

Article

Identifying Critical Nodes in Cross-Border Transportation Networks Under Geopolitical Risk

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Abstract

Cross-border transportation networks show considerable complexity and vulnerability under the influence of geopolitical risks. To identify critical nodes and simulate the propagation paths of failure risk within cross-border transportation networks, this study develops a multilayer cross-border transportation network model that integrates four transport modes: waterway, road, rail, and air transport. First, composite edge weights are calculated using the Criteria Importance Through Intercriteria Correlation (CRITIC) method based on inter-node transport distance, transport time, and geopolitical risk (GPR) exposure score. These weights capture the joint effects of transport efficiency and risk exposure across different transport corridors. Second, an Improved Weighted K-shell (IWKS) model is proposed for critical-node identification by integrating three network topological indicators: degree centrality, weighted degree, and closeness centrality. Third, an edge-risk-based Susceptible–Infected–Recovered (SIR) propagation model is introduced. Monte Carlo simulations are then used to estimate the simulation-based propagation influence of each node. Finally, the identification performance of the IWKS model is compared with that of conventional centrality indicators. The IWKS scores are also significantly correlated with the simulation-based propagation influence under three types of correlation tests. The findings support the applicability of the proposed IWKS model in critical-node identification and system vulnerability research of multilayer cross-border integrated transportation networks.

Keywords: cross-border transportation networks; IWKS model; SIR model; geopolitical risk (GPR); critical node identification

1. Introduction

In recent years, with the deepening of trade globalization, multiple factors such as geopolitical changes, trade policy adjustments, and the increasing frequency of extreme weather events have jointly exposed cross-border transportation networks to unprecedented complexity and uncertainty. On the one hand, the continuous expansion of network scale and the growing interdependence among nodes have significantly increased the complexity of transportation networks. On the other hand, these networks rely heavily on multiple actors and cross-border coordination. Disturbances arising from human-induced disruptions and geopolitical changes introduce additional uncertainty. In this context, a cross-border transportation network can be regarded as a complex network system composed of nodes and edges. Such a system is exposed not only to potential disruptions at critical nodes but also to broader shocks caused by uncertain external factors. These disruptions may affect the stability and sustainability of the entire network and lead to a



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series of problems such as transportation delays, longer delivery times, and higher costs. Therefore, while accounting for geopolitical risk, simulating risk propagation across nodes in different transport modes and identifying critical nodes in cross-border transportation networks are important approaches for assessing network vulnerability and improving network resilience.

Transportation network vulnerability refers to the degree to which a transportation system is exposed to external disturbances. It arises from multiple risk factors, including internal operational imbalances in the transportation system and uncertainty in the external environment. In recent years, geopolitical risk (GPR) has become one of the key factors affecting the vulnerability of global cross-border transportation networks [1]. Through a systematic literature review, López et al. [2] classified supply chain networks disruptions caused by geopolitics in supply chain networks into six categories and analyzed their impact mechanisms and related management decisions, providing a theoretical basis for understanding the pathways through which GPR affects supply chains. Existing studies on GPR have mainly focused on the macroeconomic level and have examined its effects on international trade and transportation systems. For example, Liu et al. [3] found that GPR has a significant negative effect on international air, maritime, and land freight volumes, although the elasticities differ across transport modes. Yang et al. [4] used a bi-level programming model to analyze container route choices between China and Russia under geopolitical risk. Mei et al. [5] used AIS trajectory data and graph learning methods to reveal that the European LNG maritime network experienced increased connectivity but also greater vulnerability during its expansion. Ren et al. [6] developed a geopolitical disruption diffusion model to quantify disruption risks in the global electric vehicle lithium-ion battery supply chain.

In studies on transportation network vulnerability, complex network theory has provided a new analytical perspective for risk propagation analysis [7] and vulnerability identification [8]. Regarding risk propagation in transportation networks, Yang et al. [9] constructed a vulnerability network based on empirical data and identified multiple types of vulnerability factors and their risk propagation paths. Berger et al. [10] applied an epidemic-modeling approach to reveal how network structure affects the diffusion of quality problems. Zhao et al. [11] proposed a disruption propagation model from both topological and operational perspectives to evaluate network resilience under node or link failures. Lyu et al. [12] developed a hierarchical risk-flow network based on the ripple effect and used an SIR-like model to simulate and analyze the factors influencing risk propagation. In terms of vulnerability identification, Liu et al. [13] combined multiple centrality measures with robustness analysis and developed a framework and supporting model for identifying and analyzing transportation network vulnerability. Vidza et al. [14] investigated the resilience of transportation networks to disruptions and developed a framework that integrates topological indicators and operational measures for transportation network vulnerability analysis and implementation of resilience strategies. Because the reliability of transportation networks often depends on the stability of critical nodes [15], Ma et al. [16] found that identifying vulnerable nodes in logistics service networks helps reveal the vulnerability mechanisms of logistics transportation networks. Ma et al. [17] further suggested, based on a review of the existing literature, that critical node identification can facilitate the identification and assessment of the intrinsic vulnerability characteristics in transportation networks.

For critical node identification in complex networks, commonly used indicators such as degree centrality, closeness centrality, and betweenness centrality have certain limitations [18]. The traditional K-shell algorithm also suffers from low resolution and tends to overlook the influence of highly connected peripheral nodes [19]. To improve the resolution

and accuracy of critical node identification in complex networks, Gao et al. [20] proposed a multidimensional identification framework that integrates network centrality, SIR propagation, and cascading failure models to capture the propagation influence of nodes during risk diffusion. Xie et al. [21] proposed a K-shell algorithm that comprehensively considers both global and local network structures for identifying critical nodes in complex networks. Wang et al. [22] proposed an improved weighted K-shell model for identifying critical nodes by considering transport mode diversity, independent transport capacity, and node connectivity. Although these methods have improved identification accuracy, most of them still rely on static topological assumptions and provide insufficient characterization of risk propagation at the network level. To further clarify the methodological position of this study, Table 1 summarizes representative critical-node identification studies in terms of indicator basis, weight logic or edge weight construction, and risk-factor consideration.

Table 1. Comparison of related critical-node identification methods.

Study	Indicator Basis	Weight Logic/Edge Weight	Risk Factor
Esfandiari & Fakhrahmad (2025) [19]	K-shell and PageRank	Topology/link structure	No
Gao et al. (2025) [20]	Centrality, SIR, cascading failure	Supply chain network links	Supply chain risk
Xie et al. (2022) [21]	K-shell, comprehensive degree, neighbor/sub-neighbor influence	Topology/neighborhood based	General node risk
Wang et al. (2021) [22]	Mode diversity, independent transport capacity, node connectivity	Multimodal transport attributes	General failure
Garas et al. (2012) [23]	Degree and weighted K-shell	General weighted links	No
Namtirtha et al. (2020) [24]	K-shell, degree, neighborhood influence	Weighted neighborhood information	No
Maji et al. (2020) [25]	Improved K-shell hybrid indicators	Topology/neighborhood based	No
Wang et al. (2024) [26]	Modified weighted K-shell, traffic demand, multi-order neighbors	Traffic demand and corridor attenuation	Operational disruption
Ding et al. (2024) [27]	Connectivity and cascading failure robustness	Land–sea transport links	Emergency/cascading failure
This study	Degree centrality, weighted degree, closeness centrality	Distance, time, GPR exposure, and mode-specific adjustment	GPR exposure

Although several studies have examined multimodal transportation networks or land–sea transport systems, their application contexts are mainly domestic transportation systems, general multimodal networks, or Belt and Road land–sea robustness analysis. These studies usually focus on network topology, traffic demand, corridor attenuation, cascading failure, or emergency robustness. In summary, existing studies have made substantial progress in network topology analysis, vulnerability assessment, and propagation modeling. However, several limitations remain. First, most studies are based on a single transport mode or a topological network structure, which makes it difficult to capture the multimodal complexity and risk propagation characteristics of cross-border transportation networks. Second, traditional critical node identification methods mainly rely on structural indicators, such as degree centrality and K-shell, and lack the systematic integration of exogenous factors such as GPR. Third, few studies have quantitatively examined the propagation mechanisms and influence paths of node failures from the perspective of interactions between propagation dynamics and network topology.

In contrast, the present study focuses on the Guangxi-ASEAN cross-border multimodal transportation network and explicitly incorporates GPR exposure into edge-weight construction. Building on the topological characteristics of complex networks, it further considers the heterogeneous sensitivity of different transport modes to GPR-induced disruptions. By simulating disruption propagation within a cross-border transportation network, this study develops a critical node identification method tailored to GPR-informed multimodal transportation risk analysis.

2. Materials and Methods

2.1. IWKS Model

In complex network modeling, nodes usually correspond to key transportation and logistics hubs, such as ports, airports, and overseas warehouses. For weighted networks, Garas et al. [23] proposed a weighted K-shell method that jointly considers the number of neighboring nodes and edge weights. This method provides a basis for incorporating weight information into the K-shell decomposition framework.

In critical node identification, attention should be paid not only to structural hierarchy but also to the node robustness under risk perturbations. To identify critical nodes in cross-border transportation networks, this study builds on the work of Garas et al. and selects three indicators—degree centrality, weighted degree, and closeness centrality—as composite indicators. These indicators are used to better characterize the structural position and connection strength of each node.

Degree centrality $C_D(i)$, weighted degree s_i , and closeness centrality $C_C(i)$ are defined as follows:

$$C_D(i) = \frac{k_i}{N-1} \quad (1)$$

$$s_i = \sum_{j=1}^N W_{ij} \quad (2)$$

$$C_C(i) = \frac{N-1}{\sum_{j \neq i} d(i,j)} \quad (3)$$

Here, N denotes the total number of nodes in the network, k_i denotes the degree of node i , and $d(i,j)$ denotes the shortest-path distance between node i and node j .

$$S_i = [C_D(i)^\lambda s_i^\eta C_C(i)^\theta]^{\frac{1}{\lambda+\eta+\theta}} \quad (4)$$

where λ , η , and θ are adjustment parameters that control the relative importance of the three indicators in the comprehensive evaluation. In an undirected weighted network, normalizing degree centrality, weighted degree, and closeness centrality can not only eliminate differences in the original scales of the indicators and reduce the influence of network size, but also avoid incomparability caused by differences in measurement dimensions. To avoid excessively small values in subsequent calculations, the standardized values are multiplied by 10. Accordingly, the normalized mapping range is set to $[0, 10]$, and the three normalized indicators are denoted as $C_D^*(i)$, s_i^* , and $C_C^*(i)$ respectively. On this basis, the comprehensive evaluation function of node is constructed as follows:

$$S_i^* = [C_D^*(i)^\lambda (s_i^*)^\eta C_C^*(i)^\theta]^{\frac{1}{\lambda+\eta+\theta}} \quad (5)$$

The evaluation score of a node reflects its hierarchical position and overall role in the network. A higher score indicates that the node is located at a more central structural level and plays a more important role in maintaining network connectivity and organizing logistics transportation. The resulting node ranking can therefore serve as the main basis for identifying critical nodes in cross-border transportation networks.

2.2. Cross-Border Transportation Network Modeling

To characterize the multimodal features of cross-border transportation networks, this study constructs a four-layer weighted undirected network model that includes four transport modes: road, rail, air, and waterway.

The network is abstracted as a graph $G = (V, E, W)$, where V denotes the node set, E denotes the edge set, and W denotes the initial edge weights. To represent the multimodal structure of the cross-border transportation network, any city node i is denoted as V_i . If a city has corresponding transport hubs, such as a road transport terminal, railway station, airport, or port, these hubs are defined as transfer nodes of the city, and the transfer nodes within the same city are connected pairwise. Different transport modes are coupled through these transfer nodes, so that the overall accessibility and risk propagation characteristics of the cross-border transportation network can be represented. According to the number of transfer nodes associated with each city, three types of transfer-node connection patterns are defined. The connection patterns among transfer nodes within the same city are shown in Figure 1.

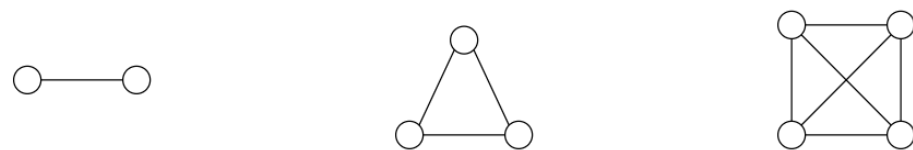


Figure 1. Intra-city transfer-node connection patterns.

Corresponding transfer nodes are defined in each transport layer and denoted as V_{hi} , V_{ri} , V_{wi} , and V_{fi} , here h , r , w , and f represent the road, railway, waterway, and air layers, respectively. For each transport mode, the edge connecting node pair (i, j) between cities is denoted as e_{ij}^h , e_{ij}^r , e_{ij}^w and e_{ij}^f respectively. Accordingly, four single-layer transportation networks are constructed, namely G_h , G_r , G_w , and G_f , corresponding to the road, railway, waterway, and air networks. Examples of the topological structures of these four single-layer networks are shown in Figure 2.

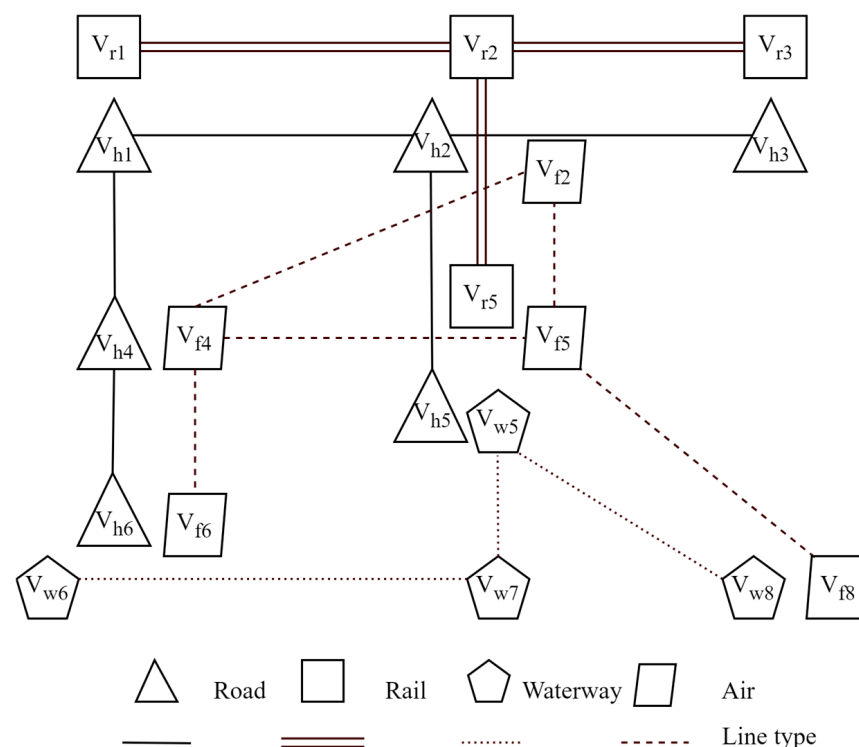


Figure 2. Schematic topologies of the four single-layer transportation networks.

Based on the four-layer transportation network model, this study further constructs a Cross-Border Transportation Network Topology Model (CBTNTM) to more intuitively characterize inter-city connections. An example of the CBTNTM is shown in Figure 3. The model is constructed according to the following principles.

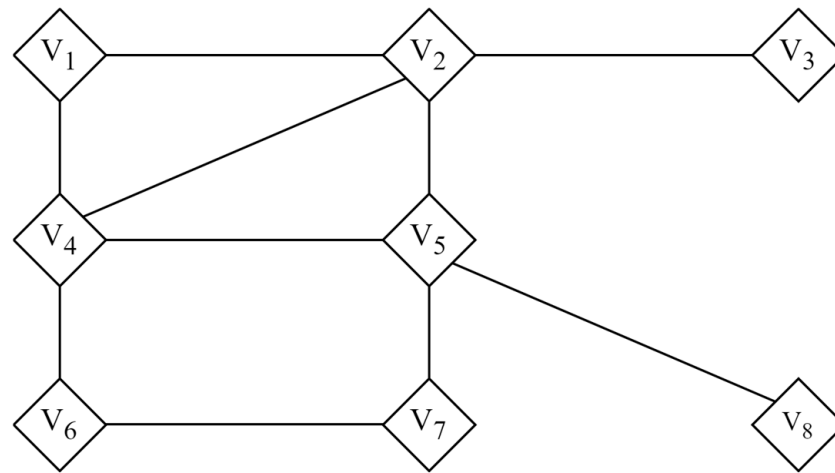


Figure 3. Schematic structure of the cross-border transportation network topology model.

(1) The regions where road, railway, air, and waterway transfer nodes are located are aggregated into composite nodes. If at least one transport connection exists between two regions, an edge is established between the corresponding composite nodes.

(2) If multiple transport modes exist between two regions, the corresponding edges in the single-layer networks are merged into one composite edge connecting the two regions. In other words, when a direct transport corridor exists between a node pair, a corresponding intra-layer edge is established in the CBTNTM.

2.3. Edge Attribute Construction and GPR-Weighted Edge Weighting

The edge attribute function is defined as $W = (d, t, g)$, where d , t and g denote transport distance, transport time, and the degree of GPR-induced transport exposure under a given transport mode, respectively. This study maps the national-level GPR exposure score to the city and transfer-node levels to characterize the manifestation of GPR exposure within the cross-border transportation network. Specifically, cities within the same country are assumed to face the same macro-level risk environment; that is, the GPR exposure score of each city is consistent with that of the country to which it belongs. The city-level exposure score is then evenly allocated to the transfer nodes within the city to represent the relatively balanced distribution of GPR-related exposure among intra-city network nodes. An adjustment factor μ_k is introduced to modify node-level exposure score, thereby obtaining the GPR exposure score of each transfer node and allowing GPR exposure to be represented across different levels of the network structure.

For multiple transfer nodes within the same city, the spatial distances are relatively short, and the cargo transfer time is much shorter than cross-border transport time. To highlight risk differences across cross-border links, this study assumes that distance and time costs between intra-city nodes are negligible and only considers g in the transfer-node weights. Since intra-city transport risk is generally lower than inter-regional transport risk, the edge weight between different transfer nodes within the same city is defined as the average GPR exposure score of the two nodes.

Transport distance data cover four transport modes: road, railway, waterway, and air transport. These data were obtained from road and railway route queries, waterway route information, and coordinate-based distance calculations. Considering differences in

infrastructure conditions across countries or regions for the same transport mode, average speeds were used to represent differences in transport efficiency. The assumed speeds are 60 km/h for road transport, 50 km/h for railway transport, 20 nmi/h for waterway transport, and 800 km/h for air transport. Transport time is then calculated based on the distance–speed relationship.

Data from sources such as World Bank Open Data and the World Trade Organization were used to obtain the Political Stability and Absence of Violence/Terrorism (PV) score and the Government Effectiveness (GE) score from the World Governance Indicators (WGI), as well as each country's GDP in current U.S. dollars and import–export trade ratio. These indicators used to construct the country-level GPR exposure score. The PV and GE scores are standardized in the original data to the interval $[-2.5, 2.5]$, which facilitates cross-country and intertemporal comparisons.

Because different attribute indicators vary in orders of magnitude and dimensions, the CRITIC method is used to objectively determine multi-attribute weights. This method considers both the variability of indicators across samples and the correlations among indicators. It can therefore generate a more objective weight allocation in a multidimensional and highly correlated indicator system, while reducing weight distortion caused by redundant indicator information.

In constructing the GPR exposure score, PV, GE, and GDP are treated as cost-type indicators and are reverse-normalized, whereas trade ratio is treated as a benefit-type indicator and is positively normalized. Higher PV and GE indicate a more stable political and governance environment, and higher GDP is interpreted as stronger economic absorptive capacity. In contrast, a higher trade ratio indicates stronger dependence on cross-border trade and therefore greater exposure to external transportation disruptions.

The original decision matrix $A = (a_{xy})_{m \times n}$ is defined as follows:

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \quad (6)$$

where a_{xy} denotes the value of the x -th edge under the y -th attribute, m denotes the number of edges, and n denotes the number of attributes.

The raw data are first made dimensionless by standardizing the decision matrix.

For benefit-type indicators, positive normalization is applied:

$$r_{xy} = \frac{a_{xy} - \min_x a_{xy}}{\max_x a_{xy} - \min_x a_{xy}} \quad (7)$$

For cost-type indicators, negative normalization is applied:

$$r_{xy} = \frac{\max_x a_{xy} - a_{xy}}{\max_x a_{xy} - \min_x a_{xy}} \quad (8)$$

After normalization, the standard deviation of the j -th attribute, denoted as s_j , is calculated to measure the variability of this attribute across samples:

$$s_j = \sqrt{\frac{1}{m} \sum_{x=1}^m (\tilde{a}_{xy} - \bar{\tilde{a}}_y)^2} \quad (9)$$

The linear correlation between two attributes, y_1 and y_2 , is then calculated. Here, $\bar{r}_{y_1}$ and $\bar{r}_{y_2}$ denote the mean standardized values of the y_1 -th and y_2 -th attributes, respectively, and $\rho_{y_1y_2}$ denotes the Pearson correlation coefficient between the two attributes:

$$\bar{r}_{y_1} = \frac{1}{m} \sum_{x=1}^m r_{xy_1} \quad (10)$$

$$\bar{r}_{y_2} = \frac{1}{m} \sum_{x=1}^m r_{xy_2} \quad (11)$$

$$\rho_{y_1y_2} = \frac{\sum_{x=1}^m (r_{xy_1} - \bar{r}_{y_1})(r_{xy_2} - \bar{r}_{y_2})}{\sqrt{\sum_{x=1}^m (r_{xy_1} - \bar{r}_{y_1})^2} \sqrt{\sum_{x=1}^m (r_{xy_2} - \bar{r}_{y_2})^2}} \quad (12)$$

where σ_y denotes the standard deviation of the y -th attribute, C_y denotes the information intensity of the y -th attribute, and ρ_{yk} denotes the Pearson correlation coefficient between the y -th and k -th attributes. These terms are calculated as follows:

$$\sigma_y = \sqrt{\frac{1}{m} \sum_{x=1}^m (r_{xy} - \bar{r}_y)^2} \quad (13)$$

$$C_y = \sigma_y \cdot \sum_{k=1}^n (1 - \rho_{yk}) \quad (14)$$

The information intensity is then normalized to obtain the weight of each attribute. Let w_y denote the weight of the y -th attribute. It is calculated as follows:

$$w_y = \frac{C_y}{\sum_{k=1}^n C_k} \quad (15)$$

For each edge, w_x denotes the composite weight of the x -th edge, w_y denotes the weight of the y -th attribute, and r_{xy} denotes the standardized value of the x -th edge under the y -th attribute.

$$w_x = \sum_{y=1}^n w_y r_{xy} \quad (16)$$

To more accurately characterize the effects of GPR across different transport-mode network layers, this study refers to the findings of Liu and Fu [3] on the mode-specific impacts of GPR. Under the GPR environment, the estimated impact elasticity is highest for sea freight, followed by air freight and road freight. Accordingly, a mode-specific adjustment factor μ_k is introduced into the edges and nodes of each transport layer to further capture the differentiated effects of GPR on different transport modes in the cross-border transportation network. Specifically, for the edge weight W_{ij}^k of transport mode k between nodes V_i and V_j , the GPR adjustment factor μ_k is incorporated. Since a directly comparable elasticity for rail freight is not available, the rail elasticity is approximated as the midpoint between road and air freight elasticities, yielding 0.056. The average elasticity of the four transport modes is then used as the normalization benchmark. Accordingly, μ_k is calculated as the ratio between the elasticity of each transport mode and the average elasticity. A larger μ_k indicates that the corresponding transport mode is more sensitive to GPR-induced disruptions in the modeled network. The values of μ_k for different transport modes are shown in Table 2.

$$W_{ij}^k = \mu_k w_x \quad (17)$$

Table 2. Mode-specific adjustment factors.

Mode-Specific Adjustment Factor	Road	Rail	Waterway	Air
Response elasticity	0.053	0.056	0.068	0.059
μ_k	0.898	0.949	1.153	1

2.4. Case Network Setting and Model Assumptions

The Guangxi–ASEAN cross-border transportation network is an important transport corridor between China and ASEAN countries. Supported by road, railway, port, and air route systems, this network has formed inter-city air connections and multimodal transport corridors, and can therefore comprehensively reflect the multilayer structure and complex network characteristics of cross-border transportation networks. This study selects eight countries or regions as the research scope, including Guangxi Zhuang Autonomous Region of China, Cambodia, Laos, Malaysia, Myanmar, Singapore, Thailand, and Vietnam. Based on the ranking of total cross-border trade volume, 26 cities and their transfer nodes are selected as the candidate set of critical nodes, and the CBTNTM is then constructed.

In the model construction process, road and railway routes were determined with reference to the road and railway maps released by the United Nations Economic and Social Commission for Asia and the Pacific, as well as the Pan-Asian Railway Network. Waterway routes and air routes were obtained through queries on the VesselFinder and online cross-border flight route information, respectively. Considering the connectivity characteristics of the cross-border transportation network, differences in transport modes among cities, and the operational feasibility of model construction, the following assumptions are made.

Since the selected 26 cities, except for Kuching, are connected to other cities within their respective countries, Assumption 1 is proposed:

Assumption 1. *Except for Kuching in Malaysia, road and railway connections exist between cities within each country or region.*

Since the Pan-Asian Railway Network covers at least one selected city in each country or region, Assumption 2 is proposed:

Assumption 2. *Each country or region has at least one city with cross-border railway transport capacity.*

For cities located far apart, road transport often needs to cross multiple national borders. In actual operations, such transport can no longer be regarded as a single cross-border road connection. Therefore, this study only retains the high-frequency, short-distance, and highly accessible road connections between Guangxi and Vietnam, namely the Pingxiang–Hanoi and Dongxing–Haiphong corridors. These two corridors are used to represent the main land gateways from Guangxi to ASEAN. Cross-border road transport among ASEAN countries is not considered in the model. Accordingly, Assumption 3 is proposed:

Assumption 3. *Except for the Pingxiang–Hanoi and Dongxing–Haiphong corridors, cross-border road transport between countries or regions is not considered.*

Since the selected cities are extensively involved in cross-border transportation, and some of them have waterway ports that play important roles in foreign trade, Assumption 4 is proposed:

Assumption 4. *Cities with waterway transfer nodes are connected at the waterway layer.*

Air transport in cross-border transportation is characterized by long-distance, high-value, and time-sensitive services. However, air transport between domestic cities within

the same country or region is usually not representative of cross-border transport organization. Therefore, Assumption 5 is proposed:

Assumption 5. *Air connections between cities within each country or region are not considered.*

Based on the above rules, 83 transfer nodes and 507 edges, including transfer-node connection edges, are identified from 26 cities. The final CBTNTM contains 26 city nodes and 224 composite edges, as shown in Figure 4.

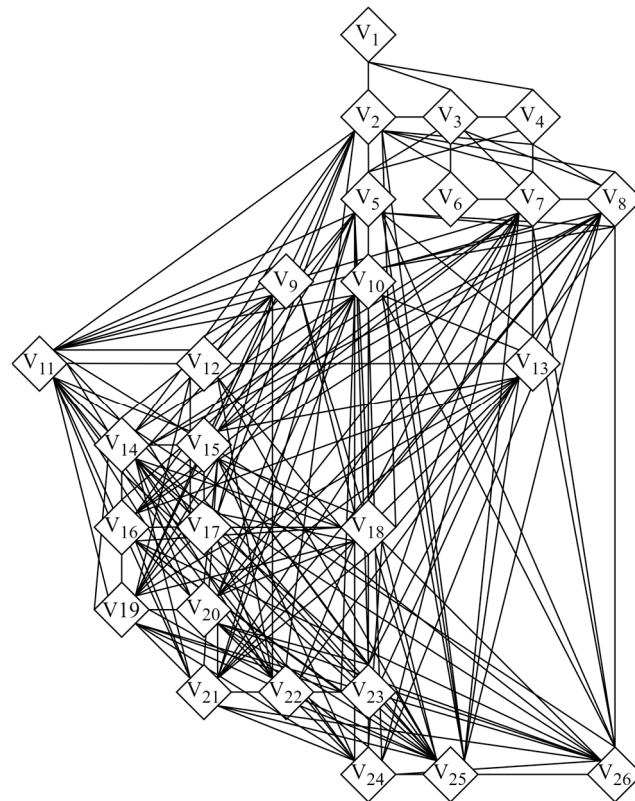


Figure 4. Guangxi-ASEAN CBTNTM.

To characterize the structural features of each single-layer transportation network, this study calculates the network indicators of each transport-mode layer in the CBTNTM using the NetworkX 2.6 framework in Python 3.12.3. The topological statistics of different transportation networks are reported in Table 3.

Table 3. Topological statistics of single-layer transportation networks.

Network Characteristic	Road	Rail	Waterway	Air
Number of nodes	25	25	17	16
Number of edges	87	131	136	58
Average degree	6.960	10.480	16.000	7.250
Network density	0.290	0.436	1.000	0.483

2.5. Dynamic Simulation and Validation Design

2.5.1. SIR-Based Propagation Simulation Design

To determine the adjustable parameters, the SIR model is used to measure the simulation-based propagation influence of all transfer nodes. The number of initially infected nodes is set to approximately 5% of the total number of nodes N . This setting allows the propagation process to start effectively while avoiding excessive initial saturation. When some cities and their transfer nodes are disrupted by GPR, adjacent city nodes fail

with probability β_{ij} . The initially infected nodes are randomly selected with probabilities weighted by node-level GPR exposure scores.

Considering that risk in cross-border transportation networks is often amplified at nodes, the propagation probability β_{ij} is determined based on the composite edge score. The edge scores are mapped to the interval $[0.1, 0.9]$ to constrain the propagation probability within a reasonable range, thereby avoiding distorted simulation results caused by extreme cases, such as impossible propagation or inevitable propagation. This mapping improves the smoothness and stability of the simulation. The probability that an infected node recovers from the infected (I) state to the recovered (R) state is set to 0.1, implying an average recovery time of 10 time steps. The maximum number of time steps for a single SIR simulation is set to 50, ensuring that the propagation process has sufficient time to spread through the network or decay to a stable state.

During the propagation simulation, the average number of infected nodes increases over time and eventually stabilizes. This study uses the Pearson, Spearman, and Kendall correlation coefficients to evaluate the consistency between IWKS scores and the simulation-based propagation influence under different parameter combinations. A higher correlation coefficient indicates that the identification result is closer to the propagation simulation benchmark.

To determine the optimal values of the IWKS parameters λ , η , and θ , a grid search is conducted over the parameter space. The evaluation criterion is the correlation between the IWKS scores and the node propagation influence obtained from the SIR simulation, measured by Pearson, Spearman, and Kendall coefficients. The parameter combination with the best overall correlation performance is selected as the final setting. To ensure interpretability and reproducibility, the candidate values of λ , η , and θ are all set to $\{0.5, 1.0, 1.5, 2.0, 2.5, 3.0\}$, resulting in 216 candidate combinations.

In this study, propagation influence is defined as the extent to which a node carries and amplifies the propagation process, rather than as its outward spreading capacity when it is selected as the sole initial source of propagation. The earlier a node enters the infected state, the longer its propagation opportunity window is, and thus the greater its propagation influence. Nodes that are never infected are assigned a propagation influence of zero.

Because node-level propagation influence is difficult to observe directly in real-world transportation networks, this study estimates it through 1000 Monte Carlo simulations. For each node, its average influence over repeated stochastic propagation processes is calculated. This approach uses repeated simulations to approximate the expected propagation influence under the specified SIR model when transmission probabilities cannot be directly observed. According to the law of large numbers, when the number of iterations is sufficiently large, the simulated average converges to the expected value of the stochastic propagation process. Therefore, the resulting value is used as a stable estimate of simulation-based propagation influence. In a single simulation run, the influence score is defined as $\frac{1}{T_i+1}$, where T_i denotes the infection time of node i .

2.5.2. Validation and Sensitivity Analysis Design

To further examine the reliability of the critical-node identification results, this study conducts three supplementary validation and sensitivity analyses. These analyses are designed to evaluate the identification results from three perspectives: changes in waterway-layer connectivity, alternative validation criteria, and different GPR averaging windows.

First, a waterway-edge sparsification sensitivity analysis is designed to examine whether the dominance of waterway nodes is mainly driven by the relatively dense connectivity of the waterway layer. In this analysis, the node set, non-waterway edges, and their attribute values are kept unchanged, while waterway-related edges are randomly

retained under different retention ratios. The retention ratios are set to 100%, 70%, 50%, and 30%. For each sparsified network, the IWKS scores are recalculated under the same methodological framework, and the stability of the critical-node rankings is evaluated by comparing the ranking results across different sparsification levels.

Second, an independent validation based on network performance loss is conducted. Unlike the SIR-based propagation influence used for parameter calibration, this validation evaluates the structural consequence of node disruption from the perspective of network efficiency. Specifically, each node is removed from the constructed cross-border transportation network, and the resulting change in global network efficiency is calculated. The global efficiency of network G is defined as:

$$E(G) = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d(i,j)} \quad (18)$$

If two nodes are disconnected, the reciprocal distance is set to zero. The performance loss caused by removing node i is measured as:

$$L_i = \frac{E(G) - E(G-i)}{E(G)} \quad (19)$$

A larger L_i indicates that the removal of node i causes a greater decline in network efficiency, suggesting a higher level of structural importance. The consistency between IWKS scores and performance-loss values is then evaluated using Pearson, Spearman, and Kendall correlation coefficients. This validation provides an additional assessment independent of the SIR-based propagation process.

In addition, a Top-K sequential deletion experiment is conducted. For each ranking method, nodes are removed according to their ranking order, and the corresponding global efficiency loss is calculated after removing the top K nodes. This experiment examines whether a method can identify a set of performance-critical nodes rather than only individual high-loss nodes. For the Top-K sequential deletion experiment, the average global efficiency loss across different K values, the mean rank of each method, and the number of scenarios in which a method ranks first are used as evaluation indicators.

Third, an averaging-window sensitivity analysis is conducted to examine whether the constructed GPR exposure scores are sensitive to the choice of time window. The full-period average from 2018 to 2024 is used as the baseline. Three sub-periods are further considered: 2018–2019, 2020–2021, and 2022–2024. For each sub-period, the GPR exposure scores of the selected countries or regions are recalculated using the same CRITIC-based weighting procedure. The resulting rankings are compared with the baseline ranking using Spearman and Kendall rank correlation coefficients. This analysis focuses on the indicator-level temporal stability of GPR exposure.

Together, these validation and sensitivity analyses provide additional evidence on the reliability and stability of the main identification results under alternative validation criteria, changes in waterway-layer connectivity, and different GPR averaging windows.

3. Results

3.1. GPR Exposure Scores

The indicators were averaged over the period from 2018 to 2024. The CRITIC method was then used for standardization and composite weighting to obtain the normalized composite scores. The resulting GPR exposure score provides a relative measure of how strongly each country or region is exposed to GPR-induced transportation disruptions within the constructed indicator system and network model. Countries or regions with

higher values are therefore interpreted as having higher transportation exposure under the modeled GPR context. The composite scores of the eight countries or regions are reported in Table 4.

Table 4. Country-level GPR exposure score of the eight countries or regions.

Country/Region	PV	GE	GDP (USD)	Trade Ratio	GPR Exposure Score
Cambodia	−0.0617	−0.4667	38,588,901,865.1038	1.1310	0.626177857
China	−0.4183	0.6111	16,748,138,658,225.3	0.3259	0.231242536
Laos	0.6567	−0.6900	17,500,861,491.374	0.8063	0.537535181
Malaysia	0.1533	0.9767	380,641,519,343.44	1.3987	0.569440602
Myanmar	−1.7533	−1.3600	70,195,352,652.0912	0.4665	0.587046909
Singapore	1.4483	2.2417	442,983,850,186.017	1.9173	0.460633278
Thailand	−0.5183	0.2050	513,621,387,774.976	1.0375	0.523592003
Vietnam	−0.0300	0.1250	383,036,197,507.739	1.6426	0.634309499

3.2. Parameter Calibration and Critical-Node Identification Results

The correlation coefficients under different parameter combinations are reported in Table 5.

Table 5. Comparison of correlation coefficients under different adjustment parameter combinations.

Rank	λ	η	θ	Pearson	Spearman	Kendall
1	0.5	1.5	3.0	0.8213	0.7838	0.6074
2	0.5	1.0	3.0	0.8194	0.7719	0.5962
3	0.5	1.0	2.5	0.8169	0.7757	0.6004
4	0.5	2.0	3.0	0.8169	0.7811	0.6051
5	0.5	1.5	2.5	0.8148	0.7793	0.6027

The results show that the correlation coefficients reach their maximum when $\lambda = 0.5$, $\eta = 1.5$, $\theta = 3.0$. Therefore, this parameter combination is selected for the subsequent analysis. The IWKS model for the cross-border transportation network is then expressed as:

$$S_i^* = \sqrt[5]{C_D^*(i)^{0.5}(s_i^*)^{1.5}C_C^*(i)^3} \quad (20)$$

3.3. Comparative Evaluation of Critical-Node Identification Results

To evaluate the effectiveness of the proposed method, commonly used indicators, including degree centrality, weighted degree, closeness centrality, betweenness centrality, and K-shell, are selected as benchmark methods. The algorithm results are compared from three perspectives, as described below.

3.3.1. Comparison of Node Agreement Rates

For each method, all nodes were ranked according to their node scores, and the Top-K nodes were selected as critical nodes. The comparison between the Top-10 critical nodes identified by IWKS and the simulation-based propagation benchmark, together with their corresponding transport modes, is reported in Table 6. The critical-node identification results obtained by the other benchmark methods are presented in Table 7. Under the model assumptions and parameter settings adopted in this study, waterway nodes appear more frequently among the highly ranked nodes across different methods. Combined with the simulation-based benchmark results, this suggests that nodes in the waterway layer generally exhibit higher propagation influence in the constructed cross-border transportation network.

Table 6. Top-10 critical nodes identified by IWKS and the simulation-based benchmark.

Rank	IWKS	Transport Mode	Simulation-Based Propagation Influence	Transport Mode
1	Perak	Waterway	Kuching	Waterway
2	Chonburi	Waterway	Perak	Waterway
3	Johor	Waterway	Chonburi	Waterway
4	Yangon	Waterway	Yangon	Waterway
5	Kuching	Waterway	Yangon	Air
6	Haiphong	Waterway	Johor	Waterway
7	Yangon	Air	Perak	Rail
8	Ho Chi Minh City	Waterway	Phnom Penh	Air
9	Da Nang	Waterway	Haiphong	Waterway
10	Klang	Waterway	Chonburi	Rail

Table 7. Top-10 critical nodes identified by conventional benchmark methods.

Rank	Degree Centrality	Weighted Degree	Closeness Centrality	Betweenness Centrality	K-Shell
1	Nanning (Rail)	Yangon (Waterway)	Perak (Waterway)	Hanoi (Road)	Penang (Waterway)
2	Penang (Waterway)	Ho Chi Minh City (Waterway)	Yangon (Air)	Beihai (Waterway)	Singapore (Waterway)
3	Singapore (Waterway)	Da Nang (Waterway)	Chonburi (Waterway)	Bangkok (Waterway)	Kuching (Waterway)
4	Johor (Waterway)	Haiphong (Waterway)	Johor (Waterway)	Pingxiang (Road)	Chonburi (Waterway)
5	Yangon (Waterway)	Chonburi (Waterway)	Johor (Air)	Fangchenggang (Waterway)	Johor (Waterway)
6	Haiphong (Waterway)	Kuching (Waterway)	Kuching (Waterway)	Bangkok (Air)	Yangon (Waterway)
7	Ho Chi Minh City (Waterway)	Perak (Waterway)	Baise (Rail)	Kuching (Waterway)	Haiphong (Waterway)
8	Da Nang (Waterway)	Sihanoukville (Waterway)	Baise (Air)	Singapore (Waterway)	Ho Chi Minh City (Waterway)
9	Beihai (Waterway)	Johor (Waterway)	Yangon (Waterway)	Haiphong (Waterway)	Da Nang (Waterway)
10	Bangkok (Waterway)	Penang (Waterway)	Haiphong (Waterway)	Haiphong (Road)	Klang (Waterway)

To further compare the identification results of different methods, the Top-K agreement rate is used as a supplementary consistency measure. For each method, the agreement rate is calculated as the proportion of overlapping nodes between its Top-K node set and the Top-K node set obtained from the simulation-based propagation benchmark. As shown in Figure 5, IWKS achieves the highest or joint-highest agreement rates under the Top-10, Top-20, and Top-30 thresholds. Specifically, IWKS reaches an agreement rate of 0.70 at Top-10 and increases to 0.80 at both Top-20 and Top-30, whereas the single-indicator methods show lower or less stable agreement rates across the three thresholds. These

results suggest that IWKS provides more consistent identification of propagation-relevant critical nodes under the modeled network and simulation settings.

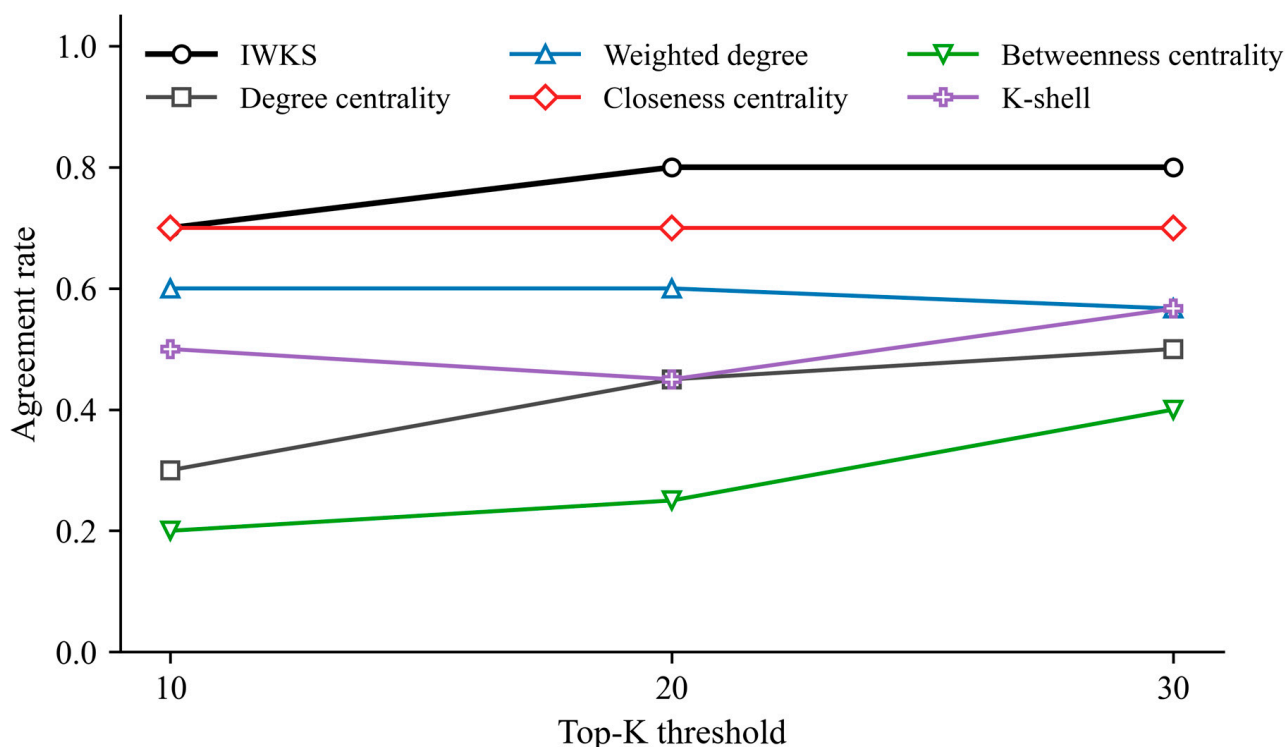


Figure 5. Top-K agreement rates between different critical-node identification methods and the simulation-based propagation benchmark.

3.3.2. Comparison of Different Methods

The correlations between IWKS and degree centrality, weighted degree, closeness centrality, betweenness centrality, and K-shell are shown in Figure 6.

The ellipses are K-means-based visual guides showing the main distributional regions of nodes. In contrast, single structural indicators such as degree centrality and closeness centrality show more dispersed scatter patterns. Methods such as K-shell, betweenness centrality, and weighted degree mainly rely on a single topological feature and therefore cannot fully capture the multidimensional drivers of the propagation process. As a result, they also have limitations in explaining and ranking node propagation influence.

Specifically, IWKS has a high correlation with closeness centrality (Pearson ≈ 0.809), indicating that its ranking is strongly consistent with the global accessibility of nodes. It also maintains strong positive correlations with weighted degree (Pearson ≈ 0.698) and K-shell (Pearson ≈ 0.674), suggesting that IWKS captures both local connection strength and core-periphery hierarchical features. Its correlation with degree centrality is moderately strong (Pearson ≈ 0.627), indicating that IWKS reflects connection scale to some extent but is not simply a linear mapping of degree. In contrast, IWKS has a relatively low correlation with betweenness centrality (Pearson ≈ 0.326), suggesting that it depends less on shortest-path bridging or bottleneck structures and is more oriented toward diffusion patterns driven by accessibility and core-level hierarchy. Overall, by integrating structural information with propagation process validation, the IWKS model improves the interpretability and consistency of node ranking.

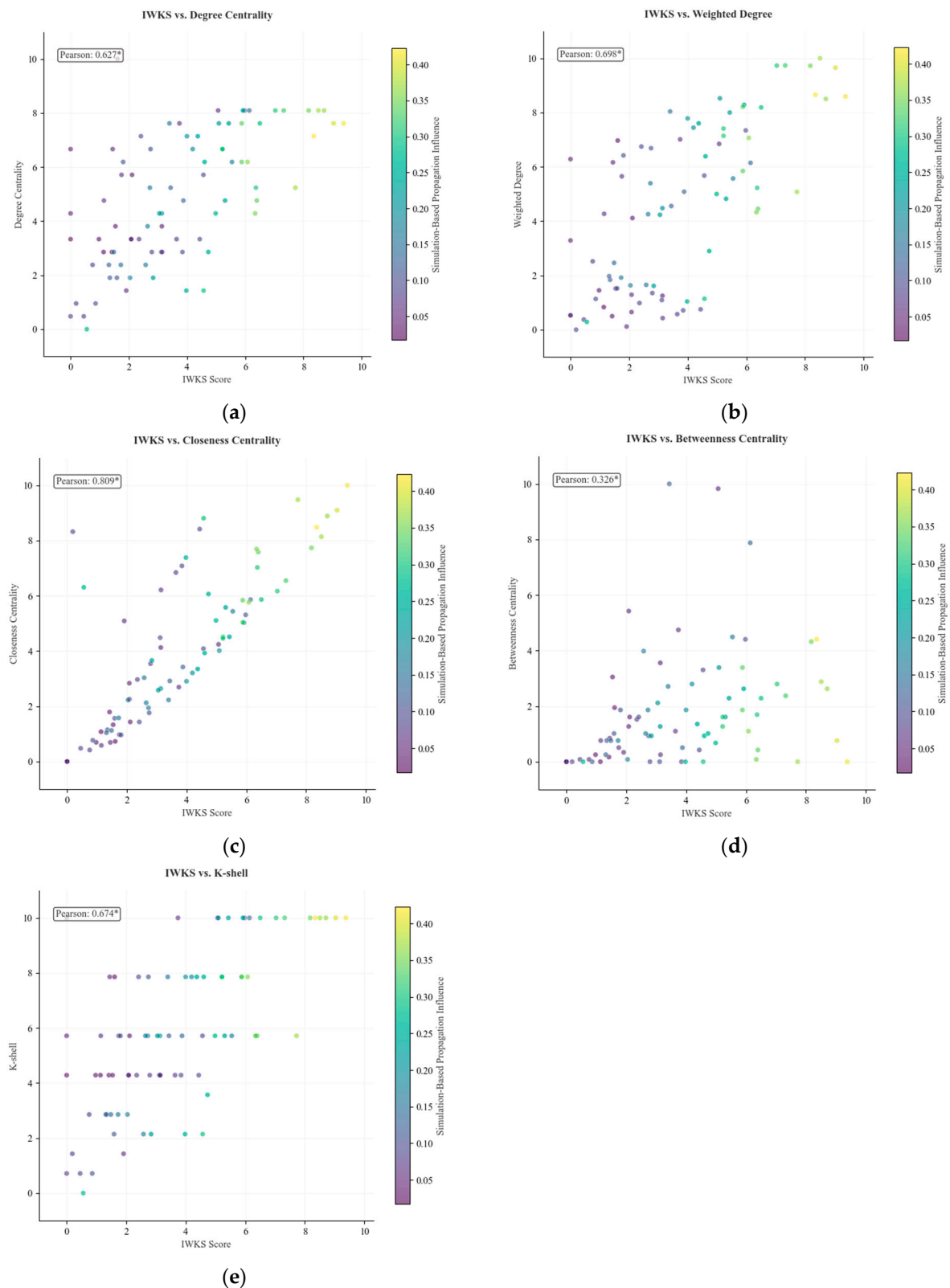


Figure 6. Correlations between IWKS and conventional indicators. (a) IWKS vs. Degree Centrality; (b) IWKS vs. Weighted Degree; (c) IWKS vs. Closeness Centrality; (d) IWKS vs. Betweenness Centrality; (e) IWKS vs. K-shell. Note: * indicates statistical significance at the 0.05 level.

3.3.3. Comparison with Simulation-Based Propagation Influence

The correlations between each method and the simulation-based propagation influence are shown in Figure 7. As the simulated influence increases, the IWKS scores show a

relatively stable upward trend, and the scatter points are more concentrated. This indicates that IWKS can better distinguish high-influence nodes from low-influence nodes. The relatively high Spearman and Kendall coefficients further suggest that IWKS provides a more stable ranking of critical nodes.

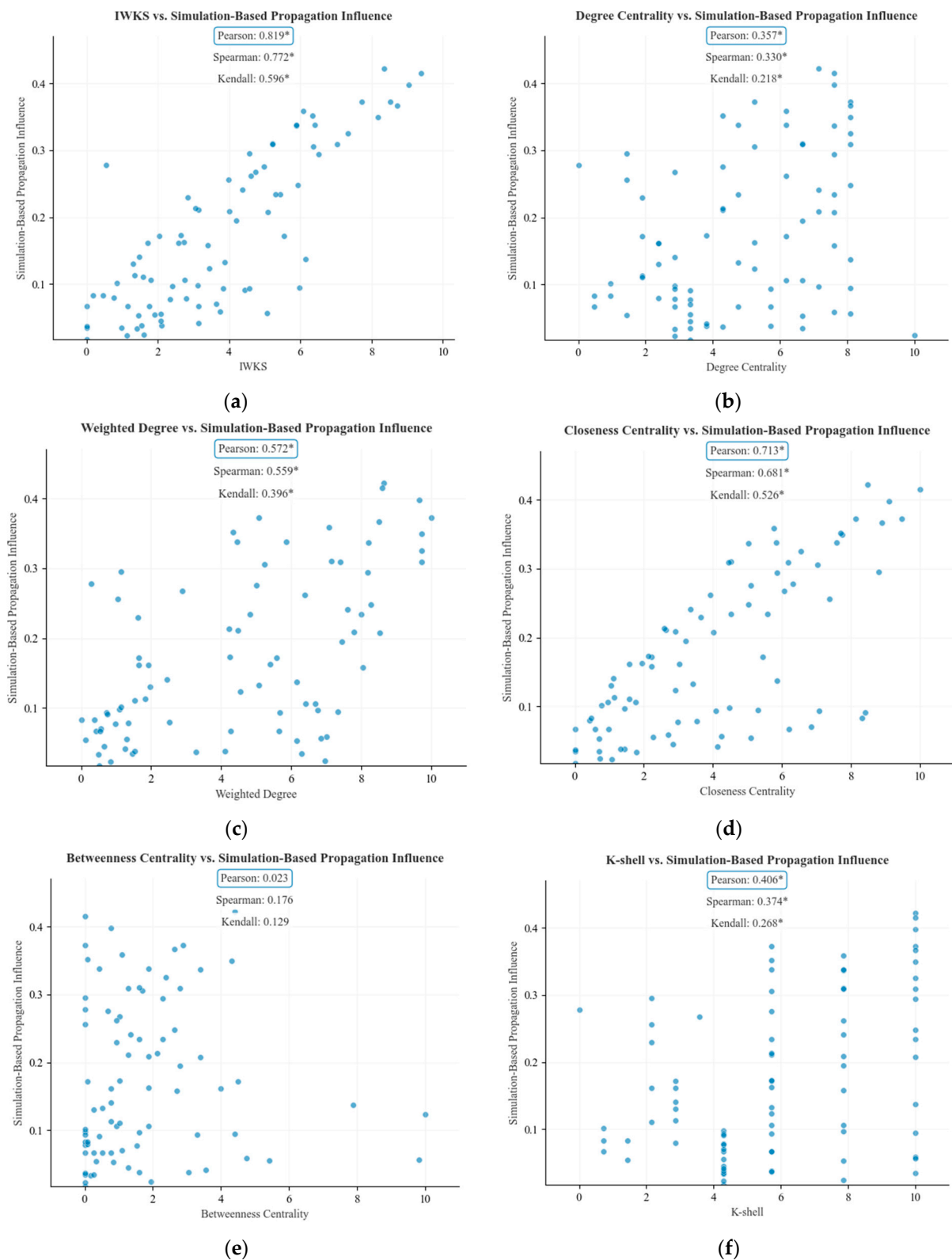


Figure 7. Correlations between each method and the simulation-based propagation influence. (a) IWKS; (b) Degree Centrality; (c) Weighted Degree; (d) Closeness Centrality; (e) Betweenness Centrality; (f) K-shell. Note: * indicates statistical significance at the 0.05 level.

The correlations between IWKS scores and the simulation-based propagation influence are significant in all three correlation tests, with Pearson, Spearman, and Kendall coefficients of 0.819, 0.772, and 0.594, respectively, all significant at $p < 0.05$. These results indicate that IWKS is highly consistent with the propagation simulation output and is suitable for Top-K critical node identification. The Pearson coefficient of 0.819 shows a strong linear consistency between IWKS scores and the simulation results at the numerical level. This suggests that, by integrating structural information, propagation dynamics, and edge-weight characteristics, IWKS can reduce the limited discriminatory power of single-indicator methods. The Spearman and Kendall coefficients further show that IWKS maintains good consistency in both overall ranking and local pairwise ordering. All three correlation coefficients are higher than those obtained by the single-indicator methods.

Considering both the correlation results and the Top-K identification results, IWKS shows stronger consistency and identification capability. Among the conventional indicators, closeness centrality performs the best, with Pearson, Spearman, and Kendall coefficients of 0.713, 0.681, and 0.526, respectively, all significant at $p < 0.05$. However, its overall performance is still weaker than that of IWKS. This indicates that, beyond accessibility information, the structural features further incorporated by IWKS, such as connection strength, contribute to the ranking of propagation influence. Weighted degree shows a moderate level of performance, with Pearson, Spearman, and Kendall coefficients of 0.572, 0.559, and 0.396, respectively, all significant at $p < 0.05$. This suggests that strong connections contribute to propagation influence but are insufficient as a standalone measure. K-shell and degree centrality show relatively weaker correlations. For K-shell, the Pearson, Spearman, and Kendall coefficients are 0.406, 0.374, and 0.268, respectively. For degree centrality, the corresponding coefficients are 0.357, 0.330, and 0.218, respectively. All of these correlations are significant at $p < 0.05$. The weaker performance of K-shell may be attributed to its discrete hierarchical structure, which makes it difficult to differentiate nodes within the same shell. Betweenness centrality is not significantly correlated with the simulation-based propagation influence, with Pearson, Spearman, and Kendall coefficients of 0.023, 0.176, and 0.129, respectively, with $p > 0.05$. This indicates that betweenness centrality cannot stably identify nodes with higher propagation influence.

Considering both the correlation tests and the Top-K identification results, conventional indicators such as degree centrality have inherent limitations in accurately characterizing simulation-based propagation influence. In contrast, IWKS integrates propagation dynamics with network structure and achieves higher ranking consistency. It is therefore more suitable under the modeled network and simulation settings in cross-border transportation networks.

3.4. Validation and Sensitivity Analysis

To further evaluate the reliability of the identification results, supplementary validation and sensitivity analyses were conducted from three perspectives. First, waterway-edge sparsification was used to examine the sensitivity of the results to the connectivity of the waterway layer. Second, network performance loss was used as an independent validation criterion to assess whether highly ranked nodes were associated with greater declines in network efficiency. Third, GPR averaging-window sensitivity analysis was conducted to evaluate the temporal stability of the constructed GPR exposure scores.

3.4.1. Waterway-Edge Sparsification Sensitivity Analysis

Considering that the waterway network uses a relatively high risk adjustment factor in edge-weight calculation and has a higher degree of connectivity under the network modeling assumptions, a waterway-edge sparsification sensitivity analysis is designed

to test whether the strong influence of waterway nodes in the propagation simulation is partly affected by the modeled waterway-layer connectivity. Specifically, while keeping the node set, non-waterway edges, and their propagation probability parameters unchanged, only waterway-related edges are randomly retained, with retention ratios set to 100%, 70%, 50%, and 30%. For each retention ratio, the sparsified network is reconstructed, and the Monte Carlo SIR simulation, IWKS calculation, and parameter training procedures are repeated. The waterway-edge retention ratios are reported in Table 8. This sensitivity analysis provides a test of conclusions under a network perturbation framework, thereby enhancing the reliability and interpretability of the results.

Table 8. Results of waterway-edge sparsification sensitivity analysis.

Waterway-Edge Retention Ratio	Optimal Parameters (λ, η, θ)	Pearson with Simulation-Based Propagation Influence	Number of Nodes	Number of Edges
100%	(0.5, 1.5, 3.0)	0.8285	83	507
70%	(0.5, 1.5, 3.0)	0.8140	83	463
50%	(0.5, 1.5, 3.0)	0.8305	83	415
30%	(0.5, 1.5, 3.0)	0.7913	83	381

3.4.2. Network Performance Loss Validation

As shown in Table 9, weighted degree has the highest correlation with the single-node deletion loss L_i , indicating that individual node-level performance loss is strongly associated with weighted connectivity.

Table 9. Comparison of IWKS and benchmark methods under single-node and Top-K deletion validation.

Method	Spearman with L_i	Kendall with L_i	Mean Loss	Mean Rank	Rank-1 Count
IWKS	0.695	0.516	0.208	1.167	5
Weighted degree	0.906	0.739	0.196	2.5	1
Closeness	0.504	0.347	0.174	4.167	0
K-shell	0.808	0.628	0.154	4.167	0
Degree	0.825	0.631	0.171	4.333	0
Betweenness	0.53	0.392	0.158	4.667	0

IWKS also shows a positive correlation with L_i , suggesting that the nodes identified by IWKS have clear structure-function relevance.

More importantly, IWKS achieves the highest average global efficiency loss and ranks first in five out of six Top-K deletion scenarios. This indicates that IWKS is more effective in identifying a set of performance-critical nodes rather than simply approximating individual node deletion loss.

Figure 8 further illustrates the performance degradation trend under different Top-K deletion scenarios. The IWKS curve is generally above the curves of the benchmark methods, especially when K increases from 9 to 25. This suggests that the cumulative removal of nodes ranked by IWKS leads to greater global efficiency loss, further supporting its ability to identify performance-critical node sets in the GPR-weighted multimodal transportation network.

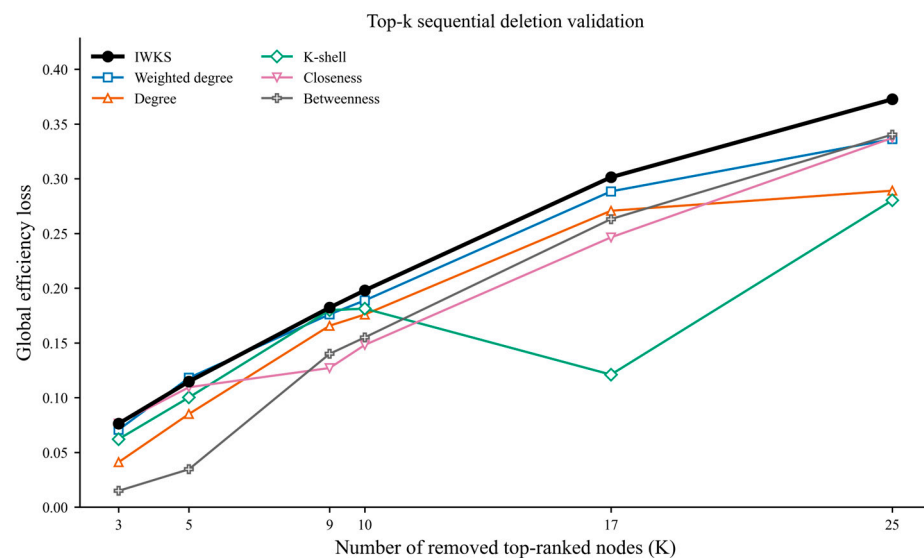


Figure 8. Global efficiency loss under Top-K sequential node deletion.

3.4.3. GPR Averaging-Window Sensitivity Analysis

To assess the temporal stability of the constructed GPR exposure scores, an averaging-window sensitivity analysis was performed. The full-period average over 2018–2024 was used as the baseline, and three alternative averaging windows, namely 2018–2019, 2020–2021, and 2022–2024, were further considered. For each period, the GPR exposure scores of the selected countries or regions were recalculated using the same CRITIC-based weighting procedure. The resulting rankings were then compared with the baseline ranking using Spearman and Kendall rank correlation coefficients.

As reported in Table 10, the GPR exposure rankings exhibit a high degree of temporal consistency across different averaging windows. The highest-exposure countries or regions are consistently Vietnam, Myanmar, and Cambodia, suggesting that the identification of the leading exposure group is largely unaffected by the choice of averaging period. The ranking obtained for 2018–2019 is identical to that of the full-period baseline. For 2020–2021 and 2022–2024, both the Spearman and Kendall coefficients remain high, and only one adjacent position exchange is observed in each period. Specifically, Laos and Singapore exchange positions during 2020–2021, whereas Thailand and Malaysia exchange positions during 2022–2024.

Table 10. Sensitivity of GPR exposure scores under different averaging windows.

Window	Spearman with Baseline	Kendall with Baseline	Main Observation
2018–2019	1	1	The ranking is identical to the baseline.
2020–2021	0.976	0.929	The top three remain unchanged; only Laos and Singapore exchange adjacent positions.
2022–2024	0.976	0.929	The top three remain unchanged; only Thailand and Malaysia exchange adjacent positions.

Overall, the results indicate that the constructed GPR exposure scores possess relatively high temporal stability with respect to the choice of averaging window. Although minor ranking adjustments occur in some sub-periods, the overall exposure pattern and the identification of high-exposure countries or regions remain stable. Therefore, the baseline scores based on the 2018–2024 average can be regarded as medium-term representations of

relative GPR exposure, suitable for capturing persistent differences in the geopolitical risk environment across countries or regions.

4. Discussion

4.1. Interpretation of GPR Exposure and Modeling Assumptions

The GPR exposure score in this study is constructed from a network-exposure perspective. The GPR index is commonly used to measure adverse geopolitical events and associated risks at the macro level [28]. In transport network risk analysis, exposure is also an important dimension because the criticality of a network element depends not only on the consequence of a disruption, but also on the extent to which the element is exposed to disruptive events [29]. Following this logic, this study does not treat GPR exposure as a direct city-level geopolitical risk index. Instead, it constructs an operational measure to describe how macro-level geopolitical conditions may be reflected in the modeled cross-border transportation network.

Specifically, PV and GE are used to characterize the political and governance environment, while GDP and trade ratio are introduced as contextual variables that condition the potential impact of geopolitical disruptions on cross-border transportation activities. GDP is used to represent economic absorptive capacity, whereas trade ratio reflects dependence on cross-border trade. Accordingly, GDP and trade ratio are not regarded as direct geopolitical risk factors.

One limitation of this construction is the mapping of national-level GPR exposure scores to city-level and transfer-node-level values. This assumption is adopted because comparable city-level or node-level GPR-related indicators are not consistently available across the selected countries and regions. However, it may smooth intra-country spatial heterogeneity. Port cities, border cities, inland logistics hubs, and air transport hubs may face different types of exposure to GPR-induced disruptions. For example, port cities may be more directly affected by maritime route changes, port control, and international trade restrictions, whereas border cities may be more sensitive to customs procedures, border control, and cross-border road or rail policy changes.

This simplification may affect the results in two ways. First, it may underestimate exposure differences among cities within the same country. Second, it may make the critical-node ranking more dependent on network topology and transport-mode structure than on city-specific risk conditions. Therefore, the results should be interpreted as network-level critical-node identification under macro-level GPR exposure rather than as a city-specific geopolitical risk assessment.

4.2. Mechanism of Waterway Node Dominance

The dominance of waterway nodes in the critical-node ranking can be explained by the joint effects of regional freight structure, network topology, GPR exposure, and intermodal coupling. From the perspective of regional freight structure, waterway transport serves as a major carrier of long-distance and bulk cross-border freight flows in the Guangxi-ASEAN region. Empirical evidence shows that GPR has heterogeneous effects across international freight modes, with sea freight being more sensitive to GPR than air and road freight [3]. This provides an empirical basis for introducing mode-specific GPR sensitivity into the constructed multimodal network.

From the perspective of network topology, waterway and port-related nodes tend to occupy highly connected and highly accessible positions. Previous studies on transport vulnerability and resilience have emphasized that connectivity and accessibility are key dimensions for understanding the performance of transport networks under disruptions [30,31]. In the constructed multimodal network, major port nodes are not

only connected to maritime routes, but also linked with road, rail, and air transport layers through transfer nodes. Such interdependencies among transport modes may influence both disruption propagation and recovery performance in multimodal transportation networks [32].

Shipping network studies further support the importance of port-related nodes. Liner shipping networks may experience cascading failures when port disruptions trigger cargo redistribution and congestion diffusion, and port reserve capacity or cooperative mechanisms can affect the resilience of the shipping network [33]. In addition, port vulnerability is influenced by port-hinterland relationships, spatial agglomeration, and geopolitical environments [34]. These findings help explain why port-related waterway nodes may become exposure concentration points in a cross-border transportation network under GPR-related disruptions.

However, the observed dominance of waterway nodes should also be interpreted together with the network construction assumptions. The modeled waterway layer has relatively dense connectivity, which may strengthen the ranking advantage of waterway nodes. The waterway-edge sparsification analysis suggests that this dominance should be interpreted together with the dense connectivity of the waterway layer. Although the modeled waterway topology contributes to the observed ranking pattern, the continued importance of major port-related nodes indicates that their role is jointly shaped by transport function, network position, and GPR exposure.

4.3. Comparison with Previous Studies

The findings are broadly consistent with previous transportation network vulnerability studies, which show that highly connected and highly accessible nodes often play important roles in maintaining network performance [30,31]. However, the present study differs from conventional topology-based vulnerability analyses by incorporating GPR exposure into edge-weight construction and propagation simulation. As a result, the identified critical nodes reflect not only structural importance, but also the potential exposure of transport corridors and transport modes to geopolitical disruptions.

The proposed IWKS also extends previous K-shell-based and centrality-based node identification methods. Existing studies have shown that single structural indicators may have limited ability to distinguish node influence, and that combining local and global structural information can improve the resolution and accuracy of influential-node identification [19,35]. In this study, degree centrality, weighted degree, and closeness centrality are integrated to capture local connectivity, weighted transport interaction, and global accessibility simultaneously.

Compared with recent multimodal transportation network studies that incorporate traffic demand, corridor interaction, or intermodal dependency [26,32], the main extension of this study lies in embedding GPR exposure into a cross-border multimodal transportation network. Therefore, the proposed framework is not only a topology-based critical-node identification method, but also a GPR-informed approach for cross-border transportation risk analysis.

4.4. Implications for Cross-Border Transportation Risk Management

The results provide several implications for cross-border transportation risk management. First, port-related waterway nodes should be prioritized in risk monitoring and resilience planning. These nodes connect international shipping routes, port operations, and inland logistics corridors. Disruptions at such nodes may therefore generate wider system-level effects than disruptions at ordinary local nodes.

Second, alternative intermodal routes should be maintained. Since major port nodes are connected with road, rail, and air transport layers through transfer nodes, disruptions in the waterway layer may propagate to other transport layers through intermodal coupling. Improving coordination among ports, railway stations, road corridors, and air transport hubs can reduce the risk of disruption accumulation in a single transport mode.

Third, differentiated risk management strategies should be adopted across transport modes. Waterway and railway layers may play important roles in maintaining regional connectivity, while road and air layers may provide local substitution or emergency support under certain disruption scenarios. This implication is consistent with multimodal supply chain risk studies, which emphasize that risks in multimodal supply chains are distributed across multiple actors, transport links, and operational stages [36].

4.5. Limitations and Future Research

Several limitations should be noted. First, the cross-border transportation network is constructed as a static network. Although this treatment makes it possible to compare the structural roles of different transport modes, it does not fully capture time-varying factors such as shipping schedules, port congestion, customs clearance delays, seasonal demand changes, and temporary border controls. This limitation is consistent with the broader distinction between topology-based vulnerability analysis and system-based vulnerability analysis in transport research [31]. Future research could construct dynamic transportation networks using monthly or event-level operational data.

Second, the GPR exposure score is mapped from the national level to the city and transfer-node levels. This approach is necessary for cross-country comparison, but it may smooth spatial heterogeneity within the same country or region. Port cities, border cities, inland logistics hubs, and air transport hubs may face different types and intensities of disruption exposure. Future studies could incorporate port-level throughput, customs delay data, city-level trade dependence, or event-based disruption records to improve the spatial resolution of GPR exposure measurement.

Third, the mode-specific adjustment factors are adapted from existing empirical findings on the differentiated effects of GPR across freight modes [3]. Although this provides an operational basis for distinguishing transport-mode sensitivity, the elasticities were not re-estimated using the data in this study. Future research could estimate mode-specific GPR sensitivity using regional freight flow data or transport-mode-level panel data.

Fourth, the validation and sensitivity analyses remain simulation-based and indicator-based. The SIR model and network performance loss analysis provide useful evidence for evaluating critical-node identification results, but they do not represent direct causal validation using observed disruption events. Similarly, the averaging-window analysis examines the stability of GPR exposure scores, but it does not reconstruct dynamic edge weights or time-varying critical-node rankings for each year or month. Future research could combine real disruption cases, dynamic GPR indicators, and time-varying network reconstruction to further validate the proposed framework.

5. Conclusions

This study develops a GPR-informed critical-node identification framework for cross-border multimodal transportation networks. Taking the Guangxi-ASEAN cross-border transportation network as the case, this study constructs a multilayer network integrating road, railway, waterway, and air transport. Transport distance, transport time, and GPR exposure are incorporated into edge-weight construction using the CRITIC method. On this basis, an Improved Weighted K-shell (IWKS) model is proposed by integrating degree centrality, weighted degree, and closeness centrality. An SIR-based propagation simulation

and Monte Carlo experiments are further used to calibrate model parameters and evaluate node propagation influence.

The results can be summarized into three main findings. First, the Guangxi-ASEAN cross-border transportation network exhibits clear multilayer and intermodal coupling characteristics. Different transport layers show distinct connectivity patterns, with waterway and railway layers forming relatively strong regional connections, while road and air layers play more localized or supplementary roles. Second, the IWKS model shows stronger consistency with simulation-based propagation influence than conventional indicators such as degree centrality, weighted degree, closeness centrality, betweenness centrality, and K-shell. The identified critical nodes are mainly concentrated in waterway and port-related nodes, suggesting that these nodes play a central role in maintaining network connectivity and carrying GPR-related disruption propagation. Third, the supplementary validation and sensitivity analyses provide additional support for the main findings. The network performance loss validation indicates that IWKS performs better in Top-K sequential deletion scenarios, indicating its advantage in identifying performance-critical node sets. The waterway-edge sparsification analysis shows that the importance of waterway nodes is not fully explained by dense waterway connectivity. The GPR averaging-window sensitivity analysis further indicates that the constructed GPR exposure scores remain relatively stable across different sub-periods and can serve as medium-term exposure indicators.

Based on the findings, this study provides several implications for cross-border transportation risk management. First, port-related waterway nodes and intermodal transfer hubs should be prioritized in risk monitoring and resilience planning. These nodes connect maritime routes, inland transport corridors, and regional logistics systems, and their disruption may produce wider network-level effects. Second, differentiated risk management should be implemented across transport modes. Waterway and railway layers should be strengthened as key connectivity backbones, while road and air transport should be used to enhance local substitution and emergency response capacity. Third, resilience planning should focus not only on individual critical nodes but also on intermodal coupling relationships. Strengthening port-hinterland coordination, maintaining alternative intermodal routes, and improving cross-border information sharing may help reduce the propagation of GPR-induced disruptions.

Future research may further extend the proposed framework from static critical-node identification to dynamic risk monitoring and resilience-oriented decision support. In particular, future studies could examine how GPR exposure evolves over time, how disruption effects propagate across transport modes under changing network conditions, and how critical-node identification results can be linked to route adjustment, capacity allocation, and resilience improvement strategies. Such extensions would help transform the proposed framework from a vulnerability assessment tool into a more operational analytical basis for cross-border transportation risk management.

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Abbreviations

The following abbreviations are used in this manuscript:

ASEAN	Association of Southeast Asian Nations
CBTNTM	Cross-Border Transportation Network Topology Model
CRITIC	Criteria Importance Through Intercriteria Correlation
GPR	Geopolitical Risk
IWKS	Improved Weighted K-shell
SIR	Susceptible–Infected–Recovered
WGI	Worldwide Governance Indicators
PV	Political Stability and Absence of Violence/Terrorism
GE	Government Effectiveness
GDP	Gross Domestic Product

References

1. Christopher, M.; Peck, H. Building the resilient supply chain. *Int. J. Logist. Manag.* **2004**, *15*, 1–14. [\[CrossRef\]](#)
2. López, C.; Morales-Contreras, M.F.; Langella, I.M.; Alonso-Monge, J. Modeling supply chain disruptions due to geopolitical reasons: A systematic literature review. *Transp. Res. Part E Logist. Transp. Rev.* **2025**, *202*, 104290. [\[CrossRef\]](#)
3. Liu, K.; Fu, Q. How does geopolitical risk affect international freight? *J. Air Transp. Manag.* **2024**, *118*, 102614. [\[CrossRef\]](#)
4. Yang, Z.; Wang, Y.; Lian, F. Optimization of the Sino-Russian trade transportation network under geopolitical risks such as the Russia–Ukraine conflict. *Transp. Res. Part E Logist. Transp. Rev.* **2025**, *198*, 104144. [\[CrossRef\]](#)
5. Mei, Q.; Hu, Q.; Hu, Y.; Yang, Y.; Liu, X.; Huang, Z.; Wang, P. Structural analysis and vulnerability assessment of the European LNG maritime supply chain network (2018–2020). *Ocean Coast. Manag.* **2024**, *253*, 107126. [\[CrossRef\]](#)
6. Ren, H.; Mu, D.; Wang, C.; Yue, X.; Li, Z.; Du, J.; Zhao, L.; Lim, M.K. Vulnerability to geopolitical disruptions of the global electric vehicle lithium-ion battery supply chain network. *Comput. Ind. Eng.* **2024**, *188*, 109919. [\[CrossRef\]](#)
7. Choudhary, N.A.; Ramkumar, M.; Schoenherr, T.; Rana, N.P. Assessing supply chain resilience during the pandemic using network analysis. *IEEE Trans. Eng. Manag.* **2024**, *71*, 12297–12310. [\[CrossRef\]](#)
8. Sharma, S.K.; Srivastava, P.R.; Kumar, A.; Jindal, A.; Gupta, S. Supply chain vulnerability assessment for manufacturing industry. *Ann. Oper. Res.* **2023**, *326*, 653–683. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Yang, M.; Qu, S.; Ji, Y.; Abdoullrahman, D. Vulnerability of fresh agricultural products supply chain: Assessment, interrelationship analysis and control strategies. *Socio-Econ. Plan. Sci.* **2024**, *94*, 101928. [\[CrossRef\]](#)
10. Berger, N.; Schulze-Schwering, S.; Long, E.; Spinler, S. Risk management of supply chain disruptions: An epidemic modeling approach. *Eur. J. Oper. Res.* **2023**, *304*, 1036–1051. [\[CrossRef\]](#)
11. Zhao, P.; Li, Z.; Han, X.; Duan, X. Supply chain network resilience by considering disruption propagation: Topological and operational perspectives. *IEEE Syst. J.* **2022**, *16*, 5305–5316. [\[CrossRef\]](#)
12. Lyu, M.; Shuai, B.; Zhang, Q.; Li, L. Ripple effect in China–Europe railway transport network: Ripple failure risk propagation and influence. *Phys. A Stat. Mech. Appl.* **2023**, *620*, 128739. [\[CrossRef\]](#)
13. Liu, H.; Tian, Z.; Huang, A.; Yang, Z. Analysis of vulnerabilities in maritime supply chains. *Reliab. Eng. Syst. Saf.* **2018**, *169*, 475–484. [\[CrossRef\]](#)
14. Vidza, M.-S.; Budka, M.; Chai, W.K.; Thrush, M.; Alves, M.T. Supply network disruption: A framework for assessing vulnerability and implementing resilience strategies. *Inf. Sci.* **2025**, *717*, 122336. [\[CrossRef\]](#)
15. Chen, H.-H.; Lin, A.-M. Complex network characteristics and invulnerability simulating analysis of supply chain. *J. Netw.* **2012**, *7*, 591–597. [\[CrossRef\]](#)
16. Ma, F.; Xue, H.; Yuen, K.F.; Sun, Q.; Zhao, S.; Zhang, Y.; Huang, K. Assessing the vulnerability of logistics service supply chain based on complex network. *Sustainability* **2020**, *12*, 1991. [\[CrossRef\]](#)

17. Ma, C.; Zhang, L.; You, L.; Tian, W. A review of supply chain resilience: A network modeling perspective. *Appl. Sci.* **2025**, *15*, 265. [\[CrossRef\]](#)
18. Zhao, X.; Zhang, Y.; Zhai, Q.; Zhang, J.; Qi, L. A multi-attribute decision-making approach for critical node identification in complex networks. *Entropy* **2024**, *26*, 1075. [\[CrossRef\]](#) [\[PubMed\]](#)
19. Esfandiari, S.; Fakhrahmad, S.M. The collaborative role of K-shell and PageRank for identifying influential nodes in complex networks. *Phys. A Stat. Mech. Appl.* **2025**, *658*, 130256. [\[CrossRef\]](#)
20. Gao, H.; Zhu, X.; Yang, X.; Liu, T.; Guo, B.; Xu, M. A multi-dimensional fusion method for identifying key nodes in new energy vehicle supply chains. *Teh. Vjesn.* **2025**, *32*, 1185–1194. [\[CrossRef\]](#)
21. Xie, L.; Sun, H.; Yang, H.; Zhang, L. Key node recognition in complex networks based on the K-shell method. *J. Tsinghua Univ. Sci. Technol.* **2022**, *62*, 849–861. (In Chinese) [\[CrossRef\]](#)
22. Wang, L.; Zheng, S.; Wang, Y.; Wang, L. Identification of critical nodes in multimodal transportation network. *Phys. A Stat. Mech. Appl.* **2021**, *580*, 126170. [\[CrossRef\]](#)
23. Garas, A.; Schweitzer, F.; Havlin, S. A k-shell decomposition method for weighted networks. *New J. Phys.* **2012**, *14*, 083030. [\[CrossRef\]](#)
24. Namtirtha, A.; Dutta, A.; Dutta, B. Weighted kshell degree neighborhood: A new method for identifying the influential spreaders from a variety of complex network connectivity structures. *Expert Syst. Appl.* **2020**, *139*, 112859. [\[CrossRef\]](#)
25. Maji, G.; Namtirtha, A.; Dutta, A.; Malta, M.C. Influential spreaders identification in complex networks with improved k-shell hybrid method. *Expert Syst. Appl.* **2020**, *144*, 113092. [\[CrossRef\]](#)
26. Wang, L.; Zhang, S.; Szűcs, G.; Wang, Y. Identifying the critical nodes in multi-modal transportation network with a traffic demand-based computational method. *Reliab. Eng. Syst. Saf.* **2024**, *244*, 109956. [\[CrossRef\]](#)
27. Ding, C.; Wang, Z.; Xu, S. Study on the cascading failure robustness of the Belt and Road land–sea transport network under emergencies. *Symmetry* **2024**, *16*, 736. [\[CrossRef\]](#)
28. Caldara, D.; Iacoviello, M. Measuring geopolitical risk. *Am. Econ. Rev.* **2022**, *112*, 1194–1225. [\[CrossRef\]](#)
29. Cats, O.; Yap, M.; van Oort, N. Exposing the role of exposure: Public transport network risk analysis. *Transp. Res. Part A Policy Pract.* **2016**, *88*, 1–14. [\[CrossRef\]](#)
30. Reggiani, A.; Nijkamp, P.; Lanzi, D. Transport resilience and vulnerability: The role of connectivity. *Transp. Res. Part A Policy Pract.* **2015**, *81*, 4–15. [\[CrossRef\]](#)
31. Mattsson, L.-G.; Jenelius, E. Vulnerability and resilience of transport systems: A discussion of recent research. *Transp. Res. Part A Policy Pract.* **2015**, *81*, 16–34. [\[CrossRef\]](#)
32. Ma, W.; Lin, S.; Ci, Y.; Li, R. Resilience evaluation and improvement of post-disaster multimodal transportation networks. *Transp. Res. Part A Policy Pract.* **2024**, *189*, 104243. [\[CrossRef\]](#)
33. Lu, B.; Sun, Y.; Wang, H.; Wang, J.-J.; Liu, S.S.; Cheng, T.C.E. Dynamic resilience analysis of the liner shipping network: From structure to cooperative mechanism. *Transp. Res. Part E Logist. Transp. Rev.* **2024**, *191*, 103755. [\[CrossRef\]](#)
34. Guo, J.; Feng, T.; Wang, S.; Qin, Y.; Yu, X. Shipping network vulnerability assessment integrated with geographical locations. *Transp. Res. Part D Transp. Environ.* **2024**, *130*, 104166. [\[CrossRef\]](#)
35. Yang, X.; Xiao, F. An improved gravity model to identify influential nodes in complex networks based on k-shell method. *Knowl.-Based Syst.* **2021**, *227*, 107198. [\[CrossRef\]](#)
36. Vilko, J.P.P.; Hallikas, J.M. Risk assessment in multimodal supply chains. *Int. J. Prod. Econ.* **2012**, *140*, 586–595. [\[CrossRef\]](#)

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