

Article

Assessment of Human Settlement Suitability and Structural Resilience in the Shenyang Metropolitan Area from the Perspective of Spatial Networks

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Abstract

A systematic assessment of the human settlement suitability (HSS) and its structural resilience in metropolitan areas, from a spatial network perspective, is essential for understanding the spatial organization and evolutionary mechanisms of regional human settlement systems. It also supports the high-quality development of metropolitan areas. This study considers the Shenyang Metropolitan Area as the research object and constructs a comprehensive evaluation model of HSS from two dimensions: natural environmental suitability (NES) and human environmental suitability (HES). This study systematically analyzes the spatial distribution pattern of HSS, characteristics of its spatial association network, and its structural resilience, by integrating a modified gravity model, social network analysis (SNA), and structural resilience measurement methods. The results indicate that NES exhibits a high-west to low-east gradient, with high-value areas primarily located in peripheral regions with better ecological conditions. HES reveals a pronounced core–periphery structure, with high suitability concentrated in core cities and their adjacent suburban areas. Under the combined influence of NES and HES, the HSS forms a layered differentiation pattern dominated by core cities. The spatial association network of HSS has an overall low density and displays the coexistence of a core–periphery structure and proximity dependence, in which the HES network demonstrates strong cross-node transmission capacity, while the NES network is significantly constrained by geographical proximity. The structural resilience of the network is characterized by a moderate hierarchy, predominantly homophilic matching, limited transmission efficiency, and pronounced spatial differentiation in aggregation, indicating an overall pattern of highly connected cores with low aggregation and moderately or weakly connected nodes with high aggregation. The findings provide a scientific basis for optimizing the human settlements and enhancing regional resilience governance in metropolitan areas, while offering a novel analytical perspective for research on human settlement systems.



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Keywords: human settlement suitability; social network analysis; structural resilience; Shenyang metropolitan area

1. Introduction

Metropolitan areas, as a key spatial form of new urbanization [1], have become crucial drivers of high-quality regional development and national competitiveness because of

their highly concentrated human activities, dynamic economic development, and frequent flow of resources and factors [2]. As China's urbanization process enters a people-centered stage [3], urban development logic is shifting from scale expansion to connotation enhancement. Consequently, the quality of human settlements has gradually become a critical benchmark for assessing regional development and spatial governance capacity. However, in the context of continued population and industrial concentration, metropolitan areas commonly face challenges associated with "large-city diseases," including intensified environmental pollution, prominent human–land conflicts, exacerbated urban heat island effects, and declining biodiversity [4,5]. Simultaneously, increasing ecological carrying pressure coupled with unregulated spatial expansion further amplifies internal spatial differentiation and systemic vulnerability [6], underscoring the urgent need to reconsider the spatial organizational mechanisms of the human settlements from a systemic perspective.

Human settlement suitability (HSS), as the spatial expression of a people-centered development philosophy, serves as an important indicator for characterizing the coordination between regional ecological foundations and human activities [7], and provides a key entry point for addressing structural contradictions in metropolitan area environments. Existing studies have pointed out that the human settlements is not merely a spatial projection of single factor attributes, but rather a spatial association network formed through interurban linkages and factor flows [8]. With the deepening of interregional economic and social connections, HSS characteristics are no longer confined to localized and static attributes. Instead, they increasingly exhibit spatially correlated patterns shaped by interregional interactions and network structures. From the perspective of relational geography, regions are interconnected through multidimensional networks shaped by population mobility, resource allocation, and information exchange, leading to a pronounced networked structure in the spatial organization of the human settlements [9]. Accordingly, re-examining HSS through the lens of complex network theory means conceptualizing "suitability" as a relational outcome generated through interregional interactions, rather than as a simple aggregation of isolated regional attributes. This conceptual shift provides a new theoretical framework for research on human settlement systems.

Existing studies have primarily relied on attribute-based evaluation frameworks, constructed indicator systems along natural and socio-economic dimensions [10–14] and employed multi-source datasets [15–17]. Methods such as analytic hierarchy process [18], expert scoring [19], principal component analysis [20], entropy weighting [17], and global sensitivity analysis [21] have been applied to measure HSS and analyze spatial patterns at various scales [22–25]. Although these studies have enriched the understanding of HSS spatial distribution, they mainly focus on attribute space and static patterns, failing to capture interregional spatial linkages and structural characteristics.

At the methodological level, traditional evaluation methods often depend on global models for indicator weighting and comprehensive measurements, inherently assuming spatial homogeneity. Although suitable for macro-level comparisons and policy evaluations, these methods may obscure spatial non-stationarity and local driving mechanisms under conditions of significant spatial heterogeneity, thereby weakening the interpretability and spatial specificity of governance recommendations. To address these limitations, some scholars have introduced multi-scale geographically weighted regression (MGWR) models that assign variable-specific bandwidths to identify local effects across multiple scales, thus enhancing the spatial adaptability of indicator weights [12,26,27].

Meanwhile, although HSS has been shown to exhibit significant spatial autocorrelation [28,29], most studies remain confined to attribute space and overlook relational perspectives in explaining spatial linkages. With increasing factor flows, regional spaces are transitioning from "field space" to "flow space" [30,31]. Under this paradigm, viewing

regions as interconnected network systems and characterizing the relationships among spatial units facilitates holistic insight into structural patterns. The gravity model is widely used to quantify inter-regional connection strengths [32–34], and when combined with social network analysis (SNA), it enables examination of network structural properties [35–37]. This provides an effective pathway for shifting HSS research from “attribute distribution” to “relational structure.”

Amid growing risks and uncertainty, the structural resilience of urban systems has become increasingly prominent [38]. Spatial association networks’ structural resilience refers to their capacity to maintain structural stability and recover functionality under external shocks or internal disturbances [39]. It reflects the adaptability and robustness of regional systems from a relational perspective [40]. Relevant studies grounded in complex network theory have measured network resilience through hierarchy, homophily, transmissibility, and aggregation [41–43], with widespread applications in transportation networks [44], population mobility networks [45], and multi-factor networks [46]. However, studies integrating HSS with spatial network structures and their resilience characteristics remains limited, and a systematic analytical framework is yet to be established.

In summary, existing studies present limitations in scale, methodology, and content. First, studies have mostly been conducted at national or single-city scales and lack a systematic analysis of metropolitan areas at the meso-scale. Second, the methods predominantly focus on attribute evaluation and fail to effectively transform the HSS into relational variables suitable for spatial network analysis. Third, network analyses often remain descriptive, with insufficient integration of suitability evaluations and structural resilience assessments.

To address these gaps, this study argues that HSS reflects not only regional natural and socio-economic conditions, but also a relational attribute embedded in spatial interaction networks. It uses the Shenyang Metropolitan Area as the research subject. Using multi-source data, we constructed an HSS evaluation framework, measured indicator weights using the MGWR model, and developed a spatial association network of HSS based on a modified gravity model. We further employed SNA and structural resilience measurement methods to systematically analyze the spatial distribution patterns, network structural features, and network resilience. This study aimed to advance the understanding of metropolitan area human settlements spatial organization through an integrated “attribute features-network structure-structural resilience” perspective.

Within this research framework, this study addresses the following questions: what spatial distribution patterns does HSS exhibit across natural and human dimensions in the Shenyang metropolitan area? What are the overall topological characteristics of the spatial association network of HSS? What is the overall level of structural resilience of the HSS spatial network? The answers are expected to provide theoretical guidance and methodological support for optimizing human settlements and managing regional resilience at the metropolitan area scale.

2. Materials and Methods

2.1. Study Area

The Shenyang Metropolitan Area, located in central Liaoning Province, is recognized as the ninth national-level metropolitan area in China and was the first to be established in Northeast China. It is instrumental in promoting regional revitalization, advancing coordinated regional development, and implementing the national strategy for new-type urbanization. Centered on the core city of Shenyang, the metropolitan area comprises seven surrounding cities and one development district, Shenyang, Anshan, Fushun, Benxi, Fuxin, Liaoyang, Tieling, and the Shenyang-Fushun Reform and Innovation Demonstration Zone

(Figure 1). Overall, the region exhibits a spatial structure characterized by core-led growth, axis-supported expansion, and cluster-based coordination and serves as a key hub linking the hinterland of Northeast China with the Liaoning Coastal Economic Belt. This region holds substantial strategic significance in shaping a new high-quality development model for Northeast China.

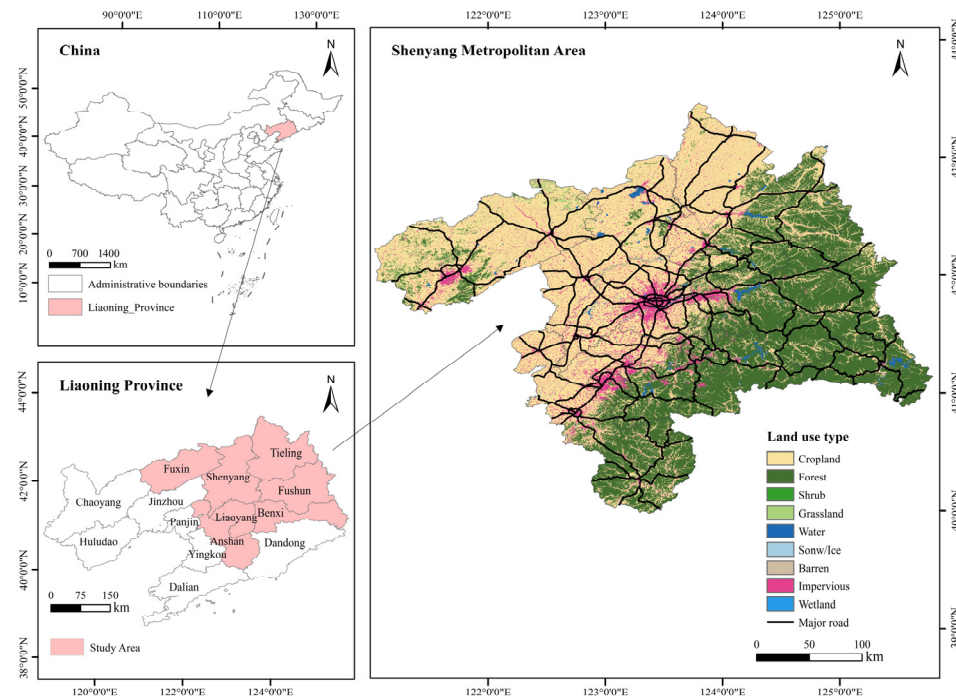


Figure 1. Location of the Research Area.

2.2. Methodology

HSS is a complex and multifaceted system that integrates natural and anthropogenic dimensions. Conceptually, HSS can be broadly categorized into two components: natural environmental suitability (NES) and human environmental suitability (HES). NES primarily reflects the objective constraints imposed by regional natural conditions on human settlements activities. NES is relatively stable, remains largely unaffected by subjective human decisions [47], and encompasses indicators including the Relief Degree of Land Surface (RDLS), Hydrological Index (HI), Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), and Temperature Humidity Index (THI). HES reflects human activities and regional levels of socioeconomic development. HES constitutes a subjective factor influencing the quality of human settlements and incorporates indicators including Night-Time Light Index (NTLI), Basic Infrastructure Index (BSI), Transport Accessibility Index (TAI), PM_{2.5} Concentration (PM), and Land Cover Index (LCI). NES and HES interact reciprocally, jointly forming the overall HSS framework.

The methodological framework of this study is summarized as follows. First, using preprocessed multi-source datasets—comprising remote sensing imagery, monitoring station data, and points of interest (POI) data—all indicators were standardized using a range-standardization method to eliminate dimensional effects. Second, an MGWR model was employed to estimate the correlation coefficients between each indicator and population density, which were subsequently used to derive the corresponding indicator weights. Third, the NES, HES, and overall HSS indices were calculated using a linear weighted-sum method. Finally, a spatial association network was constructed based on a modified gravity model. This network was further analyzed by integrating SNA and structural resilience assessment methods to examine the spatial configuration and resilience characteristics of

HSS in the Shenyang Metropolitan Area. The overall research framework is illustrated in Figure 2.

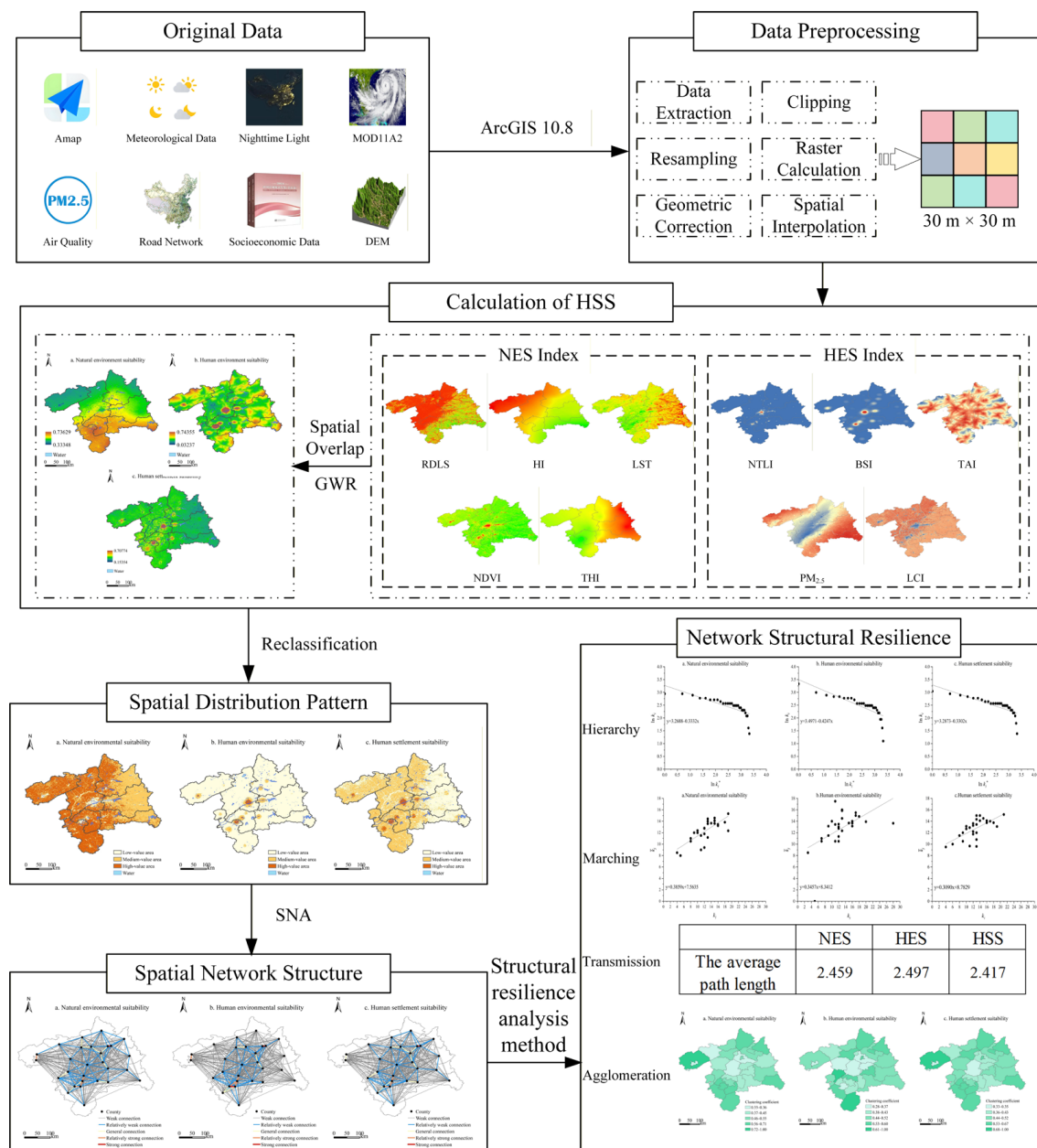


Figure 2. Research Framework.

2.2.1. HSS Comprehensive Evaluation Method

This study employed a linear weighted summation method to construct raster-based indices for NES, HES, and HSS to systematically evaluate the suitability of the human settlements in the Shenyang Metropolitan Area. The formulas are as follows:

$$NES = \alpha' RDLS + \beta' HI + \gamma' LST + \delta' NDVI + \epsilon' THI \quad (1)$$

$$HES = \zeta' NTLI + \eta' BSI + \theta' TAI + \lambda' PM + \mu' LCI \quad (2)$$

$$HSS = \alpha RDLS + \beta HI + \gamma LST + \delta NDVI + \epsilon THI + \zeta NTLI + \eta BSI + \theta TAI + \lambda PM + \mu LCI \quad (3)$$

In these formulas, α' , β' , γ' , δ' , ϵ' denote the weights of each indicator within the NES dimension, whereas ζ' , η' , θ' , λ' , μ' represent the weights under the HES dimension.

The combined weights $\alpha, \beta, \gamma, \delta, \varepsilon, \zeta, \eta, \theta, \lambda, \mu$ correspond to the indicators within the comprehensive HSS dimension.

From the perspective of human–land relationships, the quality of the human settlements fundamentally constrains regional population aggregation and spatial distribution patterns [48]. Population density can be regarded as the outcome of human spatial selection based on comprehensive environmental suitability [49], and serves as a response variable reflecting the integrated effects of natural and human factors. Therefore, when a specific evaluation indicator significantly influences population spatial distribution, it suggests that the indicator plays a more important role in shaping human settlements. Accordingly, its regression coefficient can be used as a key measure of its influence. The coefficients of suitability indicators thus reflect their marginal contributions to human aggregation behavior.

Based on this rationale, this study employs a multi-scale MGWR model, with population density as the dependent variable and evaluation indicators as independent variables, to characterize the spatially varying effects of different indicators on population distribution. Compared with traditional global and conventional geographically weighted regression (GWR) models, MGWR allows different explanatory variables to operate at distinct spatial scales. By assigning variable-specific bandwidths, the model estimates the local regression coefficients within a multi-scale framework, effectively identifying spatial heterogeneity and scale effects on the variable influence.

During the weighting process, all variables were first standardized to ensure the comparability of the regression coefficients. The local coefficients derived from the MGWR model represent the relative influence of each indicator on population distribution. These coefficients were then transformed into indicator weights, effectively converting “influence effects” into “weight assignments.” Compared with traditional weighting approaches based solely on statistical distributions, this method is grounded in human–land interaction mechanisms. By incorporating spatial heterogeneity, it improves both the spatial adaptability and explanatory power of the resulting weights.

For implementation, the study uses ArcGIS 10.8 to construct a 5 km × 5 km fishnet grid over the Shenyang Metropolitan Area, extracting each evaluation indicator to the grid centers to form spatial analysis units. Model estimation and parameter calculations were conducted using the MGWR 2.2 [50]. The model bandwidth was determined using an adaptive optimization procedure, with minimization of the corrected Akaike Information Criterion (AICc) as the objective. This ensures an optimal balance between model fit and complexity. The model is expressed as follows:

$$Y_i = \beta_0(u_i, v_i) + \sum_{j=1}^n \beta_{bjm}(u_i, v_i)x_{im} + \varepsilon_i \quad (4)$$

where Y_i represents the population density at the i -th grid cell, (u_i, v_i) denotes the coordinates of the i -th grid cell, $\beta_0(u_i, v_i)$ is the local intercept, $\beta_{bjm}(u_i, v_i)$ is the local regression coefficient of the m -th independent variable at the i -th grid cell, x_{im} is the value of the m -th independent variable at the i -th grid cell, and ε_i is the random error term. To eliminate the influence of different measurement scales on the regression results, all variables were standardized prior to the analysis.

On this basis, the final weight of each indicator is calculated using its local regression coefficients across all spatial units, and the formula is expressed as follows:

$$\bar{\beta}_{bjm} = \frac{1}{n} \sum_{j=1}^n \beta_{bjm}(u_i, v_i) \quad (5)$$

$$W_m = \frac{\bar{\beta}_{bwm}}{\sum_{j=1}^k \bar{\beta}_{bwm}} \quad (6)$$

where W_m denotes the final weight of the m -th variable (ranging from 0 to 1), k represents the total number of indicators, and $\bar{\beta}_{bwm}$ denotes the average local regression coefficient of the m -th variable across all spatial units.

2.2.2. Spatial Network Construction and Analysis Method

To reveal the spatial association characteristics of HSS in the Shenyang Metropolitan Area, this study further constructed a spatial association network at the regional scale based on the raster-scale evaluation results. First, ArcGIS 10.8 zonal statistics were used to aggregate raster-scale HSS values to county-level administrative units, calculating the average HSS for each region. This step converts raster attribute data into regional node attributes, with each county-level unit defined as a network node.

On this basis, a modified gravity model was introduced to characterize the spatial association strength of the HSS between regions. By incorporating regional development levels and distance decay effects, the model transforms node attributes into interregional relationship strengths, thereby capturing potential interactions among regions [51]. The formula is as follows:

$$Q_{ij} = k_{ij} \frac{HSS_i \times HSS_j}{d_{ij}^2}, k_{ij} = \frac{HSS_i}{HSS_i + HSS_j} \quad (7)$$

where Q_{ij} represents the HSS connection strength between region i and region j , HSS_i and HSS_j denote the HSS levels of the two regions, k_{ij} is an adjustment coefficient, and d_{ij} is the geographic distance between the regions.

To construct the spatial network structure, the gravity matrix was further binarized. Following Xu et al. [52], the row mean of each node's gravity values was used as the threshold. If Q_{ij} exceeds this threshold, a valid spatial link is considered to exist between regions i and j and is assigned a value of 1 and otherwise 0. This procedure produces a directed asymmetric adjacency matrix. This method avoids subjective threshold selection while maintaining a reasonable network density. Although threshold choice may affect network structure, the row mean is adopted due to its objectivity and operational simplicity. This approach has been widely applied in previous studies [53,54] and can ensure result robustness to a certain extent.

Based on the constructed network, SNA methods [55] were applied to examine network density, node degree, and overall structural characteristics. This analysis enables the identification of spatial organizational patterns and structural features of HSS across regions.

2.2.3. Structural Resilience Evaluation Method

Structural resilience is employed to evaluate the stability and recovery capacity of a spatial network under external perturbations. This study examines the structural resilience of a metropolitan HSS network in four dimensions: hierarchy, marching, transmission, and agglomeration.

(1) Hierarchy

Hierarchy reflects the extent of stratification among nodes within a network and serves as a core indicator of network vulnerability and robustness [56]. Node degree, representing the number of edges connected to a given node, reveals hierarchical characteristics through its distribution [57,58]; a power-law distribution curve is constructed, expressed as

$$K_i = C(K_i^*)^a \quad (8)$$

$$\ln K_i = \ln C + \ln K_i^* \quad (9)$$

where K_i denotes the degree of node i , K_i^* denotes the position sequence of node, C is a constant, and a is the slope of the degree distribution. A steeper slope indicates a stronger hierarchical structure within the network.

(2) Marching

Marching quantifies the correlation among nodes and reflects the network's stability and resilience [59]. It is calculated based on the linear relationship between node degree and mean degree of neighboring nodes:

$$\bar{K}_h = D + bK_h \quad (10)$$

where $\bar{K}_h$ denotes the average degree of neighbors of node h , D is a constant, and b is the degree correlation coefficient. A positive b indicates assortative mixing, whereas a negative b indicates disassortative mixing.

(3) Transmission

Transmission represents the efficiency of element diffusion and information propagation within the network [60]. The average path length serves as the metric for transmission efficiency and is computed as

$$L = \frac{2}{n(n+1)} \sum_{i \geq j} d_{ij} \quad (11)$$

where L denotes the average path length, n represents the total number of nodes, and d_{ij} corresponds to the shortest path distance between nodes i and j . A smaller L indicates greater transmission efficiency within the network.

(4) Agglomeration

Agglomeration describes the extent of aggregation among nodes and serves as a key indicator of network robustness [40]. This study employs the average clustering coefficient to evaluate node clustering, as expressed by

$$F_h = \frac{2M_h}{K_h(K_h - 1)} \quad (12)$$

$$F = \frac{1}{n} \sum_{h=1}^n F_h \quad (13)$$

where F_h and F denote the local and mean clustering coefficients, respectively, and M_h represents the number of actual connections among neighbors of node h . A higher F indicates a denser and more resilient network structure.

2.3. Data

This study integrated multi-source heterogeneous data, including remote sensing imagery, meteorological monitoring data, socio-economic data, and POI data (Table 1), to characterize natural ecological conditions, human activity intensity, and comprehensive human settlements features. Specifically, remote sensing imagery is used to extract natural environmental elements, such as topography and vegetation coverage. Meteorological data are employed to represent regional climate conditions, and socio-economic data reflect population and economic development levels. POI data capture the spatial distribution of public service facilities and human activities. Integrating these multi-source datasets allows for comprehensively representing HSS from both natural and human dimensions.

Table 1. Data Sources.

Data Type	Source and Processing	Years	Resolution
Topography Data	Geospatial Data Cloud (http://www.gscloud.cn/sources/ , accessed on 3 March 2025.)	-	30 m
Meteorological Data	China Meteorological Data Network (https://data.cma.cn/ , accessed on 25 March 2025.), annual cumulative mean values were interpolated using kriging	1995–2022	-
LST Data	Resource and Environmental Science Data Center (https://www.resdc.cn/ , accessed on 10 March 2025.), 8-day data were averaged to obtain monthly mean LST for January to December, then averaged over 12 months to obtain annual mean LST	2023	500 m
Vegetation Index Data	National Qinghai-Tibet Plateau Science Data Center (https://data.tpdc.ac.cn/ , accessed on 13 March 2025.)	2023	250 m
Nighttime Light Data	National Earth System Science Data Center (http://www.geodata.cn/ , accessed on 13 March 2025.)	2023	500 m
POI Data	Amap (https://www.amap.com/ accessed on 13 March 2025.)	2023	-
Road Data	Open Street Map (https://www.openstreetmap.org/ , accessed on 21 March 2025.)	2023	-
PM _{2.5} Data	National Qinghai-Tibet Plateau Science Data Center (https://data.tpdc.ac.cn/ , accessed on 21 March 2025.)	2023	1000 m
Land Use Data	Wuhan University CLCD Dataset (http://doi.org/10.5281/zenodo.4417809)	2023	30 m
Population Density Data	Landscan Population Density Data (https://landscan.oenl.gov/ , accessed on 30 March 2025.)	2023	1000 m

In terms of temporal scale, this study focuses on the cross-sectional characteristics of HSS. Therefore, all datasets, except meteorological data, were selected from the most recent publicly available data in 2023 to ensure timeliness and comparability. For meteorological variables that are significantly affected by interannual climate variability, single-year data may contain anomalous deviations and fail to reliably represent regional climate conditions. To address this issue, continuous observations from 1995 to 2022 were used to calculate long-term averages. This approach provides a more stable representation of the regional climatic background and improves the reliability of the evaluation results.

To ensure consistency in overlay analysis and model computation, and to balance accuracy with computational efficiency, all raster datasets were resampled to a uniform spatial resolution of 500 m using the resampling tool in ArcGIS 10.8.

3. Results

3.1. Spatial Distribution Characteristics of HSS

Spatial distribution of HSS in the Shenyang Metropolitan Area is jointly influenced by natural geographic conditions and socio-economic factors. NES reflects the foundational ecological conditions of the region, whereas HES captures economic development levels and provision of public services. The coupling of these two dimensions shapes the spatial differentiation of HSS, which exhibits a concentric structure centered on the core cities and displays a west-to-east gradient pattern (Figure 3).

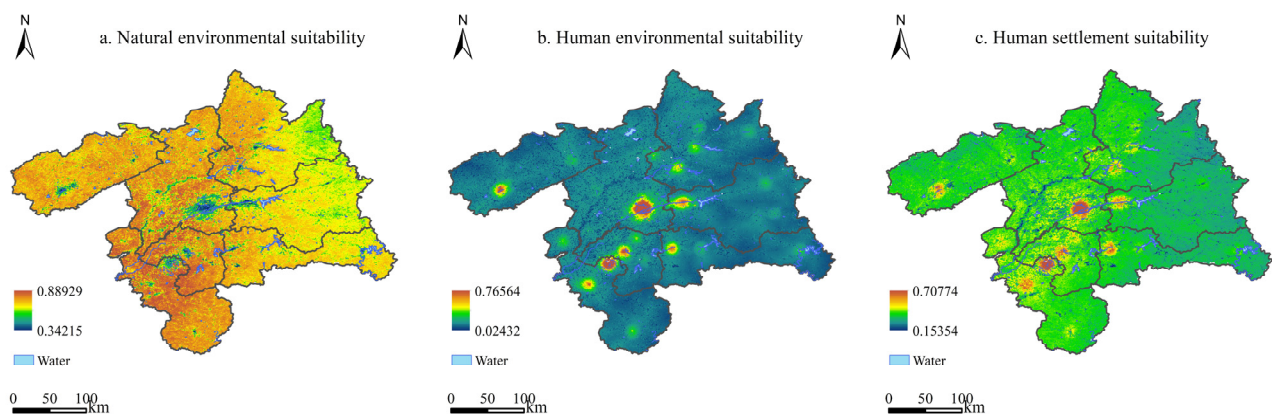


Figure 3. Spatial Distribution Pattern of HSS in the Shenyang Metropolitan Area.

From the spatial distribution perspective, the NES index ranges from 0.34215 to 0.88929 and exhibits a pattern of “low in central urban areas, higher in the west, and moderate in the east” (Figure 3a). High-value areas are primarily located in the western part of the agglomeration, where forest coverage is relatively high, ecosystems are more complete, and natural environmental quality is superior. Medium-value areas are primarily found in the eastern portion, where ecological conditions are relatively stable. Low-value areas are concentrated in central urban districts, where intensive human activities have weakened the ecological foundation. Overall, NES displays a decreasing trend from west to east (Figure 4a). This pattern reflects the natural distribution of the regional ecological baseline and reveals the erosive effects of intensive urban development on the ecological environment; in other words, the higher the intensity of human activities, the lower the level of NES.

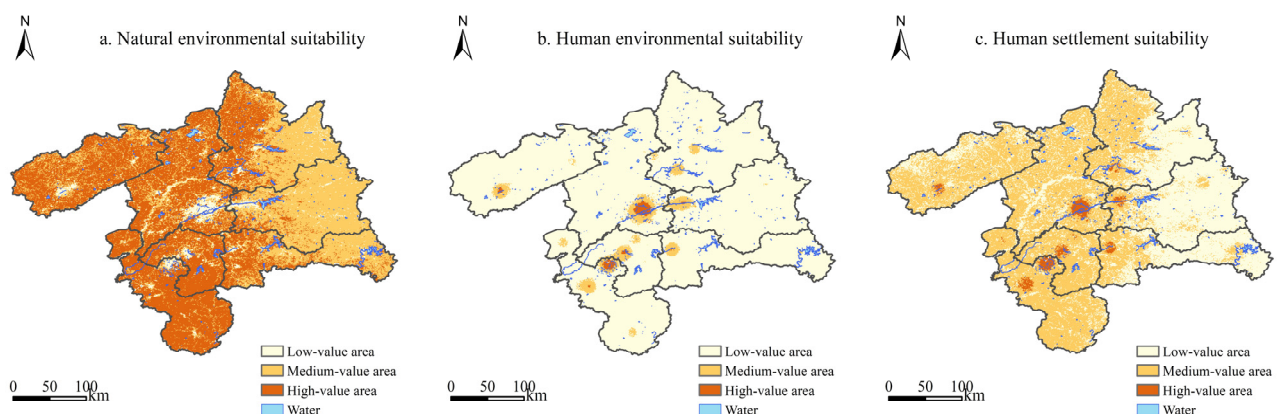


Figure 4. Spatial Distribution Pattern of HSS Levels in the Shenyang Metropolitan Area.

The HES index ranges from 0.02432 to 0.76564, exhibiting a pronounced “core-periphery” spatial pattern (Figure 3b). High-value areas are concentrated in the chief

urban districts of core cities, such as Shenyang and Anshan, as well as in their surrounding secondary core regions. These areas feature dense populations, active economic activities, and well-developed public service systems, indicating that a high concentration of socio-economic factors is a key mechanism for enhancing suitability. Low-value areas are primarily distributed in peripheral urban regions and are constrained by insufficient transportation accessibility, limited public service provision, and relatively weak economic vitality, resulting in lower suitability levels. Overall, socio-economic factors display a typical core-periphery spatial structure (Figure 4b), indicating that core cities possess significant advantages in resource allocation and public service provision, whereas peripheral areas are constrained by limited spillover of development benefits, hindering improvements in suitability and reflecting the imbalance of socio-economic development within the metropolitan area.

The HSS index ranges from 0.15354 to 0.70774, and its spatial distribution pattern largely corresponds to that of HES, suggesting the dominant role of socio-economic factors in shaping comprehensive suitability. Under the modulation of natural ecological conditions, HSS exhibits an east-to-west increasing spatial trend (Figure 3c). High-suitability areas are concentrated in core cities and their nearby suburbs, reflecting the dominant influence of socio-economic factors, whereas natural conditions impose certain constraints and regulatory effects on spatial patterns. Overall, spatial distribution of HSS reflects not only differences in regional attributes, but also the combined effects of urban centrality, resource allocation, and natural environmental constraints (Figure 4c). This indicates that, at the current stage of development, socio-economic factors are the primary drivers of spatial differentiation in overall suitability within the Shenyang Metropolitan Area, while natural ecological conditions mainly play a foundational and constraining role.

3.2. Structural Characteristics of the HSS Spatial Network

Building on the analysis of HSS spatial distribution patterns, an HSS spatial association network was constructed to reveal the structural linkages and potential interaction patterns among the regional units. Based on complex network theory, the network structure was measured and analyzed using Gephi 0.10.1, with the chief structural features and resilience indicators summarized in Table 2.

Table 2. Measurement of Network Structure and Resilience Indicators of HSS Spatial Association Networks in the Shenyang Metropolitan Area.

Network	Network Structural Characteristics		Hierarchy	Matching	Transmission	Agglomeration	
	Network Density	Average Degree	Degree Distribution	Degree Correlation	Average Path Length	Average Clustering Coefficient	Local Clustering Coefficient
NES	0.229	6.179	0.3332	0.3859	2.459	0.513	-
HES	0.237	6.393	0.4247	0.3457	2.497	0.479	-
HSS	0.234	6.321	0.3302	0.3090	2.417	0.513	-

From the perspective of the overall network structure, network density follows the order HES > HES > NES, with all three values below 0.3. This indicates relatively weak connectivity within the Shenyang Metropolitan Area. It also suggests constraints on interregional information exchange and resource flows, reflecting imbalances in internal resource allocation and socio-economic linkages.

Analyzing node-level characteristics further revealed that the HES network had the highest average degree, indicating that human factors, represented by economic develop-

ment and public service provision, are instrumental in cross-node transmission among regions. This contributes to an enhanced network diffusion capacity and improved spatial connectivity. In contrast, links in the NES network rely primarily on spatial adjacency among ecological units, with element transmission strongly constrained by geographic proximity, resulting in natural factor interactions being largely limited to neighboring regions.

To analyze the hierarchical characteristics of the spatial association networks, the Jenks method in ArcGIS 10.8 was used to classify the NES, HES, and HSS networks into five levels (Figure 5). The results show that all three networks exhibit a typical “pyramidal” hierarchy, characterized by a small number of high-level links and a predominance of low-level links. This pattern indicates that the HSS spatial network simultaneously demonstrates a “core-periphery” structure and strong “proximity dependence.”

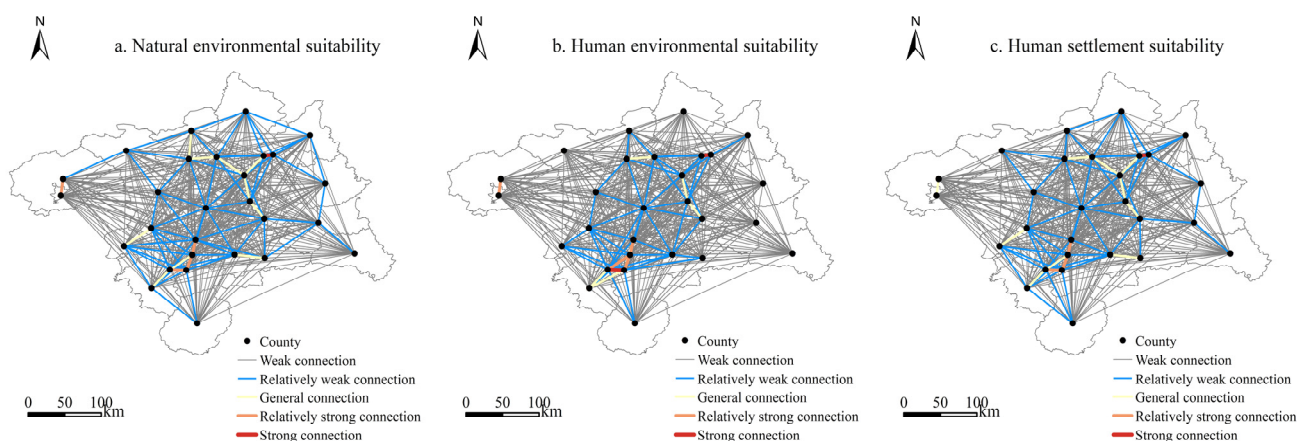


Figure 5. HSS Spatial Association Network of the Shenyang Metropolitan Area.

Regarding the spatial distribution of strong links, the high- and secondary-level connections in the NES, HES, and HSS networks demonstrate strong consistency, primarily concentrated among node pairs, such as Tieling City–Kaiyuan City, Anshan City–Liaoyang County, Liaoyang County–Liaoyang City, and Liaoyang City–Dengta City. These links are predominantly located between spatially proximate regions with well-established prior connections, further highlighting the significant dependence of HSS factors on geographical proximity during spatial transmission. Overall, the Shenyang Metropolitan Area has not yet developed a cross-regional, multi-level linkage system. Geographic distance and administrative boundaries remain major constraints on factor flows.

3.3. Structural Resilience of the HSS Spatial Network

3.3.1. Hierarchy

Regarding degree distribution, the slopes $|a|$ of the NES, HES, and HSS networks range from 0.3302 to 0.4247, following the order HES > NES > HSS, with only a small difference between HSS and NES (Figure 6). The HES network exhibits the steepest slope (0.4247), indicating that connections are highly concentrated in a few core nodes and form a pronounced core-periphery structure. This suggests that socio-economic factors promote the emergence of highly connected hub regions, which exert strong spillover and diffusion effects on surrounding areas, resulting in a clear hierarchical structure. In contrast, the NES network shows a lower slope (0.3332), with smaller differences in node connectivity and a more balanced spatial structure. This reflects the continuity and relative uniformity of natural environmental conditions across regions, reducing the likelihood of forming highly concentrated core nodes. The HSS network exhibits the smallest slope and the flattest degree distribution. Node connections are more evenly distributed, and hierarchical differentiation is relatively weak. This indicates that, under the combined influence of

natural and socio-economic factors, interregional disparities tend to be moderated. As a result, a clear hierarchical structure dominated by core nodes has not yet formed.

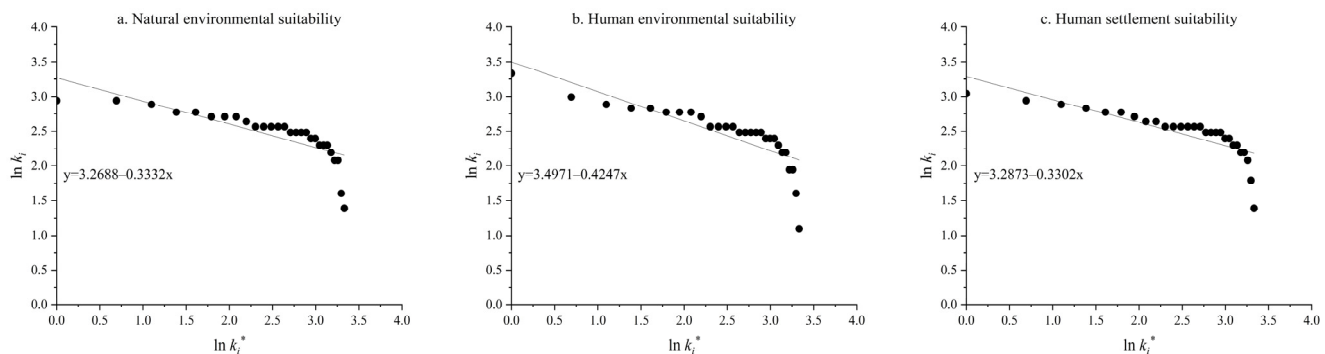


Figure 6. Degree Distribution of the HSS Spatial Association Network in the Shenyang Metropolitan Area.

3.3.2. Marching

From the degree correlation perspective, NES, HES, and HSS networks exhibit positive degree correlation coefficients, indicating assortative mixing (Figure 7). Specifically, the assortativity coefficients of the NES and HES networks are 0.3859 and 0.3457, respectively. This indicates that high-degree nodes tend to connect with other high-degree nodes, while low-degree nodes also show a tendency to cluster. Such a pattern reflects strong “same-level aggregation” within the networks, suggesting that regions with similar natural conditions or socio-economic characteristics are more likely to be interconnected. In contrast, the HSS network has a relatively lower degree assortativity coefficient (0.3090). Although it still exhibits assortative mixing, the preference for same-level connections is weaker, and interactions between nodes with different degrees occur more frequently, indicating a more mixed connectivity pattern.

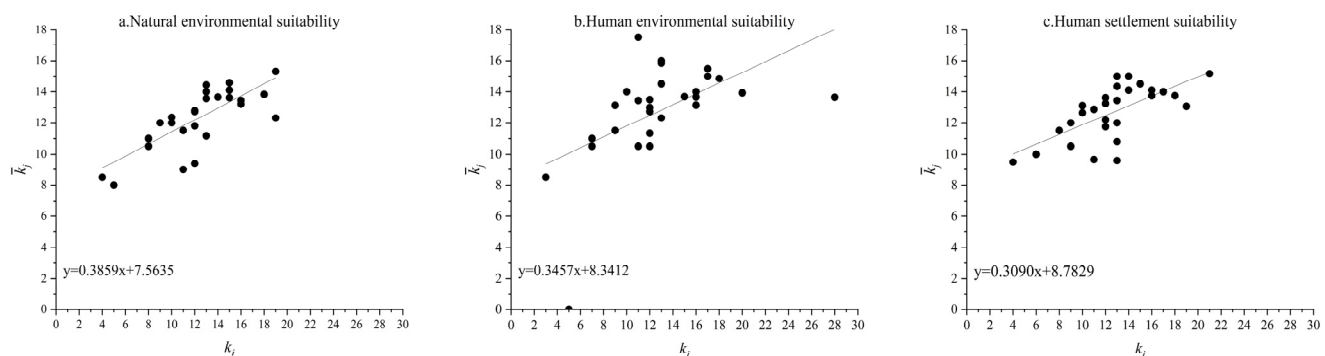


Figure 7. Degree Correlation of the HSS Spatial Association Network in the Shenyang Metropolitan Area.

3.3.3. Transmission

Regarding network transmission efficiency, the average path lengths of the NES, HES, and HSS networks range from 2.417 to 2.497 (Table 2), indicating that element transmission typically requires two or more intermediary nodes. Overall, the networks exhibit relatively low transmission efficiency, implying higher costs and slower speeds of inter-regional element flow. The HSS network has the shortest average path length, indicating closer inter-node connections, shorter transmission paths for factors, and stronger spatial connectivity. The HES network has the longest average path length, reflecting more dispersed spatial connections, greater reliance on intermediary links between nodes, and lower overall network accessibility. The NES network has an average path length of 2.459, lying between

the two, suggesting a moderate level of spatial connectivity and transmission efficiency. Overall, the HSS network in the Shenyang Metropolitan Area demonstrates relatively low transmission efficiency. Cross-regional factor flows depend on multiple intermediary nodes, highlighting the current limitations in internal integration within the metropolitan area.

3.3.4. Agglomeration

Regarding overall clustering, the average clustering coefficients of the NES, HES, and HSS networks are 0.513, 0.479, and 0.513, respectively (Table 2), all at moderate levels. This indicates that the networks exhibit some local clustering, although the node connectivity has room for improvement. Using the natural breaks method to classify local clustering coefficients into five levels (Figure 8) reveals significant spatial heterogeneity in network clustering, with a general pattern of “low clustering in core areas—high clustering in peripheral areas.”

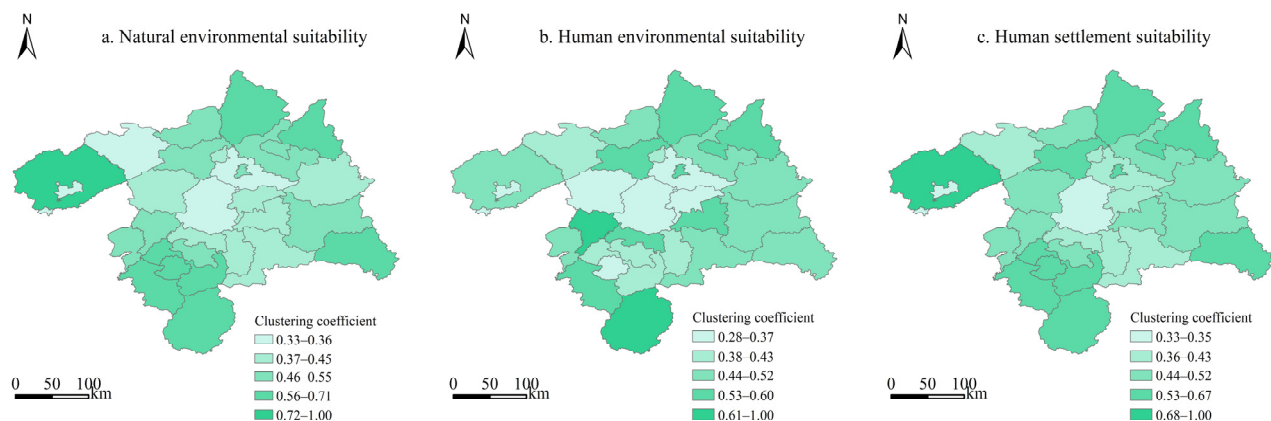


Figure 8. Spatial Pattern of Clustering Coefficients in the HSS Spatial Association Network of the Shenyang Metropolitan Area.

High-degree nodes, such as the Shenyang urban area, Tieling County, Benxi City, and Fushun City, exhibit high degree centrality across all three networks. However, their local clustering coefficients remain at medium-to-low levels. This suggests that these core areas primarily perform cross-regional linkage functions, while their intra-neighborhood connections are relatively weak. As a result, they form a typical “high connectivity–low clustering” pattern. In contrast, moderately connected nodes, including Kangping County, Faku County, Xinmin City, and Liaoyang City, generally exhibit higher clustering coefficients. This indicates stronger local network ties and more pronounced subgroup cohesion. Some low-degree and medium-low-degree nodes show even stronger clustering characteristics. For example, Xiuyan Manchu Autonomous County, Haicheng City, and Huanren Manchu Autonomous County maintain high clustering levels across all networks. Similarly, Changtu County and Xifeng County also display strong local clustering. Notably, Fuxin Mongolian Autonomous County exhibits extremely high clustering coefficients in all networks. This reflects a clear “low connectivity–high clustering” pattern. Overall, the spatial pattern can be summarized as “low clustering in the core and high clustering in the periphery.” Core cities act as hubs of the metropolitan area and are primarily responsible for cross-regional connectivity, which leads to lower local clustering. In contrast, peripheral regions have limited interaction with core areas and tend to form tightly knit local networks. This results in a “local lock-in” effect.

4. Discussion

4.1. Findings and Contributions

HSS, as a key indicator for assessing urban residents' living conditions and developmental potential, provides a comprehensive measure of the optimization of regional spatial patterns and coordination of human–land interactions [17]. With the advancement of regional integration and high-quality development in the Shenyang Metropolitan Area, analyzing HSS from a spatial network perspective helps reveal the underlying mechanisms of interregional factor flows and network structures. Based on a modified gravity model, this study constructs an HSS spatial association network. It further integrates SNA and structural resilience metrics to systematically examine spatial linkages and structural stability from a relational perspective. This approach provides an analytical foundation for optimizing spatial patterns and improving human settlement quality in metropolitan areas.

In terms of spatial distribution, HSS in the Shenyang Metropolitan Area exhibits a clear core–periphery differentiation pattern. This is consistent with the findings of Zhang et al. [13] in their study of Urumqi. However, beyond the core–periphery structure, HSS in this region is also strongly constrained by the natural ecological system (NES), resulting in a pronounced gradient differentiation pattern. This highlights the fundamental role of natural endowments in shaping the spatial configuration of human settlements. At the level of network topology, the HSS spatial association network shows relatively low overall density. Geographic proximity plays a significant role in shaping network connections. This finding is consistent with that of a previous study [8] and further confirms the applicability of the principle that the intensity of spatial interaction decays with geographic distance in the context of human settlements element linkages.

From the perspective of formation mechanisms, the spatial pattern of HSS can be explained by a coupled “human-dominated–natural-constrained” process. At the spatial distribution level, core areas strengthen their human–environment advantages through the concentration of population, capital, and public services. Meanwhile, the natural environment exhibits strong spatial continuity, driven by topography and ecosystem structure, thereby imposing fundamental constraints on suitability. At the network level, distance decay effects and uneven socio-economic resource distribution jointly shape proximity dependence and the core–periphery structure. Core nodes function as hubs by absorbing and diffusing spatial elements, whereas peripheral regions are mainly connected through adjacent linkages. Differences among subnetworks further reveal disparities in the mobility of natural and human elements. Natural elements are constrained by geographic space, resulting in more balanced and weakly hierarchical network structures. In contrast, human elements exhibit stronger cross-regional mobility and tend to form hierarchical structures dominated by core nodes. Through the interaction of these two dimensions, the HSS network displays both proximity dependence and cross-regional connectivity, reflecting a multi-factor network formation mechanism. In terms of structural resilience, the network exhibits a coexistence of “high connectivity–low clustering” and “low connectivity–high clustering” patterns. Core nodes are responsible for cross-regional connectivity and factor transmission, but they show lower local clustering. In contrast, moderately and weakly connected nodes tend to form dense local connections and exhibit higher clustering. While this structure supports local stability, it also increases reliance on key nodes. This dependence constrains overall transmission efficiency and reduces resilience to external disturbances.

Overall, this study advances HSS research by developing an integrated analytical framework at the metropolitan scale from a network resilience perspective. Its main contributions can be summarized in three aspects. First, in terms of the indicator system, this study extends existing frameworks [17,19], indicators such as land surface temperature and the basic service index were introduced to enhance the HSS evaluation framework

in two dimensions: ecological environment quality and accessibility to public services. This approach provides a more comprehensive characterization of the multidimensional conditions for resident survival and development, improving the explanatory power of the indicator system for urban ecological–social coupling processes. Second, from a theoretical perspective, this study moves beyond the traditional paradigms focused primarily on static spatial distributions or attribute differences [25,61], reconceptualizing HSS from a “regional attribute” to a “relational attribute.” Through complex network and structural resilience analyses, it reveals the transmission, diffusion, and restructuring mechanisms of suitability, achieving a shift from attribute-based description to relational interpretation. Finally, in terms of research scale and analytical framework, using the Shenyang Metropolitan Area as a case study, a spatial association network of HSS was constructed based on a modified gravity model and analyzed using social network analysis and resilience measurements. This forms an integrated analytical framework of “attribute features–network structure–structural resilience.” Compared with existing studies at provincial or single-city scales [62,63], this framework emphasizes the roles of core–periphery structure, proximity dependence, and factor flows within metropolitan areas. It thus provides a more robust analytical approach for understanding regional spatial organization and supporting governance optimization.

4.2. Policy Recommendations

Based on the spatial network structure of HSS in the Shenyang Metropolitan Area, this study proposes differentiated regulation strategies from four dimensions: structural optimization, path shortening, hierarchical coordination, and element coupling. These strategies aim to enhance overall network resilience and improve human settlement optimization capacity.

- (1) Optimizing cross-level connectivity of core nodes to reduce path dependence. Core nodes, such as Shenyang City and Anshan City, exhibit a “high connectivity–low clustering” structure. Their direct connections with secondary nodes should be strengthened to reduce reliance on intermediary nodes. This can be achieved by developing multi-level transportation networks and public service sharing platforms. Such measures would improve direct accessibility of cross-regional factor flows, reduce average path length, and enhance overall transmission efficiency.
- (2) Strengthening outward connectivity of moderately and weakly connected nodes to break local clustering lock-in effects. Regions such as Kangping County and Faku County show relatively high local clustering but weak external linkages. This condition may lead to a “locally optimal but globally constrained” structure. To address this issue, external transportation corridors should be improved, industrial coordination should be promoted, and public service spillover mechanisms should be established. These measures would enhance connectivity with core nodes and other regions, thereby transforming local clustering advantages into broader network synergies.
- (3) Establishing cross-regional coordination mechanisms to enhance interaction efficiency among nodes at different hierarchical levels. Given the pronounced assortativity of the network, high-level nodes should be encouraged to build cooperative relationships with mid- and low-level nodes. This can be achieved by promoting cross-regional allocation of educational, medical, and industrial resources. In addition, strengthening functional complementarity across hierarchical levels is essential to avoid barriers to factor flows caused by excessive stratification.
- (4) Promoting coordinated flows of natural and human elements to optimize the structural foundation of the HSS network. Given the differences in mobility and structural characteristics between NES and HES, coordination between ecological protection and

economic development is essential. For example, in ecologically advantaged areas such as Xiuyan Manchu Autonomous County and Huanren Manchu Autonomous County, ecological industries and green infrastructure should be further developed. These measures would strengthen their connections with core regions and help transform natural advantages into comprehensive human settlement advantages.

4.3. Research Limitations

Despite the methodological and conceptual advancements of this study, several limitations remain that warrant further exploration. First, the analysis of the driving mechanisms of HSS could be further strengthened. The current study mainly focuses on spatial distribution, network structure, and resilience characteristics, but does not systematically reveal the underlying formation processes or driving factors. Future research could integrate both attribute-based and relational data. Methods such as spatial econometric models and the Quadratic Assignment Procedure (QAP) could be employed to examine the combined effects of economic, social, and ecological factors on spatial association patterns. Second, the dynamic response of the network remains insufficiently explored. This study is based on a static network structure and does not fully capture the impacts of sudden disturbances or network disruptions on structural stability. Future studies could simulate disturbance scenarios and network interruptions to evaluate the stability and recovery capacity of HSS networks under external shocks. Such efforts would contribute to a deeper understanding of structural resilience mechanisms. Finally, the temporal dimensions and data consistency require further improvement. Due to data availability constraints, datasets from different periods were used, which may introduce potential biases into the results. Future research should adopt multi-period, synchronized datasets and incorporate spatiotemporal evolution models or dynamic network analysis. This would enable a more systematic examination of the evolution and long-term trends of HSS networks. Consequently, the robustness, explanatory power, and policy relevance of the findings can be further enhanced.

5. Conclusions

This study constructed a comprehensive HSS evaluation model for the Shenyang Metropolitan Area based on NES and HES. By integrating a modified gravity model, SNA, and structural resilience metrics, the study systematically examines spatial distribution patterns, network characteristics, and resilience of HSS. The main findings are as follows.

- (1) NES exhibits a “west-high, east-low” gradient, with high-value areas primarily located in ecologically favorable peripheral regions, whereas core urban areas exhibit low values owing to intense human activity. HES demonstrates a pronounced “core-periphery” structure, with high-value zones concentrated in the core cities of Shenyang, Anshan, and their adjacent suburbs. The coupling of these two dimensions results in an HSS pattern dominated by core cities, indicating that natural conditions provide fundamental constraints and regulatory effects, whereas human and economic factors play leading roles in shaping the overall suitability.
- (2) The HSS network exhibits low overall density and relatively weak interregional connectivity. This reflects structural imbalances in resource allocation and socio-economic interactions within the metropolitan area. Among the subnetworks, the HES network shows strong cross-regional transmission capacity, facilitating the diffusion of economic activities and public services. In contrast, the NES network is strongly constrained by geographic proximity, with factor flows largely limited to neighboring regions. Overall, the network simultaneously displays “core-periphery” structure and “proximity-dependent” mechanisms.

- (3) Across hierarchy, assortativity, transmission efficiency, and clustering, the HSS network exhibits integrated characteristics. Network hierarchy is moderate, with HES hub nodes exhibiting the most prominent influence. All three networks exhibit positive assortativity, indicating that spatial connections are strongly shaped by proximity and homogeneity. Overall transmission efficiency is relatively low, reflecting persistent constraints on inter-regional element flows. Network clustering exhibits marked spatial heterogeneity, with a “highly connected core–low clustering, medium-low connected periphery–high clustering” pattern. Collectively, these findings suggest that the resilience of the HSS network is structurally imbalanced, and that its stability and recovery capacity under external disturbances remain areas for potential improvement.

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References

1. Xiang, X.; Xi, G.; Zhen, F.; Shen, L. Impact of network among towns on life service supply level in metropolitan area: Taking Nanjing Metropolitan Area as an example. *Geogr. Sci.* **2025**, *45*, 1304–1317. [\[CrossRef\]](#)
2. Xi, G.; Zhen, F.; Fang, C.; Yang, F. Territorial spatial optimization and coordinated development of metropolitan regions from the perspective of “form-flow integration”. *Acta Geogr. Sin.* **2025**, *80*, 272–287. [\[CrossRef\]](#)
3. Yao, S.; Guan, C.; Ye, C.; Wang, D.; Guo, Z.; Peng, Q. Reflections on several issues of new urbanization under the background of Chinese path to modernization. *Econ. Geogr.* **2025**, *45*, 1–10. [\[CrossRef\]](#)
4. Yang, J.; Wang, Y.; Xiu, C.; Xiao, X.; Xia, J.; Jin, C. Optimizing local climate zones to mitigate urban heat island effect in human settlements. *J. Clean. Prod.* **2020**, *275*, 123767. [\[CrossRef\]](#)
5. Feng, Y.; Yang, J.; Li, Z.; Kang, X.; Zhang, Y.; Xie, P.; Wang, Y.; Xiao, X. Reducing heat vulnerability in urban regions: A human settlement optimization approach in local climate zones. *Int. J. Environ. Sci. Technol.* **2025**, *23*, 138. [\[CrossRef\]](#)
6. Liu, X.; Li, Y.; Lu, J.; Song, T.; Zhang, S. Urban growth simulation guided by ecosystem service trade-offs in Wuhan metropolitan area: Methods and implications for spatial planning. *Ecol. Indic.* **2024**, *167*, 112687. [\[CrossRef\]](#)
7. Chen, S.; Shao, C.; Yu, H.; Gao, J. Navigating urban human settlement sustainability: A multi-indicator assessment based on sustainable development goal 11. *J. Clean. Prod.* **2024**, *472*, 143509. [\[CrossRef\]](#)
8. Song, R.; Li, X.; Hou, X. Spatial network structure and driving factors of human settlements in three Northeastern provinces of China. *Front. Ecol. Evol.* **2023**, *11*, 1206808. [\[CrossRef\]](#)
9. Shao, H.; Wang, Z. Spatial Network Structure of Human Settlement Environment and Its Driving Factors of Urban Agglomerations in Middle Reaches of Yangtze River. *Resour. Environ. Yangtze Basin* **2022**, *31*, 983–994. [\[CrossRef\]](#)
10. Yuan, Z.; Yang, X.; Li, Y. Suitability evaluation of urban human settlements based on fuzzy clustering analysis a case study of Hebei Province. *Therm. Sci.* **2023**, *27*, 2009–2017. [\[CrossRef\]](#)
11. Lin, F.; Xin, Z.; Ran, L.; Qian, J. Evaluation of Human Settlement Quality of Nyingchi City, Southeastern Qinghai-Tibet Plateau, China. *Chin. Geogr. Sci.* **2025**, *35*, 1456–1472. [\[CrossRef\]](#)
12. Chen, L.; Zhong, Q.; Li, Z. Analysis of spatial characteristics and influence mechanism of human settlement suitability in traditional villages based on multi-scale geographically weighted regression model: A case study of Hunan province. *Ecol. Indic.* **2023**, *154*, 110828. [\[CrossRef\]](#)
13. Zhang, S.; Lei, J.; Zhang, X.; Fan, L.; Duan, Z. Urban human settlement quality refined assessment and its spatial relationship with human activity intensity in arid area: A case study of Urumqi, China. *Habitat Int.* **2025**, *161*, 103422. [\[CrossRef\]](#)
14. Luo, X.; Luan, W.; Yang, J.; Shi, Z.; Lin, Q.; Liu, Z.; Cao, G. Spatial heterogeneity of human settlements suitability from multidimensional perspectives in 31 provincial capital cities of China. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 1562. [\[CrossRef\]](#)

15. Liu, J.; Xin, Z. Regionalization of Human Settlement Suitability in the Natural Environment of the Tibetan Plateau. *Ecosyst. Health Sustain.* **2025**, *11*, 442. [\[CrossRef\]](#)
16. Li, Z.; Zhao, Z.; Zhang, T. Livability evaluation of urban environment based on Google Earth Engine and multi-source data: A case study of Kunming, China. *Ecol. Indic.* **2024**, *169*, 112968. [\[CrossRef\]](#)
17. Liu, H.; Li, X.; Guan, Y.; Li, S.; Sun, H. Comprehensive evaluation and analysis of human settlements' suitability in the Yangtze River Delta based on multi-Source data. *Int. J. Environ. Res. Public Health* **2023**, *20*, 1354. [\[CrossRef\]](#)
18. Nandy, S. Assessment of terrain stability zones for human habitation in Himalayan Upper Pindar River Basin, Uttarakhand using AHP and GIS. *Environ. Earth Sci.* **2021**, *80*, 356. [\[CrossRef\]](#)
19. Guan, Y.; Li, X.; Yang, J.; Li, S.; Tian, S. Spatial differentiation of comprehensive suitability of urban human settlements based on GIS: A case study of Liaoning Province, China. *Environ. Dev. Sustain.* **2022**, *24*, 4150–4174. [\[CrossRef\]](#)
20. Zhong, Q.; Xie, L.; Ww, J. Reimagining heritage villages' sustainability: Machine learning-driven human settlement suitability in Hunan. *Humanit Soc. Sci. Commun.* **2025**, *12*, 661. [\[CrossRef\]](#)
21. Wu, F.; Yang, X.; Lian, B.; Wang, Y.; Kang, J. Suitability evaluation of human settlements using a global sensitivity analysis method: A case study in China. *Sustainability* **2023**, *15*, 4380. [\[CrossRef\]](#)
22. Ghosh, B.; Farouque, M.; Das Gupta, S. Human settlement suitability in major cities of Bangladesh: A remote sensing-based grey relational analysis. *Theor. Appl. Climatol.* **2025**, *156*, 248. [\[CrossRef\]](#)
23. Xue, Q.; Yang, X.; Wu, F. A two-stage system analysis of real and pseudo urban human settlements in China. *J. Clean. Prod.* **2021**, *293*, 126272. [\[CrossRef\]](#)
24. Geng, M.; Liu, B.; Zhang, W. Study on suitability and spatial distribution of human settlement environment in arid areas based on GIS and analytic hierarchy process. *Front. Ecol. Evol.* **2023**, *11*, 1282749. [\[CrossRef\]](#)
25. Luo, X.; Yang, J.; Sun, W.; He, B. Suitability of human settlements in mountainous areas from the perspective of ventilation: A case study of the main urban area of Chongqing. *J. Clean. Prod.* **2021**, *310*, 127467. [\[CrossRef\]](#)
26. Jiang, Y.; Huang, Z.; Zhou, X.; Chen, X. Evaluating the impact of urban morphology on urban vitality: An exploratory study using big geo-data. *Int. J. Digit. Earth* **2024**, *17*, 2327571. [\[CrossRef\]](#)
27. Ma, D.; Yu, Y.; Wang, Y.; Wang, Q.; Lin, Z. Multi-scale analysis of ecosystem service values and their driving factors based on MGWR: A case study of Yellow River Delta efficient ecological economic zone. *Ecotoxicol. Environ. Saf.* **2026**, *311*, 119886. [\[CrossRef\]](#)
28. Liu, H.; Zhao, L.; Wang, H.; Li, S. Evaluation and optimization analysis of rural human settlement suitability in Anshan. *J. Green Sci. Technol.* **2025**, *27*, 155–160. [\[CrossRef\]](#)
29. Wang, Y.; Fang, B.; Zhang, Z. Evolution of human habitat suitability and the obstacles of enhancement—A case study of Shaanxi province. *J. Southwest Univ. (Nat. Sci. Ed.)* **2024**, *46*, 126–137. [\[CrossRef\]](#)
30. Tang, B.; Xie, W.; Lin, L. Research on spatial structure of flow in Guangzhou metropolitan area from the perspective of multi-source data. *Areal Res. Dev.* **2023**, *42*, 73–79. [\[CrossRef\]](#)
31. Tian, M.; Wang, Y.; Wang, Y. High-speed rail network and urban agglomeration economies: Research from the perspective of urban network externalities. *Socio-Econ. Plan Sci.* **2023**, *85*, 101442. [\[CrossRef\]](#)
32. Ren, X.; Xiong, R.; Ni, T. Spatial network characteristics of carbon balance in urban agglomerations—A case study in Beijing-Tianjin-Hebei city agglomeration. *Appl. Geogr.* **2024**, *169*, 103343. [\[CrossRef\]](#)
33. Luo, G.; Wang, X. Spatial association network structure of eco-efficiency and its influencing factors: Evidence from the Beijing-Tianjin-Hebei region in China. *Ecol. Modell.* **2023**, *475*, 110218. [\[CrossRef\]](#)
34. Sun, B.; Feng, T.; Du, M.; Liang, Y.; Feng, T. Spatially correlated network structure and influencing factors of carbon emission efficiency in the power industry: Evidence from China. *Systems* **2025**, *13*, 30. [\[CrossRef\]](#)
35. Song, J.; Guo, X.; Ding, Y.; Xiao, H. Characteristics and influencing factors of the carbon emission efficiency association network of China's marine fishery industry. *Ocean Coast Manag.* **2026**, *276*, 108143. [\[CrossRef\]](#)
36. Yang, X.; Zhu, L. Spatial correlation network of China's carbon emissions and its influencing factors: Perspective from social network analysis. *J. Clean. Prod.* **2025**, *516*, 145671. [\[CrossRef\]](#)
37. Ji, Y.; Wu, X.; Wang, L. Spatial correlation network and influencing factors analysis of supply efficiency of basic public service (SEBPS) in rust belt regions of China: An empirical study from Northeast China. *Socio-Econ. Plan Sci.* **2024**, *96*, 102058. [\[CrossRef\]](#)
38. Guan, X.; Ma, H. The impact of basic public service provision on urban economic resilience: Evidence from 281 cities in China. *Int. Rev. Econ. Financ.* **2025**, *104*, 104678. [\[CrossRef\]](#)
39. Wang, K.; Zhao, Y.; Tian, J.; Liu, M.; Gan, C. Characteristics of change of the structural resilience of China's inter-provincial tourism economic network and the formation mechanism of differences. *Prog. Geogr.* **2024**, *43*, 2442–2456. [\[CrossRef\]](#)
40. Gao, X.; Ding, C.; Wu, H.; Yu, X. Evaluation of network spatial pattern and structural resilience of Chengdu-Chongqing urban agglomeration. *J. Hum. Settl. West China* **2024**, *39*, 147–154. [\[CrossRef\]](#)
41. Du, W.; Shi, Y.; Xu, L.; Bai, O.; Xu, D. Measurement and analysis of the structural resilience of regional networks under the impact of COVID-19. *Int. J. Disaster Risk Reduct.* **2023**, *97*, 104025. [\[CrossRef\]](#)

42. Liu, H.; Li, X.; Gong, Y.; Li, S.; Cong, X. Resilience evolution of urban network structures from a complex network perspective: A case study of urban agglomeration along the middle reaches of the Yangtze River. *J. Urban Plan Dev.* **2025**, *151*, 05024042. [\[CrossRef\]](#)
43. Guan, Y.; Li, L.; Liu, C. Resilience characteristics and driving mechanism of urban collaborative innovation network—A case study of China's new energy vehicle industry. *Systems* **2023**, *11*, 214. [\[CrossRef\]](#)
44. Xiong, Y.; Tang, H.; Tian, X. Research on structural toughness of railway city network in Yellow River Basin and case study of Zhengzhou 7–20 rainstorm disaster. *Sustainability* **2022**, *14*, 12515. [\[CrossRef\]](#)
45. Che, L.; Xu, J.; Chen, H.; Sun, D.; Wang, B.; Zheng, Y.; Yang, X.; Peng, Z. Evaluation of the spatial effect of network resilience in the Yangtze River Delta: An integrated framework for regional collaboration and governance under disruption. *Land* **2022**, *11*, 1359. [\[CrossRef\]](#)
46. Liu, H.; Shi, X.; Yuan, P.; Dong, X. Study on the evolution of multiple network resilience of urban agglomerations in the Yellow River Basin. *Sustainability* **2022**, *14*, 11174. [\[CrossRef\]](#)
47. Tao, G.; Li, X.; Tian, S.; Li, H.; Song, Y. Influence of human settlements factors on the spatial distribution patterns of traditional villages in Liaoning province. *Hum. Soc. Sci. Commun.* **2024**, *11*, 1757. [\[CrossRef\]](#)
48. You, Z.; Feng, Z.; Yang, Y.; Shi, H.; Li, P. Evaluation of human settlement environmental suitability in Tibet based on gridded data. *Resour. Sci.* **2020**, *42*, 394–406. [\[CrossRef\]](#)
49. Yu, W.; Yang, J.; Sun, D.; Yu, H.; Yao, Y.; Xiao, X.; Xia, J. Spatial-Temporal Patterns of Network Structure of Human Settlements Competitiveness in Resource-Based Urban Agglomerations. *Front. Environ. Sci.* **2022**, *10*, 893876. [\[CrossRef\]](#)
50. Li, Y.; Zeng, Z. Spatial Pattern and Suitability Evaluation of Human Settlement Environment in Dongting Lake Area. *Sichuan Build. Mater.* **2024**, *50*, 43–47. [\[CrossRef\]](#)
51. Chen, X.; Di, Q.; Jia, W.; Hou, Z. Spatial correlation network of pollution and carbon emission reductions coupled with high-quality economic development in three Chinese urban agglomerations. *Sustain. Cities Soc.* **2023**, *94*, 104552. [\[CrossRef\]](#)
52. Xu, C.; Ren, Y.; Kong, F. Spatial correlation network, driving factors and planning application of land green use efficiency in Zhejiang Province, China. *Environ. Sustain. Indic.* **2025**, *28*, 100963. [\[CrossRef\]](#)
53. Zhang, Y.; Xing, M.; Zhang, X. Spatial correlation network and driving factors of inter-provincial financial risk in China. *Humanit Soc. Sci. Commun.* **2026**, *13*, 122. [\[CrossRef\]](#)
54. Liu, T.; Kong, Y.; Weng, F.; Li, J. Spatial correlation network characteristics and driving factors of carbon emissions from cultivated land use in the yellow river basin. *Sci. Rep.* **2025**, *15*, 42611. [\[CrossRef\]](#)
55. Huo, T.; Cao, R.; Xia, N.; Hu, X.; Cai, W.; Liu, B. Spatial correlation network structure of China's building carbon emissions and its driving factors: A social network analysis method. *J. Environ. Manag.* **2022**, *320*, 115808. [\[CrossRef\]](#)
56. Wang, Y.; Liu, D.; Wang, G.; Sun, S. Analysis of spatiotemporal differentiation and driving factors of knowledge innovation network structure resilience in the Yangtze River Delta urban agglomeration. *J. Geo-Inf. Sci.* **2024**, *26*, 1093–1109. [\[CrossRef\]](#)
57. Wang, K.; Chen, X.; Huang, Z. Change of structural resilience characteristics of tourism flow network and its influencing factors: A case study of Guizhou province. *Econ. Geogr.* **2024**, *44*, 229–240. [\[CrossRef\]](#)
58. Xie, Y.; Wang, C.; Han, Z.; Liu, S. Structural resilience evolution of multiple urban networks in the Harbin-Dalian urban belt. *Prog. Geogr.* **2020**, *39*, 1619–1631. [\[CrossRef\]](#)
59. Peng, C.; Lin, Y.; Gu, C. Evaluation and optimization strategy of city network structural resilience in the middle reaches of Yangtze River. *Geogr. Res.* **2018**, *37*, 1193–1207. [\[CrossRef\]](#)
60. Ji, Y.; Yin, J. Structure resilience of tourism cooperation linkage network of countries along the belt and road initiative: Comprehensive evaluation and motivation identification. *Hum. Geogr.* **2023**, *38*, 176–185. [\[CrossRef\]](#)
61. Zhu, R.; Jiang, Y.; Wang, B.; Zhang, Y. Changes in human settlement environments and their drivers in valley cities located in arid and semi-arid regions: A case study of Lanzhou in Western China. *Res. Cold Arid. Reg.* **2024**, *16*, 149–158. [\[CrossRef\]](#)
62. Wang, Y.; Jin, C.; Lu, M.; Lu, Y. Assessing the suitability of regional human settlements environment from a different preferences perspective: A case study of Zhejiang Province, China. *Habitat Int.* **2017**, *70*, 1–12. [\[CrossRef\]](#)
63. Zhou, J.; Liu, L.; Li, H.; Pei, D. Evaluation and analysis on suitability of human settlement environment in Qingdao. *PLoS ONE* **2021**, *16*, e0256502. [\[CrossRef\]](#)

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