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Synergistic CO_2 Reduction Effects in Chinese Urban Agglomerations: Perspectives from Social Network Analysis

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Abstract

China has released its ambitious target for carbon neutrality by 2060. With decades of top-down energy conservation and pollutant mitigation policies, the techno-mitigation space has gradually shrunk, while more mitigation space is required for a systematic approach. To help to uncover CO_2 mitigation effects, location and better pathways from a systematic perspective, this paper combines disparity analysis and social network analysis to investigate the synergistic emissions reduction effect of urban agglomerations in three representative Chinese urban agglomerations, namely the Yangtze River Delta urban agglomeration (YRD), Chengdu-Chongqing urban agglomeration (CY) and Guangdong-Hong Kong-Macao urban agglomeration (GHM). Based on understanding of the carbon emission disparity characteristics of the three urban agglomerations using disparity analysis, this study uses social network analysis to study the synergistic CO_2 reductions in each urban agglomeration from three perspectives: overall, individual, and connection. The findings emphasize that CY presented the greatest synergistic development capacity but with weak driving ability, indicating that overall synergistic emission reduction was difficult to achieve in a short period. GHM presented obvious fragmentation between the core and peripheral cities, resulting in a weak synergistic mitigation effect. YRD highlighted a solid synergistic development capacity with strong driving ability by its developed cities, thus generating the greatest potential to reduce CO_2 emissions in the short and middle terms. Different cities assume different roles in synergistic CO_2 reduction. Our results can be expected to enlighten more regionally oriented CO_2 mitigation policy implications from an urban agglomeration perspective.

Keywords: Urban agglomerations; Social network analysis; Synergistic CO_2 reduction; Carbon neutrality; Disparity analysis

1. Introduction

Urbanization and industrialization are the two engines driving surging greenhouse gas (GHG) emissions, particularly carbon dioxide (CO_2) emissions, over the past two centuries (Fang et al., 2017, Fang et al., 2018, Luo et al., 2017). As the world's currently largest CO_2 emitter, China has been in rapid intertwined urbanization and industrialization, generating critical challenges for its commitment to carbon peaks and carbon neutrality (Dong et al., 2021, Zhao et al., 2021). At the 2015 United Nations Climate Change Conference in Paris, China announced its goal of reaching peak CO_2 emissions by 2030. With cities as mega-sources of CO_2 emissions, urban carbon mitigation has become a critical issue in China's overcoming the challenges of carbon neutrality strategies.

China has released national-level and top-down approaches in recent decades regarding energy conservation and pollutant mitigation and has realized significant effects from technology innovation (Dong et al., 2017, Li et al., 2017a, Liu et al., 2016). However, the techno-mitigation space would and has gradually shrunk, thereby requiring more mitigation space from a systematic perspective. A systematic approach will enable the generation of a so-called synergistic CO_2 reduction effect, which would expand the current mitigation space in a more cost-effective manner (Dong et al., 2016, Liang et al., 2014, Luo et al., 2016). With the rapid urbanization process together with industrialization, urban agglomerations, as an advanced form of urbanization development in China, have a strong influence and leading role in surrounding cities and significantly impact cities' and the nation's carbon emissions with their own high economic and social levels (Fang et al., 2016, Fujii et al., 2016, Liang et al., 2016).

Therefore, exploring the synergistic CO_2 mitigation effect in Chinese urban agglomerations will benefit the national carbon peak and carbon neutrality strategy from various perspectives: 1) urban agglomerations reflect a dynamic urban development pathway, as well as the underlying CO_2 emissions patterns, which could enlighten the future policy implications in fitting local conditions; 2) urban agglomerations are a process of symbiotic networking of cities, so investigation of the synergistic CO_2 mitigation effects could reflect how the cities' network structures will reduce or drive regional CO_2 emissions, thus guiding future low-carbon urban and industrial layout planning policies, and 3) spatially, urban agglomerations are hotspots of CO_2 emissions, so an in-depth exploration of CO_2 emissions and their relation to urban agglomerations could enlighten the spatial pathway of CO_2 mitigation at the national level, which would be significant to the 14th Five Year Plan (14th FYP).

Advanced economic geography and social science approaches, with application in cities, offer a strong toolbox for exploring the above issues for policy enlightenment (Liang, Dong, 2016, Liu, Geng, 2016, Luo, Dong, 2016). Different cities have different carbon emissions profiles under the combined influence of their respective economic development levels, energy consumption differences, and industrial structures, leading to differences in the ability of different cities to meet the target of reaching a carbon peak. Such disparity requires policymakers to determine the carbon reduction policies of different cities according to each city's actual situation and the differences in carbon emissions between cities. Researchers aiming to study carbon emissions differences partly use the Gini coefficient and Theil index to study the magnitude differences in carbon emissions among regions (Pakrooh et al., 2020).

They partly use spatial autocorrelation and cold hot spot analysis to study carbon's spatial distribution characteristics and emissions among provinces and cities (Li et al., 2017c, Liu et al., 2020). There are many flows of people, materials, finance, and information running between cities, and the carbon emissions of each city are seriously influenced by other cities during this process, thus forming intercity carbon emissions connections. Therefore, each city should also consider the intercity carbon emissions correlation when reducing carbon emissions. For governmental decision makers, only by understanding the spatial correlations between cities and their spatial structures can they formulate practical overall carbon emissions reduction measures and achieve synergistic emissions reductions in the region. Studies investigating the connections of socioeconomic indicators between geographic units often use social network analysis. For instance, Alderson and Beckfield (2004) used network methods to study the position of cities in the world city system; Da et al. (2019) used SNA to investigate international trade, and Sun et al. (2015) used SNA to study economic connections at the city scale; Li, Z. et al. (2017) used SNA to examine industrial structure changes and corresponding CO_2 reduction effect. Some scholars have used SNA to study carbon emissions flows and connections between provinces and cities. Bai et al. (2020), Sun et al. (2020), and He et al. (2020) used SNA to study interprovincial carbon emissions connections. Song et al. (2018) used SNA to study carbon emissions associations in the Chengdu-Chongqing urban agglomeration.

However, to the best of our knowledge, there have still been only limited studies exploring the synergistic CO_2 reduction effects in urban agglomerations, particularly from both networking and disparity perspectives at the same time. It has now been demonstrated that the connections of carbon emissions between geographical units significantly affect their carbon emissions disparities (Lv et al., 2019), and these disparities also significantly affect carbon emissions connections (Song, Feng, 2018). Mechanistically, the connection and disparity of urban carbon emissions will influence the generation of and changes in each other. Furthermore, the analysis of disparity helps us have a more comprehensive understanding of the generation of connections, and analysis of the connections will also elaborate the reasons for the changes in disparities from a dynamic perspective, providing a comprehensive understanding of synergistic CO_2 reduction. Therefore, it is essential to analyze the carbon emissions disparities and connections among cities simultaneously. Understanding the pattern of carbon emissions disparities within each urban agglomeration and exploring the spatial association of urban carbon emissions on this basis are conducive to the formulation of detailed and targeted synergistic carbon emissions reduction initiatives, which will, in turn, promote the realization of comprehensive and effective emissions reduction in China's urban agglomerations. However, most of the existing studies have paid more attention to the patterns of carbon emission disparities or spatial connections of carbon emissions separately, while limited efforts have been applied to investigate both aspects simultaneously.

According to the above background and scientific highlights, this paper acts as a first attempt to explore this issue from both the CO_2 emissions pattern disparity and networking structure (connection of cities) perspectives. To answer such questions, the well-developed Theil index and Moran's *I* index are applied to analyze the carbon emissions disparities among three main urban agglomerations, namely the Yangtze River Delta urban agglomeration (YRD), Chengdu-Chongqing urban agglomeration (CY), and

Guangdong-Hong Kong-Macao urban agglomeration (GHM), from the perspectives of carbon emissions magnitude and spatial patterns, respectively. Social network analysis is further applied to investigate the carbon emissions networks among cities in each urban agglomeration. Indicators of SNA support measuring the synergistic development capacity of each urban agglomeration and determining the importance of different cities and intercity connections to synergistic emissions reduction. Combining disparity analysis and network analysis, synergistic carbon emissions reduction features and pathways in each urban agglomeration are discussed to enlighten an effective and efficient carbon mitigation pathway for China’s 14th FYP period.

The remainder of this study is organized as follows: after this introductory section, section 2 presents the analytical framework, methodologies, and data sources; section 3 presents the results; and section 4 discusses the results. Finally, section 5 summarizes the conclusions and policy implications.

2. Data and Methods

2.1 Analytical framework

The analytical framework is illustrated in Figure 1. First, the basic characteristics of CO_2 in each urban agglomeration are analyzed to obtain overviews; the Theil index and Moran’s I index are used to quantify the carbon emission disparities from the perspectives of carbon emissions magnitude and spatial pattern, respectively. Second, carbon emissions network models were constructed, and indicators of SNA were used to measure the synergistic development capacity of each urban agglomeration (overall analysis), judge the importance of different cities (individual analysis) and intercity connections to synergistic emissions reductions (connection analysis). Third, the key to synergistic carbon emissions reduction in each urban agglomeration is discussed by combining the above analyses. Finally, overall and individual policies for synergistic CO_2 reduction are proposed.

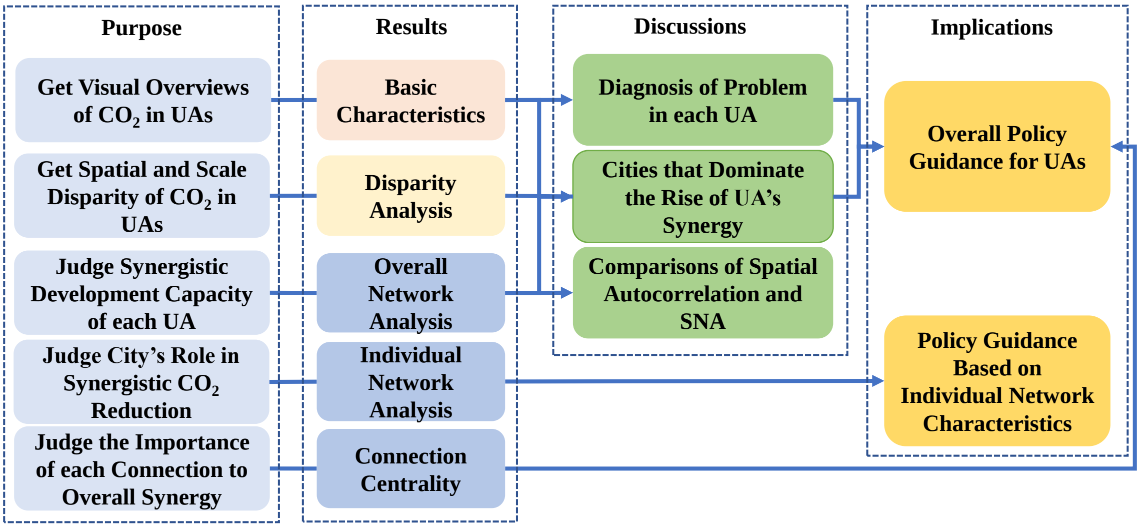

Figure 1. Flowchart of the full text. Note: UA is the abbreviation of Urban Agglomeration.

2.2 Study Area and Dataset

In this study, three representative urban agglomerations were selected for analysis (Figure 2).

(1) The Yangtze River Delta (YRD) is an important region with the highest economic development level in China and the country's demonstration area of ecological civilization. It is one of the most dynamic, open, and innovative regions in China's economy and an essential intersection between the "Belt and Road" and the Yangtze River Economic Belt, with a more important strategic position in modernization China.

(2) The Chengdu-Chongqing urban agglomeration (CY) has taken the lead in developing

Western China by integrating the Yangtze River Economic Zone Strategy with the West Development strategy.

(3) The Guangdong-Hong Kong-Macao urban agglomeration (GHM) has a significant economic scale and serves as a major international land and maritime corridor connecting countries along the Silk Road Economic Belt (Central Asia and Europe) and Maritime Silk Road (South Asia, Oceania to Africa and the Middle East). GHM in this study contains a total of 23 cities. One part consists of the 11 cities in the Guangdong, Hong Kong, and Macau Greater Bay Area mentioned in the 13th Five-Year Plan, i.e., core cities; the remainder are 12 other prefecture-level cities in Guangdong Province.

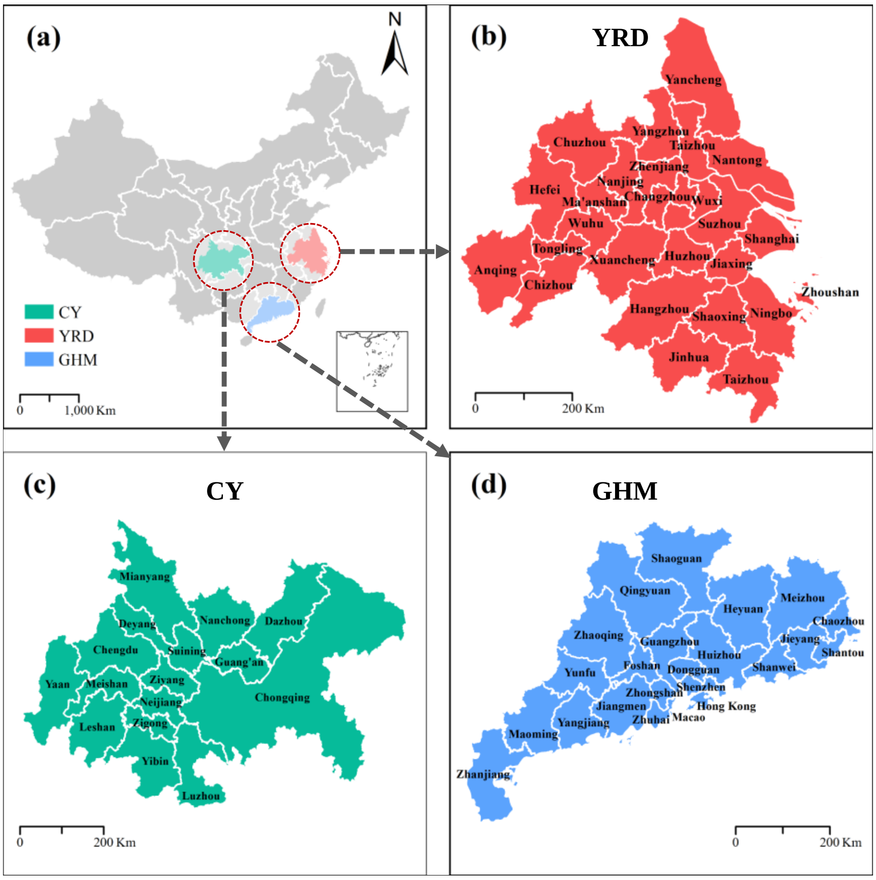

Figure 2. Locations of the study area. Note: YRD represents the Yangtze River Delta urban agglomeration; CY represents the Chengdu-Chongqing urban agglomeration; GHM represents the Guangdong-Hong Kong-Macao urban agglomeration.

The data used in this study include carbon emission data and socioeconomic data of each city in the three urban agglomerations in 2010 and 2015. (1) Carbon emissions data are obtained from the China City CO_2 Emission Dataset (2010) and the China City Greenhouse Gases Emission Dataset (2015). The calculation process of these two carbon emissions datasets is listed in detail in the study by Cai et al. (2018) and Cai et al. (2019). (2) Resident population data are obtained from the Statistical Yearbook of each province and city, Hong Kong Annual Digest of Statistics, and Macao Statistical Yearbook. (3) GDP data are obtained from the Statistical Yearbook of Chinese Cities, Hong Kong Annual Digest of Statistics, and Macao Statistical Yearbook. Some cities' industrial data come from provincial-level and city-level statistical yearbooks. The basic information (GDP, POP, CO_2) of all cities in three urban agglomerations are shown in Tables S1–S3 of supplementary material.

2.3 Methods

This section first describes the Theil index and spatial autocorrelation analysis required for the disparity analysis. We then elaborate on how the network is constructed (gravity model), what the network indicators mean, and how they are calculated (network characteristics).

2.3.1 Theil Index

This study introduces the Theil index to quantify the disparities in carbon emissions within and between urban agglomerations. The Theil index is a measure of economic or social inequality derived mainly from the concept of entropy in information theory. Its main advantage is the ability to measure the contributions of within-group and between-group disparities to the overall disparities. According to Theil (1967) and Shorrocks (1980), the Theil index is calculated as follows:

$$T_k = \sum_{i=1}^{n} \frac{P_i}{P_k} \times \ln\left(\frac{P_i}{P_k} \bigg/ \frac{C_i}{C_k}\right) \tag{1}$$

$$T_a = \sum_{k=1}^{m} P_k \times \ln\left(\frac{P_k}{C_k}\right) \tag{2}$$

where k represents agglomerations, i represents cities, n is the number of cities in agglomeration k, and m is the number of agglomerations. T_k is the Theil index representing the disparity in three agglomerations; T_a is the Theil index reflecting the disparities in carbon emissions between urban agglomerations; P_i is the proportion of the population of city i in urban agglomeration k of the total population of the study area; P_k is the proportion of the population of agglomeration k of the total population of the study area; C_i is the proportion of carbon emissions of city i in agglomeration k of the total carbon emissions of the study area; and C_k is the proportion of total carbon emissions of agglomerations of the total carbon emissions of the study area.

It should be noted that the above formula shows the steps for calculating the Theil index with the population as the weight ($\text{Theil}_{\text{POP}}$). To calculate the GDP-weighted Theil index ($\text{Theil}_{\text{GDP}}$), we need only replace the population in the formula with the corresponding city's GDP value.

2.3.2 Spatial Autocorrelation Analysis

The measure of spatial autocorrelation is used to test the correlation of spatial variables with a certain regularity in different spatial locations, which can intuitively express the spatial correlation and disparity of a specific economic phenomenon and determine the distribution characteristics and regularity of regional economic attribute indicators from geographic space, as well as whether aggregation characteristics or interdependence exists. In this study, the Global Spatial Autocorrelation Indices – Moran's *I* is used to compare and analyze the disparities in the spatial distribution characteristics of carbon emissions in different urban agglomerations from a spatial perspective (Cliff and Ord, 1981, Moran, 1950). The formula for Moran's *I* is as follows:

$$I = \frac{\mathrm{n}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2} = \frac{\mathrm{n}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{3}$$

where $S^2 = \sum_{i=1}^{n}(x_i - \bar{x})^2; \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, I is Moran's *I*; n is the number of cities in an agglomeration; x_i , x_j is the CO$_2$ emission of city i, j ; $\bar{x}$ is the average value of carbon emissions of each city in the agglomeration; and w_{ij} is spatial weight matrix. In this study, the *k*-nearest neighbor method is used in the calculation, and *k* is set at 25% of the number of cities in each urban agglomeration.

Moran's *I* index ranges between -1 and 1, and the *Z*-score tests the significance of this index. In general, a higher (or lower) *Z*-score represents a greater degree of clustering. If the *Z*-score is close to zero, there is no significant clustering in the study area. A positive *Z*-score indicates clustering of high attribute values, while a negative *Z*-score indicates clustering of low attribute values.

2.3.3 Social Network Analysis

Social network analysis (SNA) has been one of the most widely used research methods in sociology and economics in recent years. The theoretical perspective of SNA focuses on the relationships and social structures between social actors, and the object of SNA is the network structure constituted by the inner connections of different actors. During the analysis, urban agglomerations are considered overall network structures, and each city within them is regarded as a node in the network. Connections between cities are viewed as edges in the network. Furthermore, the points, edges, and overall network characteristics of the carbon emissions networks of different urban agglomerations are quantified. This study uses these indicators to investigate the synergistic capacity of carbon emissions networks in urban agglomerations.

1）Gravity Model

The first step in social network analysis is to construct a network of associations. In this study, points represent individual cities, and edges represent the connections of carbon emissions between cities. Considering that the gravity model can comprehensively consider factors such as economy, distance, and carbon emissions, this study adopts a modified gravity model to construct the spatial association relationship of carbon emissions between cities. The modified gravity model is as follows:

$$y_{ij} = k_{ij} \frac{\sqrt[3]{P_i G_i C_i} \times \sqrt[3]{P_j G_j C_j}}{{D_{ij}}^{b}} \tag{4}$$

$$k_{ij} = \frac{C_i}{C_i + C_j} \tag{5}$$

where y_{ij} is the gravitation of CO_2 emissions between city *i* and city *j*, *Pi* is the population of city *i*, *Gi* is the gdp of city *i*, *Ci* is the carbon emissions of city *i*, D_{ij} represents the spherical distance between city *i* and *j*, and *b* is the coefficient of distance. Here, we assign a value of 1 to b because the spatial impedance coefficient is reasonably small in the case of more frequent and convenient connections within urban agglomerations. K_{ij} represents the gravity coefficient of CO_2 from city *i* to city *j*. The carbon emissions gravitational force between cities is used to construct the CO_2 gravity matrix.

To facilitate network characterization, the CO_2 gravity matrix is binarized in this study. Considering that a limited number of cities will significantly influence one city, we consider each row's average value in the matrix as the threshold. When the gravitational value is greater than the average value of the row in which it is located, it is recorded as 1, indicating that the connection is significant, and the city in that column influences the city's carbon emissions in that row.

2）Network Characteristics

Based on the connection network's construction, we can use network analysis indicators to quantify the overall, individual, and connection characteristics of each urban agglomeration. There are two types of indicators commonly used for analysis (Bu et al., 2020, He et al., 2020). One is the indicator used to analyze the overall structure of the network, which is used in this study to indicate the synergistic development capability of the network; the other is the indicator used to analyze the position of network nodes in the network, i.e., the individual centrality, which is used in this study to reflect the role of cities in synergistic emissions reduction. In addition to these two types of indicators, this study innovatively introduces connection centrality to analyze the network characteristics of carbon emissions. This indicator is well suited to reflecting the importance of carbon emissions exchanges between cities for synergistic development of the overall network. Table 1 contains an introduction to each network characteristic. All of these indicators in this chapter refer to the book *Social Network Analysis: A Handbook* by Scott (2000).

Table 1 A brief description of the calculation methods of social network characteristics

Network characteristics		**Description**	
Overall Network Characteristic	Network density	$Den = \frac{M}{N(N-1)}$ (6) N is the number of cities in the network, M is the sum of all actual network connections.	Higher network density means a tighter network of carbon emissions and a stronger overall synergistic capability of the network.
	Network diameter	$Dia = Max(d_{ij}) \sim i, j = 1....N$ (7) d_{ij} is the shortcut distance from i to j.	Smaller network diameter means fewer cities that are difficult to be driven in the network.
	Network reciprocity	Number of two-way connections as a percentage of all connections.	A higher network reciprocity implies more excellent stability of the synergy.
Individual Centrality	Degree Centrality	$DC_i = \frac{L_i}{2(N-1)}$ (8) L_i stands for the number of connections with one endpoint being i.	A higher degree centrality means the city has more connections with other cities in the network, and the city has more significant impact on the synergistic CO_2 reduction of the network.
	Betweenness Centrality	$BC = \frac{2\sum_{j=1}^{N}\sum_{k=1}^{N} g_{jk}(i)/g_{jk}}{3N^2-3N+2}$ (9) $g_{jk}(i)$ denotes the number of times city i appears on the shortcut associated with the two cities(j,k), g_{jk} denotes the number of	Higher betweenness centrality means the city has a more significant influence on the interaction of carbon emission between other cities and a stronger synergistic effect on the development among other cities.

Network characteristics		Description	
		shortcuts between cities(j,k).	
	Closeness Centrality	$CC_i^{-1} = \frac{\sum_{j=1}^{n} d_{ij}}{N-1}$ (10)	Closeness centrality reflects the extent to which each city in the entire network is not controlled by other cities.
Connection Centrality		The centrality of an edge refers to the extent to which the edge lies on the short-cut between the connecting cities	Higher centrality of the connection means that the connection significantly impacts the network's synergistic emission reduction.

3. Results

3.1 Basic characteristics of CO_2 emissions

To study the relationship between carbon emissions and the economic growth of each urban agglomeration, we plotted the environmental Kuznets curve (EKC) with GDP per capita and carbon emissions per capita as variables and each city as a sample point (Figure 3).

This spatial EKC curve shows an obvious inverted U-shaped relationship between environmental and economic indicators. Assuming that each city develops along a consistent path, different cities can be seen as cities' different development stages. Most cities in CY are at a relatively early stage, in which both per capita CO_2 and per capita GDP are in a low but rapidly rising stage. Most YRD cities are near the inverted U-shaped curve apex, and these cities have almost peaked in carbon emissions with high economic levels. However, the overall development of YRD still shows a positive correlation between CO_2 and the economy. The cities in GHM are in various stages, with extremely high variability in development from city to city.

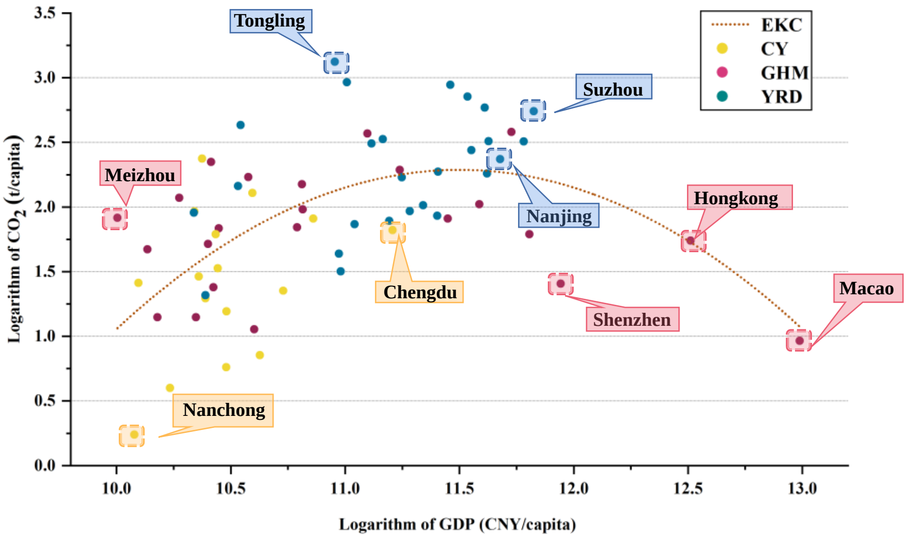

Figure 3. Environmental Kuznets curve (EKC) for CO_2 emissions. Note that the EKC curves are fitted from data for all cities in the three urban agglomerations.

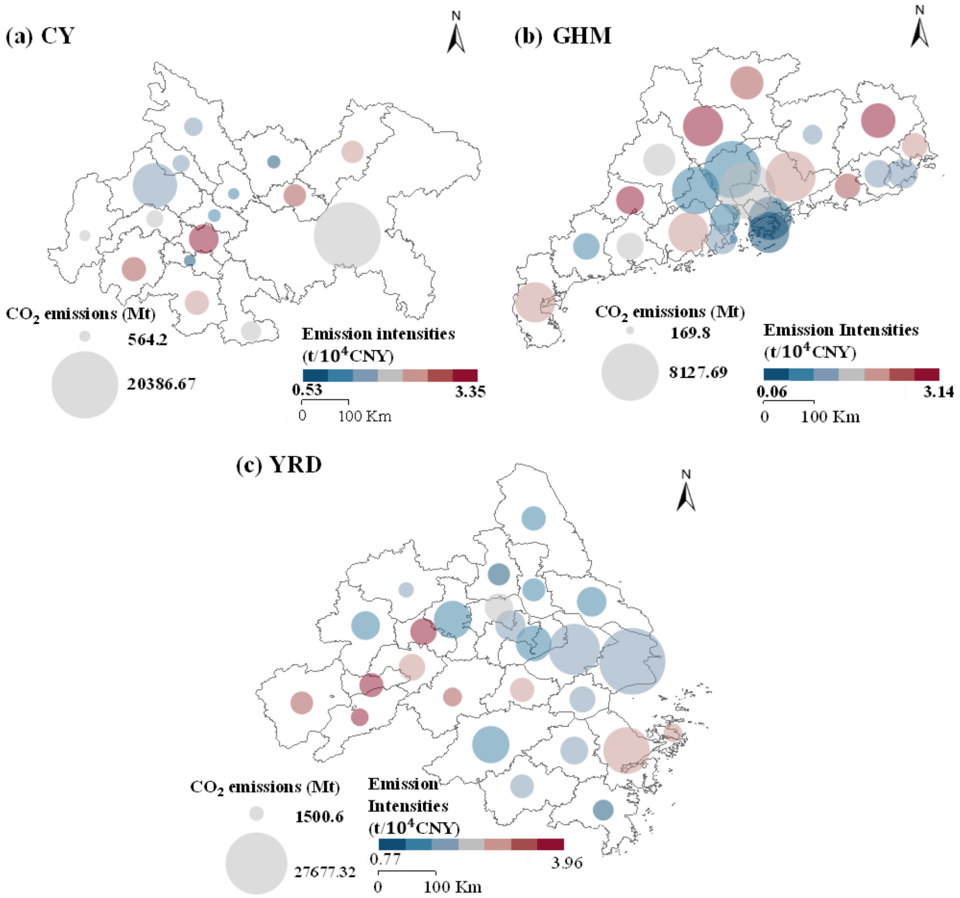

Figure 4. The magnitude and intensities of CO_2 emissions in the urban agglomeration of **(a)** CY, **(b)** GHM, and **(c)** YRD for the year 2015.

To obtain a comprehensive understanding of each urban agglomeration's carbon emissions, we must sort out the spatial structure of the carbon emissions of each urban agglomeration. Figure 4 is analyzed as follows.

First, we compare the matching relationship between carbon emissions intensity and total emissions in the three urban agglomerations: in YRD and GHM, the top cities in total emissions tend to have lower CO_2 intensity; in contrast, the top cities in CY have the highest carbon emissions intensity in the urban agglomeration, except for Chengdu and Chongqing. Combined with CY still being in a relatively primary stage, as shown by the EKC curve, the low carbon emissions intensity of the cities is mainly due to their low level of industrialization; the cities with low carbon emission intensity in the other two urban agglomerations are mainly the results of the developed economy and advanced industrial structures.

The spatial structure of carbon emissions in each urban agglomeration in 2015 is analyzed. The carbon emissions of CY show an obvious bicentric pattern, with Chengdu and Chongqing having much higher carbon emissions than other cities. Most of the cities with high carbon emissions in YRD are located on two axes: the main axis is the line between Shanghai and Nanjing, and the secondary axis is the line between Hangzhou and Ningbo. Cities on the axis tend to have lower carbon emissions intensity. The cities with high carbon emissions intensity are mainly concentrated in the western part of the urban agglomeration; i.e., Anhui Province is at a disadvantage in terms of carbon emission's intensity. Most cities with high CO_2 emissions are centered on the Hong Kong-Guangzhou line, and the magnitude of carbon emissions decreases gradually from the inside to the outside. The 11 core cities in

GHM have higher and more concentrated carbon emissions and lower carbon emissions intensity, forming a noticeable difference from other cities around them, so we define the 12 cities around them as peripheral cities hereafter.

3.2 Disparity analysis of urban CO_2 emissions

3.2.1 Theil Index

The magnitude of the disparity in CO_2 in each urban agglomeration is analyzed (see Figure 5). GHM has the largest $Theil_{GDP}$ in 2015 and has increased compared to 2010, indicating that industries' carbon emissions intensity has varied significantly in GHM. Developed cities of GHM, such as Macao, Hong Kong, Guangzhou, and Shenzhen, have mature services, finance, and retail industries, and their tertiary industry commonly accounts for more than 60% of their GDP. While the tertiary industry in less developed cities, such as Jieyang, Shanwei, Heyuan, and Yunfu, only accounts for approximately 35% of their GDP, the pillar industry in these cities is more likely to be industry.

Both YRD and CY underwent significant changes in their Theil indices within five years. The $Theil_{POP}$ of YRD saw a considerable decrease, indicating that the disparity of carbon emissions per capita in each city decreased. Section 3.1 shows that the cities in YRD could be plotted with an upward trend in the EKC curve; i.e., the economy is positively correlated with carbon emissions, and the economically developed cities have higher per capita carbon emissions. Thus, the decrease in the per capita carbon emissions disparity is likely due to the decrease in per capita carbon emissions in the developed cities or the increase in per capita carbon emissions in the less developed cities. The $Theil_{GDP}$ of CY considerably decreased from 2010 to 2015, indicating that the disparity in the carbon emissions intensity of each city decreased. Considering that the two central cities have the lowest carbon intensity (and are unlikely to increase) among the cities with high carbon emissions in CY (Section 3.1), it is likely that the carbon intensity of the other cities decreased rapidly, rendering the carbon intensity of the cities more similar overall.

Comparing the Theil indices between and within urban agglomerations, the contribution of intra-agglomeration disparity is larger than the inter-agglomeration disparity, and the inter-agglomeration disparity of both Theil indices shows a decreasing trend, revealing less carbon emissions disparity among the three agglomerations, and there is a rising similarity of carbon emissions among them, while there are still significant disparities in CO_2 within agglomerations. The focus should be on balancing intra-agglomeration disparities in carbon emissions when formulating and implementing future policies.

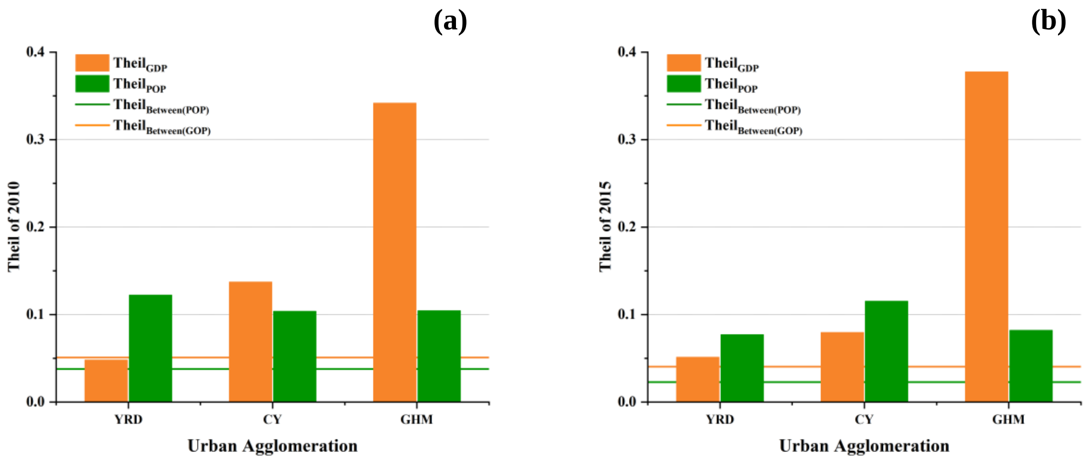

Figure 5. Theil index of CO_2 emissions between and within urban agglomerations in **(a)** 2010 and **(b)** 2015. Note that the solid lines represent the inter-agglomeration Theil index.

3.2.2 Spatial Autocorrelation Analysis

Table 2 indicates that the global Moran’s *I* of both GHM and YRD pass the 5% significance test. Comparing each urban agglomeration, the clustering characteristics of carbon emissions in GHM are greater than those in YRD, and the spatial imbalance is more significant in the former. The highest spatial unevenness of GHM is consistent with the results of the Theil index obtained from the magnitude perspective in Section 3.2.1. The difference between GHM and YRD is also in line with the spatial pattern shown in Section 3.1; i.e., the carbon emissions of YRD are mainly concentrated on two axes, while those of GHM are concentrated on only one axis. The nonsignificant Moran’s *I* of CY could be due to its unique “double-center” spatial pattern of carbon emissions (Section 3.1).

Table 2 Global autocorrelation of the three urban agglomerations in 2010 and 2015

	YRD		GHM		CY	
	2010	2015	2010	2015	2010	2015
Moran’ *I*	0.121	0.095	0.141	0.125	-0.037	-0.068
Z-score	2.288	1.999	2.3098	2.1395	0.7196	0.0196
Pattern	*C*	*C*	*C*	*C*	*R*	*R*

Note: $|z-score|>1.96$ means pass 5% significant test; $|z-score|>1.26$ means pass 10% significant test. *C* represents the spatial clustering pattern, *R* represents the spatial random pattern.

From the temporal perspective, the Moran’s *I* of both urban agglomerations somewhat decreased and moved closer to zero over the five-year period, showing that the two urban agglomerations changed from a significant clustering to a spatially random distribution. This change suggests an enhanced carbon spillover effect between cities, with a weaker polarization effect and a stronger trickle-down effect.

3.3 Social network analysis of CO_2 emissions

3.3.1 Overall network analysis

Using Gephi software, we analyzed the overall network characteristics of CO_2 emissions and visualized the connection network (see Table 3 and Figure 6).

Table 3 Overall network analysis of three urban agglomerations

	Network Intensity		Network Diameter		Network Reciprocity	
	2010	2015	2010	2015	2010	2015
YRD	0.28	0.372	5	5	0.474	0.455
CY	0.342	0.379	4	4	0.547	0.533
GHM	0.328	0.328	7	7	0.325	0.315

The network density of YRD increased from 0.28 to 0.372 during 2010–2015, indicating that the overall network synergy of YRD has improved significantly. This change can be explained from two perspectives: first, due to policy changes, YRD initially included only Shanghai, Jiangsu Province, and Zhejiang Province until 2014, when some cities in Anhui Province were included in the scope of YRD; and second, due to changes in industrial structure, some cities in YRD increased their influence and coverage by establishing high-tech development zones and introducing high-tech industries, thus increasing the overall network connectedness. Among the three urban agglomerations, CY had the highest network density in both 2010 and 2015, likely due to its unique bicentric spatial pattern of CO_2 emissions (mentioned in Section 3.1). From 2010 to 2015, the number of GHM connections did not increase, so the network density remained unchanged. The significant disparity of CO_2 emissions among cities within GHM makes it extremely difficult to develop and maintain the connection network.

The network diameters of all three urban agglomerations did not change during 2010-2015, indicating that there are still cities far from the center in each urban agglomeration network that cannot be driven by developed cities. To facilitate understanding, we further analyzed the network diameter from a geometric perspective. The overall network is considered an ellipse, the network diameter is considered the long axis, and the number of cities in the network indicates its area. We can imitate the characteristics of an ellipse and study the similarity of ellipses to circles to judge the equilibrium properties of each network. The ratio of the square of the long axis (network diameter) to the area (number of cities) is used to determine the similarity between the ellipse and the circle. The smaller that this ratio is, the greater that the similarity is. Among them, YRD has 26 cities with a network diameter of 5, and the ratio of the network is less than 1, indicating that the ellipse is very close to a circle and that there are nearly no points within the network that are too far from the center. CY has 16 cities with a network diameter of 4, and the ratio of the network is equal to 1, indicating that the ellipse is similar to a circle and that the connections between the edge cities can be guaranteed. GHM has 23 cities with a network diameter of 7, and the ratio of the network is 2.13, so relatively more cities in this agglomeration cannot receive the driving effect from developed cities. It is also evident from Figure 6 that the connection between the core cities of the GHM carbon emissions network is very dense, but the connections between the core cities and the peripheral cities are relatively weak; i.e., there is fragmentation between the core and peripheral cities.

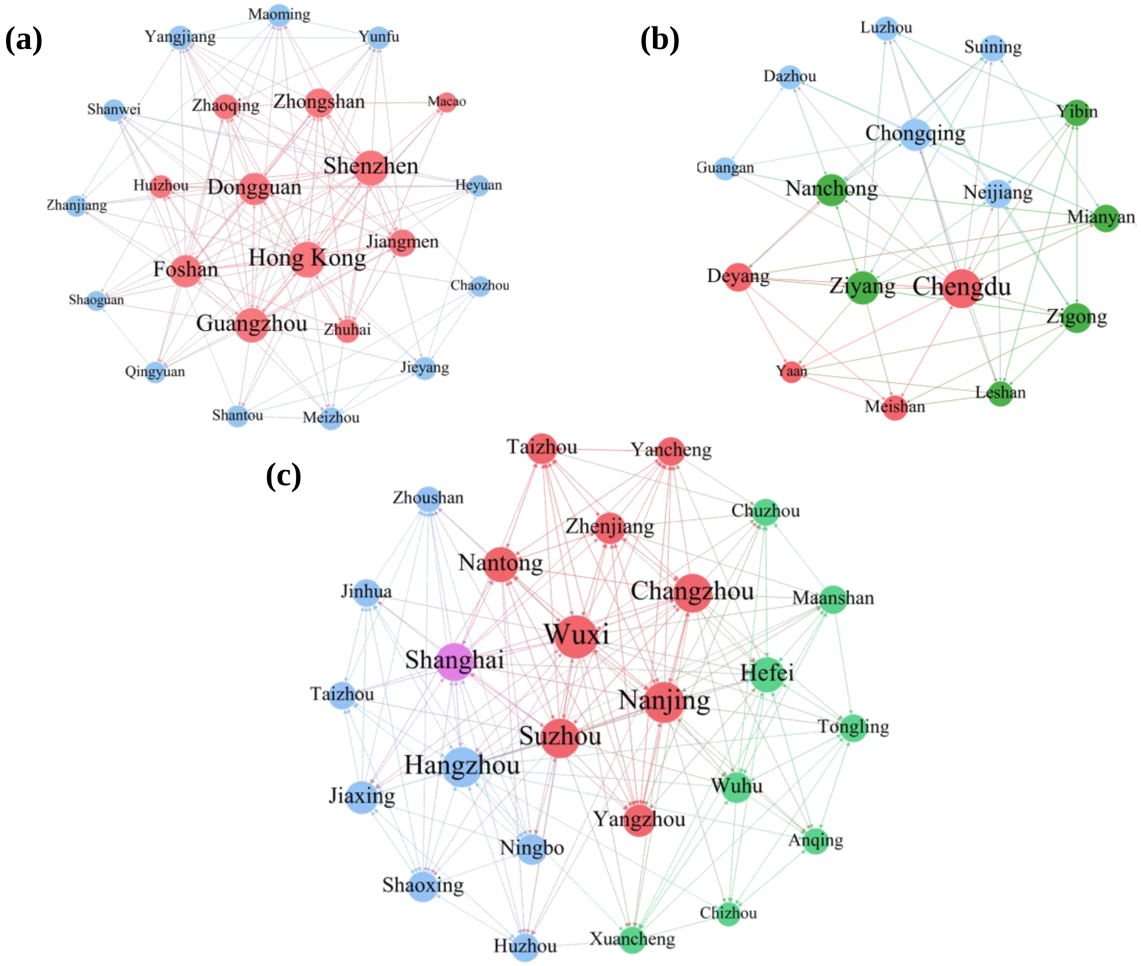

Figure 6. CO_2 emissions networks of three agglomerations in 2015. Note that **(a)** is GHM, red represents core cities, blue represents peripheral cities; **(b)** is CY, red for Chengdu and surrounding cities, green for Chongqing and surrounding cities, blue for cities that do not share a border with either center or share a border with both centers; **(c)** is YRD, red represents cities in Jiangsu Province, green represents cities in Anhui Province, blue represents cities in Zhejiang Province, and purple represents Shanghai. The bigger the pot is, the higher its degree centrality is.

Finally, the reciprocity of the network was analyzed. CY had the highest network reciprocity and the most stable network structure of carbon emissions, indicating that the existing synergies in urban agglomerations are stable. The network reciprocity of YRD was at the middle level. The network reciprocity of GHM was the lowest, indicating that its carbon emission network structure was less stable and could change. The synergies in agglomeration are changeable. The degree of reciprocity among all three urban agglomerations declined during 2010-2015. This decline is likely due to cities in the network attempting to reach out to other cities, and the connections just established were often one-way, leading to an increase in one-way connections and a decrease in the proportion of two-way connections in the overall network, further rendering the network less reciprocal. In brief, as the network expands and spreads, the rising coverage of the carbon emissions network's synergy leaves the synergy more unstable.

3.3.2 Network analysis among the individual cities

To judge the role of each city in the synergistic emissions reduction of the CO_2 network, we use centrality (degree centrality, betweenness centrality, closeness centrality) for analysis. Table 4 and Table 5 show the individual centrality analysis of some cities in YRD and CY. Figure 7 shows the individual network analysis of YRD and CY. Considering that the Theil index indicates less disparity among the three agglomerations (Section 3.2.1), one of the agglomerations can be used as an example for specific centrality analysis. Because YRD has the largest number of cities, it is used as an example for detailed individual analysis.

Table 4 Individual centrality analysis of CO_2 emissions networks of YRD

YRD (with higher DC)	2015 Indegree	2015 Out-degree	YRD (with lower DC)	2015 Indegree	2015 Out-degree
Wuxi	10	24	Jinhua	8	5
Nanjing	12	19	Taizhou	8	5
Hangzhou	11	19	Tongling	9	4
Suzhou	8	21	Chuzhou	10	2
Changzhou	9	19	Xuancheng	9	3

YRD (with higher DC)	2015 Indegree	2015 Out-degree	YRD (with lower DC)	2015 Indegree	2015 Out-degree
Shanghai	9	18	Anqing	8	3
Hefei	13	10	Zhoushan	10	0
Nantong	10	13	Chizhou	7	1

Table 5 Individual centrality analysis of CO_2 emissions networks of CY

CY (with higher DC)	2015 Indegree	2015 Out-degree	CY (with lower DC)	2015 Indegree	2015 Out-degree
Chengdu	6	15	Mianyang	6	3
Ziyang	6	10	Suining	6	2
Chongqing	5	10	Luzhou	6	1
Nanchong	8	7	Dazhou	5	3
Zigong	6	7	Guangan	4	3
Neijiang	5	7	Yaan	6	0

Note: Considering the number of connections in GHM did not change from 2010 to 2015, only the centrality analysis of YRD and CY are listed. The centrality of all cities in three urban agglomerations are shown in Table S4, S5 and S6.

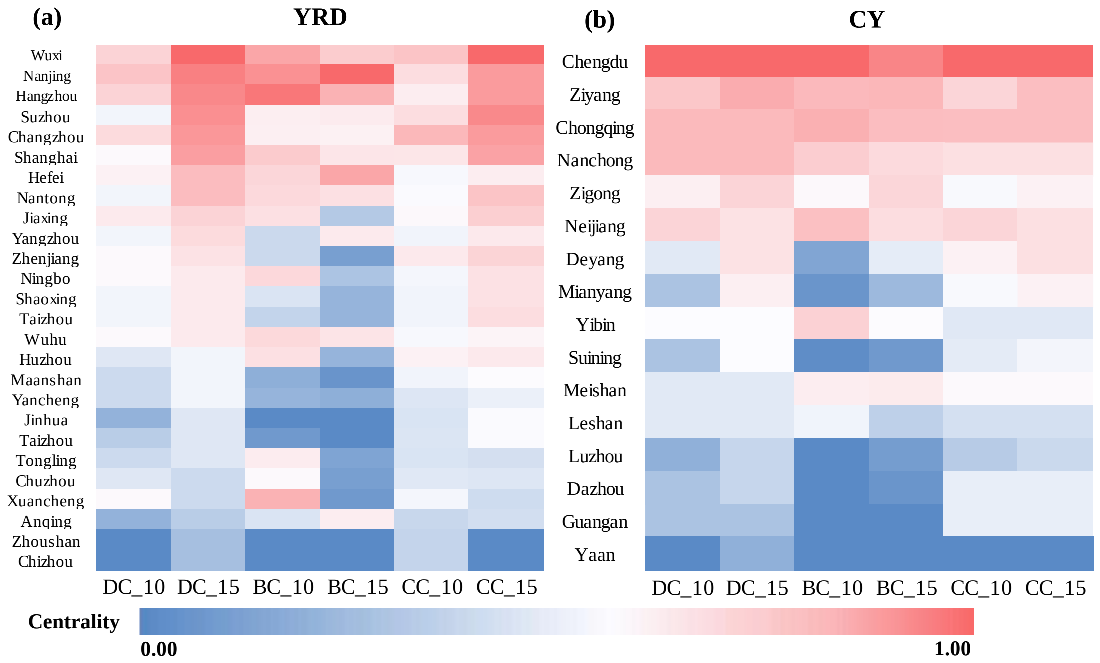

Figure 7. Individual network analysis of CO_2 emissions networks in YRD and CY. Note that DC_10 and DC_15 represent degree centrality in 2010 and 2015, BC_10 and BC_15 represent betweenness centrality in 2010 and 2015, CC_10 and CC_15 represent closeness centrality in 2010 and 2015, respectively. All these centrality indicators are standardized and the detailed data are shown in Tables S4-S6 of supplementary material.

In terms of degree centrality, the cities in the top 25% of degree centrality in 2015 were Wuxi, Nanjing, Hangzhou, Suzhou, Changzhou, and Shanghai. These cities meet two conditions: first, they have advanced industrial structures, with finance, retail, and technology industries contributing more than 20% of GDP and leading the industrial structures of other cities; and second, they are located in the center of the agglomeration, so their industrial structures can efficiently radiate and drive more cities. Specifically, Suzhou, Wuxi, Hangzhou, Changzhou, and Shanghai have advanced industrial structures, and they are located at the border of Jiangsu Province and Zhejiang Province, which is the gateway to the Yangtze River Delta. Nanjing is at the gateway between Anhui Province and Jiangsu Province and has a high driving and leading role in central Jiangsu Province and parts of Anhui Province.

In terms of betweenness centrality, the top five betweenness centrality cities in 2015 are Nanjing, Hefei, Hangzhou, Wuxi, and Nantong, and these five cities play the role of bridges in the carbon emissions network. They can be planned to control the process of synergistic carbon emissions reduction of other cities. It can be noted that the provincial capitals of each province are precisely the cities with the top three betweenness centralities, implying that cross-provincial carbon emissions are likely to be exchanged between provincial cities and provincial capitals first and then between provincial capitals, consistent with the actual political status. Therefore, in subsequent carbon reductions, attention should also be paid to the political center’s influence.

In the analysis of closeness centrality, special attention should be paid to cities with lowest closeness centrality. These cities, such as Tongling, Anqing, Xuancheng, Chizhou, and Zhoushan, have a much smaller out-degree than in-degree and are in a passive position in the network, so they are more likely to be restricted and unable to obtain positive synergies, ultimately leading to a delay in the overall carbon peak of urban agglomerations. Therefore, they will rely more on other cities to reduce carbon emissions and will require more policy support.

A comparative analysis of changes in cities in the two urban agglomerations in Figure 8 reveals that the cities with significant increases in the numbers of connections are in different positions in each urban agglomeration. The cities in YRD with numbers of connections that increased significantly were mainly those that used to have higher degree centrality (i.e., developed cities). In contrast, the cities with lower degree centrality in 2010 in CY (i.e., less developed cities) significantly increased their degree of centrality, the cities with higher centrality have remained unchanged or even decreased in their number of connections.

3.3.3 Network analysis for connections between cities

All the network connections in each urban agglomeration can be fully visualized in Figure 8. Generally, most of the connections with high centrality in the YRD carbon emission network are concentrated on the Shanghai-Nanjing-Anhui line; the connection centrality in GHM shows two opposing extremes and lacks moderate connection centrality, reflecting an uneven distribution of connections; and the connection centrality of CY is relatively even.

To clearly analyze the connections that are most important for synergistic CO_2 reductions in each urban agglomeration, we list the connections with centrality in the top 5% of each urban agglomeration in Table 6. The connections with the highest centrality in YRD can be divided into three main categories: intra-Anhui Province connections, connections between Anhui Province and Nanjing, and connections between Nanjing and other developed cities.

Nanjing plays an absolutely intermediary role in YRD. Nanjing obtained relatively high-quality industry and technology through synergy with developed cities and promoted carbon emissions reductions in less developed cities in Anhui Province by its driving effect. On the whole, the critical carbon emissions connection of YRD provides resources to the less developed regions in phases; i.e., it is preparing for the “last mile” of overall emissions reduction.

Among the essential connections in GHM, 50% of the connections are between core cities, 37.5% are between peripheral cities, and there is only one connection between the core and peripheral cities: Yunfu-Zhaoqing. The lack of important connections between the core and peripheral cities is entirely consistent with the structure shown in the previous overall network and shows the fragmentation of GHM from the view of connection centrality. If we view the important connections as a whole, Yunfu receives the influence of Zhaoqing and then influences Maoming, and Maoming establishes connections with other peripheral cities, reflecting the importance of the Yunfu-Zhaoqing connection to the GHM carbon emissions network’s synergy capacity.

The connections with high centrality are more balanced in CY, perhaps because the CY network is highly integrated and generally has strong synergy, so there is no overly critical connection. The synergy extending out of Chengdu is mainly toward the south, and the synergistic development extending out of Chongqing is mainly toward the southwest. The southern region could become the key to the overall synergistic development of CY.

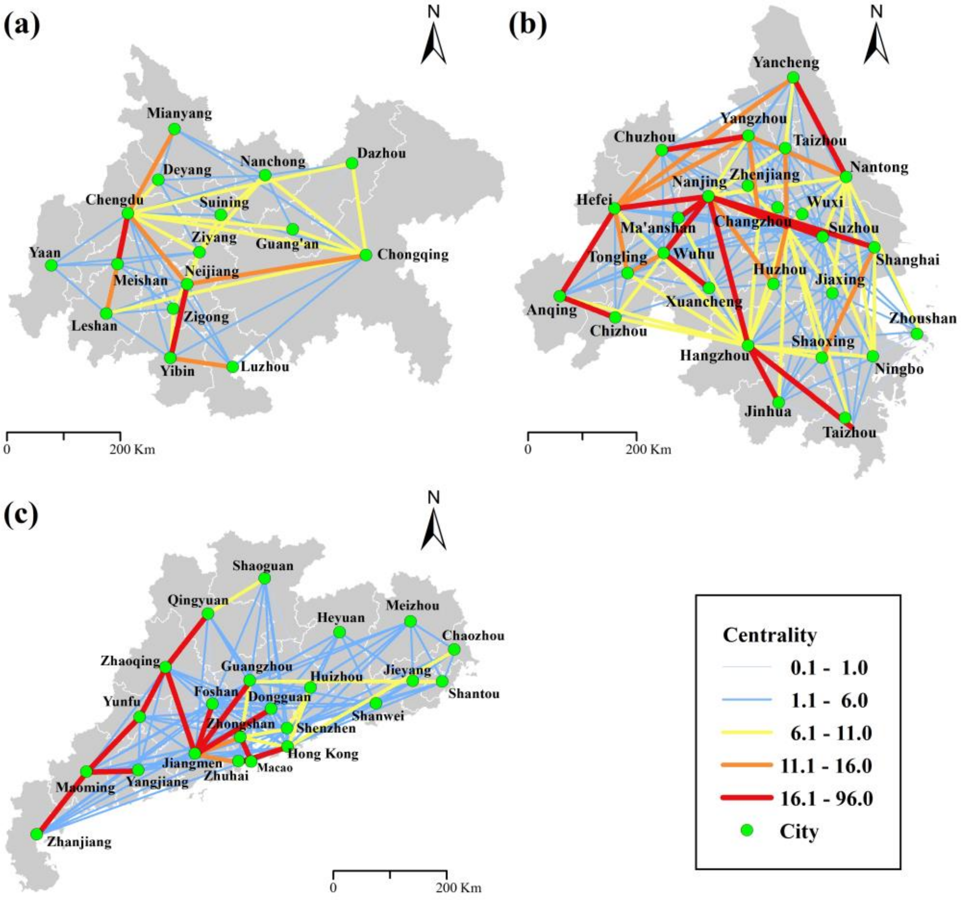

Figure 8. The centrality of network connection in three agglomerations

Table 6 Important network connections in three urban agglomerations

Agglomeration	Connection centrality in the top 5% of all connections
YRD	Hefei-Nanjing; Anqing-Hefei; Wuhu-Nanjing; Chizhou-Anqing; Xuancheng-Wuhu; Nanjing-Hangzhou; Nanjing-Shanghai; Nanjing-Suzhou; Nanjing-Wuxi; Maanshan-Nanjing; Jinhua-Hangzhou; Taizhou-Hangzhou
GHM	Zhaoqing-Jiangmen; Yunfu-Zhaoqing; Maoming-Yunfu; Jiangmen-Guangzhou; Jiangmen-Foshan; Yangjiang-Maoming; Jiangmen-Dongguan; Zhanjiang-Maoming
CY	Yibin-Neijiang; Meishan-Chengdu; Luzhou-Yibin; Neijiang-Chongqing

4. Discussions

4.1 Diagnosis of the problem in each urban agglomeration

Combining the previous results, we analyze the problems of synergistic emissions reduction in each urban agglomeration.

(1) CY: Although CY has the most muscular synergistic development capacity of carbon emissions, there is still a long way to go before it reaches the carbon peak overall. According to the good behavior of SNA, CY can easily develop as a whole. However, considering that CY is in a relatively backward stage in the EKC curve, and the most developed cities have not yet reached their peaks, the premature emergence of a more holistic network is not indeed a good thing. The mismatch between the strength of developed cities and network structures will likely lead to a weak driving effect of the two centers being dispersed by multiple connections, thus rendering the central cities' carbon emissions impacts on the less developed cities around them weaker (Chu, 2020) and eventually making the overall synergistic development of the agglomeration slow and the overall carbon peak of the agglomeration challenging to achieve. Therefore, CY not only cannot rely on its own evolution and development but also requires assistance from outside for peak carbon emissions overall.

(2) GHM: The biggest problem of GHM is the fragmentation between the developed cities at the core and the less developed cities at the periphery, i.e., the weak synergy ability of carbon emissions between developed and less developed cities. This conclusion is consistent with previous studies (Chen et al., 2021, Lin and Li, 2020, Yao and Zang, 2021, Zhou et al., 2018). The lowest network density and the largest network diameter in 2015 directly reflect the fragile synergy of the overall network. Both the magnitude and spatial disparities of carbon emissions reflect substantial unevenness, indirectly confirming the considerable fragmentation in connections from the perspective of disparity analysis. The lack of moderate connection centrality also justifies this. The situation of GHM is the opposite of CY. GHM's low carbon development level is at the forefront of China (Price et al., 2013), and the

developed cities within GHM have a more exemplary industrial structure and lower carbon emissions intensity (Zhang et al., 2020) (at the rightmost end of the EKC curve) and could produce powerful driving effects. However, they only connect with other core developed cities and lack driving effects on the peripheral cities. Therefore, GHM should guide developed cities to have more connections with less developed cities and promote overall synergistic carbon emissions.

(3) YRD: YRD has relatively fewer problems in synergistic carbon emissions than CY and GHM. The spatial clustering characteristic of CO_2 is weakening, the disparity is weaker, its network synergy ability is stronger, and the developed cities have relatively advanced industrial structures and low carbon emissions intensity (Zhang et al., 2019). Thus, YRD is prepared to achieve the goal of peak overall carbon emissions in a relatively short amount of time.

4.2 Analysis of cities that dominate the rise of urban agglomeration synergy

The carbon emissions network’s synergistic capacity can be partially reflected in the number of connections in a network. That is, the increase in the number of connections implies an increase in the synergistic capacity of the network. The analysis is performed for cities with a significant increase in the number of connections in each urban agglomeration. The study of these cities’ types and characteristics can help to determine the reasons for the improvement in synergy in each agglomeration and provide policy recommendations for maintaining and improving the synergy of these urban agglomerations in the future.

According to Tables 4 and 5, in YRD, the developed cities, i.e., cities with high degree centrality (Wuxi, Nanjing, Hangzhou, Suzhou) drive the carbon synergy of urban agglomerations. In CY, it is mainly the less developed cities, i.e., cities with low degree centrality (Dazhou, Luzhou, Suiyang, Mianyang) that drive the urban agglomeration’s carbon synergy. Considering the basic situation (Section 3.1) and the disparity pattern (Section 3.2) of each urban agglomeration, the reasons for the increase in the synergistic capacity of different urban agglomerations are analyzed comprehensively. (1) The developed cities in YRD pass the apex of the EKC curve, and economic development is gradually decoupling from carbon emissions, perhaps because of the massive introduction of high-tech industries into these cities. (Li et al., 2017b). Taking Suzhou as an example, the city vigorously developed its high-tech industry within five years, and it had four national high-tech zones and five provincial high-tech zones in 2015. With the rapid development of high-tech industries, outdated industries and technologies in developed cities are often phased out and may relocated to surrounding less developed cities (Zhang et al., 2019). This process manifests itself as a spillover effect of carbon emissions in terms of space (Liu and Liu, 2019). This is consistent with the spreading of carbon emissions as indicated in Section 3.2.2. As carbon emissions spread from developed cities, the less developed cities with lower carbon emissions in 2010 received the spillover carbon emissions, causing their carbon emissions to rise, shown as a narrowing of emissions disparities within urban agglomerations (Section 3.2.1) and more communication and collaboration between cities. Overall, it seems that developed cities promote the synergistic ability of urban agglomerations. (2) In CY, the less developed cities are in a relatively primary development stage (the relatively primary stage of the EKC curve), with rapid economic development and carbon emissions intensity coming closer to developed cities (decreasing economic Theil indices). Thus, it easier for these cities to exchange carbon emissions with developed cities. Developed cities, due to the excessive spillover effect, have a less obvious driving effect (Section 4.1) and can only barely maintain the existing synergistic capacity without further breakthroughs. Overall, it seems that the less developed cities drive the rise of synergistic network capacity.

In conclusion, in YRD, developed cities have strengthened their driving effect and increased overall network synergy; in CY, less developed cities have undertaken efforts to integrate into the overall network and increase the overall network synergy (Song, Feng, 2018). Therefore, when strengthening network synergy in the future, YRD should consider developed cities that are decoupling as the entry point and encourage them to exchange and collaborate with other cities (Li et al., 2018). The CY urban agglomeration should consider less developed cities as the entry point, improving synergistic capacity while reducing the burden on developed cities.

4.3 Comparisons of spatial autocorrelation and social network analysis

SNA expresses the synergistic ability of urban agglomerations through spatial connections; spatial autocorrelation expresses the carbon emissions characteristics of urban agglomerations through spatial clustering. Many studies have indicated that social network analysis is an extension and breakthrough of spatial autocorrelation, but they have only stayed at the conjecture stage and do not compare the results of both (Liu et al., 2015, Song & Feng, 2018). In this study, we attempt to compare the spatial autocorrelation results of three urban agglomerations with social network analysis results to investigate the connections between these two methods. The results of the two methods show obvious negative correlations: the global autocorrelation order of the three urban agglomerations is GHM> YRD> CY (CY is not significant). However, the network density order derived from SNA is CY> YRD> GHM. That is, the carbon emissions networks of urban agglomerations in the cluster case tend to be more sparsely connected, while the carbon emissions networks of urban agglomerations in the random or homogeneous case tend to have more connections.

The clustering characteristic of urban agglomerations indicates a concentrated distribution of developed (or less developed) cities, making it more likely for cities in developed areas to establish connections with neighboring developed cities, while it is difficult to influence less developed cities located at the periphery (this fact is especially evident in GHM). The non-clustering of cities, in contrast, suggests a nested distribution of developed and less developed cities, with developed cities likely to pass through less developed cities when establishing connections with other developed cities, allowing less developed cities to gain more connections and even be at the center of the network structure. In conclusion, the clustering characteristic could benefit the synergistic emissions reduction effects of local areas in urban agglomerations. However, the overall carbon emissions network’s synergistic emissions reduction ability will be reduced by overclustering, and the driving effect of developed cities will not be fully utilized.

5. Conclusions and Implications

5.1 Conclusions

This study first analyzes the magnitude and spatial disparity of each urban agglomeration using the Theil index and spatial autocorrelation analysis to obtain the actual situation of carbon emissions in each urban agglomeration. Second, SNA is used to analyze the synergistic capacity of the carbon emissions network in each urban agglomeration. Finally, we combine disparity analysis and social network analysis to identify the cities leading to the rise of synergy capacity in each urban agglomeration and the main problems of each urban agglomeration to help the government to analyze the process and devise a way of integrating the carbon emissions network of each urban agglomeration to address the existing problems of each urban agglomeration in a targeted manner.

(1) The economic Theil index of GHM is significantly larger and still rising. The matching degree of the population and the carbon emissions of YRD are significantly increasing; i.e., the disparity of per capita carbon emissions in each city is decreasing. The matching degree of the economy and carbon emissions of CY is significantly increasing, and the disparity between the carbon emission intensities of each city is decreasing. Comparing the inter-agglomeration and intra-agglomeration Theil indices, we can see that the intra-agglomeration disparity is significant. The inter-agglomeration disparity is small and decreasing, so the overall carbon emissions reduction should focus on the intra-urban agglomeration disparities.

(2) The clustering characteristics of GHM are the most obvious. YRD also showed

clustering characteristics, and the clustering pattern of CY was not significant. The clustering characteristics of GHM and YRD are weakening, and their trickle-down effect is strengthening.

(3) CY has the best overall synergistic development capability, maintaining the highest network density and reciprocity, with a slight increase in network density, and it has a solid and stable network synergistic capability. YRD has the best overall synergistic development ability, with a rapid increase in network density, the smallest network diameter, and the broadest scope of synergistic development (all cities have the opportunity to participate in synergistic development). GHM has the lowest capacity for synergistic development, and all indicators reflect considerable fragmentation between core cities and peripheral cities. Reciprocity decreases in all urban agglomerations, likely due to cities' attempts to reach out to other cities (increased instability due to the expansion of network synergy capacity).

(4) An attempt was made to analyze the role of cities in the network through individual network characteristics and the growth of the number of connections. In terms of centrality, cities with advanced industrial structures and convenient geographical locations for interaction will have a higher degree of centrality, i.e., more significant influence. The analysis of betweenness centrality shows that political centers in the network are more likely to play the role of "bridges" in connections; cities with lower closeness centrality tend to have much lower out-degrees than in-degrees and are easily influenced by other cities. From the perspective of connection growth, the increase in the synergy of YRD relies mainly on the driving role of developed cities, while the increase in the synergy of CY relies mainly on the spontaneous integration of less developed cities into the carbon emissions network.

(5) The most important connections of the YRD carbon emissions network are all concentrated on the Shanghai-Nanjing-Anhui line, reflecting the concern of developed cities for less developed cities. The connection characteristics of the GHM carbon emissions network show serious fragmentation between the core and the periphery, in which Yunfu-Zhaoqing is the only important connection between the core and the periphery. The connections of the CY carbon emissions network are more balanced, with no vital connections. The southern region could become the key to the overall synergistic development of CY.

5.2 Implications

5.2.1 Overall policy guidance for urban agglomerations

The analysis of the main problems of the three urban agglomerations and the cities with an increasing number of connections are integrated, and different emissions reduction strategies are adopted for the three urban agglomerations. 1) For the Yangtze River Delta urban agglomeration, some developed cities have achieved preliminary carbon emission peak, and the industries are transforming to develop high-tech industries and service industries, promoting the rise of the synergistic capacity of the carbon emissions network. Policy guidance for YRD can be implemented in developed cities to promote carbon emissions reductions while increasing the overall network synergistic capacity. Due to the good conditions of YRD, as long as the connections among cities are correctly guided, and the critical connections from the main axis to the cities in Anhui Province are emphasized, YRD itself is sufficient to drive the overall carbon emissions network to achieve a carbon peak by its ability. 2) For the Chengdu-Chongqing urban agglomeration, the developed cities still did not peak carbon emissions in 2015, and the cities with higher centrality have a weak driving ability due to the over-dispersed driving effect, making it challenging to promote the overall emissions reduction of the urban agglomeration by the power of developed cities themselves. The less developed cities not only require the driving effect from the developed cities but also help and support from the outside to have them quickly achieve the carbon peak. The government should import low-carbon technologies from outside, plan low-carbon industrial systems, and reorganize less developed cities’ industrial structure, which will help less developed cities to reduce CO_2 and continue to integrate into the network, thus reducing the burden of developed cities and eventually causing the overall network peak carbon emissions to occur earlier. 3) For the development of the Guangdong-Hong Kong-Macao urban agglomeration, the most important thing is to establish the connection between the core cities and the peripheral cities for the current situation of the fragmentation between its developed cities located at the core and the less developed cities located at the periphery. Therefore, the focus for the transformation of GHM is not on outside help or on planning and guidance for developed cities, but more on the balance and restructuring of the connections within the agglomeration and promoting the establishment of counterpart help between the core cities and the peripheral cities in GHM. Among them, the focus is on the exchange of information, resources, and transportation by the critical connection of Yunfu-Zhaoqing as a basis for the development of synergistic emissions reductions between core and peripheral cities.

Considering connection centrality can be used to identify the importance of the connections between cities to the synergistic CO2 reduction of each urban agglomeration, the government can also provide detailed policy guidance based on the connection centrality. The important connections within the network can be supported by policy guidance, convenient transportation, counterpart support and information exchange, which will result in lower exchange costs (Luo et al., 2017; Luo et al., 2016). The reduction in exchange costs may lead to a series of favorable factors such as the free flow of factors, the division of labor and interaction between enterprises, the clustering of green industries, and the exchange and dissemination of technology (Tian et al., 2018; Zhang et al., 2020), which will ultimately contribute to the emergence of carbon peaking and carbon neutrality in three urban agglomerations.

5.2.2 Policy guidance based on individual network characteristics

Degree centrality is the most intuitive representation of a city’s influence in the overall network of synergistic emissions reduction. Therefore, in formulating emissions reduction policies for urban agglomerations, the focus of carbon emission peak and carbon neutralization should be on cities with high levels of degree centrality. Specific measures include requiring these cities to reach the carbon peak before 2024; actively applying low-carbon technologies to transform and upgrade traditional industries in cities with a large share of traditional industries; for cities that have preliminarily achieved the carbon emission peak, accelerating the exploration of market-oriented low-carbon mechanisms, including carbon emissions trading and carbon finance; and actively exploring carbon neutral pathways. By adjusting the central cities’ industrial development planning, the whole urban agglomeration’s overall industrial development direction will be driven.

For cities with high betweenness centrality, we can focus on controlling these cities, considering their “bridge” characteristics. From the perspective of the “restriction” function of bridges, we can reduce the exchange of inefficient carbon emissions, block unnecessary carbon emissions connections, and eliminate backward production capacity. The carbon emissions spillover effects between cities can be effectively controlled. From the perspective of the “influence” function of the bridge, each city with high betweenness centrality influences the cities at both ends of the bridge, and the industrial structure development direction of these bridge cities will also greatly influence the carbon emissions of the cities at both ends. Therefore, these cities should also adjust their industrial structures and drive the cities at both ends of the bridge to transform their industries.

If a city has low closeness centrality, it is likely to be passively influenced by other cities. These cities have difficulties gaining direct influence from major cities (they are at the end of the carbon flow, and quality resources are already filtered and kept “upstream”), and they have fewer choices in receiving resources, such as industries, labor, markets, and information. Specific measures are as follows. For those with more mature industrial structures, we can promote direct interaction and contact with developed cities in urban agglomerations and directly obtain better industries and technologies according to local conditions to help their industrial structures to transform and develop rapidly. For those cities with immature industrial structures that have not yet formed a heavy industrial path dependency, they should learn from developed cities across the whole country to plan and establish a low-carbon industrial system as early as possible and to develop an innovative green economy. Policy for this part of the reactive city will lay a good foundation for the “last mile” of the overall network in reaching the peak of carbon emissions in the future.

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Abbreviation Notation:

Abbreviations	**Full names**
CY	Chengdu-Chongqing urban agglomeration
YRD	Yangtze River Delta urban agglomeration
GHM	Guangdong-Hong Kong-Macao urban agglomeration
GHGs	Greenhouse gases
CO2	Carbon dioxide
14th FYP	14th Five Year Planning
SNA	Social Network Analysis
UA	Urban agglomeration
GDP	Gross Domestic Product
Theil_{POP}	Population-weighted Theil index
Theil_{GDP}	GDP-weighted Theil index
EKC	Environmental Kuznets Curve
$\mathrm{Theil}_{Between(GDP)}$	GDP-weightes Theil indices between urban agglomerations
$\mathrm{Theil}_{Between(POP)}$	GDP-weightes Theil indices between urban agglomerations
DC	Degree centrality
BC	Betweenness centrality
CC	Closeness centrality

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