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Spatial Structure, Hierarchy and Formation Mechanisms of Scientific Collaboration Networks: Evidence of the Belt and Road Regions

GU Weinan[1, 2, 3], LIU Hui[1, 2, 3]

(1. *Institute of Geographic Sciences and Natural Resources Research*, *Chinese Academy of Sciences*, *Beijing* 100101, *China*; 2. *Key Laboratory of Regional Sustainable Development Modeling*, *Chinese Academy of Sciences*, *Beijing* 100101, *China*; 3. *College of Resource and Environment*, *University of Chinese Academy of Sciences*, *Beijing* 100049, *China*)

Abstract: Scientific collaboration has become an important part of the people-to-people exchanges in the Belt and Road initiative, and remarkable progress has been made since 2013. Taking the 65 countries along the Belt and Road (BRI countries) as the research areas and using collaborated Web of Science (WOS) core collection papers to construct an international scientific collaboration matrix, the paper explores the spatial structure, hierarchy and formation mechanisms of scientific collaboration networks of 65 countries along the Belt and Road. The results show that: 1) Beyond the Belt and Road regions (BRI regions), Central & Eastern Europe, China and West Asia & North Africa have formed a situation in which they all have the most external links with other countries beyond BRI regions. China has the dominant role over other BRI countries in generating scientific links. The overall spatial structure has changed to a skeleton structure consisting of many dense regions, such as Europe, North America, East Asia and Oceania. 2) Within the Belt and Road regions, Central & Eastern Europe has become the largest collaboration partner with other sub-regions in BRI countries. The spatial structure of scientific collaboration networks has transformed from the 'dual core' composed of China and the Central & Eastern Europe region, to the 'multi-polarization' composed of 'one zone and multi-points'. 3) The hierarchical structure of scientific collaboration networks presents a typical 'core-periphery' structure, and changes from 'single core' to 'double cores'. 4) Among the formation mechanisms of scientific collaboration networks, scientific research strength and social proximity play the most important roles, while geographical distance gradually weakens the hindrance to scientific collaboration.

Keywords: scientific collaboration networks; spatial structure; hierarchy; formation mechanisms; the Belt and Road regions

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1 Introduction

Knowledge flows are becoming more and more widespread around the world and have attracted increasing attention in the field of economic geography (Scherngell and Barber, 2011). Scientific collaboration between countries, which has given birth to scientific achievements in many frontier fields, has become an increasingly important means of exchanging scientific and technological knowledge between countries. This is because knowledge continues to flow, regardless of spatial distance (Pan et al, 2012). Knowledge collaboration has become an important driving force behind the sustainable, efficient and stable growth of regional economies (Scherngell and Barber, 2011; De Noni et al., 2018). In recent years, through the impetus of network analysis technology, regional (or global) scientific collaboration networks, which are mainly composed of knowledge flow, have become one of the core issues of innovation network research. Scientific collaboration networks

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Corresponding author: LIU Hui. E-mail: liuh@igsnrr.ac.cn

mainly include: co-patent networks (Breschi and Lissoni, 2009), co-paper networks (Scherngell and Hu, 2011), and R&D collaboration networks (Balland, 2012).

Scientific collaboration networks are theoretically well-grounded, and each network has many research points. The first point is the characteristics of scientific collaboration networks. Numerous literatures have focused on network structures, such as internal and external linkages (Breschi and Lenzi, 2016; De Araújo et al., 2019), network spatial structure (Liu et al, 2017), network hierarchy (Nepelski and De Prato, 2018), and network properties such as nodes centrality (Bergé et al., 2017), network density (De Noni et al., 2018), network gatekeepers (Breschi and Lenzi, 2015) and small-world of network (Fleming et al., 2007; He and Fallah, 2014). From the perspective of network structure, Liu et al. (2017) analyzed the global scientific collaboration network and found that the spatial structure presents a quadrilateral skeleton framework of the United States, Western Europe, China and Australia. De Prato and Nepelski (2014) and Nepelski and De Prato (2018) take all countries in the world as study areas. These researchers concluded that the global scientific collaboration network presents the characteristics of agglomeration. They arrived at this conclusion by analyzing the global co-patent network and ICT (Information and Communication Technology), R&D (Research and Development) collaboration network. Researches that explore the scientific network structure in EU (European Union) countries through co-patent data and scientific collaboration project data, respectively, are also prevalent (Fischer and Griffith, 2008; Scherngell and Barber, 2009). However, although the number of studies that discuss structures of collaboration networks is increasing, several questions remain unanswered. In particular, existing studies have focused on the collaboration links within the spatial unit of analysis, while neglecting the interregional collaboration within and beyond the spatial unit of analysis (Li and Phelps, 2018b). The notable exception to this point is Li and Phelps's (2017; 2018a; 2018b) studies, which analyze the collaboration network within and beyond the Yangtze River Delta. From the perspective of network properties, while more and more studies are paying attention to the spatial characteristics of scientific collaboration networks, several studies have considered the spatial inter-links of networks. The hierarchical structure of a network can be recognized as the result of the position of the individual nodes in the entire network. The strength of connection of the nodes and the nodes' ability to control and interact are two implications in the network hierarchy. Network hierarchy is often decided by economic ranks, administrative ranks or some other single indicators (e.g., degree centrality, betweenness centrality) (Dong and Yang, 2016), thus ignoring any comprehensive approach to analyzing network hierarchy.

The second point is that the formation of scientific collaboration networks is influenced by many mechanisms. Some scholars, represented by the French School of Proximity, derived the concept of multidimensional proximities, and their works discuss the role in network. Some researchers found that geographical proximity is the core and primary factor of the network formation and development, the importance of which is reflected in the increased network embeddedness. Geographical proximity can also create favorable conditions for the flow of regional knowledge, especially tacit knowledge (Bathelt et al., 2004; Hoekman et al., 2010; Balland et al., 2015). However, some scholars argue that the importance of geographical proximity in networks has declined; other forms of proximities may gradually be replacing geographical proximity in the network evolution process (Autant-Bernard et al., 2007; Agrawal et al., 2008; Breschi and Lissoni, 2009; Cassi and Plunket, 2015; Leszczyńska and Khachlouf, 2018). Social proximity is an amalgamation of institutional proximity, cultural proximity, and other adjacent proximity, all of which cause the collaboration network to have the characteristics of 'localization' , thereby reducing uncertainty (Caragliu and Nijkamp, 2016; Crescenzi et al., 2016; Miörner et al., 2018). Excessive social proximity also causes a network to lack any flexible mechanism of interaction between internal elements, which in turn will cause the formation of a closed network system and also cause excessive knowledge and technology spillover (Boschma and Martin, 2010; Broekel and Mueller, 2018). Cognitive proximity refers to the knowledge base and the main body of the network with similar technology. In particular, the knowledge innovation network based on patent cooperation (Nooteboom, 2000) can promote the ability to spread knowledge between subjects, thereby giving impetus to the diversification of network forming types and dynamic network structure (Balland et al., 2016). However, the excessive heterogeneity of the cognitive knowledge between adjacent subjects leads to the increased risks of knowledge and technology becoming locked in (Boschma, 2005; Romero, 2018). These existing literatures take the proximity framework as a static concept. Little attention has been paid, however, to adopting a dynamic approach to analyzing the evolution over time of the impact of different forms of proximity on scientific collaboration networks.

These studies have focused on the analysis of spatial units, such as nations, EU regions, megalopolises and cities, in which scientific collaborations occur. They also examine the geographical scales (e.g., megalopolitan, national, regional and global) at which scientific collaboration is produced (Li and Phelps, 2018b). Whereas these literatures are beneficial to our understanding of scientific collaboration in different spatial units and at different scales, relatively few studies have focused on the inter-country collaboration at the scale of the Belt and Road regions. The Belt and Road initiative is a new international cooperation platform, put forward by President Xi Jinping in 2013. Since then, the initiative has been accepted and supported by more and more countries and international organizations and has become an important platform for promoting the reform of global governance systems. Over the past five years, the Belt and Road initiative has made substantial progress in the five key areas of 1) policy coordination, 2) facilities connectivity, 3) unimpeded trade, 4) financial integration and 5) people-to-people bonds. Of the five, 'people-to-people bonds' is considered to be the foundation of the Belt and Road initiative, and scientific collaboration is one of the important contents of 'people-to-people bonds'. Since the Belt and Road initiative was put forward in 2013, the Chinese government has signed many intergovernmental scientific collaboration agreements with countries along the Belt and Road. The agreements cover many fields (e.g., agriculture, life science, information technology, new energy, aerospace, *etc*.). Joint laboratories, international technology transfer centers, science parks and other innovation collaboration platforms have been set up, in order to give full play to enhancing and promoting the joint construction of the Belt and Road Initiative, as well as the scientific collaboration network of the Belt and Road regions. The countries along the Belt and Road are mainly located in Asia, Central & Eastern Europe and North Africa. At the same time, China, India, Poland, Singapore, Turkey, and other countries that are at the core of these regions have become the emerging scientific forces in the world. The pattern of the world scientific collaboration network that is based on the United States and Europe as the cores is experiencing accelerating reconstruction. Therefore, the scientific collaboration network of the Belt and Road regions is becoming an important part of the global scientific collaboration network.

In line with the two streams of literature, the first objective of this article is to analyze the spatial structure within and beyond the Belt and Road regions, and to examine the hierarchy of the scientific collaboration network within the Belt and Road regions. The second objective of this article is to analyze the changes of mechanisms in different periods. Therefore, the paper constructs the scientific collaboration network of the Belt and Road regions based on cooperation paper data from the Clarivate Analytics' Web of Science database in the years 2013 and 2018. By adopting geographic spatial analysis and network analysis method, we explore the spatial structure and hierarchy of scientific collaboration networks; we also use the negative binomial regression model to discuss the formation mechanisms of scientific collaboration networks and the changes of those mechanisms.

This paper is to clarify the changes of scientific collaboration and its deep mechanism system, so as to provide theoretical reference for the construction of the Belt and Road Initiative and the related research fields.

2 Materials and Methods

2.1 Study area

Thus far, studies on scientific collaboration networks have mainly focused on the specific national coalitions (EU), a country, city clusters, cities, enterprises and specific industries. However, relatively little is known about the multiple characteristics of scientific collaboration networks in the Belt and Road regions. According to the document released by the Ministry of Commerce, 65 countries along the Belt and Road are identified as being in the Belt and Road regions in this paper (hereafter, BRI countries or BRI regions), which are mainly located in Asia, Europe and Africa (Table 1). In order to facilitate the analysis and reveal some of the conclusions, this paper divides BRI regions into seven sub-regions (hereafter, BRI sub-regions), according to the classification of the World Bank (Fig. 1).

Table 1 Classification of countries in BRI regions

Classification	Countries
China	China
Mongolia & Russia	Mongolia, Russia
Central Asia	Kazakhstan, Kyrgyzstan, Uzbekistan, Tajikistan, Turkmenistan
Southeast Asia	Singapore, Malaysia, Indonesia, Philippines, Brunei, Thailand, Myanmar, Laos, Vietnam, Cambodia, East Timor
South Asia	India, Pakistan, Afghanistan, Bangladesh, Sri Lanka, Maldives, Bhutan, Nepal
West Asia & North Africa	Georgia, Armenia, Azerbaijan, Iran, Turkey, Iraq, Syria, Palestine, Israel, Jordan, Lebanon, Saudi Arabia, United Arab Emirates, Kuwait, Bahrain, Qatar, Oman, Yemen, Egypt
Central & Eastern Europe	Estonia, Latvia, Lithuania, Poland, Czech Republic, Slovakia, Hungary, Slovenia, Albania, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Moldova, Montenegro, Romania, Serbia, Macedonia, Ukraine

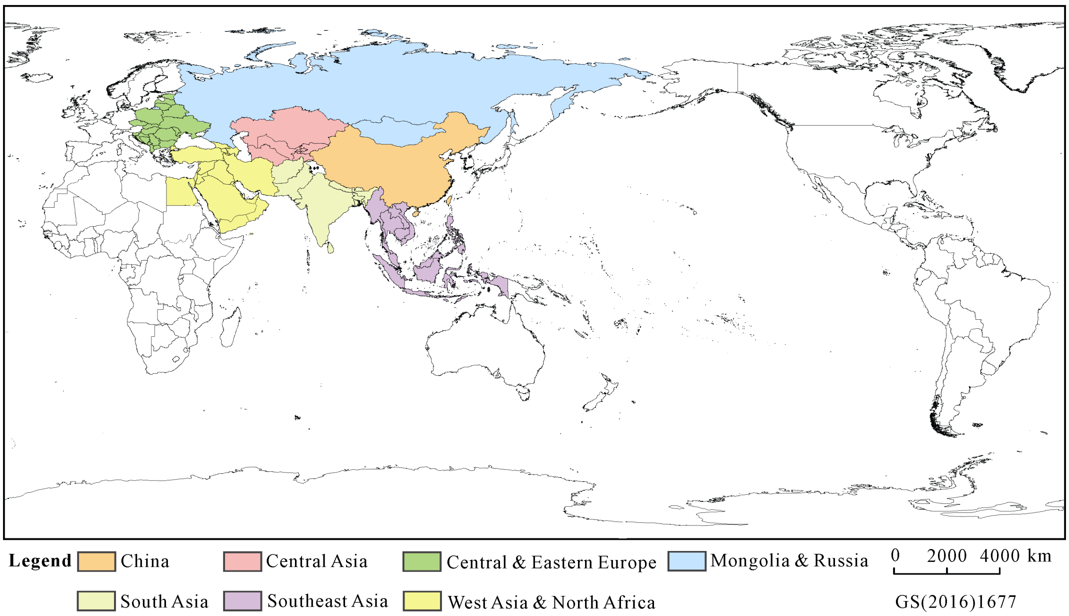

Fig. 1 The Belt and Road regions

2.2 Data source and processing

Co-papers and co-patents are the two main indexes used to measure the levels of scientific collaboration in existing literatures (Matthiessen et al., 2010; Andersson et al., 2014). In this paper, we use the co-papers index to represent the scientific collaboration network, because paper cooperation is one of the most direct forms of knowledge flow, which in turn is the result of scientific collaboration between different countries (Matthiessen et al., 2010; Li and Phelps, 2017; Ma et al., 2018). Furthermore, the data on co-papers usually contain significant amounts of longitudinal data, which are beneficial to the evolutionary analysis. The data are also attainable, which explain why this option has become the first choice of many studies on collaboration networks.

Therefore, this paper selects the Web of Science (WOS) core collection, which is consistent with relevant research (Li and Phelps, 2017; Gui et al., 2018a; 2018b). Also, we set English as the language, and the document type is article. The citation indexes are set to SCI and SSCI. The reasons for using the WOS databases and these settings are as follows: Firstly, as the main goal of the paper is to analyze scientific collaboration between different countries, it is essential to use papers pertaining to international collaboration that are mainly published in English; using WOS also makes it easier to obtain co-papers data at the global scale. Secondly, WOS, which is typical and representative, is one of the most authoritative and influential databases in the world. Accessing collaboration data between countries using Chinese domestic databases is difficult. Thirdly, it is important to ensure that the data are high-quality in academic publications and the citation indexes, which are set to SCI and SSCI, are necessary. Consequently, it is reasonable to select WOS databases that contain a large volume of international collaboration papers to analyze the scientific collaboration network within and beyond BRI countries.

The specific steps are as follows: Firstly, the paper sets the conditions from the advanced search, enters the English names of 65 countries along BRI regions, sets the year in 2013 and 2018, respectively, and extracts the paper data of 65 countries by using crawler technology. Secondly, data of the same country are merged, and duplicate paper data and paper data of one or more authors belonging to the same country are eliminated; the paper retains the data of two or more co-authors from different countries. Thirdly, the cross-over method is used to calculate the level of cooperation between countries in terms of paper data of three or more co-authors from different countries. Finally, the *R* language technology is used to construct the internal and external collaboration matrix of BRI countries, according to the country name and cooperation volume.

2.3 Methods

2.3.1 Network construction

The detailed country information of the authors contained in the co-papers makes it possible to create collaboration linkages between BRI countries. These linkages can be further used to generate country networks of scientific collaboration. It should be pointed out, however, that linkages must be formed by at least one country along the Belt and Road regions.

2.3.2 Centrality model

(1) Strength centrality

Strength centrality stands for the total weight of the edges formed by one node associated with all other nodes in a network. This represents the connection scale of a node in this network (Liu et al., 2017). Therefore, the total number of cooperative research papers between one country and other countries can represent the connection scale of the country in the cooperative research network.

$$S_i = \sum_{j=1, j\neq i}^{i} w_{ij} \tag{1}$$

where j represents the node connected to node i; N represents the total number of countries; w_{ij} is the total number of cooperative research papers between node i and node j, and S_i is the total number of cooperative research papers between country i and all other countries.

(2) Degree centrality

Degree centrality stands for the total number of other nodes connected to one node in the network. This depicts the nodes' hierarchical structure, their trading ability, and their power in this network (Mitze and Strotebeck, 2018). In the research network, the degree centrality can be represented by the total number of countries that have research cooperation with one country, which is that country's own external contact ability and power in the network.

$$D_i = \sum_{j=1, j\neq i}^{i} C_{ij} \tag{2}$$

where C_{ij} represents the paper cooperative network matrix of two countries. The value equals 1 if the two countries have cooperative research; otherwise, if they do not have cooperative research, the value equals 0. Also, D_i represents the total number of other countries cooperating with country i, which is the degree centrality of country i.

(3) Betweenness centrality

Betweenness centrality is used to measure the proportion of all the shortest paths through one node in the network (Yoon et al., 2006; Mitze and Strotebeck, 2018). The greater the betweenness centrality value of the node in the network is, the greater the control capability that node has. In a research cooperation network, the node's betweenness centrality represents the country's 'control' ability in the network, which is the ability to connect to other individuals and to play a role as the 'knowledge goalkeeper'.

$$B_i = \sum_{j}^{N} \sum_{k}^{N} \frac{P_{jk}(i)}{P_{jk}} \tag{3}$$

where P_{jk} represents the total number of all the shortest paths between node j and node k, and $P_{jk}(i)$ represents the total number of the shortest paths through node i between node j and node k. B_i represents the betweenness centrality of country i.

(4) Comprehensive centrality

The value of comprehensive centrality is the combination of the degree centrality, strength centrality and betweenness centrality. Degree centrality refers to the trading ability and power of the nodes in the network. Strength centrality represents the total external connectivity of the nodes. Betweenness centrality quantifies the position and control ability of countries in the network. The comprehensive value can be calculated as formula (4):

$$Z_i = \rho_1 \times Stand(S_i) + \rho_2 \times Stand(D_i) + \rho_3 \times Stand(B_i) \quad (4)$$

Where Z_i indicates the comprehensive centrality; *Stand* (S_i), *Stand* (D_i) and *Stand* (B_i) refer to the standardized value of strength centrality, degree centrality, and betweenness centrality, respectively, and ρ_1, ρ_2 and ρ_3 represent the weights. Here, we assign a value of 1/3 to all three weights, in order to balance the importance of each centrality value.

2.3.3 GIS network analysis

With the help of ArcGIS software platform and the Network Analyst module, the O-D (Origin-Destination) matrix is constructed. Then, the O-D network linkages of the scientific collaboration between BRI countries are visualized. The GIS natural breaks method is used to grade the strength of linkages between BRI countries, which is divided into strong linkages, upper-medium linkages, medium linkages and weak linkages.

2.3.4 Negative binomial regression model

Due to the fact that the measurement of co-papers is reasonable and widely accepted as proxies of scientific collaboration networks, we use the co-papers data between countries as the dependent variable. Existing studies argue that the node attributes (e.g., node size, attributes, status, centrality, *etc*.) and the proximities between nodes are important factors that affect the formation and evolution of networks (Hazir and Autant-Bernard, 2014; Mitze and Strotebeck, 2019). Therefore, referring to Liu et al.'s (2017) choice of the national subject attribute index and Cao et al.'s (2019) choice of the proximity index of scientific collaboration networks, the negative binomial regression focuses on two agents as the independent variables. These are composed of national subject attributes and proximities between countries (Table 1), in order to explore the formation mechanisms of scientific collaboration networks in BRI countries (hereafter, BRI scientific collaboration network). Considering that the dependent variable is a non-negative and over-dispersed integer (Andersson et al., 2014; Plotnikova and Rake, 2014; Gui et al., 2018b), the negative binomial regression method, which is considered as the discrete counting model, is chosen to explore the mechanisms of scientific collaboration networks. The equation is as follows:

$$C_{ij} = \alpha + \beta_1 Paper_i + \beta_2 Paper_j + \beta_3 Eco_i + \beta_4 Eco_j + \beta_5 FDI_i + \beta_6 FDI_j + \beta_7 Distance_{ij} + \beta_8 Socialproximity_{ij} + \beta_9 Languageproximity_{ij} + \delta_{ij} \quad (5)$$

In this empirical model, the dependent variable (C_{ij}) in the model represents the number of co-papers between countries within BRI regions. δ_{ij} represents random error of i and j. The independent variables contain two levels. The first level is the national attributes, which are formed from the scientific ability of the country (*Paper$_i$*), the economic level of the country (*Eco$_i$*) and the degree of openness in the country (*FDI$_i$*). The second level is the proximities, which are formed from the geographical proximity (*Distance$_i$*), social proximity (*Socialproximity$_{ij}$*) and language proximity (*Languageproximity$_{ij}$*). The variables are defined as shown in the Table 2. The relevant distance data are required from the CEPII dataset (Montobbio and Sterzi, 2013; Cassi et al., 2015; Gui et al., 2018b). The language data are also taken from the CEPII dataset. The strength of social ties (Boschma, 2005) can be measured by the Jaccard index (Scherngell and Hu, 2011). Therefore, social proximity is expressed by the following formula, where C_{ij} represents the number of co-papers between two countries, and S_i and S_j represent the strength centrality of countries i and j.

$$Socialproximity_{ij} = \frac{C_{ij}}{S_i + S_j - C_{ij}} \quad (6)$$

3 Results and Analysis

3.1 Spatial structure of scientific collaboration networks

In order to facilitate the analysis of collaboration between BRI countries and other countries in the world, this paper divides the other countries into a number of sub-regions. As the numbers of collaboration links are relatively dense, which in turn will obscure the main links of the network, we only show the links that are more than 500 in the global scale and more than 100 in the BRI scale. Connections between BRI countries and all countries in the world were established, with nodes and total links increasing significantly (Table 3). This

Table 2 Variables and measurement methods

		Variables	Measurement
Dependent variables	Countries' subject attributes	C_{ij}	Co-papers between countries *i* and *j*
		ECO_i	GDP per capita of country *i*
		FDI_i	The foreign direct investment in country *i*
		$Paper_i$	The total number of papers in country *i*
Independent variables	Proximities	$Distance_{ij}$	The distance between country *i* and *j*
		$Socialproximity_{ij}$	The Strength of social ties between country *i* and *j*
		$Languageproximity_{ij}$	Value is 1 if country *i* and *j* share the same language, and 0 otherwise.

Table 3 Structural parameters of scientific collaboration networks

Year	Scale	Country nodes	Links	Connectivity degree	Average connectivity degree
2013	BRI countries with all countries in the world	188	4495	8990	–
	BRI regions	65	1226	2452	37.7
2018	BRI countries with all countries in the world	199	6737	13474	–
	BRI regions	65	1676	3352	51.6

Note: '–' represents no calculation

indicates that the number of other countries in the world engaging in scientific collaboration with BRI countries increased, and the knowledge flow between countries became increasingly frequent. Furthermore, the number of total links within BRI regions grew significantly from 2013 to 2018. However, from the perspective of links and connectivity degree, the internal collaboration within BRI regions during that period was less than 30% of the total collaboration between BRI countries and all countries in the world (Table 3). This finding indicates that the degree of internal collaboration within BRI regions is not as close as that of external collaboration with countries outside BRI regions.

3.1.1 Spatial structural evolution of scientific collaboration beyond BRI regions

For scientific collaboration between sub-regions at a global scale, in 2013, Central & Eastern Europe had the most external links with the other countries beyond BRI regions, followed by China and West Asia & North Africa. Other sub-regions, especially the Central Asia, had fewer external links with the other countries beyond BRI regions. In 2018, Central & Eastern Europe, China and West Asia & North Africa formed a situation of tripartite confrontation, which all had the most external links with the other countries beyond BRI regions, and the number of external links with other BRI sub-regions also increased significantly (Table 4). In addition, all sub-regions in BRI regions had close scientific links with Europe in 2013 and 2018, accounting for the largest proportion of the total links, which basically reached 40% or above. The links between China and the United States also reached nearly 40% (Table 4).

Perhaps the most prominent feature is the dominant role of China over other BRI countries in generating scientific links at a global scale. This finding can be ascertained from Fig. 2 and Table 5, which show that China maintains the largest number of strong links and total links. In 2013, the strongest links were between China and the United States. China's links with countries beyond BRI regions, such as the United Kingdom, Australia and Japan, and India's links with the United States also remained at a large number. Meanwhile, the number of links between BRI countries (except China) and other countries in the world was medium or below. The spatial structure presented a triangular framework, which is composed of three regions (i.e., Europe, the United States and China) (Fig. 2a). In 2018, the number of stronger links increased. Examples include China's links with Canada, Germany and France, and Israel's links with the United States. China also had the largest number of total links. The spatial structure presented a skeleton structure type consisting of many dense regions, such as Europe, North America (USA, Canada), East Asia (China, Japan) and Oceania (Australia) (Fig. 2b). This view is also in accordance with the framework of the global scientific collaboration network composed of North America (the United States, Canada), Europe (Britain, France, *etc.*), East Asia (China, Japan) and Australia studied by Liu et al. (2017).

Several possible explanations could be explored here. The first relates to the fact that Europe, North America and the Asia-Pacific region have become hot spots of global scientific activity and high-value areas of scientific output. Another reason is that China has become an important node in the global scientific collaboration network; China's scientific output and collaboration are leading BRI countries and even the world.

Table 4 Sources of external scientific collaboration of BRI sub-regions in 2013 and 2018

Country	Africa		Europe		North America		South America		Oceania		Asia		United States	
	2013	2018	2013	2018	2013	2018	2013	2018	2013	2018	2013	2018	2013	2018
China	988	3053	27225	52864	5339	9876	1594	3385	6446	13691	8135	11871	30364	53123
Mongolia & Russia	454	1110	15717	22523	1082	1682	1200	2194	765	1293	1622	2509	3482	4650
S. Asia	1477	4722	15019	26116	1990	3587	1635	3963	1877	4196	3598	6269	6452	10202
SE. Asia	1205	4542	12880	27482	1440	3166	1004	3799	3551	6235	4514	7576	6057	8728
C. Asia	35	433	566	1617	38	241	19	252	28	187	74	241	148	324
W. Asia & N. Africa	3100	10668	37936	72683	4942	9070	4144	10120	3213	7787	4036	8309	13837	20927
C. & E. Europe	2499	7170	78863	121060	5253	8116	7158	14148	3893	7414	6009	9460	11311	14801

Note: South Asia (S. Asia); Southeast Asia (SE. Asia); Central Asia (C. Asia); West Asia & North Africa (W. Asia & N. Africa); Central & East Europe (C. & E. Europe); the statistical unit is the number of collaboration papers

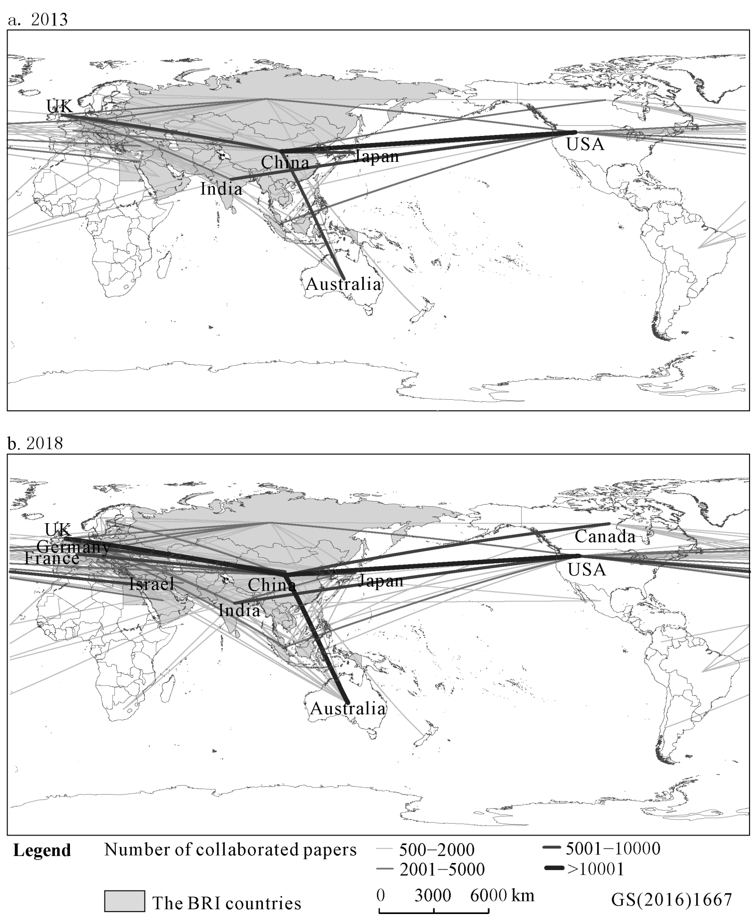

Fig. 2 Scientific collaboration networks between BRI countries and other countries in the world

Table 5 Top five BRI countries in terms of scientific links and number of collaboration countries at different scales

Rank	Global scale						BRI scale					
	2013			2018			2013			2018		
	Country	Degree	Links	Country	Degree	Links	Country	Degree	Links	Country	Degree	Links
1	China	108	80091	China	125	147863	China	60	19402	China	63	42072
2	Poland	76	24240	Poland	103	36694	Russia	55	9723	India	63	18010
3	Russia	75	23969	India	119	36164	Poland	56	9390	Russia	61	17813
4	India	102	22745	Russia	108	35214	India	59	8932	Poland	60	16790
5	Czech	79	17185	Czech	95	25712	Czech	55	8054	Saudi Arabia	60	15430

3.1.2 Spatial structural evolution of scientific collaboration within BRI regions

With regard to scientific collaboration within BRI regions, all the sub-regions have a high proportion of the total links with Central & Eastern Europe. As for the special geographical location, West Asia & North Africa region has also become an important region in the external relations of other regions. Central & Eastern Europe and West Asian & North Africa have always been the regions with the most intensive internal collaboration, due to of their similar cultural foundations and close distance (Fig. 3). Due to Russia's traditional advantages in terms of contact with Central & Eastern Europe and CIS countries, as well as Russia's 'special' relationship with the Middle East region, Mongolia & Russia are closely connected with West Asia & North Africa and Central & Eastern Europe.

This paper analyzes the connection structure of networks by combining strength centrality and the strength of links. In 2013, the overall BRI network connectivity was weak, showing a divergent structure centered in China (Fig. 4a). Specifically, the strength centrality of BRI countries has obvious spatial imbalance, with high strength centrality concentrated in a few countries like China. Strong and upper-medium links include those of China with Singapore, Russia, India and Poland, and Egypt with Saudi Arabia (Fig. 4a). The other 98% of links are mostly medium- and weak-level. Moreover, we can see from Table 5 that China became the most densely oriented country. During this period, the foundation of scientific collaboration was weak, and a framework agreement on collaboration between BRI countries had not yet been reached. In 2018, the overall BRI network connectivity improved, displaying a polygonal skeleton structure composed of 'one zone'—Central & Eastern Europe (e.g., Poland, Czech, *etc.*) and 'multi-points' (e.g., Russia, China, Singapore, India, Saudi Arabia, *etc.*) (Fig. 4b). Specifically, the strength centrality pattern of BRI countries indicates that China is the core, while other countries, such as Singapore, India, Turkey, Saudi Arabia, Egypt, Russia, and Poland, are the sub-cores. China still has advantages

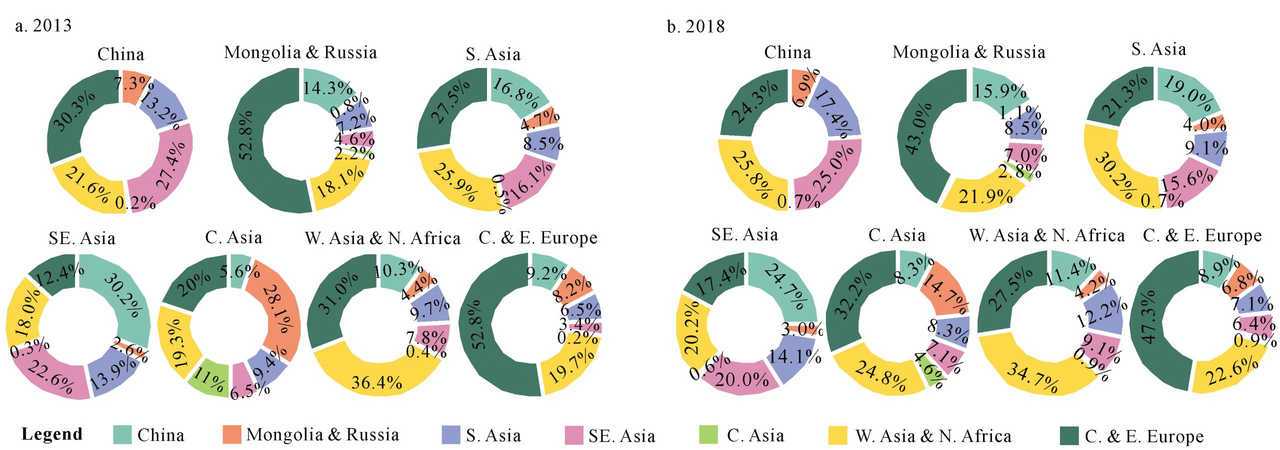

Fig. 3 The proportion of scientific collaboration among BRI sub-regions in 2013(a) and 2018(b). (South Asia (S. Asia); Southeast Asia (SE. Asia); Central Asia (C. Asia); West Asia & North Africa (W. Asia & N. Africa); Central & East Europe (C. & E. Europe))

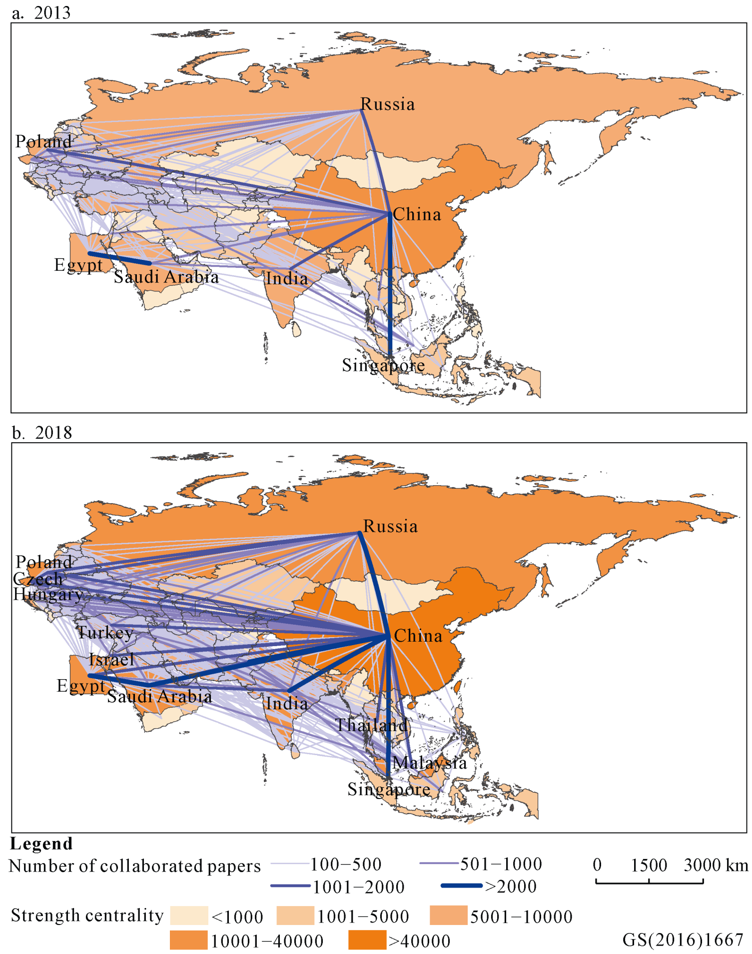

Fig. 4 BRI scientific collaboration networks in 2013a and 2018b

in external relations, connecting with more than 90% of the nodes along the BRI regions and serving as the backbone of BRI scientific collaboration networks. The number of strong and upper-medium links has increased. Examples include links between China and some Central & Eastern European countries, links between China and some West Asian & North African countries, as well as links between some countries within Central & Eastern Europe (Fig. 4b). Also, the proportion of medium links also increased to 23.4%, which promoted the overall collaboration atmosphere and network density.

3.2 Hierarchical structure of scientific collaboration networks

From 2013 to 2018, the degree of network centralization increased from 0.39 to 0.63, indicating that the whole network had an obvious trend of concentration to a certain country or some other specific countries. Inspired by the core and periphery of the ICT global innovation network (Nepelski and De Prato, 2018), this paper presents a tentative categorization of BRI countries within scientific collaboration networks by employing comprehensive centrality.

The hierarchical clustering algorithm is used to divide the Z value (comprehensive centrality) of BRI countries within scientific collaboration networks in 2013 and 2018 into four levels. Then, we convert the four levels to a Pajek partition file in 2D format, and visualize that file with VOSviewer (Fig. 5). The node size represents the strength centrality of the country, and the thickness of the line between the nodes represents the number of collaboration papers between two countries. From the perspective of two years, the number of countries in Levels 2 and 3 has increased, while the number decreased in Level 4. The BRI network presented a typical ‘core-periphery’ hierarchical structure. This finding is consistent with the fact that countries with higher ranks in the global network often possess higher positions in the scientific collaboration network.

Level 1: Over the five years covered in this study, network density, average degree centrality and strength centrality of Level 1 all improved, taking the leading position in the network (Table 6). Moreover, this level has changed from having a single core dominated by China, to having dual cores dominated by China and India. China, which is the country with the highest degree centrality and strength centrality, has the highest output of papers among BRI regions and absolute leadership in BRI scientific collaboration networks.

Level 2: All the index characteristics of Level 2 network showed an upward trend over the five years covered by the study, and the gap with the Level 1 network is small (Table 6). In 2013, these Level 2 countries included Russia, Poland, India, Czech, Turkey, Iran, Malaysia and Egypt (Fig. 5a). In 2018, the number of these countries increased to 12, by that time including Saudi Arabia, Thailand, Israel and Singapore (Fig. 5b). The degree centrality, strength centrality and betweenness centrality of these countries are also in the upper-middle value range. Although these countries have less centrality value than China, they still play a strong role in becoming the leading force in paper production and collaboration among BRI sub-regions, which are Southeast Asia, Central Asia, West Asia & North Africa, South Asia and Central & Eastern Europe. Therefore, these countries have become the sub-cores and hub points of BRI scientific collaboration networks. They are closely connected with each other and act as core nodes and other general nodes from top to bottom in networks.

Level 3: In the five years of the study period, the Level 3 network density, average degree value and other indicator values were higher than the average value of the whole network. This indicates that the internal relations are relatively close in the Level 3 network (Table 6). In 2013, the Level 3 network was composed of 27 countries, including nations such as Romania, Belarus, Ukraine, Serbia, Croatia, Singapore, Vietnam, Saudi Arabia, *etc.* (Fig. 5a). In 2018, the Level 3 network was composed of 31 countries, including such nations as Hungary, Serbia, Ukraine, Vietnam, the Philippines, Indonesia, the United Arab Emirates, Kazakhstan, *etc.* (Fig. 5b). The degree centrality, strength centrality and betweenness centrality of these countries are in the middle value range. Although these countries have a relatively high degree of collaboration and closeness within the Level 3 network, most of their external contacts were with the core and sub-core countries, while the links with marginal countries were weak. Therefore, these countries constitute the semi-periphery regions of BRI scientific collaboration networks.

Level 4: In the five years of the study period, all the indicator values of the Level 4 network were lower than the average value of the whole network (Table 6). The Belt and Road Initiative promoted closer collaboration between BRI countries, so the number of these countries decreased from 29 to 20. In 2013, these countries were mostly located in West Asia, Central Asia, South Asia, Southeast Asia and other regions (Fig. 5a). In 2018, these countries were agglomerated in Western Asia (Fig. 5b). The degree centrality, strength centrality and betweenness centrality of these countries are all in the lower-middle value or low value range. These countries in the Level 4 network are at the edge of the whole network and have slow development in terms of science and technology. This is due mainly to the relatively low level of economic development, low population density, or geopolitical influence.

3.3 Formation mechanisms of scientific collaboration networks

In order to explain the results presented in the previous sections, we must understand what determines international paper collaboration in terms of a scientific collaboration network. The negative binomial regression model was used to test the estimation results of national subject attributes, geographical proximity, social proximity,

Table 6 Network statistical characteristics of different hierarchies of BRI scientific collaboration networks in 2013 and 2018

Levels	No. of countries		Network density		Average degree centrality		Average strength centrality		Average betweenness centrality	
	2013	2018	2013	2018	2013	2018	2013	2018	2013	2018
Overall	65	65	0.59	0.81	38	52	2572	5463	0.0033	0.0060
Level 1	1	2	1	1	60	63	19402	30041	0.0139	0.0312
Level 2	8	12	0.82	0.95	56	60	7239	12365	0.0075	0.0152
Level 3	27	31	0.64	0.82	46	54	3049	4429	0.0031	0.0042
Level 4	29	20	0.39	0.47	24	38	259	465	0.0013	0.0007

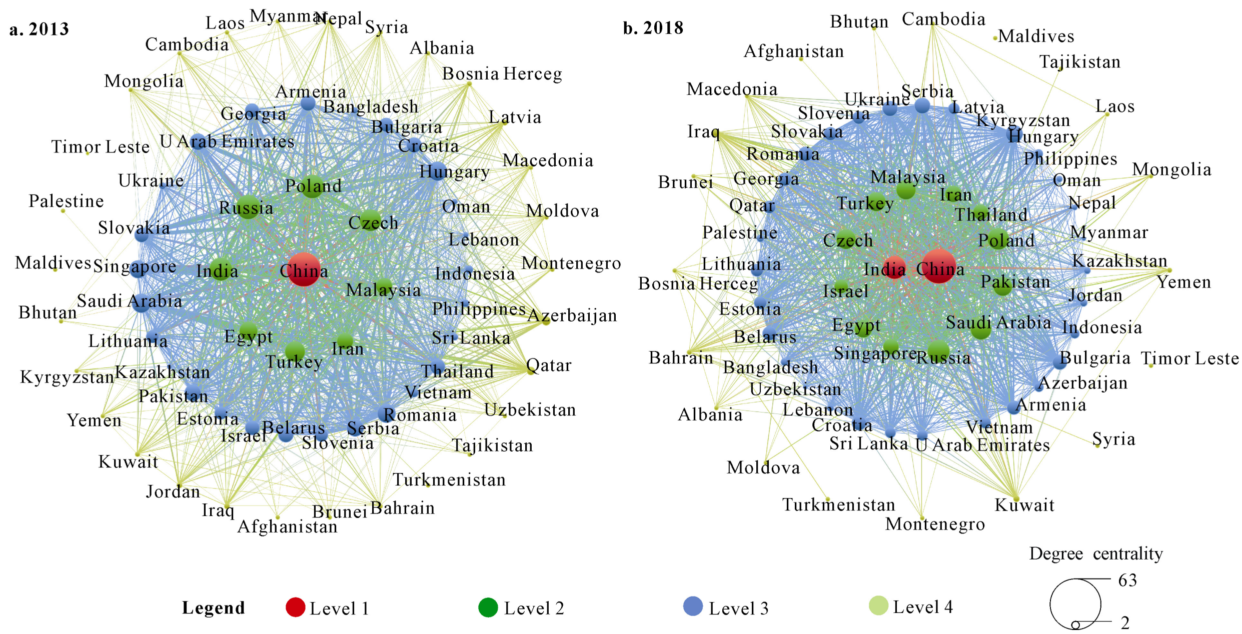

Fig. 5 Hierarchical structure of BRI scientific collaboration networks

language proximity and the amount of co-papers between countries. To ensure the reliability of the regression results, a multicollinearity test of variables was firstly carried out. The variance inflation factors (VIF) of the model were all less than 5, indicating that there was no collinearity among variables. Secondly, in order to create more robust regression results, the hierarchical regression was used to gradually introduce explanatory variables (Models 1–2). Model 1 reveals the influence of national subject attributes on BRI scientific collaboration networks, and Model 2 shows the influence of multidimensional proximities on BRI scientific collaboration networks. Finally, Model 3, which is the final model used to explain the formation mechanisms of networks, is obtained by integrating all explanatory variables. The model results are shown in Table 7.

Table 7 The negative binomial regression of BRI scientific collaboration networks

Variable	Model 1		Model 2		Model 3	
	2013	2018	2013	2018	2013	2018
Scientific ability of country A	0.368^{***} (0.058)	0.403^{***} (0.060)	–	–	0.302^{***} (0.050)	0.372^{***} (0.050)
Scientific ability of country B	0.252^{***} (0.048)	0.271^{***} (0.060)	–	–	0.205^{***} (0.030)	0.213^{***} (0.030)
Economic level of country A	0.113^{***} (0.029)	0.094^{**} (0.023)	–	–	0.109^{***} (0.028)	0.087^{**} (0.024)
Economic level of country B	0.108^{***} (0.027)	0.097^{**} (0.025)	–	–	0.101^{***} (0.026)	0.083^{**} (0.025)
Degree of openness in country A	0.172^{***} (0.025)	0.188^{***} (0.024)	–	–	0.168^{***} (0.024)	0.184^{***} (0.024)
Degree of openness in country B	0.182^{***} (0.013)	0.185^{***} (0.013)	–	–	0.171^{***} (0.033)	0.165^{***} (0.033)
Geographical proximity	–	–	-0.093^{***} (0.0040)	-0.069^{***} (0.0031)	-0.044^{***} (0.0030)	-0.028^{***} (0.0035)
Social proximity	–	–	0.477^{***} (0.081)	0.495^{***} (0.081)	0.457^{***} (0.094)	0.484^{***} (0.098)
Language proximity	–	–	0.003^{***} (0.0030)	-0.006^{***} (0.0043)	0.013^{***} (0.0030)	-0.008^{***} (0.0046)
Sample size	1226	1676	1226	1676	1226	1676

Notes: $P < 0.10(^{*})$; $P < 0.05(^{**})$; $P < 0.01(^{***})$; the figures in brackets are the robustness standard errors of the estimated coefficients; '–' means no value

Looking at the national subject attributes, the scientific ability represented by the amount of published papers is the most important factor influencing the collaboration scale. Specifically, the more papers published in the two BRI countries, the stronger the scientific ability and the greater the possibility of collaboration will be (Ter Wal and Boschma, 2011; Cassi et al., 2015). This rather surprising finding is consistent with the conclusion that a region tends to have less scientific collaboration with regions with weak scientific ability. However, a region is more inclined to have collaboration with regions with strong scientific ability (Laursen et al., 2011). Economic development level had a positive impact on the dependent variable in the two years (2013 and 2018). This finding is further strengthened by the point that the more similar two countries are in terms of economic development level, the greater the chances (and the greater the scale) of scientific collaboration will be (Plotnikova and Rake, 2014). Furthermore, the coefficient and significance of economic development level in 2018 decreased, compared with 2013. This finding reveals that many less-developed BRI countries, which have economic development levels that are too low to satisfy their input and output of scientific papers and collaboration needs, enhance their collaboration with BRI countries of high economic development level, in order to improve their scientific level. However, the main body of collaboration still exists between relatively developed BRI countries. The degree of openness is conducive to the scientific collaboration between two countries, and the effect of coefficient is significant in two years. This can be explained by the fact that openness is conducive to the acquisition of scientific progress and knowledge spillover in other countries alongside BRI regions, and is also conducive to the establishment of diversified collaboration channels.

From the perspective of the multi-dimensional proximities between countries, the collaboration volume of scientific papers between two countries is inversely proportional to their geographical distance. This finding shows some similarities to the observation made by Hoekman et al. (2010), who stated that there are close exchanges of scientific collaboration within Europe, especially among EU countries. In addition, these countries are more willing to seek neighboring scientific partners, so as to improve their scientific output. That is to say, geographical proximity plays a significant role in promoting the formation of scientific collaboration networks. The coefficient of geographical proximity gradually decreased during the study period, however, and the strongest links occurred in two distant regions, such as China and parts of Central & Eastern European countries. This finding is consistent with the above analysis. This point is also consistent with the conclusion proposed by Araujo et al. (2018) who stated that the distance (between regions) is being reduced by communication technology and convenient transport. The coefficient of social proximity has a significant positive effect on collaborations. This finding might suggest that BRI countries have established trust mechanisms for scientific collaboration and that they have signed a number of scientific collaboration plans. Also, the increasingly close social relations between BRI countries have reduced the uncertainty of collaborations undertaken to increase the possibility of scientific collaboration and output. The globalization of social relations based on the flow of talents and knowledge between the two countries has also been promoted. This conclusion also conforms with Miörner et al. (2018). Regarding the factor of language proximity, we observe that it played a positive role in promoting scientific collaborations between BRI countries in 2013. This was especially true within Central & Eastern Europe, West Asia and Southeast Asia regions given the closeness or convergence of official languages, which facilitates the exchange, learning, management and innovation of projects for the sake of promoting scientific collaboration. However, language proximity presented a negative impact in 2018, which might be interpreted as meaning that language no longer meaningfully affects the scientific collaboration between BRI countries. Also, the frequency of exchanges between BRI countries has increased, and the degree of exchanges has become closer.

4 Discussion and Conclusions

4.1 Discussion

The main contributions of this paper are in the following four aspects: firstly, economic geography and regional science has emphasized the importance of 'local buzz' and 'global pipelines' (Bathelt et al, 2004), which could be interpreted as internal and external collaboration. Meanwhile, there is a scarcity of empirical analysis about collaboration networks within and beyond the spatial unit of analysis. This study could substantially further our understanding of the spatial structure of scientific collaboration networks within and beyond the Belt and Road regions. Secondly, this article unites degree centrality, strength centrality and betweenness centrality to analyze the hierarchy of the network. Thirdly, existing studies recognize the mechanism framework as a static state (Balland et al, 2014; Broekel, 2015). This paper adopts a dynamic approach to analyze the evolution over time of the impact of different forms of mechanisms on scientific collaboration networks. Fourth, our studies provide a wide-ranging snapshot of the scientific collaboration of the Belt and Road regions. Previous studies also concentrate on a single industry or specific research field, such as pharmaceutical research (Cantner and Rake, 2014; Plotnikova and Rake, 2014), biotechnology (Heimeriks and Boschma, 2014; Ter Wal, 2014), and the navigation satellite system industry (Balland, 2012). In addition, this research may be one of the first attempts to use system theory to understand the scientific collaboration system of the Belt and Road regions.

4.2 Conclusions

Scientific collaboration has become an important part of the people-to-people exchanges in the Belt and Road initiative, and remarkable progress has been made since 2013. This paper explores the spatial structure of scientific collaboration networks within and beyond BRI regions, as well as the hierarchy structure of networks. This is done by using comprehensive centrality, which promotes the evaluation of network structure to a comprehensive transformation and enriches the structure analysis and theoretical analysis framework of innovative networks. Our study also explores the network formation mechanisms in BRI regions from two dimensions. This approach is taken in consideration of few studies that have focused on the interaction of multiple mechanisms, which enriches the theoretical research into the mechanism of innovation networks.

Based on the co-paper data of the Web of Science core collection, the main results are as follows:

At the global scale, knowledge flow is becoming more and more frequent, and the degree of internal collaboration within BRI regions is not as close as the degree of collaboration with other countries in the world. In addition, China has the dominant role in forming scientific collaborations with other countries on a global scale. The spatial structure of the network between BRI countries and other countries in the world has changed from a triangular framework type in 2013, composed of three regions (i.e., Europe, the United States and China), to a skeleton type in 2018, consisting of Europe, North America (the USA, Canada), East Asia (China, Japan) and Oceania (Australia). These conclusions may be explained by the fact that Europe, North America and China have the highest value of scientific output and have dominated scientific collaboration networks at a global scale.

From the perspective of collaboration within BRI regions, the collaboration links between BRI sub-regions and Central & Eastern Europe have the largest proportion of total links. Central & Eastern Europe and West Asia & North Africa have always been the regions with the most intensive internal collaboration. The spatial structure of BRI scientific collaboration networks has transformed from the ‘single-core’ type (i.e. China) in 2013, to the ‘one zone’ type—Central & Eastern Europe (Poland, Czech, *etc.*) and ‘multi-points’ type (Russia, China, Singapore, India, Saudi Arabia, *etc.*) type in 2018. Specifically, China still has advantages in terms of external relations, which it has with more than 90% of BRI countries.

The hierarchy of BRI scientific collaboration networks can be divided into four levels; the hierarchical structure presents a typical ‘core-periphery’ structure. The core countries of the structure changed from the single core of China in 2013, to the dual cores of China and India in 2018. The countries in Level 2 (such as Russia, Poland, India, Turkey, Singapore, *etc.*) have become the sub-cores of the network. They played a strong role in connecting Level 1 and Level 3, and became the leading force among BRI sub-regions.

We find that the country subject attributes and proximities have impacts on the formation of BRI scientific collaboration networks. Scientific ability, economic development level, and the level of foreign linkage are contained in the country subject attributes, while proximities are made up of geographical proximity, social proximity and language proximity. From the perspective of mechanism evolution, scientific ability and social proximity have always played the most important roles, while geographical distance has gradually weakened the hindrance to scientific collaboration. Language proximity has changed from having a positive impact to a negative impact, which implies that language proximity no longer affects scientific collaboration.

The cooperative matrix of papers in this study adopts the method of full counting, which fails to highlight the contributions of the first author's or corresponding author's country. The importance of different countries in the co-papers is also ignored. Therefore, future studies could be optimized by weighted counting. This paper uses co-papers to analyze BRI scientific collaboration networks. Other forms of scientific collaboration (e.g., co-patents, co-projects, R&D collaboration, *etc*.) also belong to the category of scientific collaboration. Therefore, it is necessary for comparative research to be conducted that analyzes the multiple forms of scientific collaboration networks. At present, the co-paper data is only reflected in the number of links. Further studies should also pay closer attention to refining the innovation network from the different disciplines of co-paper data and the different industries of co-patent data. In addition, some policy implications could be derived from the results of this empirical study. Firstly, although internal scientific collaboration within BRI regions is becoming more and more frequent, it is not as close as the degree of external collaboration with other countries in the world. Therefore, the governments of BRI countries need to encourage additional collaboration. This could be done by establishing permanent scientific collaboration agreements, in order to highlight the overall development of BRI regions' scientific collaboration system in the long term. Secondly, most links occur between major countries in BRI regions, so more institutional arrangements should be provided to enhance the ability of less-favored countries in BRI regions to achieve scientific collaboration with major countries.

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