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The Spatial Structure and Driving Mechanisms of Multi-Source Networks in the Chengdu–Chongqing Economic Circle of China

Ludan Zhang [1], Xueman Zuo [1], Ziyi Wu [1], Cheng Chen [1], Zibao Pan [2] and Xisheng Hu [1,*]

[1] College of Transportation and Civil Engineering, Fujian Agriculture and Forestry University, Fuzhou 350002, China; 3211341024@fafu.edu.cn (L.Z.); 1211326005@fafu.edu.cn (X.Z.); 1221326009@fafu.edu.cn (Z.W.); fjnlcc@fafu.edu.cn (C.C.)

[2] Transportation and Construction Bureau in Pingtan Comprehensive Experimental Zone, Pingtan 350400, China; zbao@fafu.edu.cn

* Correspondence: xshu@fafu.edu.cn

Abstract: The phenomenon of polarized development among regional cities has sparked extensive contemplation and indicated a need for research on multi-source regional networks. However, such research faces two obstacles: the absence of quantitative measurement of differences in network structures and the lack of a thorough examination of the degree of city clustering and the dynamics of community composition in hierarchical networks. Thus, we identified 16 cities in the Chengdu–Chongqing Economic Circle (CCEC) as the spatial units to examine the spatial network structures of population, resources, and transportation and the integrated spatial network structure. Using social network analysis, this paper describes the structural characteristics of the three networks (population, resource, and transportation), followed by an analysis of their collective and hierarchical network clustering characteristics, and explores the driving mechanisms and factors that make up each network model. Our results show the following: (1) All three networks exhibit an "east dense, west sparse" characteristic, but there are differences in the layouts of the core cities in terms of the three networks. (2) The clustering characteristics of the hierarchical networks are more pronounced than those of the overall network. The results of the analysis combined with the network formation mechanisms can help effectively plan the future coordinated development of the CCEC.

Keywords: multi-source network; urban structure; hierarchical network; quadratic assignment procedure

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1. Introduction

The organizational structure of urban agglomerations depends largely on highly developed transportation and telecommunications infrastructure, which can promote and strengthen the coordinated development of population, resources, environment, society, and economy in various regional cities [1]. On the one hand, population migration and material transfer need the support of transportation infrastructure [2]; on the other hand, in urban agglomerations that have developed economically due to the flow of various factors, to strengthen economic aggregation further and reduce the gap between the rich and the poor, the focus on the rational layout of the transportation system must not be reduced. In the next phase of urbanization development, China will promote the coordinated regional development and character growth of large, medium, and small cities and towns on the basis of city clusters and metropolitan areas [3].

The expansion of urban agglomerations often entails challenges, such as inadequate interconnectivity of infrastructure networks, insufficient intraregional collaboration, widening developmental disparities among cities, and transboundary pollution of the ecological environment. These factors lead to unfavorable symptoms that violate the development laws of urban agglomerations, such as uneconomical agglomeration and spatial imbalance [4,5]. In the past, mainstream research on these issues mainly focused on the unit of place space, neglecting the dynamic nature of flows and the interaction of multiple factors [6,7]. Currently, the spatial perspective of flows has received increasing attention, and many studies have begun to adopt a "flow thinking" approach to understand the position of cities in urban agglomerations. Creatively incorporating multiple factors into urban relationship research, analyzing the development of regional networks and the coordination and allocation of resources from a multi-source perspective of flow space, and scientifically formulating optimization strategies have significant practical implications for future research [8].

The spatial movement of the population is one of the most prominent indicators of regional spatial connections, and its association with the intercity attractiveness level can reflect the stage of development of regional urban integration [9]. Population migration encompasses the individual aspirations of residents and can be categorized into immigration and short-term mobility. With the advent of the Internet and the era of big data, websites that offer mobile phone signaling data have studied short-term mobility more efficiently and precisely. These studies mainly focus on residents' intra- and intercity trips for different purposes [10,11], compare population movement between working days and weekends, and compare population movement during the Spring Festival travel rush and during other periods. These studies solve some problems that census data cannot. The researchers aim to optimize urban planning and traffic service design by investigating the spillover phenomenon that occurs after population over-concentration and identifying urban hotspots and the influence of urban size and structure on the mobility of the urban population [12].

The intercity industrial input and output process, which involves the flow of material resources, is a direct reflection of the relationship between cities, with minimal influence of subjective factors. Numerous studies track and quantify resource flows at global, regional, or national levels. The quantification of copper resource trade evolution and the analysis of trade competition networks or community evolution based on complex network analysis can aid in maintaining trade stability and resource security. Additionally, it can assist resource-rich countries in maximizing export benefits [13]. In particular, to promote resource recycling, the most basic requirement is to understand the flow of resources in the economy and society, especially some strategic resources that have a serious impact on the national economy and people's lives (e.g., coal, oil, and food) [14]. The current perspective of logistics research, which is rooted in the capacity of transport services at the social service level, is considered too narrow. There are some limitations to measuring the mobility of factors by analyzing urban passenger and freight volumes and calculating the ratio of each interval to the whole to assess the economic development status on the basis of relevant information on urban commercial logistics [15]. Novel data sources and innovative methodologies for structural comparison should be pursued.

Transportation infrastructure has a significant impact on the flow of population and resources [16,17]. It is believed that improving transportation infrastructure can indirectly encourage the flow of population, capital, and technology; increase residents' income [13]; and significantly promote cross-regional consumption, leading to a change in residents' consumption structure [18]. Economic and production activities are linked through diversified transportation or information networks, which optimize resource allocation [1]. Therefore, the research on transportation networks is often not limited to the optimization and operation management of transportation infrastructure services [19,20] and can be extended to urban boundary identification, its gain to business activities, cooperation with information networks, industrial structure optimization, and so on [21–24]. Network studies based on aviation flow, railway flow, and road passenger flow are conducted using traffic volume data compiled by the Ministry of Transportation [19,21,22]. Due to the challenges in unifying units for passenger and freight volume, there are few studies that combine both passenger and freight transport to jointly analyze the transportation network.

Space of flows breaks through the limitation of time and space and guides the development of the future regional spatial pattern to a certain extent. It addresses issues related to the intercity flow of elements such as population, goods, capital, and information and provides spatial solutions for their accommodation [6]. Currently, research on multi-source urban networks is gaining significant attention within the academic community [25]. Some studies typically construct networks such as enterprise connections [26], technological innovation [27], population migration [28], economy [29], and information [30] and then use indicators from social network analysis to analyze the spatial characteristics of networks from the perspectives of city nodes, path connections, and community features. There are two notable limitations to the methods employed in multi-source urban network research: First, they primarily subjectively observe and describe differences in network structures but often neglect to quantitatively measure the degree of structural differences using metrics. Second, these methods fail to analyze the agglomeration characteristics of the hierarchical networks, a vital element.

The academic community generally acknowledges that cities in a network have varying abilities to span geographic distances [31]. As a result, a single indicator, often derived from attribute data, is typically used to differentiate the hierarchy of nodes [32]. Metrics such as weighted centrality [33], closeness centrality [34], and betweenness centrality [34] are commonly employed to measure the hierarchical structure of cities within networks. However, the strength of connections between nodes and the ability of nodes to control and interact with others are two significant aspects of network hierarchy [35]. Network hierarchy is often determined by single indicators, such as economic rank or administrative level, but this approach overlooks comprehensive methods for analyzing network hierarchy.

In this study, we first construct three types of networks and describe their characteristics and structural differences using social network analysis and dissimilarity metric. We then employ a "hierarchical" approach to observe urban agglomeration characteristics in high- and low-level networks. Finally, we delve into the mechanisms behind network formation. Following a "global-hierarchy-node" framework, we analyze the current state and potential risks of the CCEC's coordinated development and propose future development plans and improvement measures based on these influencing mechanisms.

The remaining sections of the study are structured as follows: Section 2 presents data sources and methodology. Section 3 further elaborates on the main empirical results. Section 4 discusses the results. The last section provides conclusions of this research.

2. Materials and Methods

We introduce a methodological scheme that summarizes the procedure used, which consists of four key steps: (1) construct three types of networks and calculate the network density (ND), the modularity index (MI), and the dissimilarity metric to identify the differences in network structures; (2) use weighted centrality to depict the statuses and functions of cities in different networks; (3) employ the natural breaks methodology to stratify the overall intercity connections, calculate hierarchical network MI indices to observe hierarchical differences and use cohesive subgroups to examine the number and composition of city clusters in the hierarchical networks; and (4) analyze the mechanism of formation of each network from four perspectives and propose recommendations for scientific development on the basis of the results.

2.1. Study Area

In 2021, the State Council City and the Central Committee of the Communist Party of China released the planning outline for the construction of the Chengdu–Chongqing Economic Circle (CCEC). This document mandates that all regions and departments implement the plan on the basis of their specific circumstances. As highlighted in the outline, the CCEC in the region is situated at the junction of the Belt and Road Initiative and the Yangtze River Economic Belt, linking the southwest and northwest regions and bridging East Asia and Southeast Asia. The Chengdu–Chongqing region is recognized as the primary foreign trade hub in the central and western regions of China, excluding the coastal areas. Figure 1 provides an overview of the study area.

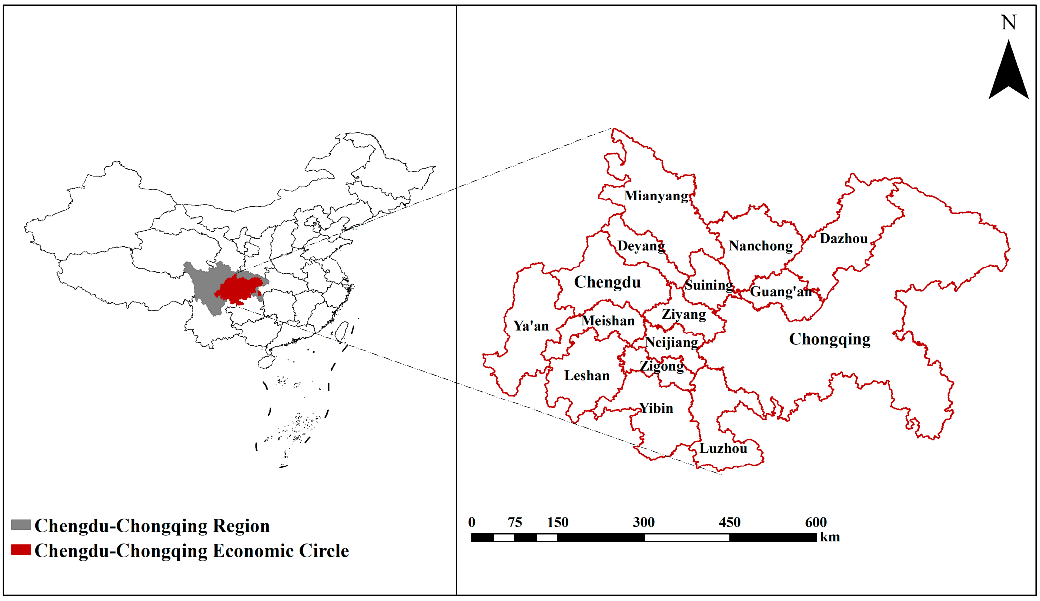

Figure 1. Location of the study area. This figure was created based on the standard map with plan approval number GS(2019)1822, and no modifications were made to the base map.

According to the planning outline, the scope of planning of the CCEC includes the central city of Chongqing and 27 districts (counties), including Wanzhou, Fuling, Qijiang, Dazu, Qianjiang, Changshou, Jiangjin, Hechuan, Yongchuan, Nanchuan, Bishan, Tongliang, Tongnan, Rongchang, Liangping, Fengdu, Dianjiang, and Zhongxian, as well as 15 cities in Sichuan, which are Chengdu, Zigong, Luzhou, Deyang, Mianyang (except Pingwu and Beichuan counties), Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Dazhou (except Wanyuan), Ya'an (except Tianquan and Baoxing counties), and Ziyang, with a total area of 185,000 sq. km.

2.2. Data Source and Processing

In this study, we considered 16 cities in the CCEC as the spatial units to examine the spatial network structure of the population, resources, and transportation and the integrated spatial network structure. The spatial scope of the CCEC is taken from the planning scope approved by the National Development and Reform Commission. The vector data, such as the urban administrative center and the administrative boundary, are from the 1:100 million National Basic Geographic Information Database of the National Basic Geographic Information Center (http://www.ngcc.cn/ngcc/html/1/391/392/16114.html, accessed on 17 November 2022). We primarily employed the Python programming language to gather data on Baidu migration (https://qianxi.baidu.com/, accessed on 20 October 2022) in 2021, China's Multi-Regional Input–Output (CMRIO) table in 2017 [36,37], and road network data in 2021 from the Open Street Map (https://openmaptiles.org/, accessed on 20 October 2022).

2.2.1. Population Flow Data

We set the daily Baidu migration data from 1 January 2021 to 31 December 2021. In 2021, China gradually allowed daily commuting, and during this period, the Chengdu–Chongqing region occasionally implemented lockdown measures for 1–3 weeks due to localized COVID-19 outbreaks. To mitigate the data fluctuations caused by these containment measures, the annual data were processed into daily averages in accordance with the policy impact. The original data consist of the proportion of population migrating from a specific departure city to a destination city relative to the total population leaving the departure city. There are 100 data points per city per day. The data were transformed into an exponential function of human flow on the basis of the research by Wang and Yan [38]. The reasons for selecting Baidu migration data are as follows: First, Baidu releases data on a daily basis, and for each originating city, the top 100 destination cities are changing every day. This ensures accuracy via collection of data for the entire year. Second, the data collection cycle for Baidu migration statistics is 8 h. Compared with the displacement of individuals for travel, visiting relatives, and other special purposes, the displacement of individuals with commuting as the purpose during a fixed period can be accurately recorded in big data collection [39]. Third, to eliminate the influence of special holidays on migration, we used data from the whole year and standardized the data before calculating the daily migration flow.

The data include the starting city, the daily list of the top 100 cities of urban migration, and a total of 93,440 pieces of data. A 16 × 16 spatial correlation matrix was constructed with cities as the carriers:

$$T^L = \begin{array}{c} \\ i_1 \\ i_2 \\ \vdots \\ i_{n-1} \\ i_n \end{array} \begin{bmatrix} j_1 & j_2 & \cdots & j_{n-1} & j_n \\ 0 & L_{12} & \cdots & L_{1(n-1)} & L_{1n} \\ L_{21} & 0 & \cdots & L_{2(n-1)} & L_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ L_{(n-1)1} & L_{(n-1)2} & \cdots & 0 & L_{(n-1)n} \\ L_{n1} & L_{n2} & \cdots & L_{n(n-1)} & 0 \end{bmatrix} \tag{1}$$

where T^L represents the population flow matrix between cities. The formula for calculating specific weight L_{ij} is

$$L_{ij} = \frac{M_{ij}}{3.24} \times 10^5 \tag{2}$$

$$M_{ij} = M_i \times l_{ij}, (i, j = 1, 2, \ldots, n; i \neq j) \tag{3}$$

where L_{ij} represents the population flow between city i and city j; M_i represents the migration scale index provided by Baidu map migration big data; M_{ij} represents the migration scale index from city i to city j; and l_{ij} represents the mobility weight from city i to city j.

2.2.2. Resource Flow Data

The resource flow data are retrieved from the 2017 China Multi-Regional Input–Output (CMRIO) table at the urban scale, which includes 313 administrative units in mainland China, covering 42 socioeconomic industries and 5 final industries (rural household consumption, urban household consumption, government consumption, capital formation, and inventory changes) [40]. The study mainly uses the intermediate input table of the 42 industries in each city as the data foundation. First, to investigate intercity resource input, the inputs between different industries within the same city are removed. Then, the top 5 industries with the most active inputs are selected as the main focus of observation. This approach has several advantages. First, mature industries with a large market share tend to experience less volatility due to temporal factors, reducing errors caused by different data years. Second, while each city may have its dominant industries according to statistical yearbooks, capital flows can occur in three directions: to other industries within the supply chain, to other cities within the same industry, and to other industries within the supply chain in other cities. This study primarily focuses on intercity element flows within the same industry. Therefore, the data selection is based on the five industries with the highest flow volumes, aligning with the research objectives.

These industries are construction (CNY 114,675.1 million); food and tobacco (CNY 773,736.49 million); agriculture, forestry, animal husbandry, and fishery industries and services (CNY 695,555.5 million); chemical products (CNY 554,314.18 million); and finance

(CNY 534,577.28 million). The initial intercity resource connectivity weights are calculated by summing up the intermediate inputs for each industry between the 16 cities.

$$T^R = \begin{array}{cc} & \begin{array}{ccccc} j_1 & j_2 & \cdots & j_{n-1} & j_n \end{array} \\ \begin{array}{c} i_1 \\ i_2 \\ \vdots \\ i_{n-1} \\ i_n \end{array} & \begin{bmatrix} 0 & R_{12} & \cdots & R_{1(n-1)} & R_{1n} \\ R_{21} & 0 & \cdots & R_{2(n-1)} & R_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ R_{(n-1)1} & R_{(n-1)2} & \cdots & 0 & R_{(n-1)n} \\ R_{n1} & R_{n2} & \cdots & R_{n(n-1)} & 0 \end{bmatrix} \end{array} \tag{4}$$

where T^R represents the resource flow matrix between cities. The resource connection value between cities R_{ij} represents the total intercity flow within the five industries.

2.2.3. Transportation Network Data

Transport accessibility is utilized to gauge intercity transit efficiency. At the provincial level, residents predominantly rely on railways and roadways for traveling. The road network comprises expressways, national highways, provincial roads, county roads, and township roads. In accordance with the research conducted by Cai, J, and their colleagues, values of 120 km/h, 120 km/h, 80 km/h, and 60 km/h are assigned to the railway, expressway, national highway, and provincial road, respectively. Subsequently, using the network analysis tools provided by the ArcGIS platform, an intercity travel cost matrix is computed [41]. The reciprocals of these travel times are then calculated to represent intercity transportation efficiency as part of the transportation network analysis:

$$T^T = \begin{array}{cc} & \begin{array}{ccccc} j_1 & j_2 & \cdots & j_{n-1} & j_n \end{array} \\ \begin{array}{c} i_1 \\ i_2 \\ \vdots \\ i_{n-1} \\ i_n \end{array} & \begin{bmatrix} 0 & T_{12} & \cdots & T_{1(n-1)} & T_{1n} \\ T_{21} & 0 & \cdots & T_{2(n-1)} & T_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ T_{(n-1)1} & T_{(n-1)2} & \cdots & 0 & T_{(n-1)n} \\ T_{n1} & T_{n2} & \cdots & T_{n(n-1)} & 0 \end{bmatrix} \end{array} \tag{5}$$

where T^T represents the traffic connection matrix between cities. The formula for calculating the traffic connection value between cities T_{ij} is

$$T_{ij} = 1/t_{ij} \tag{6}$$

where t_{ij} represents the travel time from city i to city j.

2.2.4. Integrated Network Data

After standardizing the original matrices of three sub-networks, i.e., those of population, resources, and transportation, and giving them the same weight, the comprehensive contact matrix is obtained, and its formula is as follows:

$$T^I = \begin{array}{cc} & \begin{array}{ccccc} j_1 & j_2 & \cdots & j_{n-1} & j_n \end{array} \\ \begin{array}{c} i_1 \\ i_2 \\ \vdots \\ i_{n-1} \\ i_n \end{array} & \begin{bmatrix} 0 & I_{12} & \cdots & I_{1(n-1)} & I_{1n} \\ I_{21} & 0 & \cdots & I_{2(n-1)} & I_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ I_{(n-1)1} & I_{(n-1)2} & \cdots & 0 & I_{(n-1)n} \\ I_{n1} & I_{n2} & \cdots & I_{n(n-1)} & 0 \end{bmatrix} \end{array} \tag{7}$$

$$I_{ij} = L'_{ij} + R'_{ij} + T'_{ij} \tag{8}$$

where T^I represents the comprehensive contact matrix; I_{ij} represents the integrated connect value; and L'_{ij}, R'_{ij}, and T'_{ij} represent the population flow value, the resource contact value, and the traffic contact value, respectively, standardized by a matrix for edge values.

2.3. Methodology

2.3.1. Measurements of Network Structure and City Characteristics

(1) Network Density

Network density refers to the closeness of connections between cities. The greater the ND, the better the overall connectivity of the network. Its formula is

$$ND = \sum_{i=1}^{n}\sum_{j=1}^{n} d_i\left(c_i, c_j\right)/n(n-1), (i \neq j) \tag{9}$$

where ND represents the network density, n represents the number of node cities, and $d_i\left(c_i, c_j\right)$ is the amount of connection between cities c_i and c_j. The greater the D, the greater the density of the network and the closer the connections between cities.

(2) Dissimilarity Metric

The dissimilarity metric is calculated to show the degree of similarity or difference between K-layer and K'-layer networks. Notably, the dissimilarity metric is a quantitative and effective measure for comparing a multiplex network [42,43]. The structural dissimilarity can be measured on the basis of the link-weighted-based difference and the connection-based difference. According to Zhang, the node dissimilarity can first be computed using the node's probability distribution vector [44]. The whole network difference between two networks is then obtained on the basis of differences between all nodes [45].

Specifically, we first convert the weights of networks to obtain a new value (PW_{ij}^k).

$$PW_{ij}^k = \frac{w_{ij}^k}{S_i^k}, and\ S_i^k = \sum_{j=1}^{N} w_{ij}^k, (i, j = 1, 2, \ldots, N, i \neq j) \tag{10}$$

$$PC_{ij}^k = \frac{d_{ij}^k}{D_i^k}, and\ D_i^k = \sum_{j=1}^{N} d_{ij}^k, (i, j = 1, 2, \ldots, N, i \neq j) \tag{11}$$

where N represents the number of cities ($N = 16$), and w_{ij}^k represents the connection weight from city i to city j. S_i^k represents the sum of the weights associated with the city. D_i^k is the number of chains associated with the city; if city i is related to city j, then $d_{ij}^k = 1$, otherwise, $d_{ij}^k = 0$.

We then calculate the dissimilarity between cities in different networks:

$$WND_i^{KK'} = \frac{1}{\sqrt{2}}\sqrt{\sum_{j=1}^{N}\left(\sqrt{PW_{ij}^K} - \sqrt{PW_{ij}^{K'}}\right)^2} \tag{12}$$

$$CND_i^{KK'} = \frac{1}{\sqrt{2}}\sqrt{\sum_{j=1}^{N}\left(\sqrt{PC_{ij}^K} - \sqrt{PC_{ij}^{K'}}\right)^2} \tag{13}$$

where $WND_i^{KK'}$ and $CND_i^{KK'}$ represent two metrics, weighted-based dissimilarity and connection-based dissimilarity, for city i between K-layer and K'-layer networks.

Finally, the whole network metrics of the weighted-based dissimilarity ($WBD^{KK'}$) and the connection-based dissimilarity ($CBD^{KK'}$) between K-layer and K'-layer networks are calculated, respectively, as

$$WBD^{KK'} = \sum_{i=1}^{N} \alpha_i^{KK'} WND_i^{KK'}, and\ \alpha_i^{KK'} = \frac{W_i^{KK'}}{\sum_{j=1}^{n} W_j^{KK'}} \tag{14}$$

$$CBD^{KK'} = \sum_{i=1}^{N} \beta_i^{KK'} CND_i^{KK'}, and\ \beta_i^{KK'} = \frac{D_i^{KK'}}{\sum_{j=1}^{n} D_j^{KK'}} \tag{15}$$

$$W_i^{KK'} = \sqrt{WDC_i^K \bullet WDC_i^{K'}} \tag{16}$$

$$D_i^{KK'} = \sqrt{DC_i^K \bullet DC_i^{K'}} \tag{17}$$

where $WBD^{KK'} \in [0,1]$, $CBD^{KK'} \in [0,1]$, and $W_i^{KK'}$ and $D_i^{KK'}$ represent the geometric means of the weighted centrality of cities separately.

(3) Weighted Centrality

To reveal the centrality of cities in the network, weighted centrality measures the absolute strength of a city in the network, and a higher value indicates a stronger absolute strength of the city in the network. In this paper, we choose the weighted centrality WDC_i as the primary measurement index of small-scale networks:

$$WDC_i^{out} = \sum_{i=1}^{n} T_{ij} \tag{18}$$

$$WDC_i^{in} = \sum_{j=1}^{n} T_{ji} \tag{19}$$

$$WDC_i = WDC_i^{out} + WDC_i^{in} \tag{20}$$

where WDC_i^{out} is the weighted outdegree of city i and the weighted indegree of city i.

2.3.2. Network Cluster Analysis

(1) Modularity

Modularity is an optimization algorithm based on multi-level spatial networks. It can be used to quickly and accurately discover the community and describe the intimacy of the community, and it is one of the best community discovery algorithms [46]. The MI is calculated by comparing the ratio of intracommunity flows in the actual network to the ratio in a random network [47].

$$MI = \frac{1}{2m} \sum_{ij} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta\left(c_i, c_j\right) \tag{21}$$

where A_{ij} is the weight of edge between cities i and j, $m = \frac{1}{2}\sum_{ij} A_{ij}$ represents the total weights in the whole network, $k_i = \sum_{ij} A_{ij}$ represents the total weights of the edges connected with city i, c_i is the community to which city i is assigned, and $\delta\left(c_i, c_j\right)$ equals 1 when $c_i = c_j$ and 0 when $c_i \neq c_j$. A larger MI indicates better performance in the division of communities.

(2) Cohesive Subgroup

Several small, tightly connected, and synergistic groups are often generated in the network structure of urban agglomerations [48]. When cohesive subgroups are in the network, the actors within the community are closely connected and interact frequently in terms of resource flow and information exchange [49]. In SNA, cohesive subgroup analysis is widely adopted for subsets of networks with relatively strong, tight, frequently, or actively connected nodes [50]. The model empowers us to detect potential subcommunities or subgroups in the network. A cohesive subgroup is accomplished by UCINET software in the network of the University of California, Irvine [51]. To focus on observing the reciprocity of population and resource networks at high and low levels and the accessibility of the transportation system, the connection is divided into high and low levels by combining the natural breaks methodology in ArcGIS, and then binarization and standardization are carried out to conduct clique and N-clique, respectively.

2.3.3. Driving Mechanisms of Networks

The quadratic assignment procedure (QAP) compares the similarity between the lattice values of one matrix and multiple matrices on the basis of the permutation of relational matrices and provides the correlation coefficient and the regression coefficient [47]. The difference between the QAP model and other standard statistical programs is that the values of matrices are not independent, which prevents the multicollinearity problem in traditional multiple regression models and effectively reduces the influence of errors. When selecting urban attribute indicators as explanatory variables in this article, we bear in mind that they are not entirely independent of each other. Therefore, choosing the QAP model to explore the network formation mechanism is more appropriate. The models of population network, resource network, and transportation network are explained in this paper as follows:

$$Y_i = a_0 + a_1x_1 + a_2x_2 + \ldots + a_nx_n \tag{22}$$

where Y_i represents the urban contact matrix, $i = 1, 2, 3$; a_0 is a constant; $a_1 - a_n$ are the regression coefficients; and $x_1 - x_n$ are the explanatory factors of the correlation matrix.

According to Zhu, Cui, Zhang, and Wang [44,45,47,52], the factors that affect network relations are usually divided into four levels (Table 1): economic development difference, the difference in urbanization development, policy differences, and geographical factor.

Table 1. Explanation and sources of influencing factors.

Level	Abbreviation	Variable	Explanation or Source
Economic	PG	GDP per capita	Statistics Yearbook
	SPG	square of GDP per capita	Economic disparities can promote the formation of urban relationships, but beyond a certain limit, they can hinder relationship development. SPG represents the square of per capita GDP and is used to observe the impact of excessive economic disparities on the network [47].
	TI	ratio of tertiary industry GDP to regional GDP	TI represents the proportion of the tertiary industry's gross domestic product (GDP) to the total regional GDP for the current year. It is used to gauge the importance of the service sector within the urban economy [9].
	FAI	fixed assets investment	Statistics Yearbook
Urbanization development	UR	urbanization rate	Urbanization rate refers to the proportion of the urban population to the total population, typically expressed as a percentage. Cities with a higher urbanization rate tend to have relatively more developed infrastructure and employment opportunities.
	RP	resident population	Statistics Yearbook
	UCD	urban construction degree	Statistics Yearbook
	W	average wage	The greater the disparity in average wages, the more likely it is for cities to be interconnected [53].

Table 1. *Cont.*

Level	Abbreviation	Variable	Explanation or Source
Policy	UO	urban openness	The degree of urban openness is represented by the amount of foreign direct investment in each city.
	PS	policy similarity	Using public budget expenditures to calculate policy similarity, this paper posits that when the public budget expenditures of two cities exhibit regional similarities, they share certain commonalities in policy planning [52].
	UC	urban cooperation	Urban cooperation refers to the number of relevant policies in 2021 when searching for two cities as keywords on the official website of the National Development and Reform Commission [25].
Geographical factor	P	provinces	According to the section to which the city belongs, Sichuan Province is assigned a value of 1, and Chongqing, as a municipality directly under the Central Government, should be given a value of 0 [47].
	GA	geographical adjacency	Adjacent cities to the specified city are assigned a value of 1, while others are assigned a value of 0 [39].

3. Results

3.1. Characteristics of Networks

3.1.1. Overall Characteristics of Networks

After standardizing and calculating the mean values of population migration, resource flow, and traffic efficiency value among cities in the CCEC, an integrated network of the CCEC can be obtained. In this paper, population migration is regarded as the flow of labor resources and is combined with the efficiency of intercity traffic to analyze the differences in the structure of human and material flow networks. The different cyberspace structures are as follows.

According to the comprehensive attributes of the population, resource, and transportation networks (Table 2), although all the networks have achieved full coverage of 240 links, the degree of clustering of each network is obviously different. Specifically, the MI in each network, ranked in descending order, is transportation > population > resource. Nonetheless, the integrated network does not exhibit pronounced agglomeration characteristics, implying heterogeneity in terms of the cohesive communities, participating members, and levels of involvement across the diverse networks. The network and weighted centrality are hierarchically classified according to the natural breaks methodology, and the results are shown in Figure 2.

Table 2. General genus of intercity elements of different networks.

Type	ND	MI
Population	1.000	0.094
Resource	1.000	0.021
Transportation	1.000	0.127
Integrated	1.000	0.000

It is observed that the pattern of element flows is analogous: (1) A multi-center network structure is formed. All three networks have at least one core city and two to four sub-center cities. These cities play a crucial role in efficiently managing human and material resources within the region. With a well-established transportation infrastructure, they are able to effectively allocate resources across the region. Chengdu stands at the core of all networks, with its connection weight representing a significant share of the overall network, ranging from 32.09% to 63.46%. (2) The intercity connections exhibit a “west dense, east sparse” pattern, and when compared to the close connections of Chongqing and its surrounding regions, the Chengdu-centered Chengdu–Mianyang–Leshan Development Belt holds a special position in all three networks. Chongqing and its surroundings have not yet formed a strong influential network layout, especially in the resource network, where Chongqing holds a peripheral position.

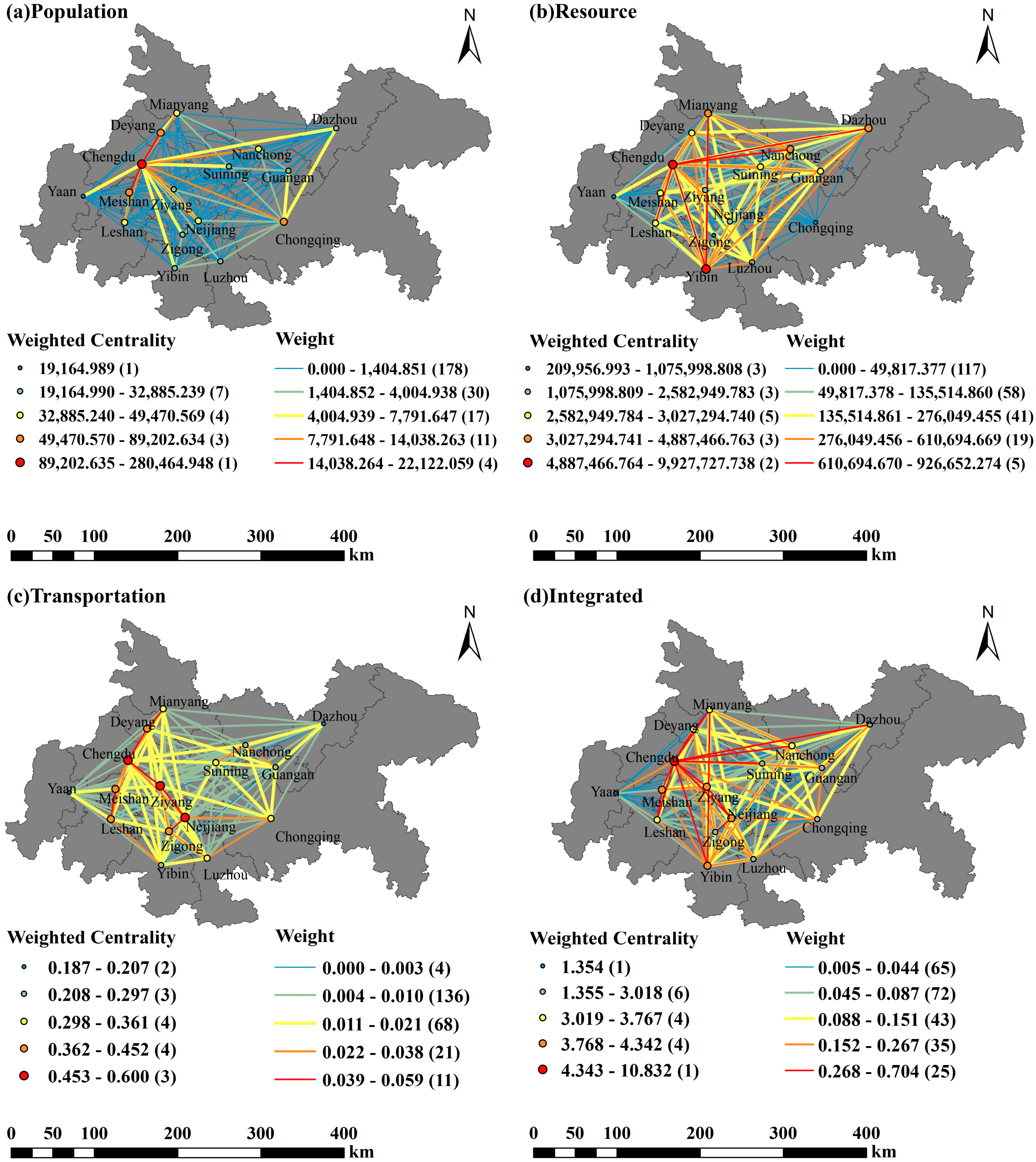

Figure 2. Different network spatial structures. (**a**) Weighed centrality and connection weight in the population network. (**b**) Weighed centrality and connection weight in the resource network. (**c**) Weighed centrality and connection weight in the transportation network. (**d**) Weighed centrality and connection weight in the integrated network. Notes: The sizes of the nodes correspond to the levels of weighted centrality, and the colors of the connecting lines correspond to the levels of connection weight, with the number in parentheses indicating the number of cities or connections included in that level.

In addition to the aforementioned apparent similarities, there are certain distinctions across networks. (1) The arrangement of central and peripheral cities varies across distinct networks. Within the population network, Chongqing, Meishan, and Deyang emerge as sub-centers orbiting the central city of Chengdu. The resource network distinctly exhibits a "triple-core" structure, with the central cities being Nanchong, Yibin, and Chengdu, accompanied by secondary centers, such as Mianyang and Dazhou. The transportation network includes the Chengdu–Mianyang–Leshan Development Belt and the Chengdu–Ziyang–Neijiang Corridor, highlighting a distribution of cities in both north–south and east–west directions. (2) All four networks exhibit a network structure dominated by multiple centers and aided by several cities, but they differ in their hierarchical layout structure. Apart from the population network, in the other two networks, cities classified into the same level based on weighted centrality are most numerous in the second and third levels, forming a "shuttle" structure. In the population network, there are seven cities allocated to the fourth level, displaying a "dual-core" structure overall, with the middle and lower levels comprising 75% of the total cities. The dual-core structure, consisting of Chengdu and Chongqing, displays the characteristics of outward radiation from the core, with insufficient communication intensity among non-core cities, indicating a "pyramid" structure (a narrow upper part and a wider lower part). This development model may lead to an increase in isolated nodes on the periphery of the city [26]; a network structure centered on three to four cities exhibits a shuttle shape (in resource and transportation networks), which makes it less prone to excessive concentration of elements flowing to upper and lower levels. Mid-level cities mostly have a certain ability to gather resources, while only two cities at the edge of the network are isolated. This form provides stability to the network.

To quantify the similarities or differences in characteristics between the two networks, we use the dissimilarity metric to calculate the network structure as per the research method of Gao [45] (Table 3). The dissimilarity metric in network structure is composed of the WBD and the CBD.

Table 3. WBD and CBD between three networks.

	WBD			CBD		
	Population	**Resource**	**Transportation**	**Population**	**Resource**	**Transportation**
Population	0.000	0.148	0.116	0.000	0.000	0.000
Resource	0.148	0.000	0.115	0.000	0.000	0.000
Transportation	0.116	0.115	0.000	0.000	0.000	0.000

Overall, considering the extent and significance of connections, the WBD is typically more significant than the CBD, thus better reflecting the disparities between networks. The population and resource networks exhibit the greatest difference, with a value of 0.148, while the difference between the traffic network and the population network is 0.115, and that between the traffic network and the resource network is 0.116.

Specifically, the traffic network serves as a conduit for the intercity flow of population and material resources. This fact, despite differences in the direction and magnitude of population and resource flows, results in relatively insignificant disparities between these two networks and the traffic network. The population and resource networks exhibit vastly different network structures and city hierarchy layouts. In the process of resource transfer, labor resources tend to be concentrated in Chengdu and Chongqing, while material resources tend to be concentrated in Chengdu, Nanchong, and Yibin. The population network leans more toward an overall network formed by the Chengdu–Mianyang–Leshan Development Belt and Chongqing, radiating outward. On the other hand, the formation of the resource network is influenced by local supply relationships, market supply and demand, industrial structure, and the nurturing of dominant industries, making the factors influencing it more complex.

3.1.2. Node Characteristics of Cities

In order to investigate the hierarchy of cities in the intercity factor flow, the weighted indegree and the weighted outdegree of the network are calculated.

(1) The internal and external balance of the city: In Figure 3, the weighted indegree and the weighted outdegree exhibit a positive correlation, with a correlation coefficient of 0.930 (p value = 0.000). The differences among cities in terms of weighted indegree and outdegree values are absolute-valued and classified on the basis of the natural break methodology. In the population network, cities exhibited a balanced inflow–outflow with minimal disparities in distribution activity in different directions. In the resource network, Chengdu, Deyang, and Luzhou followed a "higher in, lower out" pattern, while Nanchong, Dazhou, Meishan, and Neijiang displayed a "higher out, lower in" pattern. In the transportation network, Deyang and Mianyang showed mismatched in–out characteristics, indicating differences in the efficiency of flow direction.

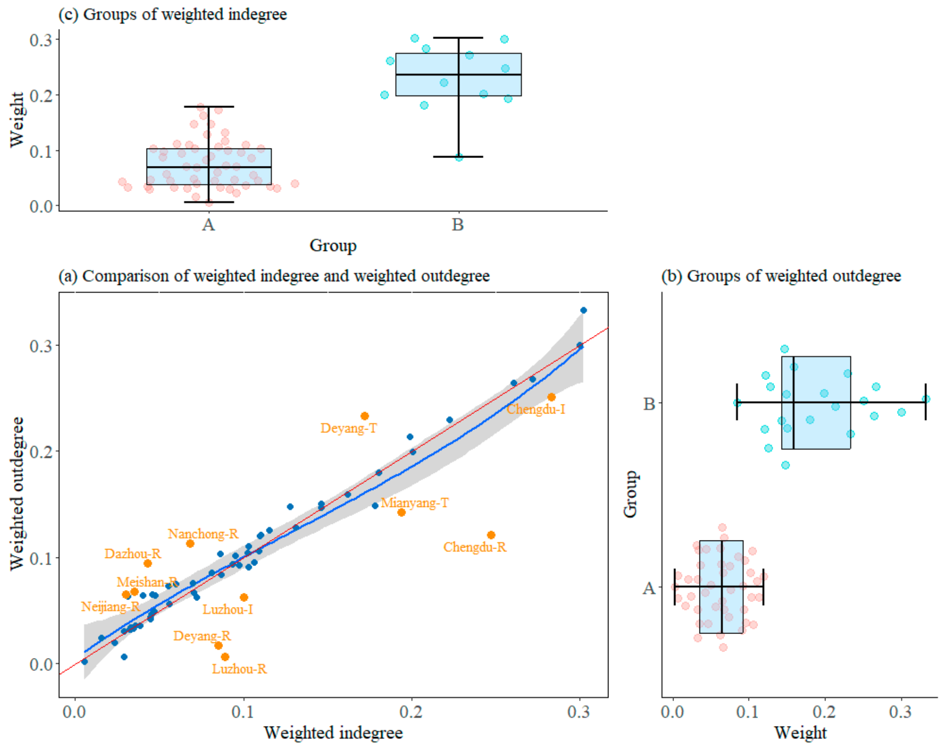

Figure 3. Comparison of weighted indegree and weighted outdegree. Notes: Using the natural break methodology, the weighted centrality is categorized into high-value (group B) and low-value (group A) groups. The red line is the balance line of weighted outdegree and weighted indegree, and the blue line is the fitting curve of the two degrees. The annotation of special points indicates the abbreviation of the city and the type of element, where R, T, and I, respectively, represent resources, transportation, and integration.

(2) Overall characteristics of the network: Combining the box plot (Figure 4), Chengdu holds an absolute central position within the region, while the other cities have not yet established a coordinated relationship between population, resource transfer, and transportation accessibility conditions. There are significant inter-group differences among them. However, there are also special points in Chengdu whose weighted outflow in the resource network is much smaller than other indices. Therefore, Chengdu has centralized control over resources to a certain extent, which may even cause the phenomenon of "siphoning." Chongqing does not play a special role in the comprehensive network due to the huge gap in its ability to transfer human and material resources. Comparatively, the comprehensive influence ability of Yibin is better, enhancing its ability to attract talent and thus strengthening its position in the population network. When a coordinated development

model is being formed, Yibin will be expected to become the deputy central city of CCEC development. Therefore, in the sustainable development of urban agglomerations, Yibin is important when identifying the formation mechanism of the network and carrying out regional coordinated planning in order to address the shortcomings.

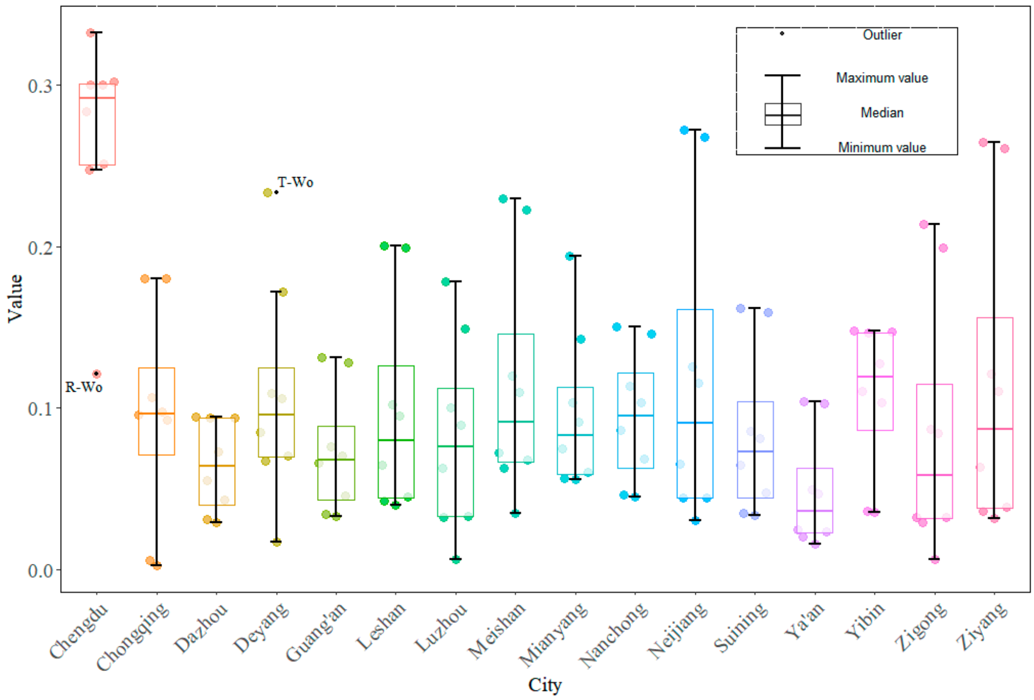

Figure 4. Weighted centrality box diagram of different network cities. Notes: The special points are labeled with the type of element and the type of weighted centrality. Weighted centrality is composed of two types of indices: Wi for weighted indegree and Wo for weighted outdegree.

3.2. Agglomeration Analysis of Networks

We utilize the natural break methodology and the modularity in Gephi software to divide the urban community structure to reflect the spatial agglomeration effect of population, resource, transportation, and integrated networks. The urban clustering degree (MI) and its contraction subnet are shown in Table 4 and Figure 5.

Table 4. MI in deference hierarchies.

	Population	Resource	Transportation	Integrated
Level 1	0.000	0.226	0.446	0.142
Level 2	0.000	0.233	0.543	0.305
Level 3	0.456	0.177	0.302	0.229
Level 4	0.321	0.202	0.094	0.155
Level 5	0.199	0.134	0.000	0.170
Overall	0.094	0.021	0.127	0.000

The population, resource, and transportation networks display pronounced effects of regional agglomeration, as evidenced by their respective overall clustering coefficients of 0.094, 0.021, and 0.127. There are notable variations in the quantity and spatial arrangement of cities in the hierarchical community structure. The average value of MI in the levels 1 to 5 hierarchical networks is generally higher than that of the overall network, indicating that dividing the overall network into hierarchical levels and subsequently identifying communities can lead to a deeper exploration of city relationships within the same hierarchical level. Furthermore, the agglomeration features of cities in levels 2 and 3 are significantly greater than those in levels 1 and 4, with level 5 ranking at the bottom. To examine the interdependence of population and resource networks at different hierarchical levels and the accessibility of transportation systems, the connections are classified into high and low groups using a combination of the natural breaks methodology. Then, binarization and standardization are conducted to conduct clique and N-clique (Figure 6).

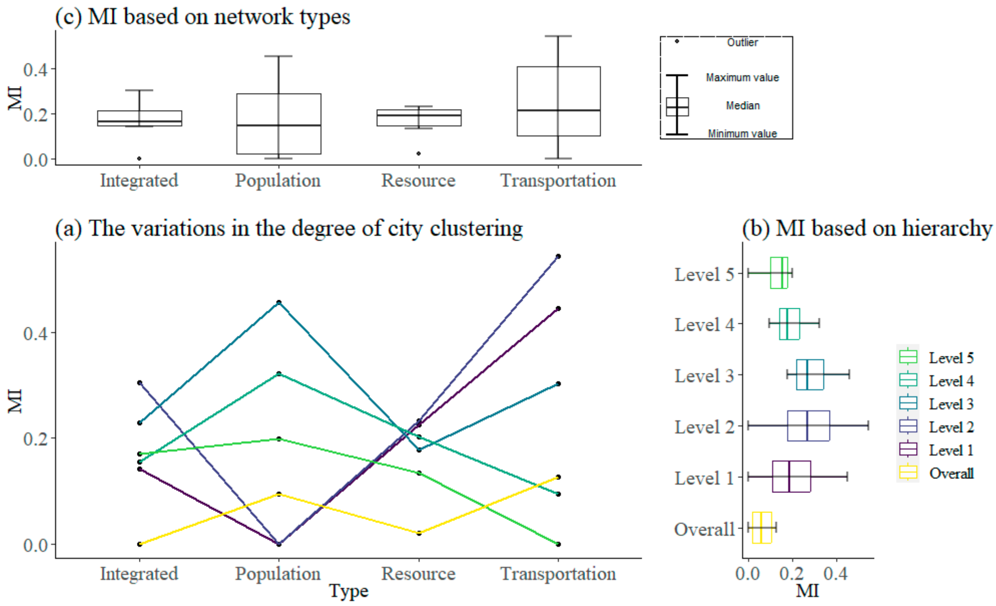

Figure 5. The variations in the degree of city clustering among different types of hierarchical networks. (**b**,**c**) represent the concentration trends of different network MI and different hierarchical MI, respectively.

The findings indicate that the high and low levels in the three networks exhibit distinct characteristics.

(1) The absence of a clustering ability in high-level networks implies a deficiency in community among cities, resulting in restricted opportunities for mutual benefit. In the high-level networks of resources and transportation, there are indeed closely connected small communities. In the resource network, two relatively tight groups have formed, one consisting of five cities (Ziyang, Ya'an, Dazhou, Meishan, and Neijiang) and one consisting of three cities (Chengdu, Nanchong, and Suining). Cities within these groups not only support high-intensity resource distribution among themselves but also have a profound impact on cities outside the communities. In the high-level transportation network, there are also two distinct community structures. Three cities, Chengdu, Ziyang, and Neijiang, form one community, while four cities, Mianyang, Deyang, Meishan, and Leshan, constitute another. Unlike the high-level resource network, these communities tend to align with neighboring cities when forming, and their ability to overcome distances is not particularly pronounced.

However, the high-level population network does not exhibit urban agglomeration characteristics. This indicates that there are issues with the current distribution of population in the region. While the excessive concentration of the population in Chengdu may have driven consumption and economic development at a certain point, it is likely to lead to problems such as housing shortages, traffic congestion, and declining environmental quality in the future. Conversely, for peripheral cities, excessive population outflow may have a negative impact on their economic development. These cities need to attract talent and investment to propel their own development.

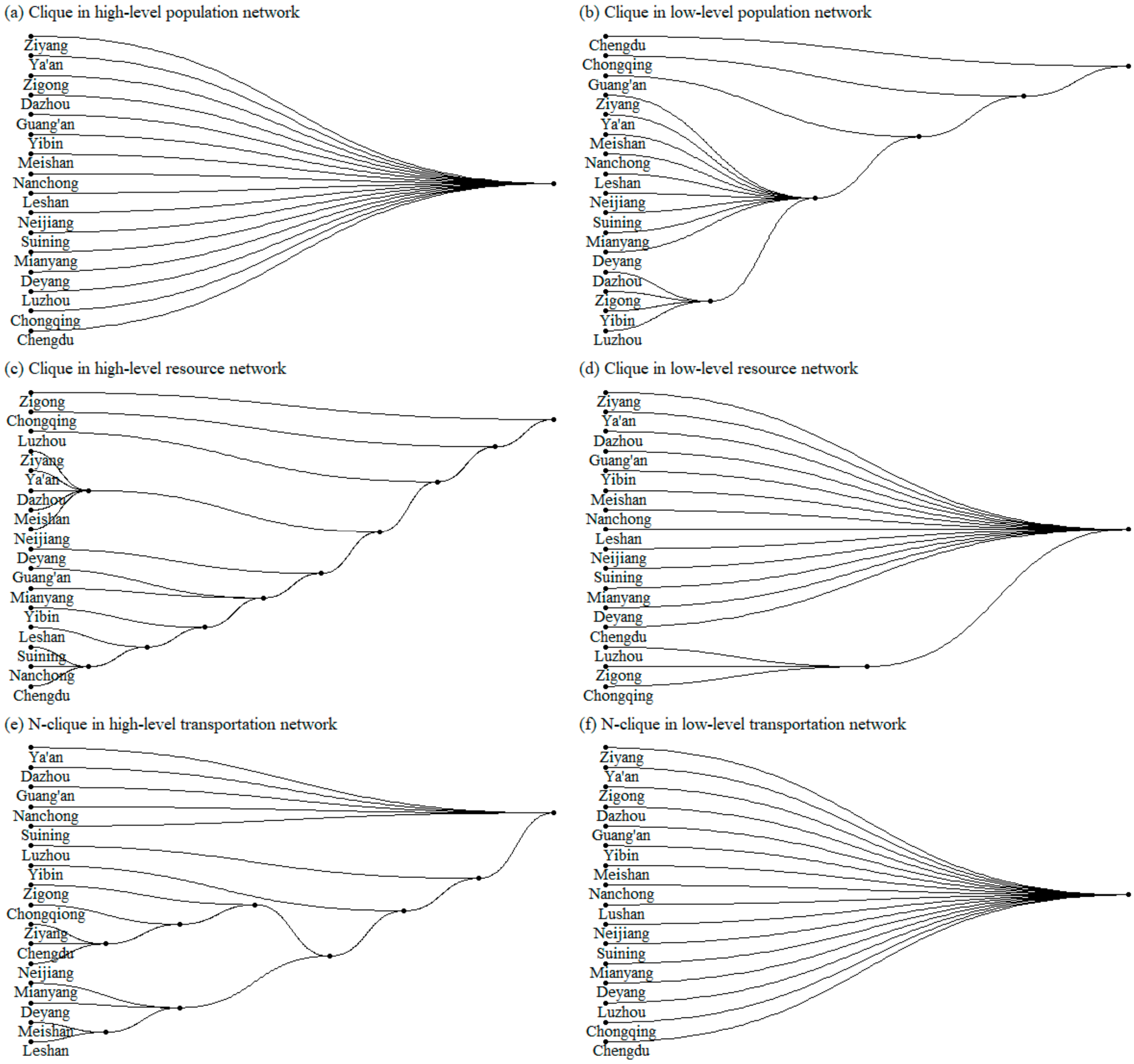

Figure 6. Analysis of cohesive subgroups. Notes: The nodes on the left of the dendrogram represent 16 cities and extend to clustering nodes on the right, where the length of the links represents the relative distance between cities. All cities connected to the same node can be classified as a community. The community with the shortest relative distance belongs to all communities.

(2) While the influence of lower-level intercity element flows may be limited, the close community relationships they form can facilitate the export and transfer of elements, playing an equally vital role in helping cities withstand crises and develop resilience. Peripheral cities that lack large-scale resources and markets often need to rely on these small communities for their development. The low-level population network forms two distinct community structures, a smaller one consisting of Dazhou, Zigong, Yibin, and Luzhou and a larger one that includes the former cities along with Ziyang, Ya'an, Meishan, Nanchong, Leshan, Neijiang, Suining, Mianyang, and Deyang. While Chengdu holds an absolute central position in the overall population network, its role in driving the surrounding cities is not prominently displayed. In the layered network considering mutual capabilities, Chengdu's absolute position disappears.

The resource low-level network only forms a small community consisting of Chongqing, Zigong, and Luzhou, while the transportation network does not exhibit any city clustering characteristics. They are more susceptible to the distance decay effect. Chongqing is close to Zigong and Luzhou, allowing for some degree of element replacement. However, in the transportation network, peripheral cities located at the endpoints with low transportation efficiency face challenges in overcoming geographical distances for trade or cooperation unless they rely on core cities or large communities. This is reflected in longer travel times and reduced efficiency in transportation.

3.3. Driving Mechanisms of Networks

After analyzing the three types of network structures and their respective clusters in the CCEC, this paper aims to investigate the factors that determine the strength of network connections. The QAP model can help avoid issues of multicollinearity that arise in many standard statistical methods, such as OLS, and it can also address the problem of correlated independent variables.

3.3.1. Correlation Analysis

In this study, the population network, the resource network, the transportation network, and 13 difference matrix data were randomly arranged 5000 times using UCINET software. Table 5 shows the correlation coefficients between the three networks and the factors influencing them. It is worth noting that the resource network is influenced only by TI and not by other factors, which may limit the explanatory power of this model for that specific network.

Table 5. Correlation results of factors influencing the networks in the CCEC.

Variables	Population	Resource	Transportation
PG	0.031 *	0.258	0.160
SPG	0.508 *	0.302	0.189 *
TI	0.030 *	0.478 **	0.216
FAI	0.412	−0.038	−0.002
UR	0.005 ***	0.300	0.302 ***
RP	0.064	0.060	0.147
UCD	−0.024	0.004	−0.057
W	0.064	0.019	0.096
UO	0.002 ***	0.480	0.272 *
PS	0.281	0.005	0.107
UC	0.014 *	0.103	0.077
P	0.062	0.251	0.011
GA	0.270 ***	−0.085	0.537 ***

Note: ***, **, and * represent significance at the levels of 0.5%, 1%, and 5%, respectively.

On the basis of the degree of correlation and significance through testing, the population network incorporates PG, SPG, TI, UR, UO, UC, and GA indices into the QAP regression model. The resource network, for now, has only passed the significance test for TI, and additional influencing factors will be added in subsequent analyses. As for the transportation network, only SPG, UR, UO, and GA have shown significance through testing.

3.3.2. QAP Regression Analysis

QAP regression analyses were conducted on the population and transportation networks on the basis of the impact factors that passed the hypothesis test (Table 6). UCINET software was used, and 2000 random matrix permutations were selected. For the resource network, it is advisable to re-evaluate the model's explanatory power after filtering out other influencing factors.

Table 6. Regression results of factors influencing the networks in the CCEC.

Network	Variables	Unstandardized Coefficient	Standardized Coefficient	Significance
Population	GA	0.327	0.261	0.000 ***
	UC	0.293	0.146	0.021 *
	UO	0.871	0.898	0.000 ***
	SPG	−0.072	−0.029	0.515
	PG	−0.158	−0.057	0.498
	TI	−0.09	−0.039	0.693
	UR	−0.21	−0.107	0.837
Transportation	GA	0.297	0.520	0.000 ***
	UO	0.090	0.204	0.125
	SPG	−0.155	−0.137	0.163
	UR	0.174	0.194	0.142

Note: ***, and * represent significance at the levels of 0.5%, and 5%, respectively.

The QAP regression model was built for the population network, and the R^2 and adjusted R^2 were found to be 0.729 and 0.722, respectively, indicating that the model can effectively explain the formation of the population network. The findings indicate that there is a higher frequency of labor transfer between cities that share borders, with a standardized influence effect coefficient of 0.261 and a significant positive correlation between spatial connection at the 0.5% level. The degree of urban openness exhibited a significant positive correlation with an influence coefficient of 0.898 at the 0.5% significance level. The urban cooperative relationship positively impacts the population network and passed 5% significance tests, with an impact coefficient of 0.146. When cities establish trade and investment relations, they tend to attract more capital investment and create additional employment opportunities, which stimulates migration activities.

In the explanatory model, the R^2 and adjusted R^2 for the transportation network are 0.368 and 0.360, respectively. Transportation infrastructure is more easily established between neighboring cities. While urbanization rates and the degree of urban openness are significantly positively correlated with transportation accessibility, a large gap in economic strength (SPG) acts as an obstacle to transportation connections. However, compared to geographical factors, these factors are not as significant.

3.3.3. Improvement of the QAP Model

It is noteworthy that only the tertiary industry appears to have an impact on the resource network. Further exploration of this aspect would certainly be meaningful. Related studies on inter-industry output interactions have been conducted using industry structure theory, economic growth theory, and economic cycle theory [54]. For instance, Zhao and colleagues conducted a study using China's input–output table for 1998, 2003, and 2008 and discovered a consistent positive correlation between productivity growth of resource-intensive, labor-intensive, and capital-agglomeration industries with productivity linkage [55]. Hence, drawing on the industry productivity linkage theory, this study employs intercity capital flows across 37 industries to explicate the resource network consisting of capital flows in construction, food and tobacco, agriculture, forestry, animal husbandry, and fishery industries and services; chemical products; and finance industry. We screen out the relevant factors through QAP correlation as follows (Table 7).

Table 7. Related factors of the resource network.

Variables	Coefficient	Significance
Textile, clothing, footwear, leather, down and their products	0.175	0.047 *
Wood processing and furniture	0.412	0.018 *
Paper printing and cultural, educational, and sporting products	0.244	0.028 *
Non-metallic mineral products	0.22	0.016 *
Metal smelting and rolling processing products	0.373	0.003 ***
Other manufacturing products	0.175	0.031 *
Electricity and heat production and supply	0.205	0.031 *
Gas production and supply	0.326	0.003 ***
Wholesale and retail	0.566	0.001 ***
Transportation, warehousing, and postal services	0.559	0.002 ***
Accommodation and catering	0.602	0.002 ***
Information transmission, software, and information technology services	0.457	0.029 *
Real estate	0.511	0.015 *
Leasing and business services	0.536	0.021 *
Water conservancy, environmental, and public facility management	0.398	0.004 ***
Residential services, repair, and other services	0.636	0.000 ***
Education	0.532	0.000 ***
Health and social work	0.459	0.001 ***
Culture, sports, and entertainment	0.434	0.031 *
Public administration, social security, and social organizations	0.325	0.01 **

Note: ***, **, and * represent significance at the levels of 0.5%, 1%, and 5%, respectively.

After augmenting the initial set of 20 factors with TI that passed the significance test, a QAP regression analysis was performed (Table 8). The resulting R^2 of 0.482 and the adjusted R^2 of 0.434 indicate that the model can provide a strong explanation for the mechanism of resource network formation.

Table 8. Result of the improvement of the QAP regression model.

Variables	Standardized Coefficient	Significance
Wood processing and furniture	0.037	0.177 *
Paper printing and cultural, educational, and sporting products	−0.071	0.167 **
Electricity and heat production and supply	0.155	0.565 *
Information transmission, software, and information technology services	−0.172	0.204 ***
Water conservancy, environmental, and public facility management	0.199	0.323 *
Public administration, social security, and social organizations	−0.650	0.234 ***

Note: ***, **, and * represent significance at the levels of 0.5%, 1%, and 5%, respectively.

Public administration, social security, and social organizations have the most profound impact on resource flow (−0.650), followed by water conservancy, environmental, and public facility management (0.199). Industries with supply and demand relationships will exhibit some positive mutual influence. The wood processing and furniture industries have a certain supply relationship with the construction industry, while they have a demand relationship with, for example, agriculture, forestry, animal husbandry, and fishery industries and services. The construction industry requires a stable supply of electricity, while the chemical products industry; the food and tobacco industry; and agriculture, forestry, animal husbandry, and fishery industries and services require the operation of production equipment or cold-chain transportation. Therefore, electricity and heat production and supply play a positive facilitating role in these industries. The water conservancy, environmental, and public facility management industry and the construction industry both serve infrastructure development. The growth of the construction industry drives the development of the water conservancy, environmental, and public facility management industry. Simultaneously, the water conservancy, environmental, and public facility management industry regulates the water supply and wastewater treatment processes in the food and tobacco industry and irrigation in agriculture, forestry, animal husbandry, and fishery industries and services, as well as production and waste treatment in the chemical products industry. Therefore, investment in the water conservancy, environmental, and public facility management industry will create a favorable living environment for these industries.

However, the paper printing and cultural, educational, and sporting products industries; information transmission, software, and information technology services; and public administration, social security, and social organizations industries do not have prominent upstream and downstream relationships with the construction industry; food and tobacco, agriculture, forestry, animal husbandry, and fishery industries and services; finance; and chemical products industries. This impedes their development when capital is invested in these industries, leading to a significant negative impact.

4. Discussion

Conducting a comparative analysis of networks across various levels within a region is important for promoting integration and development. To understand the structural characteristics of spatial networks and the clustering status of urban communities, in this study, we evaluated the differences among the three network structures and delved into the polarization features of cities. Additionally, the potential influencing factors of the three networks were explored. We found the following.

(1) At the population level, Chengdu has a siphoning effect on the surrounding areas. While Chengdu occupies an absolute central position in the population network, it does not exhibit any significant associated communities in both high- and low-level networks. This suggests that although Chengdu is a hub for regional talent distribution, its outward mutualistic capacity is limited, primarily demonstrating an inward attraction (Figures 2 and 6). This concentration of labor force may have a negative impact on the economic development of surrounding areas, possibly due to a siphoning effect, where Chengdu attracts labor from surrounding areas, leaving them with fewer resources and opportunities for economic development [9]. The resource network exacerbates this characteristic of Chengdu, with the imbalanced nature of resource inflows and outflows further highlighting that Chengdu does not exhibit "mutualism" in terms of resources (Figure 4).

(2) The cities have not yet reached a state of coordinated and sustainable development. When urban clusters reach a certain level of development, such as the Yangtze River Delta region, excessive economic disparities can have a negative impact. In contrast to what has been discussed in other studies [26], economic factors such as PG, SPG, and TI exhibit a positive correlation with population activities in the CCEC (Table 5), with SPG even accounting for 0.508, surpassing the influence of geographical factors (0.270). This further suggests that in the CCEC, most cities do not exhibit significant economic disparities, and they are all positioned at a lower hierarchy level. Their potential for external influence and their susceptibility to the influence of core cities are relatively small. Furthermore, transportation infrastructure significantly diminishes the impact of geographical distance. For example, the logistics network in the Yangtze River Delta region is less affected by geographical distance compared to the Pearl River Delta and the Beijing–Tianjin–Hebei urban cluster [56]. In more harmoniously developed urban clusters, with the improvement of transportation conditions, the influence of geographical factors tends to diminish. However, the CCEC has not yet reached this favorable developmental state.

(3) To improve this situation, we should begin by examining the mechanisms behind network formation (Tables 6 and 8). Policies that enhance a city's openness to foreign investment and actively foster cooperation with other cities can help non-core cities improve living conditions and attract labor. Second, building and enhancing intercity industrial chains, developing supply and demand relationships, reducing market competition among cities with similar industries, and promoting corporate cooperation and industrial inte-

gration among cities can guide the rational allocation of resources and prevent excessive concentration. Similarities in neighboring cities can give rise to a competitive relationship that undermines the coordinated development of urban agglomerations. As a result, actual capital flows are more likely to occur across different industries rather than among different cities within the same industry [57]. Thus, it is important to avoid industrial homogeneity, which might lead non-core cities to lose their advantageous positions in terms of network connectivity depth.

This paper will help in the following ways. First, this study is unique in that it compares different networks on the basis of the CCEC. Such comparison is not common in network structure analysis. This section is augmented by calculating the dissimilarity between different network structures, and the quantitative analysis results reduce the errors caused by subjective judgment in previous network comparisons. Second, the concept of hierarchy will help research in related fields. We found that hierarchical networks exhibit more clustered or dispersed features than whole networks (Table 4). This enriches the research methods of hierarchy theory and complements the theory of connection strength structure in addition to nodal hierarchy [35]. Building upon the highlights of this paper, future research could be considered in the following directions. First, future research could focus on the purpose of travel and comparison of passenger and freight flows. Currently, migration data cannot identify the reasons residents travel, often focusing solely on passenger flows and neglecting freight flows. Research on transportation networks should encompass the movement of both people and goods. When both can be accurately identified, urban networks will be explored from a more multi-source perspective, allowing for a deeper understanding of the underlying patterns in urban development. Second, the construction of a coupled model for multi-source urban networks should be considered. The development of big data technology has expanded the availability and depth of research data. Integration of multi-source urban networks with coupled models brings new research perspectives characterized by directionality and flow within urban networks. Simultaneously, coupled models offer more scientifically sound methods for assessing urban coordination in multi-source networks, enabling a quantitative description of urban cluster development evaluations.

However, it is essential to acknowledge the limitations of this study. (1) Inconsistent data years: The data used in this study come from various sources, and there is a lack of uniformity in data years. For instance, the resource network is based on 2017 input–output tables, which may not align with data from other sources. This inconsistency could introduce analytical errors. (2) Data year selection: Many of the data years fall within the period of the COVID-19 pandemic, including lockdown and post-lockdown phases. While daily averages are calculated for yearly data, variations in pandemic control policies across regions could lead to data fluctuations that are challenging to differentiate or isolate. Future research might benefit from collecting more refined data. These limitations should be considered when interpreting the findings and designing future studies.

5. Conclusions

In this study, we constructed three types of networks: population, resource, and transportation. Differences in network structures, urban statuses, and inflow–outflow balance mechanisms, and urban hierarchical network clustering characteristics were studied using methods such as network structure dissimilarity, weighted centrality, modularity, and cohesive subgroups. Additionally, the QAP model was used to analyze the driving mechanisms of the three networks. The conclusions are as follows.

(1) The network structure centered around the Chengdu–Mianyang–Leshan Development Belt plays a significant role in various networks, even dominating the "west dense, east sparse" feature across these networks. The trends and network structures of population and resource networks are entirely different (WBD = 0.148). In comparison, the differences between the population and resource networks and the transportation network are not significant (WBD = 0.116 and 0.115, respectively). The resulting hierarchical

patterns can be classified into two types: pyramid (population network 1:3:4:7:1) and shuttle (transportation network 3:2:7:2:2, resource network 3:4:4:3:2, and integrated network 3:2:7:2:2).

(2) The clustering characteristics of the hierarchical networks are more pronounced than those of the overall network, particularly for the hierarchical networks of resources (with a minimum index of 0.134 and a maximum index of 0.233, generally higher than the overall MI of 0.021). As per the analysis of cohesive subgroups considering reciprocity and accessibility, cities in the low-level subgroups of the population network are dominated by mutually beneficial relationships; in contrast, the cities in the high-level subgroup of the resource and transportation networks have higher bidirectional reciprocity and bidirectional accessibility.

(3) The population network in the CCEC is influenced by geographical adjacency, urban openness, and urban cooperation, while the transportation network mainly relies on the geographical proximity of cities. The resource network is heavily influenced by industry structure, with industries that have supply–demand relationships mutually promoting each other. Conversely, internal fund flow within unrelated industries can hinder the development of other industries.

Author Contributions: Ludan Zhang: writing—original draft, methodology, formal analysis, data curation, software, and visualization; Xueman Zuo: formal analysis, data curation, software, and visualization; Ziyi Wu: formal analysis, data curation, software, and visualization; Cheng Chen: formal analysis, data curation, and software; Zibao Pan: formal analysis, data curation, and software; Xisheng Hu: conceptualization, Validation, writing—Review and Editing, and supervision. All authors have read and agreed to the published version of the manuscript.

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