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Assortative Analysis of Bulk Trade Complex Network on Maritime Silk Road

NAIXIA MOU [1], YUJIE FANG [1], TENGFEI YANG [2], AND LINGXIAN ZHANG [1]
[1]College of Geodesy and Geomatics, Shandong University of Science and Technology, Qingdao 266590, China
[2]Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100094, China

Corresponding authors: Naixia Mou (mounaixia@163.com) and Lingxian Zhang (zhang_lingxian@163.com)

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ABSTRACT Assortativity, one of the mixing patterns of complex networks, is characterized by measuring whether the nodes are preferentially connected to the nodes with a similar scale. While numerous studies have examined the assortative characteristics of various real-world networks, few studies have attempted to analyze the assortativity of networks in which the subject of trade is bulk. The novelty of this research is that, for the first time, the assortative coefficient method in physics is introduced into the bulk trade network, and the Automatic Identification System (AIS) data is used to explore the assortative mixing characteristics of the network. From the perspective of multi-scale (port and country) and multi-dimensional (node, link, and network) structure, this paper reveals the tendency of trade connection and explores the trade rules of bulk in networks. The results show that: (1) The trade network of bulk on the Maritime Silk Road is assortative. With the increase of spatial scale, the extent of assortativity is also gradually increasing; (2) In the bulk network of ports, trade cooperation shows the rule of distance attenuation; In the national bulk network, it shows the rule of preferential connection; (3) Ports with high out-degree will export bulk to the ports with high out-degree with broad market, while countries with high out-degree export to high in-degree countries with strong demand. The present study is expected to provide valuable references for port planning, national formulation of scientific bulk trade strategy, and promotion of coordinated development of bulk trade network along the Maritime Silk Road.

INDEX TERMS Maritime Silk Road, AIS, bulk, trade network, assortativity.

I. INTRODUCTION

The Maritime Silk Road involves a wide scope of regions, a more complex geopolitical environment, and different levels of economic development. The trade relations between ports and countries along the road play an important role in the development of the Maritime Silk Road, the reduction of bilateral conflicts, and the promotion of regional division of labor and common prosperity. With the rapid development of economic globalization and information technology, the scale of international maritime trade is expanding. At present, shipping has become the most important mode of transportation in international trade, accounting for 90% of the total amount of international trade [1].

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In the trade research of shipping network, AIS sensor trajectory data is a kind of geographic big data [2] and it can provide reliable data including ship number, estimated arrival time, departure time, ship position (latitude and longitude) and other information, which is conductive to identify and track the ship [3]. The sensor has covered many navigation areas of ports and countries all over the world, and its coverage is expanding. It is characterized of good real-time performance, high accuracy, fine time granularity, data balance (including large and small port data), etc. [4], which can reflect the trade links in the network, support the dynamic analysis and modeling of global maritime network, and help to strengthen maritime and trade management.

For the maritime trade network, the trade connection between nodes is not a random process, but follows certain rules. Therefore, the maritime trade network often has the connection preference, showing different mixing patterns.

Newman [5] first proposes the problem of assortative mixing, and argues that many behaviors of the network systems of real world cannot be correctly reproduced if the mixing patterns are not considered [6]. The nodes degree is the number of links to the nodes. According to the correlation between the degree of nodes pairs in the network, he proposes the concepts of assortativity and disassortativity to distinguish different network structure types. If the degree-degree correlation is positive, the network is the assortative mixing network, and the nodes with similar scale tend to connect with each other; if the degree-degree correlation is negative, the network is the disassortative mixing network, and the nodes with different scale tend to connect with each other. It is found that the assortative network is of easier contact and anti-damage than the disassortative network, that is, the assortative network is more percolate of information [7], [8] and robust to nodes or links removal [9]. To explore the assortative characteristics of bulk trade network can help us to understand the closeness of bulk trade along the Maritime Silk Road, and how to develop bulk trade between countries with great disparity. Besides, it also has reference significance for the adjustment of market development direction, the optimization of foreign trade structure, and the scientific promotion of strategy of the Maritime Silk Road. Based on AIS trajectory data, this paper constructs a trade complex network of Maritime Silk Road on different spatial scales [10] with ports and countries as nodes, bulk trade contact as links and contact frequency as weights, and discusses its mixed characteristics of assortativity to provide some reference for bulk trade cooperation and exchange.

II. LITERATURE REVIEW

A. RELEVANT RESEARCH ON AIS FOR MARITIME TRANSPORTATION

As a part of geographic big data, AIS sensor trajectory data can provide scientific and technical support for monitoring and analyzing geographical events such as ship motion, marine network topology, and maritime network dynamics [11]. Through the use of AIS trajectory data, many scholars have investigated the maritime network of different modes of transportation (container, crude oil, bulk) in many aspects, and have a deeper understanding of the characteristics of the maritime network.

1) RELEVANT RESEARCH ON COMPREHENSIVE NETWORK OF CONTAINER, OIL AND BULK

Kaluza *et al.* [12] found that global cargo shipping (container, oil and bulk) possesses the small-world property as well as broad degree and weight distributions. Peng *et al.* [13], based on the AIS data of global marine cargo transportation in 2015, constructed three cargo transportation networks of crude oil, container and bulk, and analyzed the different breaking processes of the three networks under the random attack and intentional attack strategies, providing a reference for the construction of the maritime network. Based on the AIS data of containers, crude oil and bulk in 2014, Mou *et al.* [14] analyzed the spatial distribution pattern of the maritime transport network of Maritime Silk Road and the current situation of regional trade relations, putting forward suggestions for the construction of ports along the Maritime Silk Road and the sustainable development of the economy. Yu *et al.* [15], through the introduction of the time-space framework and the use of a large amount of AIS trajectory data, built and analyzed the dynamics of the global maritime transport network. Besides, they examined the dynamics of the global maritime network from the perspective of multi-layer (bulk, container, and tanker) and multi-dimensional (e.g., point, connection, and network) structure. It was of great significance for international port cooperation and reorientation, assessment of the adaptability of the changing traffic and shipping environment, and integration of the marine economy and transportation system. Fang *et al.* [16] put forward a framework of time-space analysis, introduce the method of time-space modeling, and used AIS data to measure the changes and similarities of three maritime network shipping trends before and after major international events, including containers, bulk cargo, and oil tankers, to better understand the dynamic characteristics of the global maritime network.

2) RELEVANT RESEARCH ON CONTAINER SHIPPING NETWORK AND OIL SHIPPING NETWORK

Wang *et al.* [17] provided a bottom-up driven method based on AIS trajectory data to build a global shipping network, and used this method to study the global container transportation network from the wharf, port and national level. Fang *et al.* [18] proposed a dynamic assessment method of near collision risk of port ships based on AIS data of containers, and then obtained reliable estimation of collision risk, referring to safe traffic planning of ports. Yu *et al.* [19], by using AIS data, investigated whether there was a connection between oil price fluctuation, marine network structure and traffic flow change, and studied whether the offshore network structure and traffic flow changed of oil tankers were driven by oil price fluctuation. The analysis results had important policy significance for national tanker transportation. Peng *et al.* [20] established the global crude oil transportation network between ports by using the crude oil AIS trajectory data from 2009 to 2016, evaluated the temporal and spatial characteristics of the port-port crude oil transportation network, and then analyzed the impact of each port in the global crude oil transportation network [21]. Based on the AIS data of crude oil in 2014, Mou *et al.* [22] made an in-depth study on the lag effect of the collapse of oil price on the shipping situation of oil tankers along the Maritime Silk Road, which provided a scientific basis for improving the decision-making ability of crude oil transportation market and formulating maritime operation management measures. Wang *et al.* [23] proposed autonomous statistic methods for counting daily ship traffic volume at ports only based on AIS data, then taking Shanghai port as an instance, they counted the daily ship traffic volume by using the proposed statistic methods for three common types of ship: cargo ship, passenger ship, and tanker ship, which could instruct shipping company to make sound judgment and decision for operational management.

B. RELEVANT RESEARCH ON THE ASSORTATIVITY OF DIFFERENT NETWORKS

1) RELEVANT RESEARCH ON THE ASSORTATIVITY CHARACTERISTICS OF SHIPPING NETWORK

In these maritime networks constructed by different main bodies (container, crude oil, bulk cargo), the connection tendency between elements is regular. The investigation of preference connection characteristics, that is, assortativity, can better understand the topological structure of the network, increase the insight of the network features, and provide a strong reference for the static and more in-depth dynamic analysis of the network. Peng *et al*. [20] analyzed the connection between ports in the crude oil transportation network and the distribution characteristics of port classes. The assortative coefficient of the network was less than zero, which meant that the crude oil transportation network had obvious different distribution properties, ports with more paths tending to connect with ports with fewer paths. Jian and Dong [24] explored the degree extent of the assortativity of China's coastal port network, finding that the network presented the characteristics of negative disassortativity. Ducruet [25] investigated the influence of the multiple nature of current on the network assortativity and heterogeneity, providing new insights into the development of specialization and diversification of port and shipping industry.

2) RELEVANT RESEARCH ON THE ASSORTATIVITY CHARACTERISTICS OF OTHER NETWORKS

In addition to the maritime network, many scholars also carried out a more detailed study on the assortative characteristics in the real world. Newman [5] analyzed the mixing patterns of social networks by studying the correlation between the out-degree of source nodes and the in-degree of target nodes in directed social network and the correlation between the in-degree of source nodes and the out-degree of target nodes, concluding that most social networks were of the same type. However, Liu and Tse [26] analyzed four types of degree correlations of twitter directed networks in social networks, gaining different results. He analyzed four types of degree correlation in twitter directed network, namely, the correlation between the in-degree of source nodes and the in-degree of target nodes, the correlation between the in-degree of source nodes and the out-degree of target nodes, the correlation between the out-degree of source nodes and the in-degree of target nodes, and the correlation between the out-degree of source nodes and the out-degree of target nodes, expressed as r(in, in) r(in, out) r(out, in) r(out, out). It was found that the social network presented disassortative, which could reduce the social consensus rate. In the biological network, epidemic network, neural network, aviation network, tourism network and urban network, the assortative characteristics of the network have more mature applications. Piraveenan *et al*. [27], through the study of the correlation between the out-degree of the source node and the out-degree of the target node in the directed biological network, as well as the correlation between the in-degree of the source node and the in-degree of the target node, explored the assortativity of the network, concluding that the biological network showed a positive correlation. Lopes [28] revealed the influence of degree-degree correlation on the epidemic network, finding that the epidemic network presented assortative mixing patterns. When the degree-degree correlation coefficient increased (decreased), the basic reproduction number of the epidemic would increase (decrease). Francis *et al*. [29] found that the neural network had a high degree of assortativity, and in this assortative network, the robustness of noise was enhanced. Wang *et al*. [30] studied the hybrid model of China's aviation network, concluding that China's aviation network was a disassortative mixing network. Tang *et al*. [31] concluded that the tourism destinations in Fujian Province had the characteristics of assortative mixing. Peng *et al*. [32] analyzed the degree-degree correlation characteristics of the urban network structure in the middle reaches of the Yangtze River, finding that the economic, information, and traffic networks of the urban agglomerations had disassortative characteristics.

3) RELEVANT RESEARCH ON THE ASSORTATIVITY CHARACTERISTICS OF TRADE NETWORK

In recent years, with the acceleration of economic globalization and regional economic integration, economic and trade activities among major regions have gradually become an important part of the national economy, and the scientific community has paid more and more attention to the trade network. Scholars have investigated the problems of cooperation tendency in different scopes of trade networks. Jun [33] studied the characteristics of mixing patterns in the trade network of 62 countries along the Maritime Silk Road from 2000 to 2014, and came to the conclusion that the trade network of the Maritime Silk Road was disassortative. In this network, countries with wide trade scope and strong influence tended to trade with countries with small trade scope and small influence intensity. Abbate *et al.* [34] analyzed the mixing patterns in the international trade network according to the distance change, finding that the network showed assortative characteristics when the trade connection was a short distance, while the network showed disassortative characteristics when the trade connection was long distance. Duan *et al*. [35] studied the degree correlation characteristics in the topological structure of the international trade network from 1950 to 2000. The results showed that the international trade network was disassortative mixing. Chen [36] explored the degree correlation problem in the world trade network from 2000 to 2009. Taking the country as the research node, they found that the world trade network was a negative disassortative network and rich-club phenomenon existed. Serrano and Boguna [37] investigated the topological structure of the world trade network and analyzed the degree correlation of the world trade network, finding that countries with poor connectivity preferred to rely on countries with strong connectivity, and the network showed negative disassortativity. Garlaschelli and Loffredo [38] analyzed the mixing patterns of the world trade network, and concluded that the world trade network was a disassortative network. Piraveenan *et al.* [39] quantified the mixing patterns and associated characteristics of enterprises in the international supply chain network, and drew the conclusion that the overall trade between enterprises presented the characteristics of assortativity.

In order to explore the rules of trade cooperation between ports and countries of bulk trade in the Maritime Silk Road, the paper analyzed the assortative characteristics of bulk trade networks based on the large-scale AIS sensor trajectory data. In addition, by using the degree correlation of four types of directed complex network combining with assortative coefficient method [40], the paper made a detailed study on the preference connection characteristics of bulk trade, analyzed the influence of the connection tendency between network nodes on bulk trade, which could provide a theoretical basis for the construction and development of ports along the Maritime Silk Road, the cooperation and trade between countries, and the balanced development of regions. It was conducive to the interconnection of bulk trade and the realization of the goal of sustainable development of trade.

III. METHODOLOGY

A. STUDY AREAS AND DATA

The paper investigates some countries and regions along the Maritime Silk Road. According to the description of its coverage area in the vision and proposed actions outlined on jointly building Silk Road Economic Belt and 21st-Century Maritime Silk Road, combined with the administrative divisions where the port is located and the spatial scope of the Maritime Silk Road studied by most scholars, the research area is divided into seven regions, namely Northeast Asia, Southeast Asia, South Asia, West Asia, Africa, Europe, and Oceania, including 62 countries and regions, 919 bulk ports. The distribution of ports and regions is shown in Fig. 1, and the list of research countries in Table 1.

Based on the AIS sensor trajectory data of bulk cargo in 2014 (from HiFleet Co.,Ltd), the paper extracts the ship entry and exit records, and takes each departure and arrival of each ship as an origin-destination (OD) data. In addition, 138677 bulk trade flows are obtained by combining the port attribute data provided by the World Port Index (26th Edition) published by the National Geospatial Information Administration of the United States, so as to study the assortative characteristics of bulk trade network along the Maritime Silk Road.

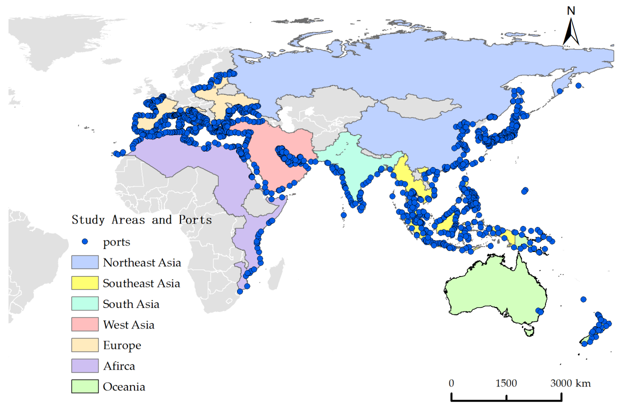

FIGURE 1. The study areas and ports (This figure is made by using ArcMap, Version 10.2).

TABLE 1. The study areas and countries.

Area	Major countries
Northeast Asia	China, Russia, Japan, Korea
Southeast Asia	Brunei, Indonesia, Cambodia, Myanmar, Malaysia, Philippines, Singapore, Thailand, Vietnam
South Asia	Bangladesh, India, Sri Lanka, Maldives, Pakistan
West Asia	UAE, Bahrain, Israel, Iraq, Iran, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, Turkey, Yemen
Africa	Algeria, Egypt, Eritrea, Kenya, Libya, Morocco, Sudan, Somalia, Tunisia, Mozambique, Tanzania
Europe	Albania, Bulgaria, Estonia, Spain, Greece, Croatia, Italy, Lithuania, Latvia, Montenegro, Poland, Romania, Slovenia, Ukraine, France, Portugal
Oceania	Australia, New Zealand, Papua New Guinea

B. METHODS

In this paper, different scales of bulk trade network on the Maritime Silk Road are constructed: at the port scale, the network takes the port as a node, the bulk trade connection between the port and port as the edge, and the trade contact frequency as the weight, a directed port network of bulk trade is constructed; at the national scale, with the country as the node, the bulk trade connection between countries as the edge, and the frequency of trade links as the weight, a national directed network of bulk trade is constructed. Extending the research of assortativity to the field of bulk trade network along the Maritime Silk Road, based on large-scale AIS trajectory data, by using the assortative coefficient method, the paper considers the correlation of four degree directions [41]: in-in correlation, in-out correlation, out-in correlation and out-out correlation, expressed as ρ(in, in) ρ(in, out) ρ(out, in) ρ(out, out), to measure the relevance of the two nodes connected by the directed edge in the degree of out or in to accurately explore the trade rules of bulk. Table 2 indicating the notions used in the paper with their meaning, that will increase the understanding of the paper.

TABLE 2. The notions and meanings.

notion	meaning
Degree	The number of adjacent edges connected with the node
In-degree	The number of adjacent edges with node as the target node
Out-degree	The number of adjacent edges with node as the original node
Node	Ports or countries
Edge/link	Bulk trade contact
Edge weight	Bulk Trade contact frequency
Closeness	The number of trade links
Scope	The ports, countries involved in bulk trade

1) COMPLEX NETWORK INDEX

a: DEGREE

As the basic attribute of nodes in the network, the degree is the basic parameter of complex network topology. In the undirected network, the degree k_i of node i refers to the number of adjacent edges connected with the node [42], indicating the scope (ports, countries involved in bulk trade) and closeness (the number of trade links) of trade relations between nodes. The larger the degree is, the stronger the connectivity of the node in the network, the closer the connection with other nodes, and the more in the center of the network topology. In the contact network of bulk trade, the degree value can initially reflect the demand for ports and countries for bulk cargo and its trade position. The calculation equation of degree index is as follows:

$$k_i = \sum\nolimits_{j=1, i\neq j}^{N} a_{ij} \tag{1}$$

In Equation (1), N is the number of network nodes, and a_{ij} is an element of the adjacency matrix. When there is an edge connection between node i and node j, $a_{ij} = 1$, otherwise $a_{ij} = 0$. For a directed network, each node has in-degree and out-degree. In-degree refers to the number of all adjacent edges with node i as the target node and out-degree refers to the number of all adjacent edges with node i as the original node. In other words, in the bulk trade network of the Maritime Silk Road, trade is directional: in-degree represents the trade connection of import bulk; out-degree represents the trade connection of export bulk.

b: DEGREE DISTRIBUTION

Degree distribution is an index reflecting the macro distribution characteristics of the network. It is defined as the probability that a randomly selecting node has degree value k. In general, the probability distribution function $p(k)$ is used to express the distribution of node degrees in the network. In Equation (2), $N(k)$ is the number of nodes with degree k.

$$p(k) = \frac{N(k)}{N} \tag{2}$$

2) ASSORTATIVE COEFFICIENT METHOD

The assortative coefficient is the Spearman rank correlation coefficient [40], which is used to measure the degree of correlation between two nodes connected by edges, reveal the assortative characteristics of the network, and explore the overall connection tendency between network nodes. In undirected networks, the random variables J and K are defined as the degree of two nodes connected by a certain edge. For edge i, the degrees of the nodes at both ends are J_i and K_i respectively. The equation [43] is as follows:

$$\rho = \frac{\sum_{i=1}^{M}\left[t_i^j - (M+1)/2\right]\left[t_i^k - (M+1)/2\right]}{\sqrt{\sum_{i=1}^{M}\left[t_i^j - (M+1)/2\right]^2 \sum_{i=1}^{M}\left[t_i^k - (M+1)/2\right]^2}} \tag{3}$$

In Equation (3), t_i^j and t_i^k are the rank after the degree ordering of the nodes at both ends of edge i, and M is the total number of edges of the network.

The calculation principle is shown in detail as follows: The two random variables are J and K (can also be regarded as two sets), and the number of their elements is N. The i-th $(1 \leq i \leq N)$ value of the two random variables is represented by j_i and k_i respectively. Sort J and K (in ascending or descending order at the same time) to get two element ranking sets t^j and t^k, where elements t_i^j and t_i^k are the ranking of j_i in J and k_i in K, respectively.

Table 3 is an example of calculating the ranking of elements in a collection.

TABLE 3. Calculation example.

The variable j_i	The variable position (in descending order)	Variable ranking t_i^j
5	2	2
3	3	(3+3)/2=3
6	1	1
3	3	(3+3)/2=3
2	4	4

Note: When two values of a variable are the same, their ranking is obtained by averaging their positions.

Similarly, t_i^k can also be calculated. Extend it to the directed network, and measure the assortative characteristics of the network among in-in degree, in-out degree, out-in degree, and out-out degree respectively. The formula is expanded as follows:

$$\rho(a,b) = \frac{\sum_{i=1}^{M}\left[t_i^{j_a} - (M+1)/2\right]\left[t_i^{k_b} - (M+1)/2\right]}{\sqrt{\sum_{i=1}^{M}\left[t_i^{j_a} - (M+1)/2\right]^2 \sum_{i=1}^{M}\left[t_i^{k_b} - (M+1)/2\right]^2}} \tag{4}$$

In Equation (4), a can be in or out, b can be in or out. When a is in, b is in, and $\rho(a,b)$ quantifies the tendency of original nodes with in-degree to connect to target nodes with in-degree, and so on, $t_i^{j_a}$ and $t_i^{k_b}$ are the in-degree and in-degree ranking of the nodes at both ends of the edge, and the rest is the same. According to the principle shown in Table 3, the assortativity of the Maritime Silk Road bulk trade network can be analyzed according to equation (4).

The assortative coefficient refers to the degree that Spearman can reflect the close relationship between variables, and its value range is $-1 < \rho < 1$. If the assortative coefficient is positive ($\rho > 0$), then the network is assortative. At this time, the nodes with high degree tend to connect with the nodes with high degree, and the nodes with low degree tend to connect with the nodes with low degree; if the assortative coefficient is negative ($\rho < 0$), the network is disassortative, and the nodes with high degree tend to connect with the nodes with low degree, and vice versa.

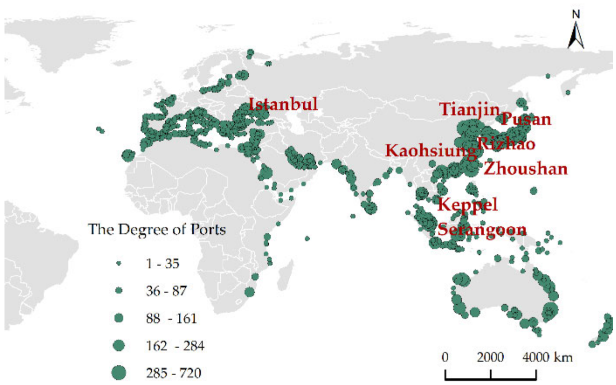

FIGURE 2. The degree hierarchy of ports (This figure is made by using ArcMap, Version 10.2).

IV. RESULTS

A. ASSORTATIVE ANALYSIS OF PORT TRADE NETWORK

In Fig. 2, the difference in the value of node degree can reflect the difference in the scope and closeness of each port trade contact. The larger the value of port degree is, the wider the scope of trade relationship is, and the closer the relationship is. According to the degree value, the top 10 ports in bulk trade are marked especially in text in Fig. 2. Obviously, Keppel Port boasts the most trade links of bulk cargo and the highest trade position, followed by Serangoon Harbor, Shanghai Port, Zhoushan Port, Tianjin Port, Hong Kong Port, Kaohsiung Port, Istanbul Port, Pusan Port and Rizhao Port, the detailed information of the degree value is shown in Table 4. Based on AIS geographic big data, a spatial distribution diagram of trade links between ports on the Maritime Silk Road bulk network is constructed, as shown in Fig. 3. The deeper the color of the link, the higher the weight of trade connections, and the closer the connections. It is obvious that the bulk trade has the phenomenon of regional agglomeration, showing an imbalance of more East and less West. Table 5 lists the top 20 port pairs in terms of connection weight. It can be seen that in the bulk trade network, China's ports trade most frequently with each other, and the trade frequency of Shanghai Port to Taicang Port ranks first, up to 1646, much higher than the second-ranked Zhoushan-Shanghai trade frequency; there is a closer bulk trade connection between Daesan Port and Pyeongtaek Port, Yosu Port and Gwangyang Port in Korea, Yokkaichi Port and Nagoya Port in Japan, Doha Port and Umm Said Port in Qatar; Australia's Port Hedland is also rich in iron ore resources, which is exported to China and other countries, and plays an important role in bulk trade. As a whole, it is found that the bulk trade connections between ports in the same country are the most. When the ports are in trade connection, they have strong geographical proximity characteristics and show a strong rule of distance attenuation.

FIGURE 3. The spatial distribution of ports bulk trade network (This figure is made by using ArcGIS server and Python program).

TABLE 4. The degree information of the top 10 ports.

Port name	In-degree	Out-degree	Degree
Keppel	351	369	720
Serangoon	246	284	530
Shanghai	236	164	400
Zhoushan	184	181	365
Tianjin	163	192	355
Hong Kong	172	171	343
Kaohsiung	157	179	336
Istanbul	168	166	334
Pusan	160	165	325
Rizhao	151	171	322

The results in the table are calculated by Gephi.

The degree distribution of the network can directly reflect the influence of the port in the whole network. In the bulk trade network of ports along the Maritime Silk Road, the degree value and degree distribution curve of the ports are shown in Fig. 4. The maximum and minimum degree values of port nodes are 720 (Keppel Port) and 1 (Port of Senj, Port of Lagos etc.) respectively. The degree distribution span is large and the spatial difference is obvious, which shows that the bulk trade connections between ports along

TABLE 5. Top 20 port pairs of bulk trade link weight.

Order	Origin	Destination	Weight	Order	Origin	Destination	Weight
1	Shanghai	Taicang	1646	11	Hong Kong	Huangpu	371
2	Zhoushan	Shanghai	833	12	Port Hedland	Tangshan	367
3	Zhoushan	Zhenhai	642	13	Tianjin	Shanghai	339
4	Shanghai	Nantong	546	14	Port Hedland	Zhoushan	316
5	Daesan	Pyeongtaek	489	15	Shanghai	Gaogang	313
6	Yokkaichi	Nagoya	449	16	Yosu	Gwangyang	312
7	Doha	Umm Said	427	17	Zhuhai	Huangpu	308
8	Qinhuangdao	Shanghai	406	18	Tianjin	Tangshan	305
9	Zhoushan	Taicang	392	19	Taicang	Zhangjiagang	297
10	Tangshan	Shanghai	379	20	Gaogang	Zhenjiang	284

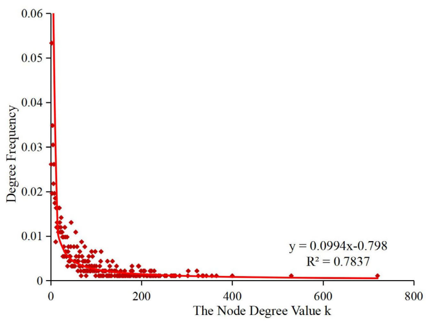

FIGURE 4. The degree distribution of ports bulk trade network (This figure is made by using Origin software).

the Maritime Silk Road are uneven. Specifically, the number of ports with larger degree value is less, and only 5.3% of them have degree value greater than 200. These ports play a role of hub port and have a great influence on bulk trade, such as Keppel Port and Shanghai Port. The number of ports with small degree value is very large, of which 39.9% have a degree value less than 20, which indicates that most of the ports have little influence and the scope of bulk trade connection is not wide enough. These ports lack the ability of self-development and are in the marginal groups in the whole network. They show a certain distance attenuation rule when conducting trade connections, mainly depending on the development of adjacent hub ports, such as Yangon Port, Jeju Port, etc. The degree distribution of port bulk trade network conforms to the rule of power-law distribution, having complex nonlinear characteristics [44], and the goodness of fit of power-law function is greater than 0.7, which has scale-free characteristics, that is, a few core ports have a large number of trade connections, while most edge ports only have a small number of trade connections [45].

In order to describe the real structure and nature of bulk trade networks of the Maritime Silk Road, except the degree and degree distribution of the network, the degree correlation between network nodes, that is, the assortative analysis of network is also very important. The mixing patterns of bulk trade networks of port scale are analyzed, and the results are shown in Table 6. It can be seen that the overall performance of the bulk trade network of ports along the Maritime Silk Road is a positive correlation, that is, an assortative network. In this network, the core ports with more trade links tend to trade with the core ports, while the marginal ports with less trade links tend to trade with the marginal ports with fewer trade links. The trend of trade connections plays an important role in the network; in addition, there is also a phenomenon of trade connections between the core ports and the marginal ports in the network. For example, in the bulk trade connection of Keppel Port, 95.39% of the ports have a trade connection with degree greater than 10, including 352 ports such as Serangoon Port, Shanghai Port, Zhoushan Port; ports with degree of less than 10 account for 4.61%, including 17 ports such as Phuket Port, Massawa Port and Manado Port. The strength and competitiveness of core ports are relatively strong, and they tend to develop trade connections and strong alliances with each other, thereby driving the development of marginal ports in the region. And because of the robustness and percolation of the trade network, when the core port nodes or links fail for some reasons, the bulk trade can still be carried out between ports, which is of positive significance.

TABLE 6. The assortative coefficient of ports trade network.

ρ	ρ(in, in)	ρ(in, out)	ρ(out, in)	ρ(out, out)
Value	0.220	0.240	0.235	0.247

When the confidence (two-sided) is 0.01, the correlation is significant. The results in the table are calculated by SPSS.

According to the experimental data and analysis, the out-out correlation has a special influence on the concordance of bulk trade networks in the four types of correlation. If ρ(out, out) is the largest, it shows that the correlation of this direction is stronger than the other three directions, that is to say, the ports with high out-degree occupy an important position in the bulk trade network. When it carries out bulk trade with another port and selects export market for bulk, it will tend

TABLE 7. Top 20 country pairs of bulk trade link weight.

Order	Origin	Destination	Weight	Order	Origin	Destination	Weight
1	China	Australia	4278	11	Japan	China	1219
2	Australia	China	4277	12	Indonesia	Singapore	1147
3	China	Singapore	2959	13	Indonesia	China	1095
4	Singapore	China	2700	14	Singapore	Indonesia	977
5	China	Indonesia	1525	15	Japan	Korea	803
6	China	Korea	1467	16	Singapore	Australia	801
7	China	Japan	1419	17	Korea	Japan	714
8	Korea	China	1318	18	Singapore	Malaysia	697
9	Australia	Japan	1309	19	Turkey	Ukraine	656
10	Japan	Australia	1260	20	Singapore	India	649

to choose a port with good connection and broad market (with a high out-degree), which can expand the scope of bulk trade connection and improve trade efficiency. The port plays a transit role to connect the high degree original port with other ports on the network, which makes the bulk trade more percolate. Therefore, in this network, compared with the other three directions of trade links, ports will rely on the export-export direction for trade links.

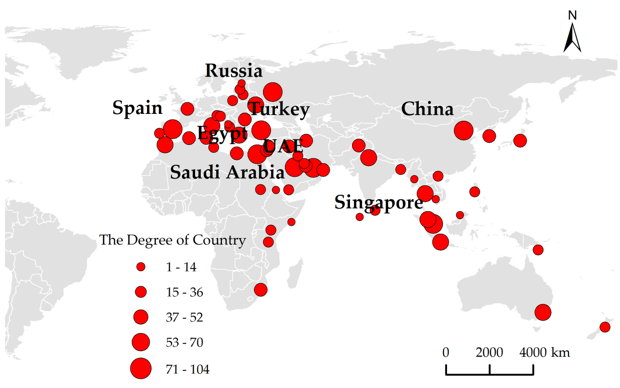

FIGURE 5. The degree hierarchy of countries (This figure is made by using ArcMap, Version 10.2).

B. ASSORTATIVE ANALYSIS OF NATIONAL TRADE NETWORK

Fig. 5 is a national degree hierarchy diagram constructed with the location of national capitals as national nodes. In Fig. 5, according to the degree of the node, it can be seen that some countries including Singapore, Egypt, Russia, Saudi Arabia, the United Arab Emirates, Turkey, China, Spain and so on, have a relatively higher degree value in bulk trade, play a key role in the bulk trade, and become a bridge for bulk trade with other countries. Fig. 6 is the spatial distribution of bulk trade links between countries. The thickness of links in the Fig. 6 can reflect the trade connection between countries and the closeness of trade, i.e. the weight of bulk trade connections

FIGURE 6. The spatial distribution of national bulk trade network (This figure is made by using ArcGIS server and Python program).

between countries. Combined with Table 7, it can be seen that there are many bulk trade connections between China, Australia and Singapore, and the frequency of trade links has an absolute advantage. As a whole, most of the cross-regional bulk trade is carried out between countries, which is greatly reduced by the constraints of spatial distance, reflecting the obvious rule of preferential connection. The Northeast Asia bulk trade community is formed with China, Japan and South Korea as the core, the Southeast Asia transit community with Singapore as the core, and the Oceania bulk trade community with Australia as the core.

TABLE 8. The assortative coefficient of national trade network.

ρ	ρ(in, in)	ρ(in, out)	ρ(out, in)	ρ(out, out)
Value	0.718	0.703	0.720	0.706

When the confidence (two-sided) is 0.01, the correlation is significant. The results in the table are calculated by SPSS.

The paper analyzes the degree-degree correlation of bulk trade networks of countries along the Maritime Silk Road, and the assortative coefficient is shown in Table 8. As a whole, the bulk trade network of the Maritime Silk Road with the country as the node is an assortative network, with the assortativity coefficient, and the degree extent of assortativity greater than that of the port trade network. In this network, countries with high trade connectivity and status tend to develop bulk trade links with countries with high trade connectivity and status. Moreover, through the percolation and robustness characteristics of the assortative network, the scope and efficiency of trade links continue to increase, which shows that core countries in each region along the Maritime Silk Road play a role of hub connectivity. In addition, thanks to the implementation of policy of the Maritime Silk Road and the enhancement of the comprehensive strength of all countries, a large number of strong trade links have been created among all member countries, and the core countries of each region are connected with each other. Bulk trade is no longer restricted by distance. Cooperation is becoming closer and communication freer. For example, in the bulk trade, in addition to connecting Singapore which owns a high position and a relatively close space, China with a higher position tends to conduct bulk trade with Australia which boasts a high position and a long space (Fig. 6), showing obvious preferential connection characteristics.

The results show that the national bulk trade network is an assortative network, and the correlations of four degrees reflect the assortative characteristics at the same time, and the bulk trade is more significantly affected by the degree of out-in correlation in this network. From the perspective of trade security and national interests, countries with high out-degree show trade connection preference to countries with large demand for bulk cargo (large in-degree), which is also in line with the characteristics of the trade network itself. At the same time, countries with high in-degree will react to countries with high out-degree, promoting the bulk trade level and rapid economic growth. Therefore, the network will show a strong dependence on the export-import direction of trade, rather than the other three directions of trade.

V. DISCUSSION

The assortativity of bulk trade networks of the Maritime Silk Road reflects the tendency of bulk cargo resources to seek active and effective trade in the region. The node degree can initially reflect the port or country's demand for bulk resources. If the node has a larger out-degree, it means that the port or country has a wide scope of bulk export trade, and it can be preliminarily considered to be relatively rich in bulk resources; if the node has a larger in-degree, it means that the port or country has a wide scope of bulk import trade, and it can be preliminarily thought to be relatively strong in demand for bulk resources. The assortative coefficients calculated based on the node degree indicate the overall trade rules of bulk in different spatial scale networks: in the port network, ports with high out-degree will export bulk to the ports with high out-degree of the same broad market to make bulk trade more percolated; in the national network, countries with high out-degree export bulk to high demand countries with high in-degree, which is in line with the characteristics of the trading network itself. Therefore, the assortative coefficient can not only reflect the location, consumption and demand of bulk resources, but also explore the rules of bulk trade connection, providing reference for port construction and national trade policy formulation. The assortativity of bulk trade networks on the Maritime Silk Road also reflects the robustness of the network. Reference [46] explores the robustness characteristics of cargo ship network after node or link deletion, as well as the importance of port nodes and connections in the network, which makes the authors of this article have a deeper thinking. Based on this, suggestions are made to the port and the country respectively:

(1) It is suggested to give full play to the regional leading role of core ports, and to build a coordinated development mechanism for core ports to lead ports at all levels, taking into account the hierarchical relationship of ports in the region as a whole, such as Keppel Port, Serangoon Harbor, Shanghai Port, Zhoushan Port, Tianjin Port, Istanbul Port, Newcastle Port, strengthen the radiation function of the core ports as the hub of bulk trade, and enhance the influence and competitiveness of the core ports and the network robustness. At the same time, trade links between core ports and marginal ports should also be strengthened. Some ports with smaller degree, such as Rangoon Port and Jeju Port, should accurately position the function and development of the port, and pay attention to the construction of trade relations with other nodes, as well as take the initiative to build cross-domain links by using the closer core ports. In addition, they should tightly depend on the core ports to achieve the efficient connection of the core groups and the coordinated development of the edge ports and the core ports.

(2) It is very important for the core countries of each region to carry on and radiate the space connection. Therefore, under comprehensive consideration, China, Singapore, Indonesia, Qatar, Turkey, Egypt, Ukraine and Australia can be selected as the strategic fulcrum in the process of promoting bulk trade, giving full play to the fulcrum regional advantages. In this way, the countries along the Maritime Silk Road will be linked into a more closely integrated network from point to surface, from line to area, gradually promoting regional bulk trade cooperation. In addition to planning and layout of core countries, it is necessary to open up more developable room for countries at different levels in space, time and other dimensions to avoid vicious competition, with special focus on the growth of countries with small connectivity and low status in bulk trade.

The paper examines the characteristics of mixing patterns in the bulk trade network of the Maritime Silk Road. The network presents assortative, which is different from the existing research. The reasons may be as follows: (1) Different study areas. The research area of this paper is the Maritime Silk Road, while in reference [37], [38], the study area is the World Trade Web; (2) Different methods of measuring assortativity. In reference [33], the Pearson correlation coefficient method is used to measure the assortative problem of the trade network. In reference [37], [38], the average nearest neighbor degree method is used to measure the assortativity. However, due to the large scale of the network and the large number of nodes and trade connections investigated in this paper, the Pearson correlation coefficient method may fail and the average nearest neighbor degree method is subjective. Therefore, the degree correlation measurement is carried out by the assortative coefficient method [47]; (3) Different subjects of trade. The trade subject in this paper is bulk, and that of the research network is bulk trade network, while references [33], [37], [38] are only trade networks, and cannot represent the trade of all subjects. Therefore, the present research can better understand the assortative characteristics of bulk trade networks and reflect in detail the relationship of bulk trade in the Maritime Silk Road.

Based on the AIS geographic big data, this paper describes the complex nonlinear characteristics of the real geographic world through the index of assortativity in physics. It reveals the rules of bulk trade cooperation in ports and countries, which further contributes to the positioning and planning of ports and the formulation of national trade policies; Furthermore, this study is the first time to introduce the assortative coefficient method that based on directed networks into the assortativity analysis of trade networks, which extend the application boundary of this method. In addition, the present study enriches the existing knowledge body in the field of assortative characteristics of trade complex networks.

VI. CONCLUSIONS AND LIMITATIONS

The paper uses the assortative coefficient method to measure the assortativity of bulk trade networks at different spatial scales, reflecting the trade connection rules of bulk cargo through a large number of AIS trajectory data. The results are as follows:

(1) The bulk trade network of the Maritime Silk Road is an assortative network. With the increase of spatial scale, the coefficient of assortativity increases gradually, which means that the extent of network assortativity becomes stronger. At this time, trade cooperation becomes more in-depth and liberal and the scope of trade becomes wider than before, which is a positive result for the world.

(2) In the bulk trade, the network of different spatial scales shows different rules of trade connection. In the port trade network, the bulk trade links are uneven, and the links have strong geographical proximity characteristics, showing a rule of distance attenuation. In the national trade network, the bulk trade is closely linked, which overcomes the distance barrier and presents a rule of preferential connection.

(3) The four types of correlation have different influences on assortativity of port and national bulk trade networks. In the bulk trade, the original ports and countries with high export value show core competence compared with those with high import value. The ports tend to export bulk to the high out-degree ports with the broad market, that is, the out-out correlation has a strong impact on the assortativity of port trade network; while the countries tend to export to the countries with strong bulk demand, that is, the out-in correlation can show the assortative characteristics of national trade network.

Despite the interesting findings of this study, there are still limitations that need to be further improved. For example, due to the difficult accessibility and confidentiality of AIS sensor trajectory data, only cross-sectional data for 2014 is obtained in this paper. In the follow-up research, if conditions permit, panel data over the years can be obtained to reveal and contrast the changes and differences of bulk trade rules.

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NAIXIA MOU is currently a Professor with the College of Geodesy and Geomatics, Shandong University of Science and Technology, China. His main research interests include data mining, big data analysis, tourism, and transport geography.

YUJIE FANG is currently pursuing the M.S. degree with the College of Geodesy and Geomatics, Shandong University of Science and Technology, China. Her research interests include data mining, big data analysis, and transport geography.

TENGFEI YANG is currently pursuing the Ph.D. degree with the Aerospace Information Research Institute, Chinese Academy of Sciences. His research interests include natural language processing and spatio-temporal data mining.

LINGXIAN ZHANG is currently a Lab Technician with the College of Geodesy and Geomatics, Shandong University of Science and Technology, China. Her main research interests include geographical information systems and transport geography.