Interdisciplinary
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Article

Analysis of Interprovincial Agricultural Carbon Transfer Association Network in China Based on MRIO Model

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Abstract: Agriculture is a significant source of carbon emissions. Agricultural trade separates the production and consumption of agricultural products. While existing research on carbon transfer has predominantly focused on industrial carbon emissions, the network characteristics of agricultural carbon transfer remain underexplored. Therefore, this paper analyzes China's interprovincial agricultural carbon transfer network from a consumption perspective, offering valuable insights for promoting regional collaborative carbon reduction in agriculture. By integrating 2017 interregional input-output tables with agricultural carbon emissions, this study constructs an agricultural carbon transfer network. It analyzes the scale and direction of carbon transfers and explores network characteristics using social network analysis. Additionally, the Leiden community detection algorithm is employed to identify tightly connected trade communities. The main conclusions are as follows: In 2017, the main grain sales areas were net carbon importers, while the main grain production areas were net carbon exporters. Agricultural carbon transfers primarily flowed from resource-rich agricultural regions to economically developed coastal areas. Although the carbon transfer network as a whole was relatively sparse, it exhibited strong connectivity. Analysis of individual characteristics revealed that Guangdong, Zhejiang, Jiangsu, Beijing, and Shandong formed the core of the association network. Finally, policy implications are proposed based on the research findings.

Keywords: agricultural carbon transfer; multi-regional input-output model; association network; social network analysis; Leiden algorithm

1. Introduction

Global warming stands as one of the most pressing challenges facing humanity today. The escalating global average temperatures, rising sea levels, and increasing frequency of extreme weather events collectively pose significant threats to human productivity and sustainable development [1]. Agricultural carbon emissions are the second largest source of global greenhouse gas emissions and play a crucial role in global warming [2]. Owing to the disparities in natural endowments and levels of economic development across different regions, the supply and demand sides of food are separated. With the conduct of agricultural trade, as consumers purchase a large number of agricultural products, they also indirectly consume the input factors such as arable land, water, fertilizers, and pesticides embedded in the production end of these products. The extensive input and consumption of these factors not only lead to ecological and environmental pollution in agricultural production areas, but also constitute an important source of agricultural carbon emissions. Therefore, to effectively advance agricultural carbon reduction initiatives, it is imperative to establish a scientifically grounded and equitable provincial carbon responsibility allocation system. This necessitates a comprehensive analysis of interprovincial carbon transfer networks resulting from agricultural trade, coupled with the implementation of a consumer-based approach to carbon responsibility allocation. In this way, regional agricultural collaborative carbon reduction plans can be explored, which is of great significance for formulating rational agricultural carbon reduction policies.

Under the background of the dual carbon goals, exploring the flow of resource elements and their associative characteristics between different regions is of great significance for revealing the environmental impacts brought about by interregional economic linkages. Input-output analysis has been widely applied in interregional resource and environmental studies, with a wealth of explorations already conducted in disciplinary fields such as environmental science [3], resource and environmental studies [4], and economic geography [5]. Due to the differences in agricultural production conditions among different regions, carbon emissions are separated between the production and consumption ends. Identifying the carbon transfer patterns triggered by domestic interregional agricultural trade helps to reveal the cross-regional environmental impacts brought about by agricultural production and trade. Existing research primarily focuses on analyzing carbon transfers across all industries, while the distinct characteristics of agricultural carbon transfers warrant further in-depth investigation. Furthermore, current research on agricultural carbon transfer primarily focuses on examining its spatial and temporal patterns, yet it lacks a thorough exploration of the associative characteristics within the agricultural carbon transfer network.

Therefore, based on relational data and a network perspective, this paper utilizes a multi-regional input-output model (MRIO) to calculate the carbon transfer volume of the agricultural sector, using the 2017 MRIO tables and agricultural carbon emission data from 31 provinces, thereby determining the agricultural carbon inflow and outflow volumes for each province. Subsequently, by considering provinces as nodes, carbon inflows and outflows as the direction of edges, and carbon transfer volumes as weights, a weighted directed network is constructed, thereby establishing the interprovincial agricultural trade carbon transfer network in China. Furthermore, social network analysis is employed to explore the overall and individual structural characteristics of the agricultural trade carbon transfer network, clarifying the positions and roles of each province within this network and identifying key provinces in agricultural trade. Finally, the Leiden community detection algorithm is employed to identify provincial communities with strong trade linkages within the carbon transfer network, aiming to explore opportunities for regional collaboration in agricultural carbon reduction. The structure of the article is organized as follows: Section 1 provides an overview of the research background; Section 2 presents the related work; Section 3 introduces the methods and data used in this paper; Section 4 provides the results and analysis; Section 5 presents the conclusions and policy implications. Figure 1 shows the research framework of this paper.

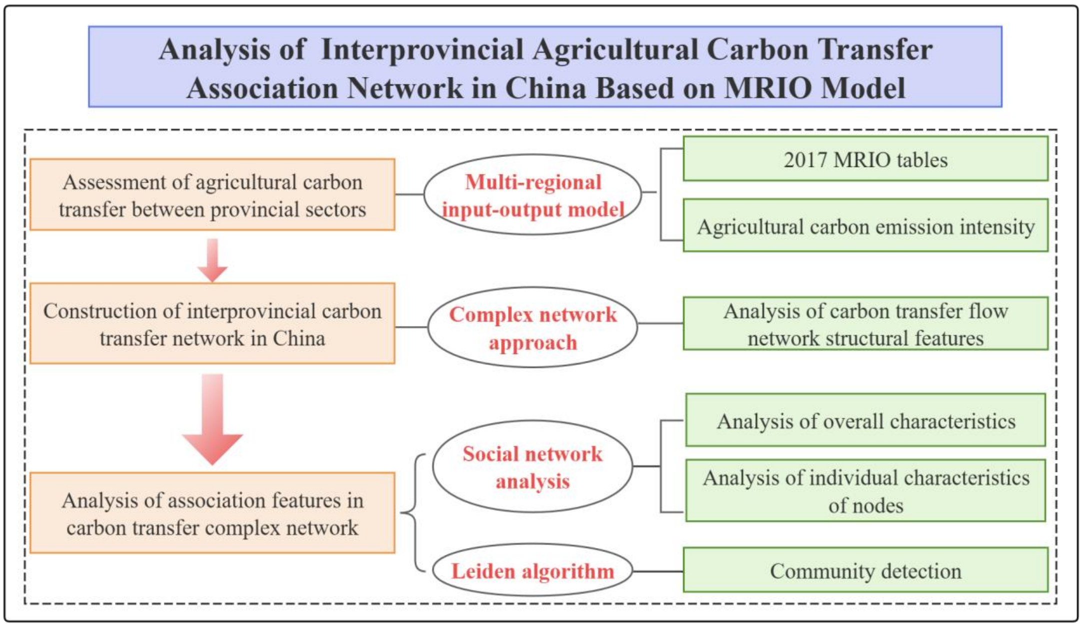

Figure 1. Research framework.

2. Related Work

Agricultural trade carbon transfer refers to the carbon emissions embedded in the production end of agricultural products within the trade flow, describing the process of carbon transfer from the production site to the consumption site of agricultural products. The Multi-Regional Input-Output (MRIO) model is the primary method for measuring the scale of carbon transfer between multiple regions, aiming to quantify the scale and direction of carbon transfer between regions. For example, Bai et al. [6] utilized the environmentally-extended multi-regional input-output model to estimate the virtual water, virtual soil, and embodied carbon in the trade of China's three major staple crops, namely rice, wheat, and corn. They also proposed the establishment of pilot projects for food trade carbon compensation to promote coordinated regional development. Pan et al. [7] employed the MRIO model to estimate the transfer of methane in interprovincial agricultural trade in China, and analyzed the spatiotemporal characteristics of methane transfer. They proposed the establishment of a cooperation mechanism for methane emission reduction among provinces. Ju et al. [8] based on the MRIO model, revealed the distribution and flow patterns of the carbon footprint in China's agricultural sector in 2015. The study identified Guangdong and Heilongjiang as the provinces with the largest agricultural carbon inflow and outflow, respectively. They proposed that the carbon transfer pressure between producers and consumers could be alleviated through carbon trading and reciprocal technical support.

Network feature mining techniques are capable of extracting valuable information from network data to reveal the structural characteristics and functional patterns of networks [9]. Social network analysis (SNA) can quantitatively analyze complex spatially-associated networks and is one of the important methods for analyzing the structural characteristics and relational patterns of carbon transfer networks. Lv et al. [10] utilized the MRIO model and SNA to investigate the interprovincial carbon transfer issue in China, quantifying the scale of carbon transfer between provinces and analyzing the spatial correlation characteristics and influencing factors of the carbon transfer network. Yang et al. [11] explored the node centrality and clustering characteristics of the industrial carbon transfer network based on complex network theory.

However, existing studies have primarily analyzed the spatial association characteristics of all industry sectors, and there is still a lack of comprehensive measurement and in-depth analysis of agricultural trade carbon transfer to effectively present the transfer paths and relational patterns of the carbon transfer network. This paper aims to investigate the spatial transfer paths and network association characteristics of China's agricultural trade carbon transfer, analyze the scale and direction of agricultural carbon transfer, thereby facilitating the exploration of horizontal ecological compensation schemes for agriculture among regions.

3. Methods and Data

The study area covers 31 provinces in China (excluding data from Hong Kong, Macao, and Taiwan due to data unavailability), and the study year is 2017. Since the latest Chinese multi-regional input-output tables are updated to 2017, the year 2017 is selected as the research year. The data for the multi-regional input-output tables are sourced from the CEADs database (https://www.ceads.net.cn/). The primary raw data required for the estimation of agricultural carbon emissions mainly come from the "China Rural Statistical Yearbook" and the National Bureau of Statistics (https://data.stats.gov.cn/).

3.1. Estimation of agricultural carbon emissions

This paper, drawing on existing literature [12–14], establishes an agricultural carbon emission estimation system based on five major carbon sources: agricultural materials input, rice cultivation, agricultural land use, straw burning, and animal husbandry. The calculation formula is as follows:

$$CE = \sum E_i = \sum T_i \times \delta_i \tag{1}$$

Where CE represents the total agricultural carbon emissions, E_i represents the carbon emissions from carbon source i, T_i denotes the absolute amount consumed by the i-th carbon source, and δ_i denotes the carbon emission factor of the i-th carbon source.

3.2. Multi-regional input-output model

Multi-regional input-output (MRIO) analysis, starting from the complex input-output relationships between sectors, integrates the economic linkages between different industries and regions. Through the Leontief inverse matrix, it is possible to calculate the direct and indirect carbon emissions of all sectors caused by final demand. Based on multi-regional input-output tables and the agricultural carbon emission data (obtained by aggregating the five major sources of carbon emissions) estimated in Section 3.1, this paper employs a multi-regional input-output model to measure the carbon transfers embodied in agricultural trade across China's 31 provinces. The calculation steps are as follows:

(1) The MRIO model is constructed based on single-region input-output tables. In an economic system comprising n regions and m sectors, the balance relationship where total input equals total output yields the following equation:

$$X_i^r = \sum_{j=1}^{n} \sum_{s=1}^{m} x_{ij}^{rs} + \sum_{j=1}^{n} y_{ij}^r \tag{2}$$

Where X_i^r denotes the total output of sector r in region i, x_{ij}^{rs} denotes the use of sector r in region i by sector s in region j, and y_{ij}^r denotes the final use of sector r in region i by region j (excluding exports).

Rewrite the equation (2) in matrix form:

$$X_i = A_{ij}X_i + Y_{ij} = (I - A_{ij})^{-1}Y_{ij} \tag{3}$$

Where X_i is the total output matrix of the MRIO model, A_{ij} is the direct consumption coefficient matrix, Y_{ij} is the final use matrix, I is the identity matrix, and $(I - A_{ij})^{-1}$ is the Leontief inverse matrix, representing the total demand for intermediate input products per unit of final product.

Dividing the intermediate use of each sector in each region by the total input yields the direct consumption coefficient:

$$a_{ij}^{rs} = \frac{x_{ij}^{rs}}{X_j^s} \tag{4}$$

(2) Calculation of agricultural carbon transfer based on the MRIO model.

The direct agricultural carbon emission coefficients are calculated as the ratio of total agricultural carbon emissions to the total output of the agricultural sector in each province. The calculation formula is as follows:

$$ac_j = \frac{c_j}{X_j} \tag{5}$$

Where ac_j is the direct agricultural carbon emission coefficient, representing the direct carbon emissions per unit of agricultural economic output, c_j is the direct carbon emissions from agriculture, and X_j is the total output of the j-th region.

Based on the multi-regional input-output tables, combined with direct agricultural carbon emission coefficients and the Leontief inverse matrix, this approach effectively quantifies the inter-regional carbon transfers embodied in agricultural trade, thereby enabling the measurement of agricultural carbon transfers. The calculation formula for the agricultural carbon transfer matrix is as follows:

$$CF = AC(I - A)^{-1}Y \tag{6}$$

Where CF is the inter-regional agricultural carbon transfer matrix, and AC is the diagonalization of the agricultural direct carbon emission coefficient ac_j.

3.3. Social network analysis

Social network analysis (SNA) can be employed to quantitatively analyze complex spatially-associated networks. By treating each province as a network node, with the direction of carbon inflow and outflow between provinces and the volume of carbon transfer as weights, an agricultural carbon transfer weighted directed network can be constructed. Utilizing SNA methods to explore the carbon transfer network, the analysis primarily focuses on both overall and individual characteristics within the social network. This approach allows for an in-depth examination of the structural characteristics of China's interprovincial agricultural carbon transfer network and the carbon transfer relationships between provinces, thereby identifying key provincial nodes based on carbon transfer relationships.

The analysis of the overall network characteristics primarily relies on five indicators: network density, the number of network connections, network connectivity, hierarchical degree, and network efficiency. These indicators help to grasp the overall characteristics and trends of the carbon transfer network. The individual characteristics of network nodes are analyzed using metrics such as degree centrality, closeness centrality, and betweenness centrality. Analysis of these indicators enables the identification of key provinces and cities within the network and exploration of the influence and control that each node exerts on the carbon transfer network.

3.4. Leiden algorithm

To reveal the clusters within the agricultural carbon transfer network, the Leiden algorithm is employed for community detection. The Leiden algorithm is an improved community detection algorithm based on the Louvain algorithm, aiming to maximize network modularity. It achieves this by moving nodes from one community to another, ensuring that such movements result in the greatest possible increase in modularity. The iteration ceases when no further increase in modularity can be achieved. The Leiden algorithm consists of three main stages: local movement of nodes, refinement of partitions, and aggregation of the network based on the refined partitions [15]. Compared to the Louvain algorithm, the Leiden algorithm exhibits superior performance in community detection, characterized by higher accuracy, faster convergence, and enhanced computational efficiency, as well as greater stability in community partitioning. Moreover, the Leiden algorithm is capable of detecting community structures in weighted directed networks, whereas the Louvain algorithm demonstrates limitations in this regard. Given that the agricultural carbon transfer network in this study is a weighted directed network, the Leiden algorithm is employed to uncover the clusters within the agricultural carbon transfer network.

The calculation formula for assessing community modularity is as follows:

$$\mathcal{H} = \frac{1}{2m}\sum_c e_c - \gamma\frac{K_c^2}{2m} \tag{7}$$

Where m denotes the total number of edges in the network, e_c denotes the actual number of edges within community c, K_c represents the total degree of nodes in community c, and γ >0 is the resolution parameter that regulates the density of connections within and between communities. A higher resolution parameter r results in a greater number of communities, while a lower value leads to fewer communities.

4. Results and Analysis

4.1. Analysis of the flow characteristics of agricultural carbon transfer

Utilizing the MRIO model, the carbon transfer outflow, inflow, and net transfer of Chinese agriculture in 2017 were calculated as shown in Figure 2. The outflow represents the amount of agricultural carbon emissions transferred from a specific province to other provinces, while the inflow represents the amount of agricultural carbon emissions transferred from other provinces to that province. Notably, both inflow and outflow exclude the portion of emissions consumed within the province itself. The net transfer is defined as the difference between the inflow and outflow of a province. A value less than 0 indicates a net outflow, meaning the amount transferred out of the province exceeds the amount transferred in, while a value greater than 0 indicates a net inflow, meaning the amount transferred into the province exceeds the amount transferred out. In other words, a net outflow reflects that the province transfers out more emissions than it receives, whereas a net inflow reflects that the province receives more emissions than it transfers out.

In 2017, the provinces with carbon emission outflow less than inflow, that is, the net transfer amount less than 0, were mainly Guangdong, Zhejiang, Shandong, Jiangsu, Fujian, Beijing, Hubei, Sichuan, Shanghai, and Shanxi, among 15 provinces. These provinces are primarily main grain sales areas and grain production and sales balance areas. The main grain sales areas are characterized by a large population and limited land, fewer agricultural resources, a higher level of economic development, and a lower proportion of agricultural production in their economy, leading to a demand that far exceeds supply, relying mainly on the supply from main grain production areas and agricultural surplus regions. Although most provinces in the grain production and sales balance areas can achieve self-sufficiency, some provinces still have an agricultural supply that is insufficient to meet the demand within the province. Therefore, the task of ensuring food security undertaken by the main grain production areas remains very arduous. Shandong, as a major agricultural province, has a large total agricultural output. While supplying itself, the surplus is transferred to other regions. However, as a populous province, Shandong has a high demand for agricultural products. With the continuous improvement of people's living standards, the convenience of transportation, and the deepening of trade with other provinces, the carbon outflow has become less than the carbon inflow.

In 2017, the provinces with agricultural carbon outflow greater than inflow, that is, the net transfer amount greater than 0, were mainly Heilongjiang, Yunnan, Xinjiang, Gansu, Guizhou, Shaanxi, Inner Mongolia, Jiangxi, Qinghai, and Tibet, among 16 provinces. These provinces are primarily main grain production areas and grain production and sales balance areas. Main grain production areas have played a significant role in ensuring national food security. Yunnan boasts unique light and heat resources. Its plateau vegetable industry has developed on a large scale, becoming an important base for the national "west-to-east vegetable transport" and "south-to-north vegetable transport". Moreover, its flower, tropical fruit, and traditional Chinese medicine material industries have large production scales, making it a key area for agricultural carbon spillover. Xinjiang has unique agricultural production conditions, with vast land and sparse population, and a large per capita arable land area. As an important cotton base and grape production area in China, its animal husbandry is also well-developed, playing an important role in the national agricultural product supply.

In 2017, the province with the largest agricultural carbon outflow was Heilongjiang, while the province with the largest carbon inflow was Guangdong. Heilongjiang is a major grain-producing province, with a large surplus of agricultural products in addition to its own consumption, which is supplied to other provinces. Located in the Northeast Plain, Heilongjiang has fertile black soil and a high level of agricultural modernization. Its moderate-scale agricultural operation is at the forefront of the country, and its status as an important national commodity grain base is continuously strengthened. Guangdong, on the other hand, is a coastal economically developed area with advanced industry and a high level of urbanization, which has occupied a large amount of arable land. With a large population and limited arable land, it is the largest grain-deficient province in China, mainly relying on the grain supply from the main production areas.

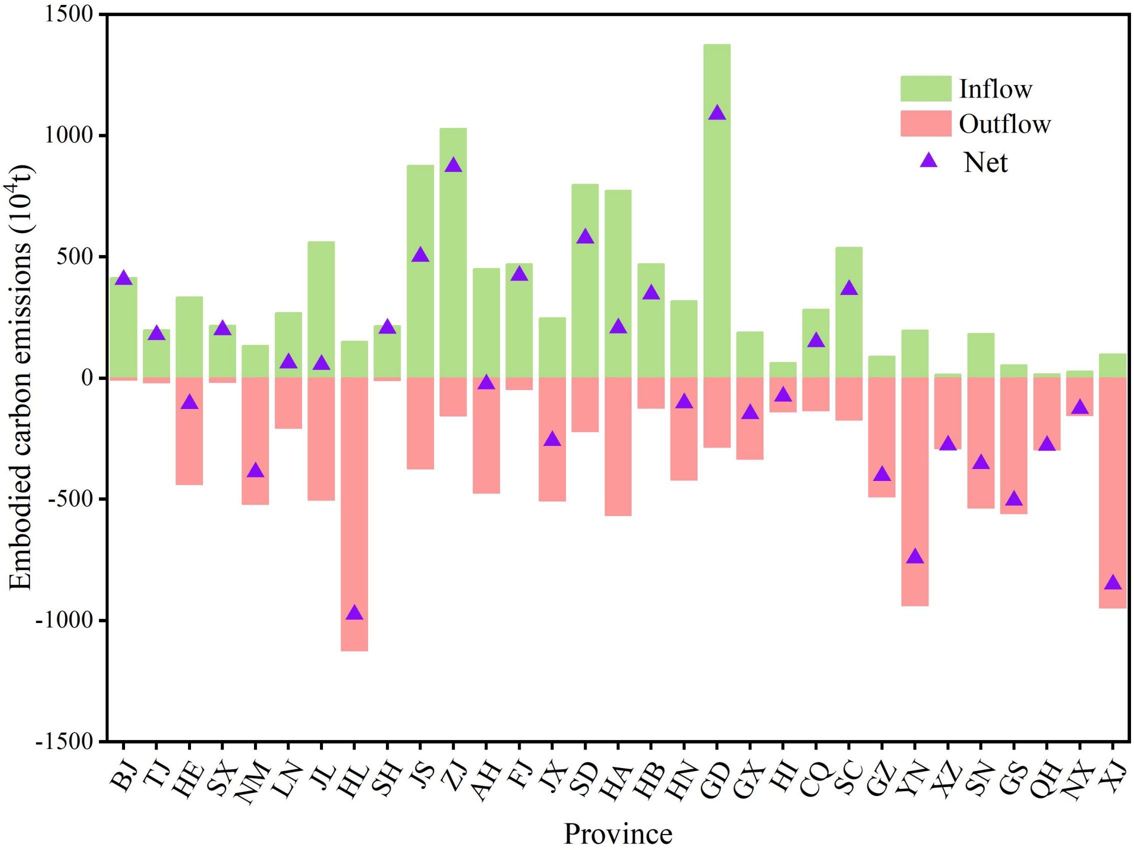

Figure 2. The agricultural carbon emissions embodied in inflow, outflow and net transfer of interprovincial trade.

Note: The abbreviations for the regions of China are as follows: Beijing (BJ), Tianjin (TJ), Hebei (HE), Shanxi (SX), Inner Mongolia (NM), Liaoning (LN), Jilin (JL), Heilongjiang (HL), Shanghai (SH), Jiangsu (JS), Zhejiang (ZJ), Anhui (AH), Fujian (FJ), Jiangxi (JX), Shandong (SD), Henan (HA), Hubei (HB), Hunan (HN), Guangdong (GD), Guangxi (GX), Hainan (HI), Chongqing (CQ), Sichuan (SC), Guizhou (GZ), Yunnan (YN), Tibet (XZ), Shaanxi (SN), Gansu (GS), Qinghai (QH), Ningxia (NX), and Xinjiang (XJ).

The agricultural carbon transfer matrix for 2017 is shown in Figure 3. The proportion of carbon emissions used for in-province consumption in each province is the largest, indicating that agricultural production is mainly to meet the demand of the province itself, and the surplus part will flow to other areas with insufficient agricultural product supply. Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Shandong, and Guangdong receive a relatively large supply from other provinces. Inner Mongolia, the three northeastern provinces, the central region, and Xinjiang provide a relatively large supply to other provinces. In terms of the direction of agricultural carbon transfer, China's agricultural carbon emissions mainly flow from the main grain production areas in the central region, the northeastern region, and the western region to the eastern and southeastern regions, from areas with relatively abundant agricultural resources and energy to economically developed areas. From the transfer matrix, it can be concluded that the flow of agricultural trade carbon transfer has the characteristic of spatial agglomeration and follows the proximity principle. For example, in 2017, the top five provinces supplying Guangdong were Guangxi, Hainan, Yunnan, Heilongjiang, and Henan.

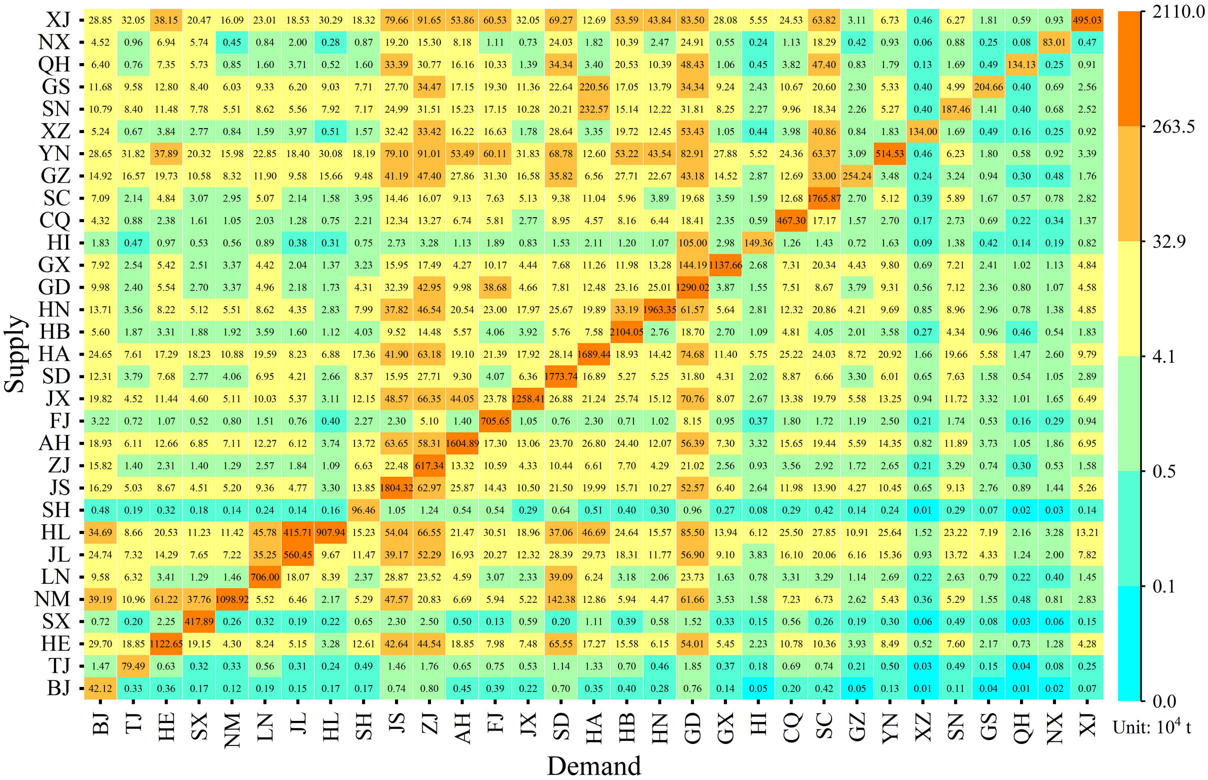

Figure 3. The agricultural carbon transfer matrix among provinces in 2017.

4.2. Analysis of the overall characteristics of agricultural carbon transfer network

To analyze the overall characteristics of the agricultural carbon transfer network, the network density, the number of network connections, network connectivity, hierarchical degree, and network efficiency of the agricultural carbon transfer network in each province across the country in 2017 were calculated. The network connectivity is 1, indicating that the agricultural trade carbon transfer network has good connectivity and stability, with a relatively significant spatial spillover effect. The network density is 0.31, which is at a relatively low level and has not yet reached the optimal state of network association, suggesting that the degree of association between provinces needs to be enhanced. Therefore, there is still considerable room for cooperation between provinces to jointly achieve resource optimization and carbon reduction. The number of network connections is 287, which is significantly lower than the maximum possible number of 930, indicating that China's inter-provincial agricultural carbon transfer network is not sufficiently dense and the degree of network density needs to be enhanced. The hierarchical degree is 0.46, suggesting a rigidly hierarchical network structure. The network efficiency is 0.54, which is relatively high, indicating an uneven spatial distribution of agricultural carbon emissions with considerable hierarchical disparities. The major carbon transfer flows are concentrated in a few core provinces, and the stability of the network structure is relatively weak, necessitating further strengthening. Additionally, the agricultural carbon transfer network is largely concentrated on a small number of transfer paths, with fewer dispersed paths.

4.3. Analysis of individual characteristics of nodes in agricultural carbon transfer networks

To analyze the individual characteristics of nodes in the agricultural carbon transfer network, the degree centrality, closeness centrality, and betweenness centrality of each node in 2017 were calculated, as shown in Table 1.

(1) Degree centrality

Degree centrality measures the extent to which an individual is central in the network based on the actual number of connections it has with other individuals. Provinces with the highest in-degree centrality are mainly located in the core area of the network. Economically developed provinces such as Guangdong, Zhejiang, Jiangsu, Beijing, and Shandong rank high in in-degree centrality. These provinces typically absorb a large amount of external carbon emissions and are classified as carbon inflow regions. These provinces are primarily located in the economically vibrant eastern coastal areas. The rapid socio-economic development and population growth in these regions have led to a continuous increase in the demand for grain and the total consumption of primary agricultural products. Given the relatively limited agricultural output in these provinces, inter-regional resource allocation is essential to fulfill the needs of their agricultural sectors. Consequently, these provinces act as recipients of carbon spillover in the carbon transfer network. Provinces with higher out-degree centrality are mainly located in the core areas of crop and animal husbandry production, which are adjacent to regions with high carbon emissions. Among them, Henan, Xinjiang, Yunnan, Guizhou, and Sichuan in the central and western regions have higher out-degree centrality. The possible reason is that these provinces have superior natural resource conditions, which are suitable for agricultural development and have a large scale of agricultural production. Through the export of agricultural products, they form significant diffusion and spillover effects with other provinces, showing strong spillover power in the carbon transfer network.

(2) Closeness centrality

Closeness centrality is a crucial metric for assessing the centrality and influence of nodes within a network. The research findings reveal that the eastern coastal and central regions of China exhibit significant clustering characteristics in terms of inward closeness centrality. Notably, economically robust provinces such as Guangdong, Zhejiang, Jiangsu, and Shandong, which boast high levels of industrialization, well-developed transportation networks, and dense populations, demonstrate substantial demand for agricultural products and raw materials. These provinces serve as primary recipients of agricultural carbon emissions and act as “convergence points” within the carbon transfer network, underscoring their pivotal roles and reflecting their core positions in the network.

From a spatial distribution perspective, the relatively high values of outward closeness centrality are primarily concentrated in regions such as Xinjiang, Tibet, Qinghai, Ningxia, Gansu, Guizhou, Guangxi, and Inner Mongolia, which are predominantly located in the western part of China. Despite their relatively remote geographical locations, these provinces are characterized by extensive agricultural production and serve as major exporters of agricultural carbon emissions, functioning as “disseminators” within the network. This region exhibits high levels of agricultural carbon emissions but relatively lower economic development, highlighting the imbalance in agricultural resource allocation and economic growth across regions. According to the “externality theory” in environmental economics, such imbalances may lead to a misallocation of responsibility for agricultural carbon emissions, further exacerbating interregional inequities. Therefore, it is imperative to establish a fair responsibility-sharing mechanism for agricultural carbon emissions and promote the implementation of interregional agricultural ecological carbon compensation mechanisms. These measures are essential to ensure equitable agricultural carbon emission reduction and foster coordinated development among regions.

(3) Betweenness centrality

Betweenness centrality indicates the extent to which a node acts as a “bridge” in connecting other pairwise associated nodes, reflecting the degree of control it exerts over the association relationships among other nodes. Provinces with high betweenness centrality include Henan, Guangdong, Beijing, Liaoning, and Shandong. These provinces either possess abundant agricultural resources or have a high demand for agricultural products, making it easy for them to establish close cooperative relationships with other provinces. They have a high overall agricultural carbon emission and transfer volume, and a strong ability to influence the carbon emission exchanges of other provinces. This indicates that these provinces play the roles of “intermediaries” and “hubs” in the carbon transfer network, significantly controlling the carbon transfer association relationships among other provinces. In contrast, due to their remote geographical locations, Ningxia, Qinghai, and Tibet in the western regions rank lower, with a betweenness centrality of 0, making it difficult for them to play a role in transmitting carbon emissions to other provinces.

Table 1. Individual characteristics of China's agricultural trade carbon transfer network in 2017.

Province	**Degree centrality**		**Closeness centrality (%)**		**Betweenness centrality**
	Out-degree centrality	In-degree centrality	Inward closeness centrality	Outward closeness centrality	Centrality

Beijing	12	17	69.77	9.65	50.81
Tianjin	12	5	46.88	9.62	2.63
Hebei	10	9	55.56	9.59	33.84
Shanxi	9	3	37.04	9.55	6.57
Inner Mongolia	7	0	3.23	10.31	0.00
Liaoning	7	3	46.15	9.46	57.84
Jilin	11	2	32.26	9.62	2.99
Heilongjiang	6	1	31.92	9.38	0.23
Shanghai	10	5	53.57	9.52	1.52
Jiangsu	10	29	96.77	9.52	21.25
Zhejiang	9	29	96.77	9.49	18.91
Anhui	9	21	76.92	9.49	5.70
Fujian	10	19	73.17	9.55	30.54
Jiangxi	10	5	43.48	9.55	2.09
Shandong	10	24	81.08	9.55	47.31
Henan	13	21	76.92	9.71	119.84
Hubei	9	21	76.92	9.49	14.09
Hunan	10	10	60.00	9.52	18.06
Guangdong	8	30	100.00	9.49	44.94
Guangxi	7	0	3.23	10.31	0.00
Hainan	1	0	3.23	9.77	0.00
Chongqing	10	6	54.55	9.52	3.67
Sichuan	11	20	73.17	9.55	14.46
Guizhou	12	0	3.23	10.53	0.00
Yunnan	12	2	48.39	9.55	12.30
Tibet	9	0	3.23	10.35	0.00
Shaanxi	6	5	53.57	9.38	0.42
Gansu	7	0	3.23	10.35	0.00
Qinghai	9	0	3.23	10.35	0.00
Ningxia	9	0	3.23	10.38	0.00
Xinjiang	12	0	3.23	10.53	0.00

4.4. Community division of the agricultural carbon transfer network

The community structure indicates that provinces in the carbon transfer network can be divided into several smaller groups, with regions within the same community being more closely connected. Figure 4 presents the community division results of China's agricultural carbon transfer network in 2017. The agricultural carbon transfer network in China is divided into seven communities, each of which is roughly spatially adjacent and exhibits a spatial clustering phenomenon. Community 1 consists of six provinces: Tianjin, Fujian, Hubei, Hunan, Yunnan, and Xinjiang. Community 2 comprises six provinces: Beijing, Hebei, Shanxi, Inner Mongolia, Shandong, and Ningxia. Community 3 encompasses six provinces: Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, and Guizhou. Community 4 includes four provinces in the western region: Chongqing, Sichuan, Tibet, and Qinghai, which are characterized by a larger scale of agricultural development and a higher proportion of agricultural economy in the overall economy. Community 5 is made up of three provinces: Guangdong, Guangxi, and Hainan. Community 6 consists of three northeastern provinces: Liaoning, Jilin, and Heilongjiang, which are distinguished by their spatial proximity. Community 7 includes three provinces: Henan, Shaanxi, and Gansu. The division results of the seven communities indicate that agricultural trade within each community is closely linked, and agricultural carbon emissions exhibit bidirectional spillover characteristics. Moreover, agricultural carbon transfer demonstrates geographical stickiness. Due to factors such as geographical location, market demand, and transportation costs, agricultural product trade typically occurs between adjacent provinces, leading to a localized clustering pattern of agricultural carbon transfer in space, which is highly correlated with economic and trade connections.

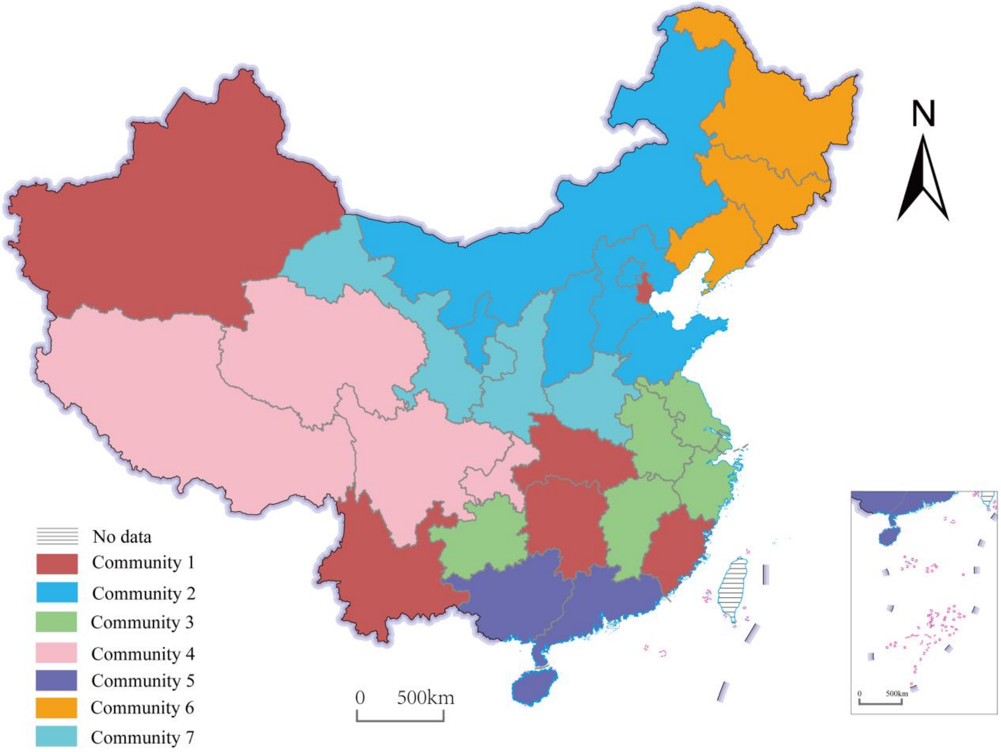

Figure 4. Spatial distribution of community division in carbon transfer network in 2017.

Note: This map is drawn based on the standard map with the map review number GS(2020)4630 from the Standard Map Service website of the Ministry of Natural Resources, and the boundaries of the base map are not modified.

5. Conclusions

This paper has calculated the interprovincial agricultural trade carbon transfer volume in China in 2017 and has analyzed the spatial transfer characteristics of interprovincial agricultural carbon transfer. It has then employed social network analysis methods to explore the relational characteristics of the agricultural carbon transfer network. Finally, the Leiden community detection algorithm has been utilized to identify communities with close connections within the carbon transfer network. The main conclusions are as follows:

(1) **In 2017, carbon transfers flowed from areas rich in agricultural resources to economically developed areas.** Regions with a net carbon transfer volume less than 0 were mainly the main grain sales areas, while those with a net carbon transfer volume greater than 0 were primarily the main grain production areas and some grain production and sales balance areas. Provinces with a large amount of carbon outflow were mainly Heilongjiang, and the province with the largest amount of carbon inflow was mainly Guangdong. The main direction of agricultural carbon transfer was from the main grain production areas in the central region, the northeastern region, and the western region to the eastern and southeastern regions.

(2) **The agricultural carbon transfer network was sparse but stable, with eastern provinces mainly at the core and western regions primarily at the periphery.** During the research period, the overall interconnections within the agricultural carbon transfer network were relatively sparse, yet the network exhibited good connectivity and stability. An analysis of individual structural characteristics reveals that provinces such as Guangdong, Zhejiang, Jiangsu, Beijing, and Shandong occupy central positions within the network, demonstrating a significant capacity to control and manage the agricultural carbon transfer network.

In contrast, western regions such as Ningxia, Qinghai, and Tibet play a more passive role in the agricultural carbon transfer network.

(3) **Within the agricultural carbon transfer network, communities exhibited strong geographical stickiness.** The community detection results indicate that agricultural trade linkages within each community are highly interconnected, with agricultural carbon emissions exhibiting characteristics of bidirectional spillover effects, while interregional carbon transfers demonstrate geographical stickiness.

Based on the research findings, the following suggestions are proposed:

(1) **Consumer responsibility should be implemented, and ways for local governments to provide compensation should be explored.** While the demand side enjoys the external benefits brought by the agricultural ecological environment, it also consumes a large amount of agricultural ecological resources. By constructing an interprovincial carbon transfer network and from the perspective of consumer responsibility, the ecological responsibility that different consumers at the market end should bear can be quantified. Local governments can identify the main bodies of compensation responsibility based on the consumption volume of agricultural products from other provinces in their regions and the carbon emissions implied therein, and implement the transfer payment of compensation funds accordingly. The compensation amount is determined by the carbon transfer volume and the carbon transaction price, which can be calculated based on the average price of the national carbon emission rights trading market.

(2) **Establish a collaborative mechanism for inter-regional agricultural carbon transfer.** By enhancing communication and cooperation between provinces, an inter-regional collaborative mechanism for agricultural carbon transfer can be established to achieve coordinated emission reduction and optimal resource allocation among regions. Regions with high carbon inflows can establish cooperative relationships with regions from which they receive a large amount of carbon emissions. Through technical exchanges and project cooperation, they can jointly promote agricultural carbon emission reduction. For example, Guangdong, as the province with the largest net carbon inflow in agriculture, can carry out agricultural project cooperation and provide modern agricultural technical support to regions such as Heilongjiang and Guangxi, which have a high amount of agricultural carbon emissions flowing into Guangdong.

The implementation of inter-regional collaborative mechanisms may face challenges, including economic disparities, policy coordination difficulties, technical and managerial capacity gaps, and insufficient funding. To address these issues, it is recommended to develop a unified policy framework, provide technical support and capacity-building programs, and establish dedicated funding mechanisms or leverage carbon trading markets to ensure effective and sustainable collaboration.

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