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THE SPATIAL ASSOCIATION NETWORK FUNCTION AND INFLUENCING FACTORS IN BOOSTING FOREST CARBON SINK EFFICIENCY：EVIDENCE FROM CHINA

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1. Abstract
Spatial association network is quite important for boost Forest Carbon Sink Efficiency (FCSE). In facing carbon peak and carbon neutrality target forest carbon sink plays a very important role. By measuring FCSE of Chinese provinces using the Super-SBM-DEA model and Social Network Analysis (SNA), the network characteristics and clustering characteristics were analysized. By combining the QAP model and the panel data regression model, the driving mechanism of the FCSE spatial association network and the contribution of the network to FCSE are revealed. The results have showed that the spatial correlation of FCSE in China has break through the limitation of geographical distance and have showed a prominent complex network characteristics and apparent core-periphery structure. Besides, the spatial clustering characteristics of FCSE in China is obvious, and the interaction relationships of elements mostly occur between different plates. In addition, geographic proximity and differences in water resources are the important natural factors which influencing the formation of the FCSE spatial association network. And the differences in economic level, forestry scale, and technology level are important socio-economic factors influencing the formation of the FCSE spatial association network. Thus, the increase of degree centrality, closeness centrality, and betweenness centrality are all contribute to FCSE significantly. Our study is a valuable attempt to apply SNA to FCSE research, which tells the importance of resource connections and spatial association network relations and this can refer to valuable suggestions for the government to develop appropriate carbon neutrality strategies at the carbon sink side.

2. Keywords: Carbon neutrality; Forest carbon sink efficiency; Spatial association network; Drive mechanism

3. Introduction

Excess carbon emissions from human activities have become an important challenge which threaten human survival and sustainable development (Karl and Trenberth, 2003; Galeotti et al., 2006; IPCC, 2018; Liu and Su, 2021). Since 2006, China has been the world's largest carbon emitter (Bai et al., 2020; Shen et al., 2021), which accounting for about 28% of global carbon emissions in 2019 (BP, 2020), and the successful achieving carbon reduction targets is not only a matter of its own sustainable development but also a matter of global environmental issues (Niu et al., 2020). Thus, China’s carbon reduction progress and action plans have become a common concern topic in the international community (Li et al., 2022).
There are two main approaches to reducing the concentration of CO_2 in the air. The first one is to reduce fossil energy consumption by developing new energy technologies from the carbon source side (Ha et al., 2021). And the second is from the carbon sink side by developing carbon sequestration technologies to absorb and fixation CO_2 in the air (Zhao et al., 2019). Since China is the world’s largest consumer of fossil energy, and the cost of shifting China's economic growth away from dependence on fossil fuels in the short term is enormous (Mallapaty, 2020), that it is necessary to focus on the carbon reduction role of carbon sink side (Li et al., 2023). The forest ecosystem is an essential system for achieving the goal of harmonious ecological and economic development and plays a vital role in CO_2 absorption and fixation. (Lin et al., 2019; Austin et al., 2020; Ke et al., 2023). According to relevant studies, the global forest ecosystem store about 80% of above-ground carbon stocks (Wang et al., 2022). Emphasizing the role of Forest Carbon Sink (FCS) in balancing the relationship between economic development, carbon reduction, and environmental protection is an essential step toward carbon neutrality in China (Zhao et al., 2023; He et al., 2023; Ge et al., 2023).

Earlier literature usually assessed FCS indicators in China based on national forest inventory datasets and remote sensing estimation methods (Ma et al., 2011; Zhou et al., 2013; Zhao et al., 2016; Zhang et al., 2016), and have found that there are significant spatial differences in the distribution of FCS in China (Liu et al., 2012). Consolidating and enhancing the carbon sink capacity of ecosystems became one of the ten action plans to reach the carbon peak in China after the "dual carbon" target was proposed (Liu et al., 2023). Analyzing the influencing factors of China's FCS from a socio-economic perspective and proposing reasonable FCS enhancement strategies have gradually become an important research direction in the literature at this stage (Cheng et al., 2021; Xu et al., 2022; Yin et al., 2022; He et al., 2023; Wu et al., 2023). Although the FCS indicator reflects the great value of forest ecosystems in carbon sequestration and emission reduction, it reflects more natural attributes. In contrast, forest carbon sink efficiency (FCSE) considers economic and environmental outputs in the analytical framework, reflecting both natural and socio-economic attributes. It is more scientific and reasonable to use FCSE as an evaluation criterion for forest carbon sink levels (Wei and Shen, 2022; Zhu et al., 2022).

Some recent literatures have referred to the FCSE in China from measurement efficiency and analysize influencing factors. About the efficiency measurement methods, the existing literature usually uses data envelopment analysis (DEA) and its various variant models to measure FCSE in China (Lin and Ge, 2019; Zhu et al., 2022; Zhu et al., 2022). The input indicators they chose usually include forest area, number of forestry employees, and investment in forestry fixed assets, while the output indicators are usually gross forestry product and forest carbon sink (Wang et al., 2022; Shu et al., 2022). And the results have showed there is a quite difference between areas. For example, Wei and Shen (2022) measured the FCSE of Chinese provinces using the SBM-DEA model and found that FCSE was high in Zhejiang, Fujian, Tianjin, and Shanghai but lacked efficiency in most other provinces. About the influencing factors, environmental and human activity factors can all influence FCSE. Wei and Shen (2022) used the PSR model to point out that the natural factors affecting FCSE in China include precipitation and temperature, and human activity factors include forestry development level and per capita GDP. Wang et al (2022) found that total annual precipitation and socio-economic development level significantly contribute to FCSE in China based on the Tobit model. Some scholars have also analyzed the spatial spillover effects of the factors influencing FCSE in China through spatial econometric models. For example, Zhu et al (2022) found that forest land use, pests, and diseases in surrounding areas have negative spatial spillover effects on local FCSE, while the opposite is true for temperature and precipitation. The above literature provides important measurement methods and analytical ideas for further related studies.

With the continuous development of communication technology and transportation infrastructure in China in recent years (Liu et al., 2022), the spatial exchange of forestry production factors among regions is becoming more frequent. The cross-regional spillover characteristics of FSC are becoming obvious (Zhao et al., 2023), and FCSE is bound to show significant spatial correlation characteristics. Zhu et al (2022) pointed out a significant spatial correlation of FCSE at the county scale in Zhejiang, China, based on the Moran'I index. Zhang and Deng (2019) also found that the net carbon sink efficiency (NCSE) of Chinese cities is spatially correlated, in the context of taking vegetation carbon sinks into account in the analytical framework.

To sum up, the literature has tell that consider the forest ecosystem's natural and socio-economic attributes and study their climate regulation role has become a critical perspective. Much work has been done on its specific measurement, influence factor, and correlation analysis. And the above work is valuable for the depth understanding of FCSE in China. But still some questions related to contact network has not been answered related to the specific characteristics of the FCSE spatial association in China and the most critical factors driving the spatial association of FCSE in China. And also, the spatial association's beneficial effect on the FCSE. And these questions can open up a new view for the network connection of resources and environment.

The Social Network Analysis (SNA) has been widely used to study the spatial association network of carbon emissions or emission efficiency (Bai et al., 2020). Amount of literature have analyzed the network structure characteristics and driving mechanisms of carbon emissions or carbon emission efficiency in China based on this method (Li et al., 2017; Sun et al., 2020; Xu et al., 2022). And this have provide some referings for applying this method for FCSE study, and this can for sure contribute to enrich the previous work in the network connection sight.

In this study the FCSE provinces level is measured in the year 2005, 2010, 2015, and 2020 by Super-SBM-DEA model. And then the SNA is used to reveal the overall network structure characteristics, individual network structure characteristics, and core-periphery structure characteristics of FCSE. Subsequently, the block model is used to analyze the spatial clustering pattern of FCSE. Finally, Quadratic Assignment Procedure (QAP) regression and panel data regression are used to analyze the driving mechanisms of spatially association networks of FCSE and the feedback of spatial network structure on FCSE.

The marginal contributions of this paper are summarized from the following ways: First, the network structure of FCSE in China has been revealed. Second, from the perspective of the sending and receiving effect way the spatial clustering pattern of Chinese provincial FCSE has been found. Third, the formation mechanism of the FCSE spatial association network in China has been investigated. Fourth, the feedback effect of the spatial association network structure in China has been examined by above all this have provided a new reference for better utilization of the network effect to improve FCSE in China.

4. Materials and Methods

4.1 Overview of the study area

The study areas are China's 30 provincial administrative units (which have excluded Hong Kong, Macau, Taiwan, and Tibet due to data limitations). Figure 1 shows the provincial administrative units' geographical location and land cover in 2020. From Figure 1, it can be found that China's forest resources have obvious differences in spatial distribution. Fujian, Jiangxi, Guangxi, Zhejiang, Hainan, Yunnan, and Guangdong provinces have higher forest cover. Provinces such as Xinjiang and Gansu have lower forest cover. In general, the southern provinces of China are relatively rich in forest resources and have greater potential for forest carbon fixation.

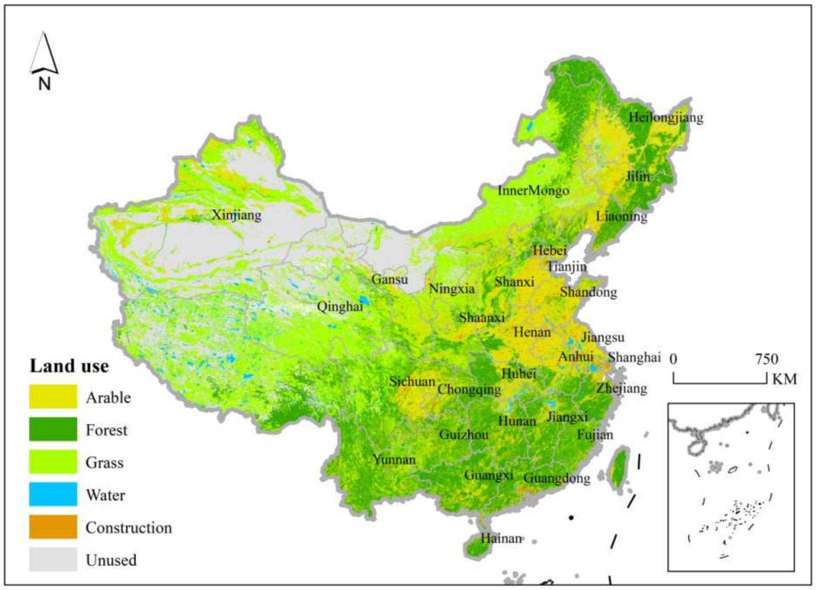

Figure 1: Spatial distribution map of land use in China in 2020 (1km×1km raster).

4.2 Calculation of forest carbon sink efficiency

Measuring the current status of FCSE in China is a prerequisite for conducting continue analysis. We use 30 provincial-level administrative units in China as decision making unit (DMU) to measure their FCSE values in 2005, 2010, 2015, and 2020 using the Super-SBM-DEA model (Jiang et al., 2021; Chen and Liu, 2022). The calculation equations are shown in Eqs.1~2:

$$FCSE = min\frac{\frac{1}{m}\cdot\sum_{i=1}^{m}\frac{\bar{x}}{x_{ik}}}{\frac{1}{s}\cdot\sum_{l=1}^{s}\frac{\bar{y_l}}{y_l^d}} \tag{1}$$

$$s.t.\begin{cases} \bar{x} \geq \sum_{j=1,j\neq j_0}^{n} x_{ij}\cdot\lambda_j\,; \quad \bar{y} \leq \sum_{j=1,j\neq j_0}^{n} y_{ij}\cdot\lambda_j \\ \bar{y} \leq y_{ij}; \\ \lambda_j \geq 0; \quad i = 1,2,\ldots,m; \quad j = 1,2,\ldots,n; \quad l = 1,2,\ldots,s \end{cases} \tag{2}$$

In the above equations, n represent the number of DMU, which is 30. m and s represents the input and output variables, respectively. x and y represents the specific elements in the input and output matrices, respectively. $FCSE$ represent the forest carbon sink efficiency. The input variables in this paper include labor input, capital input, and land input. The labor input is expressed as the number of forestry employees in each province at the end of the year (Wang et al., 2022). The capital input is expressed as the forestry capital stock (Lin and Ge, 2019) and is measured using the perpetual inventory method, with the depreciation rate set at 9.6% (Zhang et al., 2004). The land input is expressed as the forest area (Zhu et al., 2022). The output variables include the gross forestry products and FCS (Lin and Ge, 2019).

IPCC (2006) provides two methods to account for FCS: the incremental loss method and the pooled difference method. Referring to most of the literature (Wang et al., 2022; Zhao et al., 2023), we use the incremental loss method to measure FCS in 30 Chinese provinces. The specific equations are shown in Eqs.3~5:

$$\Delta C_{B_j} = \Delta C_{G_j} - \Delta G_{L_j} \tag{3}$$

$$\Delta C_{G_j} = \sum_i A_{ij} \cdot V_{ij} \cdot BEF_{F_j} \cdot SVD_{ij} \cdot CF_{ij} \cdot GR_{ij} \tag{4}$$

$$\Delta C_{L_j} = \sum_i A_{ij} \cdot V_{ij} \cdot BEF_{F_j} \cdot SVD_{ij} \cdot CF_{ij} \cdot CR_{ij} \tag{5}$$

In the above equations, ΔC_{B_j} represent the FCS in the jth province. ΔC_{G_j} and ΔG_{L_j} represents the forest carbon sequestration and forest carbon emission in the jth province. A_{ij} represent the area of tree species in the jth province. V_{ij} represent the wood accumulation of tree species in the jth province. BEF_{F_j} is the forest biomass expansion factor in the jth province. SVD_{ij} represent the stem bulk density of tree species in the jth province. CF_{ij} represent the carbon sequestration coefficient of the ith in the jth province , taken as 0.5 (Zhao et al., 2023). GR_{ij} and CR_{ij} represents the annual growth rate and annual consumption rate of ith tree species in the jth province, respectively.

We used the weighted average coefficients of tree species to calculate forest carbon sinks to avoid data discontinuity for tree species in each province (Zhao et al., 2023). The details are shown in Eqs. 6~8:

$$\Delta C_{B_j} = A_j \cdot V_j \cdot \overline{BEF_{F_j}} \cdot \overline{SVD_j} \cdot CF_j \cdot (\overline{GR_j} - \overline{CR_j}) \tag{6}$$

$$\overline{BEF_{F_j}} = \sum_{i=1}^{n} (BEF_{F_i} \cdot \frac{A_{ij} \cdot V_{ij}}{A_j \cdot V_j}) \tag{7}$$

$$\overline{SVD_j} = \sum_{i=1}^{n} (SVD_i \cdot \frac{A_{ij} \cdot V_{ij}}{A_j \cdot V_j}) \tag{8}$$

In the above equations, $\overline{BEF_{F_j}}$ represent the weighted average of forest biomass expansion factor in the jth province. $\overline{SVD_j}$ represent the weighted average of stem volume density of the ith tree species in the jth province. $\overline{GR_j}$ and $\overline{CR_j}$ represents the annual forest growth and depletion rates in the jth province, respectively. The relevant parameters required to calculate the FCS are shown in **Table 1**.

Provinces	GR	CR	$\overline{SVD}$	$\overline{BEF}$	Provinces	GR	CR	$\overline{SVD}$	$\overline{BEF}$
Beijing	6.39	4.31	0.484	1.771	Henan	11.68	6.86	0.488	1.740
Tianjin	11.66	9.44	0.423	1.821	Hubei	8.29	4.94	0.459	1.848
Hebei	7.83	4.89	0.478	1.782	Hunan	9.90	6.38	0.394	1.712
Shanxi	5.32	2.21	0.484	1.839	Guangdong	8.24	7.18	0.474	1.915
InnerMongo	2.68	0.88	0.505	1.690	Guangxi	8.94	5.90	0.430	1.819
Liaoning	5.58	3.23	0.504	1.803	Hainan	5.01	4.07	0.488	1.813
Jilin	3.67	1.91	0.505	1.784	Chongqing	7.38	2.93	0.431	1.736

Heilongjiang	3.87	1.67	0.499	1.751	Sichuan	3.04	1.06	0.425	1.744
Shanghai	9.62	6.71	0.392	1.874	Guizhou	8.45	3.70	0.425	1.842
Jiangsu	13.19	10.16	0.395	1.603	Yunnan	4.12	2.25	0.501	1.870
Zhejiang	9.35	4.46	0.406	1.755	Shaanxi	4.10	2.28	0.558	1.947
Anhui	9.78	6.14	0.416	1.742	Gansu	3.54	1.89	0.462	1.789
Fujian	6.68	5.63	0.436	1.806	Qinghai	2.40	1.27	0.408	1.827
Jiangxi	8.28	5.35	0.422	1.795	Ningxia	7.39	3.30	0.444	1.798
Shandong	15.28	9.51	0.412	1.774	Xinjiang	2.95	1.55	0.393	1.683

Note: Data were taken from IPCC (2011) *and* Zhao et al (2023).

Table 1: Calculation parameters of each province.

4.3 Calculation of spatial association matrix

A spatial association matrix needs to be constructed before using SNA to analyze the FCSE spatial association network structure in China. Granger causality test and spatial gravity model are the commonly used methods for matrix construction (Shen et al., 2021; Huo et al., 2022). However, the former lacks measurement accuracy, mainly because it cannot capture the temporal trend of network node correlation (Zeng et al., 2023). We complete constructing the spatial association matrix based on the spatial gravity model. The equation of the spatial gravity model is shown in Eq. 9:

$$q_{ij} = \frac{\frac{FCSE_i}{FCSE_i+FCSE_j} \cdot \sqrt[3]{GDP_i \cdot FCSE_i \cdot POP_i} \cdot \sqrt[3]{GDP_j \cdot FCSE_j \cdot POP_j}}{Distance_{i,j}^2/(PGDP_i - PGDP_j)^2}; \ i \neq j \qquad (9)$$

In the above equation, q_{ij} represent the spatial gravitational strength of FCSE in the ith province and jth province. When $i = j$, q_{ij} is taken as 0. GDP, $PGDP$ and POP denotes GDP, per capita GDP and year-end resident population of each province, respectively. $Distance_{ij}$ represent the shortest distance between the ith province and the jth province.

The gravitational intensity matrix (30×30) is constructed for 30 provinces in China based on the above calculation results. The row mean values of the gravitational intensity matrix are calculated. If an element in the matrix is greater than the row means, the element is assigned a value of 1, and vice versa. The final obtained binary matrix is the spatial association matrix used in this paper.

4.4 Social network analysis

4.4.1 Overall network structure characteristics: The social network is a topological graph consisting of nodes and an association matrix. Density, connectedness, hierarchy, and efficiency are commonly used indicators to assess the structure of social networks (Chen et al., 2022; Wang et al., 2023). We calculated the above indicators to assess the overall structural characteristics of the spatial association network of FCSE in China.

The network density reflects the tightness of the association of the nodes in the spatial association network of FCSE in China, and the higher the value, the higher the tightness of FCSE in each province. Its calculation method is shown in Eq. 10:

$$Density = \frac{L}{P\cdot(P-1)} \tag{10}$$

In the above equation, L and P represent the number of nodes and the number of provinces in the network, respectively.

The network connectedness reflects the stability of the spatial association network of FCSE in China. When the network connectedness is 1, it indicates that the network structure is stable. Its calculation formula is shown in Eq. 11:

$$Connectedness = 1 - \frac{2\cdot V}{P\cdot(P-1)} \tag{11}$$

In the above equation, V represent the number of interconnected groups of nodes in the network.

The network hierarchy reflects the asymmetric accessibility of the FCSE spatial association network. The higher the rank degree, the stronger the “leadership” role of the central node in the network and the more complex the network structure. Its calculation method is shown in Eq. 12:

$$Hierarchy = 1 - \frac{\theta}{MAX(\theta)} \tag{12}$$

In the above equation, θ represent the number of groups of symmetrically reachable nodes in the network.

The network efficiency reflects the number of relationships in the network. It is calculated as shown in Eq. 13:

$$Efficiency = 1 - \frac{\tau}{MAX(\tau)} \tag{13}$$

In the above equation, τ represent the number of redundant relational lines in the network.

4.4.2 Individual network structure characteristics: We further calculated degree centrality, closeness centrality and betweenness centrality (Bai et al., 2020; Yu et al., 2022) to analyze the individual network structure characteristics of FCSE in China.

Degree centrality reflects the degree of proximity of a node to the center of the network. The higher the degree centrality of a province, the stronger the “leadership” of the province in the FCSE spatial association network (Bai et al., 2020). The formula is shown in Eq. 14:

$$Degree = \frac{n}{N-1} \tag{14}$$

In the above equation, N represent the number of individuals in the spatial association network of FCSE in China. n represent the number of individuals directly associated with a point.

The closeness centrality reflects whether a node in the network is vulnerable to control by other nodes. The higher the proximity centrality of a province, the better the province is not controlled by other nodes in the FCSE spatial association network. Its calculation formula is shown in Eq. 15:

$$Closeness = \sum_{j=1}^{n} d_{ij} \tag{15}$$

In the above equation, d_{ij} represent the length of the shortcut from the ith province to jth province.

The between centrality degrees reflects the ability of a node in the network to control the relationships among other nodes. The higher the intermediary centrality of a province, the stronger the province's role as a “bridge” in the FCSE spatial association network (Huang et al., 2019). The formula is shown in Eq. 16:

$$Between = \frac{2 \cdot \sum_{j=1}^{n-1} \sum_{k=2}^{n} b_{j,k}(i)}{N^2 - 3N + 2}, i \neq j \neq k \;\&\; j < k \qquad (16)$$

In the above equation, n and N represents the number of groups associated with a certain node and the target node and all nodes, respectively; $b_{j,k}(i)$ represent the ability of the ith node to control the relationship between the jth and the kth node.

4.4.3 Core and periphery analysis: In the FCSE spatial association network, the status and importance of each province are unequal. To clarify the status and importance of each province in the FCSE spatial association network, we use the built-in CORR algorithm of UCINET software to conduct core edge analysis of the network. The results of the core-periphery analysis are mainly reflected by the core degree. The higher the core degree of a province, the higher the status and importance of that province in the FCSE spatial association network in China.

4.4.4 The block model: The block model is an important method to study the clustering characteristics of each node in a spatial association network, and the model can intuitively reflect the sent and received effects among plates of nodes in the network. We use the block model to analyze the clustering characteristics of the FCSE spatial association network. The specific steps are as follows:

1. Construct the square matrix of the FCSE spatial association network in China. It is divided into four plates to ensure that each province can be included in each plate.
2. Calculate the density matrix. Compare the elements of the matrix with the density of the network, and assign a value of 1 to the element if it is greater than the average density of the network and 0 to the opposite.
3. Sketch the board relationship based on the pixel matrix and analyze the sent and received relationship between each plate.

4.5 Quadratic assignment procedure (QAP) regression

QAP regression is a common nonparametric method for studying relational data (Kim et al., 2019). Compared with parametric regression, QAP regression can resample, thus avoiding the problem of multicollinearity among relational data and making the parameter estimation results more robust (Su and Yu, 2019). We use QAP to analyze the driving mechanism of the FCSE spatial association network in China, and the explanatory variable is the FCSE spatial association matrix (FSNM). Meanwhile, we refer to the studies of Du et al (2021), Wang et al (2022), Zhao et al (2023), and other scholars and also select geographic proximity (DIS), water resources differences matrix

(WDM), forestry scale differences matrix (FDM), economic level differences matrix (EDM) and science and technology level differences matrix (TDM) initially as explanatory variables based on the characteristics of FCSE.

Each explanatory variable is calculated as follows:
(1) DIS, represented by the matrix of inter-provincial neighboring weights in China. If two provinces are geographically adjacent, the element in the matrix reflecting their location relationship is assigned a value of 1, and vice versa is 0.
(2) WDM, using the absolute value of the difference in total water resources between provinces.
(3) FDM, using the absolute value of the difference between the scale of forestry output value between provinces.
(4) EMD, using the absolute value of the difference in per capita GDP between provinces.
(5) TDM is characterized by the absolute value of the difference in the number of patents granted between provinces in China. The patent grant includes invention, utility model, and design patent grant. To avoid the influence of data magnitude on the estimation results, the above explanatory variables are standardized for extreme differences. The final constructed QAP model is shown in Eq. 17:

$$FSNM = f(DIS, WDM, FDM, EDM, TDM) \tag{17}$$

4.6 The panel data regression model

To further clarify whether the network structure affects FCSE, we constructed a panel data regression model with degree centrality, closeness centrality, and betweenness centrality of each province in all years as explanatory variables (Wu et al., 2019; Ouyang and Xiong, 2023) and FCSE of each province in all years as explanatory variable to conduct analysis. To control for factors affecting FCSE other than the three centralities, we include total water resources, gross forestry output, per capita GDP, and patents granted in each province as control variables in the regression. The final panel regression models constructed are shown in Eqs. 18~20:

$$FCSE_{it} = \alpha + \beta_1 \cdot Degree_{it} + \sum \beta_k \cdot Control_k + u_i + v_t + \varepsilon_{it} \tag{18}$$

$$FCSE_{it} = \alpha + \beta_2 \cdot Clossness_{it} + \sum \beta_k \cdot Control_k + u_i + v_t + \varepsilon_{it} \tag{19}$$

$$FCSE_{it} = \alpha + \beta_3 \cdot Between_{it} + \sum \beta_k \cdot Control_k + u_i + v_t + \varepsilon_{it} \tag{20}$$

In the above equations, i and t represents province and time, respectively. α represent the constant term. u_i, v_t and ε_{it} represents individual fixed effects, time fixed effects and random error terms, respectively. $Control_k$ and β_k represents a series of control variables and their estimated coefficients. β_1, β_2, and β_3 represents the estimated coefficients of degree centrality, closeness centrality, and between centrality, respectively, and their sign direction and significance reflect the influence of the spatial structure of the network on FCSE.

4.7 Data sources

The Chinese land use remote sensing monitoring data and Chinese administrative boundary data used in this paper were obtained from the *Resource and Environmental Science and Data Center* (https://www.resdc.cn). Forest cover area, year-end number of forestry employees, forestry fixed asset investment and gross forestry product by province were obtained from the *China Forestry Statistical Yearbook* (https://www.data.cnki.net). Total population, per capita GDP and GDP by province are obtained from the *China Statistical Yearbook* (https://www.data.cnki.net). Total water resources by province are obtained from the *China Water Resources Bulletin* (https://www.mwr.gov.cn). The number of invention patents granted, utility model patents granted and design patents granted by each province are obtained from the *Chinese Research Data Services Platform* (https://www.cnrds.com).

5. Results and Discussions

5.1 Spatio-temporal characteristics of FCSE in China

Figure 2 shows the spatial distribution of FCSE in China in 2005, 2010, 2015 and 2020. (1) In terms of temporal characteristics, the overall FCSE in China shows an upward trend from 2005 to 2020. The provinces with faster FCSE growth rates are mainly concentrated in eastern China, among which Tianjin, Beijing and Guangdong have the highest increases, reaching 452%, 384% and 229%, respectively. The provinces where FCSE declined were mainly in western and northeastern China, with the three fastest declining provinces being Jilin, Yunnan and Gansu, with declines of -68%, -52% and -51%, respectively. The main reason for the faster growth rate of FCSE in the eastern provinces is the rising level of forest management and the increased awareness of forest conservation. The rapid decline of FCSE in the western region may be attributed to the expansion of urban areas due to rapid urbanization (Xiao and He, 2023), which has crowded the forest area. The apparent decline in FCSE in the northeastern provinces can be attributed to the decline in forestry science and technology practitioners due to population loss (You et al., 2021). (2) In terms of spatial characteristics, China's FCSE shows a significant character of “high in the south and low in the north”. The three provinces with the highest mean values are Zhejiang, Shanghai, and Hainan, reaching 2.1014, 1.3765, and 1.2201, respectively. The three provinces with the lowest mean values are Gansu, Inner Mongolia, and Qinghai, whose mean FCSE values are 0.0349, 0.1040, and 0.1102, respectively. The spatial distribution characteristics of FCSE in China are highly correlated with the distribution of forest resources and the economic level of each location (Wei and Shen, 2022), which can be corroborated by the spatial distribution map of land use types in China (Figure 1).

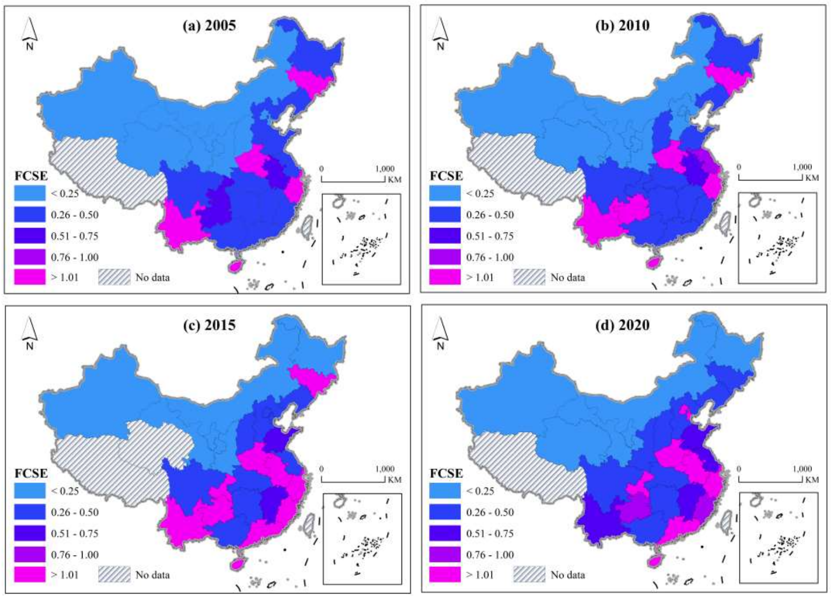

Figure 2: Spatial distribution of FCSE in China in 2005, 2010, 2015 and 2020.

5.2 Network structure characteristics of FCSE in China

5.2.1 Overall network structure characteristics: We calculated the spatial gravity values of China's FCSE in 2005, 2010, 2015, and 2020 based on Eq.9, constructed the spatial association matrix, and mapped the topology of the Chinese provincial FCSE spatial association network using ArcGIS software (Figure 3). It can be found that there are no isolated individuals in the spatial association network, and the FCSE of each province has broken through the traditional geospatial restrictions and formed cross-regional spatial association relationships. During the study period, the network relationships in the topology diagram showed a significant upward trend, specifically from 148 in 2005 to 170 in 2020. This indicates that the correlation of the network gradually increased during the study period, and the complex network characteristics became increasingly apparent.

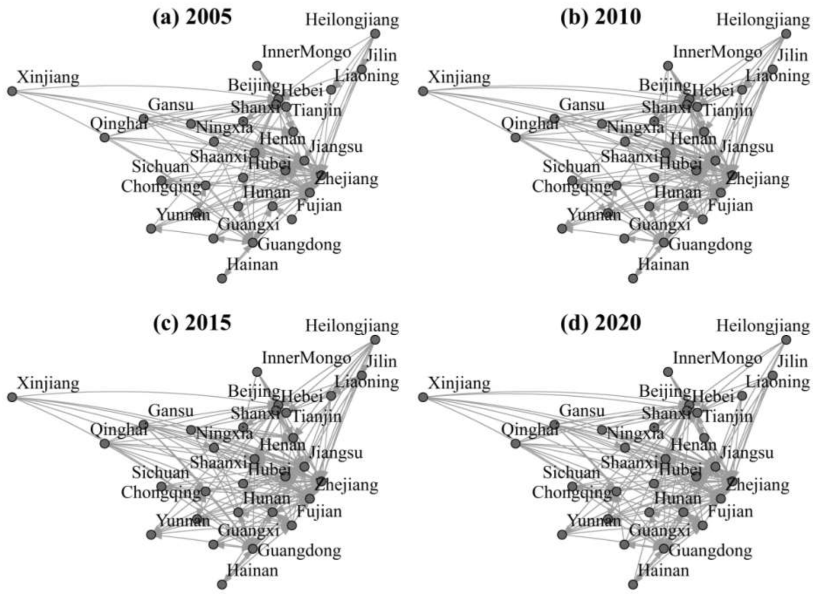

Figure 3: Topology diagram of FCSE spatial association network in China

We use UCINET software to measure the overall characteristic of the FCSE spatial association network in China (Figure 4). According to figure 4 the following conclusions can be drawn:

(1) Although the density of the spatial association network decreased in 2020, it maintained a fluctuating upward trend for the whole study period. The network density increases from 0.170 in 2005 to 0.195 in 2020 indicates that the correlation of the FCSE spatial association network in China gradually increases, further confirming the previous statement.

(2) The connectedness of the FCSE spatial association network is 1 in all periods, indicating that the FCSE of Chinese provinces are closely connected with each other. There is an obvious spatial spillover effect (Bai et al., 2020), and the network is stable.

(3) The hierarchy of the network shows a significant decline from 2005 to 2015, specifically from 0.761 in 2005 to 0.479 in 2015, which indicates that the internal hierarchy of the FCSE in China tends to be loosened during this period, and the dependence of the overall network on a single or a few provinces decreases. The hierarchical structure of the network gradually returns to the pre-2010 state after 2015.

(4) The efficiency of the network gradually decreased from 0.769 in 2005 to 0.714 in 2020, further indicating that the internal stability of the network is gradually improving (Tang et al., 2022).

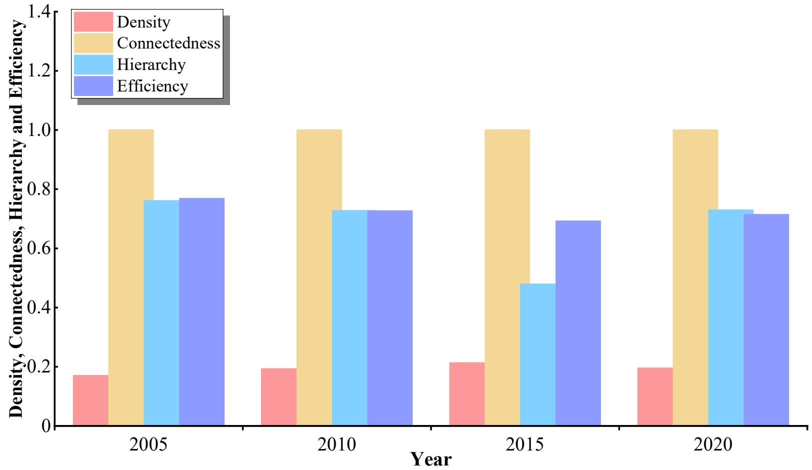

Figure 4: Overall characteristics of the FCSE spatial association network in China.

To sum up, after 2005, stimulated by technology diffusion and a series of forest sustainable development policies (NFGA, 2009; NDRC, 2017; 2018), China's forestry technology and forestry innovation capital have been distributed in a coordinated manner across the country, with increasingly significant reciprocal effects of carbon sink technologies and closer linkages between FCSE across provinces. However, the network nodes' connectivity shows that there are no free state points, but the number of connections varies greatly among provinces. Therefore, it is necessary to analyze the individual network structure characteristics further.

5.2.2 Individual network structure characteristics

The degree centrality, closeness centrality and betweenness centrality of the FCSE spatial association network were calculated using UCINET software (Figure 5).

From the perspective of closeness centrality:

(1) Shanghai has the highest degree centrality from 2005 to 2020, reaching 93.1, 93.1, 89.7 and 93.1, respectively, which is much higher than the 4-year average of all provinces (32.3). This indicates that Shanghai is at the absolute center of the spatial association network, playing the role of “leader” and guiding the overall evolution of the spatial association network.

(2) In addition to Shanghai, provinces such as Beijing, Jiangsu, Zhejiang and Guangdong have similarly high degree centrality. The above-mentioned provinces (including Shanghai), mostly located in the eastern coastal region of China, have developed economies, convenient transportation, and high levels of forestry technology (Ma et al., 2023), and can attract critical elements such as forestry funding and scientific and technological talent from other provinces (Jiao et al., 2018).

(3) Northeast, central and western provinces of China had lower degree centrality. On the one hand, the distance between the above regions and economically developed regions (northeast and west) is not conducive to realizing the cross-regional flow of critical factors to enhance FCSE. On

the other hand, the attractiveness of the above regions is limited by the development level of forestry science and technology and economic development.

From the perspective of closeness centrality:
(1) The four-year mean value of closeness centrality is 60.5, and the provinces above the mean include Beijing, Shanghai, Jiangsu, Zhejiang and Fujian, which are highly similar to degree centrality. These provinces are closer to other provinces in the network and have obvious advantages in element flow and information transfer, which can quickly create linkages and connections.
(2) Provinces such as Guangxi, Jiangxi, Inner Mongolia, and Ningxia have a low degree of closeness centrality, indicating that these provinces are less controlled by other provinces in the network and play the role of "marginal actors". The main reason is its relatively poor economic level, technology level, etc., and the lack of factor attractiveness.

From the perspective of betweenness centrality:
(1) Beijing, Shanghai, Jiangsu, Zhejiang and Guangdong and other eastern coastal areas' betweenness centrality is always at a higher level. This indicates that the above provinces not only play the role of "leader" in the network but also the role of "bridge" to control the spread of FCSE in other provinces. The possible reason for this is that the advanced forest conservation concepts and forest operation models of the provinces mentioned above have influenced forestry operations in other provinces and the flow of factors between them.
(2) Western and central provinces such as Shaanxi, Inner Mongolia and Anhui have lower betweenness centrality and a weak role as a "bridge" in the network, which is still constrained by the economic level and geographical location.

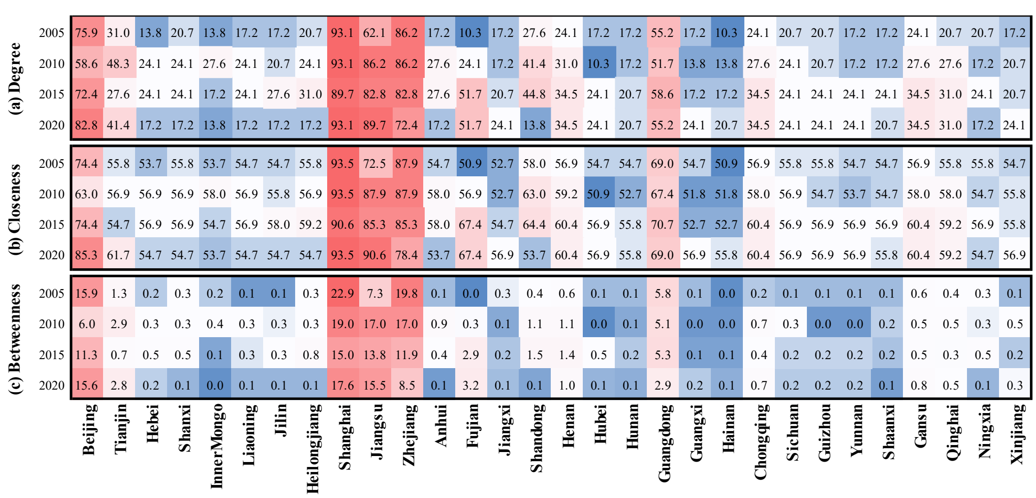

Figure 5: Degree centrality, closeness centrality and betweenness centrality by province in 2005, 2010, 2015 and 2020.

5.2.3 The core and periphery structure characteristics: By using the CORR module of UCINET, the core degrees of 30 Chinese provinces in 2005, 2010, 2015 and 2020 are further calculated. And the core degree of each province fluctuated between 0.1 and 0.4 in all years, with a maximum value of 0.354 and a minimum value of 0.103. Based on the data characteristics, we divided the core degree into three equal intervals: [0.1, 0.2), [0.2, 0.3) and [0.3, 0.4). The provinces whose core degrees fall in [0.3, 0.4) are defined as network core; the provinces whose core degrees fall in the interval [0.2, 0.3) are defined as network sub-core; and the other provinces are defined as network periphery. The core-periphery structure of the network in each phase is shown in figure 6, where the red nodes are the network core, the pink nodes are the network sub-core, and the gray nodes are the network edges.

According to figure 6, the following conclusions can be obtained:
(1) From the comparison between different provinces. The number of core and peripheral provinces in the network varies widely. Provinces such as Shanghai, Beijing, Jiangsu, and Zhejiang are closely connected with other provinces and are always in the core or sub-core position. Most provinces in the central, western, and northeastern regions are less able to establish network relationships with other provinces and are always on the periphery.
(2) Regarding the temporal changes in the core-periphery relationship, the number of provinces that become core or sub-core in the network gradually increases and has obvious dynamic change characteristics. Shanghai, Jiangsu, Zhejiang, Beijing, and Guangdong are always in the core or sub-core status of the network. Henan, Shandong, and Tianjin entered the network sub-core in 2010, and Fujian and Anhui entered the network sub-core in 2015. It is not difficult to find that these newly entered sub-core provinces are geographically adjacent or closer to the in-situ core or sub-core cities, and the dynamic changes of the network core edge structure may be more related to the geographical location.

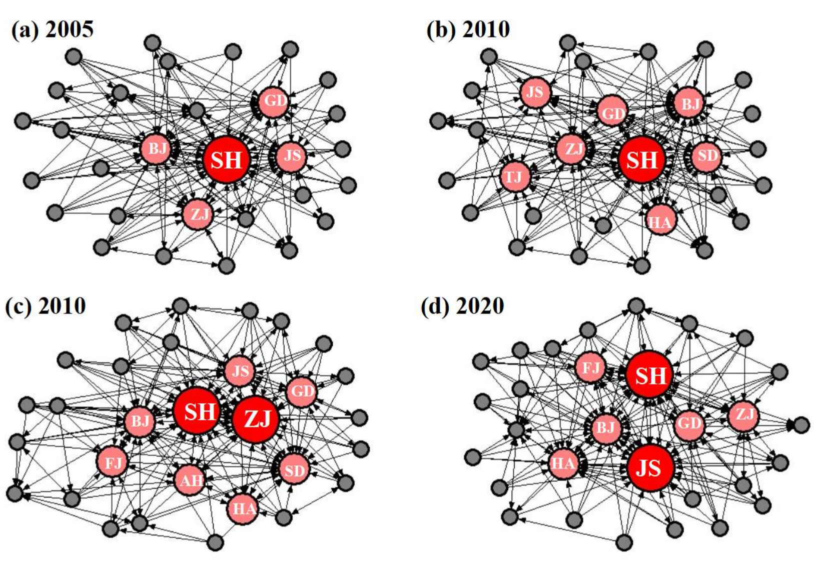

Figure 6: Core-periphery structure of network in 2005, 2010, 2015 and 2020.

5.2.4 Clustering structural characteristics of network

We used the CONCOR module in UCINET software to segment the FCSE spatial association network in 2005, 2010, 2015 and 2020. The depth was set to 2, the convergence to 0.2 (Bu et al., 2020), and finally divided into four plates. The spatial correlation of each plate is shown in Table 2. Figure 7 further shows the specific provinces included in each plate for four years.

(1) Overall, the number of external relations of the plates in all years are more than the number of internal relations. The number of internal relations of the plates in 2005, 2010, 2015 and 2020 are 18, 31, 29 and 13, respectively, and the number of external relations is 130, 137, 158 and 157, respectively. By analyzing the provinces included in the plate, it can be found that the plate consisting of most of the central, western, and northeastern provinces is the main exporter of factors in all four years, while the plate consisting of most of the eastern provinces is the receiver of elements in 2005, 2010 and 2015. This is mainly due to the high wage level and better policy environment in the east region, which are more attractive for the crucial factors to improve the FCSE.

(2) Regarding temporal trends, the element linkages among provinces are in a dynamic process of change. Shandong and Fujian were in the main outflow plate in 2005 and 2010, and both changed to the main inflow plate in 2015, implying that the factor attractiveness of the above two provinces has been increasing during this period, and their roles in the network have gradually changed from "exporters" to "receivers". However, from 2015 to 2020, Shandong reverted to the main outflow plate, indicating that the province lacks a long-term mechanism to enhance the attractiveness of forestry factors. Guangdong and Fujian changed from the main inflow plate to the agent plate in 2020, and Chongqing changed from the main outflow plate to the agent plate in 2020, which means that the "bridge" role of the above three provinces in the FCSE spatial association network strengthened gradually between 2015 and 2020.

Year	Plate	Plate role	Sent		Received		Proportion of internal relations	
			Inside	Outside	Inside	Outside	Expected (%)	Actual (%)
2005	Plate I	Main inflow	2	8	2	27	3.45	20.00
	Plate II	Main inflow	5	15	5	77	10.34	25.00
	Plate III	Main outflow	6	33	6	7	24.14	15.38
	Plate IV	Main outflow	5	74	5	19	51.72	6.33
2010	Plate I	Main inflow	2	10	2	26	3.45	16.67
	Plate II	Main inflow	5	15	5	84	10.34	25.00

	Plate III	Main outflow	14	63	14	13	37.93	18.18
	Plate IV	Main outflow	10	49	10	14	37.93	16.95
2015	Plate I	Main inflow	4	12	4	32	6.90	25.00
	Plate II	Main inflow	6	20	6	93	13.79	23.08
	Plate III	Main outflow	6	47	6	5	24.14	11.32
	Plate IV	Main outflow	11	79	11	28	44.83	12.22
2020	Plate I	Main inflow	8	10	8	102	13.79	44.44
	Plate II	Agent	1	23	1	27	6.90	4.17
	Plate III	Main outflow	2	45	2	12	31.03	4.26
	Plate IV	Main outflow	2	79	2	16	37.93	2.47

Table 2: Spatial correlation of FCSE in different plates.

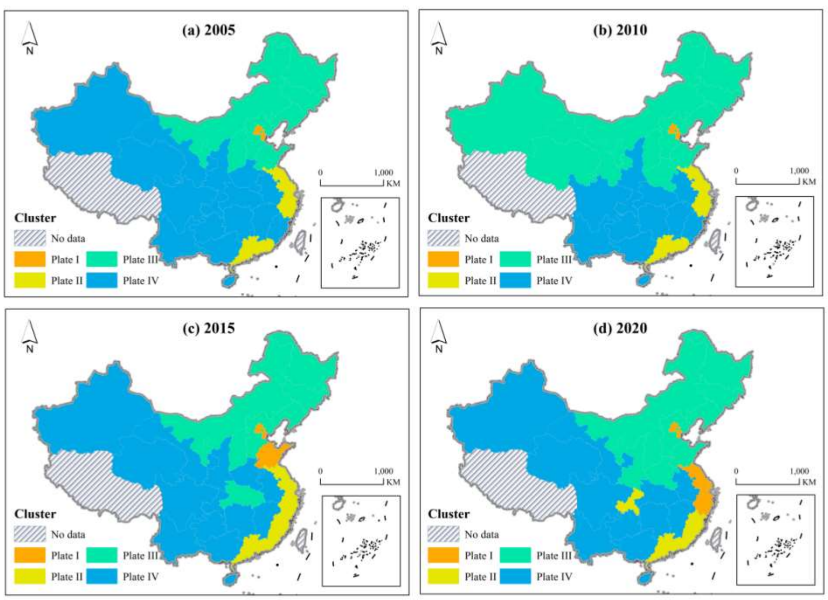

Figure 7: Provinces of each plate in 2005, 2010, 2015 and 2020.

To further analyze the spatial conduction paths between the plates, we calculated the density matrix and pixel matrix for the four plates in 2005, 2010, 2015 and 2020 using the CONCOR module in the UCINET software (Table 3). Based on the results of the pixel matrix, a sketch of the sending relationship between the plates for four years was obtained (Figure 8).

(1) Figure 8a shows that in 2005, there is a close reciprocity relationship between plates I-III and II-IV, and the elements are closely exchanged. Meanwhile, the sending paths between plates I-IV

and II-III are mainly reflected as IV→I and III→II. The sending relationship between plates I-II and III-IV is not apparent.
(2) Figure 8b shows that in 2010 the sent relationship between plates I-IV disappeared, and the spillover relationship between other plates remains the same as in 2000.
(3) Figure 8c shows that the plate sent path in 2015 remains the same as in 2005, but the sent path of plate I→III disappeared.
(4) Figure 8d shows that in 2020, the sent paths between the plates are mainly reflected as III→I, IV→I, II→I and II↔IV.

It is not difficult to find that the elemental sending relationship between plates II-IV is more solid. From the perspective of specific provinces, the provinces included in Plate II and IV are the provinces of the "Belt and Road" construction. The possible reason for the long-term and stable factor reciprocity between the segments mentioned above is that the construction of the Belt and Road has, to a certain extent, broken down the barriers to factor flows among the provinces along the route and the resulting knowledge spillover and innovation clustering effects (Zhang and Yang., 2021; Liu and Li. 2019) has led to the formation of cross-provincial collaboration mechanisms for forestry technology and talents between the southeast coastal and central and western provinces in the region. The weakest spillover effect between plates III and IV is still limited by the economy, forestry technology level, etc.

Plate	**Density matrix**				**Pixel matrix**			
	I	II	III	IV	I	II	III	IV
I	1.000	0.000	0.313	0.094	1	0	1	0
II	0.000	0.417	0.000	0.234	0	1	0	1
III	0.813	0.594	0.107	0.008	1	1	0	0
IV	0.438	0.906	0.016	0.021	1	1	0	0
I	1.000	0.000	0.333	0.083	1	0	1	0
II	0.000	0.417	0.083	0.229	0	1	0	1
III	0.958	0.813	0.106	0.007	1	1	0	0
IV	0.125	0.938	0.007	0.076	0	1	0	0
I	0.667	0.200	0.167	0.119	1	0	0	0
II	0.000	0.300	0.000	0.286	0	1	0	1
III	0.792	0.625	0.107	0.027	1	1	0	0
IV	0.310	0.929	0.009	0.060	1	1	0	0
I	0.400	0.000	0.140	0.050	1	0	0	0
II	0.467	0.167	0.100	0.361	1	0	0	1
III	0.900	0.000	0.022	0.000	1	0	0	0
IV	0.833	0.750	0.017	0.015	1	1	0	0

Table 3: Density and pixel matrix.

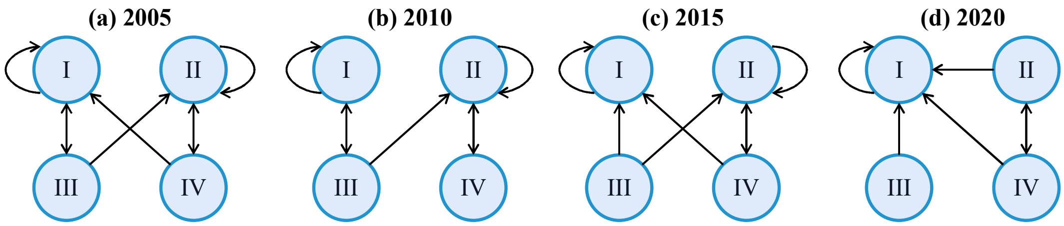

Figure 8: Simplified diagram of the relationship between the plates for 2005, 2010, 2015 and 2020

5.3 Formation mechanism of network

According to the setting of Eq.17, we use the QAP regression to analyze the driving mechanism of the FCSE spatial association network in China (Table 4). The number of random permutations is set to 10,000. From Table 4, the Adj-R^2 for each year was 0.318, 0.313, 0.303 and 0.303, respectively, and all of them passed the 1% significance test, which indicates that the influencing factors selected in this paper can well explain the changes in the FCSE spatial association network in China (Ji et al., 2023). The standardized estimated coefficients and significance levels of each influence factor matrix are different, indicating that the formation of the spatial association network of forest carbon sink efficiency in China is driven by a combination of factors.

(1) The standardized estimated coefficients for all four years of *Dis* were positive and significant at the 1% level. This suggests that the geospatial proximity of provinces is an important factor in forming the FCSE spatial association network. The mechanism of the spatial flow of elements such as forestry capital and forestry talents is more easily realized between neighboring provinces, and it also confirms the first law of geography.

(2) The standardized estimated coefficients of *WDM* are negative and significant in 2005, 2010 and 2015. This indicates that the differences in total water resources among provinces are an important resistance to forming the spatial association network. On the one hand, abundant water resource is an important factor affecting vegetation growth (Liu et al., 2014; Rachel et al., 2018; Gogoi et al., 2022). On the other hand, it is also a key factor influencing the characteristics and management mode of the forestry industry. The technical characteristics required for forestry development in arid and water-rich areas are different, and the element structure differs greatly, so it is not conducive to realizing a cross-regional flow of elements.

(3) The standardized estimated coefficients of *FDM* are significant only in 2010 and 2020, and both are negative. This suggests that expanding scale differences in forestry can impede the formation of spatial association networks. Forestry output value reflects the scale of forestry development. Generally, the demand for elements is high in provinces with larger forestry scales. In comparison, the demand for factors is low in provinces with lower forestry scales, thus limiting the flow of elements from provinces with higher forestry output values to provinces with lower output values.

(4) The standardized estimated coefficients of *EDM* were positive for all four years and were significant at the 1% level. This suggests that the widening differences in economic levels are an important factor in accelerating the formation of the FCSE spatial association network. Provinces

with higher levels of economic development have relatively better wage levels, policy environments, and relatively well-developed forest carbon sink markets and are, therefore, more attractive to forestry elements. Under this premise, elements from those economically weak provinces are more inclined to flow to economically developed provinces and more willing to transport forestry primary products to those economically developed provinces for processing (Huo et al., 2022), which will also increase the spatial correlation of FCSE in each province.

(5) The standardized estimated coefficients of *TDM* were positive for all four years and significant at the 1% level. This indicates that the widening difference in technology levels is an important factor in accelerating the formation of the FCSE spatial association network. Provinces with high technology levels have a stronger sense of innovation and are more attractive to forestry talent and other elements.

The effect of the mean value of each influence factor on the FCSE spatial association network was further estimated using QAP regression, and the results are shown in Model V in Table 4. Regarding the magnitude of the average effect in absolute terms, differences in economic levels are the most important driving force of the FCSE spatial association network. Provinces with higher economic levels become network centers first by element inputs and then influence the development of FCSE in other provinces by exporting advanced forestry management mode and forestry operation concepts outward. The differences in technology level further amplify this spatial interaction. The differences in water resource and forestry scale and geographic distance limit the further development of these spatial interactions (Figure 9).

Variables	Model I: 2005		Model II: 2010		Model III: 2015		Model IV: 2020		Model V: Mean	
	S-Coef	P-Value	S-Coef	P-Value	S-Coef	P-Value	S-Coef	P-Value	S-Coef	P-Value
Dis	0.160	0.000***	0.171	0.000***	0.204	0.000***	0.170	0.000***	0.186	0.000***
WDM	-0.089	0.001***	-0.092	0.004***	-0.091	0.005***	-0.002	0.480	-0.145	0.000***
FDM	0.005	0.429	-0.050	0.068*	0.003	0.465	-0.051	0.051*	-0.414	0.000***
EDM	0.434	0.000***	0.387	0.000***	0.440	0.000***	0.480	0.000***	0.608	0.000***
TDM	0.242	0.000***	0.267	0.000***	0.190	0.000***	0.170	0.000***	0.260	0.000***
Adj-R2	0.318	0.000***	0.313	0.000***	0.303	0.000***	0.303	0.000***	0.325	0.000***

Note: "***", "**" and "*" indicate significant at the 1%, 5% and 10% levels, respectively.

Table 4: Results of QAP regression.

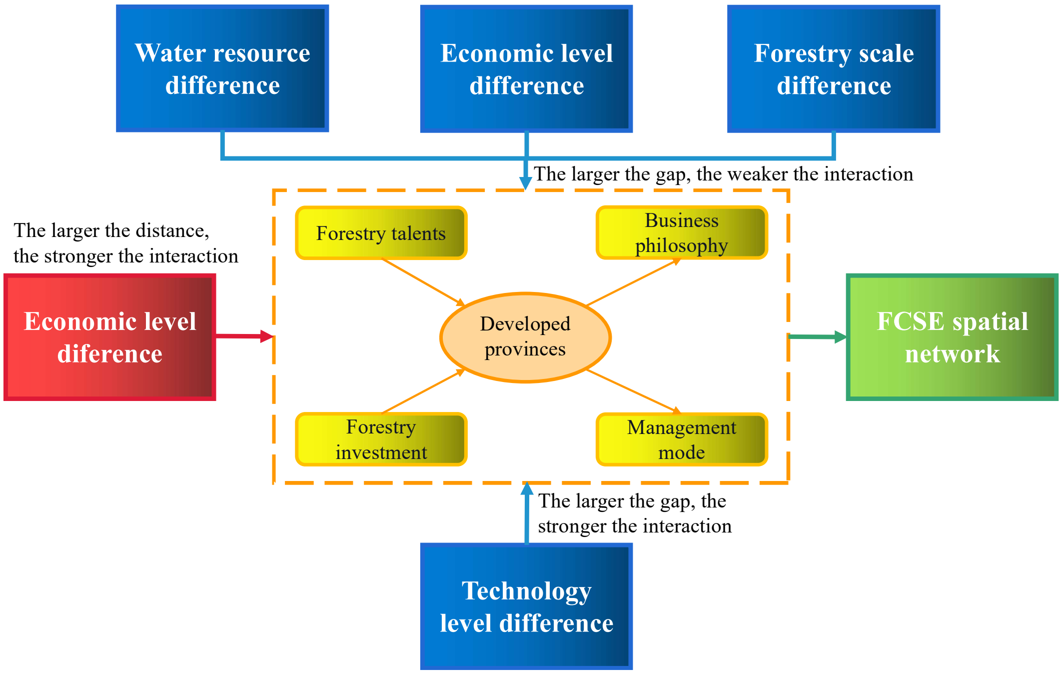

Figure 9: Schematic diagram of the formation mechanism of the FCSE spatial association network in China

5.4. Impact of network structure on the FCSE

The formation mechanism of the FCSE spatial association network in China was analyzed by the QAP regression. How does the spatial association network structure affect FCSE? We construct a panel data regression model, as shown in Eqs.18~20, to answer this question. The Variance Inflation Factor (VIF) test was performed before constructing the model. The VIF values of the explanatory variables for each of the three equations did not exceed 5 means that there is no multicollinearity. The estimation results are shown in Table 5.

(1) The estimated coefficient of degree centrality is 0.0077, which is significant at the 1% level. It indicates that every 1% increase in the degree centrality of a province causes the FCSE of that province to increase by 0.77%. The possible reason is that provinces with higher degree centrality are mostly located at the center of the network and have established closer factor linkages with other provinces. The provinces above attract factor inflows and guide changes in the association network while promoting their own FCSE.

(2) The estimated coefficient of the closeness centrality is 0.0219, which is significant at the 1% level. It indicates that every 1% increase in the closeness centrality of a province will increase the FCSE of that province by 2.19%. The main reason is that there is a significant positive spatial spillover effect of FCSE (Zhao et al., 2023). The higher the closeness centrality, the higher the connectedness between provinces and other provinces, and the easier it is to undertake the spatial spillover effects from other regions, thus enhancing its own FCSE.

(3) The estimated betweenness centrality is 0.0406, which is significant at the 1% level. It indicates that a 1% increase in the betweenness centrality of a province would increase the FCSE

of that province by 4.06%. The more betweenness centrality is, the more the province can play a “bridging” role in the network and therefore contribute to a certain extent to the improvement of its own FCSE by using the elements it “transmits”.

	Model VI	Model VII	Model VIII
Degree	0.0077*** (0.0026)		
Closeness		0.0219*** (0.0054)	
Betweenness			0.0406*** (0.0114)
Control	YES	YES	YES
Province FE	YES	YES	YES
Year FE	YES	YES	YES
R2	0.1989	0.2534	0.2523
Obs	120	120	120

Note: “***”, “**” and “*” indicate significant at the 1%, 5% and 10% levels, respectively. The values in “( )” are robust standard error.

Table 5: The impact of network structure on FCSE.

6. Conclusions and Policy Implications

By using the Super-SBM-DEA model and SNA the spatio-temporal characteristics of FCSE in province level and the FCSE spatial association network and clustering characteristics among provinces in China in 2005, 2010, 2015 and 2020 are studied. And based on this, the QAP model is constructed to futher explore the formation mechanism of the FCSE spatial association network among provinces and also the influence of network structural characteristics on FCSE are analyzed by panel data regression. The main findings are as follows:

(1) During the study period, the FCSE in China have showed an overall trend that a more significant increases in the eastern provinces and decreases in some provinces in the northeastern, central, and western regions. The FCSE in southern provinces are significantly higher than that in the northern areas, and its spatial distribution characteristics are highly correlated with the forest cover of each province.

(2) Regarding network characteristics, the FCSE spatial association network in China has gradually increased in relevance and internal stability. The dependence of the overall network on a single or a few provinces has shown a decreasing and then increasing trend. Eastern provinces such as Shanghai, Jiangsu, and Zhejiang have significantly higher point centrality, association centrality, and intermediary centrality than other provinces and play the role of both "leader" and "bridge" in the network. Shanghai has always been the network's core. At the same time, most of the central, western, and northeastern provinces are weak in establishing network relationships

with other provinces and remain in a marginal position.

(3) From the analysis results of the block model, the element linkages among provinces are always in the process of dynamic changes. Still, most of the time, most of the central, western, and northeastern provinces are mainly the senders of factors, and most of the eastern provinces are mainly the receivers of factors.

(4) The results of the QAP model explicate the formation of the FCSE spatial association network in China results from the sight of a combination of factors, among them the differences in economic level is the most central factor driving the formation of the spatial association network. And the differences in technology level also accelerate the formation of the spatial association network. Besides the geographical distance, differences in water resources and forestry scale hinder the formation of the spatial association network.

(5) From the results of the panel data regression, an increase in degree centrality, closeness centrality, and betweenness centrality of a province all raise the level of FCSE in that province.

The above findings may provide some insights into the development of FCSE enhancement policies in China:

(1) Forestry management departments should develop differentiated FCSE enhancement strategies by considering the distribution characteristics of China's forest resources and FCSE. The southern provinces of China are rich in forest resources and have high FCSE, so they can continue to maintain the current forestry management strategy and forestry support. The northern provinces of China have relatively scarce in forest resources and low FCSE and should increase afforestation efforts and control urban sprawl. In particular, Heilongjiang and Liaoning provinces are relatively rich in forest resources. However, their FCSE are lower than the national average, thus the key to improving FCSE in these provinces is to develop forestry technology, train forestry talents, and financial support for forestry technology can provide for enhancing.

(2) Constructing a more scientific cross-regional synergistic enhancement mechanism for FCSE. The results of SNA show that the spatial correlation of FCSE in China has broken through the limits of geographical adjacency, and there are obvious complex network characteristics. Forestry technology exchange workshops between core and peripheral provinces should be carried out in due course to bring into play the driving effect of key core provinces on the overall FCSE in China and narrow the network distance between peripheral and core provinces.

(3) The government should also focus on improving the income level and policy environment of relative less economical developed regions. The block model results have showed that the relative less economical developed regions, such as the central, western, and northeastern provinces, are mostly located in the net spillover block. Thus, improving the income level and policy environment can prevent further outflows of key forestry elements from these provinces.

(4) In addition, the government needs to enhance the spatial association of FCSE in China. The results of panel data regression show that forming the spatial association network improves FCSE. Appropriate measures should be taken to balance the differences in water resources and forestry industry structure among regions.

Due to data limitations, Hong Kong, Macau, Taiwan, and Tibet are excluded from the study sample. Future studies will improve this situation as statistical techniques improve and data availability increases. Besides, we did not conduct a study on the spatial association network of China FCSE at a smaller scale (prefecture-level cities) due to the limitation of the CONCOR module on the sample size, and a new method may considered to develop to replace the CONCOR module in the future. Also, predicting the future structure of the FCSE spatial association network in China is also an expandable direction for this study.

Author's contribution: All authors contributed to the study conception and design. Miao He contributed to the material preparation, data collection and revised version; Wei Xiao contributed to analysis, manuscript preparation and revised version.
Availability of data and materials: The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

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