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Geospatial Structure and Evolution Analysis of National Terrestrial Adjacency Network Based on Complex Network

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Abstract
The first law of geography is one of the most important concepts in geographical analysis, revealing the significant role of spatial proximity. At present, some current international relation studies or geographic network analysis studies tend to build corresponding network models according to different themes, but the most basic level of geographic neighborhoods is intentionally or unintentionally neglected in those processes. Based on the adjacency relationship between the terrestrial countries in the world, the model of the terrestrial adjacency network (TAN) is constructed. The model includes almost all land-based countries and is divided into three main regions, respectively, Eurasia, Africa, and America. On the mathematical model of these regions, we analyze the geospatial structure and network evolution of the adjacent networks utilizing statistical methods and network analysis methods. This study helps to map and understand the geographical attributes and characteristics of countries from the perspective of holistic structure, aiming to provide a quantitative reference for subsequent research on international relations and geographic computing. Moreover, despite some limitations, TAN represents a new advance in geographical network analysis that can be further applied by overlaying more attribute data.

Keywords Adjacency network · Complex networks · Spatial structure analysis · Network evolution · Geopolitical relations

Introduction

In recent years, with the slowdown of the global economic growth rate and the intensification of development imbalance among countries, the world situation has undergone significant changes, and the rich and diversified network relations among countries have encountered new crises. The outbreak of the Russia-Ukraine conflict in 2022 and the continued escalation of the Palestinian-Israeli situation in October 2023 indicate that the world pattern will develop in a more complex direction. How to find the relative essence of the law from the complex reality has become an urgent problem in the current international relation research. As a result, network-based research on national geopolitical relations has gradually become a hotspot in international relations and geography and other interdisciplinary disciplines (Uitermark and Van Meeteren 2021; Schottler et al. 2021).

In the early days, scholars analyzed and calculated international relations (Maoz 2012, Hafner-Burton et al. 2009; Bohmelt and Spilker 2016) and state power (Bonacich 1972, Kim 2010) with the help of network methods. With the profound changes in international relations (Jin and Huang 2013) and the continuous enrichment of geo-relations research (Song et al. 2018; Lu and Du 2013; An et al. 2016; Du and Mei 2017), some geo-relations scholars have constructed different network models by using the theories and methods of network analysis, such as the global natural gas trade network (Geng et al. 2014; Liu 2016), the oil trade network (Liu et al. 2017), the environmental expansion of the global energy network (Chen

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et al. 2018), the global agricultural products trade network (Wang et al. 2018), and the Belt and Road along the route countries food virtual water trade network research (Zhu et al. 2020).

In addition to theme-oriented network analysis, some scholars have also dissected the geosystem properties and functional evolution laws through network attributes and node characteristics (Qin et al. 2019; Yang et al. 2021). The use of gwpcorMapper (Percival et al. 2022) and geographically weighted correlation and partial correlation analysis can provide valuable insights into the study of geopolitical relations using complex networks. Karountzos et al. (2023) introduces a GIS-based decision support framework for creating zero-emission maritime networks, specifically focusing on the Greek Coastal Shipping Network (GCSN). The approach employs GIS and exploratory spatial data analysis (ESDA) to identify suitable areas for implementing zero-emission routes, adding to the body of knowledge on sustainability and decarbonization in the maritime sector.

Similarly, different scholars have explored the application of networks in different regions, such as the economic and trade networks between China and neighboring countries (Pan et al. 2015), and the study of geopolitical relations in Southeast Asia (Qin et al. 2018). Scholars have done more research (Anderson and Dragićević, 2020) on thematic networks such as political, economic, and trade ties between countries, constructing defined networks based on defined themes and studying the characteristics of their existence. However, there are fewer studies on the underlying structure of geopolitical networks, so it is necessary to start from the bottom, reveal the geopolitical proximity laws and quantitative characteristics between countries, and provide logical support for other network studies.

As far as the current international community is concerned, each country's own geographic location and its relative position (adjacent, separated, or far away) from other countries are fixed for a certain period of time, thus constituting the basic geopolitical relations among countries. Based on these basic geographic neighboring relationships, we constructed a national land neighboring network. The land adjacency network can help us to reconceptualize the geographic connotations of different countries and regions in a quantitative way, and then provide reference for avoiding geopolitical risks and guiding national development.

The research objectives of this paper are threefold: (1) to construct a terrestrial adjacency network model based on national land neighboring relationships, (2) to spatially characterize the specified region based on the network indicators, and (3) to conduct an evolutionary analysis with the help of the terrestrial adjacency network to reveal possible geo-relationship patterns.

Materials and Methods

Data Description and Network Model Generation

Geographic network is a complex network of the real type, and the terrestrial adjacency network (TAN) model based on terrestrial adjacency relationship is a typical example of geographic relationship network. TAN's construction treats countries or regions as network nodes and uses adjacencies and related attributes as constraint rules. The focus of adjacency networks is on the calculation of expression relationships and network indicators, so some factors that are not used for the time being in the construction of TAN, such as the topographical conditions of different countries, will be ignored.

The research object of this paper is global terrestrial countries, and relevant data are obtained from the Database of Global Administrative Areas (https://gadm.org/). For countries and regions in dispute in GADM, international practice prevails. Data on country attributes (e.g., national rail mileage, road mileage, territorial area, etc.) from the World Bank, with additions for missing values from Wikipedia and The World Factbook. Because of the complexity of borders between countries, there are some special circumstances that need to be explained: (a) Turkey's Edirne and Kirklareli provinces share borders with Greece and Bulgaria, respectively, despite being separated from Turkey proper by the Turkish Strait. This creates a neighboring relationship between Turkey, Greece, and Bulgaria, with Azerbaijan also considered adjacent due to their common border. (b) Bosnia and Herzegovina extends into the sea and divides Croatia's coastline, but their territorial borders connect with Montenegro, making Croatia adjacent to Montenegro. (c) Territorial adjustments resulting from a 1974 agreement between Saudi Arabia and UAE invalidated their contiguous relationship, separating UAE and Qatar. (d) West Malaysia borders Thailand to the north and Singapore to the south, with East Malaysia separated from the west by the sea. As a result, Malaysia is adjacent to both Thailand and Singapore.

Tables 1 and 2 provide examples of node set and edge data, respectively. The node set is denoted $\boldsymbol{V} = \{v_1, v_2, \cdots, v_n\}$, the edge set is denoted $\boldsymbol{E} = \{e_{i_j}\}(i,j \in [1,N], i \neq j)$, and finally, the undirected graph model $\boldsymbol{G_{ad}}$ is generated, where *ad* is the abbreviated form of *adjacent*.

Figure 1 divides the main study area into three regions based on the natural characteristics of the continents: Eurasia, Africa, and America. Notably, the 79, 49, and 23 land-based countries are included in the corresponding study areas. The TAN models are constructed as three undirected subgraphs of $G_{EA} = \left(V_{EA}, E_{EA}\right), N_{EA} = 79$, $G_{AF} = \left(V_{AF}, E_{AF}\right), N_{AF} = 49$, and $G_{AM} = \left(V_{AM}, E_{AM}\right), N_{AM} = 23$, respectively. It should

Table 1 Example of node set of TAN

VID	Country	ISO	Longitude (°)	Latitude (°)	Attribute A
v_1	Afghanistan	AFG	66.029 586	33.828 415	A_1
v_2	United Arab Emirates	ARE	54.327 280	23.914 678	A_2
⋮	⋮	⋮	⋮	⋮	⋮
v_n	Vatican City	Data	12.452 861	41.903 540	A_n

Table 2 Example of edge set of TAN

EID	Source ISO	Country	Longitude (°)	Latitude (°)	Target ISO	Country	Longitude (°)	Latitude (°)	Edge Attribute A_{i_j}
e_{1-7}	AFG	Afghanistan	66.029 586	33.828 415	CHN	China	103.915 700	36.517 460	A_{1-7}
e_{2-25}	ARE	United Arab Emirates	54.327 280	23.914 678	OMN	Oman	56.095 588	20.588 5442	A_{2-25}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
e_{7-72}	CHN	China	103.915 700	36.517 460	RUS	Russia	96.723 288	61.980 730	A_{7-72}

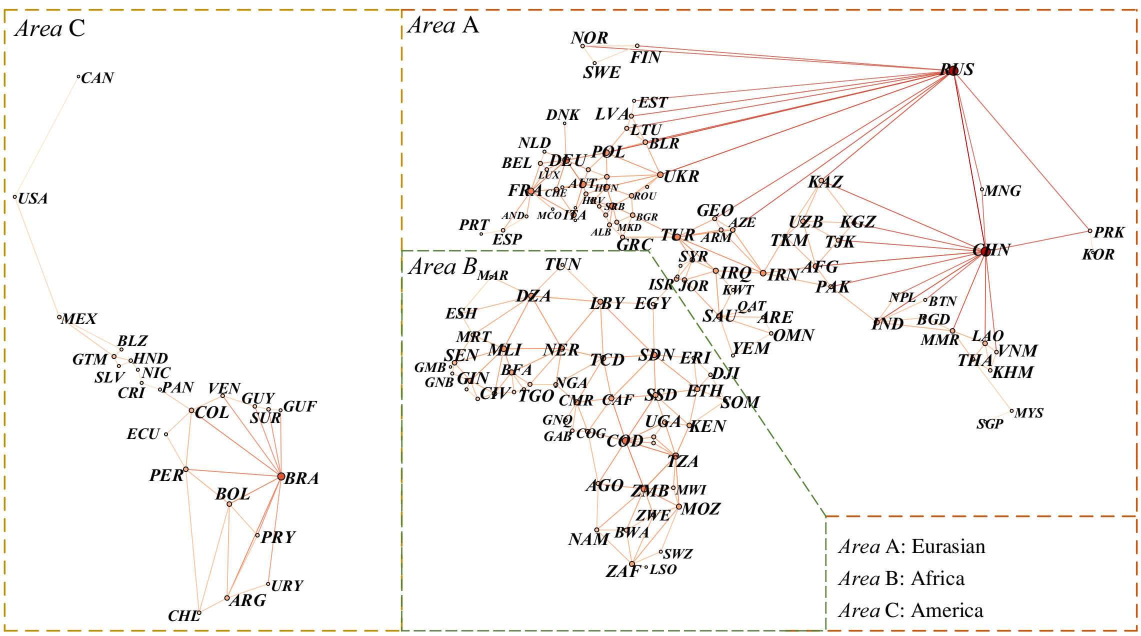

Fig. 1 Terrestrial adjacency network model diagram

be noted that because the scale of the study is large and the polar regions are not considered, it is more reasonable to construct TAN based on Mercator projection.

Geographic Meaning of Network Indicators

In the previous section, we built the TAN model. This section will focus on introducing the network indicators used and their geographical significance in spatial structure analysis and evolution analysis based on specific network indicators. As shown in Table 3, the adopted network indicators are divided into three aspects: node indicators, edge indicator, and network structure indicators.

Degree centrality is often used to measure the importance of a node, and the formula is expressed as

$$D_{c_i} = D_i/(N-1) \tag{1}$$

where N is the total number of network nodes.

Cluster coefficient refers to the proportion of neighbors of each other. The larger the cluster coefficient of the nodes in

Table 3 Summary of terrestrial adjacency network indicators

Category	Indicator	Notation	Geographical significance
Node indicators	Degree	D	The number of neighboring countries of a given country
	Degree centrality	D_{c_i}	Distribution of the importance of a country's degree value
	Cluster coefficient	C_i	The proportion of neighboring countries in a given country being neighbors to each other, the larger the cluster coefficient, the stronger the geographic clustering of countries in the region
	Closeness centrality	C_{c_i}	The ease of travel from one country to another country in the network
	Node betweenness centrality	B_i	The ability of the country to act as a bridge in the adjacency network model
	Eigenvector centrality	E_{ci}	Measure how connected a country is to countries with high influence (the primary indicator here is degree value)
Edge indicator	Edge betweenness centrality	B_{ij}	The adjacency between the two countries plays a bridge transmission role and intermediary influence in the adjacency network model
Network structure indicators	Density	$d(G)$	Represents the compactness of a network model, mainly measuring the completeness of the network diagram
	Transitivity	$T(G)$	Measures whether there are more optional paths for connectivity between countries
	Degree correlation	$r(G)$	Measures the homogeneity (small degree value nodes connected to small degree value nodes) or heterogeneity (large-small) of adjacency network in a certain region

the network, the higher the degree of tightness of the given node with the other nodes in the neighborhood is indicated by the formula:

$$C_i = \frac{2E_i}{D_i(D_i - 1)} \tag{2}$$

There can be at most $D_i(D_i - 1)/2$ edges between D_i nodes, and E_i represents the actual number of edges that exist between n_i nodes.

Closeness centrality is a reflection of the degree of convenience between a node and other nodes in the network, expressed as the reciprocal of the cumulative shortest path lengths between nodes.

$$C_c(i) = \frac{1}{d_i}, d_i = \frac{1}{N-1}\sum_{j=1}^{N} d_{ij} \tag{3}$$

where d_{ij} is the network length from node v_i to node v_j and d_i denotes the average length from node v_i to the remaining points. The more convenient the remaining nodes in this node network, the greater the value of closeness centrality.

Betweenness centrality is the ratio of the number of shortest paths from node v_l to node v_k to the number of all possible shortest paths from node v_l to node v_k. Node betweenness centrality and edge betweenness centrality reflect the bridge passing role and mediating influence of that node and neighborhood in the network model, respectively. The node betweenness centrality is calculated as

$$B_i = \sum_{j,k \in V} \frac{n_{lk}(i)}{n_{lk}} \tag{4}$$

Similarly, the betweenness centrality B_{ij} of an edge e_{ij} is defined as the proportion of the number of all shortest paths in the network that pass through that edge.

$$B_{ij} = \sum_{i,j,l,k \in V; e_{ij} \in E} \frac{n_{lk}(e_{ij})}{n_{lk}} \tag{5}$$

where n_{lk} denotes the number of shortest path entries between nodes v_l and v_k and $n_{lk}(e_{ij})$ denotes the number of shortest path entries between nodes v_l and v_k that pass through edge e_{ij}.

Eigenvector centrality reflects the degree to which a node in a network is connected to a more influential node (the influence of a node in an unweighted network is expressed as the node's degree value; the influence of a node in a weighted network is expressed as the weighted degree), which is calculated as.

$$E_{c_i} = \frac{1}{\lambda}\sum_{j=1}^{N} a_{ij}\mathrm{x}_j \tag{6}$$

where λ is the eigenvalue, a_{ij} is the adjacency matrix element, and x_j is the eigenvector.

Network density describes the tightness of a network and measures the completeness of the network graph as the ratio of the actual number of connections in the network to the maximum possible number of connections between nodes, with a value in the range of [0,1].

$$d(G) = 2M/[N(N-1)] \tag{7}$$

where M is the number of edges in the network and N is the number of nodes in the network.

Network transitivity depends on the degree and aggregation coefficient of each node in the network, i.e., connecting the same nodes may also connect each other in the network graph.

$$T(G) = 3 \times \frac{triangles}{triads} \tag{8}$$

where triangles are the number of triangles in the network and triads are the number of triples, i.e., the number of pairs of edges with common vertices.

Degree correlation refers to the fact that there is a correlation between degrees in the degree distribution of a real complex network, and describes the relationship between nodes with large degrees and nodes with small degrees in the network. The Pearson correlation coefficient method is a further simplification made by Newman based on Pastor-Satorras et al. and points out that it is necessary to calculate the Pearson correlation coefficient of the degree of the vertices only, $r(-1 \leq r \leq 1)$ to characterize the degree correlation of the network. r is defined as follows:

$$r(G) = \frac{M^{-1}\sum_{j>i} D_i D_j a_{ij} - \left[M^{-1}\sum_{j>i}\frac{1}{2}(D_i + D_j)a_{ij}\right]^2}{M^{-1}\sum_{j>i}\frac{1}{2}(D_i^2 + D_j^2)a_{ij} - \left[M^{-1}\sum_{j>i}\frac{1}{2}(D_i + D_j)a_{ij}\right]^2} \tag{9}$$

where D_i,D_j denotes the degree of two nodes v_i, v_j, respectively; M denotes the total number of edges of the networks; a_{ij} denotes the elements of the adjacency matrix A of the undirected network G, here 0 or 1; when r takes the value of the range of $r > 0$, the network is positively correlated, which means that nodes in the network with larger values of degree tend to be connected with nodes of larges values of degree; when $r < 0$, the network shows a negative correlation, and nodes with larger degree values tend to be connected to nodes with smaller degree values. When $r = 0$, the network is not correlated.

Network Structure and Evolution

A typical spatial graph can depict the flow of various resources between different geographic locations or describe the occurrence of different correlated events between multiple geographic locations. The spatial structure is crucial to us because TAN is the graphical expression and extension of geographic science. There have three main perspectives for analyzing the structure and evolution of TAN: (1) region, which measures the extent of change in specified nodes; (2) direction, indicating directional trends among network attributes; and (3) shape, where expansion or contraction forms subgraphs with varying levels of complexity. These perspectives are briefly depicted in Fig. 2.

Of course, there are dynamic changes in the adjacency network. Dynamic evolution can help us analyze geopolitical changes in real TAN using networks. When the existence of nodes and edges of the network is changed, the network structure will change accordingly, mathematically expressed as $G_0(V_0, E_0) \xrightarrow{conditions} G_1(V_1, E_1)$. Network changes caused by the mapping of realistic conditions on the network structure are called network component evolutionary analysis. The evolutionary analysis is most commonly used for network association detection and evolution under artificial conditioning for given targets. Community structure analysis can help uncover underlying patterns in TAN by identifying tight connections within communities and distant connections between communities. The goal is to separate different communities and explore their relationships in an efficient and reliable manner. When selecting community detection methods for TAN analysis, it is important to consider the neighborhood characteristics of the model and the three spatial analysis perspectives mentioned earlier. While there are many community detection methods available, the focus should be on selecting methods that align with the unique features of TAN.

To aid in community detection in TAN, k-shell analysis (KSA) and ego network analysis (ENA) algorithms are introduced. KSA is an indicator proposed by Kitsak et al. that evaluates node importance based on location information.

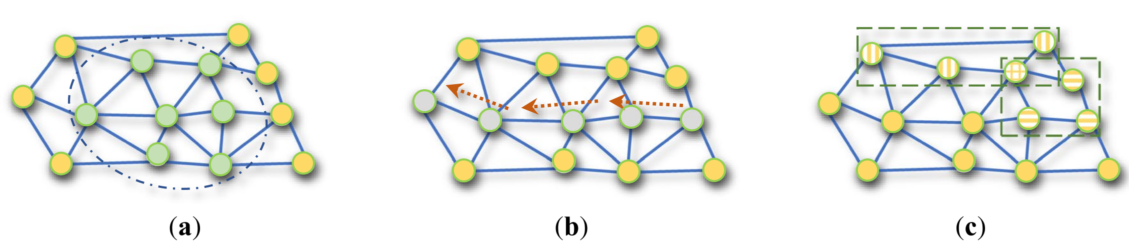

Fig. 2 Schematic diagram of the main perspectives of adjacency network structure and evolution analysis. **a** The nodes inside the dashed ellipse indicate the nodes to be studied, and the ellipse indicates the area involved in these nodes. **b** The dashed arrows represent the directional trend of the spatial distribution of network node attributes. **c** The dashed box circles the same number of nodes but takes on a different shape

The k-shell network refers to a maximal subgraph of the entire graph in which all nodes have degrees at least k (Kitsak et al. 2010). This decomposition model is most useful for analyzing large-scale networks, as nodes within the subgraph with a high number of network cores have a more stable position in the overall model and deeper structural hierarchies (the first column in Fig. 3).

In ego network analysis (Freeman 1982), there is a single focal node, which is the central node of the study. It includes the central node and all nodes that are connected to it by some path. The n-step neighborhood extends the definition of the neighborhood size by including all nodes connected to the ego network at path length n, along with all connections between these nodes. By using ENA, differences in the central node can be identified, the peripheral domain of the node can be examined, and changes in the local network structure can be described (the second column in Fig. 3). KSA is a degree-based contraction algorithm, while ENA is a path length-based expansion algorithm, and both are run using the Gephi software (https://gephi.org/).

Condition-based network component evolution analysis is a different approach to community detection. It involves adjusting the state of specified components to bring about changes in the network structure, as depicted in the third and fourth columns in Fig. 3. Through the use of TAN models, differences in attributes before and after network changes can be jointly analyzed by incorporating realistic condition factors such as setting the existence status of edges to 0 or 1 depending on whether two countries are hostile towards each other. Additionally, layer attributes $e_{ij.x}$ are integrated, which establishes neighboring networks as a tool within the framework of geographic network analysis. The evolutionary analysis offers insights into the impact of components on other members of the network, which in turn leads to a richer geographic interpretation.

It has been discovered that the connections between nodes in networks are often weight-dependent. Therefore, a purely topological model is not enough to accurately model the complex properties observed in real networks. In order to adequately capture these properties, it is necessary to construct a model that takes into account the weights of the connections. Here, we delves into the transition from unweighted networks to weighted networks and introduces a mathematical model denoted as $G = (V, E) \xrightarrow{conditions} G^{w}(V, E, W)$, where V represents the nodes of the network, E represents the edges, and W represents the weights assigned to each edge.

At the theoretical level, the accessibility index, which considers the TAN, superimposed road density, railway density, and complex network indicators, can measure the connectivity between countries over a larger area. Although it may not be as precise as traditional accessibility calculations at each pixel level, it has the advantage of considering all countries in the region. At the practical level, to measure the adjacency between two countries, the land-based adjacency network model accessibility index L_{ij}^{T} is constructed based on some indicators of the complex network. L_{ij}^{T} is an index used for comprehensive analysis, considering the topological

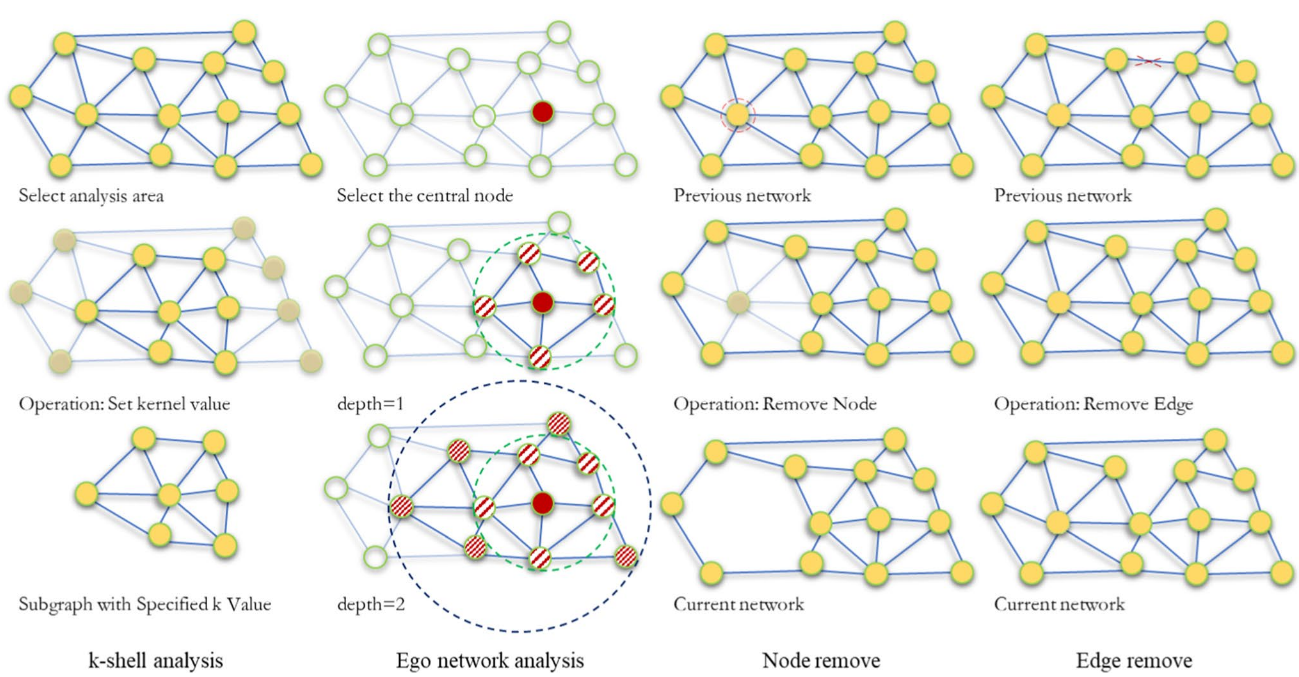

Fig. 3 Schematic diagram of network evolution analysis

characteristics of near centrality and edge intermediary centrality, combined with the actual available data, such as mileage data for railways and roads. As shown in Eq. (1):

$$L_{ij}^{T} = \frac{C_c(i) \times w_i + C_c(j) \times w_j}{2} \times B_{ij}, \tag{10}$$

Among them, $C_c(i)$ and $C_c(j)$ are the closeness centrality of nodes, and the larger the value, the stronger the ability to communicate with other nodes. B_{ij} is the betweenness centrality of the edge between the two countries, and the greater the value, the more obvious the intermediary effect; w_i and w_j are the basic weight parameters, here is the national land transportation capacity value. Here, r_i is the national railway mileage, and h_i is the highway mileage, all in kilometers (km); $Area_i$ is the territory of the country in square kilometers (km^2); the k_1 and k_2 in the formula represent the proportion of a country's road and rail transport in land transport, respectively, and we use these two coefficients to refine the country's land transport capacity.

Terrestrial Adjacency Network Spatial Structure and Evolution Analysis

The TAN model facilitates quantitative calculations, which are the focus of this chapter. Specifically, four aspects of quantitative analysis are addressed: scale-free characteristics, indicator orientation, indicator spatial clustering distribution characteristics, and network evolution analysis.

Analysis of Spatial Structure Characteristics

The two prominent complex network models are the small-world and scale-free models. Networks in scale-free models the node degrees obey a power-law distribution are called scale-free networks (Barabasi and Albert 1999). A power-law distribution is a probability distribution characterized by a power function between the frequency of a random variable and its value. In a power-law network, neither the variance nor the expectation may exist, which is why Barabási et al. called it "scale-free." The probability of distribution $P(k)$ is defined as the ratio of the number of nodes with degree k to the total number of nodes in the adjacency network, and the power-law distribution takes the form $P(k) \propto k^{-\gamma}$.

By studying power-law distributions, we can better understand the connectivity patterns between nodes in a network and thus gain a deeper understanding of the network structure, network performance, and even possible changes in the network. This is crucial for conducting geo-community division and analyzing geospatial structures.

Scale-Free Properties of TAN Models

The degree values and frequency distribution of the Eurasian TAN were obtained and presented in Fig. 4a. China (Asia) and Russia (Europe) have the highest degree value of 14. Countries with a degree value of 4 are the most frequent (16 countries). Those with a degree value of 2 are the second most frequent (20.3%). The degree values range between 1 and 6, accounting for 84.8%, indicating that most countries have neighbors ranging from 1 to 6. The average degree and weighted degree of the network are both 4.152. Nodes with degree values above 10 only account for a small proportion (2.53%).

The frequency distribution of the degree values of country nodes on Eurasia was fitted with a Gaussian distribution, which showed a right skewness (0.873) and an excellent fit. This indicates that most countries have only a few neighbors,

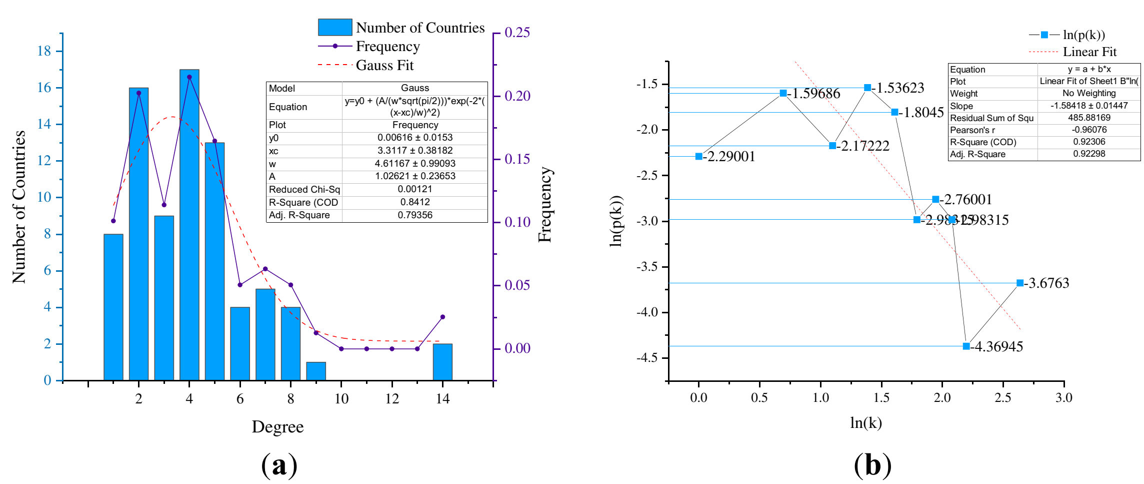

Fig. 4 **a** Node degree value distribution statistics and normal distribution fitting. **b** Scale-free detection of node degree value in Eurasian

while a few countries have many neighbors. The kurtosis of the fitted curve was − 0.549, showing that the curve is flat-topped and flatter than the normal distribution. Therefore, the degree value distribution does not follow the normal distribution.

In Fig. 4b, the logarithmic degree values and corresponding frequencies were linearly fitted in a Cartesian coordinate system to test for scale-free properties. The results showed a good fit with $R^2 = 0.923$ and a reasonable coefficient gamma value of $\gamma = 1.584$ (within the range of $1 \sim 3$). This confirms that the Eurasian TAN has a scale-free property. Figure 5 shows the scale-free detection plots for the Africa and America TANs, after calculating their degree values. The frequency distribution reveals that the Africa TAN has the highest frequency of degree value 3 and 6, while the America TAN has the highest frequency of degree value 2. However, both networks lack large numbers of nodes with small degrees connecting to nodes with large degrees. The power-law distribution tests confirm that both networks do not have the scale-free property, with low linear fitting errors R^2 of 0.03588 and 0.02426 for the Africa and America TANs, respectively.

To investigate the geographical manifestation of the scale-free properties of the Eurasian TAN, we hierarchically visualize the node degree values and compare network density, transitivity, and degree-degree correlations for all regions, as depicted in Fig. 6a.

An analysis of the geographic adjacencies shows a non-uniform structure in the Eurasian TAN, with a “core-verge” arrangement. The network has countries with small degree values at the verge and countries with large degree values at the core. East Asia shows a strong non-uniformity, whereas Europe displays a weaker non-uniformity.

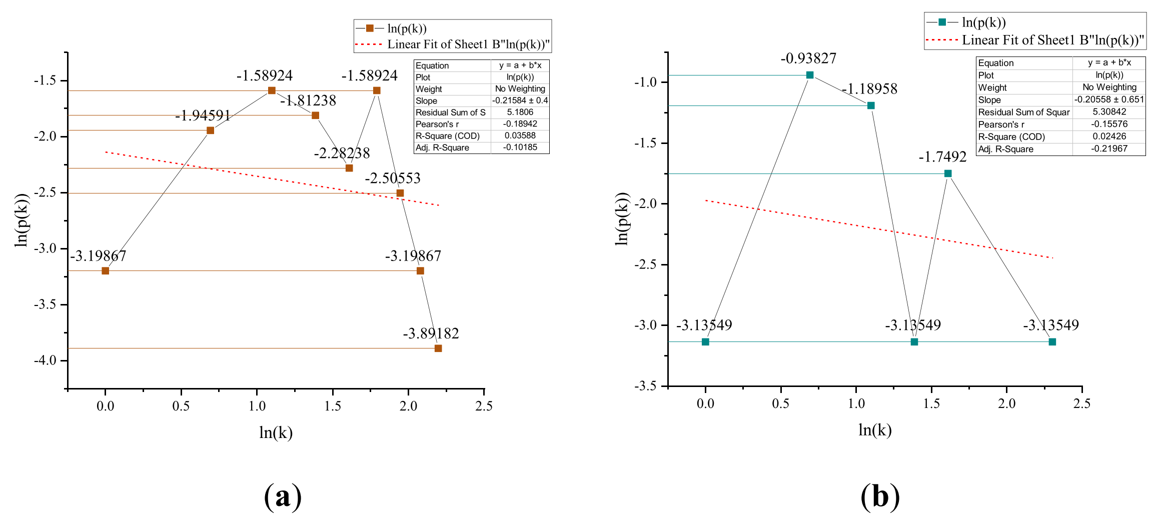

Fig. 5 **a** Free-scale detection of network node degree value in Africa. **b** Free-scale detection of network node degree value in America

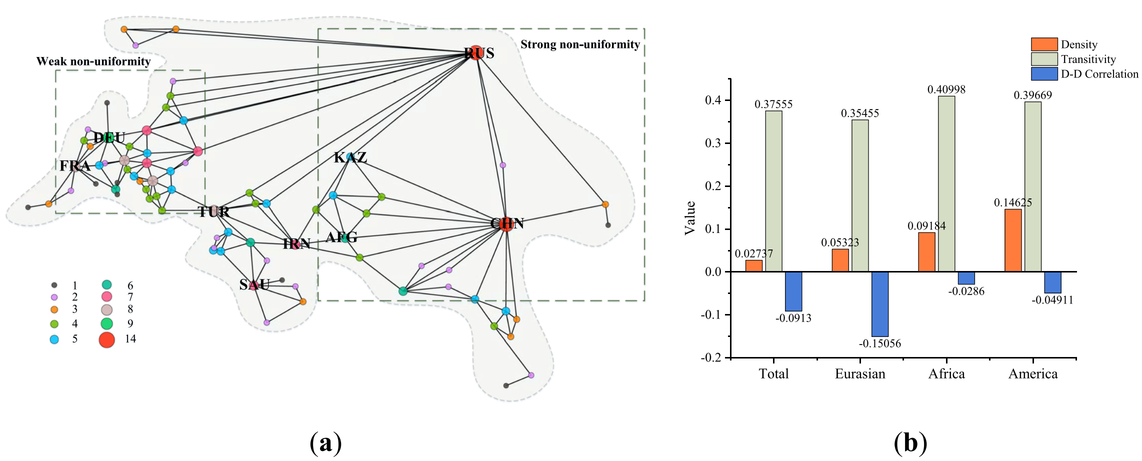

Fig. 6 **a** Diagram of hierarchical display of network node degree value. **b** Comparison of network structure indicators

Figure 6b shows an analysis of network structure indicators for various network models. The transitivity of each region ranges from 0.35 to 0.41, with Africa having the highest transitivity. Differences in terrain and transportation modes appear to have no significant impact on exchange transmission among countries within each continent. The TAN density increases in the order of Total, Eurasia, Africa, and America, with America having the highest density value of 0.14625 due to the relatively smaller number of countries in the region. The Eurasian region exhibits the highest degree correlation, while Africa shows almost zero degree correlation, suggesting weaker non-uniformity and a more regular topology for the Africa TAN.

In terms of geographic and network perspectives, the Eurasian region has the largest land area globally, but it does not have the highest network density or transitivity. On the other hand, Africa, which comprises one-fifth of the global land area, exhibits high transitivity and low heterogeneity due to the even distribution of nodes and complete connections between countries. The absence of extremely large countries in Africa contributes to its better structural connectivity.

Statistical Characteristics of Node Indicators

In terms of regional differences, the Eurasian TAN exhibits a scale-free structure, while the Africa and America TANs do not, indicating a "core–edge" structure in the Eurasian terrestrial adjacency relationships. We explore the geographic characteristics of network nodes by ranking node indicators according to their respective regions and using box plots to depict the data, which offers stability in describing the discrete distribution of data while avoiding the impact of outliers. Table 4 presents the calculation of network indicators for different regions based on the division outlined in the "Data Description and Network Model Generation" section. The countries in the table are the top five countries for this indicator.

Combining Table 4 and Fig. 7, we will explore the differences of each indicator in different regions. There are several conclusions:

The degree value refers to the number of neighbors of the countries. The Eurasian TAN's degree box plot range is 9 at the upper edge and 1 at the lower edge, with a mean value of 4.1, which is consistent with the overall network. Though the Africa TAN box size is consistent with the total TAN,

Table 4 The top five countries in each indicator by subregion

Indicator	Area	Countries
Degree (degree centrality)	Eurasia	Russia, China, Germany, Austria, France
	Africa	Democratic Republic of the Congo, Tanzania, Zambia, Algeria, Mali
	America	Brazil, Argentina, Bolivia, Colombia, Peru
Betweenness centrality	Eurasia	Russia, China, Poland, Turkey, Germany
	Africa	Niger, Democratic Republic of the Congo, Chad, Central African Republic, Mali
	America	Colombia, Panama, Costa Rica, Nicaragua, Brazil
Closeness centrality	Eurasia	Russia, Poland, Ukraine, China, Azerbaijan
	Africa	Chad, Central African Republic, Sudan, Niger, Democratic Republic of the Congo
	America	Colombia, Panama, Brazil, Costa Rica, Peru
Eigenvector centrality	Eurasia	Russia, Poland, Ukraine, China, Azerbaijan
	Africa	Democratic Republic of the Congo, Tanzania, Zimbabwe, South Sudan, Uganda
	America	Brazil, Bolivia, Argentina, Peru, Colombia

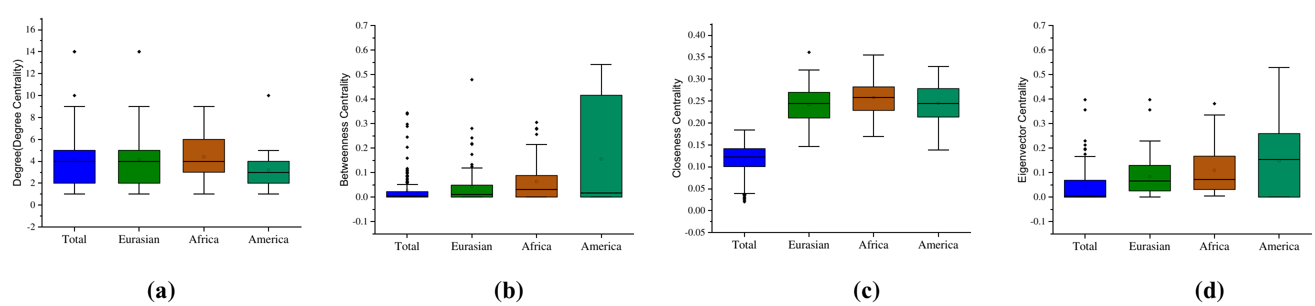

Fig. 7 Statistical distribution box diagram of different indicators. **a** Degree centrality. **b** Betweenness centrality. **c** Closeness centrality. **d** Eigenvector centrality

its box is slightly upward, indicating the concentration range is large compared with the total network node degree value distribution in this region. There are outliers present in both the Eurasian and America TAN, with Russia and China having a maximum value of 14. For the American TAN, Brazil has the highest value of 10, and the number of neighbors for these countries in the region is significantly different from other countries. The upper border of the data box is 5 with a lower border of 1, and the mean value is 3.2. Furthermore, the data dispersion in degree values of the American TAN is smaller compared to the Eurasian TAN. Although the degree values in the American TAN are generally smaller, the data distribution is more complete.

In terms of node betweenness centrality, Eurasia and Africa have more outliers with high values, such as China and Poland in Eurasia and Niger and Congo (DRC) in Africa. When considering the geographical location of each country, it is found that these countries have a strong transmission effect within their respective regions. Compared to these countries, Fig. 7b demonstrates that in the American region, the box volume is quite large, and the lower border overlaps with the minimum value. This overlap indicates that the intermediary centrality value of nodes in the Americas is more discrete, and the node delivery in this region is quite diverse.

Regarding the closeness centrality, it can be observed from Fig. 7c that some nodes in the total box plot are located beyond the observation range, below the lower border. Among the nodes located at the bottom of the numerical ranking are Canada, the United States, Belize, Mexico, and El Salvador, all of which belong to the American region. These observations can be attributed to the fact that the TAN of the American region is not connected to other networks, which has geographical implications for closeness centrality. The differences among the three regions were not significant, and the effect of data dispersion was more or less the same. Furthermore, it is worth noting that Russia, being an outlier of the Eurasian TAN, has many adjacency relations with neighboring countries due to its vast territory. In theoretical conditions, Russia has become the most accessible country to other nations.

The eigenvector centrality measure posits that the importance of a node depends on both the number of its neighbors and the importance of each neighbor node. In this study, the calculation method used considers that countries with larger degree values are of high importance. As shown in Fig. 7d, outliers in the Eurasian region include Poland, Belarus, Ukraine, and Kazakhstan, which are neighbors of Russia and China. Meanwhile, in the Americas, the data mean is below the median, indicating low eigenvector centrality in most of these countries. Furthermore, the United States has a low eigenvector centrality value, primarily because it does not have a large connectivity value. However, this observation contradicts the true importance of the United States, which should be given special attention in subsequent TAN studies.

Indicator Direction Distribution

This section investigates the spatial directionality of network indicators by plotting their directional distribution using standard deviation ellipses. The directional distribution reveals geographic features' discrete ranges and directional trends, and it is created from specified data. ArcGIS is used for spatialization mapping. The graph is first filled based on the degree value of each country, and the color is set to reflect five levels of natural grouping. Next, the directional distribution of six network metrics degree value, degree centrality, cluster coefficient, closeness centrality, node betweenness centrality, and eigenvector centrality is displayed with a 1 standard deviation ellipse. Figure 8 shows the result of this analysis.

Figure 8a shows the distribution of indicator directions under the entire region. With the exception of the eigenvector centrality error ellipse, the indicator error ellipse expands along Eurasia towards Africa and points towards South America. This indicates that the country degree distribution, degree of clustering, and ease of access to other countries expand along this direction to the vertical sides. The ellipse for betweenness centrality (L5) is the smallest and encompasses northern Africa, the Middle East, and Southern Europe. This region serves as a junction connecting Europe, Asia, and Africa, and its countries have high intermediary capacity. The eigenvector centrality ellipse (L6) is elongated, covering Eastern Europe and Central Asia. Russia and China, which have a significant influence on the degree value of these countries, are adjacent to these regions.

Figure 8b reveals that the ellipses of the Eurasian TAN indicators are more concentrated on the European side and more dispersed on the Asian side. Two points should be highlighted: (1) Following the withdrawal of the African region from the study, the elliptical aggregation center of the clustering coefficient (L2) shifted to Europe and the Middle East, where many countries gathered on one side of the ellipse, while countries with large territorial areas such as Russia, Kazakhstan, Mongolia, and China were on the other side; (2) the betweenness centrality ellipse (L5) moved and rotated northwards, indicating the mediating influence of countries such as Poland, Belarus, and Turkey without the participation of the African region.

In Fig. 8c, high degree values in countries such as the DRC, Tanzania, and Zambia cause the eigenvector centrality ellipse (L6) to lean towards this area. The betweenness centrality ellipse (L5) covers countries including Niger, Chad, Sudan, South Sudan, and Central Africa. These countries serve as a central hub connecting Northern and Southern Africa and have high intermediary centrality values. The

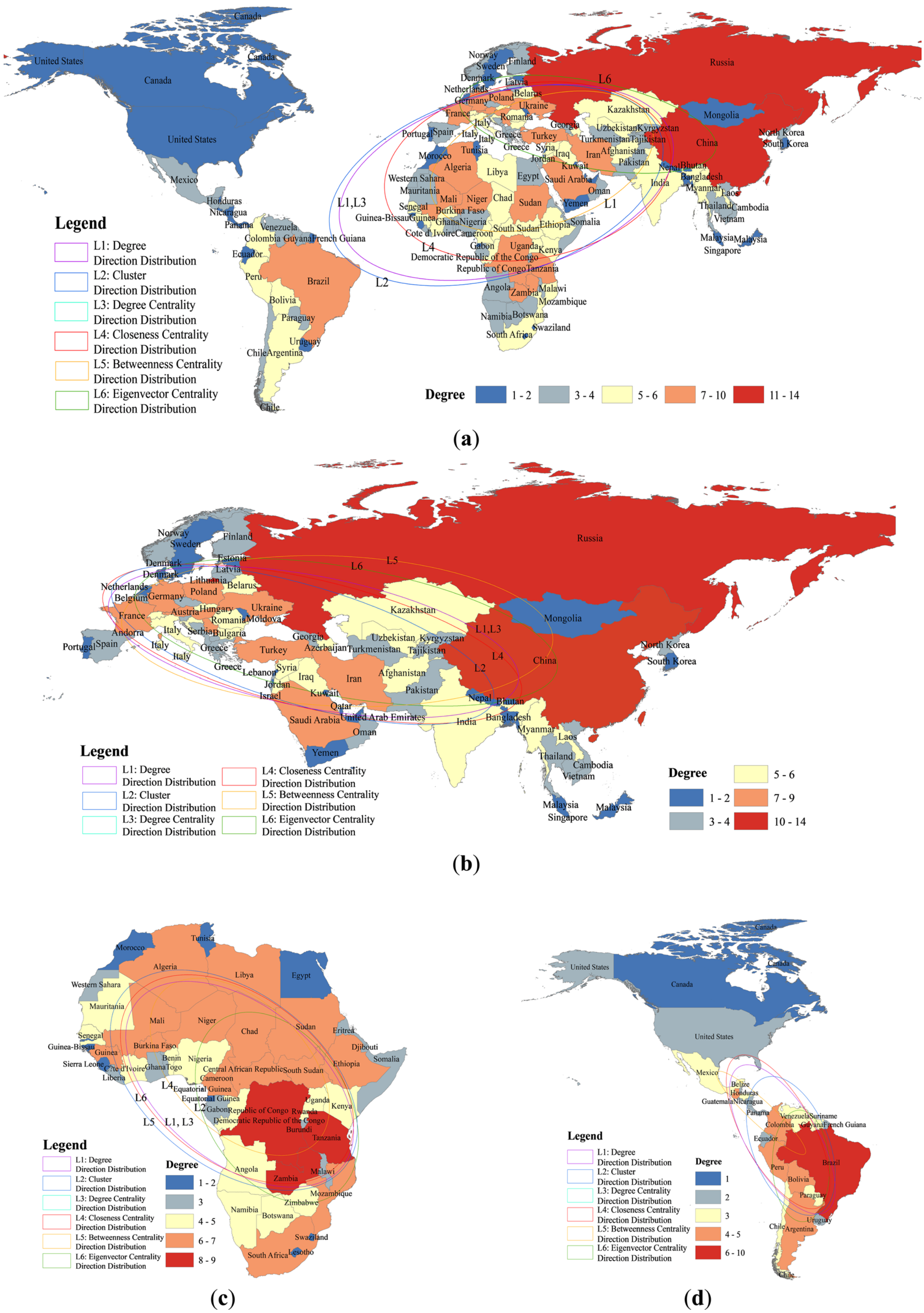

Fig. 8 The spatial direction distribution of each indicator in different regions. **a** Total. **b** Eurasia. **c** Africa. **d** America

ellipses of other indicators are relatively balanced in size and shape, in agreement with the shape of the African continent. The spatial distribution characteristics suggest that the network structure in Africa is balanced, with relatively low heterogeneity (−0.0286) in degree.

In Fig. 8d, Brazil stands out with a high degree value, and countries that connect to it most probably fall within the eigenvector centrality ellipse (L6). The betweenness centrality ellipse (L5) is narrow and links North and South America towards Costa Rica and Panama. The diagram reveals that the degree distribution, degree of aggregation, and connectivity in this area are heavily concentrated along the west coast.

Characteristics of Indicators' Spatial Clustering Distribution

Cluster analysis is a crucial data mining and law exploration method that involves dividing spatial data into regions where objects with identical or similar attributes are classified in the same set, using specialized elements and data features. In this section, we use the network indicators of each country node in the African region as weighted elements and employ the tool of Anselin Local Moran I in ArcGIS to classify clusters by identifying cases of high-high, high-low, low–high, and low-low clustering with statistical significance. Here, the confidence level of the algorithm is set to 95%, and the spatial conceptualization parameter is set to CONTIGUITY_EDGES_ONLY. The plotted thematic diagram is shown in Fig. 9.

In terms of degree value (centrality) clustering, Central Africa, which is located in the center of Africa, connects a number of highly valued countries showing high-high clustering; Algeria, which is located in the north of Africa and has the largest territory in Africa, has a high degree value, but the surrounding countries, such as Tunisia, have a small degree value, showing high and low clustering. Regarding cluster coefficients, Algeria and Tunisia correspond to low–high and high-low clustering. As for the centrality of betweenness, the countries of the central region, Niger, Chad, and Central Africa, which play a significant role in linking the east and west coasts of Africa and the northern and southern regions of Africa, show high-high clustering. Closeness centrality aspect of Central Africa to

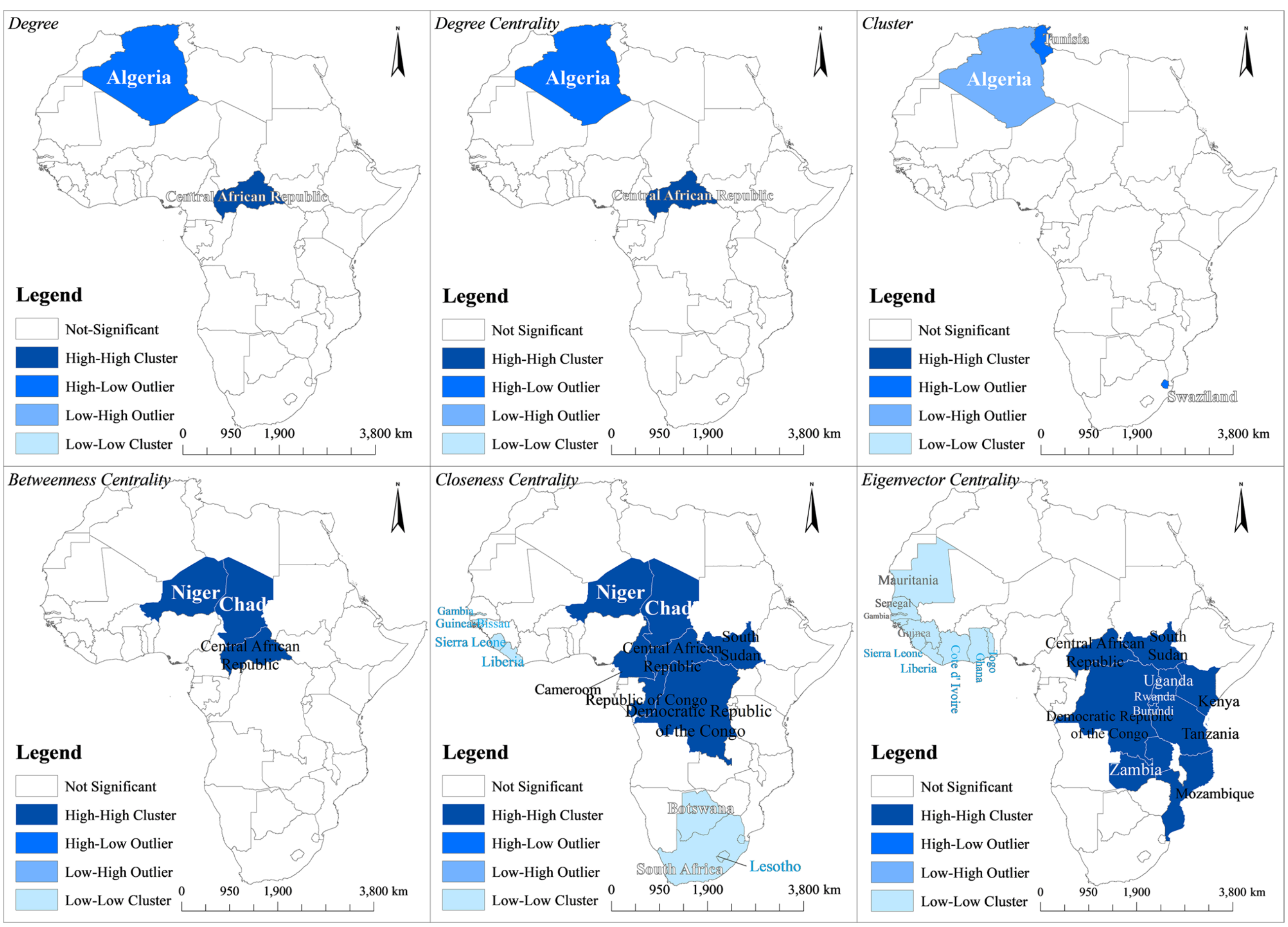

Fig. 9 Cluster distribution of different indicators in the African TAN

other regions is more convenient, showing high-high clustering; while located in the southern side of Africa, Botswana, South Africa and Lesotho in the network of limited connectivity, showing low-low clustering. Eigenvector centrality, the degree value of Central African countries is generally higher, so it presents high-high clustering; Mauritania, Senegal, Liberia, and other countries are located in the west coast of Africa around the high value of the country node is less, so it presents high-high clustering.

In the same way, we also conducted spatial clustering analysis on the Eurasian and American regions. In these regions, countries with significant territorial areas situated on the periphery of the region—such as Russia, China, and France in Eurasia and Algeria in Africa—tend to exhibit high or low clustering of degree values (centrality). In terms of cluster coefficient, we observed a tendency for high-low and low–high cluster distributions to occur in pairs, such as Mongolia and China in the Eurasian region and Tunisia and Algeria in the African region.

The clustering distribution of closeness centrality tends to be low-low in marginal areas with more homogeneous network connectivity structures, such as Yemen and Oman in the Eurasian region, the United States and Canada in the American region, and South Africa and Botswana in the African region. In theory, influential large countries tend to have large degree values, small cluster coefficients, and high intermediary centrality. The clustering distribution of complex network indicators can reveal certain geographical patterns and provide quantitative references for understanding national factors.

Terrestrial Adjacency Network Evolution Analysis

K-Shell Network Evolution

In the "Network Structure and Evolution" section, we introduced the principle and significance of k-shell analysis. To narrow the focus of our study, this section will perform KSA on the Eurasian TAN model to explore the deeper structure of adjacency networks. Using dynamic simulation with the help of Gephi software, we obtained the network evolution shown in Fig. 10.

At $k=1$, the network remains unchanged with no impact on the number of nodes and edges. The remaining 79 countries and 164 edges have a residual ratio of 100%.

At $k=2$, 70 nodes remain, a decrease of 11.39%. One hundred fifty-five edges account for 94.51%, down 5.49%. Denmark, Portugal, Monaco, Vatican, San Marino, Kuwait, Singapore, Malaysia, and South Korea exit the network structure. These countries may have a single adjacency structure or are located at the edge of the network, as indicated by the cluster coefficient distribution map.

At $k=3$, the remaining 45 nodes account for 56.96%, representing a 31.65% decrease. The remaining 108 edges account for 65.85%, a decrease of 28.66%. Countries in Northern Europe, Western Europe, South Asia, and the Arabian Peninsula withdraw from the adjacency network due to their small number of neighbors and lack of strong network adjacency support.

At $k=4$, only 13 nodes remain, accounting for 16.46% of the original network, a decrease of 40.5%. The remaining 29 adjacency relationships account for 17.68%, representing a decrease of 48.17%. Most countries in Eurasia withdraw from the k-shell range, leaving only 13 countries behind. China, Russia, Germany, Iran, Turkey, and Afghanistan form the outer ring of the network structure, while Armenia, Azerbaijan, and the five Central Asian countries form the inner ring. This forms a spatial adjacency network structure with the deepest core in the Eurasian TAN. The $k=4$ core country node network diagram is shown on the right side of Fig. 10.

Following the k-shell mining, the indicators for countries within the $k=4$ community structure are aggregated. The subgraph, consisting of 13 nodes, is considered sample data

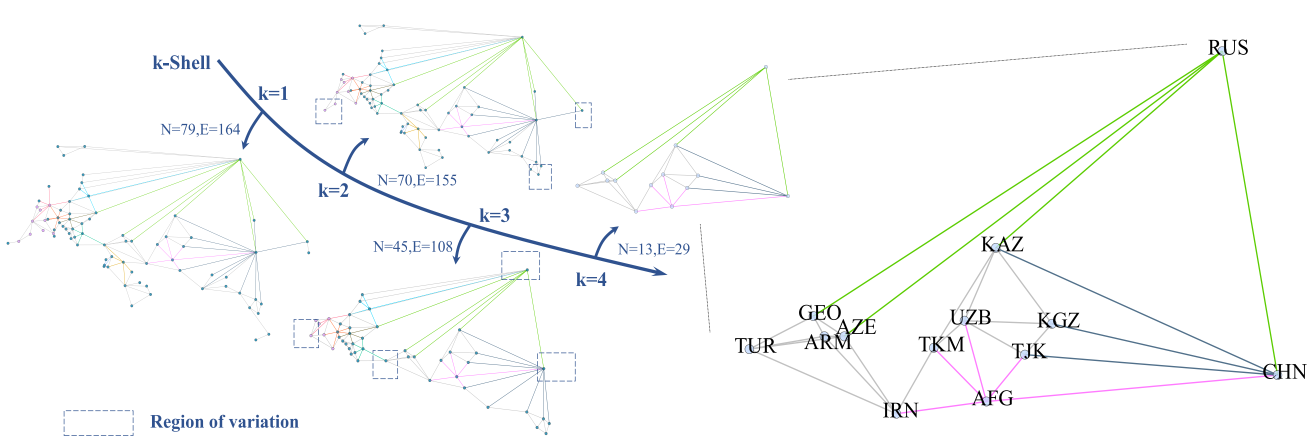

Fig. 10 K-shell network evolution process and $k=4$ country node network diagram

and compared to the overall Eurasian network of 79 nodes in terms of mean and standard deviation. The results are shown in Table 5.

It can be seen from the table that in the community space structure of $k=4$, the mean degree value of 6.462 is slightly higher than the average degree of the entire Eurasian network of 4.152, which is close to the “six-degree fractal theory” in the characteristics of the small world. The standard deviations of nodes’ closeness centrality and cluster coefficient in the subgraph are 0.030 and 0.210, respectively, with smaller data values compared to the entire Eurasian network, indicating that the two indicators fluctuate less in the community, confirming the stability of this spatial structure from the data level.

Besides, the mean value of the betweenness centrality of the sample (113.24×10^{-3}) is higher than that of the whole Eurasian network (42.66×10^{-3}), suggesting that the nodes within this structure all have high transmissibility. In terms of eigenvector centrality, the mean value of the subgraph (0.184) is much larger than the mean value of the Eurasian network (0.084). From the geographical meaning, we guess that the reason may be the community includes two countries with large degree values, China and Russia, and the eigenvector centrality of other countries is influenced by this resulting in large values, making the fluctuation of eigenvector centrality of subgraph also relatively large.

Ego Network Evolution

In the previous section, we conducted the k-shell analysis of the Eurasian TAN and obtained the network topology with the deepest core. To explore the community composition phenomenon of national nodes within the network, we will be using ego network analysis in complex networks in this section. We will analyze specific nodes and observe the laws contained in their TAN models. Four countries, France, Germany, Turkey, and Iran, were chosen for the study. Different levels of network association structures are identified based on algorithmic simulations, and the results are shown in Figs. 11 and 12.

Based on the results above, when $d=1$, Germany ($n=10$ [12.66%], $e=17$ [10.37%]) and France ($n=9$ [11.39%], $e=14$ [8.54%]) both experience comparable depth changes in the adjacency network, and the countries they are connected to remain primarily within Europe. When $d=2$, in terms of network expansion, Germany ($n=22$ [27.85%], $e=45$ [27.44%]) has better network scalability than France ($n=19$ [24.05%], $e=31$ [18.9%]), and Germany has natural conditions for expanding eastward. When $d=3$, Germany ($n=39$ [49.37%], $e=75$ [45.73%]) is readily associated with Eastern Europe, Central Asia, and even East Asia, while France ($n=39$ [49.37%], $e=75$ [45.73%]) is primarily connected to countries within Western and Central Europe.

Table 5 K-shell country node attribute statistics ($k=4$)

Country	ISO	Degree	Closeness centrality	Cluster	Betweenness centrality ($\times10^{-3}$)	Eigenvector centrality
Russia	RUS	14	0.361	0.143	479.46	0.397
China	CHN	14	0.316	0.143	280.20	0.356
Turkey	TUR	8	0.294	0.286	218.35	0.130
Iran	IRN	7	0.292	0.286	133.06	0.150
Ukraine	UKR	7	0.320	0.333	124.90	0.213
Afghanistan	AFG	6	0.283	0.400	40.34	0.176
Azerbaijan	AZE	5	0.315	0.600	89.41	0.156
Kazakhstan	KAZ	5	0.298	0.400	34.51	0.194
Georgia	GEO	4	0.310	0.667	58.34	0.134
Turkmenistan	TKM	4	0.267	0.500	9.77	0.111
Tajikistan	TJK	4	0.260	0.667	2.14	0.137
Kyrgyzstan	KGZ	4	0.245	0.667	1. 28	0.140
Armenia	ARM	4	0.265	0.833	0.36	0.098
Sample mean		6.615	0.294	0.456	113.24	0.184
Sample S.D		3.409	0.030	0.210	135.02	0.088
Overall mean*		4.152	0.242	0.531	42.66	0.084
Overall S.D.*		2.531	0.044	0.320	77.87	0.075

*The overall data here refers to the Eurasian TAN

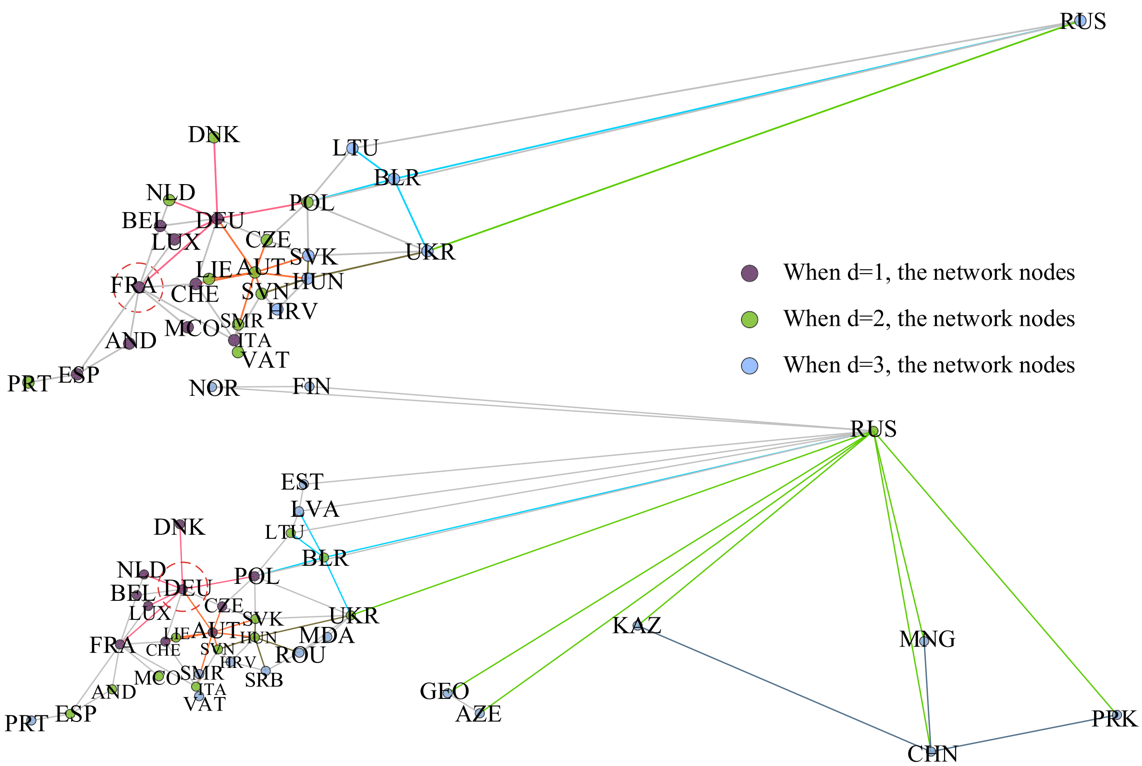

Fig. 11 Change and ego network structure of French and German nodes

Regarding Iran and Turkey, when $d=1$, they have a similar shape, connecting both eastern and western countries. The proportion of connected nodes for Iran is 10.13%, and for Turkey, it is 11.39%, with a proportion of adjacency of 7.93% and 9.76%, respectively. When $d=2$ and $d=3$, the proportion of nodes and connected edges for both countries' spatial structures are quite similar, indicating that their spatial extension characteristics are comparable. Additionally, the closeness centrality for Iran and Turkey are $C_{c\_IRN} = 0.292$ and $C_{c\_TUR} = 0.294$, respectively, and the cluster coefficients are $C_{IRN} = 0.286$ and $C_{TUR} = 0.286$, showing that their abilities to connect and aggregate with neighboring countries are relatively similar.

The main difference between Iran and Turkey is that Turkey can extend its network to Southern Europe, while Iran's network can extend to Southeast Asia, dependent on the direction of the spatial network. In terms of betweenness centrality, $B_{IRN} = 0.133$ and $C_{TUR} = 0.218$. Turkey has a higher value, indicating that Turkey performs better than Iran in terms of hub function, according to TAN analysis.

Evolution Under Node or Edge Failure

During the network evolution process, when a node fails, it can have a significant impact on neighboring countries' network indicators. For example, in Afghanistan, despite some progress in political and economic reconstruction, the security situation is still uncertain. By changing the existing attribute of Afghan nodes in the land adjacency network, we can simulate the "failure" of nodes and analyze the changes in Afghanistan's neighboring countries and network structure. After the Afghanistan node fails, the Eurasian land network has 78 nodes and 158 edges. Figure 13 shows the indicator calculations for Afghanistan's neighbors before and after the failure of the Afghanistan node.

Neighboring countries' indicators underwent four significant changes. Firstly, the degree centrality of nodes shows a downward trend when a node is missing. This is because the total number of nodes is reduced by 1, and the degree value of the surrounding country also decreases. Secondly, Pakistan's indicator decreased significantly, making it more vulnerable to Afghanistan's cluster than other countries. Tajikistan, Uzbekistan, and China, however, remained stable. Thirdly, China and Iran experienced a decline in intermediary capacity, while Turkmenistan and Pakistan showed improvement in this area according to the line graph. Finally, the indicators of closeness centrality for neighboring countries decreased, especially in Tajikistan, indicating a high reliance on Afghanistan as a gateway for communication with the rest of Eurasia compared to other neighbors.

By performing "nodal failure" simulations, we can identify alternative countries for certain indicators in land-based adjacency. For instance, we can use the change in betweenness centrality to determine that if the Afghan

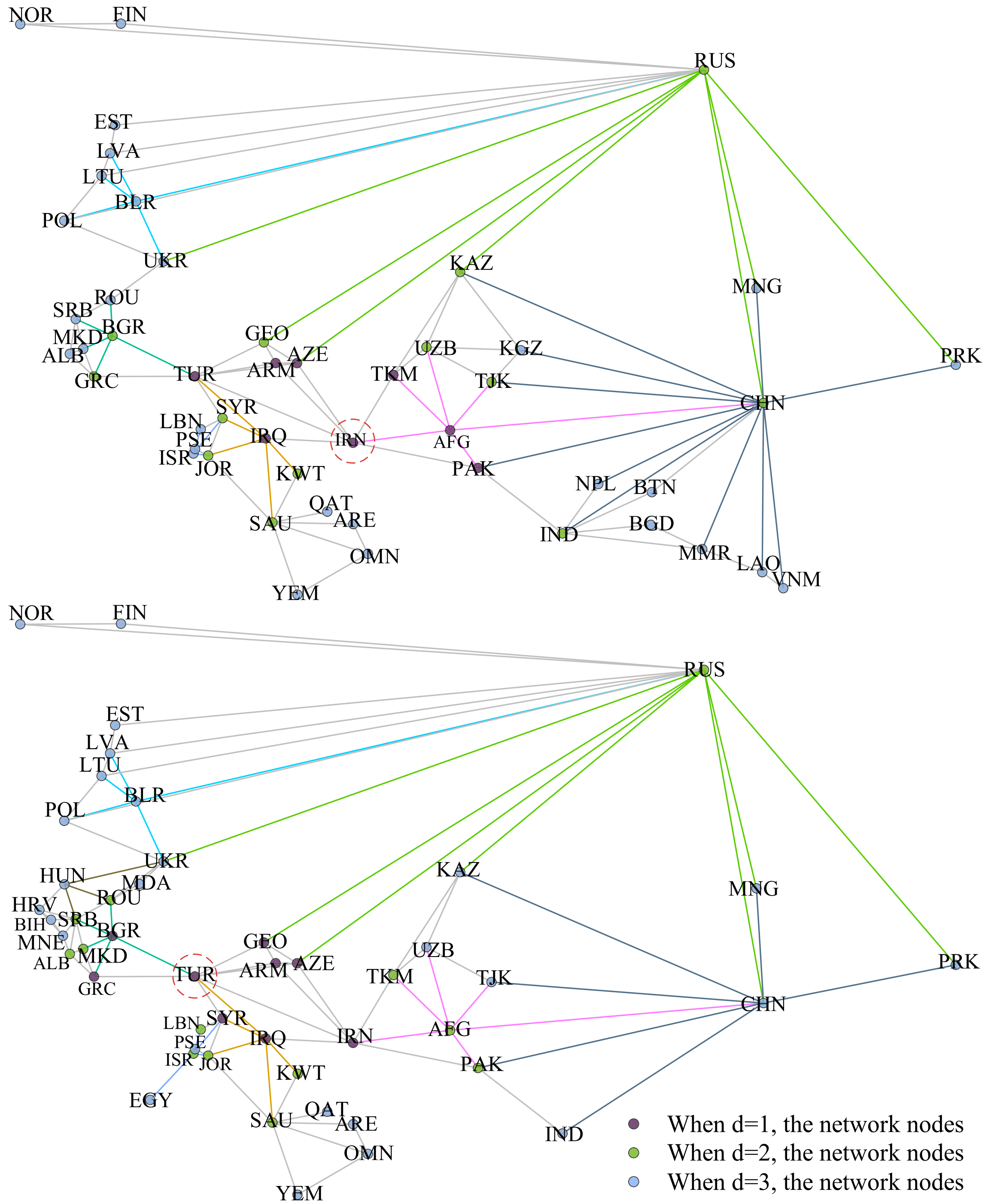

Fig. 12 Change and ego network structure of Iranian and Turkish nodes

node is "unblocked," Pakistan and Turkmenistan can be used as alternative transit countries. Moreover, Pakistan exhibits greater capability in assuming substitution than Turkmenistan.

In the case of the Russia-Ukraine conflict, on 22 February 2022, the Russian Federation Council passed a resolution allowing the Russian President to use the armed forces outside Russia, marking the beginning of hostilities between Russia and Ukraine. Figure 14 shows the calculations made by Russia's neighbors and Ukraine's neighbors before and after the rupture of bilateral relations on land.

For Russia's neighbors, a break in the Russia-Ukraine proximity will inevitably reduce Ukraine's centrality. In terms of cluster coefficients, the Belarus and Poland

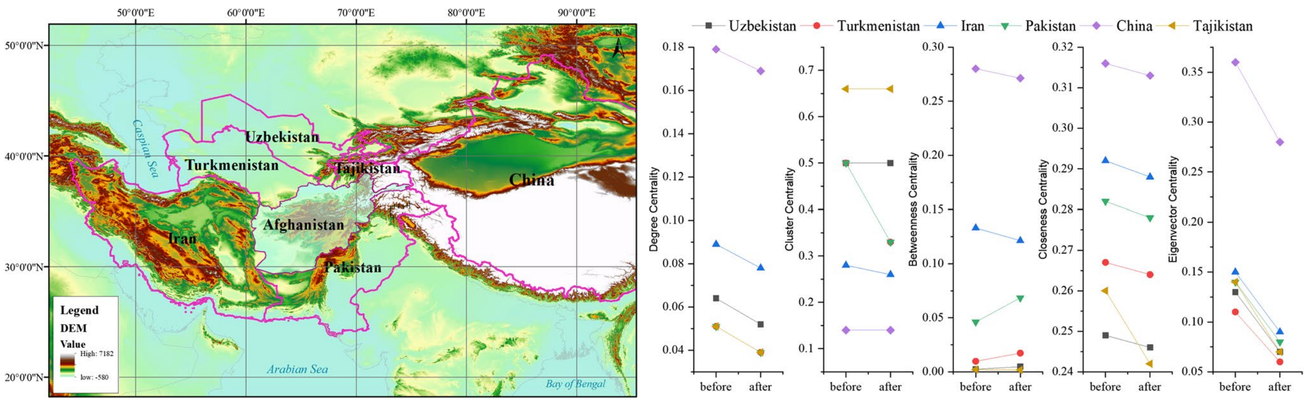

Fig. 13 Indicators change before and after the Afghanistan node fails

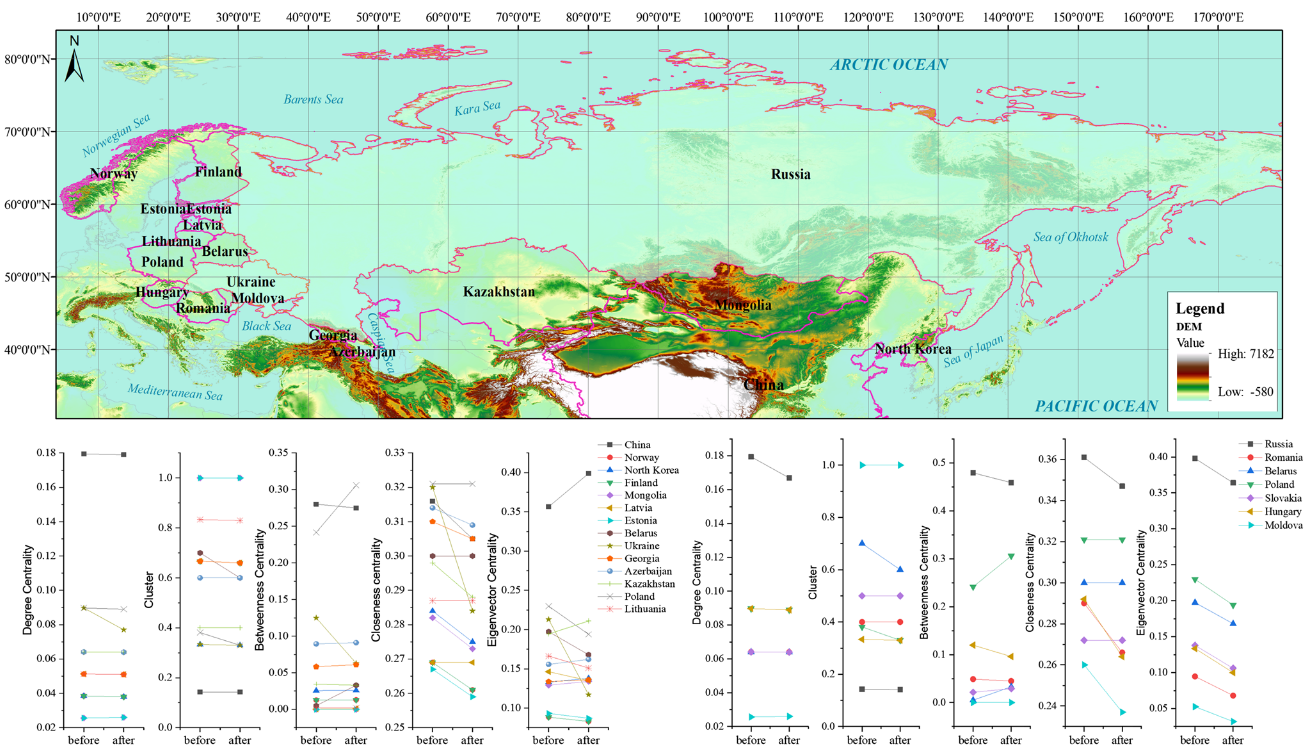

Fig. 14 Indicators change before and after the Russia-Ukraine edge fails

indicators declined because Belarus and Poland are neighbors of both Russia and Ukraine (Poland shares borders with the Russian enclave and is considered adjacent) and the adjacency structure formed is easily affected. In terms of betweenness centrality, Ukraine has seen a significant decrease in intermediary capacity, while Belarus and Poland have seen a varying degree of improvement, suggesting that Belarus and Poland can also serve as a route for Russia to Europe compared to Ukraine. China, Azerbaijan, Georgia, Kazakhstan, North Korea, Mongolia, Norway, and Estonia all have decreased their closeness centrality values compared to before, with Ukraine seeing the largest decline. This indicates that Russia has a great influence on the ability to surround land geospatial interactions, especially Ukraine, from the perspective of land-based adjacency networks.

Evolution with Attributes

As described in the "Methods" section, we consider overlaying attribute data such as roads on top of the network model to make the evolution of the network model more realistic. The evolutionary model uses data, such as closeness centrality and edge betweenness centrality, and uses it to traverse and calculate the adjacency relationship between all nodes. Figure 15 demonstrates the network accessibility after overlaying the attribute data, with thicker lines indicating greater overland accessibility between two nodes.

Remark 1 *As we expected, due to the complexity of the countries in the study region and the limited data collection capacity, there are some missing road transport coefficients and rail transport coefficients for the countries. For this problem, we averaged the available data on road transport share and rail transport share and assigned them to the countries with missing data to ensure the normal operation of the model.*

In the TAN without superimposed attributes, the top five neighboring state relationships in edge betweenness centrality B_{ij} are Poland-Russia, Russia-China, Germany-Poland, Russia-Ukraine, and Iraq- Saudi Arabia. After overlaying the land transportation attributes, the network model changes, and the top five in terms of accessibility index L_{ij}^{T} between countries becomes Germany-Poland, Poland-Russia, Germany-France, Austria-Hungary, and Russia-China.

Compared to the ranking of the B_{ij} in TAN, the L_{ij}^{T} between Poland-Russia and Germany-Poland still ranks high. Correspondingly, Russia-China, which were ranked second in B_{ij}, dropped to fifth place in L_{ij}^{T}. We hypothesize that the decline may be due to the fact that both countries are larger, weakening the ability to communicate overland between them.

In contrast, we also observe that the top ranked countries in terms of accessibility are all European countries, and the accessibility between some of them has been greatly improved, such as Germany-France and Austria-Hungary. This is likely because the European region has a well-developed system of roads and railroads, which facilitates land communication, while European countries have smaller territories, enabling better infrastructure connections.

Discussion

As O'Sullivan says, computational methods and digital data offer exciting new research opportunities across the social sciences and promise new insights (O'Sullivan and Manson 2015; Watts 2013). TANs are different from physical and virtual networks, being intermediate between the two. The nodes in TAN exist and are geographically fixed, while the edges are abstractions of national adjacency situations, rendering the network model distinct. Though the introduction of network analysis to the study of geopolitical relations is not new, incorporating terrestrial adjacency and performing spatial structure analysis is novel.

In this study, community detection in network analysis enables the induction of a "hidden order" from datasets.

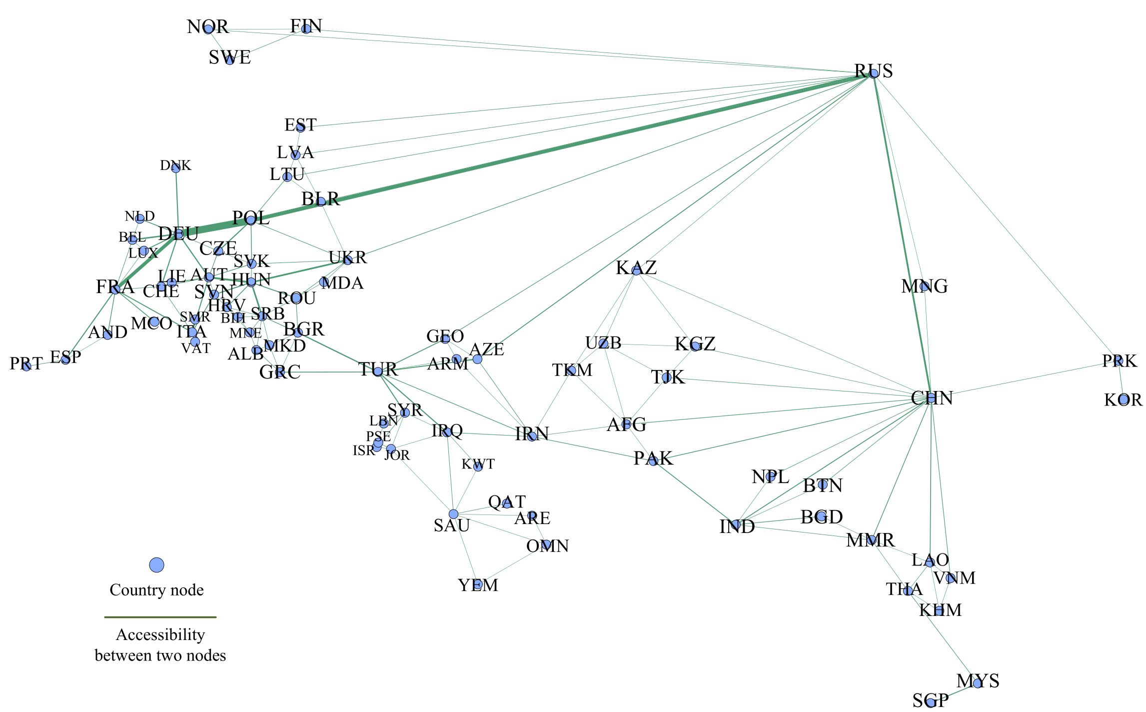

Fig. 15 The accessible network diagram with a traffic attribute network

Similar to the k-shell analysis, the final presentation of solid societies shows a strong resemblance to Brzezinski's account of the geographic situation of Eurasian countries in his noted book, *The Grand Chess Game* (Brzezinski 2016). Equally, network analysis using TAN validates some of the conclusions of qualitative analysis from a quantitative perspective, with overall convergence despite some differences. We usually refer to Turkey as the crossroads of Europe and Asia, and this fact is reinforced by the comparison of quantitative nodal indicators in the comparative analysis of the locations of Turkey and Iran.

Relatively speaking, we have made a new discovery too. In the analysis of the Russian-Ukrainian conflict, China's eigenvector centrality values increase, while Ukraine's eigenvector centrality values show a decrease. This suggests that, in response to the basic facts of the conflict between the two countries, China's influence on Russia will be even more important than other terrestrial neighbors. The "edge failure" strategy has the same effect on cluster coefficients and degree correlation indicators for two neighboring nodes but will have different effects on mediating ability and degree influence. The neighboring countries of the study will become stronger in strong indicators (e.g., eigenvector centrality of China in the Russian perspective) and weaker in weak indicators (e.g., Moldova in the Ukrainian perspective) due to "edge failure."

While our exploration of network models has delved deeper into region, direction, shape, and evolution, the scope of study and diversity of network components limit the richness of our study. We chose Eurasia for community detection and network evolution, not to diminish the importance of other networks, but because the Eurasian TAN exhibits scale-free characteristics, richer node characteristics, and complete structure and represents more significant changes.

Despite the comparative analysis above being enlightening, the study's limitation lies in the need for further cross-validation. To address these shortcomings, other studies offer potential solutions. For instance, considering trade-offs in spatial decision-making (Vahidnia et al. 2022) can aid in designing more reasonable cross-experiments. Similarly, incorporating spatial scale in disaster response (de Bruijn et al. 2017) can lead to the selection of more appropriate association analysis methods. Additionally, analyzing the spatial distribution characteristics (Adeleke et al. 2022) and influencing factors (Fang et al. 2022) of the research object can provide diverse perspectives on spatial distribution and network evolution. Furthermore, the collection of more node attribute data will be pursued. As more attributes are added and interact with each other, multidimensionality, change, mediation, and competition emerge in the network resulting in a rather complex situation. Including island countries, such as the UK and Japan, in analysis frameworks is essential for a complete simulation of the national relationship network, as they have a significant impact on Eurasian affairs despite no longer being in the Eurasian TAN. This highlights the need for a broader approach to network analysis in geography.

Conclusions

This study validates the application of complex network analysis in examining geopolitical relationships, thereby contributing to the advancement of this research field. By using complex networks to analyze geospatial structures and evolution, we can gain a deeper understanding of the characteristics, properties, and spatial changes of TANs across different continents. This includes examining their region, direction and evolution to further our understanding of complex geo-relationships.

Community detection methods, like KSA and ENA, have identified the strongest structures within the Eurasian TANs, including extended networks with one country as the central node. These discoveries offer new insights for interpreting geographic relationships and researching international relations. It provides a systematic perspective on geographical connections between land-based countries, making it a fresh addition to geographic network analysis.

In the future, understanding how networks evolve with attached properties can aid in planning infrastructure and rail transport between land-based countries. High intermediation national nodes and adjacency relationships can also guide the selection of multimodal transport sites. As network analysis gains recognition in other disciplines, geographers will demonstrate their unique strengths through its application.

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Data Availability The data are available from the corresponding author upon a reasonable request.

Declarations

Ethics Approval All ethical responsibilities for authors have been read and adhered to. The research does not involve any human participant or animal. It is strictly GIS and geospatial analysis.

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