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A Novel Analysis Method of Geographical Centrality Based on Space of Flows

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Abstract: Geographical centrality is an evolving concept that differs from one perspective to another at different stages. The unprecedented development of high-speed information and transportation networks has highlighted the important role of space of flows and has restructured the mode of spatial interaction. The geographical centrality analysis method based on relational networks currently becomes the mainstream, but most related methods ignore the spatial structure. In this study, we first analyze the impacts of space of flows on geographical space based on spatial interaction theory. We argue that geographical space and space of flows dominate short- and long-distance interactions, respectively. Based on this hypothesis, the concept of geographical centrality based on space of flows is proposed. The new concept categorizes spatial units into four types: global centers, isolated units, externally oriented units, and locally oriented units. Then, two quantitative measures, namely, global and local geographical centrality indexes, are defined. In the case study, we analyze the geographical centrality of cities in China at three different spatial scales and compare the result with three other geographical centrality analysis methods. City attribute is concluded to be more important than spatial distance in urban spatial interaction at the national scale, and this situation is caused by the effect of space of flows on geographical space. The similarities and differences between the proposed geographical centrality analysis method and the classic spatial autocorrelation analysis method of Moran's I are also discussed.

Keywords: centrality; space of flows; geographical space; spatial autocorrelation; China

1. Introduction

Geographical centrality is an evolving concept that differs from one perspective to another at different stages. A spatial unit has strong centrality when its average distance to the other spatial units is closer in the region, and such centrality is based on geographical proximity. A spatial unit with one or some attributes relatively stronger than those of the other spatial units in the region may also be considered to possess strong centrality, and this centrality is based on scale attributes. In many cases, the centrality of a spatial unit is determined by its own attributes and the distance from other spatial units, and we refer to this condition as the centrality based on geographical proximity and attributes. Central place theory is a classical location theory proposed by the German geographer Walter Christaller [1]. This theory is a typical representative of the abovementioned idea and has significantly influenced the research on geographical centrality. At present, most studies on geographical centrality adopt the centrality concept defined by central place theory. In central place theory, a central place refers to a settlement that provides central functions, such as goods and services to surrounding

settlements. The centrality in this theory is a measure that estimates the relative importance of a central place servicing other places [1–4].

The rapid development of information technology, especially the Internet, since the 1990s has facilitated the active flow of people, material, information, capital, and technology in the region and among cities, and geographical space shows different characters from the past. American scholar Manuel Castells presented the theory of space of flows, which received a wide range of academic response. Space of flows is defined as "the material arrangements that allow for simultaneity of social practices without territorial contiguity" [5,6]. Space of flows compresses and re-conceptualizes geographical space under the new technical environment. Time gradually replaces distance, and localization is weakened while the network is enhanced. The large-flow and long-distance factor mobility in a short time is realized [7,8]. Following the theory of space of flows, urban network theory was proposed. The GaWC (Globalization and World Cities Research Network) founded by Taylor and the POLYNET (Sustainable Management of European Polycentric Mega-City Regions) led by Hall have carried out considerable research on the world city [9,10] and urban agglomeration polycentric networks [11,12], respectively, which have abounded in the field of urban networks. Taylor et al. considered that the traditional central place pattern and the network pattern both contain the concept of place and flow. However, the spatial hierarchical distribution of places determines the distribution of flows in the central place pattern, while the distribution of flows determines the centrality of places in the network pattern, which is characterized by the multi-directional connections across the hinterland [13,14]. Urban network theory holds that the centrality of a city is determined by its relationship with other cities, and we refer to this situation as centrality based on relational networks. In the late 1990s, small world and scale-free network theories were proposed [15,16]. These theories set off the upsurge of complex network research and are powerful tools for urban network research. The centrality of complex networks, such as degree centrality, betweenness centrality, and closeness centrality, have also been introduced into urban network studies [17,18].

According to the five different ideas of geographical centrality summarized above, centrality based on geographical proximity and centrality based on scale attributes are one sided because they tend to define centrality from one single dimension. Central place theory constructs a spatial hierarchical system of settlements characterized by triangular settlement distribution and hexagonal market area by considering both geographical proximity and scale attributes. This system is an ideal settlement distribution pattern in traditional geography and is still the theoretical basis of residential system planning at present. In practice, some researchers developed central place theory by theoretical derivation and simulations on its basic hypotheses [19–22]. Other researchers attempted to fit the realistic settlement distribution pattern to the ideal central place pattern, which was used as the criterion for the optimal structure [23–26]. Nevertheless, these studies neglected the emergence and increasing importance of space of flows, a situation that is significantly different from that when central place theory was proposed. The irrationality of basic hypotheses and the increasing complexity of realities reduce the credibility and availability of the conclusions. Consequently, centrality based on relational networks gradually dominates the research on geographical centrality at present. Research on spatially-embedded networks is an important direction of the complex network research [27–29]. Some researchers studied the spatial effects of spatially-embedded networks through modeling and simulating methods [30,31]. Some other researchers studied the community detection method of spatially-embedded networks [32,33]. However, there are few works on the centrality analysis method, which considers both the network topology structure and the geographical spatial structure simultaneously. Most of the relevant works are limited to describing the spatial distribution of node centrality [17,34]. Therefore, the geographical centrality analysis method in the context of space of flows needs to be improved and developed.

This study proposes a novel analysis method of geographical centrality based on space of flows to fill the gap of related previous research and aims to arouse the attention of the research community on geospatial analysis methods in the context of space of flows. Based on spatial interaction theory,

we first discuss the impacts of space of flows on geographical space and summarize the main characters of geographical space and space of flows. On the basis of the main characters, we propose the concept and methods of geographical centrality based on space of flows. Furthermore, global geographical centrality index (GGCI) and local geographical centrality index (LGCI) are defined to quantitatively analyze geographical centrality. In the case study, the proposed method is validated by evaluating and analyzing the geographical centrality of cities in China using social network data that characterize urban spatial interaction. We compare the proposed method and three other methods used to analyze geographical centrality. Moreover, the similarities and differences between the proposed geographical centrality analysis method and the classic spatial autocorrelation analysis method of Moran's I are discussed.

2. Method

2.1. Space of Flows and Geographical Centrality

Spatial interaction theory indicates that the occurrence of spatial interaction among spatial units should meet three conditions: complementarity, transferability, and intervention opportunity [35]. However, the unprecedented development of high-speed information and transportation networks has prompted the generation and development of space of flows, and space of flows has restructured the spatial interaction pattern to a great degree. The information network can be considered a virtual network, which is not restricted by geographical space. High-speed information network, such as the Internet and mobile communication network, enables the transient transfer of information among spatial units with nearly no cost. Thus, the complementarity and intervention opportunity are redefined by the information network. Consequently, the supply–demand relationship of production factors and products among spatial units with a long distance becomes possible. The transportation network is a physical network embedded in geographical space. High-speed transportation network, such as expressway network, high-speed railway network, and aviation network, significantly enhances the transferability of material elements and compresses the distance of spatial interaction. This situation further greatly increases the possibility of the supply–demand relationship among spatial units with a long distance. Accordingly, given the high-speed information and transportation networks, space of flows affects spatial interaction based on geographical space. Consequently, the large-flow and long-distance factor mobility occurs in a short time. Even so, geographical space is still the foundation of spatial interaction, which shows in the dominant strength in spatial interaction. Owing to the geospatial distance or transportation cost, spatial interaction tends to occur among spatial units with a short distance. This situation results in a unique character of geographical space called spatial autocorrelation, which is also known as spatial dependence and is the main difference between geographical space and space of flows. Space of flows is a counterforce to geographical space to some extent, and this force overcomes geospatial distance or does not even depend on geographical space to enable the interaction among spatial units. Considering that the significant character of flows is rapid or even instantaneous, we can focus only on the starting and ending points of flows while ignoring their specific paths. The reason is that these paths are handled by the professional and efficient modern logistics and communications organizations. Although space of flows impacts short- and long-distance space, the performance differs. In short-distance space, spatial dependence still exists, but space of flows breaks the traditional central place hierarchical structure and gradually transfers to the network hierarchical structure. In long-distance space, space of flows enhances spatial interaction and enables strong interaction among spatial units with a long distance, a situation that rarely happened in the past.

The discussion above indicates that geographical space mainly impacts short-distance space, while the interaction of long-distance space is caused mainly by space of flows. Based on this hypothesis, we propose a novel method for analyzing and measuring geographical centrality. As shown in Figure 1a, spatial units are distributed in a geographical space with a red spatial unit as the center. The dark and light blue areas represent short- and long-distance geographical spaces, respectively. The spatial

units of strong interaction with the central spatial unit are represented in black, while the spatial units of weak interaction are represented in gray. A total of 4 out of 5 spatial units in short-distance space of the central spatial unit present strong interaction, while 2 out of 10 spatial units in long-distance space exhibit strong interaction. Therefore, for the central spatial unit, the strength of short-distance interaction dominated by geographical space is 4/5, while the strength of long-distance interaction dominated by space of flows is 2/10. The same method is applied to other spatial units to calculate their strengths of short- and long-distance interactions. Then, the strengths of short- and long-distance interactions are used as the horizontal and vertical axes, respectively. Accordingly, a scatterplot of geographical centrality is created, in which spatial units are identified as four types of geographical centrality (Figure 1b). These types are discussed in detail in the following parts.
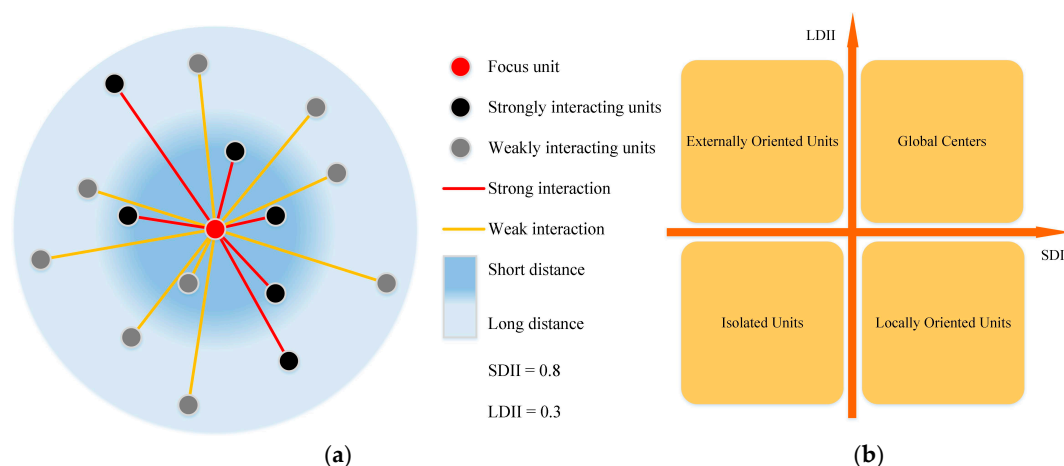

Figure 1. Geographical centrality and its scatterplot. (**a**) short- and long-distance interactions; (**b**) scatterplot of geographical centrality.

Global centers in the first quadrant. This type of unit has strong short- and long-distance interactions. Global centers are located mostly in developed areas and are the key units for local and global development. Global centers can promote the development of local units in their hinterlands, and they can also allow these local units to interact with spatial units in a long distance through their strong controllability of space of flows, which the local units do not have. In the latter case, global centers act as regional hubs. For example, Beijing, Shanghai, and Guangzhou in China have led the development of regions of Beijing–Tianjin–Hebei, Yangtze River Delta, and Pearl River Delta, respectively; these cities also become the hubs of their hinterlands interacting with the rest of the regions of the country. Therefore, they are global centers for the national development.

Externally oriented units in the second quadrant. This type of unit has strong long-distance interaction, in which space of flows plays a leading role. Usually, externally oriented units rely on their special factor endowment to interact with long-distance spatial units in the context of space of flows. Theoretically, this situation is rare. For example, the developed regions in the southeastern coastal areas of China attract labor flows from the underdeveloped areas in the Midwest where labor is abundant. Moreover, regions with special tourism resources attract tourist flows from other places.

Isolated units in the third quadrant. This type of unit rarely interacts with spatial units in either short or long distance. Isolated units are located mostly in the underdeveloped areas, and their future development should be paid much attention. Policy support and infrastructure construction should be reinforced to promote their communication with the outside world.

Locally oriented units in the fourth quadrant. This type of unit has strong short-distance interaction and is dominated by geographical space. Traditional central place theory mainly discusses this type of units. Locally oriented units interact only with spatial units in their hinterlands and thus

act only as local centers. When these units need to interact with long-distance units, they have to rely on the strong controllability of space of flows of global centers.

2.2. Geographical Centrality Index

We aim to quantify the proposed geographical centrality based on space of flows. For this purpose, we first propose short-distance interaction index (SDII) and long-distance interaction index (LDII) to measure the strengths of short- and long-distance interactions, respectively. On this basis, we propose GGCI and LGCI. GGCI measures the relationship between short-distance interaction dominated by geographical space and long-distance interaction dominated by space of flows. Meanwhile, LGCI identifies and measures the type and strength of geographical centrality for each spatial unit.

2.2.1. SDII and LDII

Two variables are necessary to measure geographical centrality based on space of flows. One variable is used to describe the strength of interactions among spatial units. This variable is often represented by network data of flows among spatial units, such as flows of people, logistics, and information. Network data acquisition is a difficulty in measuring geographical centrality. This situation is especially true in China. The other variable is used to describe the spatial relationship among spatial units, which can be presented by the spatial adjacency matrix or spatial weight matrix in spatial statistics. In the spatial adjacency matrix, the value is 1 if spatial units are adjacent and 0 if otherwise. In the spatial weight matrix, the distance between spatial units determines how proximate they are; thus, the description is more accurate than the spatial adjacency matrix. Therefore, we adopt the spatial weight matrix in this research. The Gaussian function rather than the reciprocal of the square of the distance is defined as the weight function. The reason is that the former is more appropriate and adjustable than the latter.

According to the hypothesis that geographical space and space of flows dominate short- and long-distance interactions, respectively, spatial weight matrixes of short- and long-distance interactions are created. These matrixes represent the influence scope of geographical space and space of flows, respectively. The weight of the former matrix decreases as the distance between spatial units increases, while the latter increases as the distance increases. By combining the spatial weight with the strength of interactions among spatial units, SDII and LDII are defined as follows:

$$WS_{ij} = e^{-\frac{d_{ij}^2}{\sigma^2}},\tag{1}$$

$$WL_{ij} = 1 - WS_{ij},\tag{2}$$

$$SDII_i = \frac{\sum_j^n WS_{ij} \times N_{ij}}{\sum_j^n WS_{ij}},\tag{3}$$

$$LDII_i = \frac{\sum_j^n WL_{ij} \times N_{ij}}{\sum_j^n WL_{ij}},\tag{4}$$

where d_{ij} is the distance between spatial units i and j. σ is a distance threshold to determine whether a distance is short or long. This distance threshold is a relative concept and is chosen according to the research purpose and study area. We discuss this distance threshold in the case study. WS_{ij} and WL_{ij} are spatial weights of short- and long-distance interactions, respectively. N_{ij} is the strength of interaction between spatial units i and j.

2.2.2. GGCI and LGCI

In order to have a general understanding of the effect of geographical space and space of flows, and to identify and measure the geographical centrality of each spatial unit, we proposed GGCI and LGCI, which are calculated by Equations (5) and (6):

$$LGCI_i = \frac{\left(SDII_i - \overline{SDII}\right)\left(LDII_i - \overline{LDII}\right)}{\sqrt{\frac{\sum_i^n \left(SDII_i - \overline{SDII}\right)^2}{n}} \sqrt{\frac{\sum_i^n \left(LDII_i - \overline{LDII}\right)^2}{n}}} \tag{5}$$

$$GGCI = \frac{\sum_i^n LGCI_i}{n} = \frac{\sum_i^n \left(SDII_i - \overline{SDII}\right)\left(LDII_i - \overline{LDII}\right)}{\sqrt{\sum_i^n \left(SDII_i - \overline{SDII}\right)^2} \sqrt{\sum_i^n \left(LDII_i - \overline{LDII}\right)^2}} \tag{6}$$

GGCI ranges between [–1, 1]. GGCI > 0 means that spatial units tend to interact with short- and long-distance units both, a common situation in practice. GGCI < 0 means spatial units tend to interact with short-distance units only or long-distance units only, an unusual situation in practice. When GGCI > 0, a large value means the difference between short- and long-distance interactions of spatial units is small. This condition indicates that the effect of geographical space weakens and space of flows dominates the spatial interaction. The strength of interactions among spatial units depends on their attributes rather than the distance among them. On the contrary, a small GGCI value means a significant difference exists between short- and long-distance interactions among spatial units. This condition indicates that the effect of geographical space is still strong and space of flows has not yet worked. Geospatial distance still restricts the interactions among spatial units. Moreover, the value of GGCI is relative and needs to be determined using the significance test.

For spatial unit *i*, LGCI$_i$ > 0 means the unit is located in the first or third quadrant in the scatterplot of geographical centrality. This unit is a global center unit or an isolated unit, which means this unit interacts with short- and long-distance units simultaneously or does not interact with either of them. LGCI$_i$ < 0 means the unit is located in the second or fourth quadrant in the scatterplot of geographical centrality. This unit is an externally oriented unit or a locally oriented unit, which interacts with either short- or long-distance units. The absolute value of LGCI$_i$ is the degree of their belongingness to the four types of geographical centrality.

2.2.3. Significance Test of Geographical Centrality

GGCI and LGCI vary with different spatial structures and spatial interaction structures in different regions; thus, no absolute standard exists to determine whether GGCI and LGCI are high or low. We aim to avoid random factors influencing GGCI and LGCI. For this purpose, we refer to the random permutation operation of the Moran's I method widely used in spatial autocorrelation analysis to test the significance of GGCI and LGCI and evaluate the reliability of geographical centrality. Random permutation of geographical centrality randomly permutes rows and columns of the spatial interaction matrix simultaneously and does not change the spatial weight matrix. This operation does not change the geospatial structure and spatial interaction structure and permutes the interaction relationships of a spatial unit at a specific location with other units. After numbers of random permutations and calculation of GGCI and LGCI, the simulated distributions of GGCI and LGCI are generated. Then, the corresponding significance test can be conducted accordingly. The significance level in this research is 0.05 by default.

3. Case Study

3.1. Data Sources and the Basic Characters

The primary difficulty in urban network study is data acquisition. Previous studies mostly used the distribution data of headquarters and branches of multi-location enterprises (e.g., advanced

producer service enterprises and multinational enterprises) or network data of infrastructures (e.g., air passenger flows and telecommunication flows among cities) [10]. In recent years, the development and popularization of smartphones and mobile Internet services (e.g., social network services and location-based services) have changed the data environment and facilitated the emergence of urban network studies based on big data [36]. In this research, we use urban network data containing 370 prefecture-level units in China shared by Liu et al. to validate the proposed analysis method of geographical centrality in the case study. The data are derived from a major location-based social network platform in China, containing 23.5 million valid checkin data from September 2011 to September 2012 (Supplementary Materials) [37].

The spatial distribution of spatial interaction (Figure 2a) shows strong interactions among Beijing, Shanghai, Guangzhou, and Chengdu, thereby forming a typical diamond-shaped urban network structure in China. The statistical distribution of spatial interaction (Figure 2b) shows that the strength of intercity interaction is a power-law distribution, which indicates that most intercity interactions are weak and less is strong. As the distance between cities increases, the number of city pairs interacting with each other at each distance segment decreases, and the number of city pairs with strong interaction also decreases. Furthermore, the strength distribution becomes narrow, and the mean and median become gradually small. This situation indicates that geographical space still dominates spatial interaction at the national scale. However, the diamond-shaped urban network structure also shows that high-strength and long-distance interaction have already occurred under the effect of space of flows.
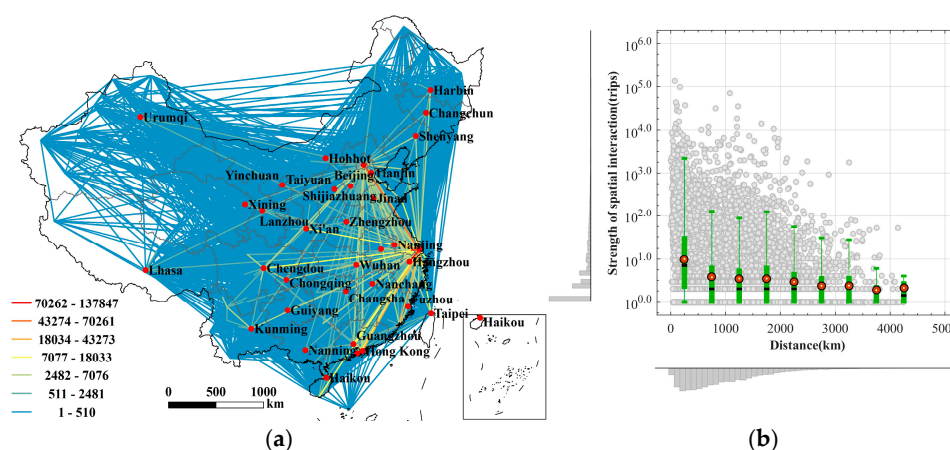

Figure 2. Spatial and statistical distribution of interaction strength among cities in China based on social network data. (**a**) Spatial distribution of interaction strength among cities (trips); (**b**) statistical distribution of interaction strength among cities and its relationship with corresponding distance.

3.2. Geographical Centrality Analysis

The proposed analysis method of geographical centrality needs a distance threshold σ to determine whether a distance is short or long. Such a problem of spatial scale selection is considered by many geospatial analysis methods. Two aspects need to be considered to solve this problem. One is determining the characteristic spatial scales for the specific geospatial problem, and the other is determining the practical significance of the selected scale. The intercity interaction data based on the social network in China (Figure 3a) show that, with the increase in σ, the averages of SDII and LDII decrease and GGCI increases. The reason is that spatial interaction is stronger in short distance than in long distance. With the increase in σ, some long-distance weak interactions are added to SDII, while some short-distance strong interactions are removed from LDII. Consequently, both SDII and LDII decrease. The increase in GGCI is due to that short-distance space expands into long-distance space actually dominated by space of flows, such that the gap between SDII and LDII

narrows. Furthermore, SDII is one order of magnitude larger than LDII at every spatial scale. This finding further indicates that geographical space plays a relatively more important role than space of flows in spatial interaction. Therefore, the proposed SDII and LDII are relative and generally need to be logarithmically transformed. Moreover, curves within 500 km are all changed rapidly, while they are stable beyond 2000 km. The spatial distribution map of cities in China (Figure 3b) with Beijing, Shanghai, Guangzhou, and Chengdu as centers shows that the radius of 250 km covers most cities in their corresponding urban agglomerations; the radius of 500 km covers most of the provincial capital cities nearby; the radius of 750 km nearly covers the entire area of provinces nearby. Therefore, we define the three spatial scales as the urban agglomeration scale, regional scale, and large regional scale. If the radius exceeds 750 km, large overlaps will exist among short-distance spaces of different cities, thereby leading to loss of practical significance of the spatial scale. Therefore, three spatial scales, 250, 500, and 750 km, are chosen for further analysis of geographical centrality.
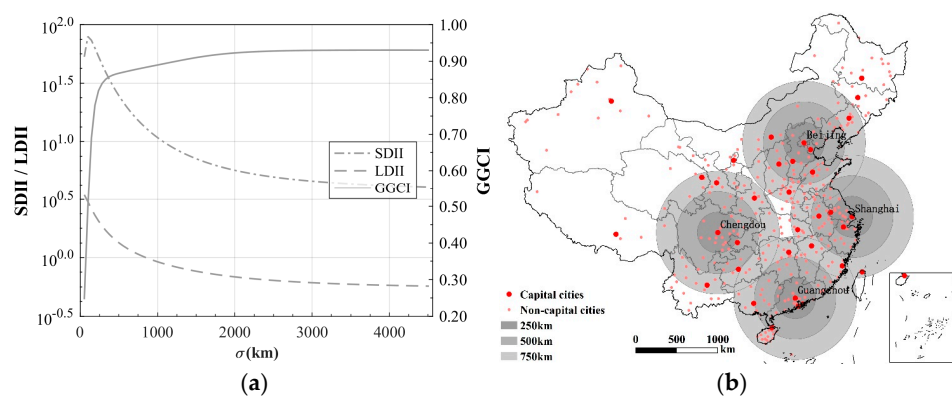

Figure 3. Geographical centrality indexes and spatial distance threshold σ. (**a**) trends of SDII, LDII, and GGCI with the increase in distance threshold σ; (**b**) schematic map of three spatial distance thresholds, 250, 500, and 750 km, in China.

As shown in scatterplots of geographical centrality (Figure 4a,c,e), the distributions of SDII and LDII at three spatial scales are all lognormal distribution, and spatial units of cities are distributed in the direction of first-third quadrants. Furthermore, most of the significant units are located in the first and third quadrants, which are identified as global centers and isolated units, respectively. This situation suggests that short- and long-distance interactions are relatively synchronous. The effects of spatial distance and geographical space are relatively limited at the national scale, while space of flows is relatively significant. This situation is proven by the large and significant GGCI. With the increase in the spatial scale, the number of significant global centers and isolated units gradually decreases, while the number of externally and locally oriented units increases. Moreover, the GGCIs at three spatial scales are 0.8262, 0.8669, and 0.8789, respectively. The corresponding significances are 0, 0.0001, and 0.1227. In other words, GGCI gradually increases but its significance decreases. The reason is due to that short-distance space expands into long-distance space actually dominated by space of flows with the increase in the spatial scale.
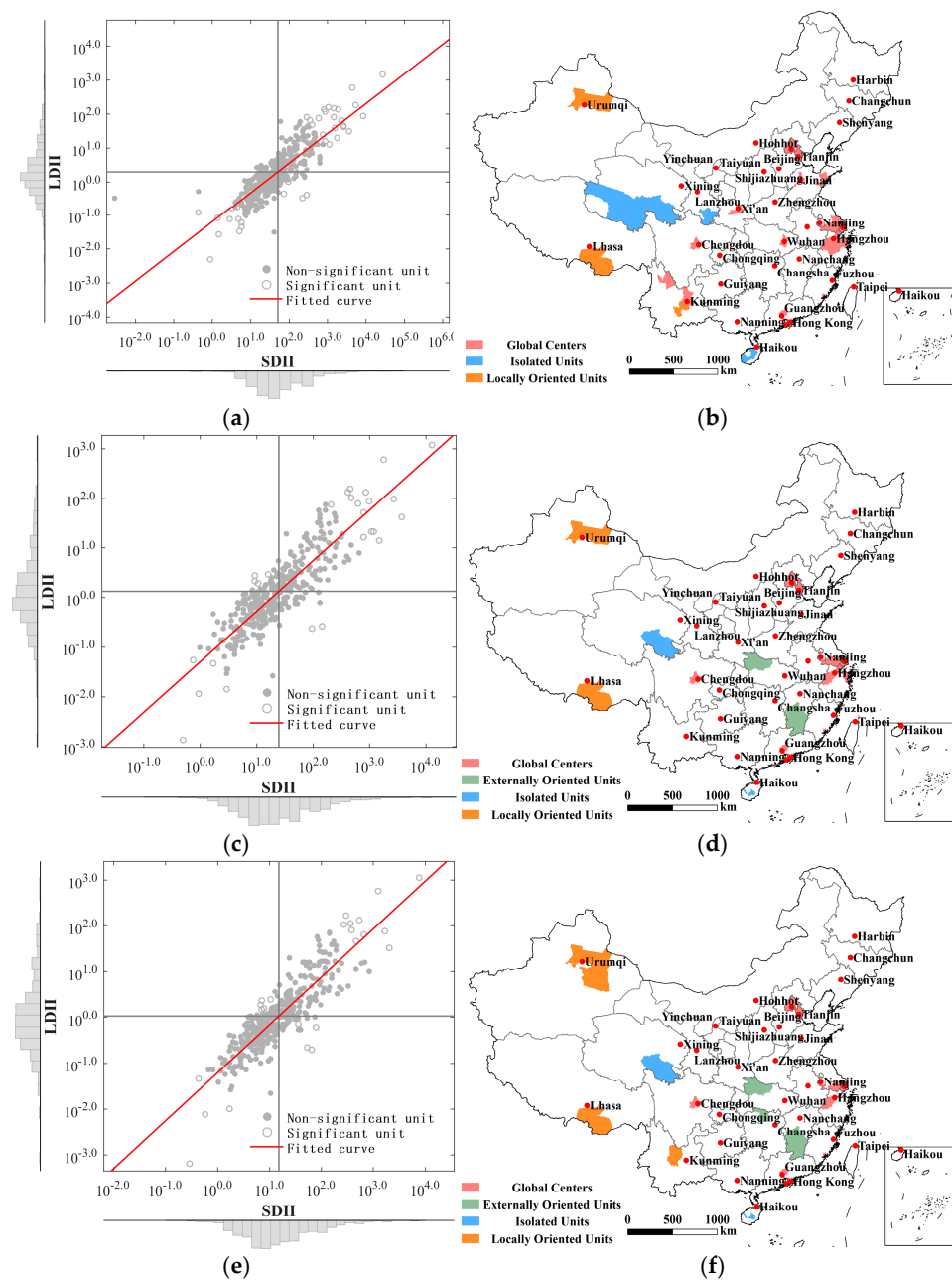
Figure 4. Scatterplots of geographical centrality for cities in China and their spatial distributions. (**a**,**c**,**e**) are scatterplots of geographical centrality for σ = 250, 500, and 750 km, respectively; (**b**,**d**,**f**) are the corresponding spatial distributions.

The spatial distribution of significant units of geographical centrality (Figure 4b,d,f) at the urban agglomeration scale of 250 km shows that core cities of the main urban agglomerations in China are all identified as global centers, such as Beijing and Tianjin in the Beijing–Tianjin–Hebei urban agglomeration, Shanghai, Hangzhou, Nanjing, Ningbo, and 13 other cities in the Yangtze River Delta urban agglomeration, Guangzhou, Shenzhen, and Hong Kong in the Pearl River Delta urban agglomeration, Chengdu in the Chengdu–Chongqing urban agglomeration, Wuhan in the Wuhan urban agglomeration, Xi'an in the Guanzhong urban agglomeration, Jinan and Qingdao in the Shandong Peninsula urban agglomeration, Xiamen in the urban agglomeration of the west coast of the Taiwan Straits, and Kunming in the urban agglomeration of the central Yunnan. Moreover,

Lijiang, which is a tourist city, is also identified as a global center. This situation may be because of the strong attraction of tourist cities shown on the social network. A total of 11 isolated units distribute in remote provinces, such as Qinghai, Gansu, and Hainan; three locally oriented units are located around western provincial capital cities, namely, Urumqi, Lhasa and Kunming; no externally oriented units are found. At the regional scale of 500 km, the number of global centers decreases from 26 to 14, and most of them are located in the Beijing–Tianjin–Hebei region, Yangtze River Delta, Pearl River Delta, and the Chengdu–Chongqing economic zone; these areas are the four endpoints of the diamond-shaped urban network structure in China. The number of isolated units decreases from 11 to 4, and these units are still located in Qinghai and Hainan. Four externally oriented units emerge in Hubei and Jiangxi, and the locally oriented units are nearly the same as those at the urban agglomeration scale. At the large regional scale of 750 km, four types of geographical centrality change in numbers but retain the spatial distributions.

According to the analysis at three different spatial scales, the urban agglomeration scale of 250 km can effectively identify the core cities of the main urban agglomerations in China. Moreover, the regional scale of 500 km and the large regional scale of 750 km have similar analysis results, which can identify the central cities in the four areas of east, west, south, and north in China. Furthermore, a global center cluster is formed in Yangtze River Delta; however, the northeast, northwest, and central regions of China lack central cities to promote their regional development. In addition, isolated units, externally oriented units, and locally oriented units are mostly located in remote areas, central provinces, and around western provincial capital cities, respectively.

4. Discussion

4.1. Geographical Centrality Based on Space of Flows and Other Centralities

Different types of centrality in geography have dissimilar starting points. Their analysis results present their own characters and exhibit a few relations. In this part, we compare and analyze three previous types of geographical centrality based on geographical proximity, scale attributes, and relational networks, and the proposed geographical centralities based on space of flows in this research. These four types of geographical centrality are referred to as proximity, attribute, network, and geographical centralities, respectively. The centrality based on geographical proximity and attributes is not discussed herein because of its complexity and difficulty of implementation. The proximity centrality is measured by the average distance between one spatial unit and the others, and the centrality is strong in the central region and weak in the marginal region. The attribute centrality is estimated by the inverse gravity model [38,39] using the spatial interaction data of cities in China, and the determination coefficient of the model is greater than 0.7. The network centrality is measured by degree centrality [40], which is the most representative one in complex network analysis. The geographical centrality uses the analysis results with $\sigma = 500$ km in the previous section.

Figure 5a shows that no clear relation exists between proximity and attribute centrality, and attributes for different distance segments are all mainly distributed between 1 and 4. Similarly, no clear relation exists between proximity and network centrality (Figure 5b), and the number of cities with strong network centrality sharply decreases with the increase in the average distance. However, a definite exponential relation exists between attribute and network centrality (Figure 5c). In particular, the strength of network centrality increases in the form of orders of magnitude with the increase in the strength of attribute centrality. The relationship between geographical and proximity centrality (Figure 5d) shows that the distributions of global centers and isolated units are very similar and have no evident distinction. In other words, no clear relation exists between geographical and proximity centrality. However, the distributions of global centers and isolated units have a similar regularity for the relationships between geographical and attribute and network centrality (Figure 5e,f). In particular, global centers correspond to strong attribute and network centrality, while isolated units correspond to weak attribute and network centrality. Furthermore, the distribution overlap of global centers and

isolated units is more for attribute centrality and less for network centrality. This situation may be due to the nonlinear distribution of network centrality.

The analysis above shows that proximity centrality nearly loses its indicative function at the national scale, while attribute, network, and geographical centrality can prove the applicability of one another. The definite exponential relation between attribute and network centrality shows that attributes are more important than geospatial distance in spatial interaction, and geographical space is affected by space of flows. This situation proves the availability of the proposed GGCI. The geographical centrality based on space of flows identifies spatial units into four types of geographical centrality by considering the spatial structure and spatial interaction simultaneously, which is an approach that is different from the three other direct measures. Furthermore, the belongingness degree of the four types of geographical centralities can be measured by LGCI and its significance test. On the one hand, geographical centrality is consistent with attribute and network centrality; on the other hand, geographical centrality has a better statistical foundation and a wide range of application.
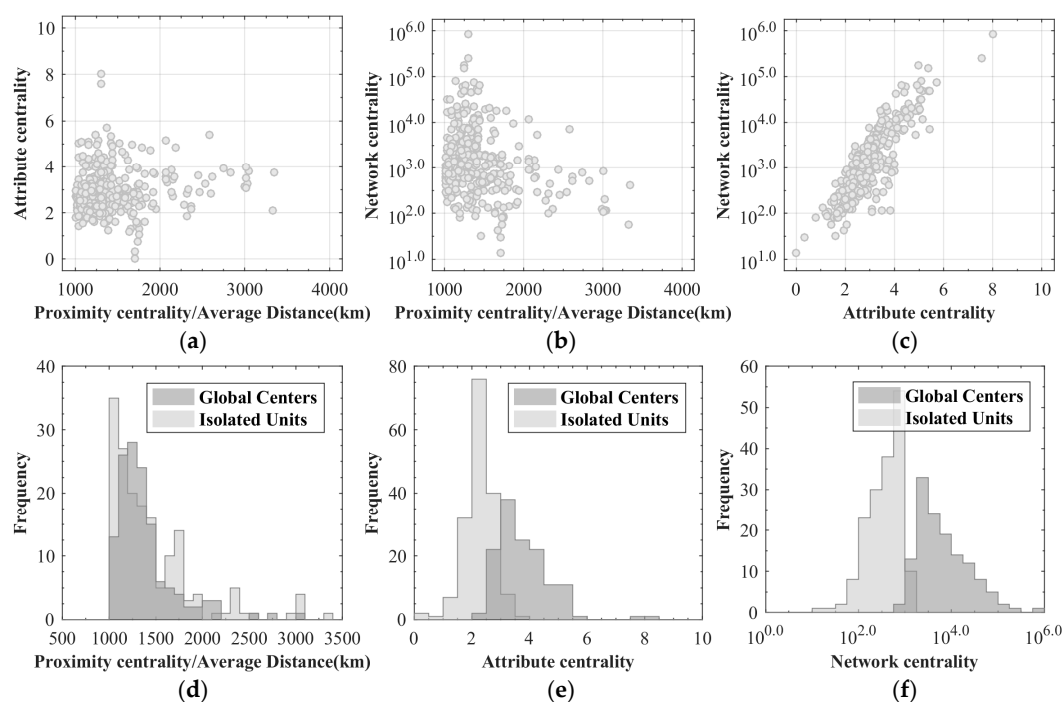

Figure 5. Analysis and comparison of four types of centralities in geography. (**a**) the relationship between proximity and attribute centrality; (**b**) the relationship between proximity and network centrality; (**c**) the relationship between attribute and network centrality; (**d–f**) are the relationships of geographical centrality with proximity, attribute, and network centralities, respectively.

4.2. Geographical Centrality Based on Space of Flows and Moran's I

The common traditional geospatial analysis methods include exploratory spatial data analysis, point pattern analysis, spatial autocorrelation analysis, spatial continuous data interpolation, spatial regression analysis, and spatial clustering analysis. However, the spatial autocorrelation hypothesis, which is the basic of these geospatial analysis methods, is weakened under the effect of space of flows. Thus, the applicability of these methods declines. For example, spatial kernel density analysis of physical networks (e.g., roads and railways) can obtain the general spatial distribution of networks. However, the same analysis of virtual networks (e.g., migration and information flows) with known positions of network nodes but unknown specific spatial paths of transmission makes little sense. The reason is that the former is the scope of geospatial analysis, while the latter is the scope of space of flows. Although the analysis methods of complex and social networks have been widely used in the

geospatial analysis in the context of space of flows, most of these methods ignore the geospatial factors. Therefore, geospatial analysis methods in the context of space of flows need to be developed urgently with the unprecedented development of high-speed information and transportation networks. The geographical centrality based on space of flows is proposed in this context.

The proposed geographical centrality based on space of flows is similar to the Moran's I method, which is commonly used in spatial autocorrelation analysis, in terms of expression form and index calculation. Specifically, the output results of the two methods both include a scatterplot and global and local indexes [41,42]. Although geographical centrality based on space of flows draws on a few ideas of the Moran's I method, the two methods are fundamentally different in terms of the basic hypothesis, analytical content, application scope, input variables, and significance tests (Table 1). With regard to the basic hypothesis, the Moran's I method hypothesizes that spatial dependence exists in geographical space. By contrast, geographical centrality based on space of flows hypothesizes that not only the spatial dependence of geographical space but also its "counterforce", namely, space of flows, exist, which dominate short- and long-distance interactions, respectively. Regarding analytical content, the Moran's I method analyzes the attribute similarity between spatial units and their neighbors. On the contrary, geographical centrality based on space of flows analyzes the relative strength of short- and long-distance interactions among spatial units. Relatively, the former is local while the latter is global. The two main differences lead to different applications. The Moran's I method is used mainly to measure the strength of spatial autocorrelation and identify local hot and cold spots and spatial outliers. Conversely, geographical centrality based on space of flows is used mainly to measure the relative effect strength of geographical space and space of flows. Furthermore, this method identifies and measures the type and strength of geographical centrality for spatial units.

Table 1. Comparison of geographical centrality based on space of flows and Moran's I.

Items	Moran's I	Geographical Centrality Based on Space of Flows
Basic hypothesis	Spatial autocorrelation/spatial dependence.	Geographical space and space of flows dominate short- and long-distance interactions, respectively.
Analytical content	Attribute similarity between spatial units and their neighbors, which is relatively local.	The relative strength of short- and long-distance interactions among spatial units, which is relatively global.
Application scope	Measure the strength of spatial autocorrelation; Identify local hot and cold spots and spatial outliers.	Measure the relative effect strength of geographical space and space of flows; Identify and measure the type and strength of geographical centrality for spatial units.
Input variables	Attributes of spatial units; Spatial weight matrix.	Spatial interaction matrix; Spatial distance matrix; A distance threshold to determine whether a distance is short or long.
Output results	Scatterplot of Moran's I; Global and local Moran's I indexes.	Scatterplot of geographical centrality; GGCI and LGCI.
Significance test	Generate simulated distribution by randomly permuting spatial unit attributes.	Generate simulated distribution by randomly permuting rows and columns of spatial interaction matrix simultaneously.

5. Conclusions

The unprecedented development of high-speed information and transportation network has highlighted that the important role played by space of flows and has restructured the mode of spatial interaction. In this context, we first present a basic hypothesis that geographical space and space of flows dominate short- and long-distance interactions, respectively. Then, the concept of geographical centrality based on space of flows is proposed, and spatial units are identified into four types of geographical centrality, namely, global centers, isolated units, externally oriented units, and locally oriented units. Furthermore, corresponding quantitative evaluation methods including the scatterplot of geographical centrality and GGCI and LGCI are proposed. The proposed concept and methods of geographical centrality develop the geospatial analysis methods in the context of space of flows. We use the proposed method and spatial interaction data among cities based on social network data to evaluate and analyze the geographical centrality of cities in China. Moreover, geographical centrality analysis methods including the proposed one and three others are compared, and an ideal result is achieved.

The geographical centrality based on space of flows has two basic applications: one is to measure the relative effect strength of geographical space and space of flows, and the other is to identify and measure the type and strength of geographical centrality for spatial units. Using time series data of spatial interactions among spatial units, a changing pattern of geographical centrality for a region or a transition track of geographical centrality types for a specific spatial unit can be analyzed. Moreover, regional patterns of geographical centrality can be analyzed and compared using spatial interaction data for regions of different natural conditions or development stages. Finally, the proposed geographical centrality analysis method is a beneficial attempt on the research on geospatial analysis in the context of space of flows. With the increasing attention of space of flows, analysis methods for space of flows such as complex network and social network will further be applied in and interact with classic geospatial analysis methods. In summary, geospatial analysis methods in the context of space of flows still have room for improvement.

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