




Club convergence and spatial distribution dynamics of carbon intensity in China's construction industry

Qiang Du¹ · Min Wu² · Yadan Xu² · Xinran Lu² · Libiao Bai¹  · Ming Yu²

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Abstract

Climate change caused by carbon emissions continuously threatens sustainable development. Due to China's immense territory, there are remarkable regional differences in carbon emissions. The construction industry, which has strong internal industrial differences, further leads to carbon emission disparity in China. Policymakers should consider spatial effects and attempt to eliminate carbon emission inequality to promote the sustainable development of the construction industry and realize emission reduction targets. Based on the classic Markov chain and spatial Markov chain, this paper investigates the club convergence and spatial distribution dynamics of China's carbon intensity in the construction industry from 2005 to 2014. The results show that the provincial carbon intensity in the construction industry is characterized by “convergence clubs” during the research period, and very low-level and very high-level convergence clubs have strong stability. Moreover, the carbon intensity class transitions of provinces tend to be consistent with that of their neighbors. Furthermore, the transition of carbon intensity types is highly influenced by their regional backgrounds. The provinces with high carbon emissions have a negative influence on their neighbors, whereas the provinces with low carbon emissions have a positive influence. These analyses provide a spatial interpretation to the “club convergence” of carbon intensity.

Keywords Club convergence · Spatial distribution · Carbon intensity · Markov chain · Spatial Markov chain

1 Introduction

The large-scale exploitation and use of fossil fuels have caused serious ecological destruction, environmental pollution, and greenhouse gas emissions. Many countries and regions have made commitments to mitigate carbon emissions (Hu and Liu 2016). Understanding the distribution of carbon emissions via spatial and temporal perspectives is beneficial to formulating more utility-effective policies to combat climate change (Burnett

✉ Libiao Bai
hanshannuanyang@chd.edu.cn

Extended author information available on the last page of the article

2016; Zhao et al. 2015). The government should consider the source and distribution of carbon emissions when designing policies. The “Contraction and Convergence” proposed by the Global Commons Institute, which is an approach to reduce emissions, aims at allocating commitments across countries (GCI 2008). This method gradually compresses the process of carbon emission reduction (contraction) and equalizes the per capita carbon emissions among countries (convergence), which could apply to a country with many regions.

China, which has become the largest carbon emitter in the world, is facing great pressure from the international community to mitigate its carbon emissions (Wang et al. 2011; Zhang et al. 2017). Due to China’s immense territory, there are significant regional differences among the economic levels, technical levels, energy structures, and energy consumption in different regions. This results in carbon emission disparity in geographical space (Du et al. 2017). As a main source of carbon emissions (Li et al. 2017), the construction industry has strong industrial differences due to high industry relevancy and the closure property of regions in the construction industry. These further lead to carbon emission disparity in the construction industry. If this regional carbon emission disparity can be weakened and provinces with higher carbon emissions can be positively influenced by provinces with lower carbon emissions, then the overall carbon emissions in China’s construction industry can then be significantly reduced. Governments should consider spatial distribution and pursue the reduction of carbon emissions, as well as the gradual equalization of carbon emissions among various provinces (Romero-Ávila 2008). The convergence of carbon emissions is necessary, whereas ignoring the convergence of carbon emissions may protract the process of collaborative emission reduction (Westerlund and Basher 2008). Thus, it is necessary to examine whether carbon emissions have the characteristic of convergence across provinces in China’s construction industry or not. This shows great significance not only in formulating differential mitigation policies and strategies but also in promoting the sustainable development of the regional construction industry.

The concept of convergence originates from the literature about economic growth. In its most general definition, convergence stands for a decrease in the economic growth disparity across regions with time. Nevertheless, convergence is not limited to the literature about economic growth alone and has been widely used in other fields, including energy economics (Burnett and Madariaga 2017; Pan et al. 2015; Duro et al. 2010; Zhu et al. 2014). Convergence tests are split into three principal methods: σ -convergence, β -convergence, and club convergence (Burnett 2016). σ -Convergence means a decline in the dispersion of any economic variable such as energy use and output. It occurs when the coefficient or the standard deviation of the variable’s variation of interest remarkably decreases over time (Wang and Zhang 2014). β -Convergence implies that emissions in regions where they are initially high will tend to increase slower than in the regions with low emissions. The β -convergence of carbon emissions has been explored in previous research (Wang and Zhang 2014; Brännlund et al. 2015). As Barro and Sala-i-Martin (2004) point out, club convergence implies that the growth speed of a group of areas with similar structural characteristics and initial conditions tend to converge to the same steady state. The existence of club convergence means that different subregion groups tend to converge to different steady states.

Research on the convergence of carbon emissions seeks to investigate whether carbon emissions across regions are converging or diverging with time in different scales. Majority of studies have concentrated on the convergence of carbon emissions across countries. Romero-Ávila (2008) proved convergence in carbon emissions in 23 countries

with strong evidence from 1960 to 2002. Ahmed et al. (2017) tested the convergence of per capita carbon emissions for 162 countries across the globe. Li and Lin (2013) investigated the club convergence of 110 countries in per capita carbon emissions from 1971 to 2008. They found evidence of the club convergence of these countries. Some scholars investigated the convergence of carbon emissions at the regional and sector level. Brännlund et al. (2015) revealed conditional β -convergence of carbon intensity in industrial sectors in Sweden. Wang and Zhang (2014) examined the σ -convergence and β -convergence of per capita carbon emissions in six sectors across China's various provinces from 1996 to 2010. They found that per capita carbon emissions in all sectors showed convergence across provinces from 1996 to 2010. Hao et al. (2015) found the existence of β -convergence and stochastic convergence in China's provincial carbon intensity by using various estimation specifications and employing different estimation methods.

However, most of these existing studies regarding the convergence of carbon emissions are based on traditional approaches, which only proved the existence of convergence but assumed that spatial units were independent. These approaches ignored the spatial interaction among spatial units, with few exceptions (Burnett 2016; Zhao et al. 2015; Huang and Meng 2013; Wu et al. 2016). According to Tobler's first law of geography, all values on the geographic surface are interrelated and closer values are more closely related than distant values (Tobler 1970.). Ignoring spatial dependence might result in unreliable statistical inferences while researching convergence. Considering the regional differences and associations via spatial and temporal perspectives is crucial to mitigating carbon emissions. In addition, carbon emissions of provinces with similar industrial structure, development level of the construction industry, and other similar features tend to converge to the same steady state. Due to the fragmental characteristic of Chinese regions and differences in the construction industry, carbon emissions of different provinces are more likely to converge to different steady states rather than the same equilibrium, which shows the phenomenon of "club convergence."

These existing studies on the club convergence of carbon emissions mostly utilize the Phillips-Sul club convergence approach. Panopoulou and Pantelidis (2009) and Herrerias (2013) applied the Phillips-Sul approach to explore club convergence of carbon dioxide emissions across countries. Using the same approach, Apergis and Payne (2017) and Burnett (2016) identified the club convergence of carbon dioxide emissions across US states, whereas Wang et al. (2014) investigated the club convergence behavior of carbon dioxide emissions across China's various provinces. In addition, based on a continuous dynamic distribution approach, Wu et al. (2016) explored the convergence of per capita carbon emissions in China using panel data of 286 cities. However, these studies provide a limited view of the spatial-temporal distribution of carbon emissions and the movement of the spatial units within the distribution (Rey 2001). Thus, the club convergence of carbon emissions is investigated in this study with the help of the spatial Markov chain approach proposed by Rey (2001), which considers the spatial interaction between regions. The spatial Markov chain has been applied extensively to the field of economics (Torres Preciado et al. 2017; Liao and Wei 2012; Maza et al. 2012). This approach has two specific advantages. First, the spatial Markov chain can characterize spatial distribution and stand out the performance of each spatial unit and the nature of its transition in exploring the tendency of convergence and divergence (Carluer 2005; Fingleton 1997). Second, the spatial Markov chain is realistic because it can identify long-term properties toward some form of convergence club or poverty trap (Fingleton 1997), which cannot be interpreted by convergence. The spatial Markov chain facilitates the study of the club convergence of

carbon emissions and the spatial distribution dynamics of carbon emissions throughout the years.

As the construction industry is a major contributor to carbon emissions, research on the club convergence of carbon emissions in China's construction industry could provide a new perspective for its sustainable development. Therefore, this study innovatively uses classic Markov chain and spatial Markov chain approaches to analyze the club convergence of provincial carbon intensity and the spatial distribution dynamics over the period from 2005 to 2014. The structure of this paper is as follows. After this introduction, Sect. 2 provides the data and the methodology used in this study. Section 3 is devoted to the empirical results and analyses. The final part presents the conclusions.

2 Data and methodology

2.1 Data

2.1.1 Formulation of carbon intensity

As carbon intensity (defined as the ratio of carbon emissions to GDP) is always used as an important indicator in carbon emissions abatement by the Chinese government, the club convergence of carbon intensity in China's construction industry is examined in this paper. This paper uses panel data of 30 Chinese provinces and municipalities during the period from 2005 to 2014 (excluding Hong Kong, Macao, Taiwan, and Tibet due to missing data), which can be defined using Eq. (1).

$$CI = C_T / CIOV \quad (1)$$

Here CI denotes carbon intensity in the construction industry, C_T represents the total carbon emissions in construction industry, and $CIOV$ stands for the output values of the construction industry, which could be obtained from statistical yearbooks at a provincial level.

Considering the characteristics of the construction industry, which has close relationships with other industries, the calculation is divided into two parts: the direct carbon emissions and the indirect carbon emissions. The direct carbon emissions are emissions directly generated by the construction industry. The indirect carbon emissions are emissions from other industries induced by the construction industry. The direct carbon emissions in the construction industry are calculated using the following equation.

$$C_D = \sum_{i=1} E_i \times NCV_i \times A_i \times O_i \times 44/12 \quad (2)$$

Here C_D refers to the direct carbon emissions in the construction industry, i denotes the type of energy, including coal, coke, crude oil, gasoline, kerosene, diesel oil, liquefied petroleum gas and natural gas. E_i is the consumption of energy i provided by the statistical yearbooks at a provincial level, NCV_i denotes the average lower-order calorific value of energy i (which could be derived from the China Energy Statistical Yearbook), A_i refers to the carbon content per unit heat of energy i , O_i is the oxidation rate of energy i , and figure 44/12 represents the molecular weight ratio of CO_2 to carbon. A_i and O_i can be obtained from The Guidelines to Make Provincial Lists of Greenhouse Gas Inventory. Average low-order calorific value, carbon content per unit heat and oxidation rate for different energy type are shown in appendix.

The calculation process of the indirect carbon emissions in the construction industry is divided into two steps. First, nine industries related to the construction industry are selected in this paper, including the mining and washing of coal; extraction of petroleum and natural gas; mining and processing of metal ores; petroleum refining, coking, and nuclear fuel processing; manufacture of raw chemical materials and chemical products; manufacture of non-metallic mineral products; smelting and pressing of metals; manufacture of metal products; and transporting, storage, and postal services of products. The equation of direct carbon emissions of industry j , which is similar to Eq. (2), is as follows.

$$C_{D,j} = \sum_{i=1} E_{i,j} \times NCV_i \times A_i \times O_i \times 44/12 \tag{3}$$

Here $C_{D,j}$ represents the direct carbon emissions consumed by industry j and $E_{i,j}$ denotes the use of energy i for industry j . Next, according to input–output analysis, the indirect carbon emissions in the construction industry are calculated as follows (Zhang and Liu 2013)

$$C_I = \sum_j (C_{D,j}/IOV_j) \times CIOV \times y_j \tag{4}$$

where $C_{D,j}$ refers to the direct carbon emissions of industry j , j is the category of industries, IOV_j denotes the total output values of industry j obtained from the statistical yearbooks at a provincial level, $CIOV$ stands for the output values of the construction industry, and y_j represents the total consumption coefficient of industry j from the construction industry provided by the input–output tables.

Finally, the total carbon emissions in the construction industry are then

$$C_T = C_D + C_I \tag{5}$$

2.1.2 Description of the data

Currently, the methods of data classification include equal area, equal interval, natural break, quartile, and standard deviation. The natural break could be used to identify the classification intervals and the similar values could be grouped more appropriately to maximize the differences between different classes. Using the natural break, the differences between the classes are obvious, while the differences within the classes are small. The club convergence means that different subregion groups tend to converge to different steady. Before the study of club convergence, this paper first needs to classify the carbon emissions data. The data with similar characteristics and small differences should be selected to be a group, and the data with large differences should be classified into different groups. Thus, the natural break is suitable for the classification of carbon emissions data in this paper. The carbon intensity in China’s construction industry each year is classified into five classes: very low (VL), low (L), average (A), high (H), and very high (VH).

2.2 Methodology

With the purpose of investigating the club convergence of carbon intensity in China’s construction industry, Markov chain approaches are implemented in this paper. The spatial distribution dynamics of carbon intensity are visualized by ARCGIS based on the results of

the Markov transition probability matrix and the spatial Markov transition probability matrix.

2.2.1 Classic Markov chain

The classic Markovian approach is a stochastic process which has the Markov property. Its distribution in the state at a particular time $t + 1$ only relies on its immediate distribution at time t , which implies that the future can be explained exclusively by the present, rather than the past. It is the basic approach to specify a vector of the state probabilities that represent the probability that a province will be a member of a specific carbon intensity class in a given year. The classes of carbon intensity in construction can be assumed k , and the state probability vector at time t is P_t , which represents a $1 * k$ vector $P_t = [P_{1,t}, P_{2,t}, \dots, P_{k,t}]$. The evolution of the carbon intensity distribution is described by the transition probability matrix M that is of dimension $k * k$, which is shown in Table 1, under the assumption of $k = 5$ states.

In Table 1, m_{ij} is the element of the transition probability matrix which denotes the probability that a province that was in state i at time t ends up in state j at time $t + 1$.

$$m_{ij} = \frac{n_{ij}}{n_i} \tag{6}$$

Here n_{ij} and n_i can be obtained by counting the number of provinces that was in state i at time t but turned into state j at the next time period and the number of provinces in state i during the observation period, respectively.

2.2.2 The spatial Markov matrix

To incorporate spatial interaction into the study of the regional dynamics of carbon intensity in China’s construction industry, the spatial Markov matrix is implemented as proposed by Rey (2001). In particular, a modification of the classic Markov transition probability matrix is used to condition the transition probabilities of a region in the initial state or class of its spatial lag, named the spatial Markov transition probability matrix.

This spatial version of the spatial Markov matrix accounts for spatial autocorrelation in the form of spatial lag. The spatial lag of carbon intensity is defined as the product of the regional carbon intensity value and the spatial weight matrix, and the first-order Queen-type spatial weight matrix is chosen in this paper. In addition, spatial lag is classified into five classes using the natural break method in accordance with the classification of carbon intensity. This way of incorporating the spatial interaction into the analysis of regional dynamics means that this matrix decomposes the classic $k * k$ transition probability matrix into a $k * k * k$ dimension system. It is clarified in Table 2 for an assumption with $k = 5$

Table 1 Markov transition probability matrix

$t/t + 1$	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_{35}
4	m_{41}	m_{42}	m_{43}	m_{44}	m_{45}
5	m_{51}	m_{52}	m_{53}	m_{54}	m_{55}

Table 2 Spatial Markov transition probability matrix

Space lag	$t/t + 1$	1	2	3	4	5
1	1	m_{1111}	m_{1211}	m_{1311}	m_{1411}	m_{1511}
	2	m_{2111}	m_{2211}	m_{2311}	m_{2411}	m_{2511}
	3	m_{3111}	m_{3211}	m_{3311}	m_{3411}	m_{3511}
	4	m_{4111}	m_{4211}	m_{4311}	m_{4411}	m_{4511}
	5	m_{5111}	m_{5211}	m_{5311}	m_{5411}	m_{5511}
2	1	m_{1112}	m_{1212}	m_{1312}	m_{1412}	m_{1512}
	2	m_{2112}	m_{2212}	m_{2312}	m_{2412}	m_{2512}
	3	m_{3112}	m_{3212}	m_{3312}	m_{3412}	m_{3512}
	4	m_{4112}	m_{4212}	m_{4312}	m_{4412}	m_{4512}
	5	m_{5112}	m_{5212}	m_{5312}	m_{5412}	m_{5512}
3	1	m_{1113}	m_{1213}	m_{1313}	m_{1413}	m_{1513}
	2	m_{2113}	m_{2213}	m_{2313}	m_{2413}	m_{2513}
	3	m_{3113}	m_{3213}	m_{3313}	m_{3413}	m_{3513}
	4	m_{4113}	m_{4213}	m_{4313}	m_{4413}	m_{4513}
	5	m_{5113}	m_{5213}	m_{5313}	m_{5413}	m_{5513}
4	1	m_{1114}	m_{1214}	m_{1314}	m_{1414}	m_{1514}
	2	m_{2114}	m_{2214}	m_{2314}	m_{2414}	m_{2514}
	3	m_{3114}	m_{3214}	m_{3314}	m_{3414}	m_{3514}
	4	m_{4114}	m_{4214}	m_{4314}	m_{4414}	m_{4514}
	5	m_{5114}	m_{5214}	m_{5314}	m_{5414}	m_{5514}
5	1	m_{1115}	m_{1215}	m_{1315}	m_{1415}	m_{1515}
	2	m_{2115}	m_{2215}	m_{2315}	m_{2415}	m_{2515}
	3	m_{3115}	m_{3215}	m_{3315}	m_{3415}	m_{3515}
	4	m_{4115}	m_{4215}	m_{4315}	m_{4415}	m_{4515}
	5	m_{5115}	m_{5215}	m_{5315}	m_{5415}	m_{5515}

states or classes. The elements $m_{ij(k)}$ specify the probability that a province that was in state i at time t ends up in state j at time $t + 1$, under the condition that its neighboring provinces were initially in state k . In particular, the notation m_{1311} expresses the probability of a province advancing from a VL state toward an A state, under the condition of interacting spatially with neighboring provinces in a VL state. Here the conditioning is in relation to the carbon intensity class of the spatial lag during the initial period.

Based on comparing the differences between elements in the classic Markov transition probability matrix and the corresponding elements in the spatial matrix, the overall influence of spatial dependence on regional transition is reflected. For example, if $m_{12} < m_{1211}$, the probability of an upward transition for low carbon intensity states regardless of their neighbors, is lower than the probability of an upward transition for low carbon intensity states with very low neighbors.

Alternatively, if $m_{12} > m_{1211}$, the very low states irrespective of their neighbors have a higher probability to move upward than very low states with very low neighbors. In other words, if transition probabilities were not influenced by regional context, then

$$m_{ij|1} = m_{ij|2} = \dots = m_{ij|k} = m_{ij} \forall i, j.$$

3 Results and discussions

3.1 Classic Markov chain

This paper analyzes the club convergence of the provincial carbon intensity in China's construction industry for the period of 2005 to 2014. Table 3 shows the transition probability matrix. In Table 3, the elements in the main diagonal represent the probability that a province remains in their original class and does not move toward a new level over time, while the elements outside the main diagonal correspond to the probability that a province moves toward a new class.

To show the transition probability in different directions intuitively, this paper employs “upward,” “downward,” and “steady” to express the transitions states in different directions, which is displayed in Fig. 1. The horizontal axis of this figure refers to the classes of carbon intensity in the construction industry, including five classes: VL, L, A, H, and VH. The vertical axis signifies the transition probability in different directions. An upward state means that provinces from relatively low carbon intensity classes shift toward higher classes, while a downward state means provinces from relatively high classes move toward lower classes. The steady state signifies that provinces remain in their original classes.

As shown in Table 3 and Fig. 1, provincial carbon intensity in China's construction industry has been globally characterized by “convergence clubs” from 2005 to 2014. The following are three major characteristics.

First, the provincial carbon intensity in the construction industry forms five levels of convergence clubs, namely VL, L, A, H, and VH. It is observed that the elements in the main diagonal are relatively greater than the elements outside it. The probability of a province with very low carbon intensity to maintain its original state is 0.875, and the probability to move upward is 0.125. The probability of a province with low carbon intensity to maintain its original state is 0.819, and the transition probability toward a different class is 0.181. The probability of a province with an average carbon intensity to maintain its original state is 0.614, with a 0.386 probability to move upward. The probability of a province with high carbon intensity to maintain original state is 0.873, and the probability to move downward and upward is 0.127. The probability of a province with high carbon intensity to keep its original state is 0.967, and the probability to move downward is only 0.033.

The spatial dependence of provincial carbon emissions in the construction industry may be caused by the flow of economic elements across provinces, innovation diffusion, the technology spillover, and the liquidity of architecture production, which can further result

Table 3 Markov matrix for carbon intensity in China's construction industry, 2005–2014

$t/t + 1$	n	VL	L	A	H	VH
VL	48	0.875	0.104	0.021	0.000	0.000
L	72	0.056	0.819	0.125	0.000	0.000
A	57	0.018	0.228	0.614	0.140	0.000
H	63	0.000	0.000	0.095	0.873	0.032
VH	30	0.000	0.000	0.000	0.033	0.967

Bold values emphasize the probability to maintain its original state and show the convergence characteristics more clearly

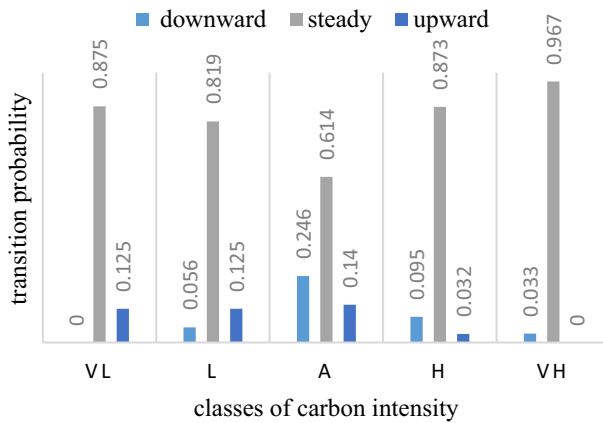


Fig. 1 Carbon intensity transitions probability in different directions in China’s construction industry, 2005–2014

in convergence. Meanwhile, there is obvious regional disparity among the modes of production, industrial structure, the economic levels, and the technology levels, which could be defined as innate or internal factors. External factors include the degree of implementation of carbon-reduction policies and related policies in the construction industry. The heterogeneity of innate factors and external factors, combined with the interaction among these factors, may make it difficult for carbon emissions to converge to the same equilibrium but, instead, converge to different clubs.

Second, very low-convergence and very high-convergence clubs have stronger stability than other levels. The probability of a province to remain in very high carbon intensity reaches 0.967, while the probability of a province to remain in very low carbon intensity is 0.875. The probabilities of low-convergence and high-convergence clubs are 0.819 and 0.873, respectively. Provinces have the minimum probability to remain in average carbon intensity (0.614). The results can fully reveal stronger convergence across provinces with very low and very high carbon intensity. This means that provinces with lower carbon intensity can promote the investment of green building material, regenerative clean energy techniques, and cleaning production measures because of their relatively higher economic technical level, which contributes to the control of carbon intensity. The closure property of regions in the construction industry leads to the weakened radiation effect of technology. Due to their relatively backward technical and economic level, it is difficult for provinces with higher carbon intensity to reduce their carbon intensity. This why convergence clubs of very low and very high carbon intensity are more stable than other levels.

Third, the carbon intensity of a province is unlikely to achieve leaping movement toward a non-adjacent level in a short period. Non-diagonal elements are extremely small, and the maximum is 0.228, which accounts for 37.13% of the minimum in the main diagonal. The elements that do not adjoin the main diagonal are less than 0.05, which means that the provinces in the very low carbon intensity class rarely move toward to an average class and above. Meanwhile, the provinces in the low class can hardly move toward a high or very high class in a period of time. Likewise, it is difficult for the provinces in the average class of carbon intensity to move toward a very high or very low class. The results suggest that carbon intensity in the construction industry is the result of

continuous development and unlikely to achieve leaping increasing and decreasing levels in a short period, and most provinces change between two adjacent carbon intensity types.

3.2 Spatial distribution dynamics

To explore the performance of each province and the effect of its state transition on the convergence and divergence of carbon intensity, this paper studies spatial patterns of carbon intensity class and class transitions in China's construction industry. Due to limited space, this study displays the graphs of carbon intensity class for the years 2005, 2008, 2011 and 2014. Spatial patterns of carbon intensity class through time are shown in Fig. 2.

On the whole, the proportion of provinces with low carbon intensity in 2014 increased compared with the proportion in 2005, indicating that carbon intensity in China's construction industry had gradually declined between the period 2005–2014. From a regional view, carbon intensity in the north and northwest regions were located in the higher classes for a long time. Carbon intensity in the Central China has decreased more significantly, especially in the regions interacting with neighbors in the eastern coastal areas, having a tendency to cluster in the low carbon intensity group. In the southern regions, carbon intensity was generally located in the lower classes since the southeast areas have mature

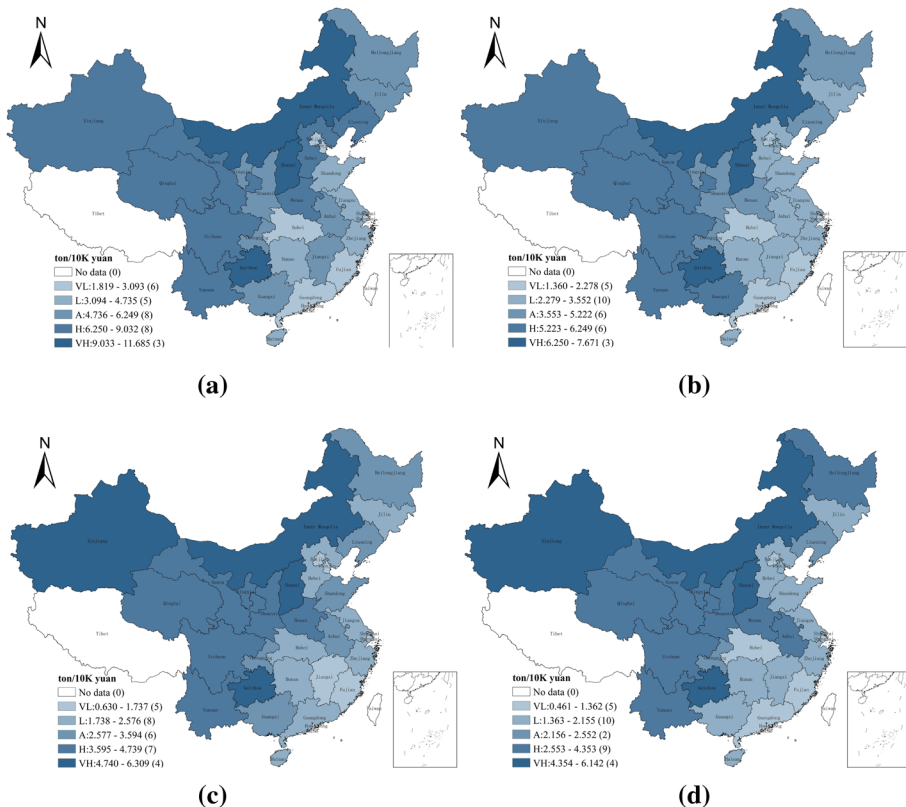


Fig. 2 Spatial patterns of provincial carbon intensity class in China's construction industry, 2005–2014. **a** Carbon intensity class in 2005, **b** Carbon intensity class in 2008, **c** Carbon intensity class in 2011, and **d** Carbon intensity class in 2014

construction technology and higher economic level. From a provincial perspective, a group with higher carbon intensity included Inner Mongolia, Xinjiang, and Shanxi et al. These areas have rich energy resources and depend mainly on industries with high consumption and high emissions.

Figure 3 shows carbon intensity class transitions of regions and neighbors and the dynamics of the spatial distribution in China’s construction industry during the period 2005–2014. The state of upward means that provinces from relatively low carbon intensity classes shift toward higher classes, while downward means provinces from relatively high classes move toward lower classes. The state of steady signifies that provinces remain in their original classes.

In Fig. 3, the provinces with an upward transition for carbon intensity were Xinjiang, Heilongjiang, Ningxia, Shaanxi, Anhui and Tianjin, which are located in the Northwest and North China. 3 provinces located in the northwest, accounting for half of all upward transfer areas. In general, these areas have rich energy resources and solid industry foundation. These areas have continuously provided resources and products for the construction industry but also met the needs of the market for construction-related industries. In addition, in order to promote construction industry development, these provinces mainly depend on the expansion of the construction scale, and the input of technological innovation and new material application is relatively limited. Likewise, the provinces with a downward transition for carbon intensity were Liaoning, Jilin, Jiangxi, Guangxi and Hebei, which are clustered in the Northeast and South China on the whole. These areas face the

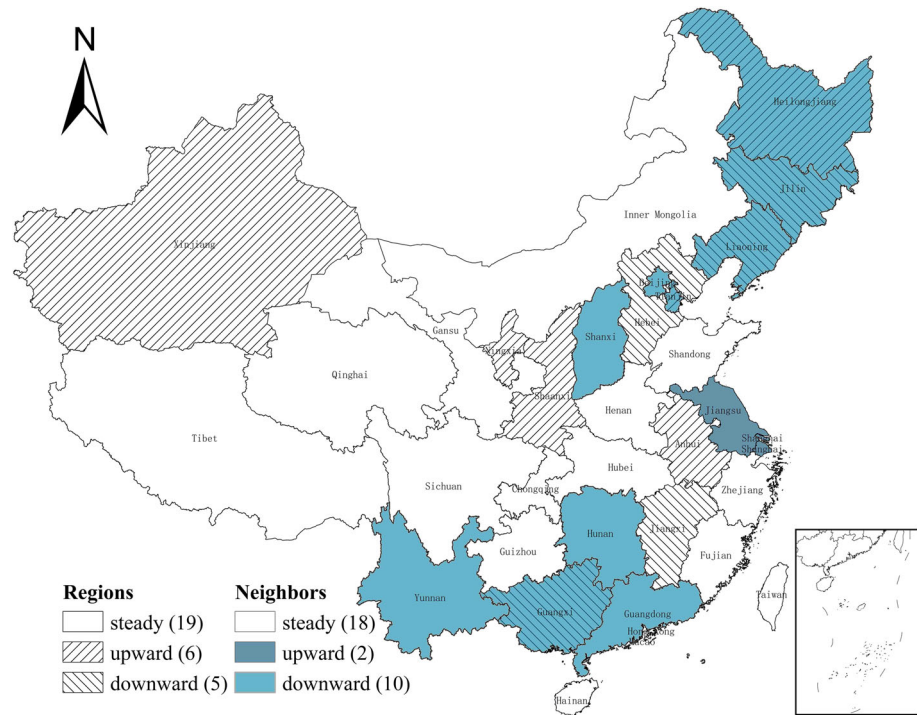


Fig. 3 Spatial patterns of carbon intensity class transitions of regions and neighbors in China’s construction industry, 2005–2014

pressure from the slowdown of construction industry investment and supply-side structural reform during the period of the economic transformation. Other provinces remain in their original class are located in central China. The results reveal that there are remarkable spatial clustering and regional convergence characteristics in China's provincial carbon intensity.

In terms of carbon intensity class transitions of neighbors, the provinces and their neighbors transfer in the same direction account for 53.3% of all study areas. The provinces and their neighbors that all have a downward transition are Guangxi, Jilin and Liaoning, but the provinces and their neighbors that have an upward transition show inconsistent space expression. In addition, the provinces and their neighbors mostly remain in their original classes. The above results suggest that carbon intensity class transitions in China's construction industry doesn't exist in isolation and shows significant spatial dependence. The carbon intensity class transitions of regions mostly tend to be consistent with class transitions of their neighbors. This space mechanism may promote the spatial agglomeration and regional convergence of provincial carbon intensity.

3.3 The Spatial Markov chain

Based on classical Markov chain, the spatial Markov chain is used to explore the influence of spatially interacting on the carbon intensity transition probability, conditional to the spatial interaction with the neighboring provinces.

Table 4 displays the probabilistic transition matrix of the provincial carbon intensity in China's construction industry conditioned to spatial dependence with neighboring regions. Figure 4 shows the transition probability of five carbon intensity classes (VL, L, A, H, and VH) with different spatial lags, which could reveal whether different regional backgrounds or neighbors have different effects on the carbon intensity classes transition or not. The horizontal axis of this figure refers to the classes of spatial lag, while the vertical axis refers to the transition probability in different directions. "Upward," "downward" and "steady" have the same meaning to these three state in Fig. 1. Four characteristics are described as follows.

First, the spatial interaction between provinces has a significant effect on the convergence clubs of carbon intensity in China. The transition probability of the provincial carbon intensity differs when conditioned to spatial interaction with provinces located in the classes with lower or higher carbon emissions. The transition probabilities of provincial carbon intensity are different to the probabilities in the corresponding elements in the classic Markov transition probability matrix. It indicated that the convergence of carbon intensity was affected by spatial interaction across areas, including the labor and capital flows across provinces, the liquidity of architecture production, the diffusion of knowledge and technology, and the demonstration and incentive effect of policy on the geographical space.

Second, different regional backgrounds have different effects on the transition of carbon intensity types. In the provinces that interact with neighbors located in high carbon emissions groups, it can be appreciated that the probability to move upward will increase and the probability to move downward will decrease. Contrarily, the probability to move upward will decrease and the probability to move downward will increase when provinces interact with neighbors in the lower classes. From 2005 to 2014, the probability of a province with average carbon intensity to move upward is 0.140 and the probability to move downward is 0.246, regardless of their neighbors. When a province with average carbon intensity is adjacent to provinces with very high carbon intensity, the probability of an upward transition increases to 0.75 and the probability of a downward transition

Table 4 Spatial Markov matrix for carbon intensity in China’s construction industry, 2005–2014

Space lag	<i>t/t + 1</i>	2005–2014					
		<i>n</i>	VL	L	A	H	VH
VL	VL	28	0.929	0.036	0.036	0.000	0.000
	L	18	0.000	0.833	0.167	0.000	0.000
	A	8	0.125	0.500	0.250	0.125	0.000
	H	4	0.000	0.000	0.000	0.750	0.250
	VH	3	0.000	0.000	0.000	0.000	1.000
L	VL	17	0.824	0.176	0.000	0.000	0.000
	L	19	0.053	0.895	0.053	0.000	0.000
	A	1	0.000	0.000	1.000	0.000	0.000
	H	9	0.000	0.000	0.000	1.000	0.000
	VH	2	0.000	0.000	0.000	0.000	1.000
A	VL	3	0.667	0.333	0.000	0.000	0.000
	L	20	0.150	0.750	0.100	0.000	0.000
	A	23	0.000	0.261	0.696	0.043	0.000
	H	23	0.000	0.000	0.087	0.870	0.043
	VH	3	0.000	0.000	0.000	0.000	1.000
H	VL	0	0.000	0.000	0.000	0.000	0.000
	L	15	0.000	0.800	0.200	0.000	0.000
	A	21	0.143	0.000	0.714	0.143	0.000
	H	17	0.000	0.000	0.235	0.765	0.000
	VH	4	0.000	0.000	0.000	0.250	0.750
VH	VL	0	0.000	0.000	0.000	0.000	0.000
	L	0	0.000	0.000	0.000	0.000	0.000
	A	4	0.000	0.000	0.250	0.750	0.000
	H	10	0.000	0.000	0.000	1.000	0.000
	VH	18	0.000	0.000	0.000	0.000	1.000

Bold values emphasize the probability to maintain its original state and show the convergence characteristics more clearly

decreases to 0. Meanwhile, if a province is adjacent to provinces with very low carbon intensity, the probability to move upward decreases to 0.125 and the probability to move downward increases to 0.625. As Anselin (1998) and LeSage and Pace (2009) pointed out, the characteristics of a local region may rely on its neighbors. Some factors such as technology, economic structure, and energy structure of a province have an obvious effect on neighboring provinces, and these factors appeared as the main factor that influences carbon emissions. This phenomenon could be interpreted as spatial spillover, which can fully explain why the carbon emission of a province is influenced by its neighbors.

Third, the probability that the construction industry carbon intensity of a province is moving upward or downward is not proportional to the degree of difference between the region and the adjacent regions. Although carbon intensity class transitions of a region will be significantly influenced by the carbon intensity of its neighbors, this effect does not increase proportionately as the difference increases. During the period of 2005–2014, the probability of a province with low carbon intensity to move upward is 0.053 when

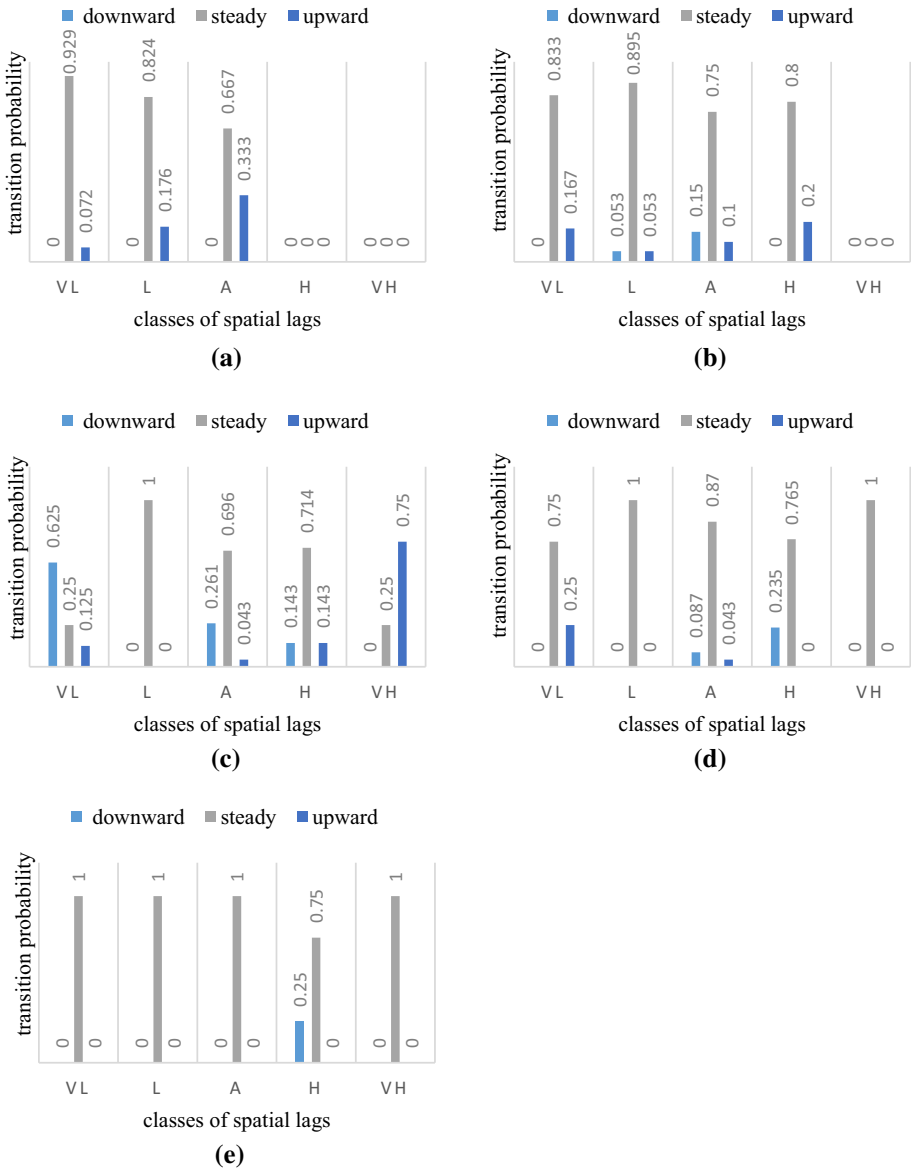


Fig. 4 Carbon intensity transitions probability with different spatial lags in China’s construction industry, 2005–2014. **a** Carbon intensity class: VL, **b** Carbon intensity class: L, **c** Carbon intensity class: A, **d** Carbon intensity class: H, and **e** Carbon intensity class: VH

interacting with neighbors with low carbon intensity. If a province is adjacent to provinces with average carbon intensity, the probability of an upward transition increases by 0.1. If it is adjacent to provinces with high carbon intensity, the probability could be more greatly increased (i.e., 0.2). The results indicate that the provinces with high carbon intensity are limited in their economic power and the technical level of the construction industry is relatively backward, which have a great effect on the surrounding area. Provinces with

high and low carbon intensity may lead to a more pronounced high-level and low-level club convergence.

Fourth, the spatial Markov transition matrix could provide a spatial interpretation for the phenomenon of club convergence. A province could be positively influenced by an adjacent area with very low carbon intensity, and the probability to move downward will increase. This may lead to club convergence of the lower carbon intensity level in China's construction industry. From 2005 to 2014, the probability of a province to maintain a very low class of carbon intensity is 0.929, if it interacts spatially with the neighboring regions initially located in the very low class. This probability is greater than the 0.875 probability to remain in the very low class, irrespective of their neighbors. Likewise, a province could be negatively influenced by an adjacent area with a very high carbon intensity and have a greater probability to move upward, which may result in club convergence of the higher carbon intensity level. The probability of a province with very high carbon intensity to maintain its original state is 1 when interacting with regions also in the very high class. This probability clashes with the 0.967 probability in Table 3 in the same period. The spatial Markov matrix illustrates that the provinces have a greater probability to move upward when interacting with neighbors in the higher classes, whereas the provinces have a greater probability to move downward when interacting with neighbors in the lower classes. This further explains the convergence phenomenon.

4 Conclusion

This paper investigates the club convergence and spatial distribution dynamics of province-level carbon intensity in China's construction industry during the period of 2005–2014, based on a classic Markov matrix and spatial Markov matrix.

From the global aspect, provincial carbon intensity in China's construction industry is characterized by convergence clubs from 2005 to 2014. The classic Markov matrix shows that the levels of convergence clubs are very low, low, average, high, and very high. The very low-level and very high-level convergence clubs have stronger stability than other levels. In addition, the carbon intensity of a province rarely achieves a leaping transfer toward a non-adjacent level in a short time. Through the spatial distribution, there are significant spatial clustering and regional convergence characteristics in the provincial construction industry carbon intensity. The provinces with an upward transition for carbon intensity are clustered in northwest and north China, whereas the provinces with a downward transition are located in the northeast and south China. Furthermore, the carbon intensity class transitions of provinces tend to be consistent with the class transitions of their neighbors. In terms of the spatial Markov matrix, the transition of carbon intensity type in China is significantly influenced by their regional backgrounds. Provinces have a greater probability to move toward higher carbon intensity classes when there is a spatial association with the regions in the high classes, while the provinces have a greater probability to move toward lower classes when interacting with neighbors in the lower classes. However, the transition probability of carbon intensity is not proportional to the difference between the province and its adjacent regions. These analyses provide a spatial interpretation for the phenomenon of club convergence.

The empirical results indicated that considering spatial interaction and spatial distribution is necessary for making and implementing emission reduction policies. The government should promote the communication and cooperation of information, technology, experience, and resources among provinces, enhance the radiation effect of provinces with

low carbon intensity through measures such as a trans-province green supply chain, realizing the reduction of carbon emission inequality, accelerating collaborative emission reduction. The provinces should undertake common but differentiated responsibilities.

In the less developed regions of China, heavy industry is the main impetus of economic development, and energy efficiency in these regions is lower. Rapid economic development and lower energy efficiency will cause carbon emissions to increase in rigidity, while these less developed regions will suffer the mitigation of industrialization and urbanization when cutting down carbon emissions because of their limited technologies and funds. Favorable policies and measures should be implemented in these regions to enhance the opening degree, thus accelerating the industrial structure adjustment and the reduction of carbon intensity in these areas.

In more developed regions, the correlation between carbon emissions growth and economic growth is relatively weak, which implies that the effect of emission reduction on economic growth in these regions is smaller than that in less developed regions. More developed regions should take more responsibility in energy conservation and emission mitigation in the construction industry and help less developed regions to reduce carbon emissions by providing them with experience and technologies. In addition, these regions should also do more for cutting down their own carbon emissions.

Furthermore, in the methods section, this paper emphasizes the prospect of using spatial analytical methods such as a spatial Markov chain and GIS in investigating the convergence and spatial distribution dynamics of carbon emissions. The research method used in this paper is not only confined to a specific country or industry. This method can also be used in other countries, industries, and even the world for understanding the dynamics and mechanisms of carbon emission disparity. Besides the energy economics field, other fields such as education and health could consider this method to investigate inequality and disparity in future studies.

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Compliance with ethical standards

Conflicts of interest The authors declare that they have no conflicts of interest.

Appendix

See Table 5.

Table 5 Average low-order calorific value (NCV), carbon content per unit heat (A) and oxidation rate (O) for different energy


	Coal	Coke	Crude oil	Gasoline	Kerosene	Diesel oil	Liquefied petroleum gas	Natural gas
NCV (TJ/ 10 ⁴ t)	209.08	284.35	418.16	430.70	430.70	426.52	501.79	3893.10
A(t/TJ)	26.37	29.50	20.10	18.90	19.50	20.20	17.20	15.30
O	0.94	0.93	0.98	0.98	0.98	0.98	0.98	0.99

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Affiliations

Qiang Du¹ · Min Wu² · Yadan Xu² · Xinran Lu² · Libiao Bai¹  · Ming Yu²

Qiang Du
q.du@chd.edu.cn

Min Wu
min_wu@chd.edu.cn

Yadan Xu
yadan_xu@chd.edu.cn

Xinran Lu
lu_xinran@chd.edu.cn

Ming Yu
ming_yu@chd.edu.cn

¹ School of Economics and Management, Chang' an Univ, Xi'an 710064, Shaanxi, China

² School of Civil Engineering, Chang' an Univ, Xi'an 710061, Shaanxi, China