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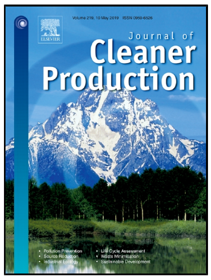

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A Study on Embodied Carbon Transfer at the Provincial Level of China from a Social Network Perspective

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Abstract: This paper incorporates the multiregional input-output (MRIO) and social network analysis (SNA) methods to investigate China's embodied carbon transfer across provinces. We estimate the amount of interprovincial embodied carbon transfer from 2002 to 2012, analyse the spatial correlation network structure of carbon transfer and its determinants. Our work can clarify the spatial distribution and different roles of provinces in the carbon transfer network. The empirical results show the spatio-temporal evolution of embodied carbon transfer; in 2002, embodied carbon transfer occurred from the energy-rich northern provinces to the developed eastern and central provinces, but in 2012, it transferred to developing southwestern and southern provinces. Moreover, the northwestern provinces act as "bridges" between the central and eastern provinces; eastern provinces play a "bidirectional spillover" role that transfers carbon internally and externally. The embodied carbon transfer network proposed here can help policy makers further clarify individual provinces' carbon emissions reduction responsibilities and curb national carbon emissions.

Key words: Carbon transfer; embodied CO_2 emissions; MRIO model; quadratic assignment procedure (QAP); social network analysis (SNA)

1. Introduction

Rapid economic growth in addition to a tremendous increase in energy use has resulted in high levels of carbon emissions, and China has surpassed the United States as the world's largest emitter (World Bank, 2016). In recent years, China's government has implemented a list of policies to reduce energy use and carbon emissions in production (e.g., measures in the eleventh and twelfth five-year plans to save energy and reduce emissions and feed-in-tariff policies for the deployment of renewables), and scholars attempt to assign responsibility for the embodied CO_2 emissions in China's international trade (products both exported for final demand elsewhere and imports of raw materials). At the same time, a rapidly increasing but easily overlooked aspect is trade between provinces in China and the resulting emissions. Nowadays China's embodied carbon transfer created in interprovincial trade at levels that exceed those of international trade (Shi et al., 2012).

The first phenomenon in embodied carbon is the creation of a "regional carbon footprint", defined as total carbon emissions required to meet final demand, including intraregional direct and indirect carbon emissions, emissions contained in interregional flows of goods and services traded, and carbon emissions from imports and exports of a country, a region, or a city (Munoz and Steininger, 2010). Wiedmann (2009) defines "embodied carbon" as "the carbon dioxide emitted from the process of raw material acquisition, manufacturing, transportation to products purchased by consumers" (Huang and Wu 2010). Regional carbon transfer is a region's inflow and outflow of embodied carbon emissions as part of its regional carbon footprint. Previous studies have investigated bilateral embodied carbon transfer in China but have seldom investigated a multilateral transfer relationship, except for some studies on city level (e.g. Feng et al. (2014) studied the spatial distribution of CO_2 emissions across China triggered by urban consumption in four Chinese megacities (Beijing, Shanghai, Tianjin, and Chongqing) in 2007); most provincial-level studies on carbon transfer are limited to only a single year or a few years (e.g. Feng et al. (2013) estimated the CO_2 emissions embodied in products traded among China's 30 subregions and the rest of the world). Some studies have investigated the network of embodied carbon transfer in some specific regions in China (e.g. Chen and Chen (2016) applied a hybrid network model to track the inter-regional carbon flows in Jing-Jin-Ji Area; and Chen and Chen (2017) established a system-based framework to model the variation of urban carbon metabolism, in which Beijing is taken as a case study to track the historical trajectory of carbon flows embodied in urban final consumption over 1985-2012). Given interprovincial trade has increased significantely, the embodied carbon is transferred more active across different provinces, and this forms a complex network of multiple bilateral relationships. The determination of such relationship is significant for the clarification of each province's carbon emissions reduction responsibility, as well as for curbing national carbon emissions.

Therefore, this paper incorporates the multiregional input-output (MRIO) and social network analysis (SNA) methods to investigate China's embodied carbon transfer across provinces. Our work clarifies the spatial distribution and different roles of provinces in the carbon transfer network, which provides a new perspective for policy makers to define emissions reduction targets for different provinces. First, we compile China's MRIO tables for 30 provinces and 31 sectors in 2002, 2007, and 2012 with provincial input–output (IO) tables and interprovincial trade matrices to estimate the amount of carbon transfer embodied in interprovincial trade. Second, we use the SNA method to evaluate China's interprovincial carbon transfer network to further investigate the spatial characteristics of the embodied carbon in trade, as well as to evaluate the network density, centrality, and block mode. Third, we analyse the characteristics of spatio-temporal evolution in the network and demonstrate which factors influence the interprovincial network structure through the quadratic assignment procedure (QAP). Finally, we offer policy recommendations on coordinating interprovincial relationships with respect to curbing emissions.

Our work aims to complement existing studies in two aspects: 1) Estimating the embodied carbon emissions and carbon transfers originating within China by constructing the most up-to-date inter-provincial input-output tables; and 2) Evaluating the characteristics of the embodied carbon transfer network and demonstrating which factors influence the network structure. The analysis can provide insights for making a fairer and more targeted allocation scheme of provincial carbon responsibilities. The remainder of the paper is organized as follows. Section 2 is the literature review; Section 3 introduces the methodology and data. Section 4 presents our empirical results. Section 5 concludes the study and discusses the policy implications of our results.

2. Literature Review

MRIO analysis is often used in analyses of embodied carbon in trade as it is a widely used tool to establish consumption-based patterns, analyse complex global supply chains, and connect distal natural and human systems. MRIO analysis can be divided into two types: the first type considers total bilateral trade between regions (the EEBT [emissions embodied in bilateral trade] approach), and the second type distinguishes intermediate inputs and trade for final consumption (the MRIO approach). The EEBT approach is commonly used to calculate the scale of pollution embodied in interregional trade (Guo et al., 2012; Zhang et al., 2014), the essence of which is multiple single-region IO analyses. For example, Zhang et al. (2014) propose a methodology for adding the pollution haven hypothesis to the EEBT approach to analyse the impacts of direct trade without considering the interregional feedback effects. However, the EEBT approach is incomplete as a consumption-based approach. Compared to the EEBT approach, the MRIO approach captures complete interregional supply chains and related spillover and feedback effects. The MRIO model is widely used to analyse China's region-specific greenhouse gas emissions (Xie et al., 2015; Zhang et al., 2016a; Zhao et al., 2016) and other environmental emissions (Li et al., 2016; Wang et al., 2017a; Yang et al., 2015).

Several studies focus on carbon emissions embodied in international trade (Andrew and Peters, 2013; Kankesu and Liu, 2016; Yu and Chen, 2017; Zhong et al. 2018). Relevant research on China focuses on the national and regional levels (Meng et al., 2013; Su and Ang, 2014; Zhang et al., 2014). For example, Su and Ang (2014) divided the Chinese economy into eight regions and further divide the world into eleven economies (including China and the rest-of-world). However, provincial economic developments and CO_2 emission intensities are quite different across the country, and there is a need to understand provincial interactions through interprovincial trade.

On the carbon transfer directions within China, Su and Ang (2014) revealed that in 1997 "carbon leakage" occurred from developed regions to developing regions. Zhang et al. (2014) stated that regional carbon spillover is concentrated mainly in the coastal regions; however, it contributes to an increase of CO_2 emissions in the central and western regions. Liu et al. (2015) found that, from 1997–2007, embodied carbon emissions in China tended to flow out of less developed regions with abundant fossil fuels. Zhou et al. (2018) found that embodied carbon emissions mainly transfer from less developed regions such as the northwest to developed regions such as the east coast through carbon-intensive manufacturing industries. However, these studies have not reached a unanimous conclusion regarding the direction of regional carbon transfer in China. In addition, Su and

Ang (2017) decomposed embodied energy (emissions) using an IO framework and present a single country based on the assumption of non-competitive imports.

At the provincial level, Guo et al. (2012) found that, in 2002, the net interprovincial embodied carbon transfer in China is mainly from the eastern provinces to the central provinces. Meng et al. (2011) stated that, in 2007, the regions with high emissions spread from the eastern coastal provinces to the central provinces. Xie et al. (2017) found that, from 2007 to 2010, the main direction of a supply-side carbon transfer was from the resource-intensive central and western provinces to the developed eastern coastal provinces. Most studies indicate that the carbon transfer was from the eastern provinces to the central provinces from 2002 to 2007 and from the central and western provinces to the eastern provinces from 2007 to 2010.

SNA is a powerful tool for revealing the characteristics of the network from a structural perspective and widely used in both natural and economic systems. Although a combination of IO analysis and SNA is used in various fields, including raw materials accounting (Nuss et al., 2016), energy use (Zhang et al., 2016b; Zhao et al., 2018) and the energy-water nexus (Wang and Chen, 2016), few studies use these tools to analyse the embodied carbon transfer network in China. For example, Chen and Chen (2016) calculated the amount of carbon flow and focus on the carbon network in Jing-Jin-Ji area in China. Wang et al. (2017b) used SNA to identify the roles of different regions in the domestic supply chain in China. Duan et al. (2018) combined MRIO and ecological network analysis (ENA) to assess carbon flows within China at regional level.

To best of our knowledge, few studies focus on the role of each province in China's embodied CO2 transfer networks. Additionally, our work contributes to previous studies as follows:

1) We combine MRIO and SNA methods to analyse the embodied carbon transfer network in China at the provincial level. The analytical framework can provide a new perspective for the studies in embodied carbon transfer.

2) We fill the gaps of previous studies by investigating the features of dynamic embodied carbon emissions in an interprovincial carbon transfer network, which clarifies the spatial distribution and different roles of provinces, and how they transfer through major provinces as well as their major drivers. Our analysis can reflect the position and participation degree of different provinces in domestic supply chains.

3) We analyse the mechanisms responsible for carbon footprint and embodied CO2 transfer among provinces via trade, which could help policy makers allocate emission mitigation responsibilities and reduction targets for each province. The more detailed analysis accounting for the heterogeneity within these large regions would lead to more effective suggestions for the whole nation's emission reduction.

3. Methodology and Data

3.1. Interprovincial IO Table in China

The MRIO model is adopted to compile Chinese interprovincial IO tables for 2002, 2007, and 2012, as it has low data requirements and high precision (Isard, 1951; Chenery, 1953; Moses, 1955, Polenske, 1970).

3.1.1. Revised IO Tables

We aggregate the IO tables and disaggregate the energy balance tables. We merge the 42 sectors of existing IO tables into 31 sectors (information transmission, computer services, and software are merged into "other"); the final use is divided into investment and consumption. The table is revised as a non-competitive imports IO table[1]; at the province scale, we define *IM, EX, DC, DR, A, F* and X as a matrix of total imports, total exports, interprovincial exports, interprovincial imports, a direct consumption coefficient, final demand and total output, respectively.

To calculate the CO_2 embodied in domestic production, we introduce an import coefficient matrix M to exclude the influence of an import on direct use and final demand. M is estimated by using the proportion of an import ends up in total domestic demand. $\mathbf{M} = \mathbf{IM}/(\mathbf{X} + \mathbf{IM} - \mathbf{EX})$ are matrices (Chen et al., 2008; China Input-Output Association, 2007). After defining *(I-M)* as a localization coefficient matrix, $\mathbf{A}^d = (\mathbf{I} - \mathbf{M})\mathbf{A}, \mathbf{IU} = (\mathbf{I} - \mathbf{M})\mathbf{AX}$, $\mathbf{F}^d = (\mathbf{I} - \mathbf{M})\mathbf{F}$, $\mathbf{DC}^d = (\mathbf{I} - \mathbf{M})\mathbf{DC}$,

[1] The competitive imports assumptions adopts the same technology assumption of different regions. Under competitive assumptions, interregional emissions transfer will be overestimated, as the emissions embodied in imports for intermediate consumption are transmitted to regional final demand (Su and Ang, 2013; Su et al., 2013). However, the assumption of noncompetitive imports can avoid it.

$\mathbf{DR}^{d} = (\mathbf{I}-\mathbf{M})\mathbf{DR}$ are the direct consumption coefficient, the intermediate use, the final demand, the interprovincial exports, and the interprovincial imports, respectively, in a non-competitive imports IO table; d means domestic, which denotes non-competitive assumption.

3.1.2. Interprovincial Trade Coefficient Matrix C

The basic form of the non-competitive imports MRIO model can be expressed as:

$$\mathbf{CA}^{d}\mathbf{X} + \mathbf{CF}^{d} + \mathbf{EX} = \mathbf{X} \tag{1}$$

where C (930×930 matrix) is an interprovincial trade coefficient matrix; CA^dX is interprovincial intermediate input; and CF^d is the product of interprovincial trade used in final demand.

$$\mathbf{C} = \begin{pmatrix} \mathbf{C}_{1,1} & \mathbf{C}_{1,2} & \cdots & \mathbf{C}_{1,30} \\ \mathbf{C}_{2,1} & \mathbf{C}_{2,2} & \cdots & \mathbf{C}_{2,30} \\ \vdots & \vdots & & \vdots \\ \mathbf{C}_{30,1} & \mathbf{C}_{30,2} & \cdots & \mathbf{C}_{30,30} \end{pmatrix}, \mathbf{C}_{R,S} = \begin{pmatrix} \mathbf{C}_{1,1} & \mathbf{C}_{1,2} & \cdots & \mathbf{C}_{1,30} \\ \mathbf{C}_{2,1} & \mathbf{C}_{2,2} & \cdots & \mathbf{C}_{2,30} \\ \vdots & \vdots & & \vdots \\ \mathbf{C}_{30,1} & \mathbf{C}_{30,2} & \cdots & \mathbf{C}_{30,30} \end{pmatrix} \tag{2}$$

$$\mathbf{c}^{\mathbf{i}}_{\mathbf{R,S}} = \mathbf{t}^{\mathbf{i}}_{\mathbf{R,S}} / \mathbf{t}^{\mathbf{i}}_{\mathbf{R,S}} \square \mathbf{R} \square \mathbf{S} \quad = \mathbf{1,2}\cdots\cdots\mathbf{30}; \mathbf{i} = \mathbf{1,2}\cdots\cdots\mathbf{31}) \tag{3}$$

where $C_{R,S}$ (31×31 diagonal matrix) indicates the interprovincial trade flowing from province R to province S; $c_{R,S}^{i}$ (diagonal elements of $C_{R,S}$) is the proportion of products flowing from province R to province S in all the products that flow into province S in sector i; $t_{R,S}^{i}$ is the products that flow from province R to province S in sector i; t_S^i are the products that flow from all provinces to province S in sector i. Since province R, S and sector i are the general case, we define that R and S range from 1 to 30, and i ranges from 1 to 31.

To solve for $t_{R,}{}^{i}{}_{S}$, the gravity model is formulated referring to Leontief and Strout (1963):

$$\mathbf{t}^{\mathbf{i}}_{\mathbf{R,S}} = \frac{\mathbf{x}^{\mathbf{i}}_{\mathbf{R}} \times \mathbf{d}^{\mathbf{i}}_{\mathbf{S}}}{\sum_{\mathbf{R}} \mathbf{x}^{\mathbf{i}}_{\mathbf{R}}} \times \mathbf{Q}_{\mathbf{R,S}} \tag{4}$$

$$\mathbf{t}^{\mathbf{i}}_{\mathbf{S}} = \sum_{\mathbf{R}} \mathbf{t}^{\mathbf{i}}_{\mathbf{R,S}} \tag{5}$$

where $x_R{}^i$ is the total output of province R in sector i; $d_S{}^i$ is total demand in province S in sector i; $\sum_R x_R^i$ is the total output of all provinces in sector i; $Q_{R,S}$ (friction coefficient) are the trade parameters from province R to province S. $x_R{}^i$, $d_S{}^i$, $\sum_R x_R^i$ are available in all provincial IO tables.

We use the transport volume distribution coefficient proposed by Ihara (1996) to calculate $Q_{R,S}$. It is assumed that the allocation proportion of material transportation volumes from one region to another approximates that of major products among the materials. The calculation formula is as follows:

$$\mathbf{Q}_{\mathbf{R,S}} = \frac{\mathbf{H}_{\mathbf{R,S}} \times \mathbf{H}_{\mathbf{O,O}}}{\mathbf{H}_{\mathbf{R,O}} \times \mathbf{H}_{\mathbf{O,S}}} \tag{6}$$

where $H_{R,S}$ is transport volumes of major products from province R to province S; $H_{R,O}$ is the total volume of products sent from province R; $H_{O,S}$ is the total volume of products received by province S; and $H_{O,O}$ is the total volume of products sent from all provinces. Railway freight data are the second-best choice and the only publicly available data for studying Chinese interprovincial trade (Xu and Li, 2012). We introduce an amplification coefficient and use the mass of modified railway freight exchange as the transport volume of major products without distinguishing among sectors. After calculating the friction coefficient, the interprovincial trade volume and the interprovincial trade coefficient matrix C can be obtained.

Finally, China's interprovincial IO tables with 30 provinces and 31 sectors can be obtained.

3.2. Carbon Footprint Estimation Model

3.2.1. Direct Carbon Footprint Estimation

Direct CO_2 emissions are calculated based on the method by the Intergovernmental Panel on Climate Change (2006), including eight major types of energy (coal, coke, crude oil, gasoline, diesel, kerosene, fuel oil, and natural gas). First, we calculate the total direct CO_2 emissions of each province by adding the emissions of the eight types of energy. Then, according to the energy use ratio data of each sector in the provincial energy balance sheet (Liu et al., 2011), we divide each province's total direct emissions by sector to ascertain each sector's emissions in each province.

$$\mathbf{P}_{R} = \sum_{j=1}^{8} \mathbf{E}_{R}^{j} \times \mathbf{NCV}_{R}^{j} \times \mathbf{CEF}_{R}^{j} \times \mathbf{COF}_{R}^{j} \times \mathbf{44/12} \tag{7}$$

$$\mathbf{e}_{R}^{i} = \frac{\mathbf{P}_{R} \times \mathbf{k}_{R}^{i}}{\mathbf{X}_{R}^{i}} \tag{8}$$

$$\mathbf{k}_{R}^{n} = \frac{\mathbf{E}_{R}^{n}}{\sum_{i=1}^{31} \mathbf{E}_{R}^{i}} \tag{9}$$

where j and i represent different categories of energy and sectors, respectively; P_R

represents total direct CO_2 emissions of province R; E_R^j, NCV_R^j, CEF_R^j, and COF_R^j represent energy use, average net heating value, average carbon content, and carbon oxidation rate, respectively, of energy j in province R; e_R^i, k_R^i, and X_R^i represent the direct carbon emissions coefficient, energy use ratio, and total output, respectively, of sector i in province R.

3.2.2. Embodied Carbon Footprint Estimation

The embodied carbon footprint is defined as the total CO_2 emissions, including direct and indirect emissions emitted by any product throughout its life cycle.

$$\mathbf{CF} = \mathbf{D}(\mathbf{I} - \mathbf{A}^{d})^{-1}\mathbf{F}^{d} \tag{10}$$

where CF is the embodied carbon footprint; D is the matrix of direct CO_2 emissions coefficient, $D=(e_1,e_2，…，e_{31})$; I is the unit matrix; $(I-A^d)^{-1}$ is the Leontief inverse matrix excluding imports; and $D(I-A^d)^{-1}$ is the embodied CO_2 emissions coefficient of a non-competitive imports IO table.

3.3. Interprovincial Embodied Carbon Transfer Estimation

Interprovincial embodied carbon transfer is calculated by combining interprovincial trade data with carbon emissions data using an MRIO model:

$$\mathbf{T}_{R,S} = \mathbf{D}_{R,S}(\mathbf{I} - \mathbf{A}_{R,S})^{-1}\mathbf{Y}_{R,S} \quad (\mathbf{R},\mathbf{S} = \mathbf{1},\mathbf{2}\cdots\cdots\mathbf{30}) \tag{11}$$

$$\mathbf{Y}_{R,S} = \mathbf{C}\cdot\mathbf{F}^{d} \quad (\mathbf{R},\mathbf{S} = \mathbf{1},\mathbf{2}\cdots\cdots\mathbf{30}) \tag{12}$$

$$\mathbf{T}_{\mathrm{R,S}} = \begin{pmatrix} \mathbf{T}_1 \\ \mathbf{T}_2 \\ \vdots \\ \mathbf{T}_{30} \end{pmatrix} = \begin{pmatrix} t_{1,1} & t_{1,2} & \cdots & t_{1,30} \\ t_{2,1} & t_{2,2} & \cdots & t_{2,30} \\ \vdots & \vdots & \ddots & \vdots \\ t_{30,1} & t_{30,2} & \cdots & t_{30,30} \end{pmatrix} \tag{13}$$

$$\mathbf{D}_{\mathrm{R,S}} = \begin{pmatrix} d_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & d_2 & \cdots & \mathbf{0} \\ \mathbf{0} & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & d_{30} \end{pmatrix} \tag{14}$$

$$\mathbf{C} = \begin{pmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,30} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,30} \\ \vdots & \vdots & \ddots & \vdots \\ c_{30,1} & c_{30,2} & \cdots & c_{30,30} \end{pmatrix} \tag{15}$$

$$\mathbf{F}^{\mathrm{d}} = \begin{pmatrix} f_{\mathbf{1}}^{\mathbf{d}} & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & f_{\mathbf{2}}^{\mathbf{d}} & \cdots & \mathbf{0} \\ \mathbf{0} & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & f_{\mathbf{30}}^{\mathbf{d}} \end{pmatrix} \tag{16}$$

where $T_{R,S}$, $Y_{R,S}$, $D_{R,S}$ and $A_{R,S}$ are the amount of embodied carbon transfer, trade matrix of products use, direct carbon emissions coefficient and direct consumption coefficient from province R to province S. C (930×930 matrix) is an interprovincial trade coefficient matrix; F^d is final demand in a non-competitive imports IO table. $t_{R,S}$ is the products that flow from province R to province S; $c_{R,S}$ (diagonal elements of $C_{R,S}$) is the proportion of products flowing from province R to province S in all the products that flow into province S. d_S is total demand in province S; $f_S{}^d$ is final demand of province S in a non-competitive imports IO table.

As province R, S is the general case, for convenience, we use province m as the specific example:

$$\mathbf{T}_{\mathrm{m}} = (\mathbf{T}_{\mathrm{m,1}}, \mathbf{T}_{\mathrm{m,2}}, \cdots, \mathbf{T}_{\mathrm{m,30}}) = \mathbf{D}_{\mathrm{m}}(\mathbf{I} - \mathbf{A}_{\mathbf{m}}^{\mathbf{d}})^{-1}\mathbf{Y}_{\mathrm{m}} \tag{17}$$

$$\mathbf{D}_m = (\mathbf{e}_m^1, \mathbf{e}_m^2, \cdots, \mathbf{e}_m^{31}) \tag{18}$$

$$\mathbf{Y}_m = (\mathbf{Y}_{m,1}, \mathbf{Y}_{m,2}, \cdots, \mathbf{Y}_{m,30}) = \begin{pmatrix} \mathbf{y}_{m,1}^1 & \mathbf{y}_{m,2}^1 & \cdots & \mathbf{y}_{m,30}^1 \\ \mathbf{y}_{m,1}^2 & \mathbf{y}_{m,2}^2 & \cdots & \mathbf{y}_{m,30}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{y}_{m,1}^{31} & \mathbf{y}_{m,2}^{31} & \cdots & \mathbf{y}_{m,30}^{31} \end{pmatrix} \tag{19}$$

$$\mathbf{Y}_{m,S} = \mathbf{C}_{m,S} \cdot \mathbf{F}_S^d = \begin{pmatrix} \mathbf{y}_{m,S}^1 \\ \mathbf{y}_{m,S}^2 \\ \vdots \\ \mathbf{y}_{m,S}^{31} \end{pmatrix} = \begin{pmatrix} \mathbf{c}_{m,S}^1 & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & \mathbf{c}_{m,S}^2 & \cdots & \mathbf{0} \\ \mathbf{0} & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{c}_{m,S}^{31} \end{pmatrix} \cdot \begin{pmatrix} \mathbf{F}_S^{d1} \\ \mathbf{F}_S^{d2} \\ \vdots \\ \mathbf{F}_S^{d31} \end{pmatrix} = \begin{pmatrix} \mathbf{c}_{m,S}^1 \cdot \mathbf{F}_S^{d1} \\ \mathbf{c}_{m,S}^2 \cdot \mathbf{F}_S^{d2} \\ \vdots \\ \mathbf{c}_{m,S}^{31} \cdot \mathbf{F}_S^{d31} \end{pmatrix} \tag{20}$$

where $T_{m,S}$ and $Y_{m,S}$ are the amount of embodied carbon transfer and trade matrix of products used, respectively, from specific province m to province S; and $C_{m,S}$ is the interprovincial trade flowing from province m to province S. D_m is the matrix of direct CO_2 emissions coefficient in province m; *and* A_m^d is the direct consumption coefficient of province m in non-competitive imports IO table. $c_{m,S}^i$ (diagonal elements of $C_{m,S}$) is the proportion of products flowing from province m to province S in all the products that flow into province S in sector i; and $y_{m,S}^i$ is the trade products use that flow from province m to province S in sector i. F_S^{di} is final demand of province S in sector i in a non-competitive imports IO table.

Then, the balance (net outflow) of CO_2 emissions embodied in interprovincial imports and exports of province m can be expressed as follows:

$$\mathbf{T}_m^b = \mathbf{T}_m^{DC} - \mathbf{T}_m^{DR} = \sum_{S=1,S\neq m}^{30} \mathbf{T}_{m,s} - \sum_{R=1,R\neq m}^{30} \mathbf{T}_{R,m} \tag{21}$$

where T^b is trade balance, $T_m^{DC} = \sum_{S=1,S\neq m}^{30} T_{m,s}$, $T_m^{DR} = \sum_{R=1,R\neq m}^{30} T_{R,m}$ represent outflow and inflow, respectively, of embodied carbon emissions by transfers that result from interprovincial trade.

3.4. Interprovincial Embodied Carbon Transfer Network

Based on the data on interprovincial embodied carbon transfer with an IO method, we set 30 provinces as nodes, the amount of interprovincial embodied carbon transfer as lines, and carbon transferred internally or externally as the direction; we then use UCINET 6.0 software to construct the interprovincial embodied carbon transfer network.

The social network graph is created using Gephi (v0.9.1). To enhance the visualization, a "Force Atlas" spatial layout algorithm is applied to the data. Force-directed graph algorithms apply forces of gravity, attraction and repulsion to roles within a network, based on the strength of their relationships to others (Brandes, 2001). Roles that are connected through lower carbon transfer will be placed farther apart in the graph, while roles that transfer more carbon will be drawn closer together. This finding means that roles with the most carbon transfer between them are more central in the visualization. Provinces with the highest degree centrality (larger nodes) are always at the centre of the network.

The network density reflects the strength of relationships among different provinces in the network, which measures the number of connected roles as a fraction of the total possible relationships, and it is based on a scale of 0-1; the block model analysis identifies different roles and their interaction patterns. The centrality measures the relative influence of the members. The degree of centrality, $C_D(p_k)$, for node k is defined as follows (Freeman, 1979):

$$C_D(p_k) = \sum_{i=1}^{n} a(p_i, p_k) \tag{22}$$

where $C_D(p_k)$ is defined as the number of links incident upon a node; n is defined as the number of nodes in the network; $a(p_i, p_k) = 1$ if and only if node i and k (i.e., p_i and p_k) are connected, and $a(p_i, p_k) = 0$ otherwise.

The betweenness centrality, $C_B(p_k)$, for node k is expressed as follows (Freeman, 1977):

$$C_B(p_k) = \sum_{i<j}^{n} \frac{g_{ij}(p_k)}{g_{ij}}; i \neq j \neq k \tag{23}$$

where $C_B(p_k)$ quantifies the number of times a node acts as a bridge along the shortest path between two other nodes; g_{ij} is the geodesic distance (shortest path) linking p_i; and p_j, $g_{ij}(p_k)$ is the geodesic distance linking p_i and p_j that contains p_k (Li et al., 2014).

3.5. QAP (Quadratic Assignment Procedure) Analysis

The embodied carbon transfer network in China is influenced by many factors, such as economic disparities, industrial structures, resource endowments, and energy use. Therefore, it is important for policy makers to identify influential factors and develop more targeted provincial emissions reduction policies.

The QAP algorithm is based on permutation matrix data. Through the element-wise comparison of two square matrices, we can obtain their correlation coefficients and then create a nonparametric test of the coefficients. The purpose is to study the regression relationship between multiple matrices and a matrix.

Compared to the traditional parameter method, the QAP method does not need to assume that independent variables are independent of one another, which is more robust (Barnes, 1954).

Adjacent provinces have spatial correlations and spillover effects; therefore, we suppose that carbon transfer is due to geographic proximity. The pollution haven hypothesis is confirmed in China (Sun et al., 2017). As polluting enterprises tend to choose areas with lower enforcement of environmental regulations, carbon transfer may be the result of industry transfers due to gaps in development levels and government policies in the eastern and western provinces that differ (Luo et al., 2016). Moreover, environmental pollution in previous years may affect the environmental quality of subsequent years, due to path dependence.

In summary, the factors that affect the spatial correlation network structure of embodied carbon transfer in 2012 are geographic location, differences in economic development, institutional differences, and environmental path dependence. According to Li et al. (2014), we define the influential factors, as shown in Table 1.

Table 1. Label, definition, and measurement of influential factors.

Influencing factor	Indicator	Meaning	Abbreviation
Geographical location	Whether the location is adjacent or not		*GP*
Economic development differences	Economic scale	GDP	*GDP*
	Economic level	Per capita GDP	*PGDP*
	Consumption level	Household consumption expenditure per unit of GDP	*CL*
	Urbanization level/rate	Urban share of total population	*UP*

	Investment and consumption structure	The ratio of gross capital formation to GDP	*KS*
	Trade openness	The ratio of import and export commodities value to GDP	*EO*
	Industrial structure	The ratio of output value in tertiary industry to GDP	*IS*
Institutional differences	Differences in the intensity of environmental regulation (normalized by 11 indicators: comprehensive utilization of solid waste, industrial pollution control investment/industrial value added, operating expenses of industrial waste management facilities/industrial value added, total energy use/industrial value added, industrial waste gas emissions/industrial value added, sulfur dioxide emissions/industrial value added, nitrogen oxide emissions/industrial value added, smoke (powder) emissions/industrial value added, industrial solid waste emissions/industrial value added, wastewater discharge/ industrial value added, chemical oxygen demand (COD) emissions/industrial value added)		*ER*
Environmental quality path dependence	The amount of inter provincial embodied carbon transfer networks in 2002 and 2007		T_{2002}, T_{2007}

The model is:

$$\mathbf{T_{2012} = f(GP, GDP, pGDP, IS, EO, UP, KS, CL, ER, T_{2002}, T_{2007})} \tag{24}$$

where data for all the indicators are a series of matrices. Considering the differences in carbon transfer intensity, we set T_{2012} (the amount of interprovincial carbon transfer matrix) as the dependent variable; *GP* is the geographic proximity matrix (if two provinces are adjacent, $GP = 1$, otherwise, $GP = 0$). *GDP, pGDP, IS, EO, UP, KS, CL,* and *ER* are the absolute differences in corresponding indicators in matrix form.

To obtain *ER*, referring to previous studies (Yuan and Xie, 2014; Zhang et al., 2010), we use SPSS statistics version 22 (IBM, Armonk, USA), with the Factor Analysis method, to normalize 11 indicators into synthetic environmental regulation intensity. We transform a negative indicator into a positive indicator to make the evaluation direction of this indicator consistent with that of other indicators. To make the real numbers of the function greater than 0, all the unit values are transformed into absolute values.

Using the Principle Component Analysis (PCA) and varimax rotation methods, factors were summarized into 2 factors. Table 2 shows components of each factor. *Factor 1* has the largest proportion (44.224) of variance, whereas *Factor 2* has the smallest proportion (30.841) of variance; therefore, *ER*=44.224%**Factor1*+30.841%**Factor2*. Thus, synthetic environmental regulation intensity is obtained.

Table 2. Component score coefficient matrix of 11 indicators

	Factor	
	Factor1	Factor2
A.comprehensive utilization of solid waste	0.169	-0.096
B.industrial pollution control investment/industrial value added	0.046	-0.248
C.operating expenses of industrial waste management facilities/industrial value added	-0.043	-0.155
D.total energy consumption/industrial value added	0.139	0.054
E.industrial waste gas emissions/industrial value added	0.16	0.021
F.sulfur dioxide emissions/industrial value added	0.16	0.009
G.nitrogen oxide emissions/industrial value added	0.094	0.11
H.smoke (powder)emissions/industrial value added	0.235	-0.1
I.industrial solid waste emissions/industrial value added	0.287	-0.245
J.wastewater discharge/ industrial value added	-0.242	0.428
K.chemical oxygen demand (COD) emissions/industrial value added	-0.1	0.303

The 11 indicators we construct can be classified as two types. a. *ER1*: the emission intensity of main industrial pollutants; b. *ER2*: the governmental supervision for environmental protection. For *ER2*, we use the ratio of industry's pollution control costs to its industrial output value. The larger the value of *ER2* is, the greater the intensity of environmental regulation for this industry becomes. However, *ER1* is negative, and the greater absolute value of *ER1* may indicate a higher level of pollution.

It should be noted that the Multi-Criteria Decision-Making (MCDM) approach can also be used to estimate the potential influential factors in the social network. However, the factors in our paper are more detailed and specific. The procedure in the MCDM-based FAHPCE approach (Zeng et al., 2007, Gandhi, 2015) for the detection of the local weights is based on expert judgement, which is, to some extent, subjective and ambiguous. The MRQAP approach used here resolves the autocorrelation in the standard error by running a number of permutations of the sample (Kilduff & Krackhardt, 1994). Moreover, given the network structure of the data and the resulting nonindependence of observations, the permutation and regression process repeats a large number of times; therefore, it can generate a distribution that provides a reference for comparison with 'real' observed values.

3.6. Data Sources

Based on the provincial single-region IO tables, this paper compiles China's interprovincial non-competitive import MRIO tables for 2002, 2007, and 2012. We modify the interprovincial railway freight data calculated by Xu and Li (2012) and Zhang and Zhao (2008) as follows; we first consider the ratio of railway freight volumes to total freight volumes composed of railway, highway and water transport as the amplification coefficient. Then, by amplifying the goods exchange data of railway administrative inter-region provinces, estimation of inter provincial goods exchange data added by three ways can be obtained. The required freight data are derived from the *China Transportation Yearbook* and *China Statistical Yearbook* in 2003, 2008, and 2013.

Sectoral energy use data are obtained from the national and provincial *Statistical Yearbook* and *China Energy Statistical Yearbook* in 2003, 2008, and 2013. The provinces of Hebei, Heilongjiang, Shanghai and Jiangsu have no sectoral energy use data in their provincial *Statistical Yearbook*; therefore, we calculate this data by multiplying the total energy use with the weights of sectoral energy use derived from the provincial *Third Economic Census Yearbook*. Additionally, the data of Shanghai's sectoral energy use are derived from the *Fudan University social science data platform*.

NCV, *CEF*, and *COF* represent average net heating value, average carbon content, and carbon oxidation rate, respectively. *CEF* and *COF* are taken from the *Provincial Greenhouse Gas Inventory Guidelines* (2007). *NCV* is taken from *China Energy Statistics Yearbook* (NBS, 2003, 2008, and 2013).

The basic data on influential factors in QAP regressions are from the *China Statistical Yearbook*, the *China Environment Yearbook*, the *China Industrial Statistics Yearbook,* and each province's *Statistical Yearbook*.

In addition, the compiled MRIO table can inherit a list of uncertainties in source data, aggregation, allocation and balancing (Su and Ang, 2010; Lenzen, 2011; Liu and Wang, 2017). To reduce the uncertainties, first we use the entire available energy dataset and IOTs at the most detailed sectoral and provincial levels to minimize the impacts of data aggregation. Second, the data for both the IOTs and emissions are based on China's official national statistical data. In addition, we use the 30 provinces MRIO table of China in 2002, 2007 and 2012 to demonstrate the spatial distribution of embodied CO_2 emissions in interprovincial trade to offset the time lag between the age of underlying data and the date of policy the research targeted.

Furthermore, the MRIO approach can ensure the validity of the embodied carbon calculation by relaxing the technical assumptions inherent in SRIO and BTIO (Su and Ang, 2014; Li et al., 2016; Zhang et al., 2017; Zhou et al., 2018). Additionally, a larger sectoral level of 31 and a provincial level of 30 with wider availability of the economic accounts, environmental accounts, and trade data can minimize the influence of spatial and sectoral aggregation.

In summary, the research framework is presented as below:

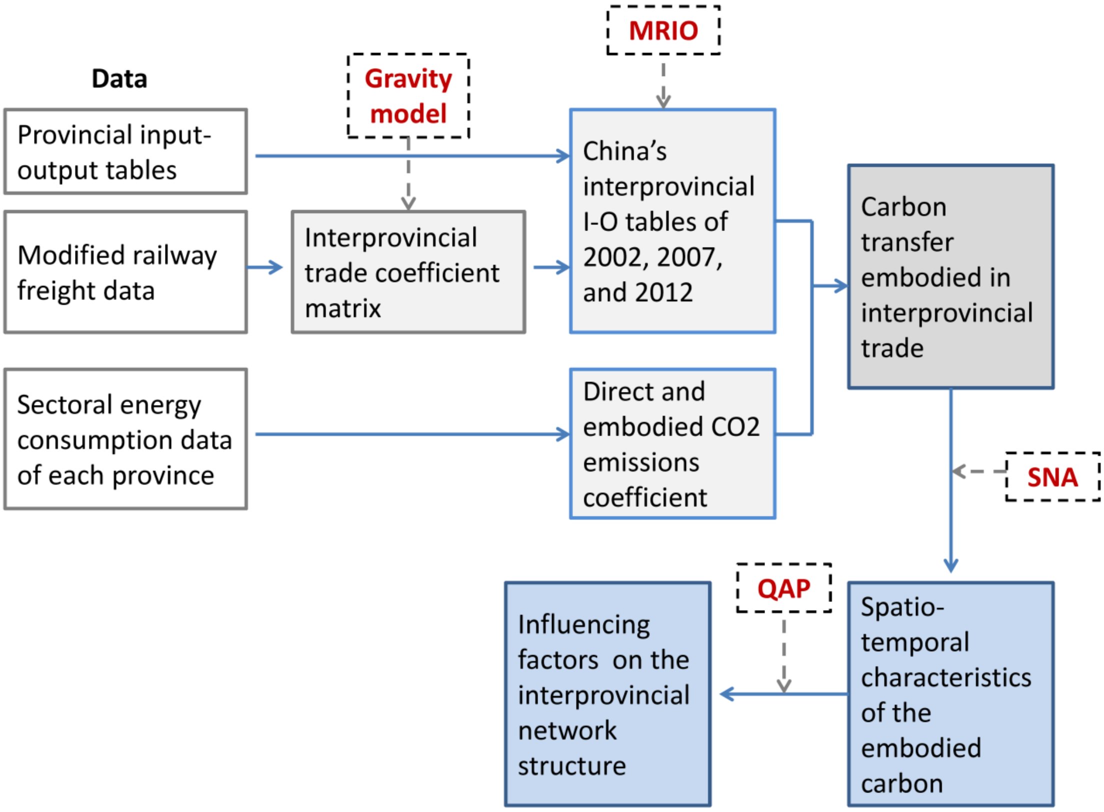

Figure 1. Analytical Framework

4. Results and Analysis

Following this process, we obtained a small-world network of embodied carbon transfer and analysed its network characteristics of density, centrality, and spatial clustering.

4.1. The Provincial per Capita Embodied Carbon Footprints

The size of the per capita carbon footprint embodied in China provincial trade increased from 4.3 tons of CO_2 in 2002, to 6.3 tons of CO_2 in 2007 and to 9.5 tons of CO_2 in 2012. As shown in Figure 1, during that period, the per capita embodied carbon footprint of Beijing, Jilin Province, and Zhejiang Province first increased then decreased, while that of Tianjin, Hainan Province, Sichuan Province, Guizhou Province, and Gansu Province first decreased then increased. The short-term decrease in carbon emissions per capita can be traced to the "Energy saving and emission reduction targets" set in the National Five-Year-Plan; the intensity of carbon emissions began to decline after the Tenth Five-Year plan. Therefore, there is a continuous process of decline. Moreover, as following each five-year plan, energy intensity and carbon intensity reduction targets were set, the carbon emissions decreased continuously. However, most of the remaining provinces experienced a continuous increase in the per capita embodied carbon footprint, especially in 2012. Additionally, the provinces with large volumes of per capita embodied carbon footprint are located mainly in northern China.

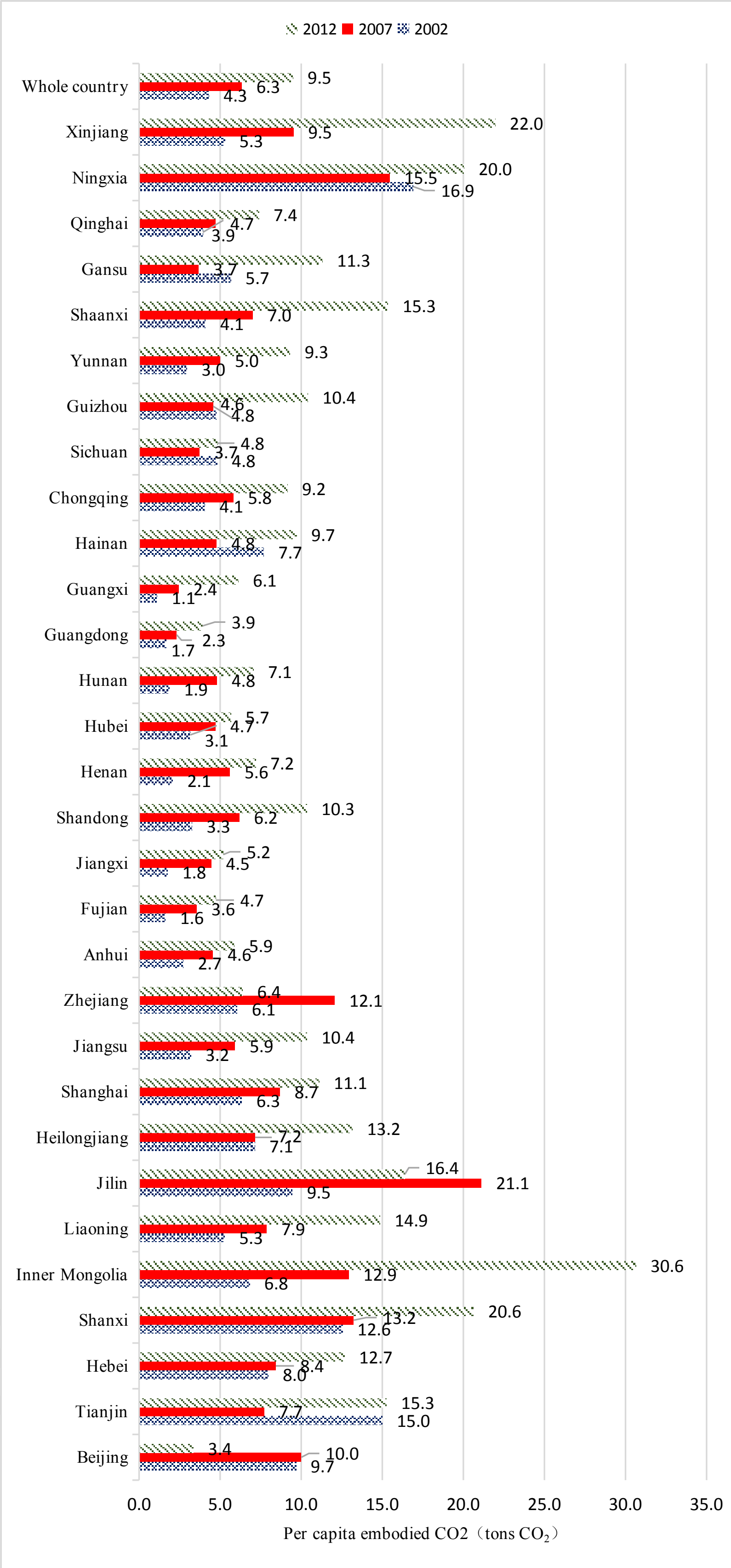

Figure 2. Provincial per capita embodied CO_2 in China, 2002–2012

In addition, our results are different from previous studies that adopt a regional classification method (Meng et al., 2013; Su and Ang, 2014; Zhou et al., 2018). The bias in databases can contribute to the diversities in calculation results. For example, Zhou et al. (2018) find that the embodied carbon emissions in China's regional domestic trade increased from 518 Mt in 2002 to 1537 Mt in 2012; its MRIO tables data are obtained from Zhang (2012) and Mi et al. (2017).

4.2. Results of Embodied Carbon Transfer Network

With the methodology proposed in Section 3, we obtain the quantity of interprovincial embodied carbon transfer in China in 2002, 2007, and 2012.

4.2.1. Network Density of Interprovincial Carbon Transfer

The overall network density of Chinese interprovincial embodied carbon transfer increased from 0.36 in 2002 to 0.86 in 2012. The increasing density indicates that the network is more intensive from 2002 to 2012 based on its bounds (0-1). This finding shows the frequency of interprovincial carbon transfer, which may be related to the development of domestic interregional trade and logistics in China. The average clustering coefficient increased from 1.15–1.21 in 2002 to 1.57–1.83 in 2012, which indicates that nodes tend to create more tightly knit groups characterized by a relatively high density of ties; the average path is approximately 1, which means one province can reach other provinces by passing through approximately one other province. Because of the small average path but large average clustering coefficient, the carbon transfer network can be characterized as a small world (which asserts that a small set of links can produce chains that connect two arbitrary and even distant members of the network). After 2000, these characteristics can be explained by the acceleration in industrial structure adjustment (Liu and Wang, 2017; Wang et al., 2018), the marketization of energy, and the improvements in regional energy allocation (Yang et al., 2016).

The topological graph shows the carbon transfer network. The node size indicates the provincial "degree centrality" value, and the line thickness indicates the amount of carbon transfer. From 2002 to 2012, the network had various centres with denser lines. Developed coastal provinces, such as Jiangsu Province, Shandong Province, Hebei Province, Guangdong Province, Liaoning Province, and Shanghai, are always at the centre of the network. These provinces are located in the Yangtze River Delta, the Bohai Rim, and the Pearl River Delta regions and are the centres of trade in natural resources and shipping logistics. These provinces have a strong impact on the overall structure of the network. Hainan is in a remote region with underdeveloped railway transportation; therefore, it became an isolated point in 2002. In 2004, with the opening of Yuehai Railway, Hainan and other provinces gradually established carbon transfer contacts.

As the network density is large, especially in 2007 and 2012, and nearly each province has carbon transfer contacts with others, it is excessively difficult to identify the characteristics of the network in the original topological graphs. We simplify the carbon transfer matrix by removing below average degree edges. In Figures 3 to 5, after removing low amounts of carbon transfer that are lower than their means (3.5, 5.7, and 8.3 million tons, respectively), the three networks for 2002, 2007 and 2012 retain only 25.99%, 25.93%, and 24.56%, respectively, of their original carbon transfer contacts. The network density decreases, which shows that the amount of most provinces' carbon transfer is below average.

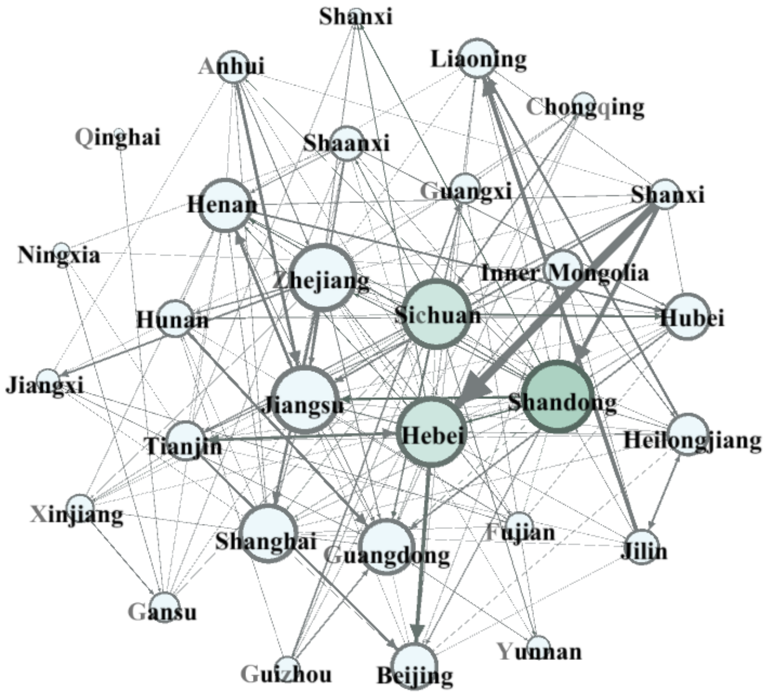

Figure 3. Interprovincial carbon transfer network in 2002

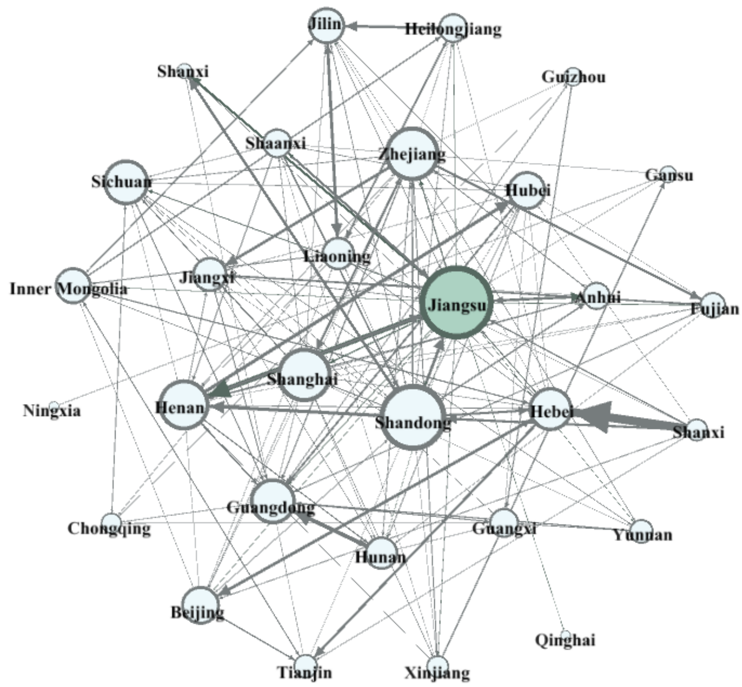

Figure 4. Interprovincial carbon transfer network in 2007

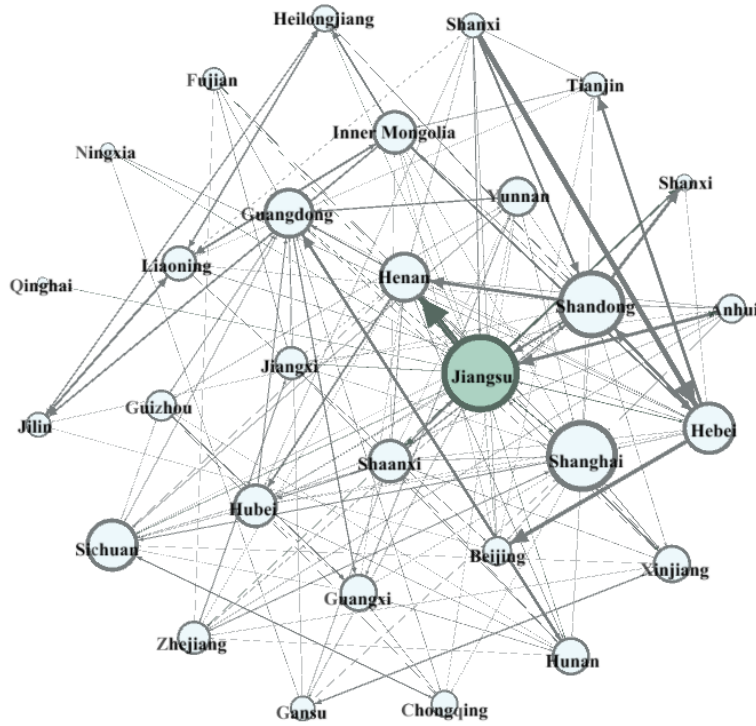

Figure 5. Interprovincial carbon transfer network in 2012

4.2.2. Network Centrality of Interprovincial Carbon Transfer

In Table 3, the degree of centrality of the network increased continuously from

2002 to 2012. Because of strengthened interprovincial trade ties, the scale of interprovincial embodied carbon transfer increased. In Figures 3–5, most of the developed eastern provinces with the highest degree centrality are at the centre of the network. Additionally, Jiangsu Province, which has intensive processing trade (an operation mode, i.e., all or partial bonded imported raw and accessory materials, parts, elements and apparatus, and packing materials are manufactured into finished products for re-export through processing, manufacturing or assembly), replaced Hebei Province, which has intensive heavy industry (mainly includes metallurgy, machinery, energy, chemical, and building material industries with the feature of high energy consumption), as the hub of the carbon transfer network.

Table 3. Centrality of interprovincial embodied carbon transfer network in China, 2002-2012.

Province	Degree centrality			Betweenness centrality			Province	Degree centrality			Betweenness centrality		
	2002	2007	2012	2002	2007	2012		2002	2007	2012	2002	2007	2012
Beijing(NC)	12.8	17.6	19.1	0	0	0	Hubei(YAR)	11.4	17.8	24.2	0	0.4	1.9
Tianjin(NC)	12.8	12.4	15.1	0	0	0	Hunan(YAR)	9	16.9	25.1	0	0	1.9
Hebei(NC)	26.7	34.3	56.8	0	0.4	0.5	Guangdong(SC)	16.2	26.9	36.1	0	0.4	1.8
Shanxi(YER)	19.3	26.2	37.4	0	0.4	0.5	Guangxi(SW)	6	9.7	18.1	0	0.4	1.9
Inner Mongolia(YER)	8.4	14.6	30.4	0	0.4	0.5	Hainan(SC)	0	1.3	0.6	0	0	0
Liaoning(NE)	12.2	16.7	29.3	0	0	0	Chongqing(SW)	6.1	7.8	14.1	0	0.4	1.9
Jilin(NE)	10.4	19.9	24	0	0	0	Sichuan(SW)	15.6	16	24.8	0	0.4	1.9
Heilongjiang(NE)	10.5	14.6	21	0	0	0	Guizhou(SW)	6.1	7	14.4	0	0.4	1.9
Shanghai(EC)	12.3	21.5	30.7	0	0.4	0.5	Yunnan(SW)	5.4	9.9	22.5	0	0.4	1.9
Jiangsu(EC)	21.8	44.1	68.5	0	0.4	0	Shaanxi(YER)	8.7	14.6	28.4	0	0.4	1.9
Zhejiang(EC)	16.5	28.8	17.6	0	0.4	0	Gansu(NW)	5.8	6.9	14.6	0	0.4	0.5
Anhui(YAR)	8.2	14.6	21.4	0	0.4	0.5	Qinghai(NW)	1.8	2.2	3.1	0	0	0.5
Fujian(SC)	4.7	12.4	8.9	0	0.4	0	Ningxia(NW)	3.3	3.5	7.4	0	0	0

Jiangxi(YAR)	5.6	14.8	14.4	0	0.4	1.9	Xinjiang(NW)	5.3	8.4	20	0	0.4	1.9
Shandong(YAR)	19.3	37.8	56.1	0	0.4	0.5	Mean	10.6	17.1	25	0	0.3	0.9
Henan(YER)	15.3	33.6	45.9	0	0.4	1.9	Median	9.7	14.7	22.0	0	0.4	0.5

A high betweenness centrality value means that the node plays an intermediary role because of its great ability to control the flow of resources (influence interactions between nonadjacent nodes). From 2002 to 2012, based on its bounds (0-1), the overall level of betweenness centrality increased (average values were 0 in 2002, 0.27 in 2007, and 0.9 in 2012), which indicates that more nodes have control over the network and more information will pass through that node. From 2002 to 2007, China's carbon transfer network was in its initial stage. In 2007, the betweenness centrality of nine provinces (Beijing, Tianjin, Liaoning, Jilin, Heilongjiang, Hunan, Hainan, Qinghai, and Ningxia) was 0. Because of geographic restrictions and the scale of industries, these provinces have difficulty controlling other provinces. Additionally, after 2007, with the development of trade, more marginal provinces, such as Hunan and Qinghai, established carbon contacts; node provinces (with the betweenness centrality above 0) also strengthened their ability to control the flow of resources.

In 2012, eleven central, southwestern, and northwestern provinces with the highest betweenness centrality had the largest intermediate node. These provinces play an important role in network linkage, controlling the critical path of the carbon transfer network. However, these provinces comprise only one-third, indicating that only a few provinces control the resources. Guangdong has a large subnode (second highest betweenness centrality), followed by northern and eastern provinces, such as Hebei, Shanxi, Inner Mongolia, Shanghai, Anhui, and Shandong, which act as secondary bridges.

4.3. Spatial Clustering Characteristics of Embodied Carbon Transfer

This paper sets the matrix mean of the embodied carbon transfer network as the threshold for binary processing then uses a convergent correlations (CONCOR) method to analyse the spatial clustering of embodied carbon transfer. Since the size of the dataset is quite small in terms of number of data points, if divided above 4 plates, each plate only consists of a few nodes, which is nearly irrational when forming a plate. To ensure that the number of provinces in each block is more than 3, relying on the method of Li et al. (2014) and Liu et al. (2015), we set the maximum segmentation depth (max depth of splits) as 2 and the convergence standard as 0.2. The 30 provinces are divided into 4 plates. Then, we rely on the method of Li et al. (2014) and Wasserman and Faust (1994) to distinguish the role of plates, as shown in Table 4.

Table 4. The division of plate roles of interprovincial carbon transfer network in China, 2002-2012.

	Plate	Region (Province)	Number of contacts received		Number of contacts sent		Expected internal relationship's proportion	Actual internal relationship's proportion	Role of plates
			Inside	Outside	Inside	Outside			
2002	I	Northern and northeast (Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Shandong)	61	21	61	34	31.0%	64.2%	Bidirectional spillover
	II	Northwest	0	8	0	6	10.3%	0.0%	Agent

		(Qinghai, Ningxia, Xinjiang, Hainan)							
	III	Eastern and central (Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Henan, Hunan, Shaanxi)	25	42	25	32	24.1%	43.9%	Main inflow
	IV	Southwest and southern (Hubei, Guangdong, Guangxi, Gansu, Chongqing, Sichuan, Guizhou, Yunnan)	29	24	29	23	24.1%	55.8%	Bidirectional spillover
2007	I	Northern and northeast (Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shandong)	52	21	52	24	27.6%	68.4%	Bidirectional spillover
	II	Northwest (Hainan, Anhui, Jiangsu, Shaanxi, Qinghai, Ningxia, Xinjiang, Gansu)	13	22	13	27	24.1%	32.5%	Bidirectional spillover
	III	Eastern and central (Shanghai, Zhejiang, Fujian, Jiangxi, Henan, Hunan, Hubei)	29	35	29	39	20.7%	42.7%	Bidirectional spillover
	IV	Southwest and southern (Guangdong, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan)	22	22	22	10	17.2%	68.8%	Main inflow
2012	I	Northern and northeast (Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shandong)	44	21	44	17	27.6%	72.1%	Main inflow
	II	Northwest (Qinghai, Ningxia, Shaanxi, Hainan)	0	9	0	12	10.3%	0.0%	Agent
	III	Eastern (Jiangsu, Zhejiang, Shanghai, Anhui, Fujian, Gansu, Xinjiang, Jiangxi, Henan)	41	22	41	42	27.6%	49.4%	Bidirectional spillover
	IV	Southwest, southern , and central	39	31	39	12	24.1%	76.5%	Main inflow

(Hunan, Hubei, Guangdong, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan)	

Notes:

Main inflow plate: the proportion of the plate's actual internal relationship is greater than that of the expected internal relationship. The plate receives more contacts from outside the plate.

Agent plate: the proportion of the plate's actual internal relationship is less than that of the expected internal relationship. Plate receives fewer contacts but sends more contacts to plates both internally and externally. Plate acts as a "intermediary" role sending relationships to other plates and receiving contacts from outside members.

Bidirectional spillover plate: The proportion of the plate's actual internal relationship is greater than that of the expected internal relationship. Plate receives fewer contacts but sends more contacts to plates both internally and externally.

4.3.1. Direction Change of the Embodied Carbon Transfer

From 2002 to 2012, the provinces can be approximately divided into four plates, namely, northern and northeastern provinces, northwestern provinces, eastern and central provinces, and southwestern and southern provinces, as shown in Figures 6–8. Because of geographic location, transport costs, and market demand for products, interprovincial trade and the corresponding embodied carbon transfer often occur between adjacent provinces within a large area; this can be called "geographic adhesiveness."

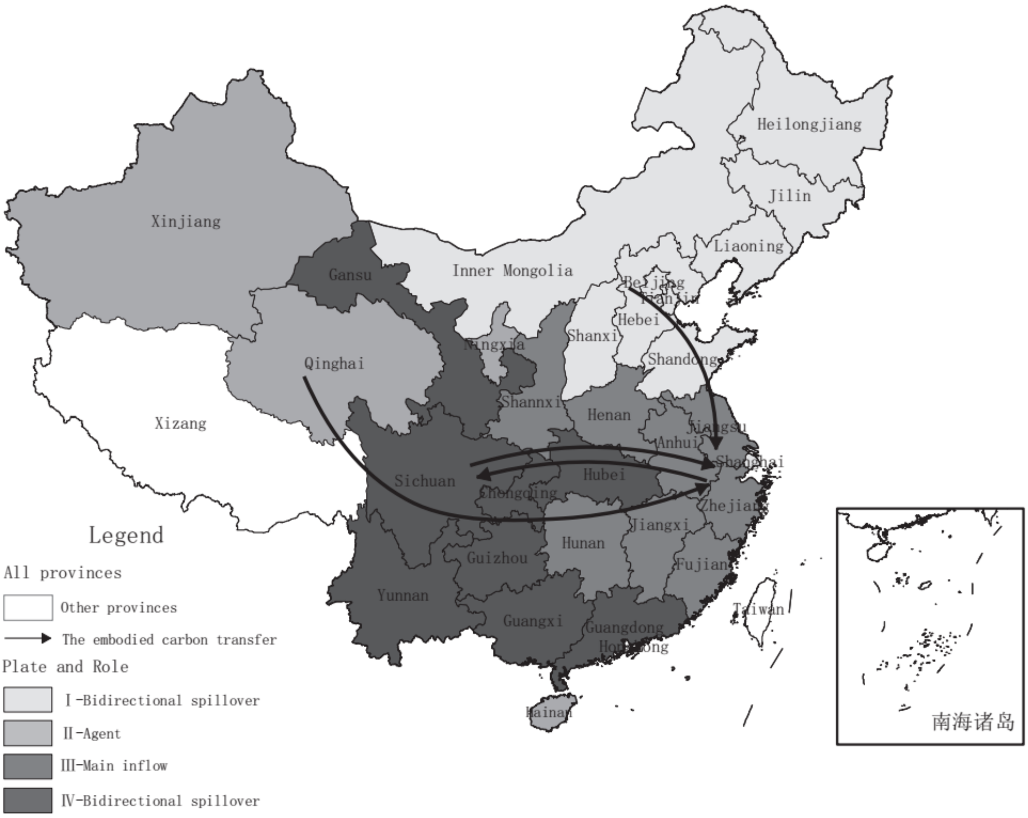

Figure 6. Composition of the four plates in China in 2002

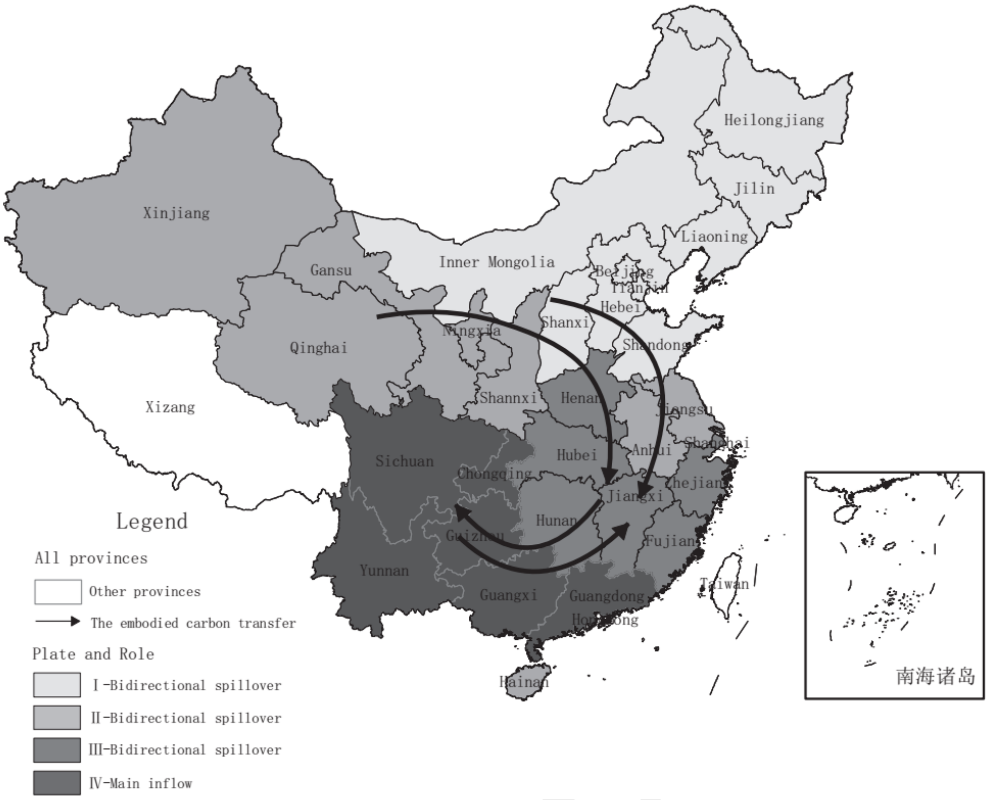

Figure 7. Composition of the four plates in China in 2007

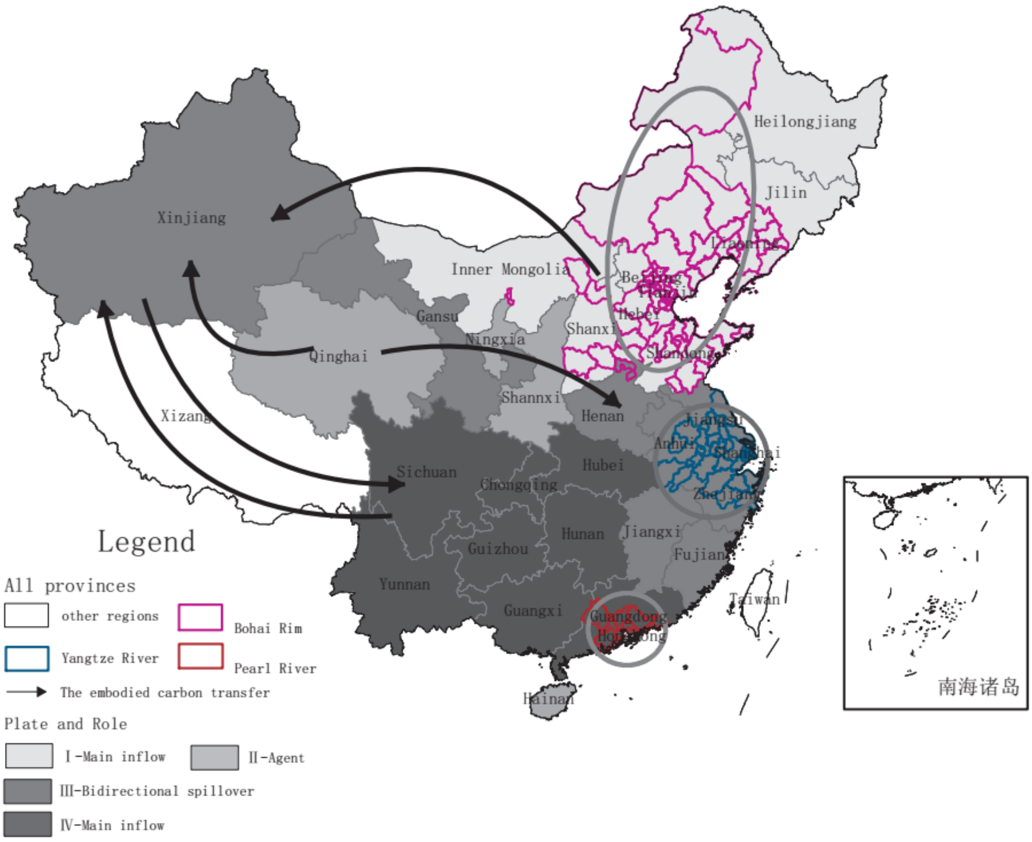

Figure 8. Composition of the four plates in China in 2012

"Intraplate density" measures the number of connected relationships as a fraction of the total possible relationships between different plates and is based on a scale of 0-1". As larger intraplate density means a larger scale of carbon transfer between different plates, the main direction of the embodied carbon transfer was from the energy-rich northern provinces to the developed eastern and central provinces in 2002 and to the developing southwestern and southern provinces in 2012. After the fifth and sixth railway speed-up in 2004 and 2007, the spatial scope centre with great accessibility gradually extended to the southwestern and northwestern provinces (Xu and Li, 2012). In addition, because of the large energy use but insufficient self-sufficiency, the eastern and central provinces needed to depend on the energy-rich northern and northeastern provinces for their energy supply. At the same time, with the upgrading of the industrial structure and the relatively higher environmental standards, the provinces in the Bohai Rim, Yangtze River Delta, and Pearl River Delta region transferred high energy use and polluting industries to the southwestern and southern provinces.

4.3.2. Roles of Provinces in the Embodied Carbon Transfer Network

The northeastern provinces are rich in fossil fuel–based energy and provide energy resources for production in the Bohai Rim, Yangtze River Delta, and Pearl River Delta. Therefore, Plate I, composed of the northern and northeastern provinces, played a “bidirectional spillover” role in 2002 and 2007. With the depletion of resources, increased mining costs, and higher intensity of energy use in the northeastern provinces (Yu and Huang, 2016), Plate I played a “main inflow” role in 2012, as it needed to obtain resources from other provinces.

Plate II, composed of the northwestern provinces, played in a typical “agent” role in 2002, as it had zero actual internal relationships but more carbon linkage with the other plates (receive and send 14 total contacts outside the plate). In 2007, certain eastern provinces were added to this plate and generated carbon links with the northwestern provinces, as Plate II received and sent 13 contacts inside. Because of the rail network’s improved accessibility, which make it easier to transport coal, Plate II played a "bidirectional spillover" role. Later, certain eastern provinces (Jiangsu and Anhui) gradually became the major region to undertake industrial transfer from Shanghai (Luo et al., 2014). In 2012, as Jiangsu and Anhui are deleted from Plate II but added to Plate III, which includes Shanghai, Plate II played an "agent" role.

Plate III, composed of the eastern and central provinces, in 2002 played a "main inflow" role as it received 42 contacts but sent only 32 contacts outside the plate. Due to the opportunities resulting from the entry into WTO, the developed eastern provinces undertook the transfer of high-tech manufacturing and received more carbon emissions from the production of such industries. As the global "fourth industrial transfer" began since the international financial crisis in 2008, coastal eastern provinces are the area in China where industry transfers out (Zhao et al., 2014). Therefore, in 2007 and 2012, Plate III exported more carbon emissions to other provinces and played a "bidirectional spillover" role.

Plate IV, composed of the southwestern, southern, and central provinces, abounds in energy resources and transfers out energy, causing carbon spillover. Therefore, this plate played a "bidirectional spillover" role in 2002. Later, because of the developing economy and increasing energy use, Plate IV had increased demand for various resources from other provinces, thus playing a "main inflow" role in 2007 and 2012.

In addition, Duan et al. (2018) found that, in 2012, the northwest is the largest controller for most regions in China from the consumption perspective, and any carbon mitigation policy in the northwest would have a fundamental and effective influence on the others. However, our results show that the central and western provinces are playing major roles in the network, which controls the critical path of the network regions in 2012.

4.4. Influencing Factors on Embodied Carbon Transfer Network

To reveal the factors that affect the spatial correlation network structure of embodied carbon transfer in 2012, we use the nonparametric QAP method to analyse the network. Notably, as the empirical regression variables are relational matrices, they can be highly correlated and cannot be tested using traditional statistical measurement methods. Krackhardt (1988) proved that the QAP algorithm is better than the least squares method in a regression analysis based on relational data. A double semi-partialling approach recommended by Dekker et al. (2007) is used to calculate the significance levels based on 2,000 random permutations that generates values as great as that in the observed statistic. Therefore, this paper uses QAP, using 2,000 random permutations, and adopts a stepwise regression to determine then exclude unremarkable variables.

In Table 5, five factors, *GDP, EO, UP, KS,* and *CL,* are not always significant. After excluding these five factors, the remaining variables are confirmed in significance tests. T_{2002} and T_{2007} pass the test at the 1% significance level. *GP* and *ER* pass at the 5% significance level; *pGDP* and *IS* are significant at the 10% level. For the same data, R^2 is generally lower in QAP regression analysis than in OLS analysis.

In this paper, the adjusted R^2 of the second regression is 0.774. The network model fits well and passes a 1% significance level test. As shown in Table 5, the dependent variable is T_{2002}, and the independent variables are T_{2002}, T_{2007}, *GP*, *ER,* and *pGDP.*

Table 5. QAP Results of Factors That Influence the Spatial Correlation Network Structure of Embodied Carbon Transfer in 2012.

Dependent variable	Influencing factors (difference matrix)	QAP regression analysis I		QAP regression analysis II	
		Standardized coefficient	Significance (P value)	Standardized coefficient	Significance (P value)
The amount of inter provincial embodied carbon transfer network in 2012 (T_{2012})	*GP*	0.039**	0.026	0.036**	0.025
	GDP	0.014	0.328	-	-
	pGDP	0.038	0.188	0.032*	0.094
	IS	-0.030	0.195	-0.038*	0.079
	EO	-0.027	0.281	-	-
	UP	0.011	0.416	-	-
	KS	0.022	0.168	-	-
	CL	-0.015	0.221	-	-
	ER	0.033*	0.072	0.043**	0.019
	T_{2002}	0.114***	0.007	0.111***	0.009
	T_{2007}	0.766***	0.000	0.772***	0.000
Determination coefficient	R^2	0.776		0.775	
	Adjusted R^2	0.773		0.774	

In Table 5, spatial adjacency relations (*GP*) and differences in economic development (*pGDP, IS*) had a small impact on the spatial correlation network structure of embodied carbon transfer in 2012; the environmental regulation intensity differences (*ER*) affected the network to some extent, while the environmental path dependence (T_{2002},T_{2007}) affected the network significantly.

Specifically, as the transportation costs of economic activities decrease, the carbon transfer occurs more easily in geographically adjacent provinces. The sign of *pGDP*'s coefficient (0.032) is positive, indicating that the greater the *pGDP* gap between provinces is, the larger the scale of carbon transfer is. The sign of *IS*'s coefficient (-0.038) is negative, showing that provinces with a similar industrial structure have a larger carbon transfer scale. This finding may be related to the characteristics of "a marriage between families of equal social rank" in the Chinese regional economy's spatial associations, which means regions with similar development conditions are more likely to generate spatial spillover (economic development in one region enlarges the market capacity and invites the influx of products manufactured in other regions with a more integrated domestic market) and closer economic ties (Li et al., 2014).

The sign of *ER*'s coefficient (0.043) is positive, indicating that the greater the difference in provincial government environmental regulation standards is, the larger the amount of embodied carbon transfer is. To circumvent the higher local environmental governance costs, pollution-intensive industry shifts from the eastern provinces, which have stringent regulations, to the central and western provinces, which have weaker regulations. The eastern provinces then import products from the western provinces, increasing the embodied emissions in traded goods.

The coefficients of T_{2002} (0.111) and T_{2007} (0.772) are the largest among the 6 factors, and they have passed a 1% significance level test. This finding shows that the embodied carbon transfer network structure in 2012 was highly positively related to those in previous years; therefore, the path dependence of interprovincial carbon transfer is the most significant. Although the negative effects of environmental degradation may not be significant in the short term, the costs can be great for the whole country in the long term. Here, it should be noted that the main object of the SNA is to determine the "relationship", and the data can have autocorrelation. Compared to the traditional parameter method, the QAP method does not need to assume the dependence among variables, which is more robust (Barnes, 1954).

5. Conclusions and Policy Recommendations

To determine the characteristics of China's provincial embodied CO_2 emissions and the complexity of carbon transfer, this paper compiles an MRIO table for China to calculate the amount of interprovincial embodied carbon transfer. We then analyse the spatial structure and determinants using the SNA and QAP methods. The purpose of this paper is to discern patterns through this analysis and outline related policy implications.

First, from 2002-2012, the provinces experienced a reduction in carbon emissions per capita due to the emissions reduction targets set in the National Five-Year-Plan. However, most of the provinces experienced a continuous increase in the per capita embodied carbon footprint. Our interprovincial network shows that the embodied carbon transfer becomes more frequent due to the development of domestic interregional trade and logistics in China.

Second, the carbon emissions have obvious regional disequilibrium characteristics (heterogeneity). Additionally, the provincial path of carbon transfer shows that embodied carbon emissions were generally transferred from the energy-rich northern provinces to the developed eastern and central provinces in 2002, then to the developing southwestern and southern provinces in 2012. In particular, in 2012, the northwestern provinces played a “bridge” role between the central and eastern provinces; the eastern provinces played a “bidirectional spillover” role to transfer carbon internally and externally.

Third, carbon transfer has “geographic adhesiveness” related to the high spatial concentration and proximity preferences of interprovincial trade. Additionally, the spatial adjacency relations and differences in economic development have a small impact on the spatial correlation network structure of embodied carbon transfer in 2012, while environmental path dependence is the most important factor affecting the network.

Based on these findings, we offer several policy recommendations as follows.

We should focus more on the mitigation of embodied CO_2 emissions. The enlarged CO_2 transfer leads to large variation in consumption-based emissions among provinces. The northern provinces can create strict emission regulations to promote the energy efficiency improvement and industrial upgrading to reduce their embodied carbon emissions. Less developed regions can accelerate their deployment of advanced emission technologies such as Amine-based post-combustion CO2 capture (PCCC) technology (Chen et al., 2018), considering the utilization of biomass waste as a substitute for fossil feedstocks (Maneerung et al.,2018). Additionally, Jiangsu, as the hub of carbon transfer, can take advantage of its location to accelerate the development of a service-oriented economy.

Provinces can formulate differential emission reduction plans based on their different levels of centrality in the network. Our approach can contribute useful commentary on Chinese provincial policies on allocating and tailoring specific emission reduction targets and responsibilities to the various provinces. The eastern coastal provinces, Jiangsu, Shandong, Hebei, Guangdong, Shanghai, and Liaoning, which have a high centrality degree, should pioneer emissions reduction and provide financial and technical support to other provinces. At the same time, Jiangxi, Henan, Hubei, Hunan, Guangxi, Yunnan, Guizhou, Sichuan, Chongqing, Shaanxi, and Xinjiang, which have the highest betweenness degree, can act as the "bridge" and promote advanced technology diffusion between different groups throughout the network. Hainan, Ningxia, and Fujian have the lowest degree and betweenness centrality and can act as "marginal actors" and improve participation in the network.

Moreover, considering the path dependence of carbon transfer, China can implement a strategy of transprovincial coordinated carbon mitigation. Our analysis identifies that carbon emissions in previous years were greatly affected by the path dependence of interprovincial carbon transfer. On one hand, with the results of spatial clustering of embodied carbon transfer, the provinces which play the same or similar roles in the network can work together to reduce emissions given there would be a strong applicability of emission reduction policies among these provinces. On the other hand, the central and western provinces which play major roles in the network can united to implement more stringent regulations on carbon contents in the goods to promote the ebodied carbon emission reduction throughout the country. Our finding can provide a foundation for transprovincial coordinated carbon mitigation cooperation to achieve the ambitious national reduction targets.

The proposed analytical framework in our paper, as well as the topics including the embodied energy, virtual water, ecological footprint and pollutant emissions associated with interregional trade, can also be adopted for other regions. In future research, the "geographic adhesiveness" will be tested with the betweenness centrality and using spatial autocorrelation to study how far from equilibrium the regional differences are. In addition, more effort will be put into investigating the city-level carbon transfer network and combining the complex social network with geo-economics to discuss carbon emissions; thus, a more comprehensive carbon transfer network relationship can be determined for deeper carbon emissions reduction in China.

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Appendix A. The contrast descriptions of 42 sectors adjusted into 31 sectors

31 Sectors	42 Sectors
1. Farming, Forestry, Animal Husbandry and Fishery	1. Farming, Forestry, Animal Husbandry and Fishery
2. Mining and Quarrying	2. Mining and Quarrying
3. Petroleum and Natural Gas Extraction	3. Petroleum and Natural Gas Extraction
4. Ferrous and Nonferrous Metals Mining and Dressing	4. Ferrous and Nonferrous Metals Mining and Dressing
5. Nonmetal and Other Minerals Mining and Dressing	5. Nonmetal and Other Minerals Mining and Dressing
6. Food Processing, Food Production, Beverage Production, Tobacco Processing	6. Food Processing, Food Production, Beverage Production, Tobacco Processing
7. Textile Industry	7. Textile Industry
8. Textile Products, Leather and Footwear	8. Textile Products, Leather and Footwear
9. Wood Products and Furniture Manufacturing	9. Wood Products and Furniture Manufacturing
10. Papermaking and Paper Products	10. Papermaking and Paper Products
11. Coke, Refined Petroleum, and Nuclear Fuel	11. Coke, Refined Petroleum, and Nuclear Fuel
12. Chemical Products Related Industry	12. Chemical Products Related Industry
13. Nonmetal Mineral Products	13. Nonmetal Mineral Products

14. Smelting and Pressing of Ferrous and Nonferrous Metals	14. Smelting and Pressing of Ferrous and Nonferrous Metals
15. Metal products	15. Metal products
16. Ordinary Machinery	16. Ordinary Machinery
17. Equipment for Special Purpose	17. Equipment for Special Purpose
18. Transportation Equipment	18. Transportation Equipment
19. Electric Equipment and Machinery	19. Electric Equipment and Machinery
20. Electronic and Telecommunications Equipment	20. Electronic and Telecommunications Equipment
21. Instrument Manufactures	21. Instrument Manufactures
22. Other Manufactures	22. Other Manufactures
23. Waste	23. Waste
24. Repair of Metal Products, Machinery and Equipment	24. Repair of Metal Products, Machinery and Equipment
25. Electric Power/Steam and Hot Water Production and Supply	25. Electric Power/Steam and Hot Water Production and Supply
26. Gas Production and Supply Industry	26. Gas Production and Supply Industry
27. Water Production and Supply Industry	27. Water Production and Supply Industry
28. Construction Industry	28. Construction Industry
29. Transport, Storage and Post	30. Transport, Storage and Post
30. Wholesale, Retail Trade, Hotels and Catering Service	29. Wholesale, Retail Trade 31. Hotels, Catering Service
31.Others	32. Information Transmission, Computer services and Software 33. Financial Industry 34. Real Estate 35. Leasing and Commercial Services 36. Research, Experimental Development and Polytechnic Services 37. Water conservancy, Environment and Public Facilities Management 38. Service to Households and Other Service 39. Education 40. Health, Social Security and Social Welfare 41. Culture, Sports and Entertainment 42. Public Management and Social Organization

A Study on Embodied Carbon Transfer at Provincial Level of China from Social Network Perspective

Research Highlights:

- The spatial correlation network structure of embodied carbon transfer in China is analyzed
- The carbon emissions is with obvious regional disequilibrium and the transfer is "geographic adhesiveness"
- Northwestern provinces act as "bridges" meanwhile Eastern provinces play a "bidirectional spillover" role in carbon transfer
- The environmental path dependence is most important in affecting embodied carbon transfer in 2012