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SPECIALTY SECTION
This article was submitted to
Environmental Economics and
Management,
a section of the journal
Frontiers in Environmental Science

RECEIVED 30 June 2022
ACCEPTED 16 August 2022
PUBLISHED 07 September 2022

CITATION
Wang Y, Wu Q and Song J (2022), Spatial
network structure characteristics of
green total factor productivity in
transportation and its influencing
factors: Evidence from China.
Front. Environ. Sci. 10:982245.
doi: 10.3389/fenvs.2022.982245

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Spatial network structure characteristics of green total factor productivity in transportation and its influencing factors: Evidence from China

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Improving green total factor productivity (*GTFP*) is an effective way to achieve efficient use of resources and low-carbon development in the transportation industry. Accurately grasping the spatial associated structure and its influencing factors of China's transportation *GTFP* is of great significance for promoting coordinated regional development. This study used the DEA-Malmquist model to measure China's provincial transportation *GTFP* from 2006 to 2019. The spatial associated matrix is constructed by the modified gravity model, and the social network analysis (SNA) method is used to analyze the structural characteristics and influencing factors of the *GTFP* spatial associated network. It is found that: 1) The tightness of the spatial associated network of China's transportation *GTFP* increased year by year, and the hierarchical spatial structure was gradually broken. 2) There are significant differences in the status of various regions in the spatial network. Among them, Shanghai plays the role of "leader" and "core participant", with the highest point centrality and eigenvector centrality; Jiangxi and Guangdong play the role of "intermediary" and "bridge"; However, Jilin, Qinghai, Ningxia, and other regions have a weak influence on the spatial correlation. 3) Spatial aggregation analysis shows that block I has a strong correlation with other regions, while the spatial correlation level of the other three plates is relatively poor. 4) QAP analysis shows that province adjacency, per capita GDP, and technological innovation have a significant positive impact on the spatial correlation. Therefore, the Chinese government should increase the level of informatization and create a regional coordinated development mechanism to optimize the overall development pattern of the transportation industry.

KEYWORDS

transportation, green total factor productivity, spatial network structure, revised gravitational model, social network analysis, QAP regression analysis

1 Introduction

The tightening of resources and environmental constraints has caused countries around the world to consider “green” development while promoting economic growth, and increasing the contribution share of green total factor productivity (*GTFP*) in economic development. As the basic carrier and strategic leading industry of economic and social development, the transportation industry accounts for about 24.34% of the total carbon emissions of global CO₂ emissions (Shao and Wang, 2021). This sector is the second-worst emitter of greenhouse gas worldwide and a key to China’s achievement of its carbon peak and neutrality strategic goals (Wei et al., 2021). Research shows that China’s transportation *GTFP* is characterized by a significant spatial imbalance and autocorrelation, and regional green development is affected by interval externalities (Yang et al., 2011; Yuan et al., 2017; Liang and Li, 2021; Wei et al., 2021). At present, investigating the role of interval relations is often based on new economic geography and spatial econometric models, and mainly focuses on “nearby” spatial effects and local spatial characteristics. There is a lack of systematic analysis of the overall network connection and the overall spatial pattern and driving mechanism of *GTFP* in China’s transportation. However, clarifying the spatial structure characteristics of China’s transportation *GTFP* and its influencing factors under the goal of “carbon peak and neutrality” is of great significance for promoting “greening” and coordinated development between regions.

The most common method for studying complex relationships is Social Network Analysis (SNA). SNA uses an incidence matrix to represent complex associations and uses graph theory and algebraic operations to measure structural features which can reflect the key features in complex networks (Steketee et al., 2015). SNA analyzes the network from the three levels of the whole, individuals, and subgroups. It not only reveals the correlation characteristics of the network from the perspective of attribute data but also discovers the relationship between network nodes from the perspective of relational data. Moreover, in social network analysis, the Quadratic Assignment Procedure (QAP) algorithm studies the correlation between two variable matrices or the regression relationship between multiple variable matrices and one variable matrix through the arrangement of matrix rows and columns (Ma et al., 2019). Because network data often have problems such as multicollinearity and autocorrelation, the QAP algorithm is more suitable for regression analysis of influencing factors than other methods. In this research, we use SNA theory to conduct comprehensive and in-depth research on the spatial association and network structure characteristics of the transportation *GTFP* in China and use the QAP method to further explore its influencing factors.

The rest of this paper is organized as follows. Section 2 is the review of related literature. Section 3 constructs the research

model and describes the variable selection. Section 4 analyzes the evolutionary trends of the carbon emission network using the research results obtained from analyzing the spatial association effect in China’s provincial transportation. This section also explores the influencing factors of transportation carbon emissions by QAP. The last section summarizes the full study and proposes corresponding policy recommendations.

2 Literature review

Under the strategic guidance of building China’s strength in transportation and green development, how to break away from the previous development model of over-reliance on high investment in infrastructure and high consumption of resources and energy to achieve high-quality development has attracted the attention of many scholars. The essence of this is the problem of transportation efficiency. For example, Sun et al. (2022) believed that the development of public rail-based transportation networks can reduce carbon emissions, promote transportation efficiency and achieve green and sustainable development of transportation. Wu et al. (2015), and Chang et al. (2013) used the data envelopment analysis method to study the transportation efficiency in various provinces in China. They found that China’s transportation industry is environmentally very inefficient, and the spatial distribution varies greatly. Jiang et al. (2020) built a three-stage DEA model to analyze the transportation carbon emission efficiency in the Yangtze River Economic Zone from 1985 to 2016. They pointed out that the optimization of industrial structure is conducive to the improvement of transportation carbon emission efficiency. Park et al. (2018) used the SBM-DEA model and state-level data to assess the environmental efficiency of the transportation sector in the U.S. from 2004 to 2012. The study discovered that the U.S. transportation sector was environmentally inefficient and the states could substantially reduce carbon emissions to improve the environmental efficiency of their transportation sectors. Peng et al. (2020) evaluated the carbon emission efficiency of transportation in 30 provinces in China from 2004 to 2016 using a Super-SBM model and used Moran I index to analyze the spatial distribution characteristics. They found that the carbon emission efficiency of transportation is characterized by “high in the east and low in the west”, and has significant spatial dependence and agglomeration characteristics.

However, the transportation efficiency analyzed by the above studies is mostly relative efficiency, which cannot truly reflect the effect of transportation resource allocation and the level of green development. Therefore, some scholars have researched total factor productivity. With the gradual attention paid to green development, scholars have tried to combine the level of carbon emissions and total factor productivity to comprehensively evaluate the level of *GTFP* in transportation. *GTFP* as the main tool to explore the source

of economic growth has become an important indicator for evaluating the efficiency of transportation resource allocation and the status of sustainable development (Peng and Wu, 2019). Yang et al. (2011) used the production function model and the Geographically Weighted Regression (GWR) model to analyze the spatial impact of technological progress on China's traffic *GTFP*. They pointed out that spillover effects of green technologies should be encouraged and regionally differentiated policies should be implemented to promote the growth of *GTFP*. Zhang et al. (2011) combined a variety of poor environmental outputs with *TFP* to calculate the *GTFP* in Chinese provinces. Kumar. (2006) and Biresh et al. (2011) incorporated CO₂ emissions into *TFP* and analyzed the *GTFP* of different countries. Huang (2020) used the Hicks-Moorsteen index to calculate the *GTFP* of road transportation and analyzed its spatial distribution characteristics. She pointed out that green technologies in various provinces are interrelated and *GTFP* should be promoted from the perspective of spatial correlation. Based on the DEA-Malmquist index method, Chen and Pan, (2016) measured the total factor productivity (*TFP*) of the logistics industry in 30 provinces in China from 2005 to 2014 under low carbon constraints. Using exploratory spatial data analysis methods, they found significant spatial correlations in *TFP* between provinces.

Nevertheless, the current research on transportation *GTFP* mainly focuses on the time series trend and spatial "nearby" dimension. Few studies have focused on the spatial correlation of transportation *GTFP*. Social network analysis, as a method based on graph theory, uses relational data to conduct an in-depth analysis of spatial network associations and system structure. In recent years, many scholars used the SNA method to analyze the spatial network relationship in the field of total factor productivity. Yan and Zhu. (2021), Huang et al. (2021), Zhang et al. (2021), Liu and Song. (2018), Zhang and Yu. (2017), and others used the SNA method to analyze the total factor productivity of China's light industry, tourism, water resources, energy, and social economy. They revealed the characteristics of their spatial network structure from three levels of integral, individual, and regional characteristics, thereby providing the theoretical basis and reference for grasping and improving total factor productivity and regional balanced development. However, there is almost no research on *GTFP* in transportation using the SNA method, and it is more used to analyze the spatial network relationship of transportation carbon emissions in China's provinces.

It can be seen that the existing research on *GTFP* in China's transportation is more of a time series evolution trend analysis. Regarding its spatial structure characteristics, the current research only uses "cross-sectional data" for analysis, which is not conducive to grasping the time-varying trend of the spatial characteristics of the transportation *GTFP*. On the other hand, existing studies usually adopt traditional measurement models and exploratory spaces data analysis, and other methods to analyze the spatial heterogeneity, clustering, and convergence

of *GTFP* in transportation. However, these methods only consider the situation of "nearby" geographical location, and the results are often "partial". It is difficult for them to outline the complex spatial correlation network, and they cannot well reflect the spatial correlation structure and aggregation of *GTFP* in transportation. Therefore, this study used the SNA method to analyze the network characteristics, evolution trends, and influencing factors of the spatial correlation effect of *GTFP* in China's provincial transportation. The results of this research will help decision-makers grasp the overall structure of the transportation *GTFP* and understand the internal connections and differences among regions. It also has important theoretical significance and application value for building a cross-regional transportation *GTFP* coordinated promotion mechanism, formulating a targeted and regional transportation reform and development policy, and achieving the "carbon peak and neutrality" and sustainable development goals.

3 Methodology

3.1 DEA-malmquist model

Compared with other measurement methods (mainly including the growth kernel algorithm and stochastic Frontier analysis), the Malmquist model based on Data Envelopment Analysis (DEA) has a lot of advantages in the measurement methods of total factor productivity (Peng and Wu, 2019): 1) There is no need to determine the form of the production function in advance, so it can avoid improper model setting that affects the accuracy of the analysis results; 2) It can handle the situation of multiple input-output and is suitable for inter-period analysis in different economic regions 3) The total factor productivity growth rate can be decomposed into factors such as technical efficiency and technological progress, which has a strong guiding significance for policy formulation. Therefore, this paper chose the DEA-Malmquist model to measure the *GTFP* of China's transportation. At present, researchers generally use the output-oriented Malmquist productivity change index constructed by Fare et al. (1994), its calculation equation can be expressed as:

$$\begin{aligned}
 M_{it+1}(x_i^t, y_i^t, x_i^{t+1}, y_i^{t+1}) &= \frac{D_i^{t+1}(x_i^{t+1}, y_i^{t+1}|V)}{D_i^t(x_i^t, y_i^t|V)} \\
 &\cdot \left[\frac{D_i^{t+1}(x_i^{t+1}, y_i^{t+1}|C)/D_i^{t+1}(x_i^{t+1}, y_i^{t+1}|V)}{D_i^t(x_i^t, y_i^t|C)/D_i^t(x_i^t, y_i^t|V)} \right] \\
 &\cdot \left[\frac{D_i^t(x_i^t, y_i^t)}{D_i^{t+1}(x_i^t, y_i^t)} \cdot \frac{D_i^t(x_i^{t+1}, y_i^{t+1})}{D_i^{t+1}(x_i^{t+1}, y_i^{t+1})} \right]^{1/2} \\
 &= PECH_t^{t+1} \cdot SECH_t^{t+1} \cdot TC_t^{t+1}
 \end{aligned} \tag{1}$$

In Eq. 1, $M_{it+1}(x_i^t, y_i^t, x_i^{t+1}, y_i^{t+1})$ is the change in total factor productivity of province "i" from period "t" to period "t+1";

(x_i^t, y_i^t) and (x_i^{t+1}, y_i^{t+1}) represent the input-output vector of province “ i ” in period “ t ” and “ $t+1$ ” respectively; $D_i^t(x_i^t, y_i^t)$ and $D_i^t(x_i^{t+1}, y_i^{t+1})$ respectively represent the output distance function of period “ t ” and “ $t+1$ ” with the cutting-edge production technology of period t as a reference; $D_i^{t+1}(x_i^t, y_i^t)$ and $D_i^{t+1}(x_i^{t+1}, y_i^{t+1})$ respectively represent the output distance function of “ t ” and “ $t+1$ ” with “ $t+1$ ” cutting-edge production technology as a reference. $PECH_t^{t+1}$, $SECH_t^{t+1}$, and TC_t^{t+1} respectively represent the pure technical efficiency change index, scale efficiency change index, and technological progress index of the province “ i ” from “ t ” period to “ $t+1$ ” period; V and C respectively represent the variable and constant returns to scale.

When measuring the *GTFP* of China’s transportation based on the DEA-Malmquist model, it is first necessary to scientifically select input and output indicators. In terms of input indicators, the capital stock, labor force, and energy consumption of the transportation industry are selected as input elements. Among them, the transportation capital stock is estimated by referring to the research of Zhang et al. (2004) and Shan (2008), using the “perpetual inventory method”; The labor force is represented by the number of employees in the transportation industry in each province; What’s more, based on the total consumption of nine types of energy in the transportation industry: raw coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, and natural gas, and the standard coal coefficient is used to convert them into standard coal, which represents the total energy consumption (Song et al., 2017).

In terms of output indicators, select the industrial added value of the transportation industry, transportation turnover, and carbon dioxide emissions as output factors. Among them, industrial added value and transportation turnover are regarded as the expected output, and carbon dioxide emissions are regarded as undesired output (Yuan et al., 2017). Considering data availability, transportation turnover was calculated by road, rail, and water. Due to the different units of passenger and freight turnover, the passenger turnover and freight turnover are converted into comprehensive turnover indicators based on the conversion factor. With reference to the passenger-freight conversion coefficient standard, because it is difficult to obtain detailed passenger turnover by berths or seats in waterway passenger transportation, so this study takes the conversion factor of waterway passenger turnover as 1. Therefore, the conversion coefficients of passenger turnover for railways, highways, and waterways are 1, 0.1, and 1. In addition, this study used a top-down approach to calculate carbon emissions (Song et al., 2017).

3.2 Revised gravitational model and spatial association matrix

The construction of the spatial incidence matrix is the basis for the application of the social network analysis method. In the existing research, the determination of the spatial association relationship mainly uses the gravity model and the vector autoregressive Granger

causality test (VAR Granger Causality). The VAR model is more sensitive to the choice of data lag order, while the gravity model is more suitable for overall analysis. In addition, the gravitational model can also describe the strength of the connection between the two regions, and even the evolution trend of the spatial relationship from the aspects of geographic distance, economic level, population size, and energy consumption (Liu et al., 2020). Therefore, this study chose the gravity model to construct the spatial correlation strength of the green total factor productivity of transportation in various provinces in China. At the same time, in order to enhance the applicability, the original equation was revised, as shown in Eq. 2 after revision (Wu et al., 2019):

$$Y_{ij} = k_{ij} \frac{\sqrt[3]{P_i T_i G_i} \times \sqrt[3]{P_j T_j G_j}}{\left(\frac{d_{ij}}{g_i - g_j}\right)^2}, k_{ij} = \frac{T_i}{T_j} \quad (2)$$

In Eq. 2, Y_{ij} is the link strength of the transportation *GTFP* in the province “ i ” to province “ j ”; P_i and P_j represent the population size of the province “ i ” and province “ j ”, which is replaced by the number of permanent residents at the end of the year; T_i and T_j are the green total factor productivity of transportation in the province “ i ” and province “ j ”; G_i and G_j are the actual regional GDP of the province “ i ” and province “ j ”, indicating the level of regional economic development; k_{ij} represents the contribution rate of the province “ i ” in the green total factor productivity link between province “ i ” and province “ j ”. Since the link strength of green total factor productivity between regions will be affected not only by geographical distance but also by economic distance, the ratio of geographical distance d_{ij} to per capita GDP difference $g_i - g_j$ is used to comprehensively express the influence of distance factors. d_{ij} is represented by the shortest road distance between province “ i ” and the capital city of province “ j ”. In addition, according to Taaffe’s research, the distance attenuation coefficient is determined to be 2 (Taaffe 1962).

Based on Eq. 2, a 30*30 contact strength matrix of 30 provinces in the year can be obtained. The average value of each row of data in the matrix is regarded as the critical value. If the value in the matrix is greater than the average value, it is recorded as “1”, which means that there is a spatial correlation between the two. Otherwise, it is recorded as “0”, which indicates that there is no spatial correlation between the two. Finally, a spatial binary (0–1) matrix of green total factor productivity of transportation was constructed and used as the data basis for spatial network structure analysis.

3.3 Social network analysis

Social Network Analysis (SNA) is based on relational data, uses graph theory tools and algebraic models to describe the relational modes between network nodes, and explores the influence of each relational model on individual members of

the network and the network as a whole (Shen et al., 2021). Through in-depth analysis of the relationship between the members of the network, the overall structural characteristics of the network and the interaction between the nodes are revealed (Liu and Song, 2018). This study used the social network analysis method and the related measurement indicators to analyze the overall spatial network characteristics, centrality characteristics, and clustering characteristics of *GTFP* in China's transportation from two dimensions of time and space. It is hoped that the development trend and influencing factors of *GTFP* in China's transportation can be discovered, so as to provide a policy basis for optimizing the spatial allocation of resources and improving green total factor productivity.

3.3.1 The integral structural characteristics of the network

Network density and network relevance (network association degree, network grade, and network efficiency) are usually used to describe the integral structural characteristics of the network (Ducruet and Beauguette, 2014).

- 1) Network density (*ND*). It refers to the closeness of contact between various points in a network. It is also defined as the ratio of the number of connections owned to the maximum number of connections possible in the entire network. Assuming that the number of nodes in the network is N and the number of associated lines that exist in the network is L , then the calculation equation for the network density *ND* can be expressed as:

$$ND = \frac{L}{N(N-1)} \quad (3)$$

- 2) Network association degree (*NAD*). It reflects the robustness of the network. If there is a direct or indirect path between each node in the network, it means that the network has good connectivity. If many lines in a network are connected by a node, it means that the operation of the network greatly depends on this node. Once the node is excluded, the network may collapse, which means that the network is not stable and the connectivity is low. Assuming that the number of network nodes is N and the number of unreachable nodes in the network is V , the calculation of the degree of network connectedness *NAD* is:

$$NAD = 1 - \frac{V}{N(N-1)/2} \quad (4)$$

- 3) Network grade (*NG*). It refers to the degree of asymmetric reachability between network nodes. The higher the network grade is, the stricter the network structure, which means that it is more difficult to integrate different regions. Assuming that the number of

symmetrically reachable nodes in the network is K , that is the maximum possible number of symmetrically reachable nodes, the calculation equation of the network grade *NG* is as follows (Vanderelst 2015):

$$NG = 1 - \frac{K}{\max(k)} \quad (5)$$

- 4) Network efficiency (*NE*). It refers to the extent to which there are redundant connections in the network. The lower the network efficiency, the more overflow channels between nodes, and the more stable the network. Assuming that the number of redundant connections in the network is M , and $\max(M)$ is the maximum possible number of redundant connections, the network efficiency *NE* is calculated as (Ducruet and Beauguette, 2014):

$$NE = 1 - \frac{M}{\max(M)} \quad (6)$$

3.3.2 The centrality analysis of the network

Centrality is an indicator used to measure the status and role of each node in the network. The higher the centrality of a node, indicating that it is in the center of the network, the greater its influence on other nodes in the network. Generally, the indicators that describe the centrality of a network include point centrality, betweenness centrality, closeness centrality, and eigenvector centrality (Borgatti et al., 2009; Wen et al., 2018).

- 1) Point centrality (*PC*). It refers to the number of nodes directly associated with a node in the network (represented by n), reflecting the degree to which each node is at the center of the network (Linton 2004). Assuming that the number of nodes in the network is N , the calculation equation for point centrality *PC* is as follows:

$$PC = \frac{n}{N-1} \quad (7)$$

- 2) Betweenness centrality (*BC*). This index characterizes the degree of resource control of a node. If a node is on the shortest path of many other point pairs, then the node has a high degree of betweenness centrality (Diez and Berger, 2005). Assuming that the number of shortcuts between node j and node k is g_{jk} , and the number of shortcuts passing through node i is $g_{jk(i)}$, then the ability $b_{jk(i)}$ of node i to associate node j with node k can be expressed as $b_{jk(i)} = g_{jk(i)}/g_{jk}$.

The betweenness centrality of all point pairs in the network corresponding to node i is added and standardized, and the betweenness centrality *BC* can be obtained:

$$BC = \frac{2\sum_j^N \sum_k^N b_{jk(i)}}{N^2 - 3N + 2}, (j \neq k \neq i, j < k) \quad (8)$$

- 3) Closeness centrality (*CC*). It describes the degree to which a point is not controlled by others (Song et al., 2019). A node has high closeness centrality if the distance between it and all other nodes in the network is short, meaning it is less likely to be controlled by other points. The calculation equation for closeness centrality *CC* is shown in Eq. 9, where d_{ij} is the length of the shortcut from point i to point j (Bai et al., 2020).

$$CC_{AP_i} = \frac{n-1}{\sum_{j=1}^n d_{ij}} \times 100 \quad (9)$$

- 4) Eigenvector centrality (*EC*). It depends not only on the number of its adjacent nodes but also on the importance of its adjacent nodes. It is a function of the centrality of adjacent nodes and reflects the importance of each node in the network. That is, the more important the adjacent node is, the more important the node is. The purpose of the study of eigenvectors is to find the core actors on the basis of the overall structure of the network (Wen et al., 2018). The calculation equation of the eigenvector centrality *EC* of node i is:

$$EC_i = x_i = c \sum_{j=1}^n a_{ij} x_j \quad (10)$$

Among them, c is a proportional constant, denoted $x = [x_1, x_2, \dots, x_n]^T$. When the steady state is reached after many iterations, it can be written in matrix form: $x = cAx$. It means that x is the eigenvector corresponding to the eigenvalue c^{-1} of matrix A , which can also be expressed as $Ax = \lambda x$.

3.3.3 Spatial aggregation analysis

The block model is the main method of spatial clustering analysis in social network analysis (Liu et al., 2020). It can analyze the role of each location (block) in the network. Through block model analysis, the development of the spatial correlation network of *GTFP* in transportation can be investigated from a new dimension, and the internal structure state of the spatial correlation network of *GTFP* in transportation can be revealed and portrayed. Furthermore, it can also display the number of blocks in the network and which provinces each section contains, which helps in analyzing the relationship between the blocks.

The blocks can be divided into four types. 1) The net-income block. The members of this type of block receive both the relationship from other block members and the relationship from the internal members of the block, and the relationship from the outside of the block is more than its overflow relationship to other blocks; 2) The net spillover block. This type of block has significantly more contact with other blocks than it receives from other blocks; 3) The two-way spillover block. Members of this block both send out contacts and receive

contacts from other blocks, and there are relatively many contacts from members within the block; 4) The broker block. This type of block not only sends contacts to other blocks, but also receives contacts from other block members, and the block has more connections with other block members.

3.4 QAP association and regression analysis

Since this study used “relational data”, there is a high similarity between explanatory variables. In order to avoid the problem of multicollinearity, the QAP analysis method was used to study the influencing factors of the spatial association network of China’s transportation *GTFP*. It mainly includes QAP association analysis and QAP regression analysis (Shao and Wang, 2021).

QAP association analysis is a method to compare the similarity of each element in two square matrices, which is based on the replacement of matrix data (Feng C et al., 2021). First, convert each matrix into a long vector of $n(n-1)$ numbers (the numbers on the diagonal are ignored), then calculate the correlation coefficient between the two vectors; Second, randomly permute the rows and columns of the matrix at the same time, then calculate the correlation coefficients and save the results. Repeating this calculation process hundreds or even thousands of times will get a distribution of correlation coefficients; Third, compare the correlation coefficient calculated in the first step with the correlation coefficient distribution obtained after random permutation. Obtain the significance level of the correlation coefficient according to the ratio of the correlation coefficients greater than or equal to the coefficient calculated for the first time in the distribution; Finally, the result is obtained by judging whether the correlation coefficient falls into the rejection area or the acceptance area. The principle of QAP regression analysis is similar to that of association analysis (Li et al., 2021). It studies the regression relationship between multiple matrices and one matrix and evaluates the significance of the coefficient of determination R^2 .

Regarding the influencing factors of the spatial association network of China’s transportation *GTFP*, the existing research believes that regional differences in income level (Yuan et al., 2017), industrial structure (Feng X W et al., 2021), technological innovation level (Du and Li, 2019; Wang et al., 2021), and environmental regulation (Shen et al., 2019) have an important impact on the spatial association: of *GTFP*. At the same time, the spatial relationship of *GTFP* in the transportation industry is also affected by the difference in the development level of the transportation system. The higher the output of the transportation system, the stronger its current transportation capacity is; The larger the investment in the transportation industry, the more complete the transportation system will be. These are conducive to promoting the flow of population and

TABLE 1 Influencing factors and variable description of the spatial associated network of China's transportation *GTFP*.

Influencing factors	Variables	Measurement method
Spatial distance	Adjacency relation (R)	If the provinces are adjacent, the value is 1, otherwise, it is 0
	Geographical distance (D)	The shortest road distance between provincial capital cities
Regional economic development level	Per capita GDP (PG)	Real GDP per capita in each province using 2006 as the base period
	Industrial structure (IS)	The tertiary industry's share of GDP
The development level of the transportation system itself	Transportation turnover (TT)	The comprehensive transportation turnover, the passenger turnover of railways, highways, and waterways is converted according to the conversion factors of 1, 0.1, and 1
	Transportation investment (TI)	The amount of investment in the transportation industry
The level of technological innovation	Technological innovation (TL)	The number of patent applications of industrial enterprises
The environmental regulation	Environmental regulation (ER)	The amount of investment in industrial pollution control

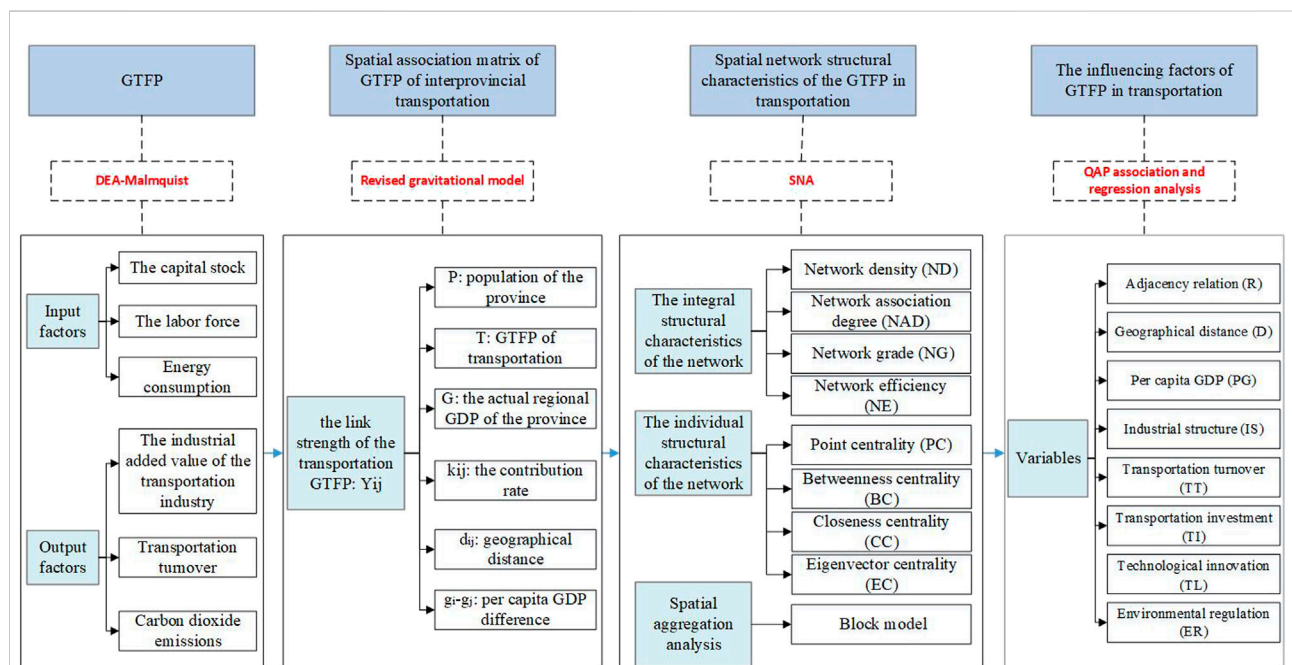


FIGURE 1 Analytical framework.

resources between regions, thereby strengthening the spatial association. Therefore, we used the comprehensive transportation turnover and investment in the transportation industry to represent the development quality of the transportation system. In addition, regions with closer distances are more likely to have spatial association relationships (Bai et al., 2020), so we used geographical distance and adjacency relation to represent the spatial distance between regions.

Therefore, 8 variables are selected from five aspects: spatial distance, regional economic development level, the development level of the transportation system itself, technological innovation level, and environmental regulation to explain the factors influencing the spatial relationship of *GTFP* in China's transportation. Correspondingly, the selection and measurement methods of each variable are shown in Table 1. Build the model as follows:

$$Q = f(R, D, PG, IS, TT, TI, TL, ER) \quad (11)$$

TABLE 2 Green total factor productivity of China's transportation in 2006–2019.

Province	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	0.93	0.96	0.95	0.99	1.01	0.99	0.99	0.99	0.99	0.99	0.99	1.00	1.00	0.99
Tianjin	0.99	1.01	0.79	1.07	1.00	0.99	0.93	0.96	0.97	0.96	0.98	1.00	1.00	1.00
Hebei	0.97	1.03	1.05	1.00	0.98	1.01	1.02	0.97	1.01	0.97	0.91	1.06	0.96	0.99
Shanxi	1.01	1.03	0.86	0.95	1.03	1.01	1.00	0.97	0.99	0.99	0.99	1.01	1.03	1.02
Inner Mongolia	0.96	0.97	0.99	0.97	0.99	0.99	0.99	1.03	1.00	0.99	1.08	1.03	1.02	0.98
Liaoning	1.00	1.00	1.00	0.99	0.99	1.00	1.00	1.01	0.99	0.99	1.01	1.00	0.99	0.99
Jilin	0.96	0.93	0.99	0.99	0.99	1.01	1.00	0.97	0.97	0.98	1.00	1.01	1.05	1.00
Heilongjiang	0.96	1.01	1.03	0.95	1.01	0.91	1.00	0.98	1.00	0.99	1.00	1.01	1.01	1.00
Shanghai	0.97	0.97	0.98	0.97	1.04	1.01	0.99	0.97	1.03	0.99	0.98	1.02	1.03	1.01
Jiangsu	1.00	0.98	1.00	0.95	1.00	1.02	1.02	0.92	0.97	0.95	0.98	1.00	0.99	1.00
Zhejiang	0.99	0.99	0.98	0.97	1.01	0.96	0.99	1.02	1.00	0.99	1.00	0.99	1.01	1.02
Anhui	0.97	0.95	1.03	0.96	0.97	0.96	0.99	0.91	0.98	0.95	0.99	0.98	1.02	1.00
Fujian	0.87	0.97	0.92	0.94	0.97	0.97	1.00	0.97	0.99	0.99	0.99	1.00	0.99	0.99
Jiangxi	0.99	0.99	1.01	0.97	0.95	0.99	1.04	0.93	0.99	0.97	1.00	0.99	0.98	0.98
Shandong	1.00	0.94	1.06	0.81	0.95	0.92	1.01	0.94	1.00	0.99	0.99	1.01	1.00	1.00
Henan	1.01	0.96	0.95	0.97	0.96	0.98	1.01	0.96	1.01	0.97	1.01	1.00	0.97	1.00
Hubei	0.97	0.99	0.99	1.02	1.01	0.98	1.02	1.02	0.99	0.99	0.96	1.01	1.00	0.98
Hunan	0.83	0.86	1.00	0.94	0.99	0.99	1.04	0.93	0.98	0.97	0.99	0.99	0.99	0.98
Guangdong	0.99	0.98	0.99	0.96	0.99	1.00	1.00	1.00	1.02	0.99	1.01	1.00	1.00	0.99
Guangxi	0.95	0.99	1.02	0.98	1.01	1.01	0.98	1.04	0.96	0.99	0.99	0.99	1.01	0.99
Hainan	0.84	0.99	0.92	0.98	0.99	1.01	1.01	0.98	1.04	0.99	1.00	0.99	1.00	1.03
Chongqing	0.99	0.95	1.01	1.03	0.97	1.00	0.96	0.97	1.01	0.96	0.99	0.99	1.02	1.00
Sichuan	0.90	0.96	0.95	0.96	1.01	1.02	0.99	1.05	0.97	1.00	0.95	0.99	1.01	0.99
Guizhou	0.95	0.97	0.96	0.99	0.98	0.99	0.98	1.01	1.00	0.99	0.99	1.02	1.00	0.99
Yunnan	1.02	1.00	0.97	1.00	0.97	1.00	1.00	1.01	0.99	1.00	1.00	1.01	1.00	0.99
Shaanxi	0.98	0.96	0.96	0.97	0.99	1.00	1.00	1.03	1.00	1.00	1.03	1.00	0.98	1.00
Gansu	1.01	1.00	1.01	0.97	0.98	1.00	0.97	0.93	0.99	1.00	0.99	1.01	1.02	1.00
Qinghai	0.98	0.84	0.97	0.99	1.02	1.00	1.00	0.99	0.98	0.98	0.98	0.99	0.99	0.98
Ningxia	0.97	1.01	1.08	1.05	1.01	1.01	1.01	0.95	0.97	0.98	0.98	0.97	1.01	0.99
Xinjiang	0.97	1.00	1.00	1.00	0.98	0.99	1.01	0.98	1.01	0.98	0.99	1.00	1.02	0.99
Average in eastern area	0.96	0.98	0.97	0.97	0.99	0.99	1.00	0.97	1.00	0.98	0.99	1.01	1.00	1.00
Average in central area	0.96	0.96	0.98	0.97	0.99	0.98	1.01	0.96	0.99	0.98	0.99	1.00	1.01	0.99
Average in western area	0.89	0.89	0.91	0.91	0.91	0.92	0.91	0.91	0.91	0.91	0.91	0.92	0.92	0.91

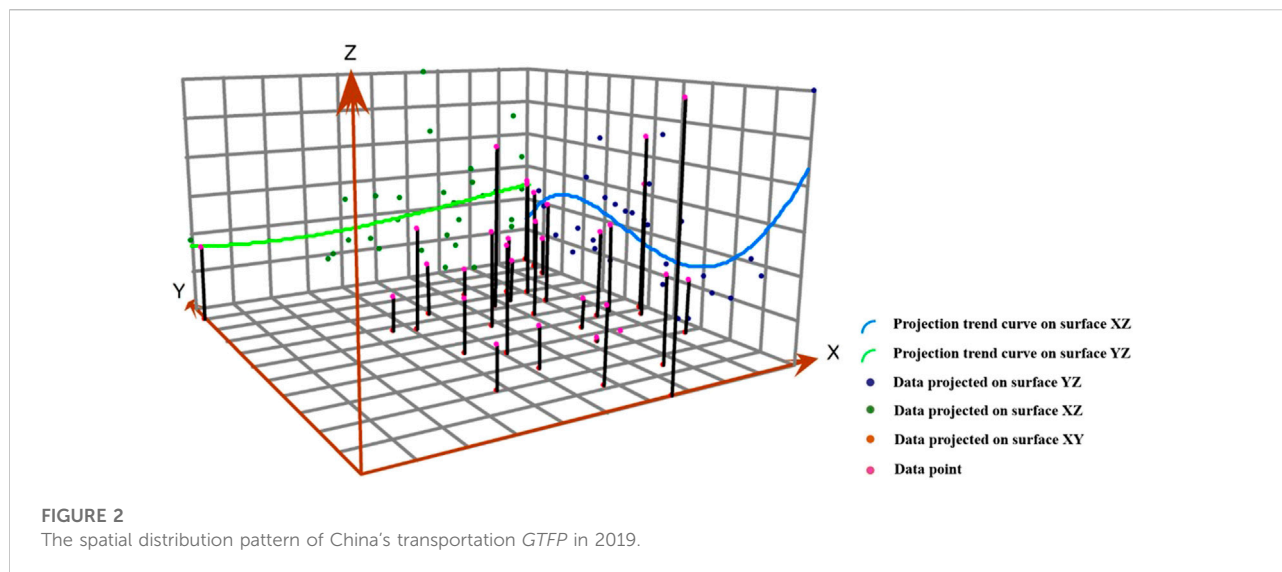
In Eq. 11, Q represents the spatial correlation matrix of the green total factor productivity of transportation in each province in China. The value of each indicator is expressed by the mean value of the corresponding indicators of each province from 2006 to 2019, and then the absolute value of the difference between provinces is used to construct a difference matrix.

In summary, this article will use the SNA methods to analyze the integral structural characteristics, individual structural characteristics, and clustering characteristics of China's transportation *GTFP* from two dimensions of time and space. Adopt the QAP association and regression analysis

to study its influencing factors. Therefore, the research framework of this article is shown in Figure 1.

4 Empirical analysis and results discussion

This study selected the data of 30 provinces (autonomous regions and municipalities directly under the central government) in China from 2006 to 2019 as the research object. Due to the lack of data for Tibet, Hong Kong, Macau, and Taiwan, this article would not analyze them. At the same



time, due to the strong special-purpose type of pipeline transportation among the five major transportation modes, and the difficulty of obtaining air transportation data, this article only studied the *GTFP* of railways, highways, and waterways. The data of relevant indicators come from the “Statistical Yearbook” and “China Energy Statistical Yearbook” of each province.

4.1 Spatial-temporal analysis of *GTFP* in transportation

This study is based on the DEA-Malmquist model and used Max DEA7.0 software to process the transportation input and output data of 30 provinces in China, and calculated the transportation *GTFP* index of 30 provinces in each year, as shown in Table 2¹.

It can be seen from Table 2 that the transportation *GTFP* of each area has improved during the sample investigation period. What's more, the average for eastern rose from 0.96 in 2006 to 1.00 in 2019, for the center rose from 0.96 to 0.99, for western rose from 0.89 to 0.91. There are significant differences in the traffic and transportation *GTFP* between the three major areas of the east, middle, and west².

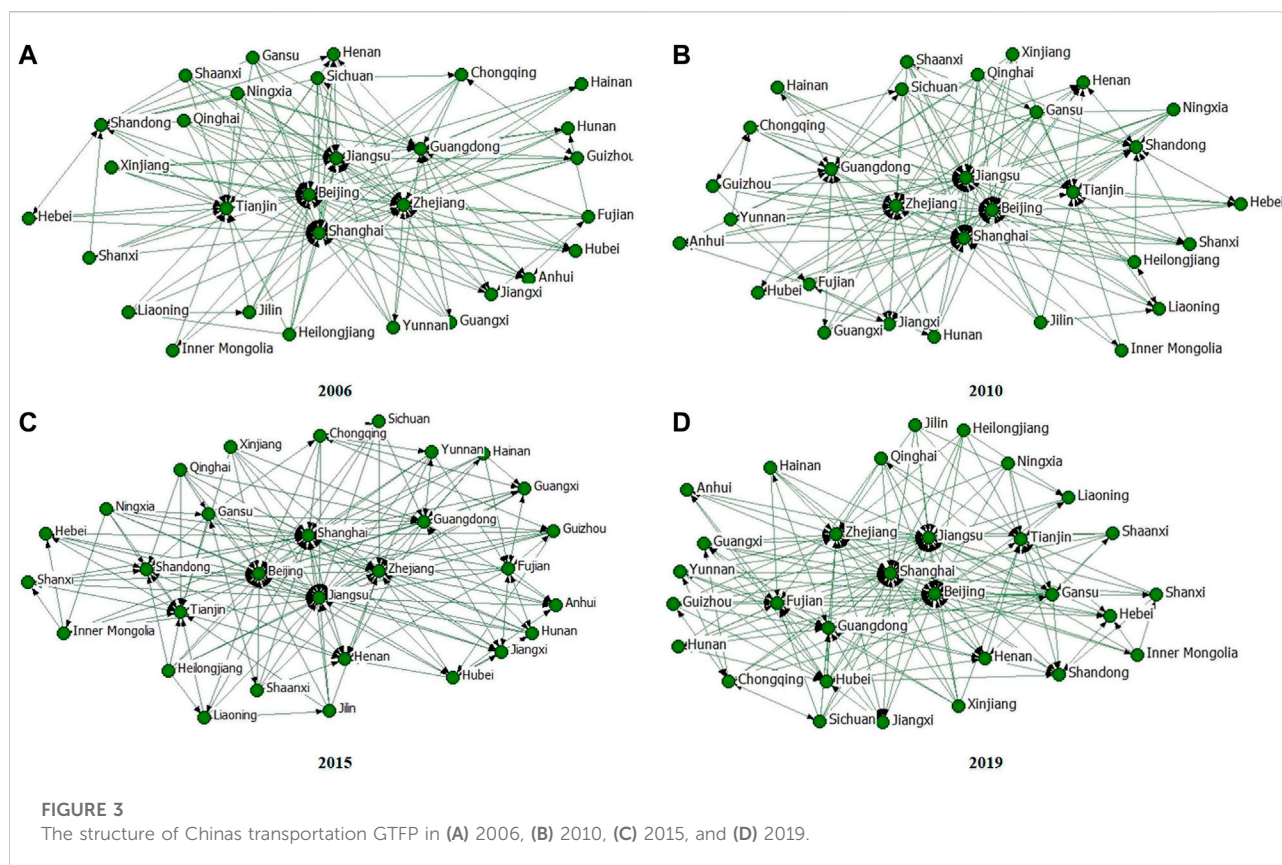
In order to further understand the provincial and regional differences in China's transportation *GTFP*, this study took 2019 as an example and used ArcGIS 10.7 to visually describe the spatial distribution trend of *GTFP* in China's transportation, as shown in Figure 2. The Z-axis represents the value of the green total productivity of transportation in each province, the X-axis represents the east-west direction, and the Y-axis represents the north-south direction. Figure 2 shows that China's transportation *GTFP* has significant regional differences in space. Specifically, in the east-west direction, the fitted curve shows a trend of “high in the east and low in the west”, indicating that the overall transportation *GTFP* in the eastern region is higher than that in the western region; In the north-south direction, the fitted curve presents an “S”-shaped curve of “the northern bulge and the southern depression”, indicating that the overall transportation *GTFP* in the northern region is higher than that in the southern region. However, the transportation *GTFP* in some provinces in the southern region, such as Hainan Province, is higher than that of the surrounding areas. This is because of its special geographical location, the area's water transportation has been vigorously developed, so the level of carbon emissions is relatively small compared to other regions, thereby increasing the level of *GTFP*.

4.2 Structural characteristics analysis of the *GTFP* network

The associated network of China's transportation *GTFP* is constructed through the revised gravity model. Based on Netdraw of Ucinet, the network structure diagram between Chinese provinces in 2006–2019 is drawn, as shown in Figure 3. As can be seen from the figures, there is an obvious

¹ Because the Malmquist productivity index measures the *GTFP* changes in adjacent years, the calculation is performed on data from 2005 to 2019, while the calculation results start from 2006.

² Eastern area: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; Central area: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan; Western area: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.



spatial correlation between the *GTFP* of the provinces during the inspection period. What's more, the spatial correlation has broken through the traditional geographic spatial constraints and is no longer limited to the correlation between neighboring provinces, but it is spatially associated with its non-neighboring provinces. The overall network presents a more complex, multi-threaded spatial network relationship. Therefore, in order to effectively achieve the overall improvement of China's transportation *GTFP*, it is necessary to implement regional cooperation methods from an overall perspective.

In the meanwhile, it can be seen from the figures that the number of centrally located provinces has increased. Overall, the centrally located provinces mainly include Beijing, Shanghai, Tianjin, Jiangsu, Zhejiang, and Guangdong. These regions have a strong correlation with other provinces. This is because these areas have better basic conditions such as transportation capital, economic development, and talents, as well as strong innovation capabilities. These factors are conducive to the effective use of transportation industry resources. In addition, because the transportation infrastructure in these areas is relatively complete, it is more conducive to exchanges and cooperation in the transportation industry. Nevertheless, the marginal cities in the network have a low degree of relevance to other provinces, and these provinces are the most central and

western. This is inseparable from the disadvantages of the remote location, backward economic development, and scarce human resources.

4.2.1 The integral characteristics of the transportation *GTFP* network

For the analysis of the integral network structure characteristics, four indicators are selected: network density, network association degree, network grade, and network efficiency. According to Eqs 3–6, the integral structural feature index levels of China's transportation *GTFP* network in each year from 2006 to 2019 are calculated, as shown in the following Table 3.

4.2.1.1 Network density

Network density reflects the closeness of the connections between nodes in a network, and it is related to the number of connections between nodes in the network. According to the calculation results in Table 3, the evolution trend of the network density and the number of network associations of China's transportation *GTFP* spatial correlation network from 2006 to 2019 is drawn, as shown in Figure 4.

From Figure 4, it can be found that the total number of network associations of China's transportation *GTFP* network

TABLE 3 The characteristics of the integral network structure.

Year	Network density	Network association degree	Network grade	Network efficiency	Number of network associations
2006	0.197701	1	0.4341	0.7365	172
2007	0.198851	1	0.4307	0.7365	173
2008	0.202299	1	0.432	0.7315	176
2009	0.210345	1	0.4361	0.7167	183
2010	0.213793	1	0.4361	0.7143	186
2011	0.216092	1	0.3	0.7143	188
2012	0.21954	1	0.3	0.7118	191
2013	0.225287	1	0.4337	0.697	196
2014	0.231034	1	0.3	0.6872	201
2015	0.229885	1	0.3482	0.6921	200
2016	0.228736	1	0.2419	0.6921	199
2017	0.226437	1	0.2419	0.697	197
2018	0.21954	1	0.2424	0.702	191
2019	0.22529	1	0.2424	0.6897	196

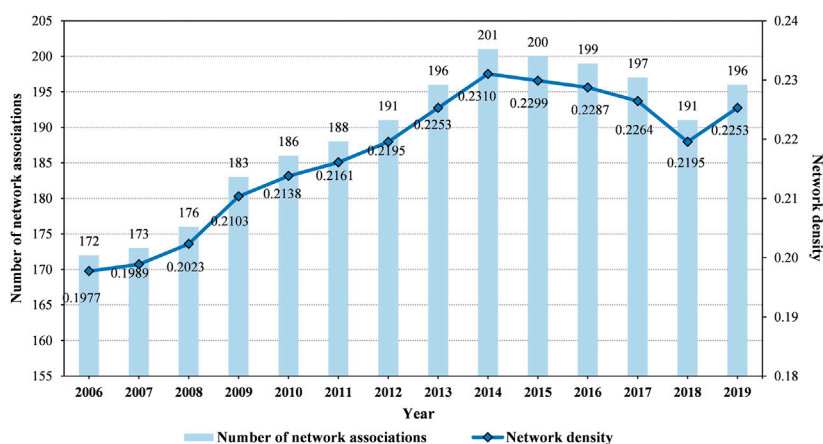


FIGURE 4 The density and the number of network associations of the transportation *GTFP* network.

first rose and then decreased during the study period. The number of network associations in 2006 was 172, then it rises slowly, reaching a peak in 2014 with a value of 201. Over the next few years, it declined slowly, dropping to 196 in 2019. Correspondingly, the network density also shows a trend of first rising and then falling, rising from 0.1977 in 2006 to 0.2310 in 2014, and slowly falling to 0.2253 in 2019.

The network density has shown a downward trend after 2014, and this period is China’s 13th Five-Year Plan period. First of all, from the perspective of the country’s overall development, during the 13th Five-Year Plan period, China is in a period of structural adjustment and a shift in growth rate. Macroeconomic

growth has entered a “new normal”, and the economic growth rate has changed from high-speed growth in the past to medium-to-high speed growth, the downward pressure on the economy is greater. Which may affect the flow of resources and people. In addition, there was very severe haze weather in 2013, which seriously endangered people’s health. Therefore, the control of haze at the two sessions in 2014 has also become a hot topic of discussion and attention. Since then, various places have introduced vehicle restrictions and increased pollution control efforts. All of these have a certain hindering effect on the connection of the development of transportation *GTFP* in various provinces in China.

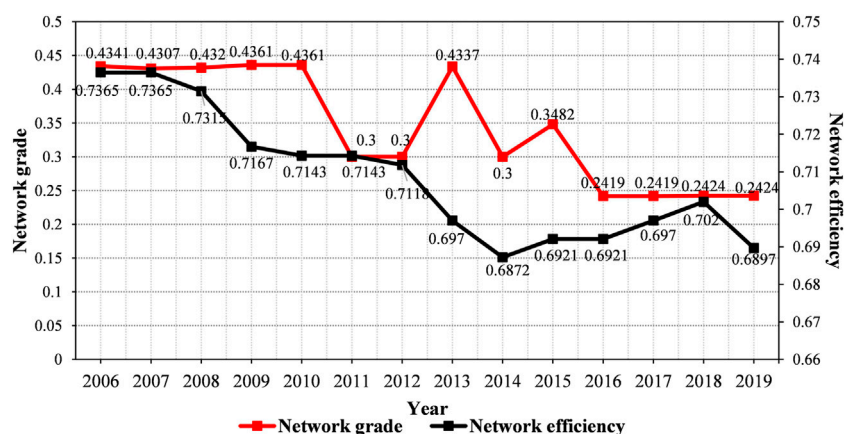


FIGURE 5

The network grade and efficiency of the transportation *GTFP* network.

On the whole, the network density has significantly improved compared to 2006 and 2019. However, the number of network associations in the network is 196 in 2019, which is far from the maximum number of associations of 870 (30×29), indicating that its spatial association is not high enough, and there is still a lot of room for improvement. Therefore, it is necessary to further deepen the communication and cooperation in the transportation industry between various regions, strengthen the spatial optimization of the resource elements of the transportation industry, and continuously improve the green total factor productivity of transportation. It is worth noting that as the network density increases, the number of redundant relationships in the overall network may increase. Once the capacity of the network is exceeded, it will increase the cost of the flow of transportation elements between various regions, thereby reducing the cost of resource usage efficiency. Therefore, while advancing the coordination and cooperation between various regions, the network density must be controlled within an ideal level to achieve the best spatial optimization configuration effect.

4.2.1.2 Network relevance

The network relevance is measured from different aspects through the network association degree, the network grade, and the network efficiency, which reflects the robustness level of the integral network.

It can be seen from Table 3 that during the study period, all the network association degree value of the network of China's transportation *GTFP* is 1, indicating that its spatial network structure has good connectivity and robustness, and all provinces are in the network of *GTFP* in China's transportation. There are no isolated provinces separated from the network, and the spatial spillover effect of the network is obvious.

Figure 5 shows that the network grade and network efficiency values of the transportation *GTFP* experienced a downward trend. Regarding the network grade, the investigation period can be divided into three stages. The first stage is from 2006 to 2010, and the network grade is stable at about 0.43. 2011–2015 is the second stage, and the network grade shows a trend of volatility and decline. 2016–2019 is the third stage, and the network grade is stable at around 0.24. Compared with the network grade of 0.4341 in 2006, it has dropped to 0.2424 in 2019, and the network grade has significantly reduced. This result shows that the previous relatively strict spatial correlation hierarchical structure of *GTFP* in transportation has been further alleviated, and the interconnection and mutual influence between various regions have gradually increased. From the perspective of national economic development, this may be due to the proposed development strategy of precise poverty alleviation in order to achieve the goal of building a moderately prosperous society in all respects. As a result, remote areas have been developed, and the gap between the rich and the poor has been narrowing, which in turn is conducive to the reduction of the level of the network. On the other hand, from the perspective of the development of the transportation industry, the provision of supply-side policies has led to the continuous development of integrated transportation. The construction of integrated transportation networks has increased the communication between regions and gradually broke the strict hierarchical structure.

The network efficiency has shown a trend of declining year by year, from 0.7365 in 2006 to 0.6897 in 2019, indicating that the redundancy relationship in the spatial network is gradually decreasing, the two-way spillover relationship is increasing, and the stability of the spatial network is improved. The decrease in network efficiency may be due to the strengthening of communication between various regions in

TABLE 4 The centrality analysis of the *GTFP* in Transportation.

Province	Point centrality		Betweenness centrality			Closeness centrality			Eigenvector centrality		
	Out-degree	In-degree	Degree	Order	Betweenness	Order	In-closeness	Out-closeness	Order	Eigenvector	Order
Beijing	7	24	24	3	117.664	3	82.857	14.721	3	0.285	3
Tianjin	3	12	12	9	4.983	16	60.417	13.488	5	0.145	16
Hebei	5	5	7	21	9.511	15	52.727	14.573	10	0.124	24
Shanxi	5	2	6	23	1.152	19	46.774	14.573	14	0.108	28
Inner Mongolia	5	1	5	29	0.619	21	46.032	14.573	16	0.095	30
Liaoning	4	3	6	22	0.0619	22	47.541	14.5	13	0.106	29
Jilin	6	0	6	25	0	26	3.333	17.059	28	0.117	25
Heilongjiang	6	0	6	27	0	27	3.333	17.059	27	0.117	26
Shanghai	6	27	27	1	86.507	5	93.548	15.426	1	0.345	1
Jiangsu	5	26	26	2	79.697	7	90.625	15.344	2	0.330	2
Zhejiang	4	18	19	4	20.569	13	70.732	15.104	4	0.260	4
Anhui	3	5	5	30	0.518	23	52.727	13.81	9	0.110	27
Fujian	8	11	15	5	77.86	9	50	16.763	10	0.205	8
Jiangxi	7	6	7	17	156.002	1	53.704	16.667	8	0.151	14
Shandong	5	9	9	11	18.145	14	59.184	14.573	6	0.158	13
Henan	7	7	10	10	39.099	11	56.863	15.847	7	0.185	9
Hubei	11	7	15	6	40.454	10	46.032	17.059	15	0.247	5
Hunan	7	3	7	16	2.623	18	36.25	16.667	17	0.151	15
Guangdong	10	10	14	7	152.459	2	49.153	17.47	12	0.224	6
Guangxi	7	3	8	12	3.902	17	35.366	16.667	18	0.162	10
Hainan	6	1	6	28	0.292	24	33.333	16.477	21	0.131	21
Chongqing	8	4	8	13	110.057	4	29.293	17.683	22	0.144	17
Sichuan	7	1	7	18	0.91	20	22.835	17.47	24	0.142	19
Guizhou	8	3	8	14	78.269	8	35.366	17.683	19	0.162	11
Yunnan	8	2	8	15	37.736	12	34.118	17.683	20	0.162	12
Shaanxi	6	1	6	24	0.143	25	19.463	17.059	25	0.129	22
Gansu	12	4	13	8	84.212	6	23.967	18.354	23	0.218	7
Qinghai	7	1	7	20	0	28	19.463	17.47	26	0.142	20
Ningxia	6	0	6	26	0	29	3.333	20.423	29	0.126	23
Xinjiang	7	0	7	19	0	30	3.333	19.728	30	0.143	18
Average in eastern area	5.73	13.27	15	-	51.61	-	62.74	15.31	-	0.21	-
Average in central area	6.5	3.75	7.75	-	29.98	-	37.38	16.09	-	0.15	-
Average in western area	7.36	1.82	7.55	-	28.71	-	24.78	17.71	-	0.15	-
National average	6.53	6.53	10.33	-	37.45	-	42.06	16.40	-	0.17	-

the information age, so that the two-way overflow in the network has increased; at the same time, the increase in the effective utilization of resources will also reduce inefficient connections such as overlapping and crossover, making the redundancy relationship in the network is reduced. However, the network efficiency in 2019 is 0.6897, which is still at a relatively high level, indicating that there are still more redundant relationships in the

spatial association network, and the network structure needs to be further improved.

4.2.2 The individual characteristics of the transportation *GTFP* network

Network density and network relevance reveal the integral structural characteristics of China's transportation *GTFP* spatial

network. While the network centrality analysis would analyze the status and role of each node in the network from an individual perspective.

Taking 2019 as an example, based on Eqs 7–10, the point centrality, betweenness centrality, closeness centrality, and eigenvector centrality of China's transportation *GTFP* network are respectively measured. The results are shown in Table 4. (The division of the three major areas is the same as above).

4.2.2.1 Point centrality

The point centrality is used to determine whether each province is at the center of the spatial association network of *GTFP* in China's transportation.

In 2019, the average value of the point centrality of the 30 provinces in China is 10.33. Above-average are Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, Hubei, Guangdong, and Gansu, and all of them belong to the eastern region except Hubei and Gansu. It means that these regions have more relationships with other provinces in the spatial association network. Among them, Shanghai has the highest degree of point centrality of 27, indicating that Shanghai is at the center of China's green total factor productivity spatial network of transportation. This is because Shanghai has a relatively complete transportation network, which is conducive to the flow of transportation production factors with other cities. At the same time, this is inseparable from its geographical location, economic development level, abundant transportation capital, and human resources; In addition, from the mean value of the point centrality of the three major regions, it can be seen that the highest mean point degree centrality in the eastern region is 15. While the central and western regions are 7.75 and 7.55, which are relatively small. This means that cities in the central and western regions have poor relevance to other cities, which is related to their relatively backward economic level and remote geographic location.

Due to the certain differences in the links between provinces, this leads to the directional nature of the spatial network. The in-degree indicates that the province is affected by other provinces, and the out-degree indicates the influence of the province on other provinces. If the in-degree is greater than the out-degree, it means that the province has a net beneficial effect; otherwise, it shows a net spillover effect. According to Table 4, the top three provinces with the highest in-degree are Shanghai, Jiangsu, and Beijing, and the in-degree of these three provinces are much higher than the out-degree, showing a net beneficial effect. This indicates that they are more dependent on other provinces. In addition, the average in-degree and out-degree of the 30 provinces in China are both 6.53, indicating that there is a better balance on the whole. However, from the perspective of the three major regions, the in-degree of the eastern region (13.27) is greater than the out-degree (5.73), the in-degree of the central region (3.75) is less than the out-degree (6.5), and the in-degree of the western region (1.82) is less than the out-degree (7.36),

which indicates that the balance of the three major regions is poor. It shows that the growth of transportation *GTFP* in the eastern region is highly dependent on other regions and requires other regions to continuously send resources to it, while the central and western regions have a strong spillover effect of resources. This unbalanced development of transportation *GTFP* is not conducive to social and economic development and needs to be taken seriously.

4.2.2.2 Betweenness centrality

The betweenness centrality indicator is used to measure the ability of provinces to dominate and control resources in China's transportation *GTFP* spatial association network.

According to Table 4, it can be seen that the mean value of the betweenness centrality of 30 provinces in China is 28.71 in 2019. The above-average provinces are Beijing, Shanghai, Jiangsu, Fujian, Jiangxi, Henan, Hubei, Guangdong, Chongqing, Guizhou, Yunnan, and Gansu, indicating that these provinces have played a good role as "intermediary" and "bridge" in the spatial association network of China's transportation *GTFP*. They are the key network nodes that facilitate the linking of other provinces. Among them, the betweenness centrality of Jiangxi and Guangdong are 156.002 and 152.459 respectively, ranking the top two in the country and much higher than other provinces, indicating that these two provinces have a strong ability to control close exchanges between other provinces. They are the important fulcrum for promoting *GTFP* growth in China's transportation. However, the betweenness centrality of Jilin, Heilongjiang, Qinghai, Ningxia, and Xinjiang is 0. This is because these provinces are located in remote areas and cannot control the links between other provinces in the network.

4.2.2.3 Closeness centrality

The closeness centrality is used to determine how difficult it is for each province to have an association relationship with other provinces in the spatial association network of China's transportation *GTFP*.

As can be seen from Table 4, in 2019, the mean value of in-closeness centrality in 30 provinces in China is 42.06, the mean value of in-closeness centrality in the eastern region is 62.74, the mean value of in-closeness centrality in the central region is 37.38, and the mean value of in-closeness centrality in the western region is 24.78. It shows that the eastern region can quickly connect with other provinces in the inward flow network of *GTFP* growth in China's transportation, and it is a key actor in the directed "inflow" network. However, the central and western regions are not easily connected with other provinces, which may be due to their poor network accessibility.

It can be seen from Figure 6 that the provinces with the lowest in-closeness centrality are Jilin, Heilongjiang, Ningxia, and Xinjiang, all of which have a value of 3.333, much lower than other provinces. This is because these provinces are remote and marginal in the space association network of China's

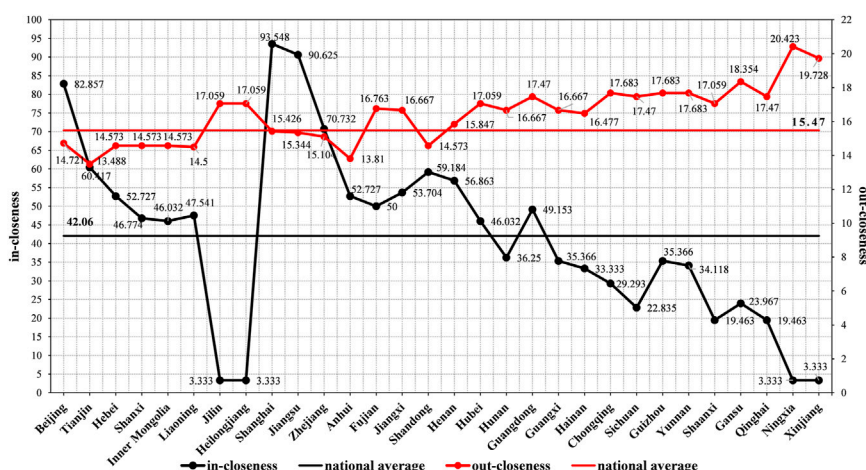


FIGURE 6 The in-closeness and out-closeness centrality of the transportation *GTFP* network.

transportation *GTFP*. As a result, it is more difficult for them to quickly connect with other provinces, and they are less driven by other provinces.

The average value of out-closeness centrality in 30 provinces in China is 16.40, and the average value of out-closeness centrality in eastern, central, and western regions is 15.31, 16.09, and 17.71 respectively. Figure 6 shows that the degree of out-closeness centrality of each province is relatively small, indicating that for each province, the difficulty of connecting with other provinces in the outward flow network of China's transportation *GTFP* growth is similar. The intensity of the radiation effect of each province on other provinces is also similar. Nevertheless, Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, and other cities with a high degree of point centrality and betweenness centrality, should assume the role of driving the development of other provinces. But in fact, their radiation effect is not strong. This is detrimental to the development of the network. Hence, in order to promote the growth of China's transportation *GTFP*, it is necessary to improve the transportation network of these provinces, strengthen their communication and cooperation with other provinces' resources and population, and enhance their radiation effect, so as to better play their driving force effect for other provinces.

4.2.2.4 Eigenvector centrality

The eigenvector centrality is used to measure the importance of each province in the spatial association network of China's transportation *GTFP* so that the core players in the network can be found.

According to Table 4, it can be seen that the mean value of the eigenvector centrality of 30 provinces in China is 0.17 in 2019. The above-average provinces are Beijing, Shanghai, Jiangsu,

Zhejiang, Fujian, Henan, Hubei, Guangdong, and Gansu, indicating that these provinces have a high influence on the spatial association network of China's transportation *GTFP*. Different from the results of point centrality, Tianjin's point centrality is higher than the national average, while the eigenvector centrality is lower than the national average, and Henan is the opposite. It means that although a node with high point degree centrality has many connection points, its eigenvector centrality is not necessarily high, which may be because the connected nodes are not important; Conversely, if a node has few but important connections, its eigenvector centrality can also be high. Therefore, although Tianjin has high connectivity with other regions, the importance of the regions it connects to is low; However, as China's transportation hub, Henan has a strong correlation with many important regions, so its influence on the network is also high.

In addition, from the mean value of the eigenvector centrality of the three major regions, it can be seen that the mean value of the eigenvector centrality in the eastern region is the highest at 0.21 and that in the central and western regions is 0.15, which is relatively small. This shows that the central and western regions have a weak influence on the transportation *GTFP* network. This is mainly because the economic development level of these regions is relatively backward, and the transportation infrastructure network is not perfect.

4.2.3 Spatial aggregation analysis of *GTFP* in transportation

Block model analysis mainly determines the role and position of each block in the network through block clustering. This study used the block model analysis to cluster and segment the spatial network of the transportation *GTFP* in 30 provinces in China. Drawing lessons from the evaluation method of Wasserman and



Faust about the network block to analyze the correlation characteristics within and between the plates (Liu and Song, 2018).

Based on the closeness and directness of the spatial association of *GTFP* in inter-provincial transportation, the block model analysis is used for spatial aggregation. Using the CONCOR method, the maximum segmentation density is selected as 2, and the convergence criterion is 0.2. The 30 provinces are divided into 4 blocks in 2019, and the results of the division are shown in Figure 7. From the results of spatial aggregation, block I has 4 provinces, namely Beijing, Tianjin, Jiangsu, and Shanghai; Block II has 3 provinces, namely Guangdong, Zhejiang, Fujian, mainly southeast coastal cities; Block III has 11 provinces, namely Jilin and Inner Mongolia, Hebei, Heilongjiang, Shanxi, Liaoning, Ningxia, Shandong, Shaanxi, Qinghai, Chongqing; Block IV has 12 provinces, namely Hubei, Guangxi, Hunan, Henan, Sichuan, Guizhou, Yunnan, Anhui, Gansu, Hainan, Jiangxi, Xinjiang.

In order to see the spatial distribution of each block more intuitively, based on ArcGIS 10.7, a block distribution map of China's transportation *GTFP* spatial association network was made, as shown in Figure 8. As can be seen from Figure 8, block I and block II are located in the eastern coastal areas of China, with a relatively high level of socio-economic development; Block III is

mainly in the northern part of China, and block IV is mainly in the southern region of China.

In order to better study the relationship of the *GTFP* in transportation among the blocks, the block density matrix of each block is calculated, as shown in the following Table 5. At the same time, according to the data calculated in the previous article, the overall network density of the spatial association network of China's transportation *GTFP* in 2019 is 0.22529. Therefore, if the network density of a certain block is greater than 0.22529, it means that the transportation *GTFP* is concentrated in that block. In order to observe the relationship among various blocks more clearly, the density matrix of the blocks can be converted into an image matrix. The specific method is to compare the network density of each block with the overall network density. If the value in the density matrix is greater than the overall network density, the image matrix is set to 1, otherwise, it is 0. The corresponding image matrix obtained by calculation is shown in the following Table 5.

It can be analyzed from the image matrix that block I not only has internal associations, but also receives spillovers from blocks II, III, and IV. This shows that the four regions of Beijing, Tianjin, Shanghai, and Jiangsu, are highly dependent on the supply of resources in other provinces. They need the input of resources from other provinces to form an agglomeration effect. These four regions are the areas with a high level of economic development

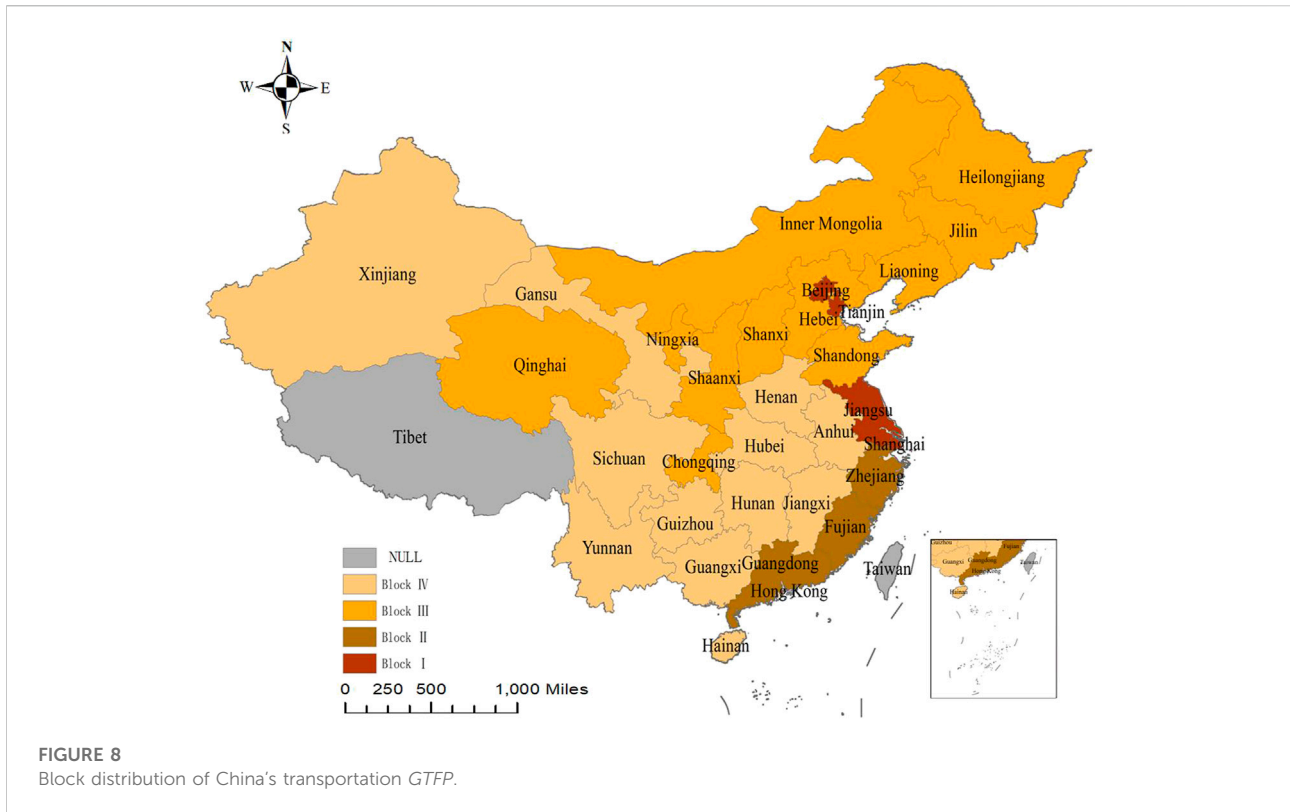


FIGURE 8
Block distribution of China's transportation *GTFP*.

TABLE 5 The block density matrix and the image matrix.

Block NO.	Density matrix				Image matrix			
	Block I	Block II	Block III	Block IV	Block I	Block II	Block III	Block IV
Block I	0.333	0.083	0.205	0.146	1	0	0	0
Block II	0.500	0.000	0.030	0.417	1	0	0	1
Block III	0.932	0.182	0.064	0.068	1	0	0	0
Block IV	0.792	0.889	0.068	0.083	1	1	0	0

and scientific and technological strength in China, and they are also the gathering places of China's resources. Therefore, this result is in line with China's reality. It should be noted that block I is only related to its internal development, and does not have spillover effects on the other three blocks. This may be because the transportation *GTFP* in these areas is still in a period of rapid development and requires a lot of resources for it. Therefore, there is no spillover effect in other provinces.

In addition, there is a two-way relationship of sending and receiving between block II and block IV, indicating that the interaction between these two blocks is better. This is because the three provinces of Guangdong, Zhejiang, and Fujian in block II are located in the southeast coastal area of China. They have a superior geographical locations, a developed economy,

and a high technological level. The development of transportation *GTFP* in block II is inseparable from the resource support of its adjacent plate, block IV. In addition, many ports are located in block II. The interactive development between block II and block IV promotes the connection of China's international and domestic trade, and at the same time promotes the flow of resources and population. This reinforces the synergies in the development of transportation *GTFP* and promotes the growth of transportation *GTFP*. As for block III, it only has a spillover effect on block I and is not affected by the spillover effects of other blocks. This means that block III has a poor correlation with other blocks, and the transportation *GTFP* development in the provinces of this block has been neglected to a certain extent.

TABLE 6 The results of QAP association analysis.

Variable	Obs value	Significance	Average	Std dev	Min	Max	Prop > = 0	Prop < = 0
R	0.175	0.000	0.000	0.038	-0.126	0.137	0.000	1.000
D	-0.277	0.000	-0.000	0.067	-0.192	0.252	1.000	0.000
PG	0.479	0.000	0.000	0.073	-0.160	0.322	0.000	1.000
IS	0.266	0.004	0.000	0.081	-0.141	0.316	0.004	0.996
TT	0.172	0.021	-0.001	0.069	-0.144	0.300	0.021	0.979
TI	-0.016	0.412	0.000	0.058	-0.157	0.260	0.588	0.412
TL	0.214	0.010	-0.002	0.078	-0.152	0.351	0.010	0.990
ER	0.059	0.184	0.001	0.075	-0.150	0.275	0.184	0.816

From the clustering characteristics of the spatial association network of China's transportation *GTFP*, it can be seen that the interaction among various blocks is relatively poor. Thereby, to better promote the improvement of the *GTFP* in China's transportation, the connections among various blocks should be strengthened.

4.3 QAP analysis of spatial association influencing factors of the transportation *GTFP*

Based on the foregoing discussion, to study the factors affecting the formation of the spatial association network structure of China's transportation *GTFP*, eight indicator factors were selected, including adjacency relation (*R*), geographical distance (*D*), per capita GDP (*PG*), industrial structure (*IS*), comprehensive transportation turnover (*TT*), the investment in the transportation investment (*TI*), the technological innovation (*TL*), the Environmental regulation (*ER*). Afterward, by constructing the difference matrix and using Ucinet software, QAP association and regression analysis are performed.

4.3.1 QAP association analysis

Table 6 shows the association analysis results after 5,000 random replacements. Among them, the correlation coefficients of the six explanatory variables of *R*, *D*, *PG*, *IS*, *TT*, and *TL* are 0.175, -0.277, 0.479, 0.266, 0.172, and 0.214 respectively, and they all pass the 5% significance level test. It shows that these factors will affect the spatial association network structure of *GTFP* in transportation. However, the association coefficients of the two explanatory variables of *TI* and *ER* are -0.016 and 0.059 respectively, but their significance level is higher than 5%, indicating that the effect of provincial differences is not obvious. This may be because transportation investment is mainly used to build transportation infrastructure, while transportation infrastructure construction has a relatively

long construction period and payback period. Therefore, the difference in transportation investment in a short period will not have a significant effect on the spatial association among provinces. The difference in environmental regulations may be since China's transportation industry is currently more dependent on energy consumption, coupled with the fact that the transportation industry's environmental regulations are not strong, and the differences in environmental regulations between provinces are relatively small, thereby weakening the effect of its influence on the spatial relationship of *GTFP* in China's transportation.

4.3.2 QAP regression analysis

In order to further quantify the effect of the influence matrix of these eight factors on the transportation *GTFP*, and to better deal with multicollinearity, a QAP regression was conducted using UCINET software. After 5,000 times of random replacement, the regression analysis results obtained are shown in Table 7.

Table 7 shows that the standardized regression coefficients of *R*, *PG*, and *TL* are 0.137, 0.562, and 0.103 respectively, and all passed the 1% significance level test. It means that these three factors can enhance the spatial relationship of *GTFP* in inter-provincial transportation. For provinces with large differences in the level of economic development and technological innovation, on the one hand, due to the "siphon effect", the developed regions have a stronger attraction to resources and talents, thereby enhancing their relationship with other cities. On the other hand, in order to improve the development level of the region, the poorly developed regions have continuously strengthened exchanges and cooperation with developed regions, thereby enhancing the spatial relationship with other provinces.

The standardized regression coefficients of *D* and *IS* between provinces are -0.182 and -0.109, and both pass the 5% significance level test. It shows that the smaller the geographical distance between provinces and the closer the industrial structure, the more conducive to the spatial

TABLE 7 The results of QAP regression analysis.

Variable	Un-stdized coefficient	Stdized coefficient	Significance	Proportion as large	Proportion as small
R	0.160345	0.137	0.004	0.004	0.996
D	-0.000091	-0.182	0.000	1.000	0.000
PG	0.118530	0.562	0.000	0.000	1.000
IS	-0.037509	-0.109	0.012	0.989	0.012
TT	-0.000005	-0.045	0.109	0.892	0.109
TI	-0.000017	-0.020	0.248	0.752	0.248
TL	0.000001	0.103	0.008	0.008	0.992
ER	0.000000	0.027	0.196	0.196	0.804

Note: $R^2 = 0.331$, $R^2 = 0.325$ after adjustment, and the significance level are 0.000.

association of the transportation *GTFP* between provinces. This is because the long distance will hinder the communication and contact between regions; while the economic development priorities of regions with large differences in industrial structure are different, and the gap in the scope of business operations is large so that there is less contact between each other. However, the standardized regression coefficients of the difference in *TT*, *TI*, and *ER* are not significant at the level of 5%. It shows that these three factors have a weak effect on the spatial association of *GTFP* in transportation. What's more, it is worth noting that the largest standardized regression coefficient is the difference in the level of per capita GDP, which is 0.562, indicating that the level of regional social and economic development is the most important factor affecting the spatial association of *GTFP* in transportation.

5 Conclusion, policy implications, and limitations

5.1 Conclusion

In this study, the transportation *GTFP* of 30 provinces in China from 2006 to 2019 has been measured based on the DEA-Malmquist model, and the modified gravity model has been used to construct the spatial correlation matrix of the transportation *GTFP*. Then, the SNA methods have been employed to conduct an in-depth analysis of the structural characteristics and influencing factors of the *GTFP* spatial association network in China's transportation provinces. The following conclusions can be drawn from the results.

1) The transportation *GTFP* of each area has improved during the sample investigation period and there are significant differences in the traffic and transportation *GTFP* between the three major areas of the east, middle, and west. In 2019, in the east-west direction, the fitted curve shows a trend of

“high in the east and low in the west”. By contrast, in the north-south direction, the fitted curve presents an “S”-shaped curve of “the northern bulge and the southern depression”. Besides, it is worth noting that the *GTFP* of transportation in Hainan is higher than that of the surrounding areas. This is because of its special geographical location. The area's water transportation has been vigorously developed, so the level of carbon emissions is relatively small compared to other regions, thereby increasing the level of *GTFP*.

- 2) From the perspective of the characteristics of the integral network structure, the spatial association network of *GTFP* in China's transportation showed complexity during the sample investigation period. In the meanwhile, the continuous increase in network density indicates that the development of *GTFP* in transportation among regions is getting closer, but the overall spatial correlation strength level is not high and needs to be further strengthened. Both the network grade and network efficiency are presenting a downward trend, which shows that the “strictly hierarchical” spatial structure is gradually being broken, and the stability of the network has been improved.
- 3) From the perspective of the central feature of the network structure: 1) The point centrality of the eastern region is higher than the national average as well as that of the central and western regions, indicating that the eastern region is in a dominant position in the network. Among them, Shanghai has the highest degree of centrality of 27, implying that it is at the center of China's transportation *GTFP* spatial association network. 2) Jiangxi and Guangdong's betweenness centrality degrees rank among the top two in the country, and are much higher than that of other provinces. This indicates that these two provinces have a strong ability to control close exchanges among other provinces, and they have played a good role of “intermediary” and “bridge” in the *GTFP* spatial association network of China's transportation. While the

- betweenness centrality of remote areas such as Jilin, Heilongjiang, Qinghai, Ningxia, and Xinjiang is 0, they are in a passive position in the network. 3) From the perspective of closeness centrality rankings, the top five in the country are Shanghai, Jiangsu, Beijing, Zhejiang, and Tianjin, which play the role of central actors in the network; while the bottom five provinces in the country are Jilin and Heilongjiang, Qinghai, Ningxia, and Xinjiang, which play the role of marginal actors in the network. 4) The eigenvector centrality in the eastern region is higher than the national average, and both are higher than those in the central and western regions, indicating that the eastern region has a greater influence on the network. Among them, the eigenvector centrality of Shanghai, Jiangsu, and Beijing ranks among the top three in China, and is much higher than other provinces, indicating that these three provinces have a high influence on the transportation *GTFP* network.
- 4) The analysis result of the block model shows that block I includes four provinces of Beijing, Tianjin, Shanghai, and Jiangsu, with a relatively high level of social and economic development. This block not only has internal correlations, but also receives spillovers from blocks II, III, and IV. But it does not have a spillover effect on other blocks, which shows that provinces in this block are highly dependent on the resource supply of other provinces. The provinces in block II are Guangdong, Zhejiang, and Fujian, which are mainly located in the coastal areas of southeastern China. Block III is mainly in central and northern China, and block IV is mainly in central and southern China. Among them, there is a two-way relationship of sending and receiving between block II and block IV, indicating that the interaction between these two blocks is better. However, block III only has a spillover effect on block I, which means that the provinces in block III have abundant resources to provide support for the development of provinces in block I, but they have poor relevance to other blocks. This may imply that the development of *GTFP* of transportation in the provinces in this block has been neglected to a certain extent.
 - 5) According to the results of the QAP analysis, the adjacency relation, the difference in per capita GDP, and the difference in technological innovation have a significant positive impact on the spatial association of *GTFP* in China's transportation. Differences in the geographic distance and industrial structure between provinces have an inhibitory effect on spatial associations. However, the differences in comprehensive transportation turnover, transportation investment, and environmental regulations have no significant effect on the spatial association of *GTFP* in transportation. What is more, it is worth noting that the largest standardized regression coefficient is the difference in the level of per capita GDP, which is 0.562, indicating that the level of regional social and economic development is the most important factor affecting the spatial association of *GTFP* in transportation.

5.2 Policy recommendations

In order to further enhance the *GTFP* of China's transportation and promote the coordinated development of various provinces, the following policy recommendations are put forward.

- 1) When formulating relevant policies, the government should pay attention to the spatial connection of the transportation *GTFP* in various provinces. It is necessary to continuously improve the level of informatization to strengthen resource exchange and cooperation between provinces, optimize the allocation of resources from the perspective of overall spatial development, and create a regional coordinated development mechanism. This is conducive to improving the intensity of inter-provincial spatial correlation and the effective use of resources, thereby optimizing the overall pattern of *GTFP* in China's transportation.
- 2) Efforts should be devoted to narrowing the development gap between regions and improving the development level of remote areas, especially the bottom five provinces, in order to strengthen their connections with other provinces, thereby altering their marginalities and breaking the hierarchical structure of the network. focus on improving the technological innovation level of Shanghai, Jiangsu, Beijing, Zhejiang, Tianjin, and other provinces that are at the center of the network and have great influence, and improve their transportation infrastructure construction network to better play their driving effect on other provinces. In addition, because the central region acts as an "intermediary" and "bridge" in the transportation network, it is necessary to strengthen the construction of transportation infrastructure in this region to provide a solid guarantee for the development of China's transportation.
- 3) Improving the connection among the four major blocks and enhancing their interactive effect are of vital importance. On the one hand, it is necessary to continuously improve the *GTFP* of transportation in the provinces in block I in order to give full play to its radiant driving effect on other blocks. On the other hand, exchanges and cooperation between the other three blocks should be enhanced, so as to increase the overall strength of the network and promote the balanced and coordinated development of *GTFP* in China's regional transportation.
- 4) It is necessary to strengthen the construction of comprehensive transportation infrastructure and improve the level of inter-regional interconnection, which will reduce the cost of factor flow. Moreover, this is conducive to promoting coordinated development between regions and reducing the differences in the development of industrial structure between regions, so as to promote the overall improvement of green total factor productivity in China's transportation.

5.3 Limitations and prospects

This study has great research value for realizing the green and sustainable development of the transportation industry and ensuring the realization of the “carbon neutral” development goal. However, it should be pointed out that this study still has the following shortcomings. First, due to the limited accessibility, it was not possible to obtain relevant data at the city level, so we constructed the spatial association network of China’s transportation *GTFP* from a provincial perspective, which will lead to relatively rough research results. In the future, further data mining is needed to refine the research results and improve the application value of the research. Second, only nine types of energy consumption and carbon dioxide emissions were considered in the calculation of the transportation *GTFP*. The measurement results are somewhat one-sided. Therefore, the index system construction method needs to be further improved, so as to enhance the accuracy of relevant research results. Third, the network relationship of *GTFP* in transportation is affected by multiple factors. It is thus one-sided to investigate only the eight influencing factors such as the neighboring relationship between provinces, geographical distance between provinces, per capita GDP, industrial structure, comprehensive transportation turnover, transportation investment, technological innovation, and environmental regulations. Other factors such as topography, marketization level, etc. need to be discussed in detail in the future.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

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Author contributions

All authors contributed to the study’s conception and design. Material preparation, data collection, and analysis were performed by JS. The first draft of the manuscript was written by YW. QW supervised and reviewed the manuscript. All authors read and approved the final manuscript.

Funding

The Social Science Foundation of Shaanxi (No. 2020D028); the Philosophy and Social Sciences Major Theoretical and Practical Issues Research Program of Shaanxi (No. 2021ND0444), Shaanxi Provincial Postdoctoral Science Fund (No. 2018BSHERZZ125).

Conflict of interest

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