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Assessing the network characteristics and structural effects of eco-efficiency: A case study in the urban agglomerations in the middle reaches of Yangtze River, China

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ABSTRACT

Crude economic development models create severe environmental pressures. Eco-efficiency (EE) is an important basis for evaluating ecological civilization in China. Under the national strategy of ecological priority and green development in China's Yangtze River Economic Belt, the urban agglomerations in the middle reaches of Yangtze River (UAMRYR) was considered as a case study and an evaluation index system of county EE was constructed based on multi-source remote sensing data, the EE values from 2009 to 2018 were measured by a super slack-based measure (Super-SBM) model, the spatial correlations of EE were revealed by an improved gravity model, the spatial network characteristics of EE were portrayed by social network analysis, and the nature of network effects were further explored by multiple linear regression models. Findings of the study included EE has been shown to be indeed spatially correlated.The EE of the nodes, the differences increased, the transmission pattern was relatively stable, and the association was characterized by bidirectional inequity. The spatial network of EE was characterized by small groups, whose tightness was small and increasingly loose overall, and the overall network operation efficiency is low. In terms of the spatial structure of individual network, the Degree Centrality (DC) showed the circle structure, the Closeness Centrality (CC) demonstrated 'central collapse', and the Betweenness Centrality (BC) evolved into five 'core-periphery' sub-groups from the 'circle distribution'. Regarding the structural effects, in terms of EE improvement, the UAMRYR nodes were mainly through the agglomeration effect as well as dissemination channels and spillover paths, the core nodes were self-sufficient, and the edge nodes mainly relied on, the radiation role of core nodes, the transmission role of intermediary nodes, and their own active integration and connection roles. This study provides a new perspective for understanding EE and these findings are important for promoting the synergistic improvement of green development in China and other countries.

1. Introduction

To achieve 'Carbon Neutrality' and 'Carbon Peaking' on schedule, countries around the world are actively looking for ways of greening their economic development. China is making positive attempts, where the economic focus is shifting from 'high speed' to 'high quality,' with the former blindly pursuing economic efficiency while causing ecological damage, and the latter requiring a balance between economic development and environmental protection, making it inevitable to study the harmonious relationship between the two. In academia, green total factor productivity (GTFP) (Zhang et al., 2021; You and Xiao, 2022; Lyu et al., 2022; Song et al., 2020; Li and Wu, 2017), green development efficiency (Yuan et al., 2022; Zhu et al., 2019a; Guo et al., 2020) (GDE), and eco-efficiency (EE) have been widely used to assess their relationships. In fact, the study of these indicators can, in turn, promote the green transformation of regional production methods, thus improving

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the relationship between the economy and environment. This in turn will contribute to the high-quality transformation of China. The rough economic development model of China since reform, has caused serious environmental pollution. Therefore, if the contradiction between economy and environment can be eased, it will play a pivotal role in solving the world's environmental pollution issues.

In this study, EE was selected based on the development and available data for the study area. EE is an important concept in sustainable theory and has important research value. It was first proposed by Schaltegger and Sturm (1990). After being promoted by the World Business Council for Sustainable Development (WBCSD), the Organization for Economic Co-operation and Development (OECD), and the European Environment Agency (EEA), the connotation of EE has gradually improved. EE has been recognized by almost all researchers as the ratio of the value of products and services to the ecological load, emphasizing the balance between the increment of economic output and the reduction of negative environmental output.

In recent years, some research on EE has been focusing on the connotation and measurement, spatial and temporal evolution, and influence mechanism of EE. The methods used to measure EE are mainly Data Envelopment Analysis (DEA) models (Kuang et al., 2020; Lu et al., 2018; Wu et al., 2022), with a few studies involving stochastic frontier analysis (SFA) (Deng and Gibson, 2019), ecological footprints (Gómez-Limón et al., 2012), and TOPSIS models (Cullinane et al., 2005; Reith and Guidry, 2003). The spatiotemporal dynamic evolution of EE is mainly expressed by GIS visualization tools (Huang et al., 2018; Ren et al., 2020; Wang et al., 2020a), and the influence mechanisms are mostly identified using regression models (Ren et al., 2020; Shen et al., 2021; Wang et al., 2020b).

Existing studies, from the perspectives of connotation, evaluation, and presentation, laid a solid foundation for this study. However, due to the inaccessibility of county data, the index system of EE constructed by some studies is not sufficiently comprehensive, and to a certain extent, EE cannot be measured accurately. Therefore, it is necessary to combine non-statistical data, such as remote sensing data, to enrich the evaluation index system of the county. Also, few studies have explored spatial correlations of EE in the context of the 'network paradigm'. Some scholars have made preliminary explorations of the spatial network characteristics of EE, as shown by the significant spatial association, agglomeration, and spillover effects of EE based on the spatial econometric research paradigm (Huang et al., 2018), and the spatial association characteristics of EE based on social network analysis (Peng et al., 2020; Shen et al., 2021), but until the network analysis, none of the spatial correlations were proven beforehand. In fact, the increasingly improved network of transportation infrastructure and the regional integrated development strategy have greatly promoted the flow of production factors and spatially expanded the scope of economic activities and environmental survival, making EE spatially autocorrelated, that is, the EE of each unit affects each other, showing correlations in the spatial dimension and forming a complex spatially related network structure (Peng et al., 2020; Shen et al., 2021). Consequently, the spatial network of EE needs to be examined in the following ways: (1) Is there a spatial correlation between EE? (2) What are the overall and individual network characteristics of the spatial correlation of EE? (3) What are the positions of the different individuals in the spatial correlation network of EE? (4) What are the roles of the different structural features? (5) Does the magnitude of the effect vary with the EE level? Answering these questions is of great theoretical significance and reference value for a comprehensive understanding of the spatial network and the spatial transmission mechanism of EE among individuals, grasping the direction of the synergistic development of EE, and formulating differentiated EE enhancement policies.

At present, the focus has shifted from 'efficiency to 'green efficiency,' indicating the necessity of studying the integrated effect of the economy and environment. Therefore, this study takes the UAMRYR as a case study, and the research period is from 2009 to 2018, which supplements and improves the existing research. First, the theoretical framework of EE was constructed based on the Driver-Pressure-State-Impact-Response (DPSIR) model as a basis for the evaluation index system of EE. The system is constructed using multi-source remote sensing data and then evaluated using the Super-SBM model. Second, based on the improved gravitational model, the spatial correlation characteristics of EE were revealed from the perspective of the inequality of attractiveness among subjects. Then, the network characteristics of EE were explored from the overall and individual network indicators using social network analysis. Finally, a multiple linear regression model was applied to analyze the nature of effects of the five centrality indicators on EE.

The objectives of this study were to (1) customize a new evaluation index system of EE of a county, (2) portray the characteristics of the spatial network of EE, (3) explore the nature of the individual network indicators of EE, and (4) propose synergistic improvement strategies for EE. This study not only provides a more accurate solution to measure the EE of a county, but also compensates for the limitation that few existing studies have considered as the 'network paradigm' of EE. It can enrich the theoretical research system of EE in terms of research unit, research perspective, and research content to provide a reference for decision making to improve EE.

This document is organized as follows: Section 2 presents the theoretical framework of EE. Section 3 introduces the study area, the methodology, and the data sources. Section 4 analyzes the spatial network characteristics and the structural effects of EE. Section 5 discusses the study's main content, policy implications, limitations, and future work. Finally, Section 6 summarizes the study.

2. Theoretical framework construction

From the definition and connotation of EE, the allocation efficiency of resources is reflected (Huang et al., 2018), focuses on the simultaneous growth of environmental and economic benefits rather than reducing environmental pollution alone, emphasizes the adaptation of environmental impact and resource utilization to the regional carrying capacity rather than the single adjustment of resource allocation rate, and is an important indicator for assessing whether the economy, resources, and environment are in harmony and symbiosis (Ren et al., 2020). Therefore, EE can be considered as a complex system with resource elements as inputs and economic benefits and environmental impacts as outputs. Academically, the DPSIR model is often used to construct theoretical frameworks for complex systems. The DPSIR model, proposed by the European Environment Agency (EEA), is both scientific and rational and aims to solve environmental and resource management problems. It is a synthesis of Pressure-State-Response (PSR) and Driver-State-Response (DSR) models (He et al., 2022), and is now widely used in sustainable development research fields such as resource management, environmental control, and ecological evaluation. Within this model, not only can the inter-relationship between economic activities and environmental quality be objectively revealed, but an autonomous and active system feedback mechanism can also be constructed to drive the system to function properly.

Therefore, by combining the definition and connotation of EE, a theoretical framework for EE with the DPSIR model was constructed (Fig. 1). The proper function of complex EE systems involves three aspects: resource inputs, economic benefits, and environmental impacts (Ren et al., 2020). Among these, resource inputs are the necessary basic conditions. In addition, labor and capital are used as input factors in the Cobb-Douglas production function. However, additional factors such as energy inputs as well as scientific and technological inputs are required to satisfy the production of consumption-oriented goods and services (Chen et al., 2020). Economic efficiency refers to the economic value derived from the transformation of products and services, which is usually reflected in the GDP. The environmental impact is usually characterized by 'three waste' emissions and PM2.5, which is also one of the indicators used to assess environmental quality.

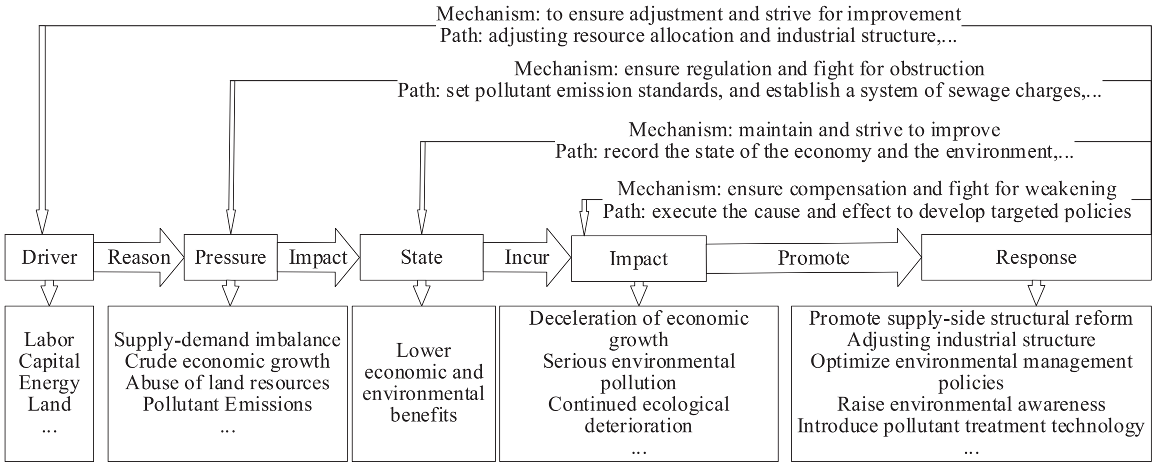

Fig. 1. Theoretical model of EE based on DPSIR model.

In the DPSIR model, EE is primarily used to reveal the coordination and constraint relationships between economic activities and environmental quality. Under the principle of circular cumulative causality, labor, capital, energy, and science and technology inputs as potential variables are the driving forces affecting EE (D). And if the regional economy grows in a sloppy manner, land resources are misused, and 'three waste' emissions exceed the standard, it will put pressure on green economic growth and environmental sustainability (P). In turn, shocks and perturbations will be generated to the state of the economy-environment binary system (S). At this moment, changes in EE will be lead due to the changes in the internal structure and state of the binary system, with positive or negative effects on economic contribution, land use, resource recycling, and atmospheric pollution (I). As a result, to reduce the negative impact and perpetuate the positive effect, each stakeholder is bound to take the initiative and adopt appropriate measures to promote and maintain the benign harmony between the economy and the environment (R), such as supply side structural reform, formulation of carbon tax and carbon trading policy, improvement of the environmental investment model, improvement of pollutant treatment technology, and raising awareness about environmental protection among the citizens. Finally, driven by these positive responses, the circular feedback effect will promote a virtuous cycle of EE by reconfiguring and integrating the internal elements of 'drivers, pressures, states, and impacts'. In this study, led by the goal management theory, the feedback mechanism and feedback paths under the effect of positive response are further summarized to enrich the DPSIR model of EE (Fig. 1).

In this study, EE, constructed using the DPSIR model, was considered to be a complex system. EE tends to be safe and smooth, spiraling only by enhancing economic and social benefits while balancing resource consumption, reducing environmental pollution, and relieving ecological pressure (Ren et al., 2020). The evaluation index system of EE is constructed based on input–output theory, which is consistent with most studies. On the input side, resource, land, capital, and labor inputs were used as input indicators in the DPSIR model, expressed as the energy consumption index, construction land area, arable land area, fixed asset investment, and total population at year end, respectively. Economic output (consensual) and environmental output (non-consensual) were used as output indicators, where GDP was chosen as the consensual output to reflect economic benefits, and annual average concentration of PM2.5 was used as the non-consensual output indicator (Table 1). It is clear that all five states of the DPSIR model play an important role in the input–output evolution of EE.

3. Research methods and data sources

3.1. Study area

Urban agglomerations are widely recognized as important engines that drive the development of the regional economy and environment. The construction of the Yangtze River Economic Belt, which has been actively identified as a national strategy by the Chinese government, is

Table 1
Evaluation Index system of *EE*.

Type	Indicator(reference)	Data type	Data source	Data processing
Inputs	Energy consumption index (Tang et al., 2020)	DMSP/OLS Night Light Data	Data Center for Resource and Environmental Sciences, Chinese Academy of Sciences	Partition statistics summation in Arc GIS 10.8
	Construction land area (Chen et al., 2020)	Remote Sensing Monitoring Data of Land Use Status in China	Geographical State Monitoring Cloud Platform	Area tabulation in Arc GIS10.8
	Arable land area (Chen et al., 2020)			
	Fixed asset investment (10,000 yuan) (Zhang, 2008; Berlemann and Wesselhoft, 2014).	Statistic data	China County Statistical Yearbook, Statistical Yearbook of each city, Statistical Bulletin of National Economic and Social Development of each district and county	—
	Total population at year end (10,000 people) (Huang et al., 2018)	Statistic data		—
Consensual outputs	GDP (10,000 yuan) (Wang et al., 2020b)	Statistic data		Deflating data using 2009 as the base period
Non-consensual output	Annual average concentration of PM2.5 (Ren et al., 2020)	Aerosol inversion remote sensing data	Atmospheric Composition Analysis Organization	Partition statistics in Arc GIS10.8 to find the mean value

one of the three major regional development strategies. However, the contradiction between economic growth and environmental pollution in the Yangtze River Economic Belt is particularly prominent (Ding et al., 2019), and General Xi Jinping has repeatedly emphasized that development of the Yangtze River Economic Belt should be premised on protection of the ecological environment. Therefore, the green transformation path of the Yangtze River Economic Belt is of utmost importance in academia. The UAMRYR, as one of the core segments of the Yangtze River Economic Belt, is of great theoretical and practical significance to study the economic and environmental effects there, which is helpful for promoting the green development process of the Yangtze River Economic Belt and thus the construction of ecological civilization in China.

According to the Development Plan of Urban Agglomeration in the Middle reaches of Yangtze River, which was approved by the State Council of China in 2015, the UAMRYR (20°09′ N ~ 33°20′ N, 180°21′ E ~ 118°28′ E), has been considered to include most areas of the Jiangxi, Hubei and Hunan Provinces, as shown in Fig. 2. It is a mega city cluster formed by Wuhan Metropolis, Changsha-Zhuzhou-Xiangtan Metropolis and Poyang Lake City Group, with a land area of about 317,000 square kilometers. It is one of the three major cross-regional city clusters supporting the Yangtze River Economic Belt and occupies an important position in China' s regional development pattern.

3.2. Measurement of EE using super-SBM model

Measurement of EE is important, hence, DEA model was used to evaluate EE. DEA model, first proposed by Charnes et al. (1978), uses linear programming with multiple inputs and outputs to assess the relative effectiveness of comparable units of the same type. It has absolute advantages in dealing with the effectiveness evaluation problem of multiple outputs and inputs (Wu et al., 2018), and is widely used to measure EE.

The DEA model contains both radial and non-radial metrics. The efficiency measures for radial features are represented by the Cooper-Charnes-Rhodes (CCR) model (Charnes et al., 1978) and the Banker-Charnes-Cooper (BCC) model (Banker et al., 1984), while the efficiency measures for non-radial features are represented by the slack-

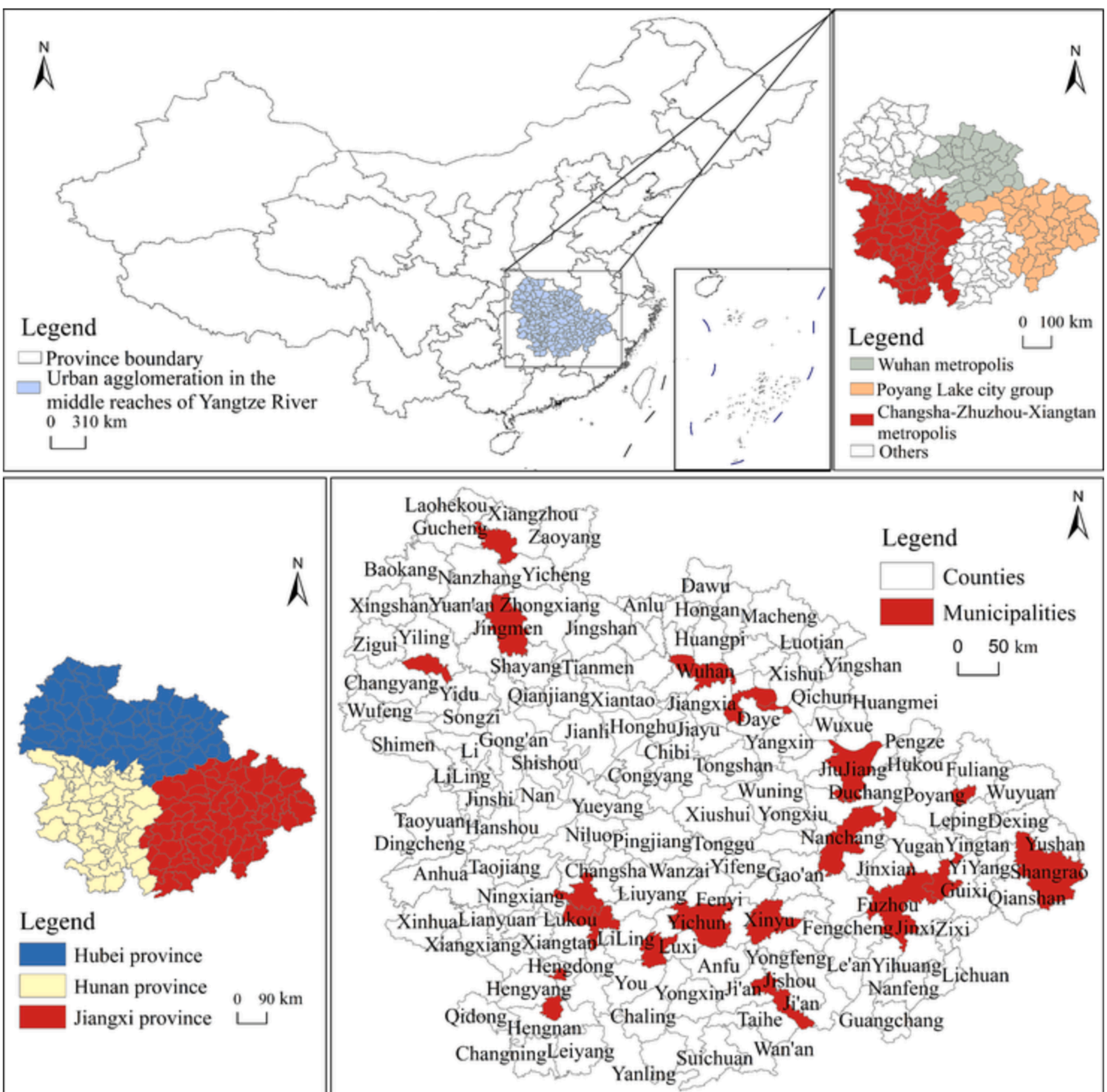

Fig. 2. The UAMRYR in China.

based measure (SBM) model (Tone, 2001). Although these two metrics are widely used, they have been shown to still have shortcomings. To overcome the shortcomings of both metric models, the super slack-based measure (Super-SBM) model containing non-consensual output terms, constructed by Tone and Tsutsui (2010), can effectively avoid the constraints of strict assumptions such as radiality, and thus accurately distinguish the magnitude of efficiency values of effective decision units, making the evaluation results more realistic and widely favored by scholars. In this study, the Super-SBM model was used to measure EE and the specific model was as follows:

$$\min\rho = \left[1+\frac{1}{m}\sum_{i=1}^{m}s_i^-/x_{ik}\right]\Big/\left[1-\frac{1}{s}\sum_{r=1}^{s}s_r^+/y_{rk}\right]$$
$$\sum_{j=1,j\neq k}^{n}x_{ij}\lambda_j - s_i^- \leqslant x_{ik} \tag{1}$$
$$\sum_{j=1,j\neq k}^{n}y_{rj}\lambda_j + s_r^+ \geqslant y_{rk}$$
$$s_i^-, s_r^+, \lambda_j \geqslant 0$$

where ρ denotes the EE value of each county; x and y are the input and output ensembles of EE, respectively; s_r^+ and s_i^- are the expected and non-expected output slack, respectively; and λ_j is the weight vector.

3.3. Evaluation of the network

3.3.1. Test of spatial association

The premise of spatial network analysis is the existence of spatial correlations among the study units (Tobler, 2004; Papadimitriou, 2022). EE has been shown to be spatially correlated (Huang et al., 2018; Ren and Fang, 2017; Zhang et al., 2022a). Consistent with the established syudies, to test whether there is spatial correlation in the counties EE in the UAMRYR, the global Moran's I index, which is widely made in the empirical analysis, is chosen to be measured with the following formula (Elhorst, 2012).

$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(x_i-\overline{x})(x_j-\overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\sum_{i=1}^{n}(x_i-\overline{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(x_i-\overline{x})(x_j-\overline{x})}{s^2\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}} \tag{2}$$

Where $s^2 = \sum_{i=1}^{n}(x_i-\overline{x})^2/n$ is the sample variance, $\overline{x} = \sum_{i=1}^{n}x_i/n$ is the sample mean of x_i or x_j, n is the number of samples, x_i and x_j represent the EE of i and j, respectively, and W_{ij} is the spatial weight matrix. Consistent with the established syudies (Huang et al., 2018; Ren and Fang, 2017; Zhang et al., 2022b), the economic geographic distance spatial weight matrix was used.

3.3.2. Construction of the spatial network matrix

The Granger linear causality test, Granger non-linear causality test, and gravity model are mostly used to construct a spatial network association matrix. It has been believed that the former two are slightly inadequate in terms of measurement accuracy and dynamic evolution (Zipf, 1946), and advocate the use of the gravity model to construct spatial network correlation matrices. In general, the gravity model is used. However, inter-regional interactions are bidirectional and asymmetric (Peng et al., 2020), i.e., the inter-subject attraction possesses inequality. Consequntly, this fact is ignored by the traditional gravity model when exploring correlations. To this end, to be consistent with established research, an improved gravity model was adopted to construct a spatial network association matrix of EE in this study. The specific formula is shown in Equation (3) (Russon and Vakil, 1995).

$$F_{ij} = K_{ij}\frac{\sqrt{E_iA_i}\sqrt{E_jA_j}}{D_{ij}^2}, K_{ij} = \frac{E_i}{E_i+E_j} \tag{3}$$

where F_{ij} is the gravity strength of the EE of the two units; K_{ij} denotes the gravitational coefficient; E_i and E_j represent the EE of units i and j, respectively; D_{ij} denotes the spherical distance between units i and j; A_i and A_j denote the GDP per capita of units i and j, respectively.

3.3.3. Analysis of the spatial network characteristics

The association relationship and structure among all nodes in the network are analyzed through the overall network indicators, including the density, average clustering coefficient, statistical inference coefficient, and average shortest path. The status and role of each node in the association network are revealed through the individual network indicators, which mainly includes Degree Centrality (DC), Closeness Centrality (CC), and Betweenness Centrality (BC) (Freeman et al., 1979). The calculations and descriptions of the overall and individual networks indicators are presented in Table 2.

3.3.4. Analysis of the structural effects

In this study, social network analysis tools were employed to portray the overall network characteristics and individual network attributes of EE, but the nature of each network indicator of EE could not be explored. Therefore, first, the core degree indicator in the Ucinet software was used to divide the UAMRYR into core and peripheral areas, and then the multiple linear regression model was chosen to investigate the properties of the network indicators of EE in the UAMRYR area, core area, and peripheral area, respectively.

4. Results

4.1. Adaptation verification of the evaluation index system of EE and temporal evolution

First, the R-value diagram of the R software was used to verify the rationality of the evaluation index system of EE and the adaptability of the corresponding indices in this study (Fig. 3). As observed in Fig. 3, although the R-values of the two years with larger time intervals were smaller, almost all the R-values were above 0.80, and those between most of the years were greater than 0.90, indicating that the evaluation index system of EE is adaptable and can respond well to the EE characteristics of the counties in the UAMRYR.

Second, the grouped graphs, produced by of the Origin Pro software, were used to analyze the time-series characteristics of EE (Fig. 3). It can be seen that the values of EE of most counties in the UAMRYR are lower than 0.071. With time migration, closer the value of EE is to 0.122, greater is the number of counties. In addition, the EE values of several counties are much higher than others, and the overall level of EE has improved but the difference between counties has been increasing. This may be because the economic development approach has been influenced by the innovation-driven model, which has improved overall environmental and economic benefits (Guo et al., 2020). However, different counties have different degrees of utilization of policy advantages such as 'green development' and 'ecological priority'. Some counties are able to take the lead and respond positively, while some do not have the transformation characteristics, which to a certain increases the spatial differences in EE (Ren et al., 2020).

4.2. Results of test of spatial association

The results of the global Moran's I index, which was used to measure the spatial association of EE, were derived by the stata software (Table 3). In Table 3, the values of global Moran's I index are all significantly positive, indicating that there is spatial association of EE in the counties of the UAMRYR, and the spatial network characteristics of EE can be further explored.

Table 2
Explanation of main indicators for characteristics of spatial correlation network of EE.

Indicator		Equation	Implication
Overall network indicators	Density	$d(n) = l/n(n-1)$	It is the ratio of the actual number of relations to the total number of theoretical maximum relations. It reveals the sparsity of the relationships among nodes.The larger the value, the stronger the association between the nodes.
	Average clustering coefficient	$C(n) = \sum_i^n C_i/n = \sum_i^n \frac{2E_i}{k_i(k_i-1)}/n$	It indicates how the nodes are embedded in the neighboring nodes, reflecting the degree of clustering in the network and showing the 'small world' effect. The larger the value, the more obvious the agglomeration characteristics.
	Average shortest path	$L(n) = 2/n(n-1)\sum_{i\neq j} d_{ij}$	It reflects the overall operation efficiency of the network. The smaller the value, the higher the network operation efficiency and the better the connectivity.
	Statistical inference coefficient		It checks whether there are cliques in the network. The larger the value, the more pronounced the degree of differentiation; the smaller the value, the more pronounced the agglomeration feature.
Individual network indicators			
	Degree Centrality (DC)	$D_i = \sum_j R_{ij}/n-1 + \sum_j R_{ji}/n-1$	It is the ratio of the number of direct associations with a node to the total number of nodes with the maximum possible direct associations. The higher the value, the stronger the control ability of a node over other nodes. Rij and Rji denote the DC-in and DC-out of node *i*, respectively. The larger the Rij, the stronger the agglomeration ability of node *i*, and the larger the Rji, the stronger the radiation ability of node *i*.
	Closeness Centrality (CC)	$C_C = \sum_{j=1}^n d_{ij}$	It represents the sum of shortcut distances between a node and other nodes in the network. The higher the value, the shorter the distance between nodes and the stronger the association and synergy. It is divided into CC-in and CC-out. CC-in represents the sum of shortest paths from other nodes to the node; CC-out represents the sum of shortest paths from the node to other nodes.
	Betweenness Centrality (BC)	$C_B = 2\sum_j^n\sum_k^n b_{jk(i)}/n^2 - 3n + 2,\ b_{jk(i)} = g_{jk(i)}/g_{jk}$	It reflects whether the node has a mediating role. The higher the value, the more obvious the intermediary position of the node in the network.

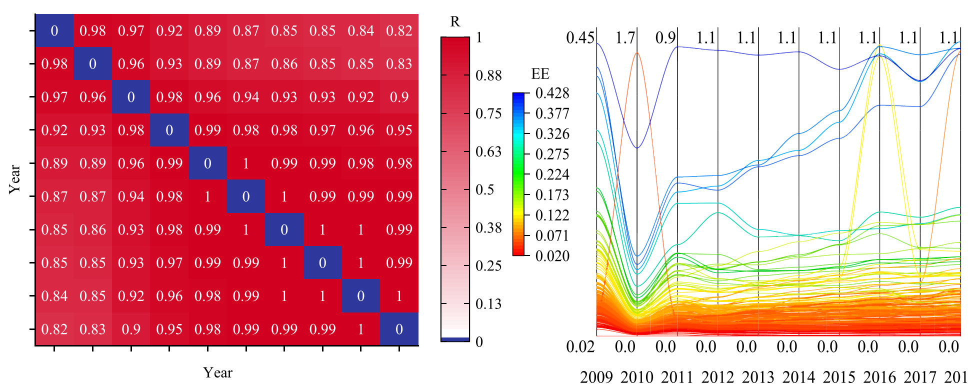

Fig. 3. Adaptation verification of the evaluation index system of EE and temporal evolution of EE in the UAMRYR (2009–2018) Note: Vertical coordinates are ordered from top to bottom for 2009–2018, and horizontal coordinates are ordered from left to right for 2009–2018. $p < 0.01$, $R > 0.60$.

Table 3
Results for global Moran's I index (2009–2018).

Time	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Results	0.085*** (11.35)	0.056*** (7.70)	0.065*** (8.84)	0.061*** (8.27)	0.065*** (8.77)	0.062*** (8.46)	0.059*** (8.12)	0.041*** (5.80)	0.061*** (8.25)	0.051*** (7.08)

Note: ***, **, * denote 1%, 5%, and 10% significance levels, respectively; t-values are in parentheses.

4.3. Characteristics and evolution of the overall network

Characteristics may be related to the direct or indirect transmission. An improved gravity model was used to explore the existence and strength of the linkages of EE in UAMRYR, and the Arc GIS10.8 tool was used to visualize the gravitational strength of EE in 2009, 2014, and 2018 respectively (Fig. 4).

As shown in Fig. 4, (1) the transmission pattern of the EE is relatively stable at all three time points, that is, the transmission direction and key nodes do not change significantly. (2) The EE network is becoming increasingly closer, and the network structure is becoming increasingly complex, evolving from 'multi-core' to 'network'. Specifically, the gravitational values of EE are obviously increasing, the number of 'county pairs' with gravitational values greater than 1 become larger, the characteristics of network structure among counties are more significant, and the directional differences of node association are more notable. (3) The linkage of EE among counties is characterized by two-way inequality. Except for the first magnitude of gravitational intensity per year, the numbers of A-B counties are significantly larger than B-A counties, indicating that most counties influence others notably more than they are influenced. (4) Counties with larger gravitational EE values gradually cluster in the eastern part of the UAMRYR, indicating that the eastern counties play a stronger role in network association, which may be related to the fact that the Poyang Lake City Group has the lowest haze concentration among several sub-regions (Li and Luo, 2022).

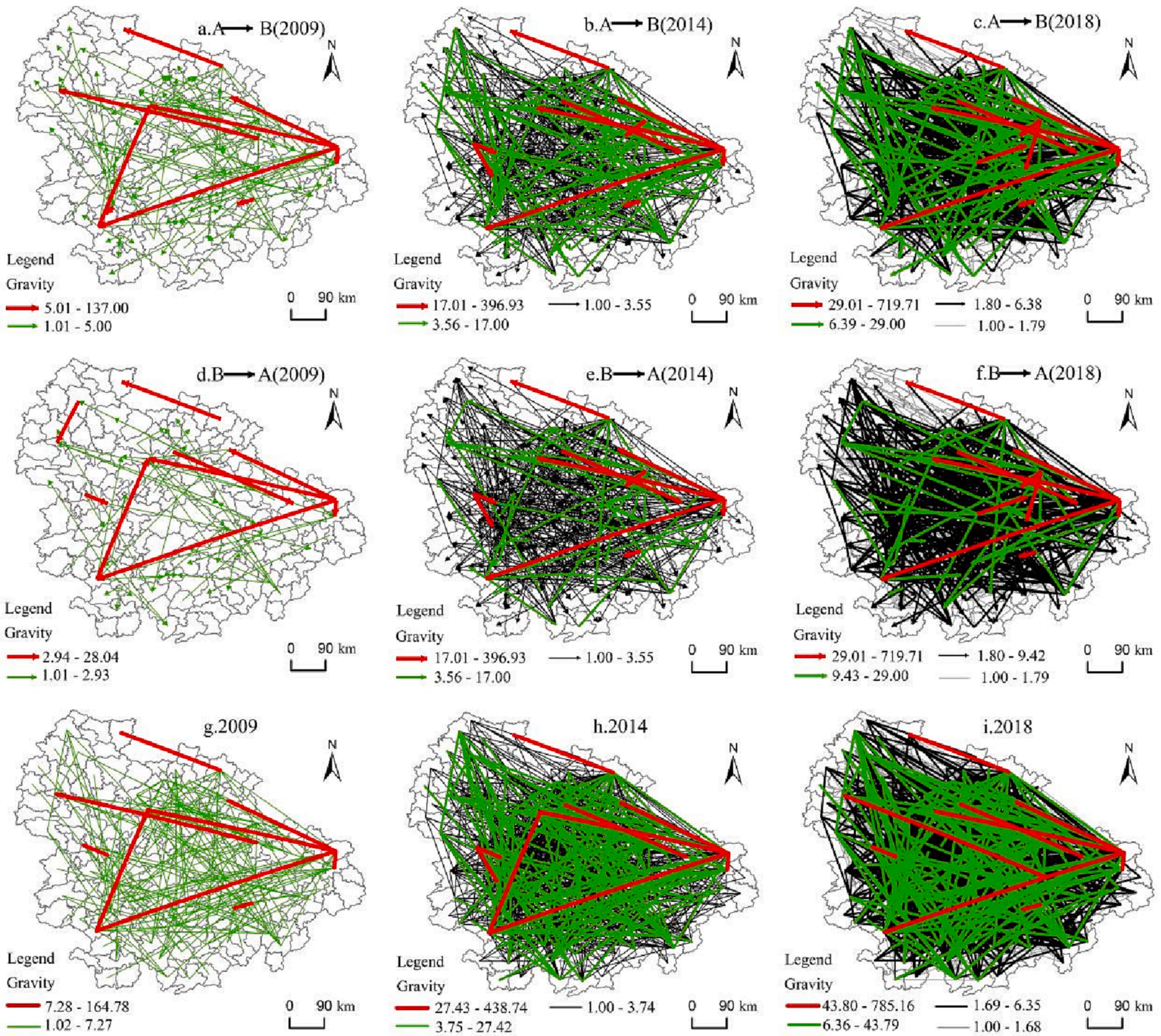

Fig. 4. Two-way spatial correlation network for EE in the UAMRYR (2000–2018) Note: ① For display purposes, only links with a gravitational value greater than 1 are shown. ② A and B reflect the difference in the direction of transmission between counties.

4.4. Characteristics of overall networks

Ucinet software and Gephi software were used to measure and analyze the overall characteristics of the spatially linked network of EE in 2009, 2014, and 2018 in terms of four aspects: density, average clustering coefficient, statistical inference coefficient, and average shortest path. Drawing on the processing methods of established studies, the mean value of each row of the matrix after removing the extreme values was used as the threshold for binarization, which was 1 if it was greater than the mean value and 0 otherwise (Liu et al., 2015). The results are presented in Table 4.

Table 4
Characteristics of the overall network of the EE in the UAMRYR (2000–2018).

Indicator	2009	2014	2018
Density	0.168	0.167	0.163
Average clustering coefficient	0.515	0.510	0.512
Statistical inference coefficient	10403.568	10421.656	10282.526
Average shortest path	2.339	2.338	2.256

From Table 4, at these three time points, the values of density were 0.168, 0.167, and 0.163, respectively, showing low tightness and small weakening of the spatial association of EE, with more 'small groups' and a hierarchical structure. In addition, the values of density were still far below 0.5, indicating that there is much room for the synergistic improvement of EE. The average clustering coefficients were 0.515, 0.510, and 0.512, respectively, which were moderate and not very different, indicating the existence of a significant clustering effect. The values of the statistical inference coefficients were 10403.568, 10421.656, and 10282.526, respectively, indicating the presence of polycentric clustering. The values of the average shortest path showed a decreasing trend, which were 2.339, 2.338, and 2.256, respectively, indicating that the connection paths between nodes shortened, the overflow channels increased, the stability of the network increased, and the operational efficiency of the network gradually improved. The reason could have been improvement of infrastructure, optimization of industrial spatial distribution, and increase in environmental constraints, which have improved the way economic activities and environmental protection work. In summary, from all four indicators, the overall spatial network of EE in UAMRYR are low in density and tend to become increasingly loose. In addition, there are many small groups, causing the direct spatial correlation of EE among nodes to be weak, and the operational efficiency is not high.

4.5. Characteristics of individual networks

Centrality is a quantification of power of each node in the network and can reveal the position and role of the nodes. DC, CC, and BC are usually used for analysis. In this study, the results of 185 counties (districts) in the UAMRYR were imported into ArcGIS 10.8 software and their spatial characteristics in 2009, 2014, and 2018 are shown in Fig. 5.

DC is divided into DC-out and DC-in. DC-out represents the diffusion effect, and DC-in represents the agglomeration effect. (1) The DC-in values are almost greater than the DC-out values, indicating that the attraction capacity is greater than the siphoning effect. In addition, the value domains of the DC-out and DC-in of the three time nodes were similarly distributed, and most values were close, suggesting that the spatial correlations of EE did not change significantly. (2) In the three time nodes, although there were some subtle differences, the nodes with high DC-in values were mainly distributed in the Wuhan Metropolis, Changsha-Zhuzhou-Xiangtan Metropolis, Poyang Lake City Group, and Jingmen-Xiangyang-Yichang City Belt, forming a circular structure. The nodes with high DC-in values are mostly concentrated in the Wuhan Metropolis and Changsha-Zhuzhou-Xiangtan Metropolis, which play a powerful role in resource absorption. In addition, there are many nodes with low DC-in values that surround the inner ring and outer edge of the area surrounded by the nodes with high DC-in values. The nodes along the outer edge are also on the periphery of the UAMRYR, which is consistent with the hypothesis of 'core-periphery' in terms of spatial structure. (3) Specifically, the number of nodes with high DC-out values gradually decreased, most of which are located in the inner ring of the area surrounded by the nodes with high DC-in values, and the spatial distribution evolved from 'relatively scattered' in 2009 to 'two major clusters' in 2018. In addition, the nodes with low DC-out values were mainly distributed in the periphery of the UAMRYR, which was also the outer edge of the area of the nodes with high DC-in values. Furthermore, nodes with high DC-out values appear in the inner ring of the enclosed area, whereas nodes with low DC-out values appear at the outer edge of the enclosed area (periphery of the UAMRYR), is that the inner link

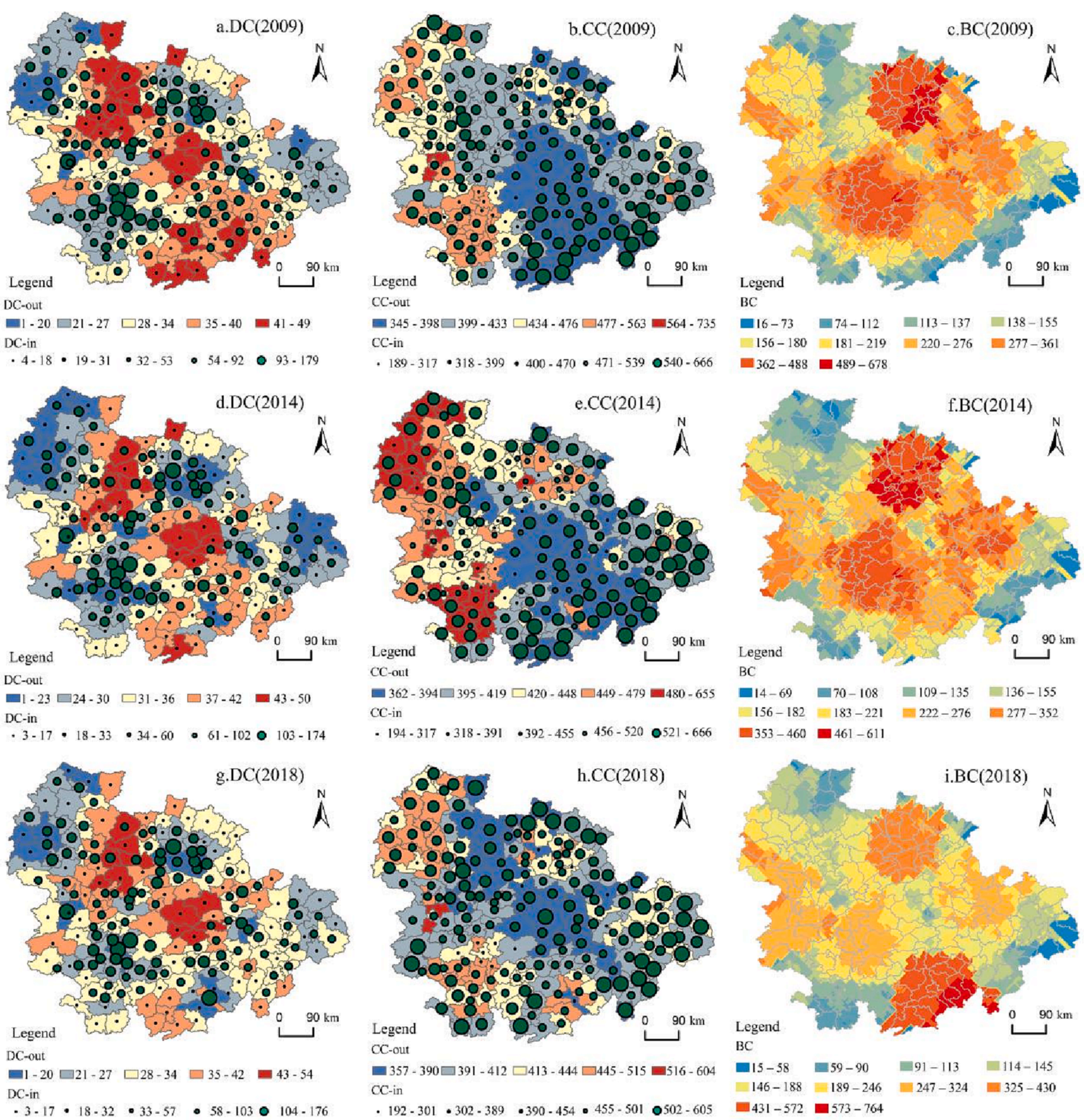

Fig. 5. Centrality analysis of inter-provincial spatial correlation of EE in the UAMRYR (2000–2018).

points are subject to the multiple effects of the three major urban agglomerations, whereas the outer edge nodes are generally subject to the effects of only a single urban agglomeration. In addition, the number of nodes with high DC-out and DC-in values both decrease, indicating that some nodes tend to equilibrate in the network game of diffusion and absorption effects. The values of DC-out and DC-in of the Poyang Lake City Group are relatively low, which may be due to the lag in economic development and the weak linkage role (Zhu et al., 2019b).

CC is divided into CC-out and CC-in. (1) For CC-out, in 2009, high-value areas were located in the northern part of the UAMRYR, and by 2018, five high-value areas were formed and the spatial gap between the nodes was reduced, all of which were located at the edge of the UAMRYR. In addition, the nodes with low values run through UAMRYR and are distributed in the periphery of the high-value areas, showing an obvious 'central collapse' feature. (2) For CC-in, the nodes with high values were distributed in the southeast of the UAMRYR in 2009, and with time migration, they expanded outward and were mostly scattered in the fringes of the UAMRYR. In addition, the number of low-value nodes was small, and they were mainly distributed in a few counties in Changsha and Xiangtan. (3) Overall, the spatial distributions of CC-out and CC-in were more coordinated in UAMRYR. In terms of spatial distribution, the nodes with high values of CC-out and CC-in are almost all distributed in the periphery of the UAMRYR, which is inconsistent with the existing studies that the nodes with high proximity to the center are generally provincial capitals or cities with developed transportation (Peng et al., 2020). This may be because small groups were formed in the peripheral areas under the four major urban agglomerations. However, the central counties in the UAMRYR are not fully integrated into any of the small groups because of the complex role of each urban agglomeration and the lack of development advantages, leading to the 'central collapse' characteristic, in which the nodes in the central region have relatively low values of CC-out and CC-in. (4) In addition, some nodes located at the periphery of the UAMRYR have relatively high values of CC-out and CC-in, indicating that their position in the network is relatively independent, and they can control both neighboring nodes and be controlled by other nodes as well.

The spatial distribution characteristics of BC were analyzed. (1) In 2009, the values of BC of the UAMRYR have obvious hierarchical differences and is circled, with the values of the BC of the Wuhan Metropolis and the Changsha-Zhuzhou-Xiangtan Metropolis being much higher than other regions. And the nodes with high BC values have higher intermediary regulation and resource control ability and are in a monopolistic position. (2) In 2014, the number of nodes with high BC values not only expands in Wuhan Metropolis and the Changsha-Zhuzhou-Xiangtan Metropolis (according to Wang et al. (2017), but a number of small and medium-sized town circles are formed, which are located in the 50–100 km area of Wuhan, Changsha, and Nanchang cities. These towns are at a suitable distance from the central cities and have close connections, and can effectively undertake the resource, technology and industrial spillover from the core cities, and also give full play to their own low-cost advantages of land, labor and other factors, thus forming a virtuous cycle), but also the number of nodes with high BC values in the Poyang Lake City Group increases significantly (according to Wang et al. (2017), the total rise of nighttime lights in the Poyang Lake City Group was also found by this study), it may be related to the fact that the regions with stronger innovation efficiency gradually spread and shift from Wuhan Metropolis and the Changsha-Zhuzhou-Xiangtan Metropolis to Poyang Lake City Group (Zhu et al., 2019b). Furthermore, 'innovation-driven' and 'green development' were listed as important development elements during the 12th Five-Year Plan period from 2011 to 2015, which is an important reason for the expansion of the spatial correlations of EE in the UAMRYR during this period. (3) In 2018, the BC values of the Wuhan Metropolis, Changsha-Zhuzhou-Xiangtan Metropolis, and Poyang Lake City Group were relatively lower, and the nodes with higher BC values were gathered in Ji' an and Yichun in Jiangxi Province. (4) In UAMRYR, the gap in BC values is reduced and relatively balanced, forming five core-periphery zones (i.e., small worlds). This indicates that the nodes with strong economic development and environmental constraints are at the hub of the EE network, occupying a greater advantage in resource transfer and being able to control and influence the flow of factors with others, while most nodes located at the periphery are unable to play a 'bridging role' due to the chain effect brought about by geographical disadvantages. Overall, the BC values of EE in UAMRYR have increased, and the characteristics of the small world are significant. (5) In addition, the northwestern areas of the UAMRYR, such as Xiangyang and Yichang cities, which have no obvious geographical advantages and are located in areas with high haze concentration values due to the large share of secondary production, have not yet established a good intermediary mechanism (Yan et al., 2021).

4.6. Analysis of structural effects

The contribution of DC, CC, and BC to EE, the extent of their effects, and whether there is variability in nodes at different EE levels need to be further analyzed. To solve the above problems, a multiple regression model with EE as the explanatory variable and DC-out, DC-in, CC-out, CC-in, and BC as the explanatory variables was constructed, which was measured by SPSS 23, and the UAMRYR was divided into core and peripheral areas with the help of core degree indicators of Ucinet software. To eliminate heteroscedasticity, all the data was treated as logarithms, and the regression results are shown in Table 5. As can be seen from Table 5, the values of R^2 for the three time points in the three areas are greater than 0.6, and the values of DW are almost close to 2, indicating that the data selected fit well, and the multiple linear regression model was properly constructed.

In the UAMRYR area, at the three time points, all constants failed the significance tests. The coefficient values of DC-out were all negative and passed the test, whereas the coefficient values of DC-in were mostly significantly positive. This may be because, at present, in UAMRYR, the integrated regional development is emphasized by government, but the diffusion effect among nodes is insufficient and the control ability of network resources is weak, so over-emphasis on the diffusion effect among nodes is not conducive to the improvement of EE. On the contrary, the agglomeration effect is the main force that positively affects EE in UAMRYR. Then, the impact of CC-out on EE is transformed from promoting to inhibiting, and the coefficient of CC-in, although not significant in 2018, is negative at all three time nodes, probably because, in the UAMRYR, with the establishment of small-group nepotism, the circulation of factors within small groups can solve the current issues, and over-emphasis on information sharing in large regions instead increases the cost of factor circulation as well as the irrational allocation of resources, which leads to an increase in the cost of constructing links with other nodes, in turn, the improvement of EE is inhibited. Finally, each 1% increase in the value of BC increases the value of EE by approximately 0.1%, indicating that the existence of multiple dissemination channels and spillover paths of resources can effectively control the correlations between nodes, coordinate the shares of agglomeration, and thus promote the improvement of EE.

In the core area of the UAMRYR, none of the constants passed the significance tests. For every 1% decrease in the value of DC-out, the values of EE is increased by 1.381%, 0.617%, and 0.816%, respectively, and none of the coefficients of DC-in were significant. This may be due to the fact that most of the core nodes screened by the software are from the central nodes of small groups. In the state of their own high barriers, a resource-sharing mechanism has not been established among core nodes. If they are forced to interact, the loss of internal resources of core nodes and the redundancy of external resources may occur, which is ultimately not conducive to the improvement of EE. This may also explain why the coefficients of both CC-out and CC-in failed the significance level test. In addition, the coefficient value of BC was significantly positive in 2009 and 2014 but not in 2018. This may be because in the

Table 5
Results of multiple regression.

Region	UAMRYR area			core area			peripheral area		
Time	2009	2014	2018	2009	2014	2018	2009	2014	2018
R^2	0.689	0.725	0.699	0.598	0.657	0.783	0.752	0.757	0.661
DW	1.976***	2.005***	1.902***	1.941***	1.867***	2.164***	1.618***	1.921***	1.899***
Constant	−0.155	−0.122	−0.053	−10.468	−5.987	5.764	−21.376***	−18.590***	−12.803***
DC-out	−0.376***	−0.260***	−0.316***	−1.381***	−0.617***	−0.816***	−0.094	−0.072	−0.135
DC-in	0.108	0.223***	0.378***	−0.128	0.003	0.207	0.182***	0.312***	0.371***
CC-out	0.303	0.448***	−0.161	0.809	0.752	−0.731	2.451***	2.286***	1.393***
CC-in	−0.661***	−0.834***	−0.265	1.008	0.040	−0.343	0.410	0.151	0.157
BC	0.142***	0.088***	0.110***	0.434***	0.228***	0.183	0.266***	0.199***	0.172***

Note: *** indicates passing the 1% significance level test.

core area of the UAMRYR, during the early formation of the core nodes, they can use some nodes that can play an intermediary role to maintain resource sharing with the outside world, which is reflected in the significant positive coefficient value of BC in this period. Gradually, their own production activities can be satisfied by internal resources, and their dependence on the outside world is weakened.Therfore, the coefficient of the BC is no longer significant.

In the peripheral area of UAMRYR, the values of the coefficients of the constant are all significantly negative, and the absolute values are very large, indicating that the structural factors affecting EE become complex, and there are other structural variables that substantially inhibit the improvement of EE. From the five centrality indicators selected in this study, the coefficient values of DC-in, CC-out, and BC are all significantly positive, indicating that the nodes in the peripheral area mainly rely on the radiation role of core nodes, the transmission role of intermediate nodes, and their own active integration and connection to obtain the improvement in EE, which is also the reason why the coefficient values of DC-out and CC-in are not significant.

5. Discussion

5.1. Discussion of the content

With the coordinated development of the economy and environment in the Yangtze River Economic Zone being formulated as a national strategy, and 'Double Carbon' being identified as an important goal in the 14th Five-Year Plan period in China, the study of the integrated effect of economy and environment has both theoretical value and practical significance. The network paradigm has driven a shift in urban research to focus on the construction of multi-scale networks of relationships and functions, which has led to a break in the traditional linear model by individual network of associations (Li et al., 2014). Therefore, studying the integrated effects of the economy and environment under the network paradigm is a vivid practice for practicing the construction of ecological civilization in the Yangtze River Economic Belt and China in general. In this study, using UAMRYR case study, the evaluation index system of EE is systematically constructed, the network characteristics of EE are vividly portrayed, and the network state and structural effects of EE are objectively reflected. This can provide an important reference for the synergistic improvement of EE in the UAMRYR and is of great significance in promoting the construction of eco-civilization in the Yangtze River Economic Belt and China.

First, based on the DPSIR model and combining multi-source remote sensing data, an evaluation index system was constructed to measure the EE of counties. However, there are few studies on the EE of counties because of the difficulty in obtaining their economic statistics. In the small amount of literature on EE in counties, for example, in the study by Tian et al. (2021), the urban built-up areas are treated as land input, and the emissions of 'three wastes' are treated as non-consensual outputs. Additionally, in the evaluation index system constructed by Ren and Fang (2017), only human and capital factor inputs were used. In fact, the EE measured by these evaluation index systems is less accurate because these indicators do not fully reflect the socioeconomic development of the region. Therefore, in this study, a more comprehensive and accurate evaluation index system for evaluating EE was constructed based on the theoretical framework of the DPSIR model. Moreover, unlike most of the studies, the suitability of the evaluation index system constructed in this study was tested with the help of the R-value diagram of R software, further improving persuasiveness. Overall, it is a good paradigm not only for calculating the EE of counties but also for other types of administrative regions, such as prefecture-level cities and countries, and it is a refinement of the existing literature in terms of both the type of study units and the construction of the evaluation index system.

Second, the improved gravity model was used to construct a spatial correlation matrix for the EE of counties in the UAMRYR. The fact that inter-subjective attraction is not reciprocal has been ignored in many studies. Therefore, the Granger linear causality test, Granger nonlinear causality test, and gravity model are mostly used to portray the association between things (Zipf, 1946). In fact, the interaction of things is bidirectional and asymmetric (Peng et al., 2020), and nodes have different positions in the network and naturally differ in their functions. And the existence of network associations was not tested before analyzing them. In geography, the relevant theories are the core–edge theory, point-axis theory, and locational theory. In this study, the results show that the mutual attraction of the node pairs differs in terms of the gravity of the EE. Therefore, this method provides a new perspective for exploring the association between things in terms of the inequality of interactions.

Then, the overall and individual network indicators in the social network analysis method were used simultaneously to explore the spatial network characteristics of EE in UAMRYR, enabling the network characteristics of EE to be revealed more specifically and comprehensively. The spatial dependence of econometrics also reflects the spatial interactions that exist in reality (Anselin and Rey, 1991), such as the flow of economic factors, diffusion of innovation, and technology spillover. These are the real components of the evolution of economic or innovation differences between regions, and are spatial interactions that do exist, for example, the spatial interactions of economic behaviors formed by the coupling of labor and capital flows, and the demonstration and incentive effects of R&D input–output behaviors and policies in geographic space. In this study, the most striking finding is the distinctive 'small world' character of EE, i.e., the existence of multiple small groups, all of which are located at the peripheral of the UAMRYR. This is consistent with previous studies, which indicate a clustering effect of EE in UAMRYR (Huang et al., 2018; Ren et al., 2020; Chen et al., 2020; Zhang et al., 2022a). In fact, this is substantially related to the fact that the UAMRYR consists of four major city clusters. This fragmentation of administrative divisions can lead to the prioritization of resource needs within small groups, and agglomerations are naturally formed during long-term accumulation.

Finally, based on the core degree index of the Ucinet software, UAMRYR was divided into core and peripheral areas, and the structural effects of EE in these three areas were explored. In spatial econometrics, the lack of homogeneity of objects in a geographic space is defined as spatial heterogeneity. It refers to the existence of economic geographic structures such as developed and backward regions and central (core) and peripheral (edge) regions, which leads to large spatial variability in the development of the economy and society (Anselin, 1988). In this study, the nature of the effect of each individual network indicator on EE varied across regions. This study also demonstrated differences in the network indicators of EE (Wang et al., 2020a). Correspondingly, the causes of structural effects in each region were analyzed from the perspective of node attributes. The results provide a theoretical basis for relevant policy formulations from multiple perspectives.

5.2. Policy implications

From the findings of this study, there are several policy insights which are described below.

First, nodes with high values of DC-out are often defined as the dominant players in the network, with more information on their own output and more influence on other nodes (Barthélemy, 2011). In the URMRYR, the overall values of the DC-in are larger than the DC-out, which indicates that most of the units are affected to a greater extent than their own impact, highlighting the characteristics of the diffusion effect rather than the linkage effect, which is also one of the reasons for the unequal information transfer of EE among the units. In addition, it can also be concluded from the heterogeneous differences in the role of centrality indicators on EE that, at present, in the URMRYR, it presents the characteristics of high information transfer efficiency of EE within small groups and high information loss in the whole region. Therefore, the cross-regional nature of relevant policies should be weakened, the small world should be used as a breakthrough to enhance EE, the sharing of resources within small groups should be reasonably utilized, and the small groups should lead to the synergistic enhancement of large regions instead of emphasizing the synergistic development of large regions. In addition, the intermediary effect of individuals with higher EE values can be brought into play to balance the resource allocation of EE, transform part of the aggregation effect into the diffusion effect, and improve EE as a whole.

Second, in the URMRYR, the factor agglomeration ability of major urban agglomerations is characterized as Wuhan Metropolis > Changsha-Zhuzhou-Xiangtan Metropolis > Poyang Lake City Group (Liu et al., 2018), which is an important reason why the five individual network indicators of Wuhan Metropolis and Changsha-Zhuzhou-Xiangtan Metropolis both account for high values, while the values of point degree centrality and near centrality of Poyang Lake City Group are not high. Therefore, if the EE of the URMRYR is to be improved, the focus should be on the Poyang Lake urban agglomeration. From the outside, it can give full play to the radiation-driven role of Wuhan Metropolis and Changsha-Zhuzhou-Xiangtan Metropolis, release part of the factor resources, provide a model for regional development to learn from, and drive the Poyang Lake City Group to improve the associated network. Internally, the counties of Nanchang and Jiujiang are relatively well developed and can play the role of leaders of small groups, encourage technological innovation, introduce new energy technologies, improve production methods, and strive for the harmonious co-existence of ecological environment and economic growth, thus leading to the overall improvement of EE.

Finally, in the URMRYR, the individual network indicators of EE exhibit an obvious circular structure, (high-value areas are surrounded by low-value areas), which, to some extent, indicates the lack of environmental cooperation among counties, such as environmental management and pollution control (Guo and Zhang, 2017), which is consistent with the findings of Zhang et al. (2022). Therefore, the core individuals of each small group should take the initiative to share the development path, formulate policies to help marginal individuals in environmental management, exploit the spatial spillover effect, actively disseminate the importance of environmental management between the government and the market, and establish a mechanism for marginal individuals to take the initiative to undertake energy conservation and emission reduction to promote the overall improvement of EE.

5.3. Limitations and future work

This study provides a theoretical framework for constructing an evaluation index system to measure EE, using UAMRYR as a case study. However, whether this can be carried out in other regions requires further multi-case studies. In addition, the results show that the structural variables of EE in the peripheral area of UAMRYR are complex. In addition to the five centrality indicators, it is also influenced by other structural indicators, which needs to be further explored.

6. Conclusions

In this study, using the UAMRYR as a case study, multi-source remote sensing data were combined, and the Super-SBM model was used to measure the value of EE from to 2009–2018, an improved gravity model was used to construct a gravitational matrix, social network analysis was used to characterize the spatial network of EE, and multiple linear regression models were used to explore the centrality nature of the role of indicators on EE. The main findings are as follows:

In UAMRYR, EE has been shown to be indeed spatially correlated, and the gap in the EE values increased. The network of EE has a stable shape, with increasingly tight network connections and a complex network structure. In addition, the linkage of EE among nodes is characterized by two-way inequality. Moreover, the nodes with higher gravitational values of the EE are gradually clustered in the eastern part of the UAMRYR.

The overall spatial network of EE in the UAMRYR is low in density, with a hierarchical structure with more small groups. The linkage paths between nodes are shortened and the overflow channels are increased, the operational efficiency of the network is gradually improved but the overall operational efficiency is low, existing much room for improvement of EE.

The overall values of DC-in were greater than those of DC-out, indicating that the attraction ability of nodes was greater than the siphoning effect. In addition, the nodes with high DC-in values were mainly located in four major urban clusters, forming a circular structure. The nodes with low DC-in values were mostly around the inner ring and outer edge of the enclosed area of the nodes with high DC-in values. The nodes with high DC-out values are distributed in the inner ring of the enclosed area, whereas the nodes with low DC-out values are found in the periphery of the enclosed area, which is also the periphery of the UAMRYR. Then, the nodes with low CC-out values run through the central part of the UAMRYR and are distributed in the periphery of the high values, showing a clear 'central collapse' feature. The nodes with high CC-in values expanded from the southeast to the periphery of UAMRYR, and the number of nodes with low CC-in values was small. Finally, the BC is discussed. At the beginning, its high-value nodes were clustered in the Wuhan Metropolis and Changsha-Zhuzhou-Xiangtan Metropolis. Migration over time, five relatively balanced 'center-periphery' areas were formed, and its low-value nodes were surrounded by high-value clusters.

Finally, the structural effects of the EE are discussed. For UAMRYR, the agglomeration effect, dissemination channels, and spillover paths of multiple resources are the main forces to improve EE. In the core area of UAMRYR, a resource-sharing mechanism has not been established among the core nodes, and mandatory interaction measures may be ultimately detrimental to the improvement of EE. In the peripheral area of UAMRYR, the edge nodes mainly rely on the radiation role of core nodes, the transmission role of intermediary nodes, and their own active integration and connectivity to obtain an improvement in EE, and there are other structural effects affecting EE, in addition to the five individual network indicators.

CRediT authorship contribution statement

Xiangjing Zeng: Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Yong Ma:** Conceptualization, Funding acquisition, Supervision. **Jie Ren:** Writing – original draft, Writing – review & editing. **Biao He:** Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References

Anselin, L., 1998. Spatial Econometrics: Methods and Models. Kluwer Academic Publishers, Dordrecht.

Anselin, L., Rey, S., 1991. Properties of tests for spatial dependence in linear regression models. Geogr. Anal. 23, 112–131. https://doi.org/10.1111/j.1538-4632.1991.tb00228.x.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manage. Sci. 30, 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078.

Barthélemy, M., 2011. Spatial networks. Phys. Rep. 499, 1–101. https://doi.org/10.1016/j.physrep.2010.11.002.

Berlemann, M., Wesselhoft, J.E., 2014. Estimating aggregate capital stocks using the perpetual inventory method. Rev. Econ. 65, 1–34. https://doi.org/10.1515/roe-2014-0102.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision-making units. Eur. J. Oper. Res. 2, 429–444. https://doi.org/10.1016/0377-2217(78)90138-8.

Chen, W., Si, W., Chen, Z.M., 2020. How technological innovations affect urban eco-efficiency in China: A prefecture-level panel data analysis. J. Clean. Prod. 270, 122479 https://doi.org/10.1016/j.jclepro.2020.122479.

Cullinane, K., Ji, P., Wang, T.F., 2005. The relationship between privatization and DEA estimates of efficiency in the container port industry. J. Econ. Bus. 57, 433–462. https://doi.org/10.1016/j.jeconbus.2005.02.007.

Deng, X., Gibson, J., 2019. Improving eco-efficiency for the sustainable agricultural production: A case study in Shandong. China. Technol. Forecast. Soc. Chang. 144, 394–400. https://doi.org/10.1016/j.techfore.2018.01.027.

Ding, Y.T., Zhang, M., Qian, X., Li, C., Chen, S., Wang, W., 2019. Using the geographical detector technique to explore the impact of socioeconomic factors on PM2.5 concentrations in China. J. Clean. Prod. 211, 1480–1490. https://doi.org/10.1016/j.jclepro.2018.11.159.

Elhorst, J.P., 2012. Dynamic spatial panels: Models, methods, and inferences. J. Geogr syst. 14, 5–28.

Freeman, L.C., Roeder, D., Mulholland, R.R., 1979. Centrality in social networks: ii. experimental results. Social Netw. 2, 119–141. https://doi.org/10.1016/0378-8733(79)90002-9.

Gómez-Limón, J.A., Picazo-Tadeo, A.J., Reig-Martínez, E., 2012. Eco-efficiency assessment of olive farms in Andalusia. Land Use Policy 29, 395–406. https://doi.org/10.1016/j.landusepol.2011.08.004.

Guo, Q., Zhang, Z., 2017. Spatial-temporal evolution of factors aggregating ability in urban agglomeration in the middle reaches of the Yangtze River. Acta Geogr. Sinica 72, 1746–1761.

Guo, Y., Tong, L., Mei, L., 2020. The effect of industrial agglomeration on green development efficiency in Northeast China since the revitalization. J. Clean. Prod. 258, 120584 https://doi.org/10.1016/j.jclepro.2020.120584.

He, N., Zhou, Y., Wang, L., Li, Q., Zuo, Q., Liu, J., Li, M., 2022. Spatiotemporal evaluation and analysis of cultivated land ecological security based on the DPSIR model in Enshi autonomous prefecture. China. Ecol. Indicat. 145, 109619 https://doi.org/10.1016/j.ecolind.2022.109619.

Huang, Y., Li, L., Yu, Y., 2018. Do urban agglomerations outperform non-agglomerations? A new perspective on exploring the eco-efficiency of Yangtze River Economic Belt in China. J. Clean. Prod. 202, 1056–1067. https://doi.org/10.1016/j.jclepro.2018.08.202.

Kuang, B., Lu, X., Zhou, M., Chen, D., 2020. Provincial cultivated land use efficiency in China: Empirical analysis based on the SBM-DEA model with carbon emissions considered. Technol. Forecast. Soc. Chang. 151, 119874 https://doi.org/10.1016/j.techfore.2019.119874.

Li, J., Chen, S., Wan, G.H., Fu, C., 2014. Study on the spatial correlation and explanation of regional economic growth in China: Based on analytic network process. Econ. Res. J. 49, 4–16.

Li, H., Luo, N., 2022. Will improvements in transportation infrastructure help reduce urban carbon emissions? Motor vehicles as transmission channels. Environ. Sci. Pollut. Res. 29, 38175–38185. https://doi.org/10.1007/s11356-021-18164-0.

Li, B., Wu, S., 2017. Effects of local and civil environmental regulation on green total factor productivity in China: A spatial Durbin econometric analysis. J. Clean. Prod. 153, 342–353. https://doi.org/10.1016/j.jclepro.2016.10.042.

Liu, H., Liu, C., Sun, Y., 2015. Spatial correlation network structure of energy consumption and its effect. China Indus. Econ. 5, 83–95.

Liu, C., Wang, T., Guo, Q., 2018. Factors aggregating ability and the regional differences among china's urban agglomerations. Sustainability 10, 4179. https://doi.org/10.3390/su10114179.

Lu, X., Kuang, B., Li, J., 2018. Regional differences and its influencing factors of cultivated land use efficiency under carbon emission constraint. J. Nat. Resour. 33, 657–668.

Lyu, Y., Wang, W., Wu, Y., Zhang, J., 2022. How does digital economy affect green total factor productivity? Evidence from China. Sci. Total Enviro. 159428 https://doi.org/10.1016/j.scitotenv.2022.159428.

Papadimitriou, F. 2022. Spatial entropy of directional geographical data and landscape networks, in: Spatial Entropy and Landscape Analysis. Springer Fachmedien Wiesbaden, Wiesbaden, pp. 31–55. 10.1007/978-3-658-35596-8_3.

Peng, B., Wang, Y., Wei, G., 2020. Energy eco-efficiency: Is there any spatial correlation between different regions? Energy Pol. 140, 111404 https://doi.org/10.1007/s11356-022-21434-0.

Reith, C.C., Guidry, M.J., 2003. Eco-efficiency analysis of an agricultural research complex. J. Environ. Manage. 68, 219–229. https://doi.org/10.1016/S0301-4797(02)00161-5.

Ren, Y., Fang, C., 2017. Spatial pattern and evaluation of eco-efficiency in counties of the Beijing-Tianjin-Hebei Urban Agglomeration. Progress Geogr. 36, 87–98.

Ren, Y., Fang, C., Li, G., 2020. Spatiotemporal characteristics and influential factors of eco-efficiency in Chinese prefecture-level cities: A spatial panel econometric analysis. J. Clean. Prod. 260, 120787 https://doi.org/10.1016/j.jclepro.2020.120787.

Russon, M.G., Vakil, F., 1995. Population, convenience and distance decay in a short-haul model of United States air transportation. J. Transp. Geogr. 3, 179–185. https://doi.org/10.1016/0966-6923(95)00002-K.

Schaltegger, S., Sturm, A., 1990. Ökologische rationalität: ansatzpunkte zur ausgestaltung von ökologieorientierten managementinstrumenten. Die Unternehm 44, 273–290. https://www.jstor.org/stable/24180467.

Shen, Y., Sun, X., Fu, Y., 2021. The spatial network and its driving factors for sustainable total-factor ecology efficiency: The case of China. Environ. Sci. Pollut. Res. 28, 68930–68945. https://doi.org/10.1007/s11356-021-15456-3.

Song, K., Bian, Y., Zhu, C., Nan, Y., 2020. Impacts of dual decentralization on green total factor productivity: Evidence from China's economic transition. Environ. Sci. Pollut. Res. 27, 14070–14084. https://doi.org/10.1007/s11356-020-07953-8.

Tang, M., Li, Z., Hu, F., Wu, B.J., 2020. How does urban land expansion promote urban eco-efficiency? The mediating effect of sophistication of industrial structure. J. Clean. Prod. 272, 122798 https://doi.org/10.1016/j.jclepro.2020.122798.

Tian, P., Wang, H., Li, J., Cao, L., Hu, Q., 2021. Eco-efficiency evaluation and influencing factors analysis of county-level cities in the East China Sea coastal zone. Geogr. Res. 40, 2347–2366.

Tobler, W., 2004. On the first law of geography: A reply. Ann. Assoc. Am. Geogr. 94, 304–310. https://doi.org/10.1111/j.1467-8306.2004.09402009.x.

Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. Eur. J. Oper. Res. 130, 498–509. https://doi.org/10.1016/S0377-2217(99)00407-5.

Tone, K., Tsutsui, M., 2010. An epsilon-based measure of efficiency in DEA: A third pole of technical efficiency. Eur. J. Oper. Res. 207, 1554–1563. https://doi.org/10.1016/j.ejor.2010.07.014.

Wang, H., Lan, Z., Jin, H., Zhang, C., 2017. Study on spatial evolution of urban system in Middle Reaches of Yangtze River based on night lighting data. Inquiry Econ. Issues 3, 107–114.

Wang, R., Xia, B., Dong, S., Li, Y., Li, Z., Ba, D., 2020b. Research on the spatial differentiation and driving forces of eco-efficiency of regional tourism in China. Sustainability 13, 280. https://doi.org/10.3390/su13010280.

Wang, K., Zhang, S.W., Gan, C., Yang, Y., Liu, H., 2020a. Spatial network structure of carbon emission efficiency of tourism industry and its effects in China. Scientia Geogr. Sinica 40, 344–353.

Wu, X., Chen, Y., Guo, J., Gao, G., 2018. Inputs optimization to reduce the undesirable outputs by environmental hazards: A DEA model with data of PM 2.5 in China. Nat. Hazards 90, 1–25. https://doi.org/10.1007/978-981-16-1319-7_19.

Wu, H., Fang, S., Zhang, C., Hu, S., Nan, D., Yang, Y., 2022. Exploring the impact of urban form on urban land use efficiency under low-carbon emission constraints: A case study in China's Yellow River Basin. J. Environ. Manage. 311, 114866 https://doi.org/10.1016/j.jenvman.2022.114866.

Yan, J.W., Tao, F., Zhang, S.Q., Lin, S., Zhou, T., 2021. Spatiotemporal distribution characteristics and driving forces of PM2.5 in three urban agglomerations of the Yangtze river economic belt. Int. J. Environ. Res. Public Health 18, 2222. https://doi.org/10.3390/ijerph18052222.

You, J., Xiao, H., 2022. Can FDI facilitate green total factor productivity in China? Evidence from regional diversity. Environ. Sci. Pollut. Res. 29, 49309–49321. https://doi.org/10.1007/s11356-021-18059-0.

Yuan, H., Zou, L., Feng, Y., Huang, L., 2022. Does manufacturing agglomeration promote or hinder green development efficiency? Evidence from Yangtze River Economic Belt, China. Environ. Sci. Pollut. Res. 10.1007/s11356-022-20537-y.

Zhang, J., 2008. Estimation of China's provincial capital stock (1952–2004) with applications. J. Chin. Econ. Bus. Stud. 6, 177–196. https://doi.org/10.1080/14765280802028302.

Zhang, J., Lu, G., Skitmore, M., Ballesteros-Pérez, P., 2021. A critical review of the current research mainstreams and the influencing factors of green total factor productivity. Environ. Sci. Pollut. Res. 28, 35392–35405. https://doi.org/10.1007/s11356-021-14467-4.

Zhang, R., Ma, Y., Ren, J., 2022a. Green development performance evaluation based on dual perspectives of level and efficiency: A case study of the Yangtze River Economic Belt, China. Int. J. Environ. Res. Public Health 19, 9306. https://doi.org/10.3390/ijerph19159306.

Zhang, Y., Wang, L., Tang, Z., Zhang, K., Wang, T., 2022b. Spatial effects of urban expansion on air pollution and eco-efficiency: Evidence from multisource remote sensing and statistical data in China. J. Clean. Prod. 367, 132973 https://doi.org/10.1016/j.jclepro.2022.132973.

Zhu, L., He, R., Zheng, W., Wang, S., Han, L., 2019b. Study on spatial-temporal pattern and driving factors of urban innovation efficiency of urban agglomeration in the Middle Reaches of Yangtze River. Resour. Environ. Yangtze Basin 28, 2279–2288.

Zhu, B., Zhang, M., Zhou, Y., Wang, P., Sheng, J., He, K., Wei, Y., Xie, R., 2019a. Exploring the effect of industrial structure adjustment on interprovincial green development efficiency in China: A novel integrated approach. Energy Pol. 134, 110946 https://doi.org/10.1016/j.enpol.2019.110946.

Zipf, G.K., 1946. The P 1 P 2/D hypothesis: On the intercity movement of persons. Amer. Sociol. Rev. 11, 677–686. https://doi.org/10.2307/2087063.