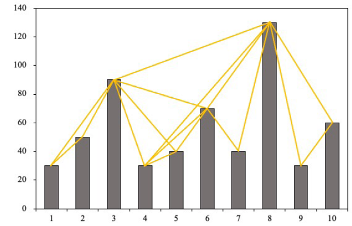
Throughput properties and clustering analysis of coastal ports in mainland China: an analysis method by time series complex network



Propiedades de rendimiento y análisis de agrupación de los puertos costeros de China continental: un método de análisis mediante una red compleja de series temporales

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RESUMEN

- Las orientaciones explícitas de desarrollo de los puertos son fundamentales para promover que las agrupaciones portuarias pasen de las competiciones caóticas a un desarrollo colaborativo jerárquico. Para investigar la orientación del desarrollo y las jerarquías de los puertos costeros de China continental, en este estudio se construyó una red de gráficos de visibilidad para un análisis de series temporales de los rendimientos portuarios de China desde 2000 hasta 2020. En este modelo, se utilizaron los cuatro índices de rendimiento de la carga, la carga de comercio interior, la carga de comercio exterior y los contenedores para medir la escala de los puertos. Se calcularon las características estructurales topológicas de la red de rendimiento de los puertos, incluyendo su grado medio, su diámetro y su coeficiente medio de agrupación. A continuación, los puertos se dividieron en cuatro tipos en función de las características de su red. Los resultados muestran que la red de series temporales de rendimiento de los puertos costeros de China continental tiene una estructura jerárquica evidente y, en general, presenta las características de las redes de mundo pequeño. Estos puertos están estrechamente conectados y tienen una gran capacidad de transbordo. Sin embargo, en esta red no existe un "centro absoluto" y estos puertos se encuentran en un estado de competencia desordenada y caótica con una grave homogeneización. El modelo propuesto proporciona un método adecuado para la futura planificación y diseño de clusters portuarios.
- **Palabras clave:** Rendimiento portuario, Características del rendimiento, Gráfico de visibilidad, Redes complejas de series temporales, Análisis de clustering.

ABSTRACT

Explicit development orientations of ports are critical to promoting port clusters from chaotic competitions to a hierarchical collaborative development. To investigate the development orientation and hierarchies of coastal ports in Mainland China, a visibility graph network was constructed in this study for a time series analysis of China's port throughputs from 2000 to 2020. In this model, the four throughput indexes of cargo, domestic trade cargo, foreign trade cargo, and container were used to measure the scale of ports. The topological structural features of the throughput network of ports, including its average degree, diameter, and average clustering coefficient, were calculated. The ports were then divided into four types based on their network characteristics. Results show that the throughput time series network of coastal ports in Mainland China has an obvious hierarchical structure and generally has the characteristics of small-world networks. These ports are closely connected and have a strong transshipment capacity. However, an "absolute center" does not exist in this network, and these ports are in a state of disorderly and chaotic competition with serious homogenization. The proposed model provides an appropriate method for the future planning and design of port clusters.

Keywords: Port throughput, Throughput characteristics, Visibility graph, Time series complex networks, Clustering analysis.

1. INTRODUCTION

As a basic element of shipments, ports have waterways, transport equipment, and conditions for the in and out transportation of ships and cargo handling. Ports are rally points and hubs of land and water transportation that have become comprehensive resource allocation centers integrating finance, business, services, and logistics. Port construction also transits to multi-port collaborative construction in a region. For this reason, countries all over the world are taking the initiative to promote a coordinated development of regional port clusters. However, the construction of key ports needs to be strengthened. In 1993, the European Union (EU) established the European Port Association to realize a coordinated development of ports in the EU and to implement a unified management of 1600 ports in 20 EU countries. In more than 30 years since its foundation, the association has played a significant role in coordinating benefit conflicts among port members and ensuring a fair competition among ports in Europe.

With the recent increase in rapid port infrastructure construction, the cargo throughput of ports in China increased from 280 million tons in 1978 to 14.55 billion tons in 2020, whereas its container throughput increased from 32,900 twenty-foot equivalent units (TEU) in 1979 to 260 million TEU in 2020. Globally, China has consistently ranked at the top in terms of number of ports and ships and port throughput. Chinese shipping lines and networks are spread all over the world. At present, China's role in the global supply chain and international trade is gradually increasing, and

Chinese ports play an important role in the world shipping network. According to the Liner Shipping Connectivity Index (LSCI) published by the United Nations Conference on Trade and Development, China obtained an LSCI index score of 151.9 in 2019 and maintained the highest index in the world for 10 continuous years. Most ports in the country are still at a stage of "independent" development and lack overall planning and coordinated management. Moreover, the global industrial chain is experiencing a reverse globalization trend due to the COVID-19 pandemic, thereby significantly reducing international and domestic trade volumes. These problems greatly hinder the production, management, and development of ports.

Therefore, Chinese ports must accelerate their transformation and upgrading from a single port construction to a coordinated development of multi-level port clusters, determine new port orientations, and maintain their competitiveness and adaptiveness to new development situations. To address the problems being faced by coastal ports in Mainland China, a port throughput network was built in this study based on the visibility graph of time series and complex network theory. The topological structures of the port throughput network were analyzed, and various topological indexes, including average degree of network nodes, diameter, and clustering coefficient, were calculated. Those ports with the same throughput characteristics were classified using the clustering algorithm to achieve a reasonable orientation of different ports in the development of port clusters.

The rest of this study is organized as follows. Section 2 reviews the related work. Section 3 proposes the research model and methodology. Section 4 analyzes the structural characteristics of a port throughput network by building a visibility graph of the complex network and searches for port clusters with different characteristics in the network by using the K-means clustering algorithm. Section 5 concludes the study.

2. STATE OF THE ART

Ocean shipping development has attracted the attention of geographers since the 1970s. These geographers have been exploring the formation mechanism of complex port shipping networks and the connections among ports. For instance, Hayuth proposed a five-stage model of container port network in the US and found through a Lorenz curve and Gini coefficient analysis that the port network structure of the country has gradually become dispersed due to the competition among ports and shipping systems [1-2]. This model has also been applied in scientifically analyzing the evolution of port clusters in Southeast Asia and East Africa and the development process of the container port network in the US [3-5]. Previous studies have also explored the evolutionary characteristics of the container port network in Europe, Japan, and Korea and found that the competition among ports, technological progress, and market connections promote the development of port networks [6-8]. Wang discussed the development of container ports in Hong Kong in the background of different development levels and institutions and concluded that the development path of port clusters changes along with the regional environment [9]. Yang et al. examined the competition and coordinated development of port networks in Northeast Asia and evaluated the competitiveness of major local ports by building an index system; they found that Chinese ports may have become transportation hubs in the region [10]. Camarero et al. studied the structures and characteristics of port clusters in Spain through clustering analysis by choosing port indexes and hinterland city indexes [11].

Complex networks are critical to describe the topological structures and behaviors of a complex system. Accordingly, these networks have become a research hotspot in recent years [12-13]. With the crossing and continuous integration of different disciplines, scholars have begun to conduct cross-over studies on the science of complexity and the characteristics of complex networks by using graph theory, statistical analysis, and other methods. In the 1960s, the Entity Relationship Diagram proposed by Erdos and Renyi symbolized the birth of complex network theory. To further describe the topological structural characteristics of a real network, Watts and Strogtz proposed the small-world network model in 1998 [14]. In 1999, Barabasi perfected complex network theory by constructing a scale-free network model [15-16]. Studies on complex networks have also rapidly developed against the theoretical background of small-world and scale-free networks. Researchers from many fields have proposed their own complex network models. For instance, Newman and Moore, May, and Lloyd et al. studied viral transmission in small-world, Internet, and scale-free networks, respectively [17-25]. Guimer et al. analyzed the network characteristics of American Airlines based on a complex network [19]. Sen et al. disclosed the properties of a small-world railway network by studying the railway network in India [20].

The international ocean shipping network is one of the most complex networks in the world. Many scholars have analyzed the structure and dynamic characteristics of this network by using economic geography and statistical physics. Kaluza and Deng built global and regional container transport networks based on their complex topological structure and physical properties and measured the "small-world" effect of network structure based on the average path length and clustering coefficient. They also described the scale-free characteristics of the network structure via measurement distribution [25-26]. On this basis of their work, other scholars engaged in complex network theory recently identified additional statistical characteristics of container shipping networks, including their degree, vertex strength, and closeness centrality. By analyzing the global shipping network from 1996 to 2006, Ducruet et al. systematically described the dynamic development and evolutionary process of the global container port system, measured the degree of connection among ports in the shipping network, graded the ports in the system, and concluded that the global shipping network has some robustness [27]. Fernando et al. analyzed the container cargo transportation network using graph theory and explored the structural changing modes of the global container transport network before and after the 2008 global financial crisis by using complex network indexes, including degree, centrality, and vulnerability [28].

In sum, while previous studies have focused on shipping lines or regional shipping networks, a time-series-based quantitative analysis of port throughput networks remains lacking. Moreover, no previous study has proposed an effective classification of port clusters based on port throughput. To fill these gaps, this study innovatively combined the visibility graph of time series with complex network theory based on findings from the literature. A complex network quantitative study of cargo throughput, domestic trade cargo throughput, foreign trade cargo throughput, and container throughput of ports was performed through a visibility graph by using panel data of coastal port throughput in Mainland China from 2000 to 2020. The topological structures of the port throughput network were analyzed, and its parameters were clustered to discover ports having the same throughput characteristics, to determine the orientation of ports in the development of port clusters, and to strengthen the division of labor of port clusters.

3. METHODOLOGY

3.1. TIME SERIES NETWORKS

A complex network was constructed by using the visibility graph method proposed by Lacasa. The visibility graph of time series is a scientific research method for describing the throughput network of coastal ports. The new connections between time series and the complex network provide extensive possibilities for studying the latter [29-30].

The time series data related to the throughput of coastal ports in Chinese mainland were transformed into a complex network. First, the discrete time series data of subsystem $x(t)$ were linked to the nodes of the network, and network connections were established according to the visualization criteria, that is, any two points between (t^a, x^a) and (t^c, x^c) within the series data were connected through visualization. In other words, for any point (t^b, x^b) between (t^a, x^a) and (t^c, x^c), the connection side can be built when $(t^a < t^b < t^c)$ by satisfying:

$$x^b < x^a + (x^c - x^a)(t^b - t^a)/(t^c - t^a) \tag{1}$$

Fig. 1 illustrates the procedure of converting time the series data (Fig. 1(a)) to its visibility graph (Fig. 1(b)). The gray line in Fig. 1(a) indicates the two observations can see each other. The visibility graph is always connected because each observation is certainly connected to its previous and next views except for the first and last observations. The visibility criteria ensure that visibility graph is invariant under vertical (linear) rescaling, translation and superposition of a linear trend of a time series.

Second, an adjacent matrix was built based on the corresponding time series or visibility graph network. Methods or measures from network science were then applied to analyze the time series data (Fig. 2).

3.2. COMPLEX NETWORK STRUCTURE

A specific network was abstracted into a graph $G = (V, E)$ which comprised the vertex set $V(G)$ and edge set $E(G)$. The number of nodes was $N = |V|$, and the number of edges was $M = |E|$. In $E(G)$, each edge corresponded to a pair of vertexes in $V(G)$. To characterize the complex network properties, some parameters were chosen, including average degree, network diameter, average path length, and average clustering coefficient.

3.2.1. Average degree

For node i, degree is defined as the number of other nodes connected to a fixed node, that is, the number of nodes adjacent to another node. Generally, different nodes correspond to different degrees. The mean degree of all nodes is viewed as the average degree of the complex network and can be expressed as:

$$k = \sum_{i=1}^{N} k_i / N \tag{2}$$

In the complex network, degree is used to characterize the degree of importance of nodes.

3.2.2. Average path length

The distance between two nodes is represented by the number of edges on the shortest path between these nodes. Meanwhile, the maximum distance between any two nodes is represented by diameter D, which is defined as:

$$D = \max_{i,j} d_{ij} \tag{3}$$

The average path length of the network expresses the mean distance between any two nodes, where N is the total number of nodes in the network.

$$L = 2\sum_{j=1}^{N-1}\sum_{i=1}^{N} d_{ij} / (N(N-1)) \tag{4}$$

3.2.3. Average clustering coefficient

If node i is connected to other nodes through edges, then these nodes are viewed as adjacent nodes of node i. There's a node on number of connecting edges to each node. The clustering coefficient can be determined by the ratio between the number of edges E_i and the maximum number of edges $(k_i(k_i - 1/2)$.

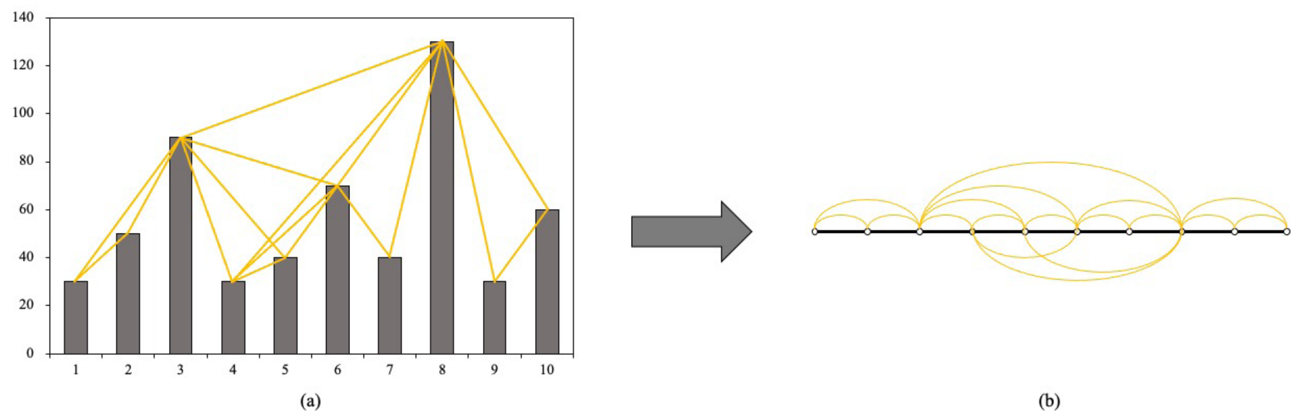

Fig. 1. Visibility graph and its associated graph

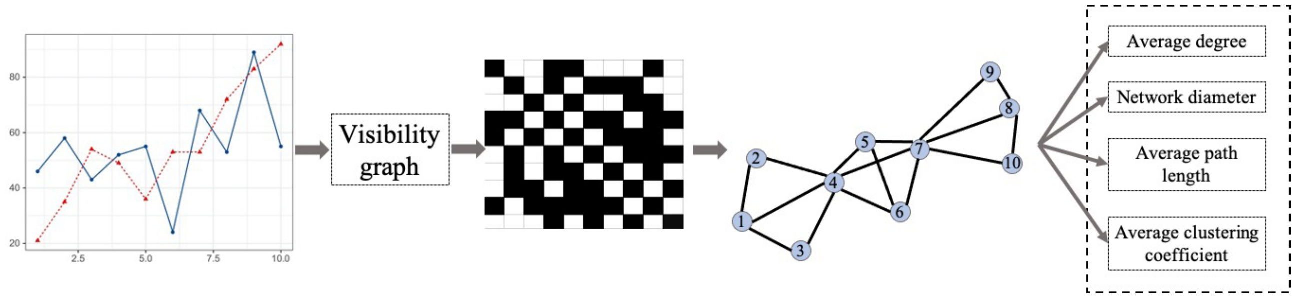

Fig. 2. Procedure for constructing time series networks and related network analyses

For each node, the clustering coefficient is calculated as:

$$C_i = 2E_i /(k_i(k_i - 1/2) \tag{5}$$

For the whole network, the clustering coefficients of all nodes are averaged, and the corresponding clustering coefficient C is calculated.

The clustering coefficient of the whole network is defined as the average clustering coefficient of all nodes i in the network, which is denoted by C and calculated as:

$$C = \sum_{i=1}^{n} C_i / N \tag{6}$$

3.3. K-MEANS CLUSTERING ALGORITHM

According to the characteristics of high similarity between samples of the same category and low similarity between samples of different categories, the algorithm that divides data samples into several categories through the internal relationship between data without any data label is called clustering algorithm. Among them, K-means clustering algorithm is the most basic clustering algorithm, which is widely used in related fields of clustering due to its strong local search ability, high clustering efficiency of big data sample space, fast convergence speed and easy implementation. The basic idea is to find K clusters iteratively to minimize the loss function corresponding to clustering results. The loss function describes the tightness between clustering centers. The smaller the value of the loss function is, the higher the similarity between samples in the cluster is, the better the clustering effect is.

3.4. DATA

According to the National Coastal Port Planning issued by the Ministry of Communications of China, the coastal ports in Mainland China, which rank among the top 25 coastal ports in the world in terms of cargo throughput, were chosen as the research object. The cargo throughputs of these ports from 2000 to 2020 were used as basic data to build the cargo throughput complex network and to perform the clustering analysis. The distribution of the chosen coastal ports is shown in Fig. 3. Data on these ports were collected from https://data.worldbank.org.cn/ and https://data.stats.gov.cn/. The original data are plotted in Fig. 4 (see section: supplementary material).

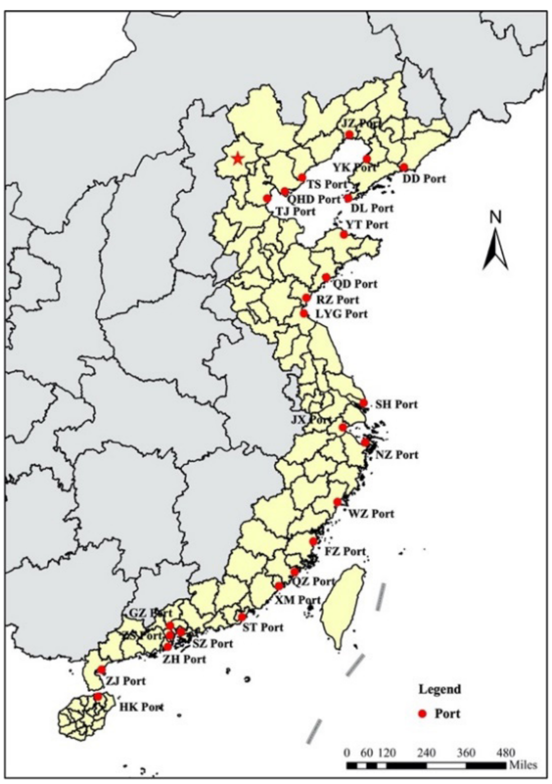

Fig. 3. Distribution map of coastal ports in Mainland China

4. RESULT ANALYSIS AND DISCUSSION

The complex network of the cargo throughput of ports can reflect shipping connections and mutual dependence relations. The evolution of the cargo throughput network of ports is a consequence of the interactions among ports across different regions. Evolution is a characteristic of dynamics and stages. Some studies have proven that complex network theory can effectively elaborate the formation mechanism of a complex system and reflect the characteristics of a complex network. Average degree reflects the importance and distribution capacity of ports in the cargo throughput network and serves as a basic property of ports. The clustering coefficient of ports reflects their local regional concentration, whereas the average path length of port nodes reflects the throughput capacity of ports. Therefore, average degree, clustering coefficient, and average path length can comprehensively reflect the properties of ports in a complex network. Complex network theory can help disclose the structural features of and existing problems in the cargo throughput network of ports and provide references for the sustainable development of port clusters.

4.1. REGIONAL TIME SERIES NETWORK UNDER A SINGLE INDEX

Based on the throughput data of the coastal shipping network in Chinese mainland, time series networks under cargo throughput, domestic trade cargo throughput, foreign trade cargo throughput, and container throughput were constructed using the visibility graph method (Table 1). The correlation network properties of these four regional networks were analyzed from the network science perspective. In this section, the average degree, network diameter, average path length, and average clustering coefficient of each network were described. Subsequently, time series networks under different indexes may show various characteristics, indicating the presence of different infrastructures, production capacities, business environments, development goals, cargo distribution capacities, and transshipment capacities among the coastal ports in Chinese mainland. Therefore, time series networks must be combined with four different indexes, and a deep exploration of the properties and structures of the cargo throughput network of ports is warranted.

The following conclusions can be drawn from the above analysis: (1) network topology can inherit the characteristics of the corresponding time series, and the gained network can reflect the properties of relevant time series under specific indexes. (2) The combination of time series and a complex network can provide a universal method for studying a complex network and has extensive possibilities.

4.2. CLASSIFICATION OF PORT CLUSTERS UNDER FOUR DIFFERENT INDEXS

Based on the parameters of the visibility graph network, a clustering analysis of a regional time series network comprising 25 major coastal ports in Mainland China was performed using the K-means clustering algorithm. The clustering results of coastal ports in Mainland China under different indexes were then analyzed.

Port	Cargo throughput				Domestic trade throughput				Foreign trade throughput				Container throughput			
	k	D	L	C	k	D	L	C	k	D	L	C	k	D	L	C
JX Port	5.10	4	1.62	0.73	5.10	4	1.63	0.75	3.81	4	1.81	0.67	5.62	3	1.52	0.77
RZ port	4.10	4	1.81	0.75	3.29	4	1.95	0.74	3.24	4	1.97	0.77	7.29	2	1.27	0.86
TS Port	4.57	4	1.88	0.85	3.76	3	1.81	0.75	3.95	5	2.14	0.80	6.52	3	1.39	0.84
FZ port	2.76	4	2.02	0.80	3.43	4	1.88	0.80	3.10	5	2.01	0.78	4.95	3	1.58	0.76
ZJ Port	4.24	4	1.74	0.78	4.81	3	1.60	0.83	2.86	3	1.93	0.81	5.62	3	1.45	0.77
HK port	6.00	3	1.45	0.81	5.90	3	1.46	0.79	2.67	3	1.85	0.74	6.00	3	1.42	0.72
GZ Port	2.43	5	2.37	0.72	2.48	6	2.45	0.71	2.10	7	2.88	0.69	3.00	5	2.34	0.78
SH port	2.43	4	2.36	0.86	2.38	4	2.33	0.85	2.33	6	2.94	0.73	2.71	5	2.55	0.74
SZ Port	2.10	7	3.12	0.74	2.71	5	2.24	0.74	2.14	9	4.01	0.75	2.00	5	2.62	0.72
QZ Port	2.71	5	2.40	0.72	2.62	7	2.92	0.75	4.29	4	1.80	0.75	2.62	5	2.21	0.75
YT port	3.52	4	1.85	0.75	3.33	3	1.87	0.76	3.71	4	1.85	0.72	2.67	4	2.12	0.78
XM port	2.86	5	2.14	0.71	3.14	3	1.84	0.80	2.86	5	2.35	0.80	2.24	4	2.24	0.65
ZS Port	3.86	4	1.80	0.76	4.14	4	1.71	0.73	2.43	4	2.12	0.80	1.95	5	2.57	0.78
TJ port	2.10	7	3.01	0.75	2.57	3	1.99	0.81	2.52	6	2.74	0.71	3.29	4	2.30	0.85
ST Port	4.38	5	2.33	0.85	3.10	5	2.50	0.80	2.81	7	2.75	0.67	3.71	4	2.05	0.79
ZH Port	3.10	5	2.18	0.59	3.14	6	2.24	0.65	2.86	4	2.01	0.69	4.33	3	1.62	0.74
QHD Port	2.10	6	2.85	0.71	2.24	6	2.79	0.68	3.71	5	2.04	0.66	2.95	3	1.89	0.79
NZ Port	3.14	3	1.91	0.80	2.81	3	1.87	0.84	3.10	4	1.99	0.78	3.43	3	1.88	0.79
WZ Port	2.10	7	3.10	0.71	2.19	5	2.65	0.74	2.62	5	2.39	0.73	3.33	3	1.80	0.80
JZ port	2.86	5	2.17	0.73	2.29	6	2.50	0.72	2.95	3	1.89	0.72	3.52	3	1.80	0.79
LYG port	3.95	4	2.28	0.81	3.71	4	2.06	0.80	2.76	6	2.63	0.69	3.19	5	2.28	0.82
DL port	3.43	5	2.31	0.78	3.10	5	2.39	0.80	2.38	6	2.46	0.67	3.76	5	2.23	0.72
QD Port	2.95	5	2.46	0.81	3.29	4	2.03	0.81	2.90	4	1.91	0.81	2.71	6	2.74	0.82
YK Port	3.90	7	2.75	0.79	3.95	5	2.37	0.85	3.38	4	1.93	0.77	4.19	5	2.37	0.87
DD port	5.24	6	2.31	0.82	4.67	5	2.20	0.83	3.57	3	1.86	0.85	4.71	5	2.28	0.81

Table 1. Regional time series networks of ports in Chinese mainland based on visibility graphs

4.2.1. Classification of port clusters under cargo throughput

The clustering results of coastal ports in Mainland China under cargo throughput are shown in Fig. 5, where each color represents the same cluster, and the ports under each type are similar under the corresponding index. Fig. 5 shows that the 25 coastal ports in Mainland China can be divided into 4 clusters according to their cargo throughput. Cargo throughput can reflect the scale and layout capacity of ports to some extent. The import nodes of the cargo throughput network of ports can be recognized by analyzing the coastal port throughput network in Mainland China. The first cluster has an average degree of 6.00, which suggests that Haikou Port is connected to 6 ports in the cargo throughput network. Meanwhile, the average path length of this cluster is 1.45, indicating that the Haikou Port has the best cargo transshipment capacity among all ports in the network. Haikou Port also has the lowest cargo exchange cost and highest network exchange efficiency. The second port cluster has an average degree, average clustering coefficient, and average path length of 4.21, 0.79, and 1.95, respectively. The average degree and average clustering coefficient of this cluster are relatively high, indicating that these nodes are closely connected in the network. These ports also have relatively high cargo throughputs and distribution capacities. Meanwhile, the third cluster has moderate average degree, network diameter, average path length, and average clustering coefficient. However, these ports are not as important as those in the first two clusters, which suggest that the cargo throughputs of the second and third port clusters are slightly connected to some extent in the network. The fourth cluster has an average degree, average path length, and average clustering coefficient of 2.46, 1.45, and 0.74, respectively. The fourth cluster has the largest network diameter yet the lowest average path length and average clustering coefficient, which suggests that Shenzhen Port and Wenzhou Port have the lowest throughput, weakest connections with other ports, and smallest concentrated transportation capacity among all ports in the network.

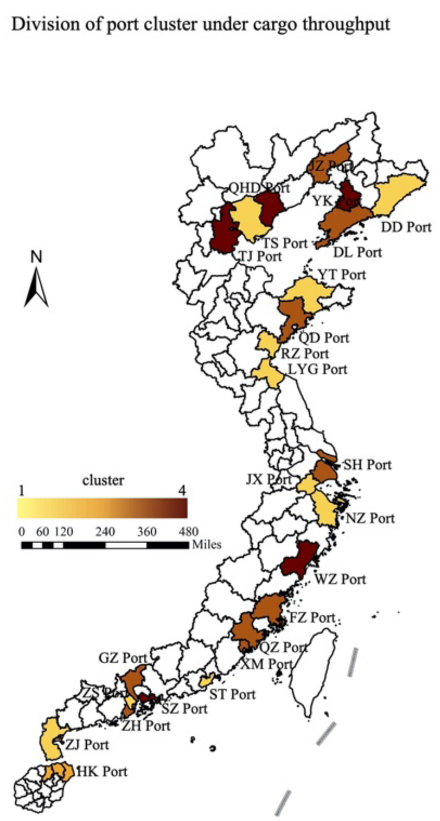

Fig. 5. Clustering results of coastal ports in Mainland China under cargo throughput

4.2.2. Classification of port clusters under domestic trade cargo throughput

The regional visibility graph of the time series of the domestic trade cargo throughput of 25 coastal ports in Mainland China was analyzed by using K-means clustering algorithm. The clustering results are shown in Fig. 6, where each color represents a cluster. These 25 coastal ports are divided into 4 clusters. Domestic trade cargo throughput reflects the proportion of domestic shipping in the cargo transportation of ports and is determined by the development level of domestic trade, domestic market demands, shipping capacity, and port management level. The importance of ports in the domestic trade cargo throughput network can be recognized through a clustering analysis of the complex network. The first cluster has an average ownership of 5, which suggests that these ports are connected to an average of 5 other ports in the domestic trade cargo throughput network. In addition, this cluster has an average path length of 1.56, indicating that these 3 ports have the best domestic cargo transshipment capacity, the lowest domestic cargo exchange cost with other ports, and the highest transportation efficiency in the network. The average degree of the second cluster is 3.29, indicating that ports in this cluster are connected to ports in 3 other clusters in the domestic trade cargo throughput network. This cluster has an average clustering coefficient and average path length of 0.79 and 2.39, respectively, both of which are relatively high, indicating that the ports in this cluster are closely related in the domestic trade cargo network and have strong domestic cargo distribution capacity. The third cluster has a moderate average degree, network diameter, average path length, and average clustering coefficient, indicating that these ports are connected in the domestic trade cargo throughput network. However, these connections are relatively weak, and these ports are not very important in the network. The average degree, average path length, and average clustering coefficient of the fourth cluster are 2.46, 2.55, and 0.70, respectively. Despite having the largest network diameter, the fourth cluster has a relatively low average path length and average clustering coefficient, which implies that the ports in this cluster are the weakest in the domestic trade cargo throughput network and have very weak connections to the other ports. These ports also have the lowest domestic trade cargo transshipment capacity.

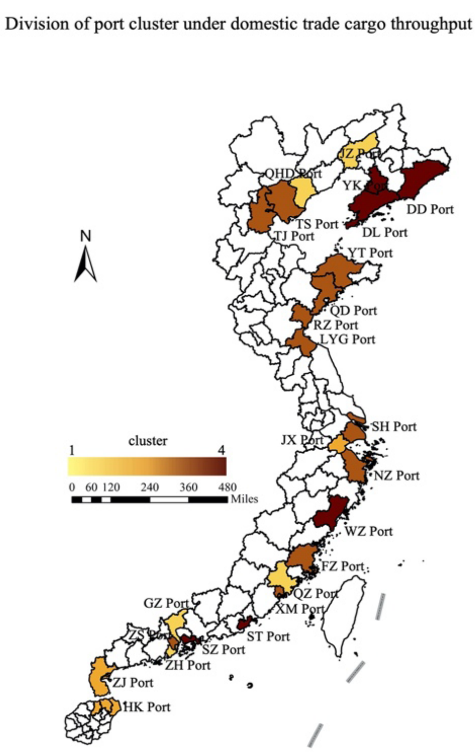

Fig. 6. Clustering results of coastal ports in Mainland China under domestic trade throughput

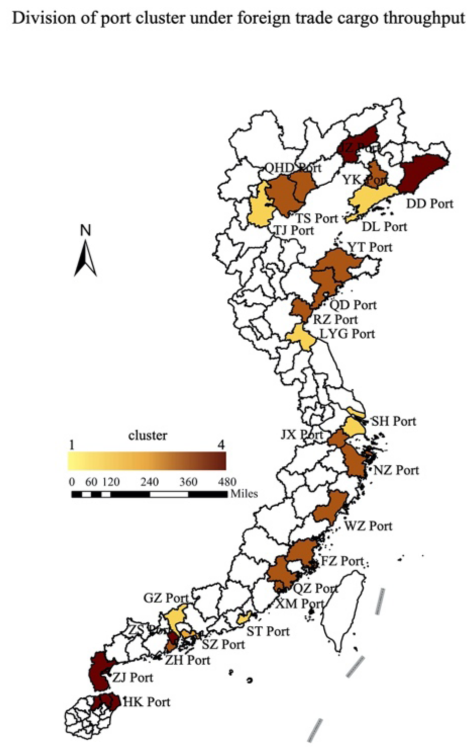

Fig. 7. Clustering results of coastal ports in Mainland China under foreign trade throughput

4.2.3. Classification of port clusters under foreign trade cargo throughput

The regional visibility graph of the time series of the foreign trade cargo throughput of 25 coastal ports in Mainland China was analyzed by using K-means clustering algorithm. The clustering results are shown in Fig. 7, where each color represents a cluster. These 25 coastal ports are divided into 4 clusters. The foreign trade cargo throughput of a port refers to the total quantity of foreign trade cargos moving in and out of the port through a waterway. This throughput not only is an important index that reflects the foreign business outcomes of ports but also serves as a reference index for measuring the foreign trade development level of ports and relevant hinterlands. The visibility graph network of the regional time series network was analyzed by using the K-means clustering algorithm, and the ports were divided into four optimal clusters. The first cluster has an average degree of about 3, which suggests that these ports are connected to ports from 3 other three clusters in the network. For the first cluster, the average path length is about 2, whereas the average clustering coefficient is 0.75. At the port level, the average degree of Quanzhou Port is 4.29, which is the highest in the foreign trade cargo throughput network, hence suggesting that the Quanzhou Port is connected to approximately 4 other ports in the foreign trade cargo throughput network and has the best transshipment capacity and highest foreign trade goods transportation efficiency in the network. Meanwhile, the second cluster has an average degree of 2.90, indicating that the ports in this cluster are connected to ports from 3 other clusters in the foreign trade cargo throughput network. The clustering coefficient and average path length of this cluster are 0.78 and 1.93, respectively, whereas its average degree and average clustering coefficient are relatively high, indicating that these nodes are closely connected in the foreign trade network. The ports in the second cluster have a relatively strong foreign trade cargo distribution capacity and a relatively good distribution capacity, transshipment capacity, and centrality. The average degree and average clustering coefficient of the second cluster are lower than those of the first and second clusters, which suggest that all three clusters are connected in the foreign trade cargo throughput network but their connections are relatively weak and less important. At the port level, Shenzhen Port has an average degree of 2.14, which is the lowest in the network, whereas its average path length and clustering coefficient are 4 and 0.75, respectively. Shenzhen Port has the maximum network diameter but the lowest average path length and clustering coefficient in the network. In sum, this port is the weakest in the foreign trade cargo throughput network, has very weak connections to the other ports, and has the lowest foreign trade transshipment capacity.

4.2.4. Classification of port clusters under container throughput

The global container transportation industry has developed rapidly along with the construction of container ships and increase in containerization rate. Container throughput reflects the current scale and strength of ports. The container throughput visibility graph network of the regional time series network was then analyzed by using the K-means clustering algorithm. The container throughput of coastal ports in Mainland China is shown in Fig. 8, where each color represents a cluster.

The first cluster has an average degree of 6, indicating that each of the above ports is connected to 6 other ports in the network. Rizhao Port shows the highest average degree and is connected to 7 other ports in the network, and its average path length and average clustering coefficient are 1.44 and 0.79, respectively. In the container throughput network, the first cluster has the best

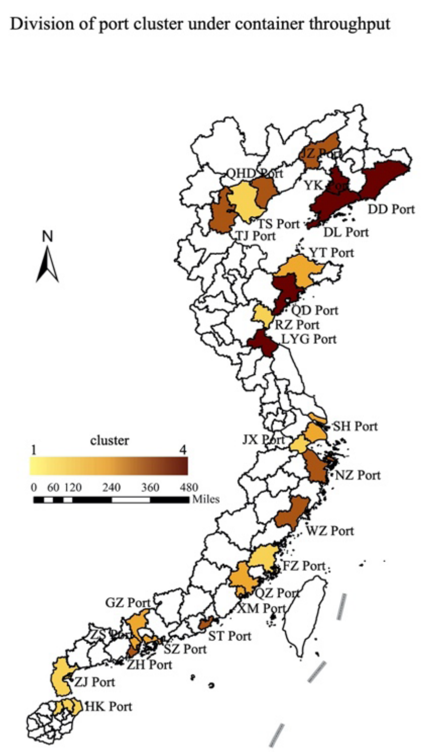

Fig. 8. Clustering results of coastal ports in Mainland China under container throughput

container cargo transportation capacity and transportation efficiency. The second cluster, which includes Dalian Port and Qingdao Port, has an average degree of 3.71, indicating that these ports are connected to 4 other ports in the network. Meanwhile, the second cluster has relatively high average clustering coefficient and average path length of 0.81 and 2.38, respectively, indicating that these ports are closely related in the container throughput network and have relatively strong container distribution capacity, transshipment capacity, and centrality. The third cluster, which includes Tianjin Port, Shantou Port, Zhuhai Port, Qinhuangdao Port, Ningbo-Zhoushan Port, Wenzhou Port, and Jinzhou Port, have obtained a relatively low average degree and average clustering coefficient, indicating their low importance in container transportation and weak connections to other ports. The fourth cluster, which includes Guangzhou Port, Shanghai Port, Shenzhen Port, Quanzhou Port, Yantai Port, Xiamen Port, and Zhongshan Port, has obtained the lowest average degree in the container throughput network. The cluster has an average path length and clustering coefficient of about 2.46 and 0.74, respectively, indicating that while these ports have the highest network diameter, they are the weakest in the container throughput network as reflected in their average path length and clustering coefficient.

5. CONCLUSIONS

To promote the planning, construction, and coordinated management of port clusters in Mainland China, the original time series data of throughput of 25 coastal ports in Mainland China were transformed into a visibility graph network by using the visibility graph algorithm. Then, the structures and properties of the throughput networks of coastal ports in China were examined from perspectives of complex network parameters (e.g., network diameter, average degree, and clustering coefficient) by using complex network theory. On this basis, the ports were clustered according to the network parameters by using the K-means clustering algorithm. The following conclusions could be drawn:

(1) The cargo throughput network of coastal ports in Mainland China shows obvious community structures that are closely related to the development policies, cargo types, hinterland economies, and geographic locations of different ports. The formation of the throughput network and its internal transportation mechanism are significantly restricted by various external factors.

(2) Similar to many practical networks, the throughput networks of coastal ports in Mainland China have a relatively short average path length and relatively high clustering coefficient. All these networks demonstrate small-world clustering and scale-free characteristics without port nodes of an "absolute center."

(3) The coastal ports in Mainland China are divided into four clusters according to the characteristics of the throughput complex network. However, the status of ports in different clusters is not obvious, and the ports are in a state of chaotic development. Therefore, new strategic orientations should be determined according to the hierarchical clustering of throughput networks, and the connections and cooperation among ports should be strengthened by forming a hierarchical layout of port clusters, including hub, branch, and feeding ports.

Nevertheless, the planning and management of ports are influenced by practical politics, geography, and economy, all of which significantly restrict the formation of shipping networks and affect the internal transshipping mechanism. Therefore, a future research requires the consideration of more factors given the long transportation distance, multiple links, and complex conditions (e.g., geological and climate factors) of shipping trade.

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