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Analysis of the impact of transportation infrastructure investment on regional economic resilience from the perspective of complex networks

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Abstract

Against the backdrop of multiple shocks to regional economies, enhancing economic resilience has become the key to achieving sustainable development. This article starts from the perspective of complex networks and regards transportation infrastructure as a network system composed of nodes and edges, studying the impact mechanism of its investment on regional economic resilience. Based on panel data from a certain province from 2004 to 2024, a composite transportation infrastructure investment network consisting of 110 nodes and 455 edges was constructed. The entropy weight method was used to construct a regional economic resilience index from three dimensions: resistance recovery, adaptation regulation, and innovation transformation. Empirical analysis using spatial Durbin model and geographic/economic distance matrix. The results indicate that investment in transportation infrastructure has a significant promoting effect on regional economic resilience and has a marginal diminishing effect, Regional economic resilience exhibits significant spatial dependence, and spatial spillover effects are more pronounced under the economic distance matrix.

Keywords - complex network, transportation infrastructure, infrastructure investment, economic resilience

1. Introduction

Against the backdrop of increasing global economic uncertainty, "regional economic resilience" - the ability of regional economic systems to withstand, adapt to external shocks, and achieve transformation and recovery - has become a core issue in regional development research. Traditional research often analyzes the economic effects of transportation infrastructure from a linear causal perspective, neglecting its structural characteristics as a complex system [7]. The complex network perspective views transportation infrastructure as a network composed of nodes (such as transportation hubs and cities) and edges (such as road and railway connections), emphasizing the systematic impact of its topological structure (such as centrality, connectivity, clustering coefficients) on economic behavior and shock transmission. Adopting this perspective can provide a deeper understanding of how transportation investment affects the spatial transmission mechanism of economic resilience through network structure, and compensate for the shortcomings of traditional analytical frameworks [5]. This article aims to construct an integrated analysis framework of "complex network spatial econometrics", systematically explore the impact path and spatial effects of transportation infrastructure investment on regional economic resilience, and provide theoretical basis for resilience oriented infrastructure planning.

In recent years, many scholars have conducted research and have achieved certain research results. Chen et al. [3] constructed a general equilibrium model of multi-city space, incorporated the density of Internet infrastructure into the analytical framework, and deeply explored the promoting effect of infrastructure agglomeration on regional economic development through mechanisms such as promoting regional innovation spillover, accelerating market integration, and alleviating spatial misallocation of labor force. This research provides an important reference for understanding the economic effects of networked infrastructure. However, its analytical framework pays insufficient attention to the interaction mechanism between physical transportation networks and digital networks, especially the dynamic response process of infrastructure systems in response to external shocks has not been fully explained. For example, Ma et al. [8] conducted a study on the impact of the digital economy on export resilience using provincial panel data from 2008 to 2019 in China. The study found that the digital economy can directly enhance its resilience and also has significant spatial spillover effects, which are more prominent in the central and western regions and high scoring areas of export resilience. However, this study is mainly based on the regression of regional attribute data, and fails to concretize economic connections such as trade and factor flows between regions into a network topology structure. Therefore, it is difficult to intuitively reveal the dynamic process of economic shocks transmitted along specific network paths and their clustering characteristics at key nodes. Xing Lan et al. [13] conducted a study using a multi period DID model based on data from coastal cities in China from 2007 to 2020, focusing on analyzing the differential impact of policy interventions on the resilience of two types of economies. The research results show that the policy has significantly improved the regional economic resilience, but the COVID-19, as a moderating variable, weakened the policy effect, and showed a differentiated impact on the economic resilience of the central and southern coastal areas and the tourism economic resilience of the eastern coastal areas in terms of regional heterogeneity. This research provides strong evidence for policy evaluation. However, the empirical design regards policy shocks as exogenous variables, and the analysis of factors with strong network externalities such as transportation infrastructure is limited in depth, which is difficult to reveal how the policy effect is differentiated with the structural position difference of regions in the infrastructure network. Wu et al. [11] used the mediation effect model and the generalized matrix method to reveal the mechanism of the impact of industrial diversity on regional economic recovery at the micro level, and provided new ideas for revealing the mechanism of the impact of industrial diversity on regional economic recovery within a region. However, the analytical scale of this study is still mainly limited to the internal attributes of administrative units, and fails to examine individual regions in a larger cross regional infrastructure network, thus ignoring the moderating effect of the global status of nodes in the network on the relationship between industrial diversity and economic resilience. These studies have advanced the theoretical exploration of regional economic resilience from different perspectives, but there is still room for further deepening in the perspective of system integration network and dynamic analysis.

As a key support for regional economic development, investment in transportation infrastructure has a direct impact on the region's ability to cope with external shocks due to its network structure characteristics. Traditional research often starts from linear causal relationships and focuses on the direct economic benefits of transportation infrastructure investment, but neglects its important role as a structural attribute of complex network systems in economic resilience. In this context, conduct an analysis and research on the impact of transportation infrastructure investment on regional economic resilience from a complex network perspective. I hope that through this research, we can break through the limitations of traditional analytical frameworks, deeply reveal the inherent mechanism of how the structural characteristics of transportation infrastructure networks affect regional economic resilience, and construct a comprehensive research paradigm that integrates complex network analysis and econometrics. This will provide scientific basis and practical guidance for optimizing regional infrastructure investment layout and enhancing the risk resistance of regional economic systems, thereby helping to build a more resilient new pattern of regional economic development.

2. The transmission mechanism of the impact of transportation infrastructure on economic resilience from the perspective of complex networks

Regional economic resilience refers to the comprehensive ability of a regional economic system to resist initial losses, quickly adapt, and achieve structural transformation and recovery in the face of external shocks. To quantify this concept, this study constructs a multidimensional evaluation system and uses the entropy weight method to comprehensively calculate the regional economic resilience index, which includes the following three dimensions:

1. Resilience: measures the ability of the economic system to withstand shocks and restore its original level, characterized by indicators such as GDP volatility,
2. Adaptive adjustment ability: reflect the ability of the system to adjust resources and structure to maintain operation in the impact, and use indicators such as employment recovery speed,
3. Innovation and transformation capability: refers to the ability of a system to achieve higher levels of development through structural upgrading and innovation, characterized by indicators such as the Industrial Structure Diversification Index.

From the perspective of complex networks, transportation infrastructure is not only a capital investment, but also a network system with a specific topology structure. The structural characteristics of its nodes (such as transportation hubs and cities) and connecting edges (such as highways and railways) directly affect the flow efficiency and impact transmission path of economic factors, thereby shaping regional economic resilience. This chapter starts from the network structure and explains the direct and indirect mechanisms by which transportation investment affects economic resilience. The path diagram of the impact of transportation infrastructure investment on regional economic growth is shown in Figure 1.

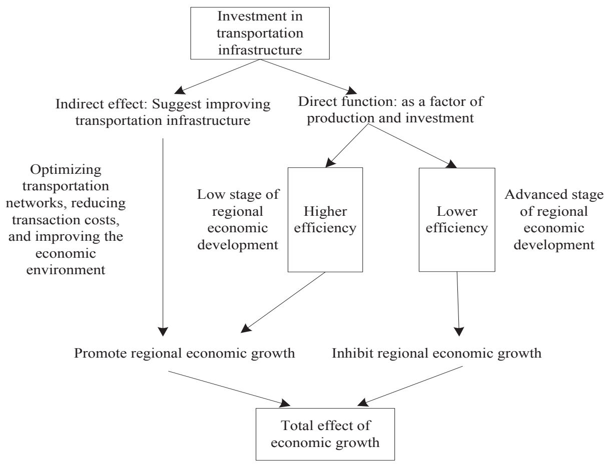


Fig. 1 - Path diagram of the impact of transportation infrastructure investment on regional economic growth

As shown in Figure 1, its mechanism of action is mainly reflected in two dimensions: firstly, the direct transmission path. Transportation investment, as a capital factor input, directly drives economic growth through the multiplier effect, which is particularly significant in the early stages of economic development, Secondly, there are indirect transmission pathways that enhance the adaptability and resilience of the economic system by optimizing the transportation network structure, reducing the cost of factor flow, and improving regional connectivity [1, 9]. From the perspective of network topology, investment in transportation infrastructure reshapes the economic connectivity pattern between regions by changing the structural characteristics such as node centrality, connection strength, and clustering coefficient of the network. Specifically, investment not only improves the accessibility of local nodes, but more importantly, by enhancing the overall connectivity efficiency of the network, promoting knowledge spillover, technology diffusion, and industry collaboration, thus building a multi-level protection system against external shocks. It is worth noting that there are significant differences in the investment effects of different network locations, and investments in core nodes often generate stronger network externalities.

2.1. Analysis of spillover effects of investment space in transportation infrastructure

The externalities of transportation infrastructure are rooted in its public goods attributes, which have profound impacts on both industrial and spatial dimensions. On the industrial dimension, its external effects exhibit significant duality: positive effects include transportation cost savings and economic efficiency improvements, while negative effects manifest as ecological and environmental pressures. In terms of spatial dimension, relying on the characteristics of networked structure, transportation infrastructure can reconstruct the regional economic geographic pattern - by enhancing regional accessibility and optimizing factor circulation paths, it not only promotes the dynamic balance of industrial agglomeration and diffusion, but also forms cross regional spatial spillover effects, ultimately promoting the benign interaction between specialized division of labor and economic agglomeration.

From the perspective of complex networks, the spatial spillover effects of transportation infrastructure have obvious directional characteristics. When production factors gather in developed regions, the negative spatial spillover effects on underdeveloped areas will exacerbate regional development disparities, On the contrary, if factors flow to underdeveloped areas, it will form positive spatial spillover and promote regional coordinated development. From a temporal perspective, China's transportation investment exhibits significant cyclical characteristics. The short-term economic driving effect is mainly reflected in the construction sector and related industrial chains, achieving economic stimulus through the multiplier effect of employment creation and income growth. However, the multiplier effect at this stage may be accompanied by crowding out effects, where the government raising funds through issuing bonds or other means may lead to an increase in interest rates, thereby suppressing private sector investment. It should be noted that short-term spatial spillover effects are often limited to local areas and difficult to reflect the complete network characteristics. In the long run, investment in transportation infrastructure generates more profound network effects by expanding network scale and enhancing network connectivity. The improvement of transportation networks not only enhances the mobility of production factors, but also changes the location choices of enterprises and residents, promoting the formation of agglomeration economies [10]. Specifically, the improvement of a certain transportation route will not only enhance the transportation efficiency of the route itself, but also affect other connected routes through network transmission mechanisms, resulting in distribution and creation effects. The distribution effect manifests as the redistribution of trade flows, while the creation effect is reflected in the expansion of overall trade scale. The existence of this network effect often results in long-term returns on transportation infrastructure investment far exceeding short-term returns, and exhibits significant spatial heterogeneity [6]. It is worth noting that there is a complex feedback mechanism between transportation infrastructure and regional economic development. Regional economic growth provides necessary funding and technological support for investment in transportation infrastructure, while changes in demand brought about by economic development also guide the optimization and upgrading of transportation infrastructure. Economic growth provides feedback on transportation infrastructure through two channels: firstly, it changes the attractiveness of the location and influences the government's transportation investment decisions, The second reason is that the increase in residents' income has led to a structural change in travel demand, thereby promoting the expansion of the quality and scale of travel services. This bidirectional interactive relationship presents a dynamic evolution of spatial spillover effects in transportation infrastructure, which requires systematic examination within the framework of network analysis [12, 2]. From the perspective of complex networks, the evaluation of spatial spillover effects of transportation infrastructure investment needs to focus on the topological characteristics of the network structure, including node centrality, connection strength, and network density. These structural features not only determine the transmission path and scope of spillover effects, but also affect the resilience and stability of regional economic systems.

3. Construction and structural analysis of transportation infrastructure investment model based on complex network

3.1. Data source of regional transportation infrastructure investment network

This study constructs a complex network model based on panel data from a certain province from 2004 to 2024, focusing on examining the impact mechanism of transportation infrastructure investment on regional economic resilience. The data collection work of this study is mainly divided into two parts: firstly, the system collected transportation infrastructure investment data from various regions, Then, construct an economic resilience evaluation system that includes three dimensions. The system selects key indicators from three dimensions: resistance to recovery (GDP volatility), adaptation regulation (employment recovery speed), and innovation transformation (industrial structure diversification index). This data is sourced from the China Statistical Yearbook, China Population and Employment Statistical Yearbook, China Science and Technology Statistical Yearbook, etc. All raw data have been standardized and preprocessed, and the entropy weight method is used for weight calculation, ultimately constructing a comprehensive regional economic resilience index.

3.2. Modeling of regional transportation infrastructure investment network

This article selects all districts and counties within the jurisdiction of a certain province as highway investment nodes, major railway freight stations as railway investment nodes, and major ports as water transportation investment nodes, and names them according to cities. The specific settings are shown in Table 1.

Based on this, construct a network structure. This network model can be represented as a directed weighted graph $G=(V,E,W)$, where the node set V contains 110 nodes, the edge set E contains 455 edges, and the weight set W represents the traffic flow intensity of each connected edge. The network consists of three levels: highway level, railway level, and waterway level, forming a composite transportation network investment system for a certain urban agglomeration.

The composite transportation investment network of the Beibu Gulf urban agglomeration is shown in Figure 2.

Tab. 1 Information on Investment Nodes of Transportation Infrastructure

City	Highway investment node number	Railway investment node number	Water transportation investment node number
A	A-HW-1~9	A-RW-1~6	A-WT-1
B	B-HW-1~5	B-RW-1~2	B-WT-1
C	C-HW-1~4	C-RW-1~2	C-WT-1
D	D-HW-1~12	D-RW-1~4	0
E	E-HW-1~4	E-RW-1~2	E-WT-1
F	F-HW-1~4	F-RW-1~2	F-WT-1
G	G-HW-1~4	G-RW-1~3	G-WT-1
H	H-HW-1~7	H-RW-1~3	0
I	I-HW-1~7	I-RW-1~4	0
J	J-HW-1~4	J-RW-1	0
K	K-HW-1	K-RW-1	K-WT-1
L	L-HW-1	L-RW-1	L-WT-1
M	M-HW-1	M-RW-1	0
N	N-HW-1	N-RW-1	0
O	O-HW-1	O-RW-1	0

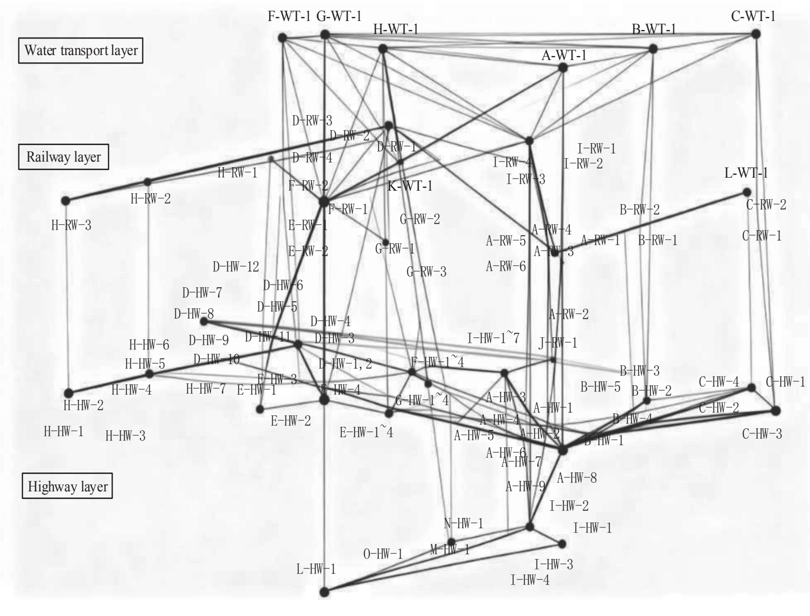
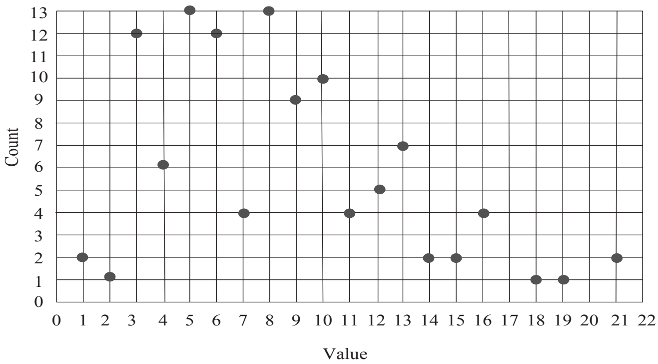
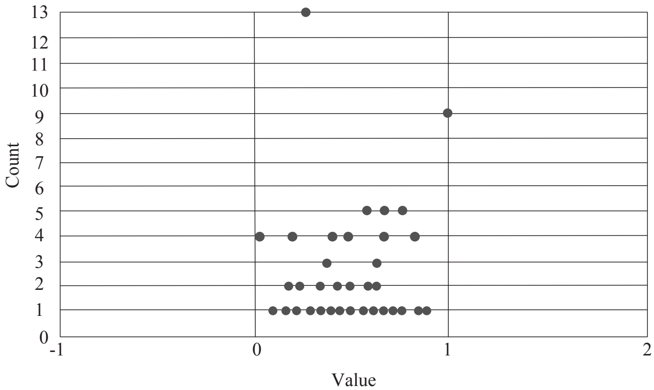


Fig. 2 - The urban agglomeration in the study area conforms to the transportation investment network diagram

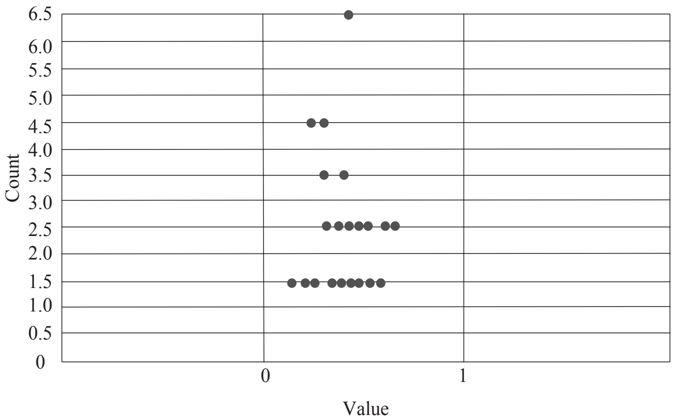
The analysis of the network topology structure resulted in the following Figure 3:



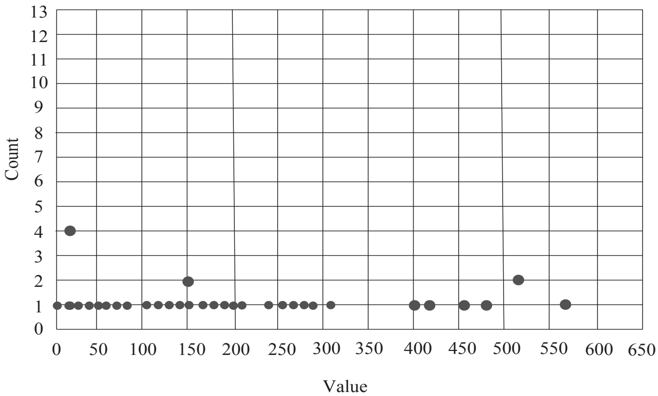
(a) Degree distribution of network nodes



(b) Cluster coefficient distribution diagram of network nodes



(c) Network closeness centrality distribution diagram



(d) Network node betweenness distribution diagram

Fig. 3 - Analysis results of network topology structure

From the analysis of Figure 3, it can be seen that the degree distribution of network nodes presents typical characteristics, with most nodes' degrees concentrated between 1 and 10. The average degree of the network is 8.273, and the node connectivity is high, reflecting the good connectivity of the transportation network in the Beibu Gulf urban agglomeration. In terms of network efficiency, the average path length is 3.166, indicating that it only takes an average of 3 intermediate nodes to reach from any node to another node. The network diameter is 8, indicating that the two farthest nodes in the network need to pass through 8 intermediate nodes, and the overall network efficiency is high. The clustering coefficient analysis shows that the average clustering coefficient of the network is 0.556, reflecting that there is relatively less node clustering phenomenon and the network structure tends to be more evenly distributed, which is in line with the characteristics of modern composite transportation networks. In terms of centrality analysis, the proximity centrality distribution of network nodes is between 0.3-0.5, and there is no region with a proximity of 0, further verifying good network connectivity, The analysis of intermediary centrality shows that the majority of nodes have betweenness centrality values concentrated between 0-200, with the highest betweenness centrality value reaching 612.77 in the F city node. This is mainly due to its location advantage, as it is adjacent to the sea and has a well-developed network of highways and railways, making it an important hub in the transportation network.

4. Construction of network space model for regional transportation infrastructure investment

Based on the aforementioned complex network analysis, transportation infrastructure forms a tightly connected network system in space, with significant spatial interaction effects between nodes. To quantify the spatial dependence brought by this network structure, this chapter introduces a spatial econometric model to transform the network topology features into a spatial weight matrix, thereby empirically testing the spatial spillover effect of transportation investment.

Construct a regional transportation infrastructure investment network and analyze its topology structure. The analysis results indicate that transportation infrastructure has formed a closely interconnected network system in space, and there are significant spatial interactions between nodes. To further quantify the impact mechanism of spatial dependence on regional economy, spatial econometric methods are introduced to construct a spatial model that can capture the interaction effects between geographic units, thus revealing the spatial spillover effects of transportation investment in more depth. Spatial econometric models are an important branch of econometrics, and their main difference from traditional econometric models is the introduction of spatial weight matrices, which can effectively identify and handle spatial dependencies and interaction effects between different geographic units. The spatial Durbin model is used to estimate the spatial impact of transportation infrastructure networks on regional economic development, and its expression is as follows:

$$lnResilience=pWLnResilience+a_1LnINT+a_2LnINT\_q+a_3LnX+b_1WLnLNT +b_2WLnINT\_q+b_3WLnX+n_i+m_{it} \tag{1}$$

In the formula, p is the spatial autoregressive coefficient, a_1 and a_2 respectively represent the contribution rates of the year-end resident population and capital stock to regional economic development, a_3 represents the impact of different levels of transportation infrastructure functions on economic growth, b_1 and b_2 respectively represent the spatial lag effects of year-end resident population and capital stock, b_3 represents the spatial lag effect of different levels of transportation infrastructure functions, n_i is the time fixed effect, m_{it}t is the random error term, W is the spatial weight matrix, which is the core of the model to identify spatial correlation structures.

The key to the spatial Durbin model lies in how to reasonably set the spatial weight matrix to reflect the interaction between regional economy and geography. The setting of the weight matrix is subjective and usually requires multiple matrix comparisons or robustness tests to enhance the credibility of the results. This article refers to existing research and selects two common weight matrices, geographic distance matrix and economic distance matrix, whose expressions are as follows:

$$w_{ij}=\begin{cases}\frac{1}{d_{ij}},i\neq j\\ 0,i=j\end{cases} \tag{2}$$

$$w_{ij}=\begin{cases}\frac{1}{\left|gdp_i-gdp_j\right|},i\neq j\\ 0,i=j\end{cases}\text{n} \tag{3}$$

In the formula, d_{ij} represents the geographical distance between regions i and j, gdp_i and gdp_j represent the average gross domestic product of regions i and j, respectively.

Based on this, this empirical analysis of the spatial Durbin model is conducted to explore in depth the spatial economic benefits generated by transportation infrastructure investment through network structure, providing a foundation for understanding the formation mechanism of regional economic resilience.

5. Empirical study on the impact of transportation infrastructure investment network on regional economic resilience

5.1. Descriptive statistics

To systematically examine the impact of transportation infrastructure investment network on regional economic resilience, this study selected panel data of urban agglomerations in the research area from 2004 to 2024 for statistical analysis, and the results are shown in Table 2. Among them, the regional economic resilience index (Resilience) is comprehensively measured based on the entropy weight method, covering three dimensions: resistance recovery, adaptation regulation, and innovation transformation, The scale of investment in transportation infrastructure (INT) is characterized by the actual investment amount, Simultaneously introducing industrial structure (Indu_stru), foreign trade dependence (Imp-exp), urbanization level (urban), and human capital (hc) as control variables.

Tab. 2 - Descriptive statistical results of each indicator

Variable	obs	Mean	Std.dey	min	max
Resilience	651	0.052	0.124	0.221	0.843
INT	651	9.93e-04	3.97e-04	9.42e-04	2.37e-03
INT_q	651	1.22e-06	1.19e-06	8.69e-07	5.68e-06
Indu_stru	651	1.023	0.527	0.472	4.321
Imp_exp	651	0.281	0.371	0.014	1.721
urban	651	0.452	0.151	0.242	0.892
hc	651	0.193	0.084	0.011	0.524

As shown in Table 2, the mean of the regional economic resilience index is 0.502, with a standard deviation of 0.124, indicating that there are certain differences in economic resilience among different regions.

The average investment scale of transportation infrastructure is 9.93×10^{-4}, and its square term is used to examine nonlinear effects, The remaining control variables also showed certain regional heterogeneity, providing a data foundation for subsequent spatial econometric analysis.

5.2. Spatial autocorrelation test

Before constructing a spatial econometric model, it is necessary to conduct diagnostic tests on the spatial dependence of variables. This study uses the global Moran's I index as a testing tool to systematically evaluate the spatial autocorrelation characteristics of the regional economic resilience index. By calculation, the results are shown in Table 3.

Tab. 3 - Global Moran Index test results of regional economic resilience index under different matrices

Year	Geographic distance matrix	Economic distance matrix
2004	0.149***	0.646***
2006	0.149***	0.648***
2008	0.149***	0.647***
2010	0.147***	0.649***
2012	0.145***	0.650***
2014	0.143***	0.651***
2016	0.142***	0.652***
2018	0.140***	0.651***
2020	0.139***	0.650***
2022	0.139***	0.649***
2024	0.138***	0.649***

Note: *** indicates significant at the 1% level of significance.

According to Table 3 analysis, the Moran index remains in the range of 0.138~0.149 in the geographic distance matrix and reaches as high as 0.646~0.652 in the economic distance matrix. This indicates that the Moran index is significantly positive in both matrices, suggesting a spatial positive correlation in the economic resilience of the study area. The Moran's index under the economic distance matrix is generally higher than that under the geographical distance matrix, indicating that economic connections have a stronger impact on resilient spatial patterns. Over time, the Moran's index under the geographic matrix has slightly decreased, reflecting that the development of transportation networks has weakened the constraints of geographic distance, The index under the economic matrix shows an upward trend, indicating that the spatial correlation driven by economic connections is constantly strengthening.

5.3. Estimated results

In order to better grasp the direct impact and spatial spillover effects of investment in transportation infrastructure construction on regional economic resilience, this project has established a spatial Durbin model and estimated based on geographic economic distance, resulting in the following estimation results:

Tab. 4 - Model estimation results under different matrices

Variable	OLS	Geographic distance matrix	Economic distance matrix
lnINT	0.198***	0.278***	0.432***
lnINT_q	-0.051**	-0.061**	-0.081***
lnIndu_stru	0.164***	0.138***	0.143***
lnImp_exp	0.151***	0.103***	0.058***
lnurban	0.132***	0.237***	0.133***
lnhc	0.567***	0.749***	0.400***
_cons	1.230***	-	-
ρ	-	0.829**	0.015
W×lnINT	-	0.144*	0.917***
W×lnINT_q	-	-0.594*	-0.375***
W×lnIndu_stru	-	0.908***	0.053
W×lnImp_exp	-	-0.551***	0.421***
W×lnurban	-	0.102	0.116*
W×lnhc		0.148	0.787***

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

According to Table 4, the marginal effect of transportation infrastructure investment on regional economic resilience is 0.198, which is statistically significant. However, traditional OLS estimation may result in biased coefficient estimation due to the lack of consideration for spatial dependence. The empirical results of the spatial econometric model further show that there is a significant spatial interaction effect, and its mechanism of action is more complex than traditional estimates. In the geographic distance matrix, the direct effect coefficient of transportation infrastructure investment is 0.278, In the economic distance matrix, its direct effect coefficient is higher, at 0.432. This indicates that after controlling for spatial dependence, the promotion effect of transportation investment on local economic resilience is stronger than the OLS estimation results, and this effect is more prominent between regions with close economic ties. Meanwhile, the quadratic term of investment is significantly negative in all models, clearly revealing the marginal diminishing impact of transportation infrastructure investment on regional economic resilience. The coefficient of spatial lag term is significantly positive in the geographic matrix, with a coefficient of 0.829, further verifying the strong spatial dependence of regional economic resilience itself, that is, the economic resilience of a region will be positively affected by the resilience of neighboring regions. From the perspective of spatial spillover effects, transportation infrastructure investment shows positive spillover effects in both matrices, but the intensity and significance are different. In the geographic distance matrix, the significance level of overflow is 10%, with a coefficient of 0.144, In the economic distance matrix, the spillover effect is not only highly significant at the 1% level, but the coefficient value of 0.917 is much higher than that of the geographic matrix. This result indicates that the spatial linkage effect of transportation infrastructure investment depends more on the strength of economic connections between regions, rather than simply geographical proximity. Transportation investment in a region can have a stronger resilience enhancing driving effect on other regions with similar levels of economic development.

The spatial spillover effect coefficient in the regression results of Table 4 can only qualitatively describe the spatial effect of variables on regional economic resilience. To quantitatively analyze the size of the spatial spillover effect of variables, further partial differential decomposition is needed. The partial differential decomposition results of each variable are shown in Table 5.

Tab. 5 - Partial differential decomposition results of models under different matrices

Matrix	Geographic distance matrix			Economic distance matrix		
Variable	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
lnINT	0.245***	2.160**	2.405***	0.136***	0.098***	0.233***
lnINT_q	0.749***	0.148	0.897**	0.422***	0.787***	1.209***
lnIndu_stru	0.302***	5.686*	5.988**	0.482***	1.635***	2.117***
lnImp_exp	0.126***	-1.468	-1.342	0.157***	0.480***	0.638***

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

As shown in Table 5, under the geographical distance matrix, the indirect effect of transportation infrastructure investment is 2.160, which is much greater than its direct effect of 0.245, indicating that the spatial spillover effect of investment is the main way to enhance regional economic resilience, with a total effect of 2.405. In contrast, the effect under the economic distance matrix is relatively small. This comparison indicates that there are significant differences in the impact mechanism of transportation investment on resilience based on different spatial correlation logics: geographical proximity is more conducive to the cross regional diffusion of investment benefits, while economic proximity limits the impact of investment to local and a few similar regions. In addition, the decomposition results of the investment quadratic term further confirm the complexity of the nonlinear relationship. In the geographic matrix, its direct effect is 0.749 but the indirect effect is not significant, In the economic matrix, both the direct effect of 0.422 and the indirect effect of 0.787 are significantly positive. This collectively indicates that excessive or inappropriate investment scale may have complex nonlinear effects on resilience enhancement, and their spatial effects depend on the nature of regional connections.

6. Conclusion

This study is based on the perspective of complex networks, abstracting the transportation infrastructure system into a network model composed of nodes and edges, and combining spatial econometric methods to systematically analyze its impact on regional economic resilience. Research has found that, firstly, investment in transportation infrastructure can significantly enhance regional economic resilience, but there is a marginal diminishing effect, Secondly, regional economic resilience has significant spatial dependence, and economic connections are more likely to drive the spatial pattern of resilience than geographical proximity, Thirdly, the spatial spillover effect of transportation investment is more prominent under the economic distance matrix, indicating that its resilience enhancement effect depends more on the strength of economic interaction between regions. The innovation of this article lies in the integration of complex network analysis and spatial econometric models, revealing the transmission mechanism of transportation infrastructure network structure on economic resilience, providing theoretical support for resilience oriented transportation planning and regional collaborative policies. Future research can further introduce dynamic network evolution and multi-scale spatial interaction models to comprehensively grasp the complex relationship between transportation infrastructure and regional economic resilience.

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Rapid allocation of large-scale dynamic traffic flow under enclosure construction conditions

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Abstract

In order to solve the problems of long single dynamic allocation time, high memory occupation, and high DDR in traditional traffic flow allocation methods, a rapid allocation method of large-scale dynamic traffic flow under enclosure construction conditions is proposed. Analyze the characteristics of traffic flow in the construction area and its spatiotemporal impact mechanism on path impedance, construct a fusion BPR function and an improved cellular transmission model to calculate the mixed impedance, and then establish a dynamic user optimal allocation model with the goal of minimizing the total impedance of the system. Design a heuristic iterative algorithm for fast solution and achieve rapid flow allocation. The experimental results show that after the proposed method is applied, the single dynamic allocation calculation time in a medium-sized road network is less than 312s, the memory occupation is 4.2GB, and the DDR always remains at a low level, proving its good adaptability.

Keywords - enclosure construction, dynamic traffic flow, path impedance, rapid allocation

1. Introduction

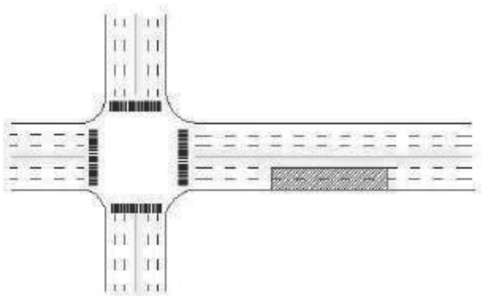
With the acceleration of urbanization and the continuous growth of motor vehicle ownership, urban road traffic systems are facing increasingly severe congestion challenges. As a core theory in the field of transportation planning and management, traffic flow allocation aims to simulate the path selection behavior of travelers in the road network, and is a key basis for evaluating road network performance and formulating traffic control strategies [20, 4]. The traditional static traffic assignment model is difficult to capture the time-varying characteristics of traffic demand and the dynamic decision-making process of travelers, especially when facing large-scale road networks and complex traffic scenarios, its limitations are more prominent. Dynamic traffic flow allocation can more accurately reflect the spatiotemporal evolution of traffic flow, which is of great significance for achieving refined management and intelligent guidance of transportation systems [17]. However, when the road network is large in scale or experiences sudden or persistent interference, existing dynamic allocation models often face challenges such as low computational efficiency, slow convergence speed, and difficulty in meeting real-time analysis requirements. Therefore, conducting research on rapid allocation methods for large-scale dynamic traffic flow has urgent practical significance and important theoretical value for improving the practicality and responsiveness of traffic simulation and decision support systems, and ensuring the efficiency of road network operation under special conditions.

Many scholars have conducted in-depth research and proposed corresponding methods for dynamic traffic allocation and traffic optimization problems in complex scenarios. Jiang et al. [6] focuses on the collaborative optimization of road segments and intersections at the micro level. The upper level model proposes a lane changing strategy based on lane speed induction and misalignment, aiming to improve lane changing efficiency and balance lane flow through spatial organization optimization, The lower level model adopts dynamic programming methods to collaboratively optimize the trajectory of connected vehicles and intersection signal timing, in order to minimize average vehicle delay. However, this method has obvious shortcomings, and its optimization effect highly depends on the high penetration rate of connected autonomous vehicles. In the current and future long-term, mixed traffic flow is still mainstream, and its universality is limited, Moreover, this model mainly focuses on fine control of isolated intersections or short-circuit sections, without considering the global, long-distance propagation, and mutual influence of traffic flow in large-scale road networks, making it difficult to directly apply to macro allocation and control at the road network level. Xu et al. [15] shifts the research perspective to urban rail transit systems, with a focus on handling passenger flow allocation under multi route co line operation. This method constructs a co line operation service network based on train operation plans, transforms the passenger path selection problem into the shortest super path problem, and proposes a super path passenger flow allocation model based on departure frequency. Its shortcomings lie in the fact that the model is essentially based on static or quasi-static allocation of service frequency, and fails to fully consider the real-time waiting of passengers at the platform, the dynamic information of train arrival, and the dynamic aggregation and dissipation process of passenger flow in the time dimension. It belongs to the planned allocation of "vehicle based flow", and has limited reference significance for simulating individual travel behavior that is more random and dynamically interactive in ground road traffic. The focus of Zhang and Gu [18] is to improve the automation and efficiency of passenger flow allocation in urban rail networks. The core of its method design is to develop an automated calculation program based on VISUM commercial software, which integrates network supply, demand modeling, allocation calculation, and data output processes through modular design. The contribution of this study is mainly reflected in the engineering application level, which reduces repetitive manual operations through tool development. But its shortcomings also stem from this: this method heavily relies on specific commercial software platforms, the core of the algorithm is not its original improvement, and the adaptability and computational speed of the model are essentially limited by the core of the software it relies on. For large-scale dynamic road traffic assignment problems that require deep customization of algorithms, handling special traffic conditions, or pursuing ultimate computational performance, this approach based on general software encapsulation has limitations. Peng [10] attempted to combine traffic allocation with infrastructure maintenance by constructing a multi-objective dynamic traffic flow allocation model that takes into account the shortest travel time and the least degradation of road durability. The model was solved using a teaching and learning optimization algorithm. The innovation of this study lies in the introduction of road performance as a long-term influencing factor. However, its shortcomings are significant: First, the model has divided 13 categories of vehicles and optimized the streamline for vehicle types, which will sharply increase model dimensions and computational complexity in large-scale road networks, sacrificing computational efficiency, Secondly, the teaching and learning optimization algorithm used as a meta heuristic algorithm is difficult to guarantee its solving speed and global convergence when facing large-scale, high-dimensional dynamic allocation problems, and cannot meet the requirements of "fast" allocation.

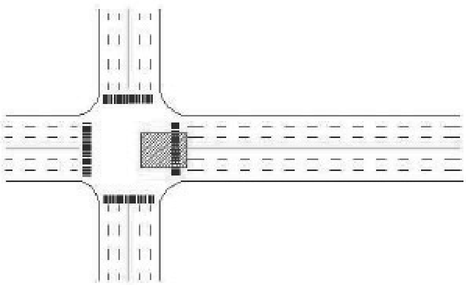
Therefore, this article focuses on the research of rapid allocation method of large-scale dynamic traffic flow under enclosure construction conditions. The aim is to provide a fast and scientific decision support tool for the formulation of traffic organization plans, impact assessment, and dynamic induction strategies during enclosure construction, so as to optimize traffic resource allocation, alleviate congestion, and improve the resilience and operational efficiency of urban road networks under special conditions.

2. Analysis of traffic flow characteristics in road occupying construction area under enclosure construction conditions

The layout of construction fences for large-scale municipal engineering is mainly divided into two categories: road section fences and intersection fences, as shown in Figure 1.



(a) Road section fence



(b) Intersection fence

Fig. 1 - Schematic diagram of construction enclosure layout

The setting of fences will directly change the physical structure and traffic conditions of the road, thereby having a significant impact on the characteristics of traffic flow, and this impact will ultimately be reflected in the significant changes in the path impedance of vehicle travel [16]. The so-called path impedance refers to the generalized travel cost, including travel time, delay, fuel consumption, etc. [19]. Accurately characterizing this impedance change is crucial for subsequent scientific allocation and guidance of traffic flow.

(1) Road section fence

When the construction fence is located on a road section, if fully enclosed measures are taken, the path impedance of the road section theoretically tends to infinity, completely blocking traffic flow and forcing travelers to choose alternative paths, resulting in a redistribution of traffic flow and dynamic adjustment of impedance in the surrounding road network. A more common situation is the partial occupation of lanes, where the effective width of the road is reduced, creating a bottleneck for traffic flow [13]. Due to the reduction in the number of lanes at the bottleneck, the traffic capacity C significantly decreases, which easily leads to vehicle queues. According to classical traffic flow theory, the relationship between travel time t, flow rate x, and traffic capacity C can be approximated by the BPR function:

$$t=t_0[1+\alpha(x/C)^{\beta}] \tag{1}$$

In the formula, t_0 is the free flow travel time, α,β are parameters in the transportation system, where α=0.15 and β=4. Under construction conditions, the C value decreases, and at the same flow rate x, the travel time t will increase sharply and nonlinearly. Especially upstream of bottlenecks, vehicles frequently change lanes and interweave to merge into open lanes, generating a large amount of friction and conflict, further increasing driving delays and psychological pressure, all of which constitute additional impedance increments [2, 21]. Therefore, the dynamic path impedance $\tau(t)$ of the construction section and its associated paths is no longer stable, but a strong correlation function between traffic flow and the degree of construction occupation, and exhibits dynamic fluctuations of congestion generation, queue growth, and dissipation over time t.

(2) Intersection fence

Intersections themselves are key nodes in the road network, with concentrated traffic flow conflicts. When the construction fence is located at an intersection, the impact is more complex and severe. Fences may encroach on some entrance lanes, compress turning radii, obstruct visibility, or alter signal phase design [9]. This directly leads to:

1) Capacity reduction: The saturated flow rate of the affected inlet road decreases, resulting in a decrease in effective capacity.

2) Sudden increase in delay: According to Webster's delay formula, construction leads to a decrease in traffic capacity, and in situations where demand remains constant or increases, saturation increases, resulting in a significant increase in control delays [5].

3) Path selection change: Some turning movements may be prohibited or become extremely inconvenient, and the impedance of the corresponding turning path may become extremely high or even infinite.

Therefore, the intersection enclosure not only significantly increases the direct impedance passing through the node, but also through the correlation of the nodes, it will affect the wave to the upstream section and spatially adjacent alternative paths, triggering the reconstruction of the entire local road network impedance matrix. The typical impact of intersection fencing on traffic flow and conflict points in multiple directions is shown in Figure 2.