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The spatial spillover effect of transportation networks on ecological footprint

Tianyu Lv [a], Chen Zeng [a,*], Lindsay C. Stringer [b], Jing Yang [c], Pengrui Wang [a]

[a] Department of Land Management, Huazhong Agricultural University, Wuhan 430070, China
[b] Department of Environment and Geography, University of York, York YO10 5NG, UK
[c] Guangzhou Urban Planning & Design Survey Research Institute Beijing Branch, Beijing 100032, China

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ABSTRACT

In the context of rapid urbanization and regional development worldwide, the efficient and rational spatial distribution of transportation networks is vitally important in achieving sustainable development. In this study, we used an adjusted three-dimensional ecological footprint model (EF_{3D}) to assess regional sustainable development. We explored the driving factors and spatial influence of transportation networks on the EF_{3D} in the urban agglomerations in the middle reaches of the Yangtze River (UAMRYR), China, in 2010 and 2017, integrating the STIRPAT model and spatial econometric model alongside the transportation network in the research framework. The results show that the EF_{3D} has been reduced by 1.46% from 2010 to 2017. Although the overall level of sustainable development in UAMRYR has improved, 94.69% of the county units were still in ecological overshoot in 2017. In addition, population density, GDP per capita and the proportion of non-tertiary industries had positive local influences on EF_{3D}. At the county level, EF_{3D} had positive spatial autocorrelation, and the spatial spillover effect of EF_{3D} was confirmed through the transportation network, indicating that the spatial influence of the transportation network was an important factor in explaining EF_{3D}. Population density and GDP per capita had negative and positive indirect spatial effects, respectively. In the future, the function of transportation systems should be improved to transfer the population pressure of cities and increase natural capital flexibility to reduce the EF and ultimately achieve balanced development.

1. Introduction

In the context of globalization and regional integration, the negative impacts of infrastructure construction on the environment have received much attention in recent years (Zambrano-Monserrate et al., 2020). Massive expansion of infrastructure such as roads and railways poses a threat to ecosystems globally, but such development are also needed to support development. In China, the rapidly expanding transportation network is a key element in supporting urbanization but causes various ecological problems, including habitat destruction, biodiversity decline, land degradation, shortage of natural resources, and environmental pollution (Yang et al., 2020). To promote Sustainable Development Goals (SDGs) that focus on ecological sustainability, the function of transportation networks should be considered to meet the diverse needs of urbanization while minimizing adverse ecological impacts (Ahmed et al., 2020b; Erdogan, 2020).

The ecological footprint (EF), a holistic indicator for tracking the effects of human activities on ecosystems, has been increasingly used to assess the level of regional sustainable development (Rees, 1992; Uddin et al., 2017; Ulucak & Khan, 2020; Zafar et al., 2019). Recently, the exploitation of global natural resources that promotes socio-economic development has accelerated declines in ecological carrying capacity (EC) while increasing the EF (Ulucak & Khan, 2020). The latest data of the Global Footprint Network (GFN) reveals that the equivalent of 1.73 planets is needed to provide the necessary resources and absorb waste, indicating that natural resource regeneration has lagged behind the needs of socio-economic development (GFN, 2020). Currently about 75% of countries are facing ecological deficits (GFN, 2020). To compensate for natural capital in the process of economic growth, many countries turn to trade or internal resource allocation through their transportation networks. China is one of the world's largest ecological overshoot countries. A global consumption level in line with China will

* Corresponding author.
E-mail addresses: lvtianyu97@126.com (T. Lv), zengchen@igsnrr.ac.cn (C. Zeng), lindsay.stringer@york.ac.uk (L.C. Stringer), yangjinghzau@126.com (J. Yang), wpr@webmail.hzau.edu.cn (P. Wang).

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require 2.22 planets (GFN, 2020). Given that natural resources and the EC of megacities are so threatened, China's Ministry of Natural Resources and the 14th Five-year National Plan have emphasized that efficient transportation systems should ensure rational allocation of resources in urban agglomerations and metropolitan areas. In this sense, improving and upgrading the transportation network is essential for cities and societies attempting to transition to sustainable development.

The EF in different regions interacts spatially through transportation networks. This indicates that the consumption of natural resources will be affected by neighbors through transportation infrastructures such as roads and railways. Transportation is vital to increase the mobility of capital, natural resources, information, and technology, thus strengthening regional cohesion and weaken administrative boundaries (Arbués et al., 2015; Xu et al., 2019). In this sense, a transportation network is bound to function as a "channel" of spatial spillover effects on the EF. Despite these relationships, the spatial spillover effects of transportation networks on the EF are often ignored (Zambrano-Monserrate et al., 2020). This article takes up this challenge, which is the innovation of this study to explore the magnitude of the spatial spillover effects on EF by treating the transportation network as a "channel" for cross-regional spatial interaction.

To address this issue, China's UAMRYR is used as the case study area to examine the spatial spillover effects of transportation networks on EF in 2010 and 2017. An original quantitative evaluation framework to link transportation networks with EF is provided. The transportation network is embedded into a spatial econometric model to measure its spatial influence on EF. The outline of the paper is presented as follows. Section 2 reviews the existing literature on this topic. Section 3 introduces our method of integrating the STIRPAT model and a spatial econometric model to test the magnitude of the spatial influence. This section also presents the study area and the data used in our analysis. Section 4 reports the results of the spatio-temporal variation of the EF and complex road and railway networks, as well as the regression results from the spatial econometric model. Sections 5 and 6 provide the discussion and conclusion, respectively.

2. Literature review

2.1. Evaluation model of EF

The EF has emerged as an extensive and comprehensive measure of sustainable development level in the recent literature (Hassan et al., 2019; Ulucak & Khan, 2020). The EF was proposed by Rees and Wackernagel in the early 1990 s (Rees, 1992; William & Mathis, 1996), when it compared profit and loss of natural capital relationships. Since then, numerous scholars have further adjusted the model, using input–output analysis (Liu et al., 2018), energy accounting (Li et al., 2019), system dynamics models (Guan et al., 2011), life cycle assessment (Liu et al.,2017), and the EF_{3D} model (Xun & Hu, 2019). One of the most noteworthy improvements has been the transformation from the traditional EF to the EF_{3D} (Xun & Hu, 2019). Environmental economists have reached a consensus that the minimum level of sustainable development is the non-consumption of natural capital stock (Ekins et al., 2003). However, the importance of keeping the natural capital stock constant to maintain the stability of ecosystems is difficult to reflect in the traditional EF (Fang, 2013; Niccolucci et al., 2009). To address these inherent defects, Niccolucci et al. (2009) proposed an EF_{3D} model by using EF_{depth} and EF_{size} to reflect the depletion of capital stock and capital flow, thereby providing a multi-dimensional perspective for sustainable development assessment. The EF_{3D} can track specific biophysical thresholds. Exceeding the threshold value indicates a shift away from using natural capital flows toward using natural capital stocks, an approach that destroys the long-term ability of the natural system to provide ecosystem services (Mancini et al., 2017). Fang (2013) developed an optimized EF_{3D} which solved the limitation of offsetting the ecological deficit (where natural capital demand exceeds supply) and surplus (natural capital supply exceeds demand) of different land types. The EF_{3D} has become widely used in sustainable development assessment across many locations, including cases at the global scale (Bi et al., 2021; Niccolucci et al., 2009), national scale (Fang, 2015; Wu et al., 2021), provincial scale (Xun & Hu, 2019), and city scale (Chen et al., 2019).

2.2. Determinants of EF

Despite improvements to the EF model, analysis of EF determinants has remained contentious. The most widely used techniques for examining driving forces of EF are Decomposition Analysis (IDA), Structural Decomposition Analysis (SDA), Logarithmic-Mean Divisia Index (LMDI) and Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) (Liu et al., 2018; Zhao et al., 2014). However, the first three methodologies are incapable of taking stochastic shocks and statistical inference into account, which are always regarded as useful for policy implication (Zhang et al., 2017). The STIRPAT model is dedicated to exploring the impact of population (P), affluence (A) and technology (T) on the EF. Compared with the other three methods, the STIRPAT model allows for the expansion of more factors and less data limitation, providing more specific and reliable information for shaping strategies for sustainable development (Zhao et al., 2014; Wang et al., 2019). Due to its flexibility, the STIRPAT model is commonly used for examining the drivers of the EF (Jia et al., 2009).

Findings from studies using STIRPAT have yielded wide discrepancies given the complexity of geographic dynamics (Nathaniel & Khan, 2020). Many scholars have explored the determinants of the EF on a global scale. York et al. (2003) pioneered the application of the STIRPAT model for the analysis of the influencing factors of the EF. The diversified influences of socio-economic development on the EF have subsequently been revealed (Ahmed et al., 2020b). For example, Nathaniel and Khan (2020), and Destek and Okumus (2019) both validated the negative influence of GDP and urbanization on environmental quality for ASEAN countries and newly industrialized countries respectively, whereas economic development and urbanization were shown to improve sustainable development in BRICS countries (Ulucak & Khan, 2020) and Europe (Alola et al., 2019). Trade and the use of renewable energy have received special attention (Nathaniel & Khan, 2020; Zafar et al., 2019). Trade between countries supported by global transportation networks has caused dirty imports to increase environmental degradation in developing countries with weaker environmental regulations and enforcement (You & Lv, 2018). However, improvement techniques also increase the use of renewable energy, reducing the carbon footprint (Nathaniel & Khan, 2020; Zafar et al., 2019). Together, these studies have identified some important ways forward for the realization of SDGs, in terms of increasing the budget allocation of renewable energy projects to reduce the adverse effects of development, and strengthening international cooperation to reduce environmental pollution.

Another body of studies has considered the determinants of the EF at a national scale or its internal regions. Studies have identified the role of GDP (Jia et al., 2009), urbanization (Nathaniel & Khan, 2020), population size (Jia et al., 2009; Kongbuamai et al., 2020), and industrial structure (Jia et al., 2009). As the country with the largest EF, China has received extensive attention. Ahmed et al. (2020a) found that urbanization and economic growth hindered sustainable development, while human capital alleviated environmental degradation in China. Population size is the main driving force for the growth of EF nationally. It is also found that affluence is playing an increasingly prominent role in the growth of EF in the eastern and northeastern provinces, while technology restrains the increase in EF in the western provinces. This provides a realistic and reliable reference for the identification of the positive and negative factors of sustainable development.

2.3. EF and transportation network

In addition to the common factors revealed to influence EF, a further body of work has focused on the influence of transportation infrastructure on the EF. Transportation infrastructure is the key to a sustainable city and society (Erdogan, 2020). However, limited research has explored the influence of transportation infrastructure on the EF. The EF of transportation infrastructure is an important part of the total EF of tourist cities. In Amsterdam, approximately 70% of the environmental pressure of inbound tourism stems from transportation system (Peeters & Schouten, 2006). A similar positive correlation between transport and the EF has been confirmed in Lanzarote (Martín-Cejas & Sánchez, 2010). The positive relationship between aeroplanes, trains, and automobiles in relation to the EF of tourism was also captured in Shanghai (Lin et al., 2018b). By tracking various types of transportation in OECD countries, the role of railway infrastructure investments in reducing EF and environmental degradation was recognized because of the clean technology, cost-effectiveness, and scale effect of the railway system (Erdogan, 2020). Conversely, investment in road and air infrastructure was found to exacerbate environmental degradation (Erdogan, 2020). Considering the role of public transportation in achieving sustainable development, Gassner et al. (2018) captured the environmental impact of different public transportation systems in Vienna. They found that the subway was the primary contributor to the EF, but the contribution of trams and buses was much lower (Gassner et al., 2018).

The EF may be affected not only by the endogenous characteristics of the transportation infrastructure, but also by the exogenous spatial spillover effect of the transportation network on neighboring units. Extensive literature has confirmed the spatial spillover effect of transportation on CO_2. For example, Yang et al. (2019) found a spatial spillover effect of transportation infrastructure on CO_2 in China. Wang (2019) also confirmed transportation factors have positive and significant spillover effects on CO_2 emissions. In particular, the railway network has more obvious impacts than the road factor. Nevertheless, very few studies have focused on the spatial influence of transportation networks on EF, let alone on the EF_{3D}.

Although previous studies have identified common driving forces of EF and the function of transportation infrastructure, the spatial spillover effect generated from the transportation networks has not yet been systematically studied. It is admitted that population, urbanization, economic structure, trade, and energy use are taken as the driving factors of EF (Ahmed et al., 2020b; Alola et al., 2019; You & Lv, 2018). The EF captures the demand from human activities for natural capital during which a spatial interaction may occur between production and consumption of goods and services across regions (Baloch et al., 2019). Empirical studies have demonstrated that a transportation network promotes the inter-regional movement of production factors and increases the availability of resources in the destination location (Pradhan & Bagchi, 2013; Wu et al., 2017), thereby supporting the spatial interaction of the EF. If the spatial effect of the EF is justified and measured, policies are thus formulated to achieve balanced regional development with the consideration of this spatial effect (Zambrano-Monserrate et al., 2020). In summary, the spatial interactions through transportation among the observations have seldom been investigated when studies are made on EF. To bridge these gaps, this study integrates the STIRPAT model, transportation network into the spatial econometric model, with the hypothesis of the spatial influence on the EF_{3D}.

3. Materials and methods

3.1. Materials

3.1.1. Study area

The urban agglomerations in the middle reaches of the Yangtze River (UAMRYR, 108.37–119.66°E; 24.50°–34.66° N) are located in the central regions of the Yangtze River Economic Belt of central China. The area includes three urban agglomerations: the Wuhan agglomeration (WHA) in Hubei Province, the Chang-Zhu-Tan urban agglomeration (CZTA) in Hunan Province, and the urban agglomeration around Poyang lake (APL) in Jiangxi Province (Fig. 1). The UAMRYR has a total area of 32.7×10^4 km^2 with 153 million permanent residents and a GDP of 7.9 trillion yuan (321.61 billion USD) in 2017. The location accounts for 3.41% of the total area, 11.01% of the total population, and 9.58% of the GDP of China. Given its central position in China, the UAMRYR has become a transportation hub with an integrated traffic corridor. The total mileage of roads in the UAMRYR increased from 68,890 km to 91,046 km with a growth rate of over 32% from 2010 to 2017. The total railway length increased from 6430 km in 2010 to 9694 km in 2017 with a growth rate of over 50%. The area is also rich in biodiversity and has a variety of ecosystems (Dai et al., 2020). However, challenges in achieving sustainable development abound as the area faces critical tensions between high-speed economic growth and limited EC.

Cities within the UAMRYR are spatially interconnected, geographically compact, economically comparable, and highly dependent on a developed transportation network, while the UAMRUR is traversed by the Yangtze River and is a key area for maintaining ecological functions. According to the above description, the UAMRYR offers a suitable area for studying transportation networks and EF from a spatial perspective, particularly given its steep development trajectory.

3.1.2. Data description

The spatial unit of our analysis is the county level, an administrative level lower than the city. The UAMRYR consisted of 206 county units in 2010 and 207 county units in 2017 due to the adjustment of administrative divisions. The data used in this study include that on the production of biological resources, energy consumption, socio-economic data, land use data, road network layer data, and railway network layer data. We use the production of biological resources instead of consumption because no detailed county-level trade data is available (Yang et al., 2018) and trade data has a negligible impact on the local EF (Gu et al., 2015). Statistical data from the counties of UAMRYR could not directly meet our requirements to calculate the EF in terms of the fossil energy account, so we utilized statistical data for “energy consumption per unit GDP”, “composition of energy consumption”, “GDP”, and “GDP Index” from the Statistical Yearbooks of Hubei, Hunan, and Jiangxi to calculate energy consumption at the county scale (Yang et al., 2018). The “GDP Index” was employed to calculate the GDP Index for which the value was designated at 100 in 2010. Each county’s GDP in 2017 was converted into 2010 prices by using “GDP index = 100” and “county GDP”. After multiplying the above GDP by the energy consumption per unit of the GDP, the energy consumption of each county can be calculated. Finally, the consumption values of raw coal, oil, natural gas, and electricity were determined for each county’s outputs from the province’s energy consumption ratios. Detailed data sources and descriptions are shown in Table 1.

3.2. Methods

A complex network model and EF_{3D} model were integrated into the spatial econometric model to explore pathways to sustainable development by considering both direct and indirect spatial influences. Direct spatial influences refer to the influence of neighboring EFs on the local EF through the transportation network. Indirect spatial influences refer to the driving forces of neighboring population, economic, and technical aspects under the STIRPAT model that influence the local EF. To study the spatial influence, the spatial weight matrix based on the transportation network was embedded into a spatial econometric model to explore the spatial spillover effect of the transportation network on the EF. The establishment and the integration of EF_{3D} model, STIRPAT model, complex road and railway network model, and the spatial econometric model are described in detail in the following sub-sections.

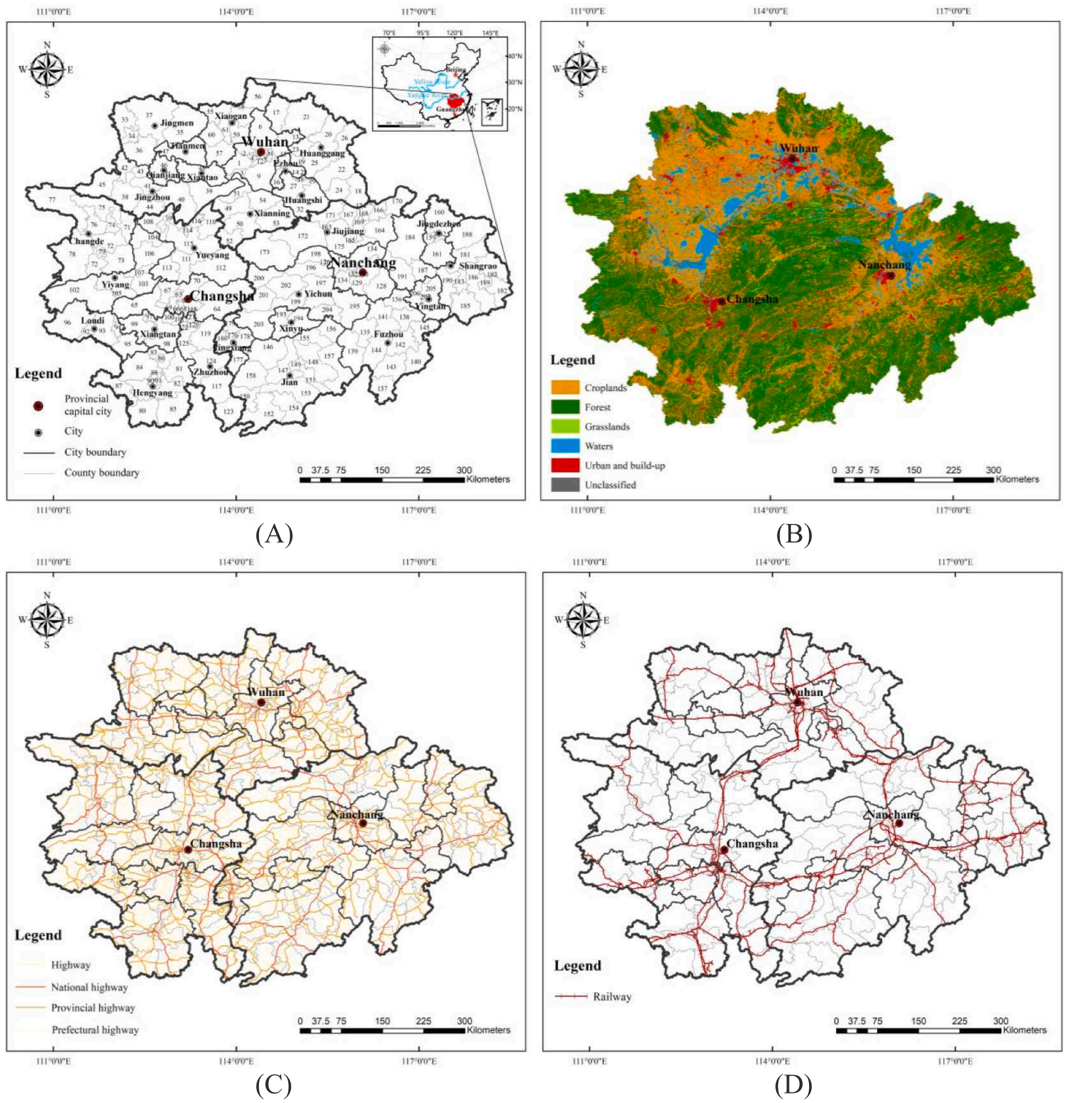


Fig. 1. The study area of (A) the administrative division, (B) the land use map, (C) the road transportation network, and (D) the railway transportation network of UAMRYR in 2017.

3.2.1. *The EF_{3D} accounting*

The EF measures the impact of human activities according to six account categories: cultivated land, grassland, woodland, water, construction land, and fossil energy land, which is ultimately unified as a single indicator of global land (Ahmed et al., 2020b). EC pertains to the largest supply of natural resources available for current consumption and waste assimilation (Li et al., 2019; Uddin et al., 2017). The general form of EF and EC is:

$$EF = N\cdot ef = N\cdot \sum_{j=1}^{6}\left[r_j\cdot \sum_{i=1}^{n}\left(\frac{c_i}{p_i}\right)\right] \tag{1}$$

$$EC = N\cdot \sum_{j=1}^{6}(a_j\cdot r_j\cdot y_j) \tag{2}$$

where N is total population, j is the consumer goods category, and r_j is the equalization factor. In EF, p_i is the average production capacity of the ith consumer good, c_i is the per capita consumption of the ith commodity, and ef is the per capita EF. In EC, a_j is the per capita biological production area and y_j is the yield factor.

To distinguish between the flow and stock of natural capital, the EF_{3D} model is used. The calculation formulas are as follows:

$$EF_{size} = \sum_{i=1}^{n} min\{EF_i, EC_i\} \tag{3}$$

$$EF_{depth} = 1 + \frac{\sum_{i=1}^{n} max\{EF_i - EC_i, 0\}}{\sum_{i=1}^{n} EC_i} \tag{4}$$

$$EF_{3D} = EF_{size} \times EF_{depth} \tag{5}$$

where EF_{depth} is the consumption level of capital stock, expressed as a multiple of the production land area required to maintain the current resource consumption level. EF_{size} is the consumption level of capital flow, which represents the inter-annual demand for biological production land by human beings (Fang, 2013). EF_{3D} represents the three-dimensional ecological footprint, i denotes the different ecologically productive land types, and EF_i and EC_i represent the EF and EC of the given land category, respectively. An EF_{depth} value of 1 indicates sustainable development in relation to the unconsumed natural capital stock. An EF_{depth} value exceeding the original value of 1 indicates ecological overshoot (Xun & Hu, 2019).

3.2.2. *Construction of the transportation complex network*

The transportation system is essentially a complex network and so

Table 1
Data source overview.

Data	Data type	Data source
Land use classification data (Interpreted from Landsat TM/ETM images in 2010 and 2017 with a spatial resolution of 30 m)	Cropland, grassland, forest, urban and build-up land, water, and unclassified land	Geographical Information Monitoring Cloud Platform (http://www.dsac.cn/DataProduct/Index/200804)
Road and railway network data	Dataset of roads and railways	Geographical Information Monitoring Cloud Platform (http://www.dsac.cn/DataProduct/Detail/201843)
Biological resource production data	Production data of rice, wheat, corn, soybeans, cotton, vegetables and melons, pork, beef, lamb, poultry, eggs, tung oil tree seeds, tea, fruits, wood, and aquatic products	The Statistical Yearbooks of Hubei, Hunan, and Jiangxi Province in 2010 and 2017, the Rural Statistical Yearbook of Hubei in 2010 and 2017, the Statistical Yearbooks of the UAMRYR prefecture-level cities in 2010 and 2017
Energy consumption data	Consumption data of coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas	The Statistical Yearbooks of Hubei, Hunan and Jiangxi Province in 2010 and 2017
Socio-economic dataset	Population, GDP, and sector structure	The Statistical Yearbooks of Hubei, Hunan, and Jiangxi Province in 2010 and 2017, the Rural Statistical Yearbook of Hubei in 2010 and 2017
Administrative division dataset	Provincial, city, and county boundaries	Map World in National Platform for Common Geospatial Information Services(https://www.tianditu.gov.cn/)
Equivalence factor	Cultivated land (2.52), grassland (0.46), woodland (1.29), water areas (0.37), fossil energy land (1.29), and construction land (2.52)	《National Ecological Footprint Accounting Guidance 2018》 (Lin et al., 2018a)
Yield factor	Cultivated land (1.74), grassland (0.51), woodland (0.86), water areas (0.74), fossil energy land (0), construction land (1.74)	《Estimation of China ecological footprint production coefficient based on net primary productivity》 (Liu et al., 2010)

Note: Equivalence factor is the conversion coefficient for converting the biological productivity area of six types of land with different biological productivities to the area with the same biological productivity. The yield factor serves to convert various types of local land area into a corresponding overall area.

topological analysis can be used to reveal its pattern and structure (Wang et al., 2017). This research regards road intersections and railway station as nodes and the road and railway as edges to construct road complex networks and railway complex networks, respectively. In addition, the complex network constructed in this work is unidirectional and unweighted. We use the average degree in the complex network model to construct the spatial interaction of the transportation network. The degree of a node represents the number of edges owned by node i. The degree is the most intuitive and simplest statistic used to measure the importance of a node in the network. More specifically, the greater the degree of the node, the higher the importance of the node. The calculation of the degree is specified as follows:

$$k_i = \sum a_i \tag{6}$$

where k_i the degree of node i; a_i is the edge connected to node i.

The average degree is the average of the degrees of all nodes in the network. The calculation of the average degree is specified as follows:

$$\overline{d} = \frac{1}{N}\sum_i k_i \tag{7}$$

where N is the number of nodes in the network.

3.2.3. Intra-Interaction of transportation network

The EF change is a spatially dependent process combined with the influence of other counties through the transportation network. Hypothetically, the transportation network is a "channel" that promotes the spatial interaction of the regional EF_{3D}. The eigenvalues of the transportation network according to the complex network were calculated, and then the gravity model was employed to evaluate the intensity of the transportation interactions between regional spatial units.

Based on the gravity model, we use the integrated average degree of roads and railways to establish the spatial interactions between the county units. The average degree is an important indicator to describe the dominant position of regional transportation and reflect the potential of regional external accessibility. Considering the differences between roads and railways, we use passenger traffic of each as weights to construct the integrated average degree (Eqs. (8)) so as to reveal the external access potential of a road–rail system. Then, we employed a gravity model to construct a spatial weight matrix of the transportation network based on the integrated average degree. The gravity model is designed to calculate the volume of flow or the interaction of specific properties between different regional spatial units (Zeng et al., 2019) and has been successfully applied in many fields such as the economy, trade (Mátyás, 1997), and transportation (Zeng et al., 2019). Gravity value is positively correlated with the volume of flow or attribute and negatively correlated with distance. We use the gravity model to correlate the integrated average degree of county units to construct the spatial weight matrix because the county units with high traffic superiority and high external accessibility tend to produce stronger spatial interaction of EF_{3D}. Eqs. (9) is used to generate the spatial interaction.

$$\overline{d} = w_1\overline{d_{road}} + w_2\overline{d_{railway}} \tag{8}$$

$$\overline{D}_{ij} = \mathrm{r} \times \frac{\overline{d_i}\,\overline{d_j}}{d_{ij}^2} \tag{9}$$

where $\overline{d}$ is the integrated average degree, d_{road} is the average degree of road, $d_{railway}$ is the average degree of railway, w_1 is the proportion of road traffic passengers, w_2 is the proportion of railway traffic passengers, D_{ij} is the traffic gravitation between i and j, d_i and d_j are the integrated average degree of i and j, respectively. r is the gravitational coefficient, usually taken as 1.

3.2.4. Driving factors and spatial influences

(1) STIRPAT Model-based driving factor of EF_{3D}

The STIRPAT model examines environmental impacts from the perspective of three aspects: population (P), affluence (A), and technology (T). The model also allows for empirical hypothesis testing to incorporate the potential impacts of human-driven factors on the environment (Zeng et al., 2021). Consequently, the STIRPAT model has become one of the most commonly used models in the study of EF driving factors (Jia et al., 2009). The logarithm on both sides of the equation reduces heteroscedasticity because the STIRPAT model is nonlinear (Zeng et al., 2021). The model expression after taking the logarithm is as follows:

$$lnI = a + b(lnP) + c(lnA) + d(lnT) + e \quad (10)$$

where I is the environmental impact, P is the population size, A is the affluence,and T is technology level. b, c, and d are the coefficients of P, A, and T, respectively. a is the constant term, and e is the error term. In this study, I is the EF_{3D}.

According to data availability, P is set as the population density (PD), A is the GDP per capita (PGDP), and T is the proportion of non-tertiary industry in relation to the GDP (NTGDP), that is, the proportion of primary and secondary industries in GDP. The specifications of adjusted STIRPAT model are as Eqs. (10). Three explanatory variables were selected. First, PD refers to the number of people per square kilometer of land (Ahmed et al., 2019). The multiple effects of PD on sustainable development have been confirmed in the literature. Kongbuamai et al. (2020) found that PD has an inhibitory effect on Thailand's EF. By contrast, Ahmed et al. (2019) confirmed that Malaysia's EF is positively influenced by PD. When we focus on the UAMRYR in China, the positive or negative impact of PD on the EF remains unclear. Therefore, we incorporate PD as a proxy variable of P into the STIRPAT model. Second, GDP is the most commonly used indicator to measure the overall performance of a country (Zeng et al., 2020). GDP per capita has been widely used as a wealth proxy indicator under the STIRPAT framework. Third, the industrial structure is usually regarded as the technological level. The economic shift from extractive, manufacturing, and construction industries toward service industries (such as computer, warehousing, and catering industries) may reduce environmental degradation (Dietz et al., 2007). For some regions, the rise of tertiary industry means the transfer of material production to other regions to achieve economic "dematerialization" (Ausubel, 1996). Therefore, the proportion of non-tertiary industries in relation to GDP may have a positive influence on the EF, as confirmed by Wu (2020) and Dietz et al. (2007).

$$lnEF_{3D} = a + b(lnPD) + c(lnPGDP) + d(lnNTGDP) + e \quad (11)$$

(2) Spatial econometric model specification

In spatial econometrics, it is assumed that certain attribute values of regional spatial units may be affected by neighboring observation values (Anselin, 2013). To explore the spatial influence of transportation network on EF_{3D}, a spatial econometric model was used after identifying the existence of spatial autocorrelation. The spatial weight matrix is key to establishing the spatial econometric model, which represents the spatial interaction mode among observation values of different regional spatial units. Eqs. (9) is used to generate the spatial weight matrix of the spatial econometric model. The general form of the spatial econometric model is as follows:

$$y = \beta_0 + \alpha W_1 y' + \lambda_i x_i + \sum_{i=1}^{m} W_2 \beta_i x_i' + \eta W_3 \varepsilon + \varepsilon \quad (12)$$

where y is $\ln(EF_{3D})$ and y' is its neighboring value. x_i and x_i' denote the local and neighboring explanatory variables, which are PD, PGDP, and NTGDP, respectively. α is the coefficient of the spatial lag term of dependent variable, λ_i represents the coefficients of the explanatory variables, β_i is the spatial lag coefficient of explanatory variables, β_0 is a constant term. ε is the error, and η is the spatial error coefficient. W is a 206 × 206 spatial weight matrix in 2010 and 207 × 207 in 2017. W_1 is the spatial weight matrix for the lag term, W_2 is the spatial weight for the explanatory variable, and W_3 is the spatial weight matrix for the error term. When W_1 and W_2 are equal to 0, the general form is transformed into a spatial error model (SEM). When W_2 and W_3 are equal to 0, the general form is transformed into a spatial lag model (SAR). When W_3 is equal to 0, the general form is transformed into the spatial Durbin model (SDM).

4. Results

4.1. Spatial temporal change of EF_{3D}

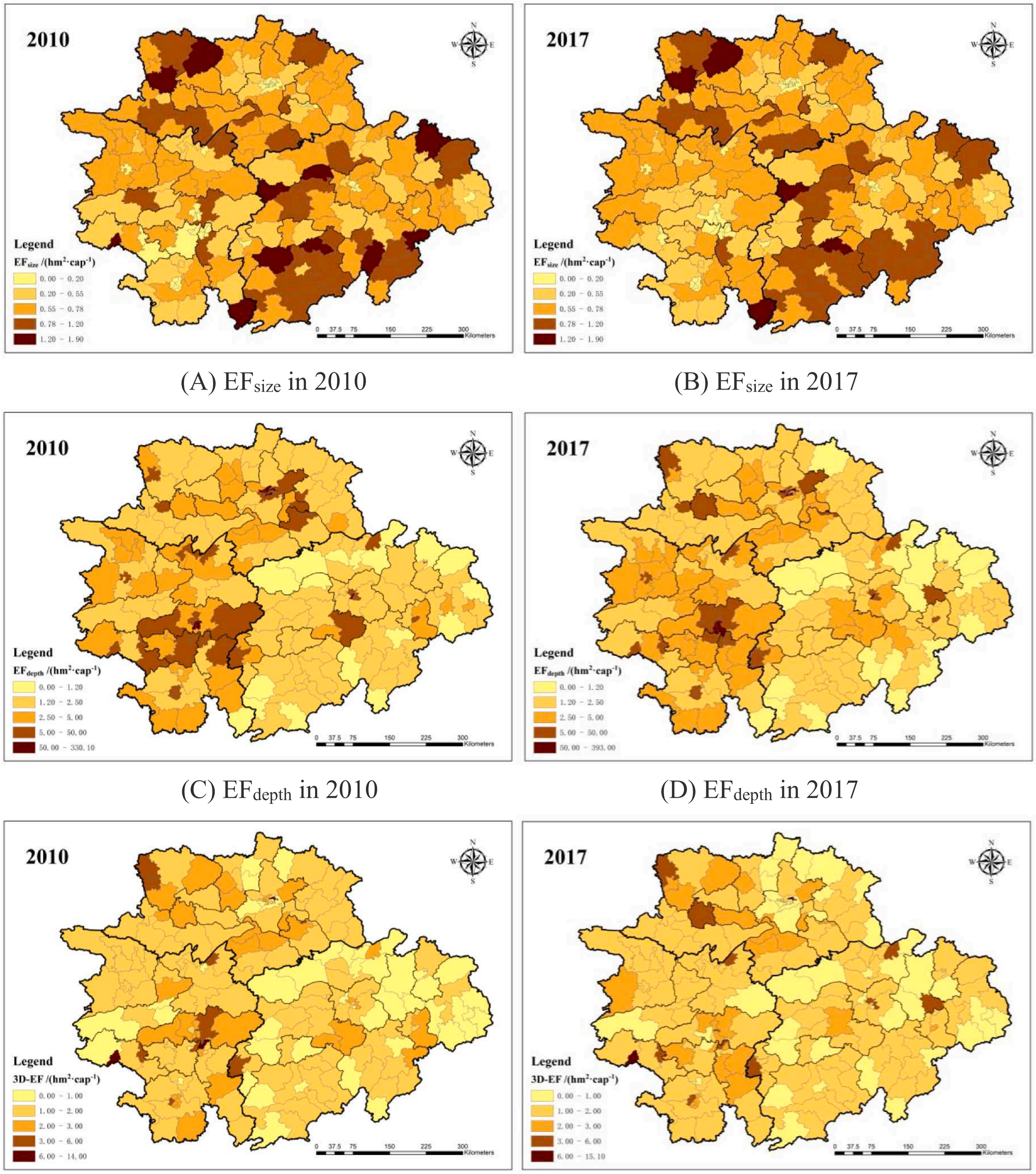
EF_{size}, EF_{depth}, and EF_{3D} values exhibited spatial and temporal changes between 2010 and 2017 in the UAMRYR. EF_{size} represents capital flow occupancy. Fig. 2 (A and B) present the spatial distribution of EF_{size} in the UAMRYR in 2010 and 2017. The mean values of EF_{size} in the UAMRYR declined from 0.5684 gha/capita to 0.5525 gha/capita during this period; thus, the capital flow occupancy was declining. The high values of the EF_{size} were mostly concentrated in suburban districts with abundant resources and low PD in the northwestern, southeastern and part of the central areas. Low values were clustered in densely populated and relatively resource-poor urban districts in the northeastern and southwestern areas. Maximum values appeared in Yanling County (1.4820 gha/capita in 2010) and Jingshan County (1.3031 gha/capita in 2017), which are located in the southern and northern fringe of the UAMRYR, respectively. Donghu District (0.0135 gha/capita in 2010) and Jianghan District (0.0144 gha/capita in 2017) had the minimum values in 2010 and 2017, and are located in downtown areas of the provincial capital cities of Nanchang City and Wuhan City, respectively.

EF_{depth} represents the capital stock consumption. Fig. 2 (C and D) illustrate the spatial patterns of EF_{depth} in the UAMRYR in 2010 and 2017. Mean values of EF_{depth} in the UAMRYR declined from 12.07 gha/capita to 10.68 gha/capita over the period from 2010 to 2017. Therefore, the average consumption level of the county's capital stock decreased. The spatial distribution of EF_{depth} is opposite to that of EF_{size}, with high-value areas mostly distributed in urban areas and low-value counterparts mostly concentrated in suburbs. The EF_{depth} of most county units breached 1, an outcome which indicated that without the support of capital stock consumption, capital flows were insufficient to maintain socio-economic development. In particular, Qingshan District has the largest EF_{depth} in UAMRYR (330.10 gha/capita in 2010 and 392.94 gha/capita in 2017) and traditionally a heavy industry county. Although Qingshan District faces industrial transformation and upgrading, its consumption of capital stocks continues to increase. A few rural areas in Yichun, Zhuzhou, Shangrao, Jiujiang, and Jingdezhen Prefectures had the original EF_{depth} of 1, and the number of those county units with no consumption of capital stock reduced from 12 in 2010 to 11 in 2017.

Fig. 2 (E and F) show the spatio-temporal changes of the EF_{3D} in each county in 2010 and 2017. From 2010 to 2017, the per capita EF_{3D} in the UAMRYR increased from 1.7292 to 1.6631 gha/capita. The spatial distribution of EF_{3D} is similar to EF_{depth} as it was high in the urban areas and low in the suburbs. Although the average EF_{3D} of the UAMRYR decreased from 2010 to 2017, 46% of the counties' EF_{3D} increased. Thus, the gap among different counties widened further. Meanwhile, most counties with increased EF_{3D} were concentrated in the APL in the southeast of the UAMRYR. However, the average value of the EF_{3D} of the APL in 2017 was lower than that of the WHA and the CZTA, indicating that despite the high level of sustainable development of the PLA, the pressures of natural resource utilization have been highlighted in recent years. It is worth noting that, Wannian District, has the largest increase in the EF_{3D} from 2010 (0.8904 gha/capita) to 2017 (4.3872 gha/capita) and borders the eastern part of the UAMRYR. As a typical resource-based industrial city, Wannian District relies on a path of resource dependence that exacerbates its ecological deficit.

4.2. Complex transportation network characteristics

Fig. 3 illustrates the degree and proportion of the corresponding number of nodes in the road and the railway networks in 2010 and 2017. In both years, the road network nodes with degrees of 3 dominated, followed by those with degrees of 4, showing that most nodes in a complex network of roads have 3 or 4 edge connections. Nodes with degrees of 6 were least abundant. The railway network has the largest



(A) EF_{size} in 2010 (B) EF_{size} in 2017

(C) EF_{depth} in 2010 (D) EF_{depth} in 2017

(E) EF_{3D} in 2010 (F) EF_{3D} in 2017

Fig. 2. Spatial patterns of EF_{size}, EF_{depth}, and EF_{3D} in UAMRYR.

number of nodes with degrees of 2, thereby indicating that most railway stations have 2 connecting edges. From 2010 to 2017, the number of nodes with degrees of 3 in the road and railway networks increased substantially, but the number of nodes with degrees of 2 decreased.

Fig. 4 shows the topological structure of the complex road network. The road network had 4359 nodes and 6546 edges in 2010, and 5684 nodes and 8854 edges in 2017. The overall road node coverage and density of the UAMRYR have increased, and the average degree increased from 3 to 3.12. Spatial distribution of the road network shows an unbalanced pattern, and the nodes of provincial capital cities (Wuhan, Changsha, and Nanchang) are highly clustered, especially in Wuhan and Changsha. In 2017, the number of nodes in Nanchang City increased, but the average degree didn't increase substantially. The average degree of Wuhan and Changsha increased to a certain extent, thereby indicating that Wuhan and Changsha have better topologies and higher accessibilities than Nanchang. Notably, the density of nodes between provincial capital cities increased significantly, and the "triangular, radial" inter-provincial connectivity network between provincial capital cities has gradually improved to achieve a two-hour access circle.

Fig. 5 shows the topology of the complex railway network. From 2010 to 2017, the nodes of the railway complex network increased from 109 to 187, edges increased from 119 to 217, and the average degrees increased from 2.18 to 2.34. Thus, the scale of the network expanded and accessibility was enhanced in UAMRYR. UAMRYR's railway network presents a structure that radiates from Wuhan, Changsha, and Nanchang as the center, and connects major cities in UAMRYR. In

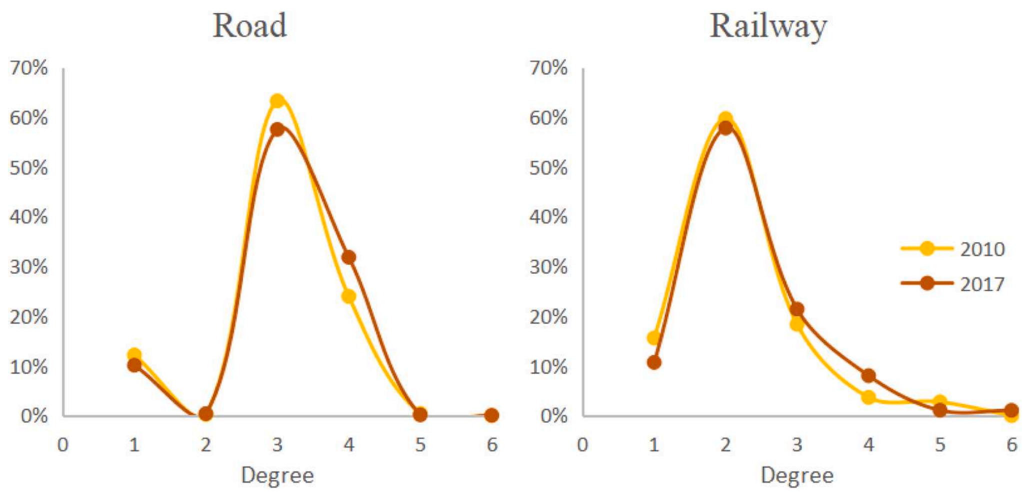


Fig. 3. Network characteristics of degrees in the UAMRYR.

particular, the intercity railways reduce travel time between provincial capital cities and surrounding cities. Furthermore, WHA, CZTA, and APL present different railway layout modes. WHA and CZTA showed a tendency to gather, but APL revealed a divergent spread to increase the railway coverage.

Fig. 6 illustrates the integrated average degree of roads and railways. The integrated average degree of the UAMRYR dropped from 2.90 in 2010 to 2.88 in 2017. Thus, when the passenger volume of the transportation is considered, the connectivity of the transportation network decreases. This situation may be caused by a mismatch between the capacity and spatial distribution of transportation network. The spatial distribution of the integrated average degree presents a multi-level circular distribution structure with a low center that initially increases and then decreases. The high-value circle connects three provincial capital cities (Nanchang, Wuhan, and Changsha), and the structure becomes clearer over time. Qingshan District is the county unit with the highest increase in the integrated average degree, which may be caused by the demand for industrial development in Qingshan District.

4.3. Spatial interaction of transportation networks among counties

Fig. 7 illustrates the portion of gravity generated by the integrated average degree of the transportation network between different counties. The gravity force between two counties is calculated as specified in Eqs. (9) and by considering the integrated average degree and the geographic distance. The highest gravity forces in 2017 are shown for each county's top three values in Figs. 7 and 8. The Donghu District (No.127) of Nanchang City has the largest share of connections with the top three values of the other counties, followed by Wuchang District of Wuhan City (No. 7), both of which are central urban areas of the provincial capital. The biggest interactions occurred between Hengshan City (No.83) and Nanyue District (No.86) in Hengyang City in 2010, and between Qingshanhu District (No.130) and Donghu District (No.127) in Nanchang City in 2017.

Fig. 8 illustrates the visualization of the gravitational connection on the map in 2010 and 2017. By analyzing the spatial distribution of the gravitational connection in UAMRYR, it is shown that the interaction in UAMRYR is unbalanced, and the spatial pattern of "three nuclei" is presented. Wuhan, Changsha, and Nanchang occupied the interactive core positions, showing that the interactive influence of those cities is obviously stronger than for other cities in UAMRYR. The high gravity of WHU spreads around Wuhan, the gravity of CZTA spreads from Changsha to the south, including Changsha, Xiangtan, Zhuzhou, and Nanchang is the pole of high gravity, and it strongly connects the cities in the west (Jingdezhen, Yingtan and Shangrao) and the north (Jiujiang). Therefore, the distribution of high gravity is polarized in the UAMRYR, and transportation are given priority over the connections between the central city and surrounding cities. We also find that the spatial pattern inside UAMRYR has not undergone fundamental changes during the study period, however, the spatial interaction intensity between surrounding cities and provincial capital cities (Wuhan, Changsha, Nanchang) has enhanced.

4.4. Spatial influences of the transportation network on EF_{3D}

The diagnosis of spatial autocorrelation is shown in Table 2. Moran's I was significant in 2010 and 2017, indicating that the spatial econometric model is suitable for analyzing the spatial influence of EF_{3D}. Significant spatial correlation was observed in both focal years through the Moran's I test on errors. The Lagrange multiplier (LM) tests of the spatial lag and spatial error models are equally significant in 2010 and 2017. Therefore, we implemented the SDM to examine the spatial spillover effects of EF_{3D} through the transportation network and check the indirect spatial influence of PD, PGDP, and NTGDP on EF_{3D}.

Table 2 also shows the OLS regression and SDM regression results of the EF_{3D}. From 2010 to 2017, the coefficient of W_ln EF_{3D} decreased from 0.6195 to 0.5596 but still remained statistically significant. Thus, when a neighboring EF_{3D} increases by 1%, the local EF_{3D} will increase by 0.6195% and 0.5596% in 2010 and 2017 respectively through the transportation network. PD, PGDP, and NTGDP are significant local positive drivers of the EF_{3D} under the STIRPAT framework. Indirect spatial spillover effects of PD and PGDP are also observed. PGDP showed a significant positive indirect spatial influence in 2010 and 2017, while that of PD showed a negative spatial influence and was only significant in 2017.

From 2010 to 2017, three primary changes occurred. First, the local and indirect spatial influence of PGDP show an increasing trend, and the indirect spatial effects is stronger than local positive influences. Second, the local influences of the NTGDP on the EF_{3D} show a declining and positive trend, but its influence is the strongest among all explanatory variables. Third, although the local influences of PD have positive effects, the spatial spillover effects of W_PD have become negatively significant in 2017. Furthermore, the robustness of the spatial regression model is confirmed given that R^2 increased significantly in 2005 and 2010. Given that the R^2 in the SDM model was significantly higher than the OLS in 2010 and 2017, the robustness of the spatial econometric model is established.

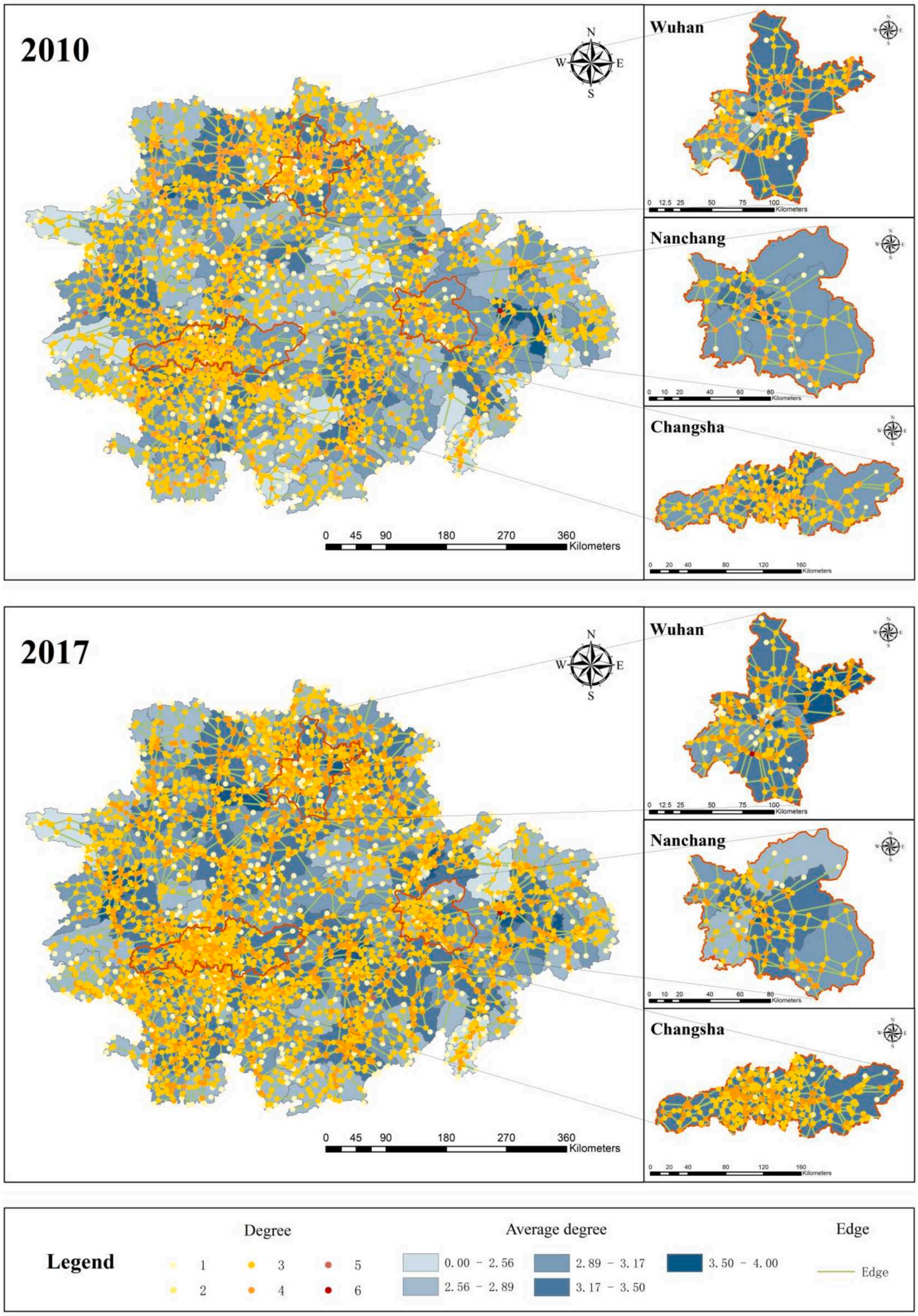


Fig. 4. Road network in the UAMRYR.

5. Discussion

This study is motivated by an attempt to investigate the spatial influence on EF_{3D} through the transportation networks by taking transportation networks as the "channel" of spatial influence. The novelty of our study lies in our conceptualization of the transportation network as "channels" for inter-regional cooperation to achieve sustainable development, rather than as a potential driving factor. Our results demonstrate that the EF_{3D} is driven by socio-economic factors and confirm the existence of spatial spillover effects with varying magnitudes through transportation networks.

EF is a powerful tool to assess the level of sustainable development. China proposes an ecological civilization strategy to guide urban sustainable development (Yang et al., 2020). As a key transportation hub in China, the sustainable development of the UAMRYR is crucial to achieving China's ecological civilization goals and realizing green

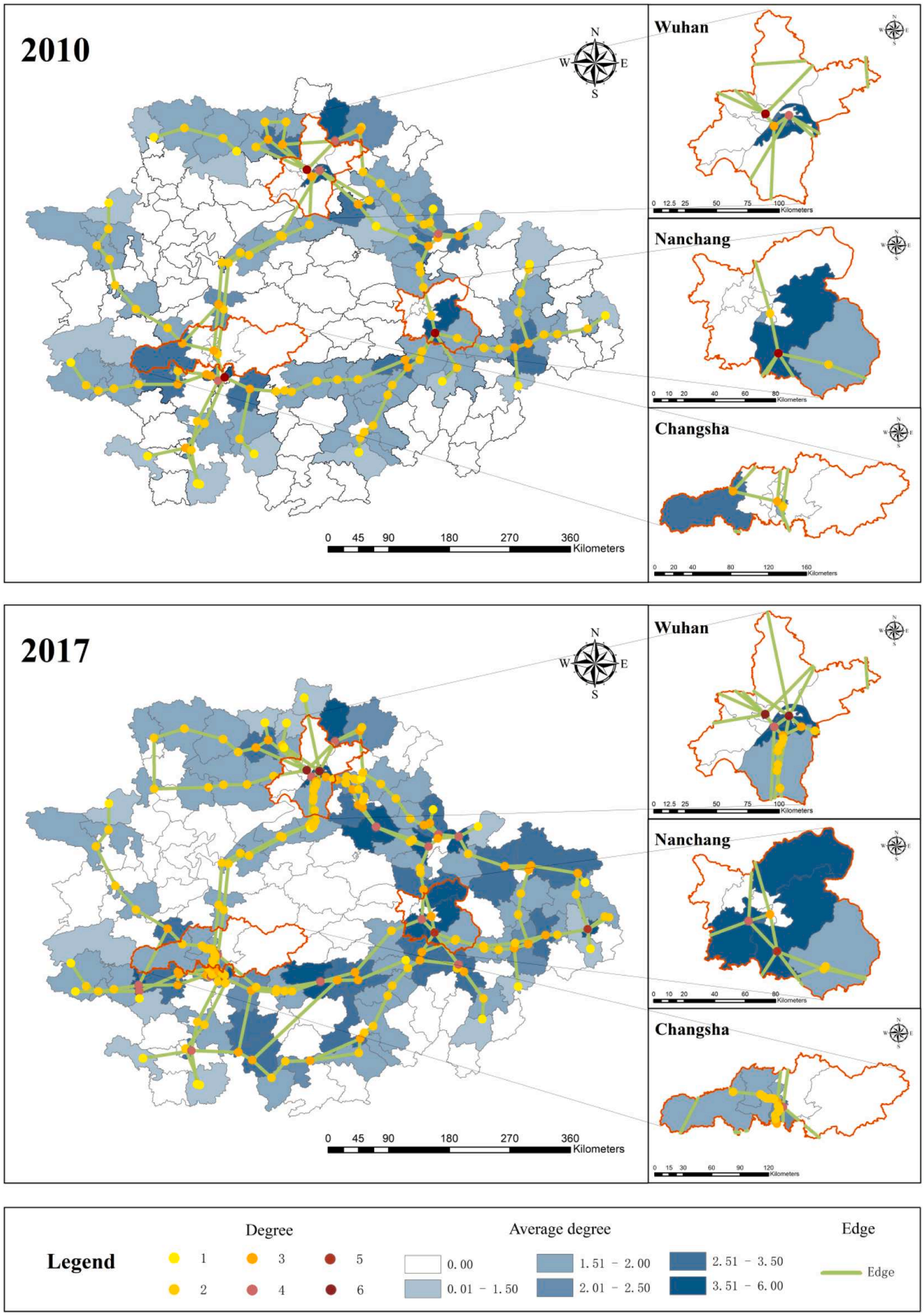


Fig. 5. Railway network in the UAMRYR.

transformation. Our findings show that the tensions between the economic growth and environmental protection have slightly alleviated in the UAMRYR. This finding is attributed to the efforts of the authorities to formulate and implement a multi-pronged policy framework. Due to the huge differences in the development level and physical geography in UAMRYR, there are obvious spatial differences in counties' EF_{3D} status. The EF_{3D} of the UAMRYR shows obvious spatial heterogeneity, exhibiting the spatial pattern with high values in provincial capital cities (Wuhan, Changsha, Nanchang) and low values in the suburbs. Inner central cities have consumed their capital stocks in advance and shoulder ecological debts, showing a conflict between economic development and a sharp decline in EC. As less natural capital flows become available among countries, the spatial correlation of EF between counties through the transportation network could further strengthen the flexibility of capital circulation between the central city and the surrounding areas. Resource movement through transportation

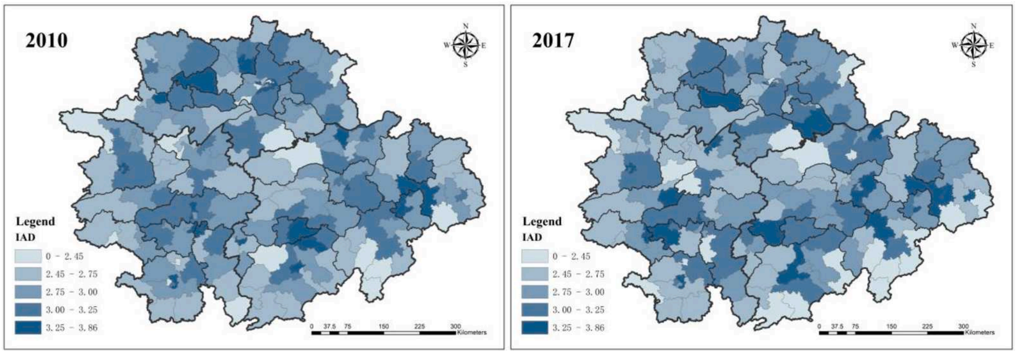


Fig. 6. Spatial patterns of the integrated average degree in the UAMRYR. Acronyms: IAD: integrated average degree.

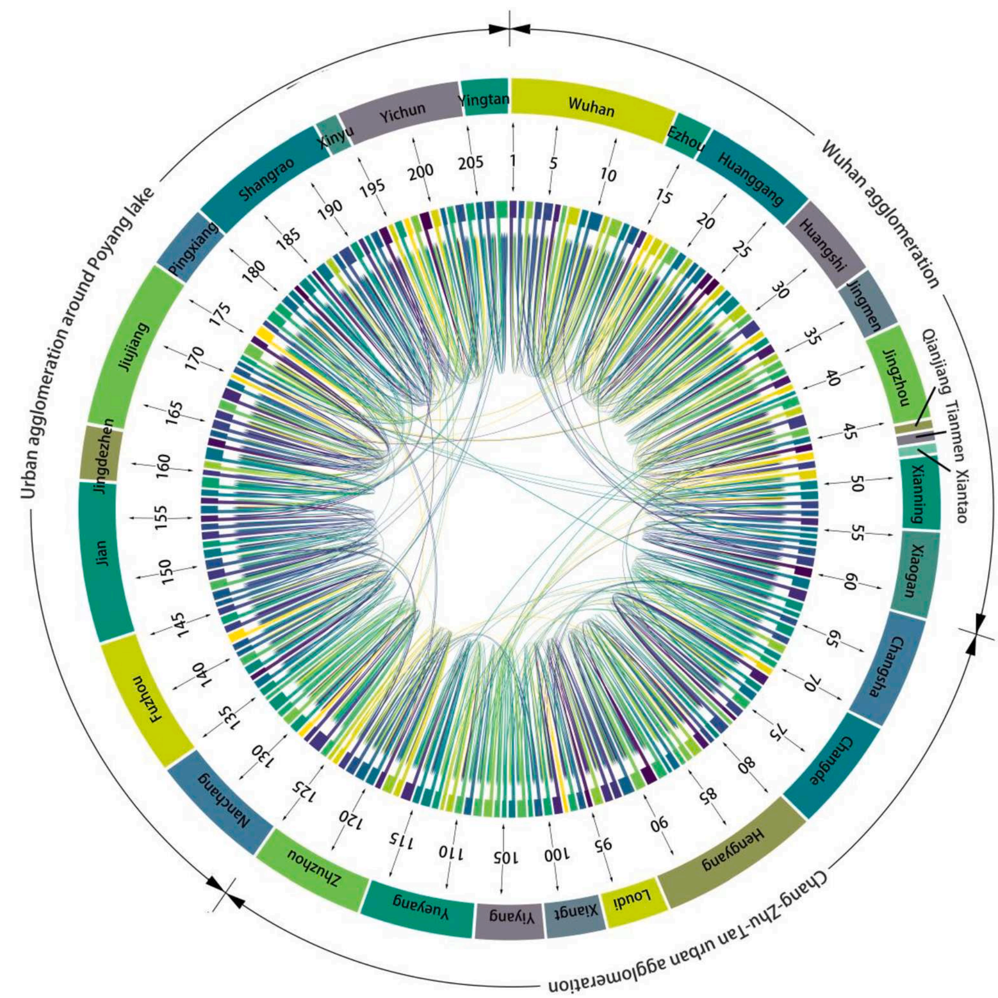


Fig. 7. Transportation connections for each county in 2017.

networks is regarded as an essential component of regional cooperation and coordination. Therefore, the positive environmental externalities of transportation networks is supposed to be utilized to alleviate the ecological debt of the central city, and to realize the regional sustainable development.

The strong driving force of the socio-economic system on the EF_{3D} is confirmed in this study, which provides the empirical evidence for the efforts to reduce EF_{3D}. PD, PGDP and NTGDP have played a positive role in the EF_{3D}. Overloaded population and excessive economic activities will continue to exert pressure on the regional ecosystem, resulting in increasing capital consumption and waste discharge while damaging EC (Gu et al., 2015). Similarly, unreasonable industrial structure and excessive reliance on heavy industry sectors are undoubtedly aggravating regional environmental burdens (Liu et al., 2018). These results are conductive for policymakers in identifying priorities for curbing pre-consumption of capital stock and making decisions regarding socio-economic development to improve sustainable development level. In the short term, actions should be taken with respect to the upgrading of industrial structure and rational optimization of production capacity. High-pollution and low-efficiency industries shall be gradually eliminated. And it is advisable to implement strict population policy and population attraction policy in central cities and suburbs (satellite

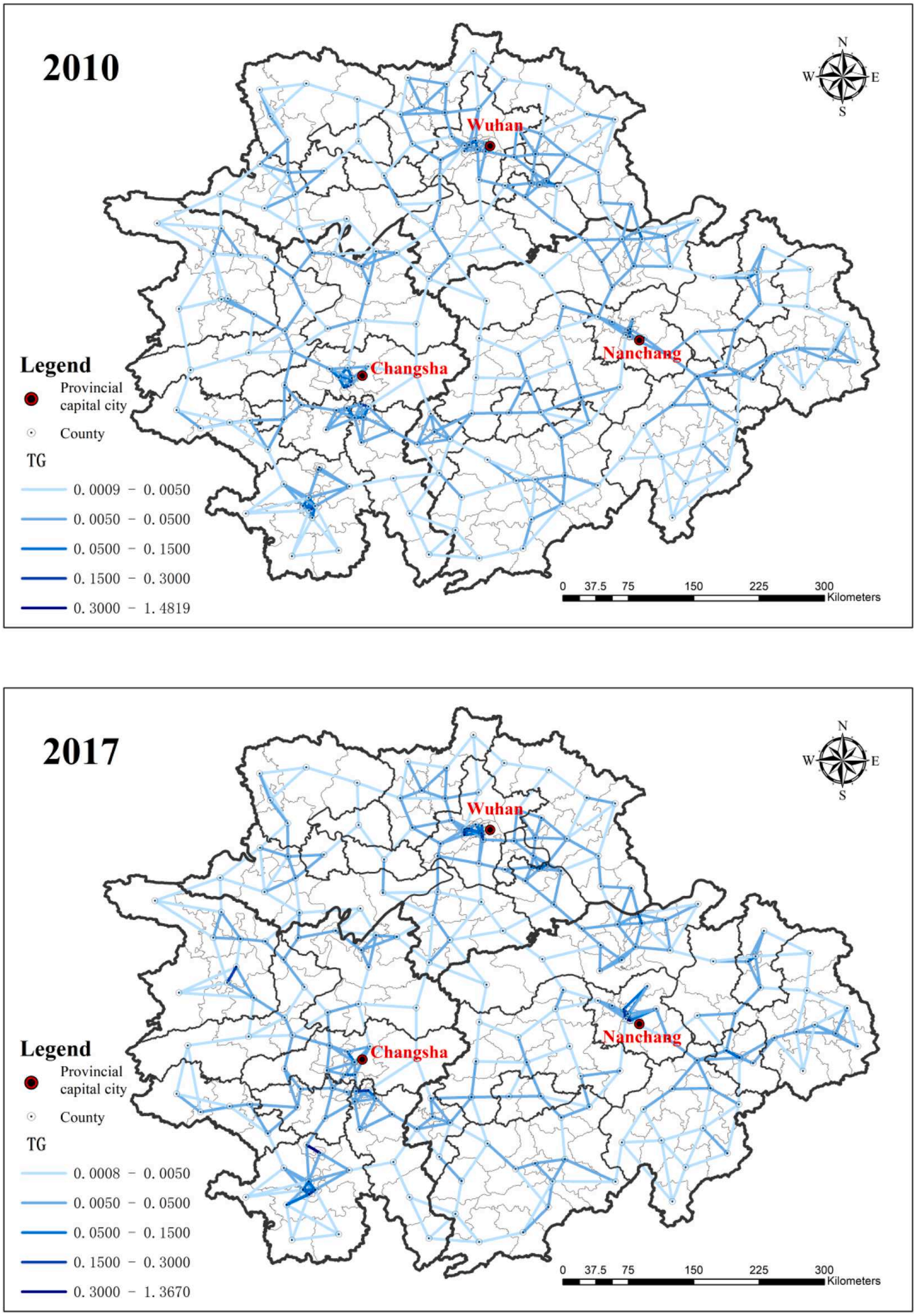


Fig. 8. Traffic gravity network for each county in 2010 and 2017. Acronyms: TG: traffic gravity.

cities), respectively, so as to the reasonable spatial distribution of population and ecological balance.

The utilization of the spatial influence of the transportation network is a key issue for the implementation of sustainable development policies at the regional level. The spatial spillover effect of the transportation network on the EF_{3D} was found to be positive and significant and seems to aggravate environmental degradation in urban agglomerations. However, with the transformation and development of cities, new requirements for modern roads and railways with network, connectivity, and ecological attributes, have been proposed, so that the negative spatial spillover effect is weakened, and the favorable function of the transportation network in urban space is strengthened. Counties with high transportation accessibility tend to use various trade-offs to break the blockages that restrict the rational flow of resources, correct the imbalance and mismatch of resource elements, and strengthen inter-regional coordination of the environment in urban agglomerations (Yang et al., 2020). Accordingly, long-term planning should emphasize various capitals, including natural and human capitals, to complement

Table 2
Results of OLS regression and SDM in 2010 and 2017.

Variable	OLS 2010	OLS 2017	SDM 2010	SDM 2017
ln PD	0.1214***	0.1833***	0.1076**	0.1402**
ln PGDP	0.3476**	0.2069**	0.1711*	0.1727***
ln NTGDP	0.5794***	0.5787***	0.6707***	0.6122***
W_ln EF_{3D}	—	—	0.6195***	0.5596***
W_ln PD	—	—	−0.1259	−0.2859**
W_ln PGDP	—	—	0.4159*	0.5601**
W_ln NTGDP	—	—	−0.1755	−0.4644
Moran's I	—	—	0.2440***	0.2000***
Moran's I-error	—	—	7.918***	6.608***
LM error	—	—	51.934***	35.836***
LM lag	—	—	57.466***	38.112***
Sigma	—	—	0.5867***	0.6499***
R^2	0.1413	0.1340	0.9972	0.9974
Constant term	6.8273***	7.7560***	−2.6856	−1.6368

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

one another and to maintain an optimal allocation through transportation network (Mancini et al., 2017). The indirect spatial effect of the neighborhood also shows some interesting phenomena. The neighboring PD had a negative influence on the local EF_{3D} while PGDP had a positive influence. As a tightly coupled system, the UAMRYR relies on a well-developed transportation network. Economic integration seems to inevitably put pressure on the environment of the entire urban agglomeration. However, the transportation network, especially the intercity railway centered on Wuhan, Changsha, and Nanchang, supported smooth population mobility, helping to alleviate the ecological pressure caused by population overload in the central city. Thereby, to cope with the spatial effects of the transportation network, urban planners, resource managers, and decision makers should consider an ecologically efficient transportation system to promote the substantial expansion of resource flows between counties. The implementation of spatial coordination strategies according to the construction of the intercity transportation network accelerates the circulation of labor, technology, services, and resources that shorten the urban spatial distance, thereby generating a positive spillover effect of the transportation system. Furthermore, the transnational environmental impact of transportation networks should be emphasized by international organizations and scientists, not least because it has global significance in promoting the international transition of sustainable development from theory into practice. Transnational ecological cooperation based on transportation systems should be urgently added to the global agenda to avoid the transnational pollution currently seen under globalization, so as to ensure the realization of SDGs.

6. Conclusion

This study investigated the spatial spillover effect of a transportation network on the EF_{3D} in UAMRYR in 2010 and 2017. Results show that although EF_{size}, EF_{depth}, and EF_{3D} in 2017 were reduced compared by 2.80%, 11.49%, and 3.82%, respectively, compared with their 2010 values, 94.69% of the county units were still in ecological overshoot in 2017. In 2010 and 2017, the degree of complex networks of roads and railways increased from 3 to 3.12 and from 2.18 to 2.34, respectively, indicating the transportation network became increasingly advanced and effective. The EF_{3D} is also highly influenced by the socio-economic system, in which PD, PGDP, and, NTGDP exerted positive influences. Meanwhile, neighboring PD has a significant negative spatial influence on the EF_{3D}, but PGDP exerts a positive spatial influence. These findings are of great importance in building collaborative efforts to achieve the SDGs through transportation networks.

Some limitations still need attention. First, road and railway networks should be compared. Road and railway systems are integrated to serve as a spatial interaction channel, but the heterogeneity of roads and railways has not been distinguished in this research. Second, aviation and shipping should also be considered. Work presented here only regards the physical network of roads and railways as the channel of spatial interaction and disregards the efficiency of the flow (human, resource, and technology) because of data unavailability. In the future, a comprehensive transportation network including multiple transportation modes should be considered to provide policy suggestions to achieve sustainable development under three-dimensional integrated transportation.

CRediT authorship contribution statement

Tianyu Lv: Conceptualization, Methodology, Software, Resources, Visualization, Writing – original draft. **Chen Zeng:** Conceptualization, Methodology, Supervision, Funding acquisition, Writing – review & editing. **Lindsay C. Stringer:** Supervision, Writing – review & editing. **Jing Yang:** Writing – review & editing. **Pengrui Wang:** Writing – review & editing.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2021.108309.

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