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Spatial spillover effect of carbon emission efficiency in the construction industry of China

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Abstract

The construction industry plays an important role in energy saving and carbon emissions mitigation of China. Promoting carbon emission efficiency is seen as an efficient way to abate carbon emissions. Using 2005-2016 data, the carbon emission efficiency of the construction sector in 30 provinces is estimated, and the spatial distribution characteristics of the carbon emission efficiency of the construction industry is explored. The spatial Markov transition probability matrix is employed to investigate the influence of the spatial spillover effect on the regional distribution pattern of carbon emission efficiency. The results demonstrate that the carbon emission efficiency of the construction industry exhibits an unbalanced regional distribution, which is high in the east and low in the west. The spatial autocorrelation indicates that the carbon emission efficiency has a spatial dependence and is characterized by spatial agglomeration. Markov Chain results show a significant spatial spillover effect in carbon emission efficiency. The provinces with higher carbon emission efficiency have a positive effect on their neighbors, while the provinces with lower efficiency have a negative effect on neighbors. The findings are of great importance to understand the differences in and interactions of carbon emission efficiency between regions.

Keywords Temporal and spatial distribution \cdot Spatial dependence \cdot Spatial spillover effect \cdot Carbon emission efficiency \cdot Construction industry . Spatial Markov chain

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Introduction

Over the past 30 years, China's economy has achieved speedy progress (Li et al. [2020a\)](#page-12-0). This economic development has been mainly driven by infrastructure construction and energy-intensive industries, which contribute to huge energy consumption and carbon emissions. Since 2007, China has been number one in the world in regards to the amount of carbon emissions generated (Du et al. [2019b](#page-12-0)), which puts the government under intense pressure to reduce carbon emissions. In an effort to deal with the issue, the Chinese government submitted an enhanced action report, which is aimed at decreasing the carbon intensity to 60%-65% based on the 2005 level and stop the growth of carbon dioxide emissions by 2030 (Li and Li [2020;](#page-12-0) Qi et al. [2020](#page-12-0)).

In order to maintain sustainable development, it is vital for an energy-intensive industry to control carbon emissions (Du et al. [2019a;](#page-12-0) Li et al. [2019b;](#page-12-0) Zhou et al. [2019\)](#page-13-0). Based on the estimation of the Building Energy Research Center of Tsinghua University, in 2015, the energy consumption of the construction industry, which was 1.07 billion tce, accounted for 25% of the total energy consumption in China

(Li et al. [2017;](#page-12-0) Zhang et al. [2019](#page-13-0)). In 2017, carbon emissions from this sector accounted for one-third of the entire carbon emissions of China (Wang and Feng [2018](#page-12-0); Xu and Wang [2020\)](#page-13-0). The pillar of economic development in China, the construction industry faces a dual challenge of reducing carbon emissions while ensuring sustainable economic growth. To achieve this goal, the construction industry should focus not only on reducing the amount and intensity of carbon emissions but also on efficiency (Huo et al. [2020](#page-12-0)). Carbon emission efficiency is a crucial indicator which is consistent with sustainable development (Wen et al. [2020a;](#page-12-0) Du et al. [2021\)](#page-12-0). Improving the carbon emissions efficiency of the construction sector is critical to promote regional low-carbon transition under the new normal of the economy, and it is beneficial to the coordinated development of energy, the economy, and the ecological environment (Chen et al. [2019](#page-12-0); Li et al. [2020b](#page-12-0); Wang and Feng [2018](#page-12-0)).

It is worth noting that there is a significant disparity in economic development, technological level, and resource consumption among different regions, resulting in regional heterogeneity in carbon emission efficiency (Cheng et al. [2018;](#page-12-0) Li et al. [2020b](#page-12-0)). The distribution of carbon emission efficiency is significantly different across regions. Different regions can be linked by many aspects of spatial interactions such as economy, society, energy, and carbon emission (Zeng et al. [2021](#page-13-0)). Because of geographical proximity, the crossregional flow of production factors, the spillover effect of technologies, and the mutual imitation of production innovations, the neighboring regions have relatively close connections (Wen et al. [2020a\)](#page-12-0). For these reasons, the carbon emission efficiency of the construction industry of each province not only depends on its own construction development but it also is influenced by its neighboring provinces. Wen et al. [\(2020b\)](#page-12-0) pointed out that the carbon emission efficiency of the construction industry was characterized by high in the east and low in the north. However, in previous researches, each decision-making unit (DMU) was regarded as independent, and the potential spatial spillover effects of carbon emission efficiency of the construction industry of a region on its neighbors were generally neglected leading to possible measurement deviation in the results. According to the Law of Tobler's First Geography, all variables are related to each other geographically. Due to externality, the economic activities in a region will directly affect its surrounding regions, also known as the spatial spillover effect (Liu and Liu [2019](#page-12-0); Long et al. [2016](#page-12-0); You and Lv [2018](#page-13-0)). Peng et al. ([2019\)](#page-12-0) employed spatial autocorrelation analysis to investigate the spatial characteristics of carbon emission efficiency in the transport sector and found a significant spatial dependence of carbon emission efficiency among regions. There are significant spatial spillover effects and agglomeration characteristics in China's industrial carbon emission efficiency, and the provinces with high- and low-level carbon emission efficiency

have a much higher tendency of agglomeration (Yang et al. [2021\)](#page-13-0). When exploring the dynamic evolution of carbon emissions, the spatial spillover effect cannot be ignored, and changes in carbon emissions are influenced by adjacent regions (Chen et al. [2020](#page-12-0); Koch and Robert [2019](#page-12-0)). It is necessary to clarify the spatial distribution features of carbon emission efficiency in the construction sector and explore the impact of its spatial spillover effect.

This study uses the Markov chain model to examine the spatial spillover effect of carbon emission efficiency in the construction industry and explores the influence of the spillover effect on the state change in carbon emission from the perspective of spatial analysis. First, the carbon emission efficiency of the construction industry is calculated from 2005-2016 for 30 provinces. Moran's index is then employed to present the distribution pattern. Finally, the traditional Markov and spatial Markov chain are introduced into research on the carbon emission efficiency of the construction industry. The dynamic interaction between provinces is revealed through analysis of analysis of the state transfer probability of carbon emission efficiency. The results obtained could help policymakers formulate differentiated carbon emission abatement policies instead of employing similar policies in all provinces. In addition, some reference could be provided for local government to promote the coordinated regional development of the construction industry.

The paper is organized as follows: Section 2 reviews relevant literature. The methods and data used in this paper are introduced in Section 3. The results and discussion are presented in Sections 4 and 5. Section 6 summarizes the findings and puts forward policy recommendations.

Literature review

Carbon emission efficiency describes the proportional relationship between carbon emissions, economic growth, and energy consumption (Yu and Zhang [2021\)](#page-13-0). Current methods of measuring the carbon emission efficiency include the parametric method (SFA) and the non-parametric method (DEA). Due to the non-efficiency term and form of the function should be set in advance in SFA, which is easy to cause result deviations. Thus, a growing number of studies use DEA (Data Envelope Analysis) to evaluate carbon emission efficiency. DEA calculates efficiency by constructing a production frontier using linear programming and evaluates the efficiency from the perspective of the inputs and outputs (Xie et al. [2021\)](#page-13-0). Compared with other DEA-based methods, the superefficient SBM model has the advantage of considering carbon emissions as undesirable outputs as well as both radial and non-radial possible enhancements in the production process, thereby delivering more comprehensive and realistic performance evaluation results (Tang et al.2020). Therefore, this

study employs the super SBM model to evaluate the carbon emissions efficiency of the construction industry.

Research on the spatial distribution characteristics of carbon emissions has appealed to many scholars (Dissanayake et al. [2020](#page-12-0); Morales-Lage et al. [2019;](#page-12-0) Tian et al. [2020](#page-12-0)). Cheng et al. [\(2020\)](#page-12-0), Rios and Gianmoena [\(2018\)](#page-12-0), and Zhao ([2019](#page-13-0)) applied the convergence theory to confirm the sigma, beta, and stochastic convergence of provincial carbon emissions across 28 provinces in China. Li et al. [\(2019a](#page-12-0)) used the kernel density estimation method to depict the dynamic evolution of carbon emission intensity, and the results revealed significant spatial heterogeneity between the provinces. Wang et al. ([2019b](#page-12-0)) employed the Markov transition probability matrix to predict the change tendency of the carbon emission intensity. However, the above studies ignored the effect of geographic proximity on the spatial features of the carbon emissions.

In research concerning regional development issues, the spatial spillover effect is not negligible. Anselin and Griffith [\(2010\)](#page-12-0) indicated that the characteristic of a certain region depends on its neighboring regions. There was significant spatial dependence of carbon emissions, and a spatial spillover effect existed between different regions (Burnett et al. [2013\)](#page-12-0). Some scholars employed the spatial Durbin model to verify the spatial spillover effect of carbon emission performance. Liu and Liu [\(2019](#page-12-0) and Wang et al. (2019a) noted that the total-factor efficiency of the industrial sector between neighboring provinces has an interactive effect. Song et al. ([2020](#page-12-0)) found the local energy intensity could influence the energy intensity of the surrounding regions. If the spatial spillover effect is ignored, it may cause deviation in estimation results (Hong et al. [2020](#page-12-0)). The existing studies on the spatial spillover effect have mainly concentrated on a certain region or on industries than the construction industry, and few have focused on the construction industry. Therefore, it is necessary to examine the interactional carbon emission efficiency in the construction industry.

With the purpose of further exploring the influence of geographic location on the dynamic spatial and temporal distribution of the observed variables, the spatial Markov chain was first proposed by Rey ([2001](#page-12-0)). This method added spatial lag into the traditional Markov chain. Using this method, the spatial spillover effect could be quantitatively identified, based on the comparison of the traditional and spatial probability transfer matrix. Thus, the spatial Markov chain has been widely implemented in research unfolding the spatiotemporal inequality of economy, society, and environment elements. Wang et al. [\(2019a\)](#page-12-0) employed the spatial Markov chain to examine the spatial spillover effect of city's carbon intensity and found that obvious spillover effect exists in surrounding cities. Liu et al. [\(2019\)](#page-12-0) used the spatial Markov chain to identify the spatial distribution dynamic of carbon emission intensity in

China. They observed that the carbon emission intensity of neighboring provinces has a strong effect on local carbon emissions. Taking foreign direct investment (FDI) in Mexico as study the object, Torres Preciado et al. [\(2017\)](#page-12-0) analyzed the spatiotemporal distribution of FDI and confirmed that the process of transitioning toward higher FDI inflows occurred in regions spatially adjacent to regions with lower FDI. The spatial Markov chain has also been employed to describe the phenomenon of regional-reinforcing agglomeration (Pan et al. [2015](#page-12-0)), as well as to analyze the spillover effect on cities' dynamic evolution of carbon intensity (Liao and Wei [2012\)](#page-12-0).

This paper reveals the influence of the spatial spillover effect on regional distribution pattern of carbon emission efficiency of the construction industry. Comparisons reflect the interaction effect of neighboring carbon emission efficiency according to the corresponding changes in probability in the traditional and spatial Markov chain. The results provide referable values for the government to utilize to formulate regionally oriented carbon reduction policies for the construction industry.

Methods and data

Theoretical framing

The theoretical framing of this research is as follows: production elements, such as labor, capital, and energy will be consumed accompanied by production activities. These input elements are transformed into output through resource processing and integration, and the final achievement of production activities includes desirable output (GDP) and undesirable output (carbon emissions). Prominent in the actual situation in China is the uneven regional distribution, uneven regional resources, uneven economic development, and uneven technology levels. The evaluation of the carbon emission efficiency of the construction industry needs to consider the unbalance in these spatial characteristics in order to achieve coordinated regional development. Furthermore, as the relationship between neighboring regions is close and frequent, increases in provincial carbon emission efficiency influence the carbon emission efficiency of surrounding provinces. Innovation ability and scale economy have a positive effect on a province's carbon emission efficiency while also having a positive influence externally, such means as the spatial spillover effect brought by technical renovation, improvement in productivity, and industrial agglomeration. This paper takes the spatial spillover effect as the main entry point, constructing the spatial analysis model and Markov chain to explore the state transition process, the influence level, and the scope of the spatial spillover on carbon emission efficiency in the construction industry.

Methods

Based on the Super-Slack Based Measure (Super-SBM), the carbon emission efficiency of the construction industry was evaluated in this paper. The spatial dependence of the carbon emission efficiency was analyzed by the global Moran's Index. The traditional and spatial Markov chain was applied to unfold the spatial spillover effect.

Super-SBM model

The super-slack-based measure (Super-SBM) was first put forward by Tone [\(2002](#page-12-0)). Compared with the traditional DEA model, Super-SBM added the slack variables to the target function and effectively distinguished the efficient decision-making units (DMU) at the frontier. It is an effective method for estimating carbon emission efficiency, which assumes that there are n DMU, each of them containing three factors: input, desirable output, and undesirable output. This model considers carbon emissions as undesirable outputs by a non-linear measurement based on input-output analysis to estimate the efficiency value. Referring to studies by Hong et al. [\(2020\)](#page-12-0), Wang et al. [2021,](#page-12-0) and Zhang et al. ([2017](#page-13-0)), the super-SBM DEA method was constructed in this paper. Capital, labor, energy consumption, and machines were selected as inputs; industrial economic output was regarded as the desirable output; while carbon emissions were regarded as the undesirable output.

Global Moran's index

Tobler [\(1970](#page-12-0)) considered that everything is related to one another, and the closer the proximity, the stronger the relationship between them. The global Moran's index is a spatial autocorrelation analysis method (Moran [1950](#page-12-0)) which could be applied to describe the spatial distribution pattern of observed objects (clustering, discrete, or random), according to the location and value of the elements. To test whether the dependency of annual carbon emission efficiency in China's construction industry exists, this paper adopted the global Moran's index to examine the spatial autocorrelation. The specific calculations are shown as follows:

$$
I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(x_i - \overline{x}\right) \left(x_j - \overline{x}\right)}{s^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}}
$$
(1)

$$
\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i
$$
 (2)

$$
s^{2} = \frac{\sum_{j=1}^{n} (x_{j} = \overline{x})}{n-1}
$$
 (3)

Where I stands for the global Moran's index, it reveals the interdependence among different DMUs; x_i and x_j represent the observed value of elements in province i and j , respectively; *n* denotes the number of regions; and w_{ii} is the element of the spatial weight matrix. This paper chooses the first-order adjacency matrix. If common boundaries or edges exist between province i and province j , they are considered as contiguous to each other, the $w_{ii}=1$, if not, the $w_{ii}=0$. The range of the Moran's index is [-1, 1]. If the index is greater than 0, it means a positive spatial correlation exists, indicating that areas with high values cluster together and areas with lower values are close to each other; if the value approaches 0, it reveals that the index value is randomly distributed; if the value is less than 0, it means a negative spatial dependence exists. Moreover, the closer the index value approaches to 1, the greater the aggregating of the pattern; the more the index value approaches to -1, the greater the dissociation of the pattern.

Markov chain

(1) Traditional Markov chain The traditional Markov Chain is a discrete state sequence, each of which is extracted from a discrete state space (finite or infinite) and follows the Markov properties. That is, the state distribution of a DMU at specific time $t+1$ relies on its current state distribution at time t , rather than the initial state. The probability transfer matrix of the carbon emission efficiency is a data set expression that defines the state of the carbon emission efficiency in each period and the state transfer during the period of time. The matrix is expressed by M (see Table 1). The carbon emission efficiency value is divided into five states, namely, very low, low, middle, high, and very high. The element k represents the state of the carbon emission efficiency at a certain time. Then, the probability distribution of the corresponding type at time t is expressed as $1*k$ vector, named $p_t=[p_{1,t}p_{2,t},...,p_{k,t}].$

The m_{ij} is an element in the transition probability matrix, representing the probability that a region transfers from state i in year t to state j in year t+1. It can be calculated by $m_{ii} = n_{ii}/$ n_i . The n_{ij} is the number of provinces that are in state i in year t and transferred to state j in year $t+1$, n_i denotes the total amount of provinces in state i during the observation period.

Table 1 Traditional Markov transition probability matrix

$t/t+1$		2	3	4	5
1	m_{11}	m_{12}	m_{13}	m_{14}	m_{15}
2	m_{21}	m_{22}	m_{23}	m_{24}	m_{25}
3	m_{31}	m_{32}	m_{33}	m_{34}	m_{25}
4	m_{41}	m_{42}	m_{43}	m_{44}	m_{45}
5	m_{51}	m_{52}	m_{53}	m_{54}	m_{55}

(2) Spatial Markov matrix Compared with the traditional Markov chain, the spatial Markov chain could effectively investigate the interaction between provinces by adding the spatial lag term (Qin et al. [2020;](#page-12-0) Zhu et al. [2019](#page-13-0)). Thus, the traditional and the spatial Markov transfer probability matrix were constructed in this paper to explore the influence of the spatial spillover effect on the state transfer of the carbon emission efficiency of the construction industry.

The spatial Markov transition probability matrix decomposes the traditional $k \times k$ Markov matrix into $k \times k \times k$ conditional transition probability matrices. The spatial lag of carbon emission efficiency is regarded as the product of the provincial carbon emission efficiency and the spatial weight matrix. Based on the queen adjacency principle, the first-order spatial weight matrix is constructed in this paper. The $m_{ij(k)}$ denotes the probability of a region in state i at the beginning transfers to state j at the next time while the adjacent regions are in state k at the beginning. Just as shown in Table 2, the $m_{23(2)}$ indicates the probability that a province with a low carbon emission efficiency state will move to a middle carbon emission efficiency state when the neighboring provinces are in a low carbon emission efficiency state.

Table 2 Spatial Markov transition probability matrix

Spatial lag	tl $t+1$	1	2	3	$\overline{4}$	5
	1	$m_{11(1)}$	$m_{12(1)}$	$m_{13(1)}$	$m_{14(1)}$	$m_{15(1)}$
	\overline{c}	$m_{21(1)}$	$m_{22(1)}$	$m_{23(1)}$	$m_{24(1)}$	$m_{25(1)}$
$\,1$	3	$m_{31(1)}$	$m_{32(1)}$	$m_{33(1)}$	$m_{34(1)}$	$m_{35(1)}$
	$\overline{4}$	$m_{41(1)}$	$m_{42(1)}$	$m_{43(1)}$	$m_{44(1)}$	$m_{45(1)}$
	5	$m_{51(1)}$	$m_{52(1)}$	$m_{53(1)}$	$m_{54(1)}$	$m_{55(1)}$
	$\mathbf{1}$	$m_{11(2)}$	$m_{12(2)}$	$m_{13(2)}$	$m_{14(2)}$	$m_{15(2)}$
	\overline{c}	$m_{21(2)}$	$m_{22(2)}$	$m_{23(2)}$	$m_{24(2)}$	$m_{25(2)}$
2	3	$m_{31(2)}$	$m_{32(2)}$	$m_{33(2)}$	$m_{34(2)}$	$m_{35(2)}$
	$\overline{4}$	$m_{41(2)}$	$m_{42(2)}$	$m_{43(2)}$	$m_{44(2)}$	$m_{45(2)}$
	5	$m_{51(2)}$	$m_{52(2)}$	$m_{53(2)}$	$m_{54(3)}$	$m_{55(2)}$
	$\mathbf{1}$	$m_{11(3)}$	$m_{12(3)}$	$m_{13(3)}$	$m_{14(3)}$	$m_{15(3)}$
	\overline{c}	$m_{21(3)}$	$m_{22(3)}$	$m_{23(3)}$	$m_{24(3)}$	$m_{25(3)}$
3	3	$m_{31(3)}$	$m_{32(3)}$	$m_{33(3)}$	$m_{34(3)}$	$m_{35(3)}$
	4	$m_{41(3)}$	$m_{42(3)}$	$m_{43(3)}$	$m_{44(3)}$	$m_{45(3)}$
	5	$m_{51(3)}$	$m_{52(3)}$	$m_{53(3)}$	$m_{54(3)}$	$m_{55(3)}$
	$\mathbf{1}$	$m_{11(4)}$	$m_{12(4)}$	$m_{13(4)}$	$m_{14(4)}$	$m_{15(4)}$
	\overline{c}	$m_{21(4)}$	$m_{22(4)}$	$m_{23(4)}$	$m_{24(4)}$	$m_{25(4)}$
4	3	$m_{31(4)}$	$m_{32(4)}$	$m_{33(4)}$	$m_{34(4)}$	$m_{35(4)}$
	$\overline{4}$	$m_{41(4)}$	$m_{42(4)}$	$m_{43(4)}$	$m_{44(4)}$	$m_{45(4)}$
	5	$m_{51(4)}$	$m_{52(4)}$	$m_{53(4)}$	$m_{54(4)}$	$m_{55(4)}$
	$\mathbf{1}$	$m_{11(5)}$	$m_{12(5)}$	$m_{13(5)}$	$m_{14(5)}$	$m_{15(5)}$
	\overline{c}	$m_{21(5)}$	$m_{22(5)}$	$m_{23(5)}$	$m_{24(5)}$	$m_{25(5)}$
5	3	$m_{31(5)}$	$m_{32(5)}$	$m_{33(5)}$	$m_{34(5)}$	$m_{35(5)}$
	$\overline{4}$	$m_{41(5)}$	$m_{42(5)}$	$m_{43(5)}$	$m_{44(5)}$	$m_{45(5)}$
	3	$m_{51(5)}$	$m_{52(5)}$	$m_{53(5)}$	$m_{54(5)}$	$m_{55(5)}$

Compared with the corresponding variables in the traditional Markov transition matrix, the spatial Markov transition matrix could explain the spatial effect on state transition. If the state transition of carbon emission efficiency is not affected by its neighbors, the probability of the traditional and spatial Markov transition matrix should be equal. For example, if $m_{23} < m_{23(2)}$, it indicates that an interaction effect of carbon emission efficiency exists between regions, and the spatial spillover effect has a positive effect on neighboring regions. When the state of the neighboring region is also low, the probability of the region moving up is higher. On the contrary, if $m_{23} > m_{23(2)}$, the low state has a higher probability of transferring toward a middle state regardless of the adjacent states. It indicates that the carbon emission efficiency of neighboring regions has no significant impact on the region.

Data sources

Due to the data availability, this research obtained panel data from 30 provinces in China (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2005 to 2016. The original data was collected from the China Energy Statistical Yearbook (2006-2017), China Statistical Yearbook (2006-2017), China Construction Statistical Yearbook (2006-2017), and relevant China Statistical Yearbooks of Provinces. The input-output index of the carbon emission efficiency of the construction industry is shown in Table [3](#page-5-0).

Results

Based on the research method described in Section 3, this study calculated the provincial carbon emission efficiency of China's construction industry. The spatial distribution characteristic and dynamic evolution process of carbon emissions efficiency were further discussed from the perspective of spatial spillover effect.

Provincial carbon emission efficiency analysis

Based on the super-SBM, the carbon emission efficiency of the construction industry in 30 provinces of China from 2005- 2016 is calculated in this paper. The detailed information on carbon emission efficiency in each province during the study period is provided in the Appendix Table [7.](#page-11-0) As shown in Figure [1](#page-5-0), the national average value of carbon emission efficiency is 0.57. The average efficiency of each province fluctuates between 0.4 and 0.8, and nearly two-thirds of the provinces have lower carbon efficiency than the national average. It presents that the potential for improving g carbon emission efficiency is greater in most regions. Especially, the carbon emission efficiency of the construction industry shows a significant provincial difference. Zhejiang has the highest

Table 3 The input-output index of the carbon emission efficiency of the construction industry

efficiency, with a value of 0.81. It is about 1.98 times that of the lowest efficiency value of 0.41. This illustrates that Zhejiang is far ahead of other provinces in economic development and technological level, promoting the low-carbon development of the construction industry. The carbon emission efficiencies of Shanghai, Beijing, and Tianjin are 0.77, 0.79, and 0.77, respectively, significantly higher than the national average. Beijing reached the highest efficiency in 2012, with 1, and retained this level of efficiency until 2016. In the main, this is because Beijing had a more reasonable input-output scale, and the structure of the construction industry has been continuously optimized. However, Xinjiang, Qinghai, Shandong, and Ningxia have lower carbon emission efficiency, and the lowest efficiency is 0.41 of Xinjiang. It is worth noting that the efficiency value of Shandong province is 0.44, which is lower than that of other provinces located in the eastern area. This may be due to the large population and insufficient resources in Shandong, resulting in relatively backward production technology and low carbon emission efficiency of the construction industry.

Spatial autocorrelation analysis

Geoda software was applied to test the dependency of annual carbon emission efficiency in China's construction industry from 2005 to 2016. The specific results are displayed in Table [4](#page-6-0). The index of each year is higher than zero and satisfies the significance test at the 95% level. It indicates that the yearly carbon emission efficiency of the construction industry has an

Fig. 1 The average carbon emission efficiency of China's construction industry in 2005-2016

Table 4 The global Moran's index of the carbon emission efficiency in construction

Year	Global Moran's index	P value	Z value
2005	0.251	0.019	2.458
2006	0.247	0.015	2.432
2007	0.247	0.017	2.428
2008	0.247	0.015	2.422
2009	0.243	0.018	3.396
2010	0.275	0.015	2.632
2011	0.275	0.013	2.581
2012	0.281	0.011	2.651
2013	0.287	0.014	2.648
2014	0.279	0.012	2.585
2015	0.272	0.014	2.586
2016	0.281	0.010	2.647

obvious dependence and exhibits a positive spatial autocorrelation. That is, the provinces with high carbon emission efficiency inclined to be neighboring to provinces with high efficiency, while provinces with low efficiency prefer to cluster together. In addition, the Global Moran's Index shows a trend of fluctuant growth, increasing from 0.251 in 2005 to 0.287 in 2016, which means that the characteristics of spatial agglomeration are becoming increasingly noticeable. This is because capital flow, technology diffusion, and population mobility would enhance the interaction of carbon emission efficiency among provinces.

Traditional Markov chain

The Markov state transition probability matrix of the carbon emission efficiency of the provincial construction industry from 2005 to 2016 is estimated based on the Matlab software; the results are shown in Table 5. Different states present an uneven distribution pattern in space, and the transition between states could further reveal the changes in carbon emission efficiency over

Table 5 Traditional Markov matrix of carbon emission efficiency in construction industry, 2005-2016

t/ $t+1$	\boldsymbol{n}	VL	L	M	H	VH
VL	74	0.716	0.284	0.000	0.000	0.000
L	110	0.018	0.736	0.236	0.009	0.000
\overline{M}	96	0.000	0.052	0.760	0.178	0.010
Н	34	0.000	0.000	0.176	0.618	0.206
VH	16	0.000	0.000	0.00	0.125	0.875

the years. The element's values on the main diagonal represent the probability that a region will remain in its original state. Instead, the values of elements outside of the main diagonal denote the probability of a regional shift in state in the next time.

As observed from the results, the elements on the diagonal are higher than those off the main diagonal, indicating that the carbon emission efficiency of the alternate years is more inclined to maintain the original state. Among them, the minimum probability on the diagonal is 0.618, which means that no matter what state a province is in, the probability of it being in the same state in the next period is at least 62%. The probability of the main diagonal corresponding to the very high state is the highest, which is 0.875, indicating that the efficiency distribution in the very high state is the most stable. The main reason may be that the provinces with the highest carbon emission efficiency will invest more capital in developing clean energy, green building techniques, and clean production management, which is conducive to maintaining the high carbon emission efficiency.

It can be seen that the state transfer of provincial carbon efficiency mainly occurs between adjacent states. The probability of transferring upward is higher than that of transferring downward, and the different states show different transfer probability. Specifically, the provinces with very low and low state are more likely to transfer upward. For example, the probability is 0.245 for a province with low carbon emission efficiency moving upward at the next year, while the probability for a province with middle state moving upward is 0.178.

Spatial distribution pattern dynamics

To research the spatial distribution pattern change of provincial carbon emission efficiency, this study used ArcGIS to show the spatial layout and state over four cross-sectional years (2005, 2008, 2012, and 2016). The results are shown in Figure [2](#page-7-0). On the whole, the number of provinces with higher carbon emission efficiency increased significantly compared with the number in 2005, indicating that carbon emission efficiency in China's construction industry had gradually improved between 2005 and 2016. From a regional perspective, the spatial distribution of the carbon emission efficiency of the construction industry is heterogeneous, characterized by a decreasing trend from east to west. By analyzing the carbon emission efficiency change of provinces and their neighbors, the results showed that eastern regions have a positive spatial effect. For example, the carbon emission efficiency in Zhejiang, Beijing,

Fig. 2 Spatial distribution pattern of provincial carbon emission efficiency type in China's construction sector, 2015-2016. (a) Carbon emission efficiency in 2005. (b) Carbon emission efficiency in 2008. (c)

Carbon emission efficiency in 2012. (d) Carbon emission efficiency in 2016

Tianjin, Shanghai, Jiangsu, and their neighbors is upward. The growth speed of carbon emission efficiency in the east is higher than that of provinces located in the west. As for the central region, Henan has a better

spatial spillover effect. The carbon emission efficiency of Henan transferred from very low, middle to high state, and the neighboring provinces such as Shaanxi transferred from very low, middle to high state and Hubei transferred upward from very low, middle to very high state.

Spatial Markov chain

The spatial Markov transition probability matrix of carbon emission efficiency is shown in Table 6, and the space lag represents neighboring state. It could provide more information on the spatial interaction impact on the dynamic evolution of carbon emission efficiency in China's construction industry.

First, it shows a pronounced spatial spillover effect on the state transition of carbon emission efficiency. It

Table 6 Spatial Markov matrix of carbon emission efficiency in construction industry, 2005-2016

Space lag	tl $t+1$	\boldsymbol{n}	VL	L	M	Н	VH
	VL	47	0.830	0.170	0.000	0.000	0.000
	L	14	0.000	0.857	0.143	0.000	0.000
VL	\boldsymbol{M}	$\mathbf{0}$	0.000	0.000	0.000	0.000	0.000
	Н	$\mathbf{0}$	0.000	0.000	0.000	0.000	0.000
	VH	$\mathbf{0}$	0.000	0.000	0.000	0.000	0.000
	VL	24	0.583	0.417	0.000	0.000	0.000
	L	70	0.029	0.786	0.171	0.014	0.000
L	M	23	0.000	0.043	0.870	0.087	0.000
	H	$\mathbf{0}$	0.000	0.000	0.000	0.000	0.000
	VH	$\mathbf{0}$	0.000	0.000	0.000	0.000	0.000
	VL	$\mathfrak{2}$	0.000	1.000	0.000	0.000	0.000
	L	21	0.000	0.524	0.476	0.000	0.000
M	\boldsymbol{M}	56	0.000	0.054	0.732	0.196	0.018
	Н	19	0.000	0.000	0.105	0.684	0.211
	VH	3	0.000	0.000	0.000	0.333	0.667
	VL	$\mathbf{0}$	0.000	0.000	0.000	0.000	0.000
	L	$\mathbf{1}$	0.000	0.000	1.000	0.000	0.000
Н	\boldsymbol{M}	12	0.000	0.083	0.667	0.250	0.000
	H	12	0.000	0.000	0.250	0.583	0.167
	VH	9	0.000	0.000	0.000	0.000	1.000
	VL	$\boldsymbol{0}$	0.000	0.000	0.000	0.000	0.000
	L	$\mathbf{0}$	0.000	0.000	0.000	0.000	0.000
VH	\boldsymbol{M}	$\mathbf{0}$	0.000	0.000	0.000	0.000	0.000
	Н	$\overline{2}$	0.000	0.000	0.000	0.500	0.500
	VH	$\overline{4}$	0.000	0.000	0.000	0.250	0.750

can be seen that the transition probabilities in the spatial Markov matrix are different from the corresponding elements in the traditional Markov matrix. For example, the provinces with a very low state had a 0.284 probability of transferring upward (Table [5\)](#page-6-0). However, if the provinces with a very low state were neighboring provinces with a low state, the probability shifting upward is 0.417 (Table 6). The probability of transferring upward increased 66%. It indicates that the neighboring provinces have a positive spillover effect on the province in the very low state.

Second, different neighboring types show different effects on the state transition of the carbon emission efficiency. The probability of transferring to a higher state will increase, and the probability transferring downward will decrease when they are surrounded by provinces with a higher state. On the contrary, if the provinces are neighboring areas with lower efficiency, the carbon emission efficiency is more likely to maintain the original state. For example, the provinces with a low state of carbon emission efficiency had a 0.236 chance to shift upward (Table [5](#page-6-0)). Surprisingly, if it is surrounded by provinces with a middle state, this province has a 0.476 probability of transferring to a middle level (Table 6), which increased about two times. However, if neighboring provinces are in a very low state, the chance of shifting upward decreased to 0.143, and the province has a 0.857 chance of maintaining the low state.

Third, the spatial effect on state transition does not proportionately increase or decrease as the neighbors' changes, even though state transfers of the carbon emission efficiency of provinces are significantly affected by their neighbors. As shown in Table [5,](#page-6-0) from 2005 to 2016, the probability of provinces with a middle state of carbon emission efficiency transferring upward is 0.188. If a province was neighboring with one with a high state, the probability of moving upward increased to 0.250. However, for neighboring provinces with a very high state of carbon emission efficiency, the chance of shifting upward decreased to zero. It indicates that the spatial interaction effect is finitely effective.

Fourth, the spatial Markov transition matrix offers an interpretation for spatial clustering. The provinces with very low carbon emission efficiency will be negatively affected by the neighbors with the same state. The probability of maintaining a very low state is 0.716 in the traditional Markov matrix, while the probability will increase to 0.830, if a province spatially interacts with the very low state. This may result in the clustering of provinces in a very low state. On the contrary, the provinces with a high state of carbon emission efficiency will be positively affected by the surrounding areas with a very high state. The probability of transferring toward a very high state increased to 0.500, which is greater than 0.206 in the traditional Markov matrix. This may result in the agglomeration of high carbon emission efficiency. The spatial Markov transfer probability matrix indicates that the provinces with a relatively high state (high, very high state) have greater probabilities of moving upward when the neighbors are in a relatively high state. Meanwhile, the provinces with a relatively low state (low, very low state) have less chances to move to a relatively high state when the neighbors are in a relatively low state. This further explains the spatial agglomeration phenomenon of the carbon emission efficiency of the construction industry in China.

Discussion

In regards to carbon emission efficiency measurement in 30 provinces, this research is consistent with existing results (Wen et al. [2020b;](#page-12-0) Wang et al. [2021\)](#page-12-0). The results demonstrate that there is an obvious regional imbalance in the distribution of China's construction carbon emission efficiency, displaying a gradual decline from the east to the middle and then to the west. The provinces with high efficiency are mainly clustered in the east, while the provinces with low efficiency are mainly located in the west. This state is highly related to the development of regional economics and technology. As a matter of fact, the special geographical conditions promote the playing by the eastern area of a leading role in national economic development. Correspondingly, the construction industry in the eastern area can obtain better capital input and produce more economic output. Meanwhile, these provinces have advanced technology and management experience, which is beneficial to increase carbon emission efficiency. In contradistinction to this, the development of the construction industry in the west is highly dependent on traditional energy. The small production and poor technology in this region lead to lower carbon emission efficiency than other regions.

These different states of provincial carbon emission efficiency may be caused by both innate and external factors. Internal factors refer to the provincial disparity in the construction industry and the development of the construction industry. External factors, such as technical communication and cooperation and knowledge diffusion and other spillover effects, might cause a state

transfer of carbon emission efficiency. The development of the construction industry is complex, and areas with higher carbon emission efficiency have great demand for neighboring areas in terms of labor, energy, and other factors. Anselin ([1988](#page-11-0)) pointed out that the characteristic of regional development is affected by their neighbors. The spatial interaction of advanced technology exchange, knowledge diffusion, and policies to reduce emissions may affect the neighboring province's carbon emission efficiency. This could explain why the carbon emission efficiency of a province is affected by their neighbors. However, the spatial interaction effect is finite. This means the distribution of the evolution of carbon emission efficiency in the construction industry is a continuous and gradual process of improvement. Due to the spatial cluster and disparate features of carbon emission efficiency, in most situation, provinces in a very low state are not adjacent to those in a high or very high state. The flow of resources and technology between these provinces may be restricted by distance, leading to relatively slow improvement in the carbon emission efficiency of construction industry over a short time.

Many previous studies in other areas, such as the agricultural industry, China's energy efficiency, and Chinese city's carbon intensity, have indicated that carbon emission efficiency has spatial autocorrelation and shows a significant spatial spillover effect (Wang et al. [2020](#page-12-0); Tang et al. [2020](#page-12-0); Zhang et al. [2021](#page-13-0)). In this study, the spatial correlation and spillover of carbon emission efficiency of the construction industry are analyzed, and the results are similar to those of others. The results indicated that neighboring provinces have great spatial spillover, and the carbon emission efficiency will be influenced by a province's neighbors. However, in this study, the probability of carbon emission efficiency in the construction industry to transfer upward is higher than others. These different research results are mainly due to the fields of study. For the construction industry, much attention is paid to the regional connection of cooperation and production factors, such as construction energy trade, labor support, and population migration during urbanization and industrialization. Therefore, there is a more obvious spatial correlation in construction industry compared with the agricultural industry. Noteworthy, with the further development of modernization and urbanization, crossregional connection and cooperation in the construction industry will continue to strengthen and demonstrate a more evident spatial spillover effect in the future.

This research provides a deep analysis of the carbon emission efficiency of the provincial construction industry in China, helping the relevant departments, government, and enterprises understand the current level of carbon emission efficiency in the construction industry. In addition, it grasps the regional differences and spatial interaction effect of carbon emission efficiency among various provinces. Thus, the results could provide a policy reference for the future direction of overall carbon emission efficiency improvement in the construction industry of China from the viewpoint of regional cooperation. The research framework and methods applied in this paper are applicable to the analysis not only of the construction industry in China but also of other industries and other countries.

Conclusion and policy recommendations

Based on the super-SBM model, this paper examined the carbon emission efficiency of the construction industry from 2005 to 2016 in 30 provinces in China. A global Moran's index was constructed to reveal the spatial distribution characteristics of the carbon emission efficiency. The state transition of carbon emission efficiency in the construction industry and the spatial spillover effect between provinces was explored by combining the traditional Markov and the spatial Markov transition probability matrix. The main conclusions are summarized as follows.

The carbon emission efficiency of the construction industry showed an uneven spatial pattern that was high in the east and low in the west. The results of the spatial autocorrelation analysis indicated that the carbon emission efficiency of the construction industry had an obvious spatial dependence. From the perspective of the dynamic evolution of carbon emission efficiency, the distribution pattern was stable in carbon emission efficiency. When considering the spatial interaction effect, the results indicated that the distribution pattern of the carbon emission efficiency was related to that of the neighbors' state. Provinces had a higher probability of transferring upward if they were surrounded by provinces with a higher state, while provinces had a lower probability of transferring upward if they were surrounded by provinces with a lower state. However, the transfer probability of the carbon emission efficiency did not change proportionately to the difference between a province and its neighboring provinces.

Based on the empirical results, this study provides the following policy recommendations which can be used to reduce the carbon emissions of China's construction industry.

Uneven spatial distribution and interaction effect of the carbon emission efficiency of the construction industry should be considered when promulgating emission reduction policies across different areas. The government should promote communication and cooperation in technology innovation, energy-saving, and industry structure adjustment to improve overall carbon emission efficiency. Meanwhile, policymakers could enhance the spatial radiation influence of the provinces with high carbon emission efficiency. For example, a transprovincial green supply chain and multilateral regular exchange mechanism could be established.

For the less developed areas, policymakers could optimize the regional resource structure by introducing a new energy source to reduce traditional energy dependence. The utilization of new construction materials and new technology could be reinforced to improve carbon emission efficiency. Some favorable policies and measures should be formulated to promote the development of the construction industry in these provinces such as introducing investment, accelerating the importation pace of advanced enterprises and enhancing the opening of communication with eastern regions.

For relatively developed regions, DMUs in these areas should take advantage of advanced technology and abundant funds to maintain technological innovation. Due to the obvious positive spillover effect of these provinces, it is beneficial to strengthen the cooperation and sharing with other provinces to promote the development of the construction industry in the middle and western regions. The government could introduce policies such as reducing the tax of the construction enterprise applying lowcarbon technology and encouraging the inter-provincial exchange of advanced technology and management practices.

This paper analyzed the distribution pattern and spatial interaction effect of the carbon emission efficiency in the construction industry, which could shed light on the change in carbon emission efficiency of this industry. The analytical framework utilized in this paper could provide referable value for other industries and fields. Some limitations did exist; this paper only covered the research scale at the provincial level. Selecting a narrow scale such as an urban perspective will make the results more comprehensive. In addition, this paper did not analyze the underlying mechanism affecting the spatial distribution pattern of the carbon emission efficiency. Therefore, the factors influencing provincial carbon emission efficiency should be discussed in future work.

Appendix

Table 7 The carbon emission efficiency of 30 provinces of China's construction industry, 2005-2016

Province	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Beijing	0.49	0.53	0.56	0.59	0.66	0.77	0.89	1.00	1.00	1.00	1.00	1.00
Tianjin	0.57	0.60	0.63	0.59	0.62	0.71	1.00	0.86	0.92	1.00	0.75	1.00
Liaoning	0.46	0.49	0.52	0.55	0.52	0.59	0.62	0.75	0.74	0.70	0.65	0.67
Hebei	0.34	0.37	0.38	0.41	0.45	0.50	0.57	0.61	0.74	0.82	0.65	0.61
Shanghai	0.52	0.60	0.64	0.70	0.76	0.78	0.77	0.79	0.83	0.85	1.00	1.00
Jiangsu	0.45	0.49	0.55	0.59	0.63	0.67	0.69	0.73	0.81	0.84	0.92	1.00
Zhejiang	0.60	0.62	0.66	0.69	0.72	0.74	0.84	0.89	0.95	1.00	1.00	1.00
Fujian	0.47	0.51	0.55	0.49	0.50	0.54	0.63	0.67	0.70	0.71	0.74	0.77
Shandong	0.29	0.30	0.32	0.35	0.38	0.40	0.44	0.48	0.53	0.60	0.58	0.56
Guangdong	0.32	0.37	0.39	0.42	0.47	0.46	0.54	0.52	0.60	0.61	0.58	0.59
Hainan	0.42	0.51	0.53	0.57	0.56	0.58	0.61	0.64	0.69	0.72	0.68	0.71
Shanxi	0.39	0.40	0.41	0.44	0.52	0.53	0.58	0.60	0.64	0.65	0.56	$0.58\,$
Anhui	0.44	0.43	0.47	0.49	0.52	0.56	0.59	0.61	0.64	0.65	0.72	0.74
Jiangxi	0.44	0.46	0.49	0.51	0.57	0.57	0.59	0.63	0.67	0.69	0.68	0.72
Henan	0.39	0.46	0.52	0.58	0.59	0.59	0.61	0.65	0.68	0.72	0.61	0.67
Jilin	0.46	0.45	0.46	0.51	0.52	0.60	0.62	0.61	0.64	0.69	0.71	0.71
Heilongjiang	0.36	0.34	0.45	0.43	0.51	0.51	0.56	0.52	0.57	0.61	0.63	0.61
Hubei	0.34	0.38	0.38	0.44	0.47	0.50	0.65	0.69	0.83	1.00	0.77	0.94
Hunan	0.39	0.42	0.47	0.47	0.50	0.54	0.74	0.68	0.78	0.76	0.67	0.71
Inner Mongolia	0.34	0.37	0.43	0.42	0.45	0.48	0.55	0.55	0.57	0.49	0.45	0.45
Guangxi	0.33	0.33	0.36	0.43	0.47	0.54	0.59	0.68	0.74	0.75	0.73	0.74
Chongqing	0.39	0.40	0.43	0.45	0.51	0.60	0.64	0.72	0.74	0.75	0.78	0.81
Sichuan	0.31	0.36	0.37	0.42	0.48	0.46	0.54	0.62	0.64	0.69	0.67	0.72
Guizhou	0.34	0.36	0.38	0.39	0.45	0.45	0.55	0.61	0.65	0.64	0.63	0.55
Yunnan	0.31	0.33	0.34	0.36	0.43	0.46	0.53	0.53	0.60	0.61	0.60	0.62
Shaanxi	0.43	0.43	0.54	0.49	0.54	0.58	0.60	0.70	0.64	0.65	0.63	0.69
Gansu	0.31	0.33	0.35	0.34	0.37	0.46	0.51	0.55	0.62	0.59	0.52	0.53
Qinghai	0.37	0.36	0.35	0.38	0.38	0.40	0.42	0.45	0.43	0.51	0.54	0.55
Ningxia	0.32	0.36	0.36	0.37	0.41	0.49	0.46	0.42	0.51	0.54	0.54	0.57
Xinjiang	0.34	0.33	0.37	0.37	0.33	0.38	0.41	0.42	0.43	0.50	0.51	0.54

Author Contribution (1) Qiang Du: conceptualization, methodology, and formal analysis. (2) Yunge Deng: writing-original draft, visualization, writing-review, and editing. (3) Jie Zhou: resources, writingreview and editing, and supervision. (4) Jiao Wu: investigation, writing-review and editing. (5) Qiaoyu Pang: supervision. Correspondence to Yunge Deng.

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Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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