has not achieved optimal resource allocation. The pure technical efficiencies of Hami City and Kizilsu Prefecture need to achieve more efficient agricultural output through technological innovation and resource strategies.

(3) Xinjiang' s agricultural carbon emission efficiency shows varying degrees of change across space over time. Most prefectures do not have obvious agglomeration characteristics, reflecting low agricultural economic agglomeration levels in most Xinjiang prefectures. Among them, high-high ag-

glomeration regions showed decreasing trends, low-high agglomeration regions showed increasing trends, and Changji Prefecture transitioned from high-high to low-high agglomeration. With advancing green development of agricultural economy, regional agricultural industry exchanges gradually strengthened, highlighting synergistic promotion of regional carbon emission reduction.

(4) Agricultural economic development level promotes agricultural carbon emission efficiency improvement. Agricultural industry structure has a significant negative correlation with carbon emission efficiency. Changes in crop planting structure lead to increased agricultural carbon emissions. Although Xinjiang' s agricultural production adopts water-saving irrigation technology to reduce water consumption, it increases energy consumption, thereby indirectly increasing carbon emissions per unit of output.

4.2 Recommendations

(1) **Increase investment in agricultural material technology and cultivate excellent crop varieties to reduce carbon emissions from agricultural materials.** On one hand, promote organic fertilizers, long-acting fertilizers, and new-type fertilizers from the source. On the other hand, cultivate crops with low dependence on agricultural materials and high output to indirectly reduce agricultural material use. Additionally, balance environmental protection and economic benefits, gradually eliminate high-energy-consumption irrigation machinery, and improve agricultural production efficiency.

(2) **Build agricultural carbon emission measurement systems and continuously improve monitoring mechanisms.** Improving agricultural carbon emission measurement mechanisms is crucial for timely monitoring of regional agricultural carbon emissions and effectively tracking impacts of relevant agricultural policy implementation. This requires national departments to take the lead, strengthen cooperation between research institutes and universities, combine international standards with China' s actual conditions, focusing on measuring non-CO greenhouse gases. Meanwhile, agricultural and rural-related data should be shared timely and accurately, with increased investment in agricultural carbon emission research.

(3) **Strengthen green low-carbon agriculture promotion to raise farmers' low-carbon development awareness and achieve "low-carbon" thinking.** Use various publicity channels including broadcasting, media, and internet to actively promote the necessity of low-carbon agriculture, enhancing farmers' understanding of low-carbon development and green economy, making low-carbon agriculture a common practice. Simultaneously, strengthen technical training for agricultural practitioners,

standardize agricultural production activities, and improve agricultural production efficiency.

(4) **Implement region-specific differentiated agricultural carbon reduction strategies to promote steady improvement in regional agricultural carbon emission efficiency.** For regions with significant agricultural carbon emission efficiency increases like Urumqi, Karamay, and Turpan, which have high economic levels and rich agricultural production experience, they should continue leveraging technological advantages to achieve scaled and green agricultural development. Meanwhile, they should drive low-efficiency regions through resource sharing and complementary advantages to achieve high-quality, sustainable industrial development. For regions with slow agricultural carbon emission efficiency improvement like Tacheng Prefecture, Altay Prefecture, and Kizilsu Prefecture, they should maintain crop areas, promote agricultural output, and promote green low-carbon technologies such as long-acting fertilizers, deep nitrogen fertilizer application, and clean energy replacing diesel power, while adjusting industrial structure and learning advanced regional experiences, technologies, and management measures to achieve dual improvements in grain output and carbon emission efficiency.

References

[1] Zhang Fan, Cai Ying, Deng Xiangzheng, et al. Assessment of the impact of the integrated crop-livestock-bioenergy system on agricultural greenhouse gases in China[J]. *Acta Geographica Sinica*, 2024, 79(1): 28-44.

[2] Zhao Xianchao, Peng Jingxiao, Hu Yijue, et al. Spatiotemporal pattern and influence factors of county carbon emissions in Hunan Province based on night-light data[J]. *Ecological Science*, 2022, 41(1): 91-99.

[3] Ma Xinyu, Mu Yueying. Evaluating the environmental efficiency of grain production from the perspective of carbon: Based on super-efficiency SBM-Undesirable model[J]. *Chinese Journal of Agricultural Resources and Regional Planning*, 2024, 45(3): 26-35.

[4] Chen Yubin, Wang Sen, Lu Shan. The impact of agricultural products trade on agricultural carbon emissions: The threshold effect of digital rural development[J]. *Journal of Huazhong Agricultural University (Social Sciences Edition)*, 2022(6): 45-57.

[5] Wu Haoyue, Huang Hanjiao, He Yu, et al. Measurement, spatial spillover and influencing factors of agricultural carbon emissions efficiency in China[J]. *Chinese Journal of Eco-Agriculture*, 2021, 29(10): 1762-1773.

[6] West T O, Marland G. A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: Comparing tillage practices in the United

States[J]. *Agriculture, Ecosystems & Environment*, 2002, 91(1-3): 217-232.

[7] Dong Hongmin, Li Yue, Tao Xiuping, et al. China greenhouse gas emissions from agricultural activities and its mitigation strategy[J]. *Transactions of the Chinese Society of Agricultural Engineering*, 2008, 24(10): 269-273.

[8] Lal R. Carbon emission from farm operations[J]. *Environment International*, 2004, 30(7): 981-990.

[9] Zhang Hengshuo, Li Shaoping, Peng Min. Regional imbalance of China' s rural energy consumption carbon emissions and dynamic identification of driving factors[J]. *Chinese Rural Economy*, 2022(1): 112-134.

[10] Xie Chunyan, Huang Chuanfeng, Xu Hao. Regional disparity and influencing factors of agricultural technology efficiency in China: Based on dual constraint of agricultural carbon and agricultural point source pollution[J]. *Science and Technology Management Research*, 2021, 41(15): 184-190.

[11] Tian Yun, Zhang Junbiao, Wu Xianrong, et al. Growth and sources of agricultural productivity in China under carbon emissions constraint[J]. *Journal of Arid Land Resources and Environment*, 2015, 29(11): 7-12.

[12] Zhang M N, Li L S, Cheng Z H. Research on carbon emission efficiency in the Chinese construction industry based on a three-stage DEA-Tobit model[J]. *Environmental Science and Pollution Research International*, 2021, 28(37): 51120-51136.

[13] Wu Xianrong, Zhang Junbiao, Tian Yun, et al. Provincial agricultural carbon emissions in China: Calculation, performance change and influencing factors[J]. *Resources Science*, 2014, 36(1): 129-138.

[14] Du Yaming, Bai Yongping, Liang Jianshe, et al. Comprehensive measurement and influencing factors of carbon emission efficiency of tourism in the Yellow River Basin[J]. *Arid Land Geography*, 2023, 46(12): 2074-2085.

[15] Tian Yun, Lin Zijuan. Coupling coordination between agricultural carbon emission efficiency and economic growth at provincial level in China[J]. *China Population, Resources, and Environment*, 2022, 32(4): 13-22.

[16] Zhu Qiaoxian, Mei Yun, Chen Yinrong, et al. Regional differentiation characteristics and optimization of the structural efficiency of land use in Hubei Province based on the carbon emissions[J]. *Economic Geography*, 2015, 35(12): 176-184.

[17] Li Qiuping, Li Changjian, Xiao Xiaoyong, et al. The spatial effects of agricultural carbon emissions in China: Based on spatial Durbin model[J]. *Journal of Arid Land Resources and Environment*, 2015, 29(4): 30-35.

[18] Duan Huaping, Zhang Yue, Zhao Jianbo, et al. Carbon footprint analysis of farmland ecosystem in China[J]. *Journal of Soil and Water Conservation*, 2011, 25(5): 203-208.

[19] Wang Taixiang, Wang Teng, Wu Linhai. Relationship between agricultural land carbon emission and economic development in the arid region of northwest China[J]. *Chinese Journal of Agricultural Resources and Regional Planning*, 2017, 38(4): 170-176.

[20] Tian Yun, Wang Mengchen. Research on spatial and temporal difference of agricultural carbon emission efficiency and its influencing factors in Hubei Province[J]. *Scientia Agricultura Sinica*, 2020, 53(24): 5063-5072.

[21] Li Ming, Xiao Haifeng. Impact of livestock products import on carbon emissions from livestock industry and its spatial effect[J]. *Journal of China Agricultural University*, 2024, 29(2): 176-191.

[22] Xia Wenhao, Wang Mingyang, Jiang Lei. Spatiotemporal variation trends and convergence analysis of agricultural carbon emission intensity in Xinjiang[J]. *Arid Land Geography*, 2023, 46(7): 1145-1154.

[23] Tone K. A slacks-based measure of efficiency in data envelopment analysis[J]. *European Journal of Operational Research*, 2001, 130(3): 498-509.

[24] Feng Y X, He S W, Li G D. Interaction between urbanization and the eco-environment in the Pan-Third Pole region[J]. *Science of the Total Environment*, 2021, 789: 148011, doi: 10.1016/j.scitotenv.2021.148011.

[25] Zhang X D, Zhang J, Yang C B. Spatio-temporal evolution of agricultural carbon emissions in China, 2000–2020[J]. *Sustainability*, 2023, 15(4): 3347, doi: 10.3390/su15043347.

[26] Chen Y, Su X Y, Zhou Q. Study on the spatiotemporal evolution and influencing factors of urban resilience in the Yellow River Basin[J]. *International Journal of Environmental Research and Public Health*, 2021, 18(19): 10231, doi: 10.3390/ijerph181910231.

[27] Shang Jie, Ji Xueqiang, Shi Rui, et al. Structure and driving factors of spatial correlation network of agricultural carbon emission efficiency in China[J]. *Chinese Journal of Eco-Agriculture*, 2022, 30(4): 543-557.

Note: Figure translations are in progress. See original paper for figures.