

Article

Spatiotemporal Evolution, Constraints, and Configurational Driving Paths of District-Level Urban Resilience: A Case Study of Xi'an, China

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Abstract

Addressing meso-scale sensing voids and resource misallocations, this study constructs an integrated “Performance Sensing–Bottleneck Diagnosis–Configuration Identification” framework to evaluate the spatiotemporal evolution of resilience across Xi'an's districts (2018–2023). This research operationalizes a diagnostic-driven analytical pipeline coupling multi-source parameters with the CRITIC method to complement static stock accounting with dynamic performance sensing. This logic integrates Dagum Gini decomposition to pinpoint spatiotemporal bottlenecks and fuzzy-set QCA (fsQCA) to uncover driving pathways, utilizing an “Obstacle–Correlation” matrix to provide an objective basis for antecedent selection. The results show the following: (1) A “V-shaped” spatiotemporal trajectory and 2020 “resilience inversion” (dipping to 0.364) highlight the sensitivity of dynamic performance sensing in exposing latent vulnerabilities. (2) Persistent “center-periphery” gradients exist, with administrative siphoning driving 66.7% of inequality; diagnosis identifies distinct spatiotemporal pathologies: rigid spatial constraints in urban cores versus service imbalances in expansion zones. (3) Three equifinal pathways and an “asymmetric cancellation” effect prove that resilience hinges on configurational fit rather than linear stacking, where extreme single-dimension shortfalls neutralize collective gains. By bridging situational pathologies and governance pathways, this framework provides a robust empirical basis for the refined allocation of resources in complex environments.

Keywords: urban resilience; county scale; configurational paths; fuzzy-set qualitative comparative analysis (fsQCA); obstacle degree model; grey relational analysis

Academic Editors: Scira Menoni and Veronica Gazzola

Received: 30 January 2026

Revised: 26 February 2026

Accepted: 1 March 2026

Published: 4 March 2026

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1. Introduction

The profound interconnection between rapid urbanization and climatic uncertainty has transformed compound risks from sporadic shocks into perpetual challenges for the survival and evolution of urban systems [1,2]. As China elevates urban safety and resilience to a core national strategy [3,4], the implementation of macro-level institutional designs is increasingly contingent upon the responsiveness of grassroots administrative units. As the primary echelon for resource allocation and emergency policy transmission, districts act as the administrative forefront responsible for safeguarding the “last mile” of urban security [5,6]. As a quin-

essential high-density inland megacity, Xi'an's resilience-building faces a unique contradictory context. Geographically, its strategic maneuverability is constrained by the rigid boundaries of the Qinling Mountains to the south and the Weihe River to the north. Demographically, the surge of over 4.4 million residents in the past decade, coupled with high-intensity development, has significantly amplified systemic exposure. Since 2018, Xi'an has frequently encountered localized waterlogging and extreme heatwaves [7]. These pressures have not only widened the "resilience divide" between aging urban cores and rapidly expanding outskirts but also exposed the risks of perceptual lag in grassroots governance. Current evaluation tools often rely on static statistics [8]. However, these methods struggle to capture the spatiotemporal heterogeneity of latent functional decay within annual cycles, resulting in a misalignment between governance investment and actual vulnerabilities. Evaluation mechanisms must accurately match the spatiotemporal evolutionary characteristics of grassroots units. Otherwise, the gap between evaluative logic and reality may lead to misallocated disaster prevention resources, ultimately weakening the recovery efficacy of urban systems under multi-source shocks.

The cognitive misalignment within conventional resilience paradigms necessitates a more targeted evaluative framework for district-level governance. Addressing this research gap, this study constructs an integrated Sensing–Diagnosis–Configuration framework for district-level governance. This framework complements traditional static indicators with dynamic processual parameters—such as vegetation productivity and road-grid efficiency—to characterize the spatiotemporal evolution of resilience. These sensed evolutionary signals then provide the evidentiary basis for a diagnostic analysis where an Obstacle–Correlation matrix identifies situational bottlenecks and eliminates subjective bias in variable selection. Ultimately, this study maps these diagnostic insights onto configurational pathways via fuzzy-set Qualitative Comparative Analysis (fsQCA) to achieve a precise match between specific vulnerability profiles and optimized governance strategies.

Adhering to this analytical pipeline, this study characterizes a distinctive non-linear trajectory across Xi'an's districts. A resilience inversion in 2020, quantified by a contraction to 0.364, points to latent functional decay typically obscured by macro-averages. Concurrently, spatial deconstruction identifies administrative siphoning as the primary driver behind 66.7% of systemic inequality. These patterns suggest that resilience enhancement may hinge on configurational fit rather than linear resource stacking, potentially providing an empirical basis for optimizing grassroots governance.

The remainder of this paper is organized as follows: Section 2 determines the research positioning through a literature review. Section 3 elaborates on the study area, multi-source data, and the diagnosis-driven analytical pipeline. Section 4 presents empirical results regarding spatiotemporal evolution, bottleneck identification, and configurational pathways. Section 5 provides an in-depth interpretation of findings and governance implications. Section 6 concludes this study and outlines limitations and future prospects.

2. Related Work

Against the backdrop of persistently evolving global risk governance paradigms, academia has scrutinized the observational dimensions and spatial carriers of urban resilience from multiple perspectives. Within this horizon, research granularity exhibits distinct regional polarization: international perspectives tend to focus on micro-dynamic deconstruction at the community and household levels, prioritizing the core value of social capital and grassroots self-organization in risk buffering [9,10]. Conversely, domestic scholars often prioritize macro-regional scales [11], systematically analyzing the spatial polarization and scale-driven mechanisms of city clusters [12,13] and provinces [14,15]. Although recent scholarship has begun to venture into the spatiotemporal evolution of resilience across county-level units [16,17], systematic inquiries into the internal district-

and-county strata of Western China’s inland megacities remain notably sparse. Within the prevailing dichotomy between macro-strategy and micro-governance, these district-level units—acting as the administrative “last mile” and the pivot for policy transmission—frequently reside in an observational vacuum. In inland megacities with complex geographical constraints, this “missing middle” scale allows localized spatiotemporal vulnerabilities to be masked by macro-averages. Consequently, such masking limits the efficacy of research findings for precision governance. The logical downscaling of observation naturally necessitates a transition in evaluative attributes from “stock redundancy” toward “functional performance” status.

The recalibration toward a performance perspective reflects a deepening understanding of resilience attributes. Existing empirical models rely heavily on annual statistics. For instance, Chen (2023) and Zhao (2024) used GDP and infrastructure density to measure structural redundancy [18,19]. However, these “terminal snapshots” often exhibit a perceptual lag when characterizing functional evolution under external pressure. Addressing these logical limitations, theoretical advancements integrating long-term remote sensing to monitor vegetation productivity [20] or utilizing spatial big data to capture the processual evolution of road network efficiency [21] confirm that processual features offer higher sensitivity than traditional survival statistics [22,23]. Building upon this cognitive shift, the current study integrates traditional census data and processual performance metrics to improve spatiotemporal sensing and overcome the limitations of single-source data in reflecting systemic health.

Coupled with the spatiotemporal dynamic trend of observational data, the paradigm of causal identification is undergoing a transformative leap from unidimensional reductionism toward complex system attribution. To dissect the discrete contributions to resilience, scholars have employed various models. These include geographical detectors for infrastructure drivers [24], grey relational analysis for economic correlations [25], and obstacle degree models for systemic bottlenecks [26]. Although these linear pathways offer computational simplicity, their reliance on factor independence fails to reveal the synergistic and compensatory mechanisms inherent in resilience dynamics. Subsequent non-linear shifts drove the application of machine learning (ML) [27,28] and configurational analysis (fsQCA) [29,30], yet their deconstructive logics differ fundamentally. While ML focuses on enhancing predictive precision through high-dimensional associations, its “black-box” nature dilutes the causal interpretability [31]. In contrast, set-theoretic fsQCA identifies multiple equivalent “governance recipes,” catering to the need for operable policy pathways [32]. However, these attribution pipelines often operate in silos. Linear diagnosis and non-linear configuration are treated as discrete phases; consequently, variable selection in fsQCA remains heavily dependent on subjective deduction or empirical experience. This logical decoupling separates diagnostic findings from governance responses and weakens the focus of mechanism analysis on actual pathologies.

To clarify the academic positioning, Table 1 provides a comparative marking of the proposed framework against contemporary methods across several dimensions, including observational scale, spatiotemporal sensing depth, and causal deconstruction logic.

Table 1. Comparative marking of the proposed framework against contemporary evaluation methods.

Dimensions	Linear Weighting/Attribution [18,19,33]	Spatial ML + SHAP [27,28,34]	Traditional fsQCA [29,30,32]	Proposed Framework (This Study)
Observation Scale	Macro-regional (focuses on provincial or regional totals)	Polarized: either macro-clusters or micro-urban blocks	Macro-city scale (regional capitals or city strata)	Meso-scale focusing (filling district-level voids)

Sensing Logic	Static stock snapshots (census-based; perceptual lag)	Statistical association (correlation-oriented fitting)	Cross-sectional (static sets; No sensing phase)	Dynamic spatiotemporal evolutionary sensing
Variable Protocol	Generic reporting (includes all indicators; no screening)	Fitting-driven (feature importance via algorithms)	Subjective deduction (theory-led variable choice)	Objective calibration (diagnostic-driven screening)
Logical Architecture	Descriptive parallelism (siloed evaluation/attrition)	Post hoc explanation (Explanation as an afterthought)	Processual truncation (lacks prior sensing stage)	Sequential coupling (closed-loop logic)
Sample Adaptation	Universally applicable (simplified calculation)	Vulnerable to overfitting (requires large N; 100–2000+)	Small-N robustness (small/mid-sample logic)	Optimized for small-N ($N = 13$) meso-governance

The systematic integration of meso-scale spatiotemporal focusing, processual parameter introduction, and diagnosis-driven mechanisms provides a coherent logic for analyzing the resilience evolution of grassroots units. Admittedly, the proposed framework is less scalable for large-N datasets than simpler linear models or fitting-oriented ML algorithms; however, this trade-off is a necessary cost of pursuing high-precision spatiotemporal sensing and mechanistic interpretability. By achieving a closed-loop coupling between situational diagnosis and pathway identification, the framework ensures that governance responses are grounded in actual evolutionary pathologies rather than subjective deduction.

Addressing the observational and methodological gaps identified in the preceding review, the novelty of this study resides in three primary dimensions: (1) Meso-scale spatiotemporal focusing: targeting district-level units across Xi'an captures localized resilience gradients and spatiotemporal heterogeneity, thereby bridging the “missing middle” between macro-city averages and micro-community cases. (2) Hybrid performance sensing: integrating annual census data with processual metrics (e.g., road efficiency) shifts the evaluative logic from static stock accounting toward dynamic spatiotemporal performance sensing. (3) Diagnostic-driven pathway logic: utilizing an “Obstacle–Correlation” matrix to calibrate fsQCA antecedents establishes an objective, quantitative link between situational lesions and configurational governance recipes.

3. Materials and Methods

3.1. Study Area Overview

Xi'an is situated in the central part of the Weihe River basin, spanning 33°42'–34°45' N and 107°40'–109°49' E, with a total area of approximately 10,108 km² (see Figure 1).

The stepped topography, bounded by the Qinling Mountains to the south and the Weihe River to the north, has shaped a binary spatial configuration consisting of a southern ecological barrier and a northern plain development zone. The city currently governs 11 districts and 2 counties. In 2023, its GDP reached RMB 1.2 trillion, with a permanent population of 13.16 million. Since its designation as a National Central City in 2018, Xi'an has experienced accelerated administrative expansion, which has revealed significant resource mismatches and functional imbalances.

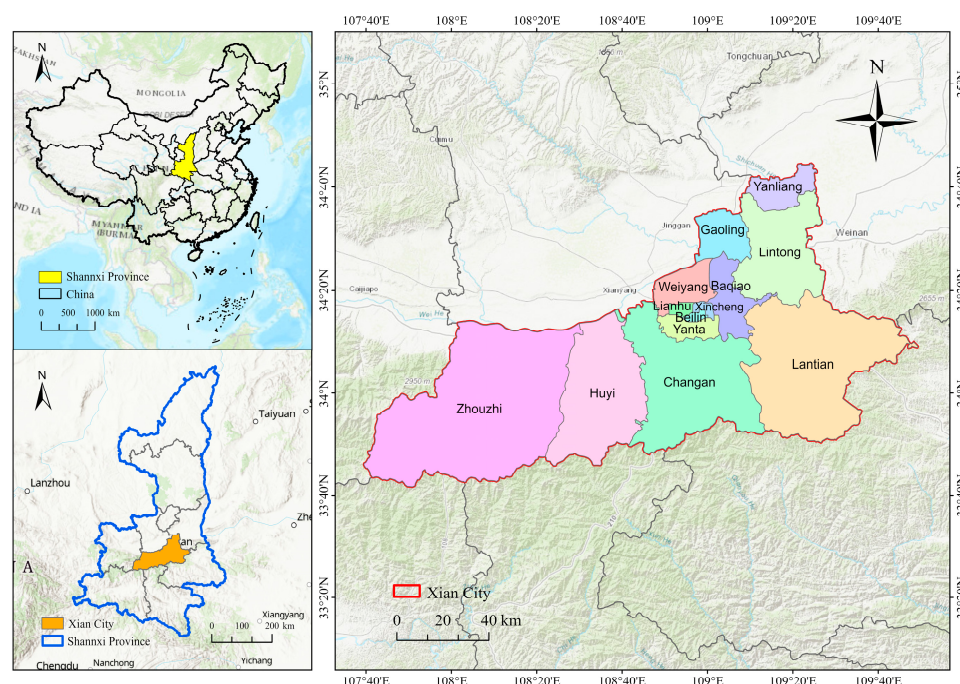


Figure 1. Study area.

Between 2018 and 2023, the high-density megacity of Xi'an underwent rapid socio-economic development. Simultaneously, the system faced rigorous 'stress tests' from multi-source risks, including public-health emergencies, extreme meteorological disasters, and infrastructure-related disturbances. The sharp differentiation between infrastructure saturation in the urban core and emergency response deficiencies in peri-urban districts and counties under these shocks has created a distinct evolutionary trajectory. This interplay of "high-intensity agglomeration" and "multi-dimensional shocks" provides a highly valuable empirical arena for identifying the sensitivity characteristics and spatial evolution patterns of resilience systems at the district and county scale.

3.2. Indicator System Construction and Optimization

3.2.1. Indicator System Construction

Based on authoritative frameworks (e.g., UNISDR and ARUP) and previous research [35], this study develops a candidate indicator pool structured around four systemic dimensions: economy, society, ecology, and health [36]. This evaluative reservoir is specifically engineered to align with the unique characteristics of inland high-density megacities while simultaneously integrating the distinct policy context and governance imperatives of Xi'an as a National Central City and a strategic nexus of the "Belt and Road" Initiative.

Within the economic domain, resilience is characterized by industrial structural diversity, fiscal self-sufficiency, post-disaster employment restoration, and consumer market recovery. Specifically, the Herfindahl–Hirschman Index (HHI) for industrial structure and the proportion of fiscal revenue are employed to characterize the system's risk diversification capacity and institutional regulatory potential under external market fluctuations. Furthermore, the indicator of "new employment per 1000 people" is selected to evaluate the livelihood restoration elasticity of the system following shocks.

The construction logic of the society system emphasizes the precision accessibility of emergency resources and the buffering role of informal networks. By introducing isochrone analysis of fire departments and emergency shelters, this study measures the spatial distribution efficiency of security resources. Concurrently, the number of legal entities

in social organizations is utilized to quantify the mobilization and self-rescue capabilities of the grassroots governance system during crises.

The ecological system focuses on the natural endowment of Xi'an—characterized by its proximity to the Qinling Mountains in the south and the Wei River in the north—while addressing the spatial erosion resulting from rapid urbanization. Indicators such as the rate of change in vegetation coverage and the Shannon Diversity Index, which reflects landscape disturbance resistance, are selected to dynamically monitor the self-regulation and restoration thresholds of the ecological base under long-term risks.

The health system accounts for the protection demands of an aging society and existing bottlenecks in public health emergencies, establishing evaluation dimensions that span from grassroots medical penetration to specialized care for vulnerable groups. Through indicators such as medical institution accessibility and the number of nursing home beds per 1000 people, the system not only calibrates the medical support capacity of megacities under public health risks but also encapsulates the features of institutionalized resilience, moving from proactive prevention to long-term security. Based on the aforementioned mechanistic analysis, this study initially establishes a candidate indicator system comprising 40 factors (see Table A1 in Appendix A).

3.2.2. Optimization of the Indicator System

The scientific validity and interpretability of resilience assessment depend fundamentally on the rigor of the underlying indicator system. To ensure discriminatory power and mitigate informational overlap induced by redundancy, a structured statistical refinement pipeline was implemented on the initial pool of 40 candidate indicators. Utilizing standardized data, the standard deviation (SD) and coefficient of Variation (CV) were calculated to examine the capacity of each factor to capture heterogeneous disparities across districts (see Appendix A, Table A2). With SD values predominantly within the 0.270–0.428 range and CV values spanning 0.516–1.616, the results confirm that the selected parameters possess significant sensitivity to the dynamic evolution of resilience in the study area. Following the sensitivity test, Pearson's correlation coefficients were calculated; variables with $|r| > 0.9$ were identified as redundant [37] (see Appendix A, Figure A1). Highly correlated variables were further clustered via dendrogram analysis [38] (see Appendix A, Figure A2), while the information entropy method was introduced as the optimal retention criterion to ensure that only indicators with the highest information load and superior representativeness were retained from redundant groups (see Appendix A, Table A3). The efficacy of this refinement was verified through the redundancy degree (RD) index, which remained consistently below 0.5 across all sub-systems post-exclusion [39] (see Appendix A, Table A4). This transformation from a theoretical candidate pool to a refined sensing grid ensures that the finalized 37 indicators maintain systemic structural integrity and statistical robustness, establishing a high-quality data foundation for subsequent non-linear mechanism deconstruction (the final optimized indicator system is detailed in Table 2).

Table 2. Urban resilience assessment system for districts and counties.

Urban System	Indicator	References	Indicator Weight
Economy	Industrial structure HHI (–)(+)C1	[40]	0.0266
	Proportion of fiscal revenue in GDP (%)C2	[41]	0.0253
	Energy consumption per unit of GDP (%)C3	[42]	0.0257
	Number of newly employed people per 1000 persons (person)(+)C4	[43]	0.0338
	Total retail sales of consumer goods (100 million yuan)(+)C5	[44]	0.0274
	Proportion of fiscal expenditure in GDP (%)C6	[45]	0.0264
	Growth rate of fixed asset investment (%)C7	[42]	0.0256

	GDP growth rate (%) (+)C8	[17]	0.0230
	GDP per capita (yuan) (+)C9	[19]	0.0244
	Proportion of science and technology-related fiscal expenditure (%) (+)C10	[18]	0.0161
Society	Number of emergency shelters (unit) (+)C11	[46]	0.0250
	Proportion of expenditure on emergency management and public safety (%) (+)C12	[37]	0.0264
	Proportion of social security expenditure (%) (+)C13	[18]	0.0309
	Fire station coverage rate (within 5 min drive) (+)C14	[47]	0.0360
	Accessibility of emergency shelters (completed and permanent) (+)C15	[48]	0.0254
	Number of persons receiving special care and subsidies (person) (+)C16	[49]	0.0333
	Change rate of newly employed urban population (+)C17	[43]	0.0286
	Legal entities in public and social sectors per 1000 persons (+)C18	[43]	0.0252
	Per capita disposable income of urban residents (yuan) (+)C19	[50]	0.0259
	Number of social organizations per 1000 persons (unit) (+)C20	[49]	0.0319
Ecology	Change rate of fractional vegetation cover (%) (+)C21	[51]	0.0205
	Number of days with good air quality (day) (+)C22	[41]	0.0242
	Blue-green connectivity (−) (+)C23	[22]	0.0255
	Proportion of green space (PLAND) (%) (+)C24	[43]	0.0319
	Annual change rate of NPP (%) (+)C25	[52]	0.0284
	Environmental investment in projects completed and accepted this year (+)C26	[53]	0.0228
	Industrial sulfur dioxide (SO ₂) emissions (ton) (−)C27	[54]	0.0336
	Industrial chemical oxygen demand (COD) emissions (ton) (−)C28	[55]	0.0269
Health	Proportion of public healthcare expenditure in government expenditure (%) (+)C29	[56]	0.0352
	Number of medical institutions per 1000 persons (unit) (+)C30	[57]	0.0255
	Number of hospital beds per 1000 persons (unit) (+)C31	[18]	0.0266
	Accessibility of medical and health institutions (%) (+)C32	[48]	0.0237
	Accessibility of cooling facilities (%) (+)C33	[58]	0.0309
	Number of community health service centers and stations per 1000 persons (+)C34	[59]	0.0307
	Number of nursing homes per 1000 persons (+)C35	[59]	0.0247
	Number of cooling facilities per 1000 persons (+)C36	[58]	0.0261
	Number of sports venues per 1000 persons (+)C37	[59]	0.0201

3.3. Data Sources and Processing

This study constructed a multi-source panel database covering 13 districts and counties in Xi'an from 2018 to 2023. Socioeconomic statistical indicators were primarily extracted from the Xi'an Statistical Yearbook, the Statistical Bulletins of National Economic and Social Development of various districts and counties, and relevant environmental status bulletins. Ecological evolution data were integrated from long-term MODIS NDVI and NPP imagery via the NASA Earthdata platform, as well as the China Land Cover Dataset (Wuhan University, Wuhan, China) with a 30 m spatial resolution. Spatial functional parameters were derived from points of interest (POIs) and road networks. The POIs (medical, fire, shelter, and cooling facilities) were obtained via the Gaode Maps API (AutoNavi, Beijing, China), while the vector road networks were provided by OpenStreetMap (OSM Foundation, Cambridge, UK). Detailed data sources are provided in Table A5 of Appendix A.

During the data-processing stage, sporadic missing values were supplemented using linear interpolation, and all indicators underwent min–max normalization (range standardization) to eliminate dimensional differences. For the advanced processing of statistical data, the Herfindahl–Hirschman Index (HHI) and annual growth rates were selected as

representative indicators of industrial structure stability and labor market elasticity. Regarding remote sensing and landscape pattern analysis, Fragstats version 4.3 (developed by Eduard Ene and Kevin McGarigal) was employed to extract landscape metrics, including the green space proportion and connectivity, which were combined with interannual variation parameters to measure the dynamic restoration efficiency of the ecosystem. The calculation of spatial functional dimensions involved constructing a refined network model based on the topological repair of the OSM road network. Speed impedance was assigned according to the Code for Design of Urban Road Engineering. This ensured that the baseline road network capacities across different districts were comparable and accurate. Service area modeling in ArcGIS Pro version 3.4.3 (Esri, Redlands, CA, USA) was used to set multi-level travel time thresholds (4, 8, 12, 15, and 30 min) for various facilities. This approach transformed discrete facility locations into quantifiable spatial service capacities. The integration and processing logic of these multi-dimensional datasets provide an empirical foundation for deconstructing resilience differentiation patterns at the district and county scale. Detailed calculation formulas for specific indicators, and network analysis parameter settings are provided in Table A6 of Appendix A.

3.4. Research Methods

To systematically present the technical implementation logic of this study, the overall research design follows a progressive paradigm: “Theoretical framework construction-Spatio-temporal characteristic measurement-Influence mechanism diagnosis-Governance path response” (as shown in Figure 2). Based on this framework, the following sections provide a detailed elaboration of the core research methods involved.

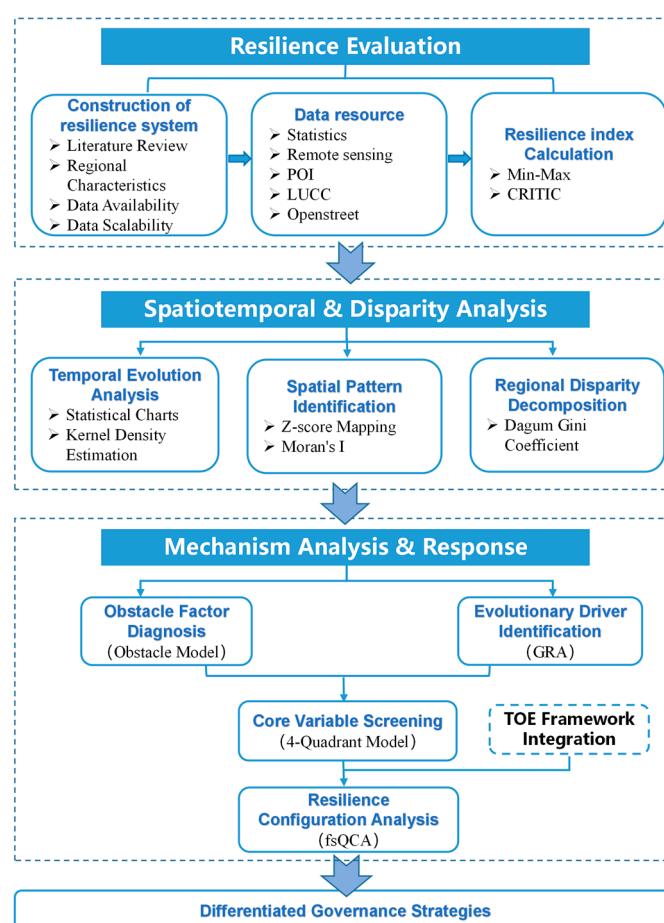


Figure 2. Research flowchart.

3.4.1. CRITIC Weighting Method

This study employs the CRITIC method [60]—an objective weighting technique that integrates data variability and inter-indicator correlations—to calculate composite resilience indices for each district. Compared to EWM, AHP, and PCA, this method provides a more robust protocol: it captures the synergistic relationships often ignored by EWM, avoids the a priori bias of AHP [28], and maintains the physical interpretability frequently compromised by PCA. By ensuring both objectivity and semantic clarity, this approach effectively identifies and eliminates redundant information, thereby enhancing the overall precision of the assessment.

The specific calculation formulas are as follows:

$$C_j = \sigma_j \sum_{i=1}^n (1 - r_{ij}) \quad (1)$$

$$W_j = \frac{C_j}{\sum_{j=1}^m C_j} \quad (2)$$

$$R = \sum W_j y_{ij} \quad (3)$$

where C_j represents the information content of indicator j ; σ_j is the standard deviation; r_{ij} is the correlation coefficient between indicators i and j ; W_j denotes the weight of indicator j ; n is the number of indicators; and R_i represents the resilience index of the evaluation object i .

To ensure the robustness of the assessment, we implemented a methodological cross-test [61]. The entropy weight method (EWM) was introduced as a benchmark to verify rank stability. The results show that the resilience scores from both methods achieved a Spearman's correlation coefficient of 0.941 ($p < 0.001$). This high degree of convergence in both evaluative rankings and evolutionary trajectories (detailed in Appendix A, Table A7) quantitatively substantiates the superior endogenous robustness of the indicator framework, confirming that the assessment findings are not stochastic artifacts dictated by specific algorithmic logic.

3.4.2. Kernel Density Estimation

Kernel density estimation (KDE) is employed to analyze the temporal evolution characteristics of urban resilience across the districts and counties of Xi'an [62].

$$f(y) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{y - y_i}{h}\right) \quad (4)$$

3.4.3. Spatial Autocorrelation Analysis

Everything in geographic space is interrelated, and this correlation varies with distance. Spatial autocorrelation analysis is a widely used method for investigating the spatiotemporal evolution of geographical attributes. In this study, spatial autocorrelation analysis is employed to identify the spatial clustering characteristics of urban resilience across the districts and counties of Xi'an [63].

$$\text{Moran's } I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^n \sum_{j=1}^n w_{ij}) \sum_{i=1}^n (x_i - \bar{x})^2} \quad (5)$$

$$\text{Local Moran's } I = \frac{n(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \sum_{j=1, j \neq i}^n w_{ij} (x_j - \bar{x}) \quad (6)$$

3.4.4. Dagum Gini Coefficient

The Dagum Gini coefficient was applied to decompose the spatiotemporal regional disparities of resilience levels. By categorizing Xi'an into core, near-suburban, and far-suburban areas, we identified distribution gaps and the sources of imbalance [64]. The application of the Dagum Gini coefficient allows for an in-depth analysis of the distribution disparities and the sources of UR levels across different regions, facilitating the identification of developmental imbalances. The Dagum Gini coefficient is defined as follows:

$$G = \frac{\sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |ct_{ji} - ct_{hr}|}{2n^2\mu} \quad (7)$$

where $ct_{ji}(ct_{hr})$ represents the urban resilience level of district $i(r)$ within region $j(h)$, μ is the average UR level of all districts, k is the number of regional groups, and $n_j n_h$ denotes the number of districts within region $j(h)$. The total Gini coefficient can be decomposed into three components: the contribution of intra-group inequality (G_w), the contribution of net inter-group inequality (G_{nb}), and the contribution of transvariation (G_{nt}), such that $G = G_w + G_{nb} + G_{nt}$.

$$G_w = \sum_{j=1}^k G_{jj} p_j s_j \quad (8)$$

$$G_{nb} = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) D_{jh} \quad (9)$$

$$G_{nt} = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) (1 - D_{jh}) \quad (10)$$

3.4.5. Obstacle Degree Model

The obstacle degree model is widely utilized in spatial analysis, urban planning, and environmental protection to identify spatiotemporal obstacle factors constraining the improvement in urban resilience [18]. By incorporating the obstacle degree (Y_j), factor contribution degree (F_j), and indicator deviation degree (V_j), this model diagnoses the impact of specific indicators to provide a reference for enhancing resilience at the district and county level. The calculation formulas are as follows:

$$V_j = 1 - E_j \quad (11)$$

$$F_j = W_j \quad (12)$$

$$y_j = \frac{V_j \times F_j}{\sum_{j=1}^n (V_j \times F_j)} \times 100\% \quad (13)$$

where E_j represents the standardized value of the j -th indicator; V_j is the indicator deviation degree; W_j denotes the weight of the j -th indicator (i.e., the factor contribution degree, F_j); and y_j represents the obstacle degree of a single indicator.

3.4.6. Grey Relational Analysis

Grey relational analysis (GRA) is an effective method for quantitatively evaluating the strength of associations between various factors by comparing the geometric similarities of sequence curves [65]. This study employs GRA to quantify the correlation intensity between each evaluation indicator and the overall urban resilience level of Xi'an's districts and counties.

(1) Dimensionless processing of sequences:

$$Y'(k) = \frac{Y(k)}{\bar{Y}}, \quad X_i'(k) = \frac{X_i(k)}{\bar{X}_i} \quad (14)$$

(2) Calculation of the relational coefficient:

$$\xi_i(k) = \frac{\min_i \min_k \Delta_i(k) + \rho \max_i \max_k \Delta_i(k)}{\Delta_i(k) + \rho \max_i \max_k \Delta_i(k)} \quad (15)$$

(3) Calculation of the relational grade:

$$S_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \quad (16)$$

where S_i represents the grey relational grade; $\xi_i(k)$ is the relational coefficient; $\Delta_i(k)$ is the absolute difference between the reference sequence and the comparison sequence; and ρ denotes the resolution coefficient, which is typically set to 0.5. A higher value of S_i indicates a more significant influence of the indicator on the urban resilience of the districts and counties in Xi'an.

3.4.7. Fuzzy-Set Qualitative Comparative Analysis (fsQCA)

Urban resilience is a synergistic outcome of technology, organization, and environment, exhibiting complex non-linear causal characteristics. Given the over-fitting risks of machine learning on a limited sample ($N = 13$), this study adopts set-theoretic fsQCA [66] using fsQCA software version 4.1 (University of California, Irvine, CA, USA). This method ensures robustness for small datasets and identifies equifinal pathways, providing explicit “governance recipes” for decision-making. The specific procedures are as follows:

- (1) Data calibration: The direct calibration method is employed, selecting the 95th, 50th, and 5th percentiles of each variable as qualitative anchors for “full membership,” the “crossover point,” and “full non-membership,” respectively. This process transforms raw data into fuzzy membership scores ranging from 0 to 1.
- (2) Necessity analysis: the consistency index is utilized to verify whether a single antecedent condition is a necessary prerequisite for the occurrence of the outcome, with the threshold typically set at 0.90.
- (3) Sufficiency analysis: A truth table is constructed and subjected to logical minimization. By comparing complex, parsimonious, and intermediate solutions, various configurational paths driving the generation of high resilience are identified.
- (4) Robustness Check: The stability of the configurational results is verified by adjusting the consistency thresholds or recalibrating the qualitative anchors. This process validates the findings under different parameter settings to ensure the reliability and robustness of the conclusions.

4. Results

4.1. Spatiotemporal Differentiation and Regional Disparities in District-Level Urban Resilience

4.1.1. Analysis of the Temporal Evolution of District-Level Urban Resilience

This study calculated the urban resilience index of 13 districts and counties in Xi'an from 2018 to 2023 based on the CRITIC weighting method. The results show that the resilience of each district exhibits a clear tiered hierarchy and significant temporal disparities. Macro-evolutionary trends indicate that urban resilience in Xi'an followed a “V-shaped rebound followed by high-level plateau oscillations.” This pattern is characterized by three stages: fluctuating bottoming out, strong rebound, and differentiated restoration.

Impacted by external shocks, the city-wide average resilience bottomed out in 2020 (0.409), reflecting a profound stress test of the urban system by external pressures. Subsequently, under the influence of policy interventions and restoration mechanisms, a robust rebound was achieved in 2021 (with the mean rising to 0.437, representing a recovery magnitude of 6.8%), and the system gradually entered a structural adaptation stage from 2022 to 2023. By 2023, Weiyang and Lantian set new six-year highs, indicating that resilience restoration was shifting from passive response to structural adaptation. In terms of distribution structure, temporal evolution shows a trend of “convergence of extreme values and differentiation of the middle layer.” The overall resilience baseline rose, slightly narrowing the gap between extreme values. However, the city-wide coefficient of variation (CV) escalated from 0.173 in 2019 to 0.233 in 2021. This indicates that internal differentiation among middle-layer districts intensified significantly during this period. In particular, Beilin, as a high-level outlier, not only highlights the strong systemic robustness of the core urban area but also reinforces the time lag existing in the resilience evolution of different regions.

Based on the non-synchronicity of temporal evolution, the resilience paths of each district and county can be summarized into four typical modes: first, the “beyond-recovery type” (Weiyang, Lantian), which experienced a strong rebound after a “deep squat,” with their 2023 levels (0.482 and 0.430, respectively) significantly surpassing the initial baseline; second, the “high-level equilibrium type” (Beilin, Xincheng), whose resilience index has been consistently maintained at a high level above 0.5 (mean 0.547), which has maintained a leading position for a long time but with slowing growth momentum and a trajectory of high-level fluctuations; third, the “low-level steady-state type” (Zhouzhi, Huyi), which maintained a defensive slow rise with low fluctuations during the observation period (with the mean oscillating around 0.34); and fourth, the “impaired slow-release type” (Chang’an, Baqiao), which underwent a slow restoration process following a significant decline from the 0.42–0.45 level after the 2020 shock and had not returned to pre-shock levels by 2023, exhibiting a clear recovery lag effect (see Table 3 and Figure 3).

Table 3. District-level urban resilience index.

County \ Year	2018	2019	2020	2021	2022	2023
Xincheng	0.515	0.457	0.510	0.609	0.528	0.513
Beilin	0.616	0.575	0.526	0.606	0.596	0.580
Lianhu	0.495	0.498	0.446	0.501	0.452	0.449
Baqiao	0.455	0.425	0.311	0.403	0.361	0.383
Weiyang	0.462	0.466	0.376	0.408	0.379	0.482
Yanta	0.497	0.466	0.450	0.566	0.519	0.515
Yanliang	0.405	0.384	0.428	0.395	0.414	0.406
Lintong	0.468	0.412	0.477	0.425	0.388	0.417
Changan	0.427	0.384	0.294	0.348	0.304	0.319
Gaoling	0.358	0.357	0.409	0.355	0.352	0.354
Huyi	0.335	0.318	0.331	0.304	0.310	0.346
Lantian	0.426	0.365	0.405	0.410	0.364	0.430
Zhouzhi	0.329	0.336	0.346	0.347	0.365	0.363
Mean	0.445	0.419	0.409	0.437	0.410	0.428
Std.	0.079	0.072	0.074	0.102	0.089	0.078
CV	0.178	0.173	0.181	0.233	0.216	0.182

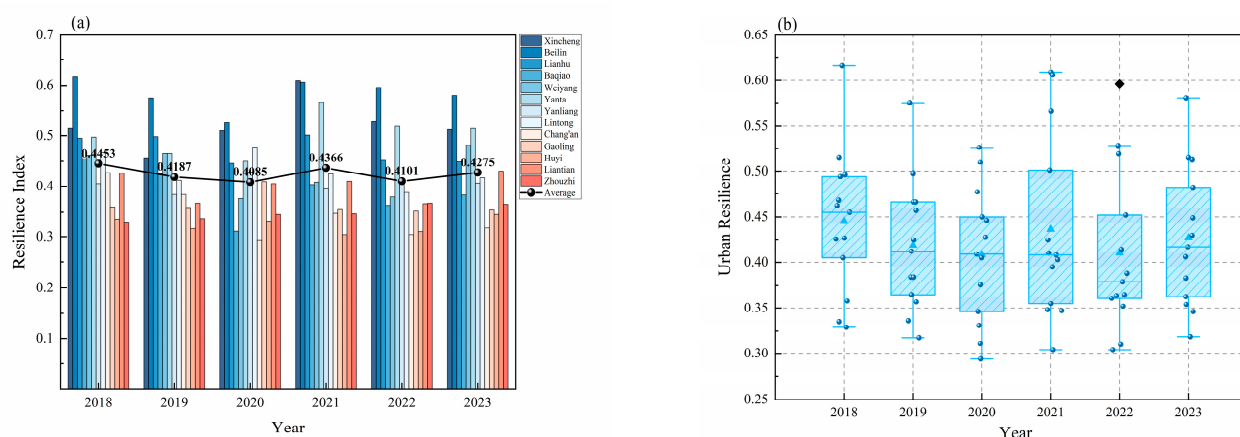


Figure 3. Bar charts and box plots of district-level urban resilience. (a) Bar charts of district-level comprehensive urban resilience; (b) box plots of district-level comprehensive urban resilience. In (b), the triangles within the boxes represent the mean, the scattered dots denote individual data points, and the black diamond indicates an outlier.

According to the dimensional variations in Figure 4, the economic system exhibited the most pronounced vulnerability; its index fell to 0.364 in 2020 and dropped again to 0.332 in 2022, failing to regain its initial baseline. During this period, spatial heterogeneity within the economic sector widened significantly, peaking at a CV of 0.266 in 2022, reflecting deep-seated issues in industrial structure and resource allocation elasticity. In contrast, ecological resilience maintained a superior level throughout the cycle, with 2021 and 2023 means of 0.466 and 0.470, respectively, demonstrating robust systemic stability. Similarly, the social system remained relatively steady, returning to 0.447 in 2022 with minimal fluctuation. This stability stems from Xi'an's long-term accumulation in social security and community governance, where grid-based management played a decisive role in bolstering resilience. The health system, however, oscillated sharply, receding to 0.411 in 2020 and sliding further to 0.408 in 2023 despite a temporary 2021 uptick. Notably, spatial polarization within the health sector intensified, as the CV rose from 0.347 in 2018 to a peak of 0.393 in 2023. This confirms an unbalanced contraction of medical resources under sustained stress. These fluctuations mirror structural imbalances in asset distribution and fragile grassroots medical capacity, which hindered resilience stabilization during the phase of normalized pandemic prevention and control.

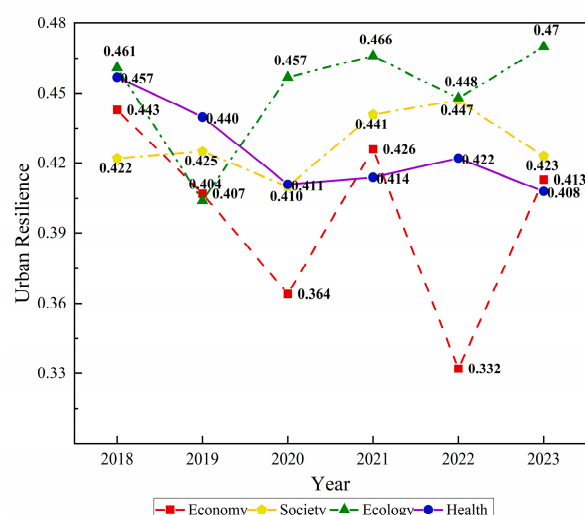


Figure 4. Annual average variation in system-level resilience dimensions (2018–2023).

To clarify the temporal dynamics of district-level resilience, this study further employs kernel density estimation (KDE) to examine distribution shifts and analyze temporal trends. Overall, comprehensive resilience exhibits a transition from initial concentration to late-stage dispersion, progressively shifting toward higher resilience levels (see Figure 5). Between 2018 and 2021, resilience scores were primarily concentrated in the medium-low interval (0.1–0.4). In 2021, the distribution peaked at a density of approximately 5.5 within the 0.2–0.3 range. This distinct unimodal distribution reflects a balanced yet fragile foundation for resilience during the early observation period. Since 2022, the distribution's center of gravity has exhibited a notable rightward shift toward the medium-high interval (0.4–0.6). The peak evolved into a bimodal structure at the 0.3–0.4 and 0.5–0.6 intervals. The broadening distribution curve indicates that inter-district disparities expanded despite universal resilience improvements. By 2023, a clustering tendency of samples emerged within the high-resilience interval near 0.6, indicating that district-level resilience is evolving from “unimodal concentration” toward “tiered polarization.” Although the coefficient of variation (CV) in 2023 (0.182) exhibited a slight convergence relative to its peak value, it remained elevated compared to the pre-shock baseline level.

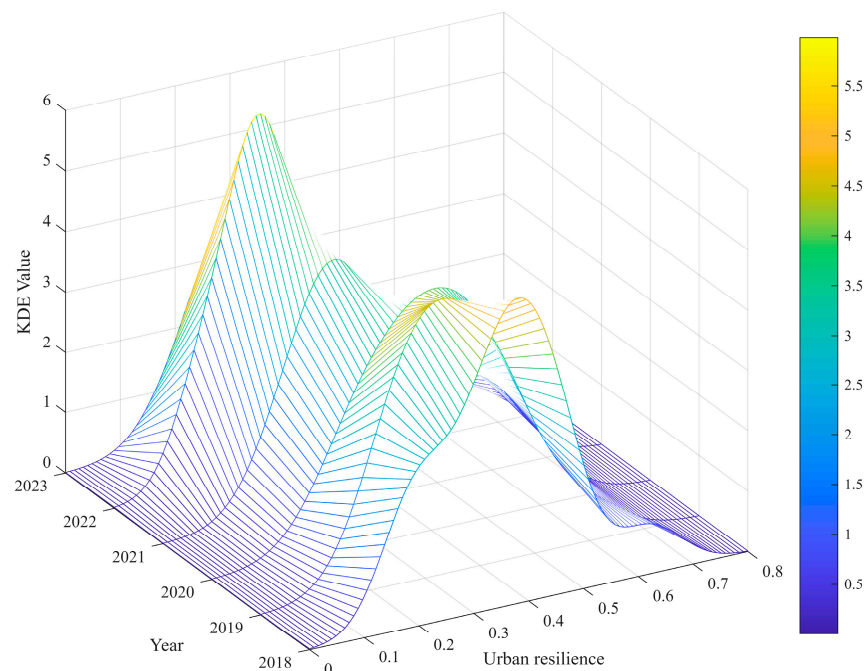


Figure 5. District-level urban resilience kernel density map.

Viewed through the lens of the four sub-systems, resilience scores between 2018 and 2021 were primarily concentrated in the lower 0.1–0.4 interval (see Figure 6). The economy system displayed a concentrated unimodal structure, where a low early-stage CV (0.211) reflected pervasive systemic weakness coupled with minimal regional disparities. In contrast, the social system exhibited a distinct bimodal trend—peaking at the 0.2–0.3 and 0.4–0.5 intervals—indicating that certain districts achieved superior outcomes in governance and organizational innovation. By 2022, the distribution centers of all four systems generally shifted rightward into the 0.4–0.6 range, signaling widespread improvement. During this stage, the economy and ecology systems recorded smaller gains, primarily populating the 0.3–0.4 interval; this indicates that the former remained hampered by unitary industrial structures, while the latter faced limited growth potential due to its inherent natural endowment. Conversely, the social and health systems manifested bimodal structures as inter-district disparities expanded, with specific districts achieving significant resilience leaps through decentralizing healthcare and advancing community governance. Data

from 2023 further corroborated this non-synchronous restoration: the ecological system maintained a leading systemic magnitude (mean of 0.469), whereas the health system reached a peak level of heterogeneity (0.393), thereby exacerbating the structural imbalance of the city-wide resilience landscape.

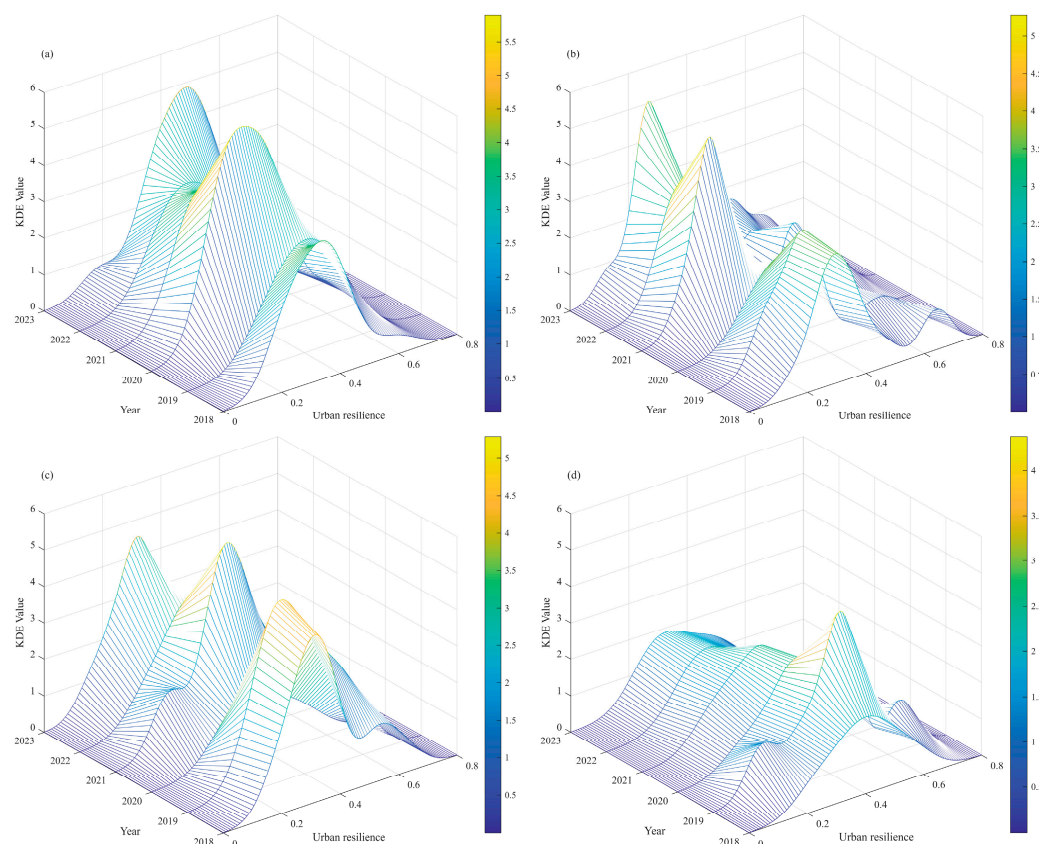


Figure 6. Subsystem resilience kernel density map. (a) Economic system; (b) social system; (c) ecological system; (d) healthy system.

4.1.2. Spatial Pattern Analysis of District-Level Urban Resilience

The evolution of urban resilience is reflected not only in temporal fluctuations but also in spatial patterns that manifest hierarchical gradients and regional disparities. Based on the resilience index, this study employs the Z-score standardization method to categorize resilience into five levels: high ($Z > 1.5$), relatively high ($0.5 < Z \leq 1.5$), medium ($-0.5 \leq Z \leq 0.5$), relatively low ($-1.5 \leq Z < -0.5$), and low ($Z < -1.5$). Hierarchical maps were generated to visualize the spatiotemporal trajectories across the study period [67].

From 2018 to 2023, the urban resilience of Xi'an exhibited a concentric gradient decreasing from the urban core toward the periphery. Quantitative analysis indicates that by 2023, the mean resilience of core districts (Xincheng, Beilin) stood at 0.547, approximately 1.51 times that of peripheral units such as Zhouzhi, Huyi, and Chang'an (mean = 0.362). Xincheng and Beilin exhibited high-level stability throughout the study period, particularly in 2021 and 2022, demonstrating robust adaptive and transformative capacities. The Lianhu and Yanta districts, situated in the inner-ring area, showed stable resilience fluctuating between "medium" and "high" levels, reflecting significant restorative potential. In contrast, transitional districts like Baqiao and Chang'an experienced notable declines. Specifically, Chang'an descended to the "low resilience" category in 2020, highlighting its vulnerability to acute external shocks. Finally, distal districts and counties, including Gaoling, Huyi, and Zhouzhi, remained consistently at low resilience levels, revealing persistent structural bottlenecks in their recovery processes (see Figure 7).

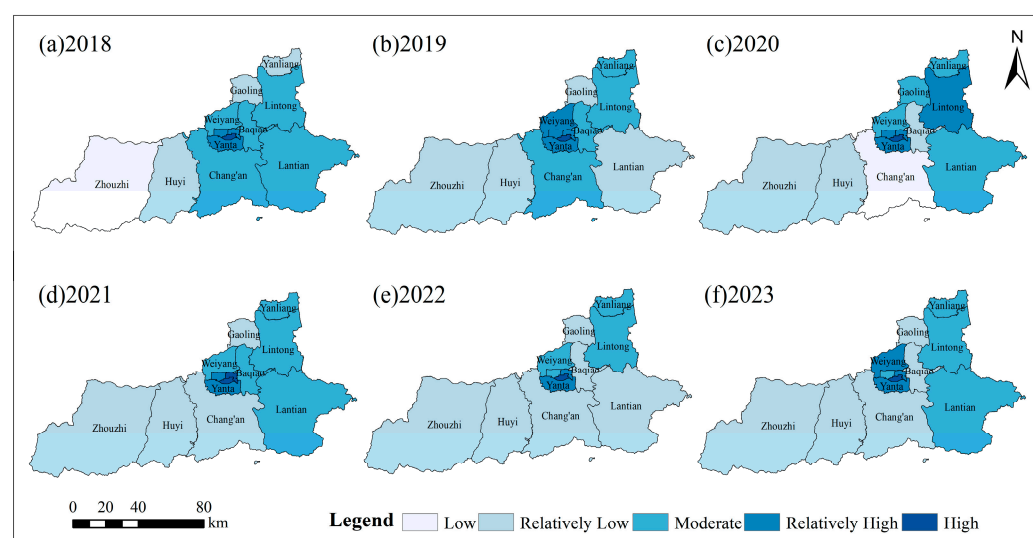


Figure 7. Spatiotemporal visualization of urban resilience (2018–2023).

From a systemic perspective, core districts such as Xincheng and Beilin generally exhibit high and overlapping resilience levels, demonstrating robust systemic synergy (see Figure 8). In contrast, peripheral units including Lantian and Zhouzhi maintain high ecological resilience but remain at lower levels in the economic and healthy systems. Statistics from 2023 reveal that city-wide means for economic and health resilience were 0.413 and 0.408, respectively. Notably, the peripheral areas consistently fell below these thresholds. Their “single-system advantage” underscores their vulnerability during multi-system recovery. Eastern districts—such as Gaoling, Lintong, and Yanliang—exhibit significant cross-dimensional disparities. Their restorative capacities are uneven, as evidenced by acute fluctuations in economic and health indicators. Districts such as Huyi, Lantian, and Zhouzhi sustain low resilience scores across multiple systems, forming “multi-system low-value zones” within Xi’an’s spatial landscape. This identifies their structural vulnerability under multi-source shocks; for instance, during the pandemic, the combination of thin economic foundations and sparse medical resources hindered their ability to respond effectively to the crisis.

To gain a deeper understanding of the spatial distribution of district-level urban resilience, spatial autocorrelation analysis was applied to reveal the spatial dependence and clustering characteristics among districts. As shown in Table 4, the Global Moran’s I for Xi’an’s comprehensive resilience exhibited distinct temporal fluctuations, with positive Z-scores and *p*-values consistently below 0.05, indicating statistically significant positive spatial autocorrelation. From 2018 to 2019, the index remained relatively high ($I = 0.548$ in 2019), reflecting pronounced spatial clustering where districts with similar resilience levels (either high or low) tended to aggregate. In 2020, resilience levels fluctuated under the impact of the pandemic, causing Moran’s I to drop to 0.388, which signified a widening of regional disparities and a temporary weakening of spatial dependence. During 2021–2022, the index rebounded to 0.582 and 0.524, respectively, suggesting a resurgence of the spatial clustering trend. Although the index moderated to 0.425 in 2023, it remained relatively high, indicating that the overall spatial agglomeration of resilience persisted, supported by continuous policy interventions and resource allocation.

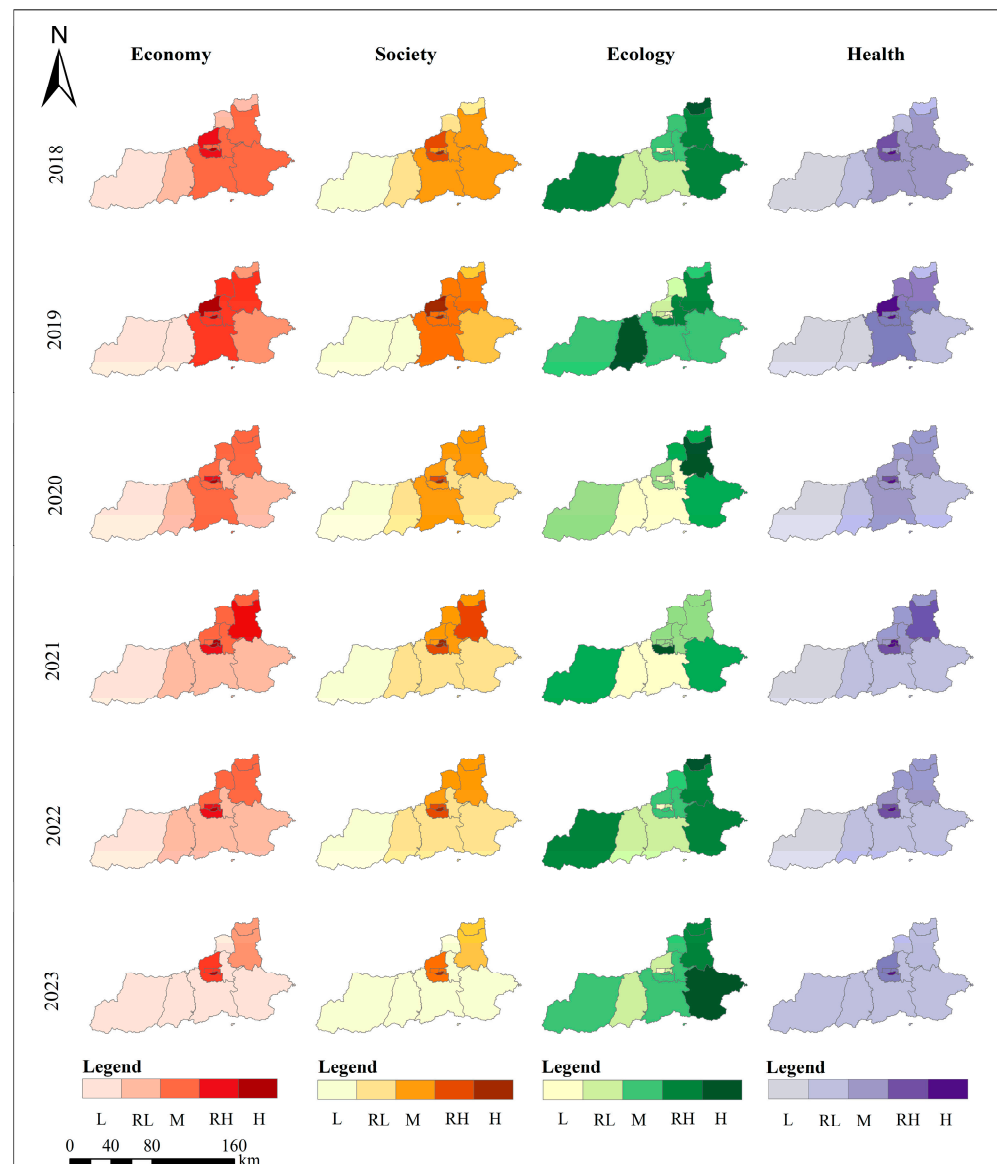


Figure 8. Visualization of urban resilience across economic, social, ecological, and healthy systems.

Table 4. Global Moran’s I index of district-level comprehensive resilience.

Year	Moran’s I	Z	p	Year	Moran’s I	Z	p
2018	0.50085	3.085398	0.002033	2021	0.582315	3.363781	0.000769
2019	0.548015	3.301408	0.000962	2022	0.523612	3.149015	0.001638
2020	0.388404	2.358916	0.018328	2023	0.424956	2.586075	0.009708

From a local perspective (see Figure 9), central urban areas such as the Beilin and Yanta districts have long exhibited a “High-High” (H-H) clustering pattern. This suggests that these core areas leverage significant advantages in industrial development, public service provision, and infrastructure to form robust resilience hubs, generating positive spatial spillover effects on neighboring districts. Specifically, Beilin’s resilience index (0.580) was 35.5% higher than the city-wide average (0.428) in 2023. Conversely, regions such as the Huyi and Chang’an districts were characterized by “Low-Low” (L-L) clustering in certain years, reflecting persistent structural constraints and development bottlenecks. In 2023, Huyi’s resilience (0.346) stood at only about 60% of Beilin’s; this marked gap underscores the center-polarized nature of Xi’an’s resilience landscape. These stage-

specific clustering states provide a critical empirical basis for optimizing regional development strategies and promoting the balanced enhancement in urban resilience.

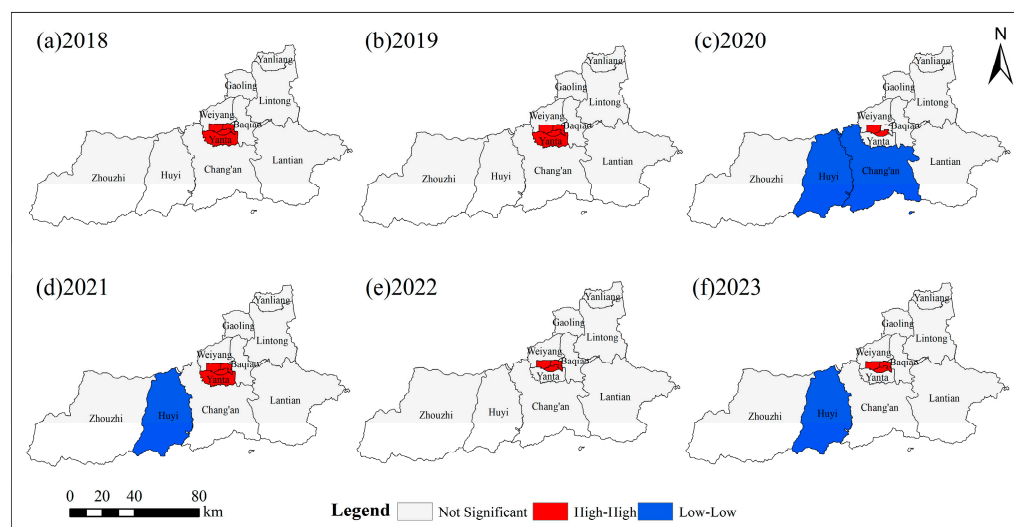


Figure 9. District-level comprehensive resilience LISA cluster map.

4.1.3. Analysis of Regional Disparities in District-Level Urban Resilience

To characterize the spatial hierarchy and internal disparities of district-level urban resilience, the 13 districts and counties were categorized into three functional zones: core urban area, suburban area, and exurban area. The Dagum Gini coefficient method was employed to decompose these disparities from 2018 to 2023. Between 2018 and 2021, the resilience disparity exhibited a widening trend, with the Gini coefficient rising from 0.095 to 0.122 (see Table 5). Subsequently, this disparity gradually contracted, dropping to 0.099 by 2023—below the six-year average—reflecting that the post-pandemic recovery process effectively mitigated regional polarization (see Figure 10).

Table 5. Overall, intra-group, and inter-group Gini coefficients.

Year	Overall	Intra-Group Gini Coefficients			Inter-Group Gini Coefficients		
		Core	Suburban	Exurban	Core & Suburban	Core & Exurban	Suburban & Exurban
2018	0.095	0.053	0.053	0.059	0.102	0.165	0.085
2019	0.093	0.05	0.027	0.031	0.112	0.172	0.064
2020	0.1	0.094	0.088	0.045	0.103	0.12	0.098
2021	0.122	0.091	0.044	0.067	0.154	0.188	0.067
2022	0.113	0.099	0.063	0.035	0.141	0.155	0.061
2023	0.099	0.069	0.058	0.049	0.137	0.13	0.06
Avg.	0.104	0.076	0.056	0.048	0.125	0.155	0.125

Decomposition analysis reveals that resilience disparities primarily stem from inter-group gaps (detailed data supporting this decomposition analysis are provided in Table A8 of Appendix B). Over the study period, the average contribution of inter-group differences reached 66.7%, significantly higher than intra-group differences (24.4%) and the intensity of transvariation (hypervariable density) (8.9%), confirming a stable gradient differentiation among the three zones. Further comparison shows that the gap between core urban and far-suburban areas was most pronounced, with the inter-group Gini coefficient peaking at 0.188 in 2021, highlighting substantial imbalances in resource endowment and recovery capacity. During the 2020 shock, the contribution of inter-group differences fell to 38.9%, while the intensity of transvariation surged to 29.2%, indicating that certain far-

suburban districts exhibited unexpectedly robust resilience due to low population density and strong ecological buffering, leading to a temporary overlap in resilience performance across zones. As the shock subsided, the influence of transvariation receded to 9.4% by 2023, and the hierarchical disparity structure stabilized. Although internal differences within far-suburban areas have converged, their overall resilience remains constrained by infrastructure supply, and the gradient gaps between the urban core and the periphery persist (see Figure 11).

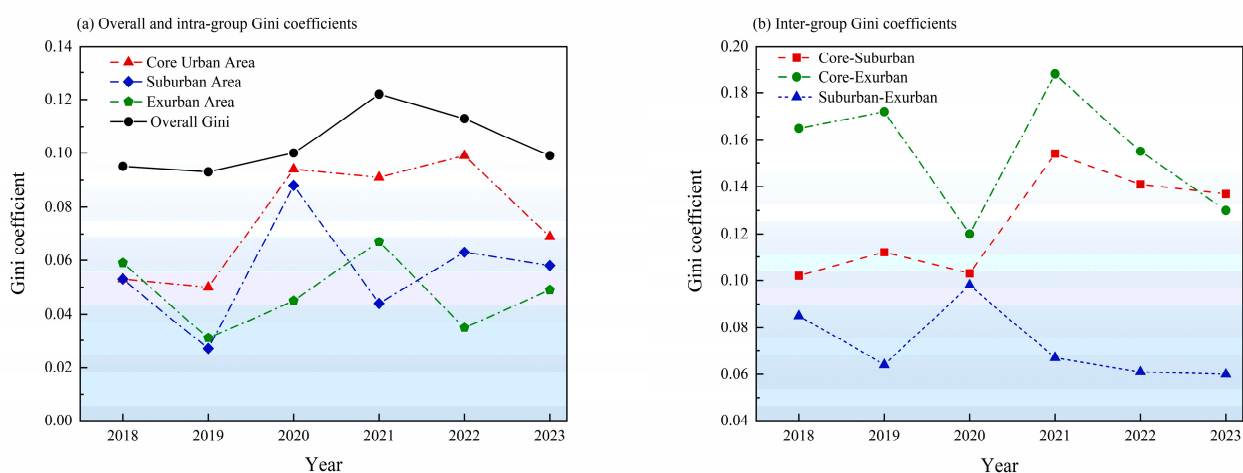


Figure 10. Changes in the Gini coefficient.

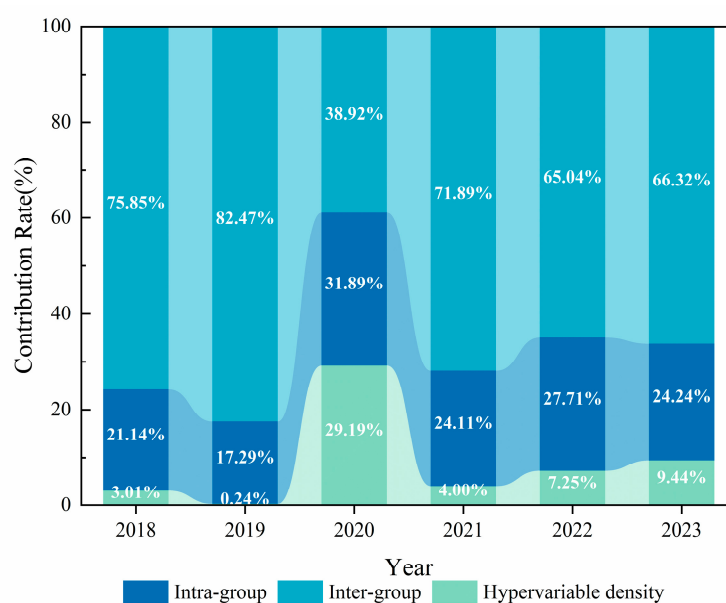


Figure 11. Cumulative bar chart of contribution rates.

4.2. Analysis of Influencing Factors of District-Level Urban Resilience

4.2.1. Analysis of Indicator Obstacle Degree

Building upon the identified spatial dependence, this study conducts an obstacle degree analysis to identify specific factors constraining resilience enhancement across districts (see Table 6). The evolution of obstacle factors from 2018 to 2023 exhibits significant spatiotemporal coupling. Core urban areas (Xincheng, Beilin, Lianhu, and Yanta) displayed pronounced path dependence, with the proportion of green space (C24) consistently ranking as the primary constraint, maintaining high obstacle values of 7%–10%.

Alongside fiscal expenditure (C6) and medical institution density (C30), these findings reflect that resilience in high-density built-up areas is long-term constrained by the ecological base and primary healthcare allocation under the dual pressures of spatial resource hard constraints and fiscal rigidity.

Table 6. Top five obstacle factors for urban resilience in districts and counties.

County	Year	Rank				
		1	2	3	4	5
Xincheng	2018	C24 (7.90%)	C7 (7.12%)	C25 (6.91%)	C6 (6.81%)	C30 (6.55%)
	2020	C24 (7.87%)	C25 (6.83%)	C8 (6.70%)	C35 (6.02%)	C6 (5.96%)
	2023	C24 (7.95%)	C25 (6.83%)	C3 (6.43%)	C6 (6.18%)	C30 (5.84%)
Beilin	2018	C24 (9.85%)	C25 (8.46%)	C6 (8.36%)	C26 (6.54%)	C18 (6.53%)
	2020	C24 (7.98%)	C25 (6.85%)	C6 (6.73%)	C17 (6.31%)	C3 (6.21%)
	2023	C24 (9.01%)	C7 (7.97%)	C25 (7.74%)	C6 (7.63%)	C8 (6.44%)
Lianhu	2018	C24 (7.72%)	C25 (6.63%)	C6 (6.18%)	C30 (5.42%)	C18 (5.31%)
	2020	C24 (7.00%)	C25 (6.01%)	C18 (5.55%)	C30 (5.55%)	C3 (5.46%)
	2023	C24 (7.06%)	C25 (6.07%)	C18 (5.76%)	C6 (5.59%)	C7 (5.44%)
Baqiao	2018	C3 (5.78%)	C27 (5.29%)	C6 (5.22%)	C18 (4.46%)	C30 (4.23%)
	2020	C18 (4.76%)	C30 (4.49%)	C17 (4.36%)	C3 (4.23%)	C20 (4.18%)
	2023	C18 (5.66%)	C30 (5.30%)	C6 (5.08%)	C20 (4.72%)	C27 (4.66%)
Weiyang	2018	C24 (6.40%)	C6 (6.18%)	C25 (5.73%)	C2 (5.43%)	C22 (5.36%)
	2020	C30 (5.43%)	C6 (5.32%)	C24 (5.29%)	C18 (5.26%)	C29 (5.21%)
	2023	C34 (6.75%)	C6 (6.52%)	C18 (6.52%)	C8 (6.42%)	C30 (6.19%)
Yanta	2018	C24 (7.39%)	C18 (7.27%)	C30 (7.02%)	C6 (6.97%)	C2 (5.83%)
	2020	C24 (6.77%)	C18 (6.62%)	C30 (6.39%)	C6 (6.34%)	C25 (5.89%)
	2023	C24 (7.79%)	C18 (7.56%)	C30 (7.30%)	C6 (7.25%)	C25 (6.24%)
Yanliang	2018	C22 (5.46%)	C25 (5.18%)	C16 (4.45%)	C6 (4.40%)	C29 (4.38%)
	2020	C8 (5.27%)	C22 (4.76%)	C16 (4.75%)	C6 (4.53%)	C26 (4.09%)
	2023	C16 (4.59%)	C17 (4.51%)	C30 (4.37%)	C26 (4.37%)	C6 (4.34%)
Lintong	2018	C25 (5.62%)	C20 (4.50%)	C37 (4.23%)	C23 (4.22%)	C18 (4.19%)
	2020	C20 (4.97%)	C8 (4.60%)	C23 (4.45%)	C10 (4.22%)	C5 (4.21%)
	2023	C8 (4.67%)	C20 (4.39%)	C26 (4.19%)	C21 (4.04%)	C23 (3.97%)
Changan	2018	C6 (5.06%)	C20 (4.99%)	C2 (4.55%)	C26 (4.43%)	C23 (4.16%)
	2020	C22 (4.60%)	C30 (4.55%)	C6 (4.33%)	C18 (4.13%)	C20 (4.05%)
	2023	C30 (4.96%)	C22 (4.77%)	C6 (4.60%)	C18 (4.44%)	C20 (4.18%)
Gaoling	2018	C8 (5.07%)	C29 (5.00%)	C25 (4.76%)	C13 (4.40%)	C26 (4.11%)
	2020	C8 (4.79%)	C6 (4.63%)	C30 (4.51%)	C22 (4.26%)	C20 (4.18%)
	2023	C35 (4.67%)	C28 (4.56%)	C13 (4.38%)	C6 (4.37%)	C30 (4.37%)
Huyi	2018	C35 (4.46%)	C28 (4.35%)	C34 (3.71%)	C23 (3.57%)	C10 (3.41%)
	2020	C28 (4.33%)	C27 (4.21%)	C35 (4.20%)	C25 (4.17%)	C26 (3.89%)
	2023	C26 (3.99%)	C27 (3.96%)	C6 (3.93%)	C34 (3.78%)	C22 (3.75%)
Lantian	2018	C2 (4.91%)	C4 (4.34%)	C34 (4.26%)	C37 (4.18%)	C23 (4.17%)
	2020	C7 (5.63%)	C8 (5.32%)	C2 (4.16%)	C34 (4.12%)	C23 (4.08%)
	2023	C29 (5.28%)	C17 (5.25%)	C8 (4.82%)	C4 (4.27%)	C23 (4.27%)
Zhouzhi	2018	C17 (4.46%)	C2 (4.30%)	C35 (3.70%)	C4 (3.68%)	C13 (3.66%)
	2020	C25 (4.90%)	C3 (4.68%)	C35 (4.50%)	C2 (4.22%)	C8 (4.00%)
	2023	C29 (4.94%)	C17 (4.69%)	C2 (4.53%)	C26 (3.96%)	C4 (3.92%)

The 2020 external shock disrupted the regional evolutionary equilibrium, triggering a citywide convergence toward “public service and social mobilization” bottlenecks. Emerging development zones, such as Weiyang and Baqiao, were particularly representative; obstacle factors rapidly shifted from ecological indicators to social governance dimensions. The obstacle degrees for medical facilities (C30) and social organization legal entities (C18) surged, exposing systemic lags in emergency support and social mobilization within rapid population inflow areas under extreme stress tests.

By the 2023 restoration period, far-suburban districts (Lantian, Zhouzhi, Huyi, and Lintong) exhibited an evolutionary transition from economic self-sufficiency constraints to social security deficiencies. While these regions were primarily hindered by fiscal revenue (C2) and employment fluctuations (C17) in 2018, by 2023, the obstacle degrees for nursing home capacity (C35) and public health expenditure (C29) became prominently significant. This indicates that social welfare and healthcare investment in ecological functional zones, against the backdrop of an aging population, have emerged as core bottlenecks for resilience restoration. Consequently, Xi'an's resilience construction is pivoting from early ecological and economic reinforcement toward a systematic improvement in structural risk response and comprehensive social governance efficacy.

4.2.2. Analysis of Indicator Correlation

To quantitatively assess the core explanatory factors affecting urban resilience, this study performed a Grey Relational Analysis (GRA) on all 37 indicators. Table 7 presents the top ten indicators ranked by their relational grades with urban resilience, alongside their corresponding mean values from 2018 to 2023. Among them, the Industrial Structure HHI (C1) emerged as the predominant factor with a mean relational grade of 0.775; however, its dynamic trajectory reveals high sensitivity to systemic shocks. Specifically, C1 dropped sharply to 0.692 in 2020, rebounded to 0.820 in 2021, and subsequently gradually receded to 0.773 and 0.746 in 2022 and 2023, respectively, exhibiting a notable fluctuation range of 0.128. This indicates that while industrial structural optimization serves as a primary cornerstone of systemic stability, it remains highly vulnerable to disturbances from external shocks (see Table 7).

Table 7. Top 10 indicators of grey relational degree.

Indicator Code	Indicator Name	Grey Relational Grade	Rank
C1	Industrial Structure HHI	0.775	1
C33	Accessibility of Cooling Facilities	0.769	2
C36	Number of Cooling Facilities per Thousand People	0.761	3
C31	Number of Hospital Beds per Thousand People	0.761	4
C10	Proportion of Science and Technology-Related Fiscal Expenditure	0.760	5
C4	Number of New Jobs per Thousand People	0.744	6
C9	Per Capita GDP	0.737	7
C12	Proportion of Emergency Management and Public Safety Expenditure	0.736	8
C15	Accessibility of Emergency Shelter	0.728	9
C14	Accessibility of Fire Services	0.724	10

The response patterns of cooling facilities and medical resources highlight the heterogeneous characteristics of the public safety service system. Cooling facility accessibility (C33) peaked at 0.817 in 2022, while the per capita provision (C36) formed two peaks in 2018 and 2022. Both indicators declined simultaneously in 2020 before rebounding in 2022; however, they significantly receded in 2023, revealing a periodic decay in the marginal contribution of climate-adaptive infrastructure. The mean relational grade for hospital beds per 1000 people (C31) was 0.761, reaching its pre-pandemic peak in 2019. It did not experience a significant surge during the 2020 shock (0.737) and remained relatively stable, indicating that the supporting role of medical resources for resilience exhibits inelastic or “rigid” characteristics.

The evolutionary trends of innovation drive and emergency systems exhibit structural differentiation. The proportion of science and technology expenditure (C10) is the only indicator showing a continuous upward trajectory, with its relational grade climbing from 0.743 to 0.794 (an average annual growth of 1.1%), highlighting the strengthening marginal effect of innovation drive in resilience construction. In contrast, economic foundation indicators, such as new jobs (C4) and GDP per capita (C9), remained periodic yet stable. Simultaneously, indicators related to the emergency management system show an attenuating trend: the relational grades for emergency expenditure (C12), fire department accessibility (C14), and emergency shelter accessibility (C15) all exhibited varying degrees of decline by 2023. This suggests that the perceived importance or functional efficacy of traditional physical emergency facilities within the resilience framework is experiencing a relative decline compared to dynamic innovation factors (see Figure 12).

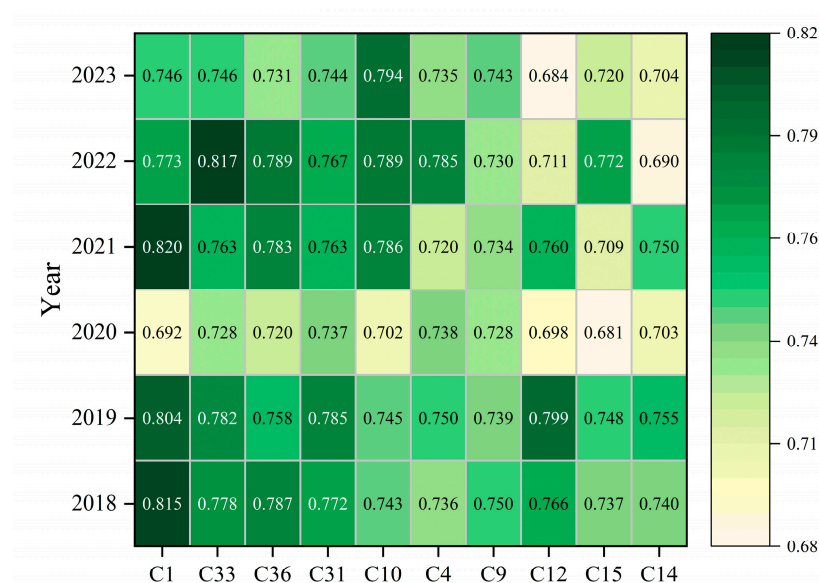


Figure 12. Heatmap of grey relational degree for the top 10 indicators (2018–2023).

4.2.3. Comprehensive Analysis of Indicator Obstacle Degree and Relational Grade

The preceding analyses of obstacle degrees and grey relational grades have delineated the key bottlenecks and the relative influence of various factors on the evolution of urban resilience. However, a unidimensional perspective remains insufficient to comprehensively capture the intricate interactions and strategic priorities among these drivers. To bridge this analytical gap, this study constructs an “Obstacle Degree-Relational Grade” quadrant model. By adopting the medians of both dimensions as thresholds, the 37 factors are categorized into four distinct strategic zones, facilitating a more nuanced identification of core constraints and hierarchical priorities in the resilience evolution process (see Table 8).

Table 8. Obstacle–relational degrees of indicators and their quadrant classification.

Code	Obstacle Degree	Grey Correlation Degree	Quadrant	Code	Obstacle Degree	Grey Correlation Degree	Quadrant
C1	0.775	2.27%	I	C6	0.594	4.40%	III
C4	0.744	2.64%	I	C7	0.635	3.01%	III
C9	0.737	2.12%	I	C8	0.644	3.47%	III
C12	0.736	2.14%	I	C17	0.673	2.65%	III
C13	0.706	2.47%	I	C18	0.585	3.81%	III
C14	0.724	2.09%	I	C20	0.664	3.36%	III

C15	0.728	1.50%	I	C22	0.645	3.12%	III
C16	0.677	2.42%	I	C23	0.67	3.66%	III
C33	0.769	1.24%	I	C24	0.482	3.69%	III
C34	0.722	2.08%	I	C25	0.636	3.22%	III
C36	0.761	2.49%	I	C26	0.662	3.33%	III
C37	0.708	2.35%	I	C29	0.638	3.12%	III
C2	0.677	3.35%	II	C30	0.62	4.16%	III
C5	0.691	2.72%	II	C3	0.629	2.37%	IV
C10	0.76	2.84%	II	C19	0.675	1.53%	IV
C11	0.704	3.12%	II	C27	0.572	1.49%	IV
C21	0.721	3.00%	II	C28	0.625	1.70%	IV
C31	0.761	2.65%	II	C32	0.652	1.38%	IV
C35	0.68	3.02%	II				

Note: The categories in the table are defined as follows: I represents low obstacle and high correlation; II represents high obstacle and high correlation; III represents high obstacle and low correlation; IV represents low obstacle and low correlation.

Quantitative analysis reveals that the urban resilience of Xi'an's districts exhibits a structural configuration characterized by deficiencies in critical resource reserves and lagging technological investment, contrasted with robust economic foundations and optimized spatial configurations. Indicators in the "High Obstacle-High Relational" quadrant constitute the pivotal bottlenecks, primarily involving medical reserves and science and technology (S&T) support. For instance, although hospital beds (C31), nursing homes (C35), and emergency shelters (C11) possess strong explanatory power, their high obstacle degrees reflect a capacity deficit in physical infrastructure when responding to sudden public health emergencies. Simultaneously, the high obstacle degree for S&T expenditure (C10) reveals that fiscal allocation toward technological disaster mitigation remains inadequate.

In contrast, the "Low Obstacle-High Relational" quadrant highlights foundational strengths; the low obstacle values for industrial structure (C1) and GDP per capita (C9) confirm robust economic support. Furthermore, the low obstacle degrees for fire department (C14) and emergency shelter accessibility (C15) suggest that the spatial siting and road network planning of public service facilities are relatively scientific, achieving high service coverage efficiency under existing stocks. Additionally, the "High Obstacle-Low Relational" quadrant exposes deep-seated structural contradictions. The obstacle degree for fiscal expenditure (C6) reflects the constraints imposed by rigid fiscal burdens on flexible resource allocation. Meanwhile, the high obstacle degrees for green space ratio (C24) and blue-green connectivity (C23) reveal diminished disaster-buffering functions due to ecological fragmentation. Indicators in the "Low Obstacle-Low Relational" quadrant, such as industrial emissions (C27, C28), suggest that environmental governance has reached a stable efficacy and no longer constitutes a major constraint. Consequently, future resilience-building in Xi'an should prioritize "infrastructure supplementation" and "technological empowerment." While leveraging existing spatial planning advantages, focus should shift toward bridging physical gaps in medical and shelter facilities, increasing investment in technological disaster prevention, and optimizing ecological network connectivity to achieve systemic resilience enhancement (see Figure 13).

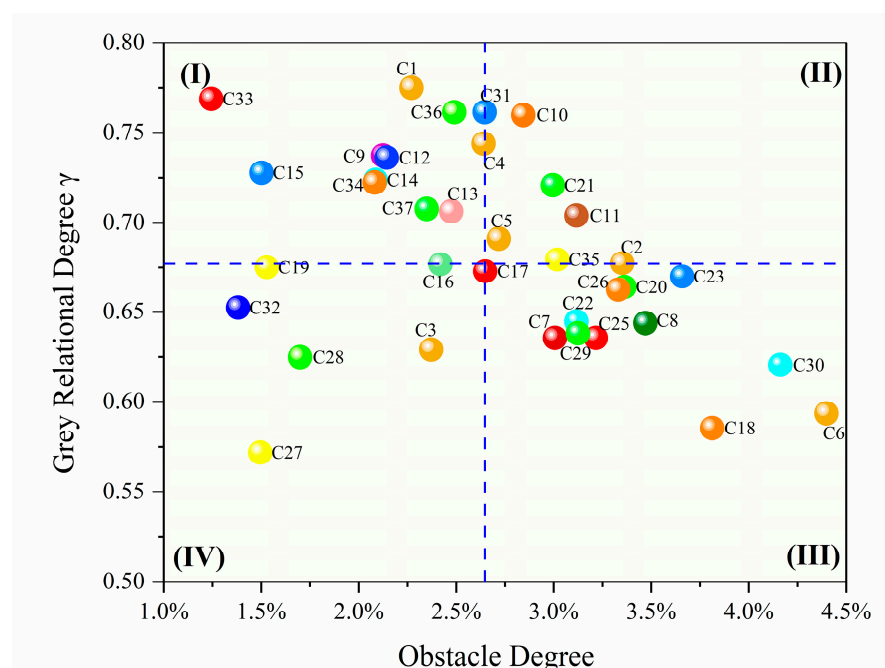


Figure 13. Four-quadrant distribution of obstacle and relational degrees.

4.2.4. Analysis of Resilience Enhancement Paths for Districts and Counties

The preceding analysis primarily focused on the independent impacts of individual indicators, which is limited in capturing the intricate synergies and conjunctural causation among various elements. Consequently, this study introduces the fuzzy-set qualitative comparative analysis (fsQCA) method. From a “holistic configurational” perspective, this approach explores how key constraints interact and combine to form multiple pathways for enhancing urban resilience, thereby identifying differentiated development strategies tailored to the specific resource endowments of each district.

Variable selection is underpinned by a synthesis of empirical diagnosis and theoretical frameworks. The outcome variable is defined as the longitudinal mean of resilience indices (2018–2023) to mitigate transient fluctuations and reflect the steady-state performance of the system. The selection of antecedent conditions focuses on the “High Obstacle–High Relational” indicators identified in the quadrant model, which are systematically integrated into the Technology–Organization–Environment (TOE) framework. Specifically, proportion of science and technology-related fiscal expenditure (TI) to examine the leveraging effect of innovation on resilience. The organizational dimension integrates fiscal revenue (FS), total retail sales (MV), and hospital bed density (PH) to represent governmental regulatory power, market momentum, and social security capacity, respectively. Instead of green space proportion (PLAND), the environmental dimension selects Shannon’s Diversity Index (SE) to characterize the risk-buffering efficacy of the ecological structure, as resilience theory prioritizes structural diversity and heterogeneity over mere quantity. Data were transformed using the direct calibration method, with the 95th, 50th, and 5th percentiles serving as qualitative anchors to map raw values into fuzzy membership scores. This procedure establishes a logical closed-loop, transitioning from the identification of realistic bottlenecks to the deconstruction of driving pathways.

(1) Necessity Analysis

Before identifying configurational paths, a necessity analysis was conducted for each antecedent condition. The results indicate that when high urban resilience is the outcome variable, the consistency of all individual conditions falls below the 0.9 threshold, suggesting that no single factor is a necessary condition for high resilience. Notably, in the

analysis of the absence of high resilience, the consistency of “Science and Technology (S&T) Innovation Investment Intensity” (~TI) reaches 0.944. This underscores that a lack of technological funding is a pivotal bottleneck constraining resilience improvement. The absence of single-factor necessity for high resilience, contrasted with the prominence of a necessary condition for low resilience, confirms that resilience enhancement in Xi’an is driven by complex coupling rather than isolated conditions, further reflecting the causal asymmetry inherent in the system (see Table 9).

Table 9. Necessity analysis of single conditions.

Precondition	High Resilience Level		Non-High Resilience Level	
	Consistency	Coverage	Consistency	Consistency
FS	0.633540	0.637500	0.525915	0.539062
~FS	0.541925	0.528788	0.646342	0.642424
TI	0.790372	0.932235	0.356707	0.428571
~TI	0.515528	0.440318	0.943598	0.820955
MV	0.700310	0.768313	0.375000	0.419080
~MV	0.470497	0.424965	0.792683	0.729313
SE	0.447205	0.425343	0.797409	0.772560
~SE	0.760869	0.786643	0.406860	0.428480
PH	0.726708	0.772277	0.477134	0.516502
~PH	0.545031	0.505764	0.789634	0.746398

(2) Configurational Path Analysis

By constructing a truth table and performing Boolean algebraic operations, this study identified three equifinal configurational paths leading to high urban resilience (UR) based on intermediate and parsimonious solutions. The results show an overall solution consistency of 0.937 and a coverage of 0.734, with each individual path exceeding the 0.800 consistency threshold. This indicates that the model demonstrates high empirical sufficiency and robust explanatory power for the high-resilience phenomenon (see Table 10).

Table 10. Configurational analysis of high urban resilience in districts and counties of Xi’an.

Precondition	H1	H2	H3
Fiscal Security Capacity (FS)	—	●	⊗
Science and Technology (S&T) investment intensity (TI)	●	●	●
Spatial Environmental Background (SE)	⊗	⊗	—
Public Health Capacity (PH)	—	●	●
Market Momentum (MV)	●	—	●
Consistency	0.937500	0.963934	0.969957
Original Coverage	0.605590	0.456522	0.350932
Unique Coverage	0.155280	0.076087	0.052795
Solution Consistency		0.936634	
Solution Coverage		0.734472	

Note: ● represents core conditions; ● represents auxiliary conditions; ⊗ represents peripheral conditions; and — indicates that the condition may or may not be present.

Observing the constitutive logic, science and technology (S&T) investment intensity (TI) emerges as a universal core condition, playing a cross-contextual foundational role in all pathways. Correspondingly, fiscal security (FS) and market momentum (MV) exhibit substitution and complementarity relationships, reflecting that district-level resilience is

a product of multi-dimensional coupling between “technical capacity” and “organizational/market conditions.” Furthermore, the negation of landscape ecological diversity (~SE) appears in multiple paths, suggesting that technical empowerment and resource security can effectively compensate for the inherent limitations of physical space. This study further refines these pathways into three driving modes:

Path H1: “Innovation-led Market Compensation” (MV TI ~SE). This path identifies S&T investment as the core driver, supplemented by high market vitality. In core urban areas like Beilin and Yanta, where ecological patch complexity is constrained (~SE), robust market consumption accelerates factor flow. Combined with high-level S&T transformation, this forms an effective “compensation mechanism.” For instance, Yanta District, leveraging its dense research resources, demonstrates quintessential “innovation-driven resilience,” successfully mitigating the ecological carrying capacity limitations of high-density built-up areas through technical-commercial integration.

Path H2: “Government-led Resource Synergy” (FS TI ~SE PH). This path reveals the synergistic linkage between fiscal capacity and public health resources under the aegis of S&T investment. For districts like Beilin and Yanliang, a substantial fiscal reserve provides institutional security for the optimization of public health facilities. This “resource stacking” mode ensures the system maintains strong risk absorption and recovery capabilities through the “fiscal–technical–health” linkage structure, even under conditions of extreme physical densification.

Path H3: “Social-Market Compensatory” (~FS MV TI PH). This path proves that a relative lack of fiscal security is not an insurmountable barrier to resilience. Represented by Xincheng and Weiyang, these districts face fiscal self-sufficiency constraints but achieve “social filling” of resilience by leveraging market momentum and a comprehensive public health system. This endogenous economic resilience relies on the self-repair function of industrial vitality to reduce the negative impact of economic fluctuations on systemic stability.

Based on the principle of causal asymmetry, the configurational paths for non-high resilience (~UR) were further deconstructed. The overall consistency and coverage reached 0.846 and 0.797, respectively. The necessity score for the absence of S&T investment (~TI) reached 0.944, reinforcing the core status of TI and establishing technical empowerment as a “bottom-line” attribute for systemic advancement (see Table 11).

Path N1 (~FS*~TI*SE*~PH): “Transformation Dilemma.” This path characterizes the constraints of distal ecological districts like Zhouzhi and Lantian. Their position on the periphery of fiscal support and S&T investment prevents high-quality natural assets from being activated into effective defensive momentum, confirming that a singular resource endowment cannot independently sustain systemic stress resistance.

Path N2 (FS*~MV*~TI*SE): “Fiscal Efficiency Deficit.” Represented by Lintong and Gaoling, this path manifests how fiscal capacity—lacking market vitality and technical leverage—fails to produce a meaningful catalytic effect. This reflects a structural paucity: districts losing endogenous growth momentum cannot rely on the mere accumulation of external fiscal resources.

Path N3 (FS*MV*TI*~SE*~PH): “Bottleneck Constraint.” This configuration identifies the vulnerability of Baqiao, which despite leading in fiscal strength and S&T intensity, remains susceptible due to extreme shortfalls in public health. This mismatch proves that the deprivation of a core dimension will exert a cancellation effect on otherwise superior elements, leading to a structural breach of the overall defense line.

Table 11. Configurational analysis of non-high urban resilience in districts and counties of Xi'an.

Precondition	N1	N2	N3
Fiscal Security Capacity (FS)	⊗	●	●
Science and Technology (S&T) investment intensity (TI)	⊗	⊗	●
Spatial Environmental Background (SE)	●	●	⊗
Public Health Capacity (PH)	⊗	—	⊗
Market Momentum (MV)	—	⊗	●
Consistency	0.910194	0.822064	0.978723
Original Coverage	0.571647	0.387348	0.210366
Unique Coverage	0.317073	0.13125	0.0838415
Solution Consistency		0.846303	
Solution Coverage		0.797409	

Note: ● represents core conditions; ● represents auxiliary conditions; ⊗ represents peripheral conditions; and — indicates that the condition may or may not be present.

(3) Robustness Testing

To verify the reliability of the findings, a sensitivity analysis was conducted. By maintaining the original case set, condition set, and prime implicant settings, the consistency threshold for sufficiency was increased from 0.80 to 0.85. The re-analysis showed that the overall solution consistency improved from 0.936 to 0.972, while the solution coverage moderated from 0.734 to 0.658. The fundamental configurational structures remained stable, and core mechanisms—such as the “fiscal–S&T–public health synergy” and the “market–S&T–public health compensation under weak fiscal constraints”—underwent no substantive alterations. The variations were limited to marginal adjustments in the stringency of conditions and case membership. These results confirm that the research findings are highly robust and less sensitive to threshold adjustments.

5. Discussion

The “V-shaped recovery” of district-level resilience in Xi'an (2018–2023) results from non-linear evolution and resource competition among four subsystems. This pattern departs from the steady upward trend identified by city-level stock indicators [68], revealing that macro statistics often obscure the functional decay of grassroots units during shocks. Our meso-scale framework effectively captures the non-linear stress logic and localized vulnerabilities that aggregate growth often conceals. The drastic fluctuations in economic resilience—evidenced by the index's decline to 0.364 in 2020—dictate the overarching “V-shaped” morphology, mirroring its extreme sensitivity to external shocks and its rigid coupling with growth objectives. In contrast, ecological resilience exhibits remarkable stability (0.470 in 2023), underscoring its role as a passive buffer. Crucially, the relative robustness of social resilience (0.447 in 2022) stands in contrast to the sustained strain on health resilience (0.408 in 2023). This divergence implies a zero-sum tension between maintaining social operations and safeguarding public health under resource constraints. This asymmetric pattern proves that enhancing urban resilience is not a simple additive process. Instead, it constitutes a non-linear optimization characterized by intrinsic trade-offs and adaptive resource prioritization.

This logical decoupling translates spatially into a complex synergy formed by the “high-level plateau oscillation” of core areas and the “impaired-lagged recovery” of sub-urban zones. The evolution of kernel density from “unimodal concentration” to “bimodal differentiation” reveals a structural decoupling of Xi'an's internal resilience logic: core districts, such as Beilin and Yanta, have established formidable defensive resilience

through the deep accumulation of administrative resources. Conversely, districts at the frontier of spatial expansion, like Chang'an and Baqiao, saw their lags in social mobilization and emergency response rapidly amplified under extreme stress, resulting in a significant time-lag effect in resilience repair. These endogenous differences are rooted in the resource endowment gaps solidified by the "Qinling Mountains–Weihe River" geographical divide. The fact that inter-group differences account for 66.7% of the Gini coefficient is a spatial projection of imbalances in functional positioning. While core urban areas build stable resilience bastions through superior infrastructure, the surge of the transvariation intensity (Gt) to 29.2% in 2020 reveals a "resilience inversion" under extreme shocks: remote counties like Zhouzhi exhibited more robust survival resilience due to lower population density and strong ecological buffering, providing empirical support for the asymmetric role of ecological foundations in risk hedging. It further corroborates the vital compensatory role of the ecological foundation in mitigating the vulnerabilities of socio-economic systems under extreme conditions, providing a robust empirical basis for deciphering the substitution and complementarity across multi-system resilience at varying spatial scales.

The analysis elucidates a mechanism where "flow efficiency compensates for physical stock deficiencies" within high-density environments. The finding that core districts lead the city despite restricted green space ratios suggests that resilience does not absolutely depend on physical spatial redundancy. Xi'an's dense grid-based layout in the core provides significant scheduling elasticity, compensating for the lack of physical buffer space. Consequently, the focus of resilience has shifted from mere material reserves to dynamic response based on spatial configuration efficiency; by enhancing accessibility and turnover efficiency, high-density areas demonstrate an inherent capacity to dissolve external shocks. By embedding dynamic parameters—such as isochrone accessibility and vegetation productivity evolution rates—the framework captures how core areas utilize extreme scheduling capabilities to offset ecological deficiencies. The high relational ranking of facility accessibility further confirms that in resource-constrained inland districts, security relies more on precise resource delivery via transportation advantages rather than the indiscriminate expansion of large green spaces in land-scarce centers. This downscaling and dynamization of the evaluation perspective proves that scalar downscaling is a fundamental return to the "resource-function" transformation logic.

To transition from diagnosis to mechanism exploration, this study logically links "Obstacle-Relational" dual diagnosis with fsQCA, effectively mitigating the subjective limitations of variable selection. Following the 2020 shock, city-wide obstacles rapidly shifted from ecological to governance dimensions (e.g., social organization and medical reserves), particularly in population-import districts like Weiyang, exposing the "hard infrastructure over soft governance" structural chronic ailment [69]. The pre-diagnostic phase identified S&T expenditure and medical reserves in the "high obstacle-high correlation" quadrant, reflecting Xi'an's status as a scientific powerhouse with grassroots security shortcomings. Variable screening based on objective pain points ensures that the configurational paths are a logical response to governance realities: S&T investment serves as the "universal leverage" because technological empowerment is the core endogenous driver for overcoming spatial congestion and achieving leapfrog resilience enhancement.

The aforementioned logic shifts from situational diagnosis toward mechanistic deconstruction, restoring the differentiated evolutionary trajectories across Xi'an's districts. This discovery of "equifinality" from a configurational perspective proves that urban resilience is not a linear blueprint but a systemic emergence achieved through creative reconfiguration under resource constraints [70]. Pathways in Beilin, Yanliang, and Xincheng reveal strategic compensation mechanisms where "technical capability" offsets "resource

deficits”, validating “Factor Substitution” [71]—the functional equivalence between market vitality and fiscal capacity across diverse contexts. This highlights the feasibility for grassroots units to achieve resilience through state optimization rather than linear stacking. Conversely, cases like Zhouzhi and Baqiao define the resilience “feasibility domain” [72]. Zhouzhi faces an “asset lock-in” where ecological potential remains untapped, while Baqiao demonstrates the “asymmetric cancellation” effect. Specifically, extreme shortfalls in a single dimension—such as public health—neutralize cumulative techno-fiscal dividends, triggering the structural collapse of the defensive line. This inherent asymmetry in element influence is corroborated by empirical research on multi-scale resilience interactions [73]. Such mechanistic insights mandate that governance must break bottlenecks through configurational optimization, securing rigid bottom lines while pursuing higher marginal returns. This paradigm shift from “universal” to “context-optimal” solutions enriches resilience theory and provides empirical evidence for refined resource allocation. Ultimately, this approach aligns with the grassroots logic of context-strategy matching under resource constraints [74].

Based on the aforementioned mechanistic insights, Xi’an’s resilience improvement should undergo a governance transformation from “standardized resource allocation” to “differentiated path matching.” Decision-makers must scientifically weigh opportunity costs and marginal outputs of resource investment based on distinct conflict structures, implementing hierarchical optimization at the district scale. For core urban areas with limited physical space, micro-renewal should focus on “efficiency compensation for physical stock.” Given the prohibitive cost of blindly expanding redundancy, governance should pivot toward nature-based solutions (NbSs) [75] and digital twin systems to enhance spatial allocation efficiency [76]. This pathway secures higher marginal returns through optimized configuration, representing the optimal strategy to mitigate structural vulnerabilities under high-density rigid constraints. For emerging zones with rapid population influx, the strategic focus must shift from chasing economic increments toward disrupting “negative interactions” among antecedents. Prioritizing shortfalls in grassroots health facilities and social organizations prevents specific bottlenecks from exerting an “inhibitory reduction” on growth dividends, avoiding the brittle collapse of defensive lines caused by element-wise cancellation. For remote ecological zones, governance should focus on breaking the “asset lock-in” dilemma by coupling natural capital with healthcare security for an aging society, thereby fortifying social defense baselines through activating dormant ecological stocks. Furthermore, administrators should leverage the spatial autocorrelation of resilience to establish pairing mechanisms between core and peripheral districts. Through cross-regional resource sharing, the “low-resilience lock-in” pattern can be disrupted, ultimately constructing a self-adaptive urban resilience community through the dynamic interactions of heterogeneous units.

6. Conclusions

6.1. Main Conclusions

Based on a multi-source data-driven serial analytical framework, this study deeply deconstructed the spatiotemporal non-equilibrium and causal complexity mechanisms of urban resilience in Xi’an’s districts and counties from 2018 to 2023. The main conclusions are as follows:

- (1) Non-linear “V-shaped” trajectory and asymmetric systemic response: The empirical units followed a sequence of “fluctuation, trough, and recovery” during 2018–2023. Sub-system analysis reveals profound asymmetry: the economic system remained most fragile with delayed recovery; the health system exhibited severe spatial polar-

ization (CV reaching 0.393); meanwhile, the ecological and social systems demonstrated superior recovery rigidity. The desynchronization of response cycles emphasizes that governance interventions must be phased and graded based on the disparate sensitivity–robustness profiles of different resilience dimensions.

- (2) Stable center-oriented polarization and the “resilience inversion” effect: Inter-group differences (mean contribution 66.7%) driven by administrative siphoning constitute the primary source of spatiotemporal non-equilibrium. The “resilience inversion” observed under extreme shocks confirms that resource-rich urban cores are prone to functional collapse due to saturated capacity. This phenomenon reinforces the sensitivity advantage of processual monitoring in identifying latent vulnerabilities, suggesting that shifting the paradigm toward “operational efficiency” is essential for the accurate assessment of grassroots resilience.
- (3) Dual configurational logic of “synergistic compensation” and “synergistic offset”: Equivalent pathways (e.g., “Market-Tech Compensation”) reinforce the compensatory value of tech-innovation for physical defects. Conversely, the analysis of non-high-resilience configurations reveals a “synergistic offset” effect, where an extreme bottleneck in a single dimension can neutralize other strength-driven dividends, leading to systemic failure. Such non-linear associations prove that resilience leaps depend on configurational optimization of governance elements rather than simple linear resource accumulation.

6.2. Main Contributions

Methodologically, this study facilitates a paradigm leap in resilience evaluation, transitioning from static “resource stock description” to dynamic “spatial allocation efficiency assessment.” By integrating POI network analysis and remote sensing monitoring, the framework more precisely captures the dynamic functional performance of urban systems. This research not only provides an empirical sample for the meso-level governance of inland megacities but also—via a logical closed-loop of situational diagnosis, trend correlation, and configurational paths—overcomes the subjectivity in antecedent variable selection. Ultimately, it establishes a replicable scientific paradigm for deconstructing non-linear causal mechanisms within complex environments.

6.3. Limitations and Future Outlook

Despite these insights, this study is constrained by data frequency; the annual-scale analysis lacks the resolution to capture the micro-evolutionary nuances of urban systems during instantaneous shocks. Similarly, strategic simplifications made for analytical tractability—including standardized speed impedance and fixed calibration anchors—imply that our findings characterize the system’s structural baseline rather than its stochastic, transient performance. Future research should incorporate real-time sensing data—such as transportation and social media flows—to construct models with higher temporal resolution.

Furthermore, the specific coupling mechanisms induced by divergent risks (e.g., floods, earthquakes) across subsystems warrant deeper investigation. Particularly through the lens of complex disaster chains, the trade-offs between opportunity costs and negative cancellation effects require precise mathematical modeling via multi-scenario simulations. Such advancements will yield proactive strategic schemes for optimized resource allocation and resilience-oriented policy-making in megacities facing extreme uncertainty.

Author Contributions: Conceptualization, Y.W., T.H. and S.Y.; methodology, Y.W. and S.Y.; software, S.Y.; validation, Y.W., T.H. and K.C.; formal analysis, S.Y.; investigation, S.Y. and K.C.; resources, Y.W. and T.H.; data curation, S.Y. and K.C.; writing—original draft preparation, S.Y.; writing—review and editing, Y.W., T.H. and K.C.; visualization, S.Y. and K.C.; supervision, Y.W. and T.H.; project administration, Y.W.; funding acquisition, Y.W. and T.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by (1) National Key R & D Program (Grant No. 2022YFE0119200); (2) “Scientists + engineers” team development project of YuLin High Tech Industrial Development Zone (Grant No. YGXKG-2023-105).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Indicator definitions.

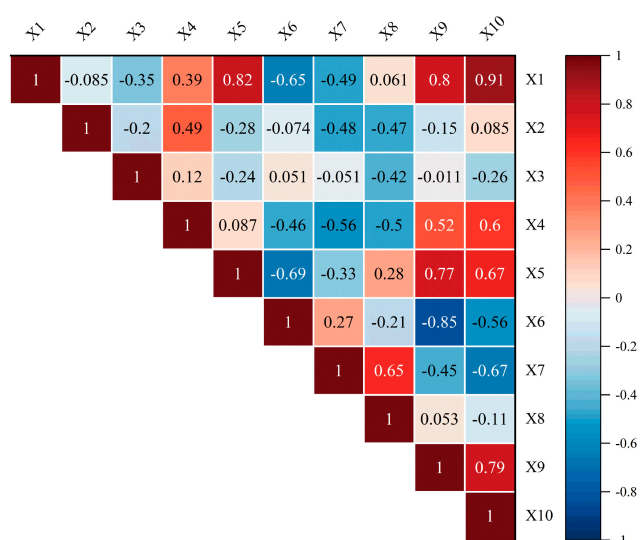
System	Indicator Name	Code	Indicator Definition
Economy	Industrial Structure HHI	X1	Measures the degree of industrial diversification and risk dispersion capacity.
	Fiscal Revenue as a Share of GDP	X2	Indicates government fiscal autonomy and the potential for emergency resource reserves.
	Energy Consumption per Unit of GDP	X3	Reflects resource-use efficiency and low-carbon resilience of economic development.
	New Jobs per 1000 People	X4	Measures the labor market’s capacity to absorb and buffer external shocks.
	Total Retail Sales of Consumer Goods	X5	Reflects domestic demand vitality and the stress-response capacity of the economy system.
	Fiscal Expenditure as a Share of GDP	X6	Indicates the government’s capacity to mobilize resources for pre-disaster prevention and in-crisis support.
	Growth Rate of Fixed Asset Investment	X7	Measures the speed of post-disaster infrastructure reconstruction and capital reinvestment.
	GDP Growth Rate	X8	Reflects output recovery and rebound momentum after economic shocks.
	GDP per Capita	X9	Represents the level of regional economic fundamentals supporting long-term adaptive adjustment.
	Share of Science and Technology–Related Fiscal Expenditure	X10	Measures the capacity to upgrade emergency governance systems through technological innovation.
Society	Number of Emergency Shelters	X11	Reflects government investment intensity in social safety and security.
	Share of Emergency Management and Public Safety Expenditure	X12	Reflects government investment intensity in social safety and security.
	Share of Social Security Expenditure	X13	Measures the capacity of the social safety net to buffer risks faced by vulnerable groups.
	Fire Service Coverage Rate within 5-Minute Drive Time	X14	Indicates the rapid response capacity and spatial coverage efficiency of emergency services.
	Accessibility of Emergency Shelters	X15	Reflects residents’ spatial accessibility and absorption efficiency of shelter services.
	Number of Special Assistance Beneficiaries	X16	Measures the capacity of the social system to provide minimum security and stability for special groups.

	Growth Rate of Urban New Employment	X17	Reflects the pace of post-shock recovery and stabilization of livelihoods.
	Number of Grassroots Social Organizations	X18	Reflects the robustness and organizational capacity of grassroots social governance.
	Per Capita Disposable Income of Urban Residents	X19	Measures individual adaptive capacity to post-shock livelihood changes.
	Number of Social Organizations per 1000 People	X20	Reflects social capital vitality and community participation coordination.
Ecology	Rate of Change in Vegetation Cover	X21	Reflects baseline ecological stability and resistance to environmental stress.
	Shannon Diversity Index	X22	Measures structural stability derived from biodiversity.
	Number of Days with Good Air Quality	X23	Reflects environmental quality status and regulation of health risks.
	Blue–Green Connectivity	X24	Measures spatial connectivity of water–green infrastructure and risk-buffering capacity.
	Proportion of Landscape Area in Green Space, PLAND	X25	Indicates the capacity of green space to absorb urban heat island effects and flooding impacts.
	Annual Rate of Change in Net Primary Productivity, NPP	X26	Reflects vegetation carbon sequestration capacity and ecosystem self-recovery potential.
	Monthly Rate of Change in NDVI	X27	Reflects dynamic recovery sensitivity of ecosystems to seasonal variation.
	Environmental Investment in Approved Projects	X28	Measures long-term investment in environmental governance and climate adaptation.
	Industrial SO ₂ Emissions	X29	Reflects the level of pollution load control and atmospheric environmental stress.
	Industrial Chemical Oxygen Demand Emissions	X30	Reflects water pollution control performance and long-term ecological system resilience.
Health	Share of Public Health Expenditure	X31	Measures preventive investment and emergency preparedness of the public health system.
	Health Technicians per 1000 People	X32	Reflects the capacity of health workforce reserves to cope with sudden risks.
	Medical Institutions per 1000 People	X33	Measures spatial density and baseline provision of healthcare resources.
	Hospital Beds per 1000 People	X34	Indicates surge capacity of the healthcare system in large-scale health shocks.
	Accessibility of Healthcare Facilities	X35	Reflects timeliness of healthcare access and efficiency of risk buffering.
	Accessibility of Heat-Relief Facilities	X36	Measures social health protection effectiveness under extreme heat stress.
	Number of Community Health Service Centers	X37	Reflects penetration of primary healthcare networks in post-disaster health recovery.
	Number of Nursing Homes per 1000 People	X38	Measures long-term rehabilitation support for vulnerable groups and social resilience.
	Number of Heat-Relief Facilities per 1000 People	X39	Reflects long-term urban adaptation capacity to extreme heat waves.
	Number of Sports Facilities per 1000 People	X40	Reflects baseline physical fitness and sustainability of community health infrastructure.

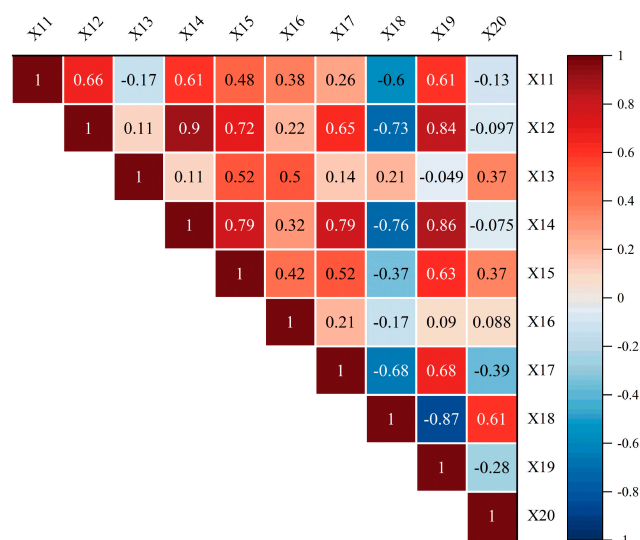
Table A2. Standard deviation, coefficient of variation, and information entropy of indicators.

Indicator	Standard Deviation	Coefficient of Variation	Information Entropy	Indicator	Standard Deviation	Coefficient of Variation	Information Entropy
X1	0.334	0.841	1.498	X21	0.278	1.188	1.225
X2	0.297	0.884	1.337	X22	0.395	0.685	1.234
X3	0.271	0.516	1.343	X23	0.264	0.592	1.499

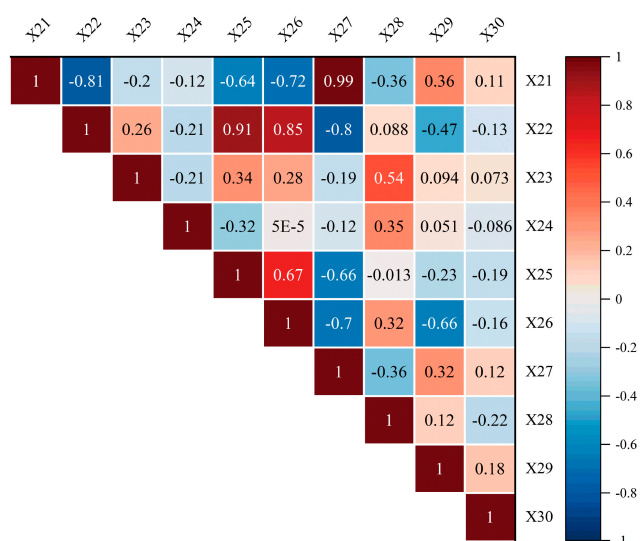
X4	0.347	0.926	1.393	X24	0.283	1.616	0.922
X5	0.331	1.124	1.233	X25	0.413	0.812	1.211
X6	0.332	1.101	1.221	X26	0.337	0.814	1.389
X7	0.271	0.556	1.473	X27	0.279	1.177	1.256
X8	0.293	0.766	1.402	X28	0.326	1.253	1.155
X9	0.327	0.725	1.370	X29	0.335	0.516	1.249
X10	0.304	1.187	1.031	X30	0.282	0.566	1.288
X11	0.263	1.071	1.144	X31	0.291	0.662	1.473
X12	0.341	0.753	1.412	X32	0.332	1.154	1.326
X13	0.328	0.685	1.438	X33	0.281	0.851	1.407
X14	0.428	1.033	1.182	X34	0.315	0.969	1.294
X15	0.383	0.753	1.431	X35	0.359	0.556	1.234
X16	0.314	0.652	1.535	X36	0.375	0.628	1.289
X17	0.292	0.623	1.383	X37	0.348	0.700	1.325
X18	0.322	0.776	1.468	X38	0.286	0.678	1.497
X19	0.373	0.609	1.266	X39	0.305	0.803	1.467
X20	0.295	0.881	1.315	X40	0.318	0.753	1.473



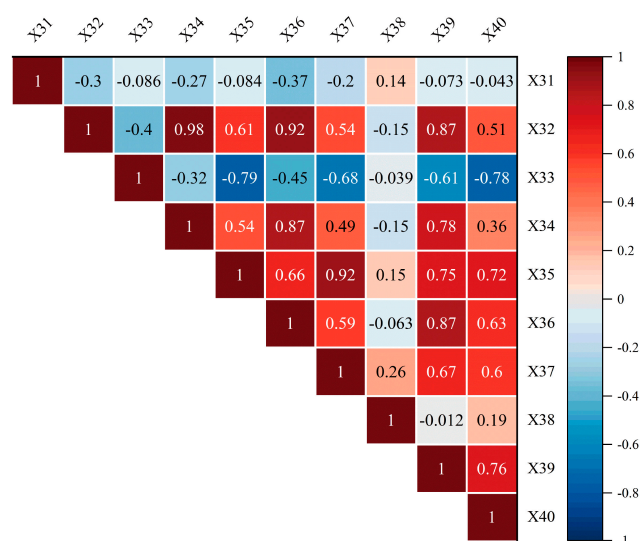
(a) economic system



(b) social system



(c) ecological system



(d) healthy system

Figure A1. Pearson's correlation coefficient heatmap.

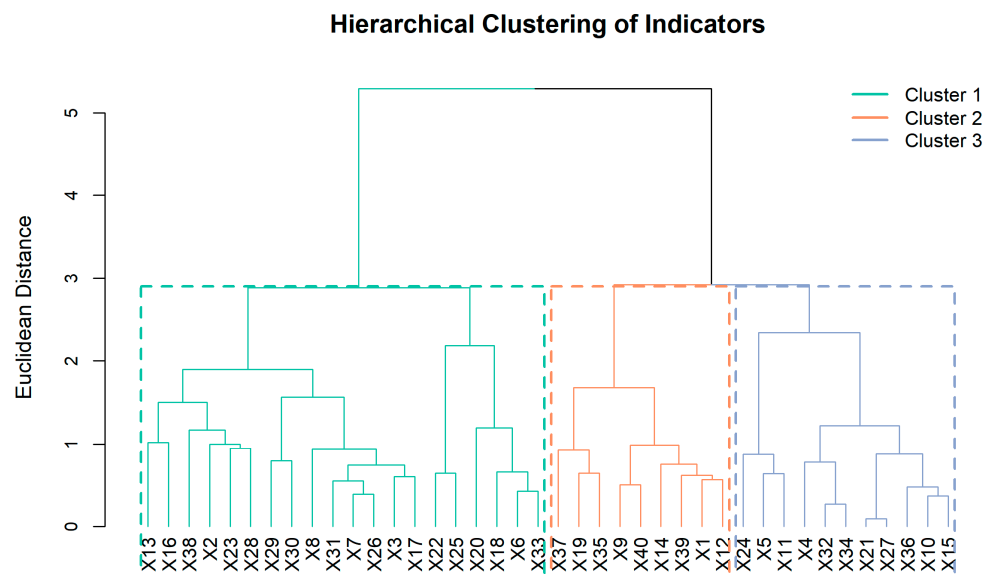


Figure A2. Cluster analysis dendrogram.

Table A3. Results of indicator exclusion.

System	Highly Correlated ($ r > 0.9$)		r	Excluded Indicators
Ecological	X21 *	X27	0.985	X27
	X25 *	X22	0.911	X22
Health	X34 *	X32	0.980	X32

Note: Indicators marked with an asterisk (*) have higher information entropy compared to their paired indicator.

Table A4. Redundancy.

System	Redundancy
Economy	0.402
Society	0.445
Ecology	0.271
Health	0.443
Total	0.401

Table A5. Data sources.

Data Category	Data Description	Time Period	Spatial Resolution/Accuracy	Data Source
Socioeconomic Data	Population density, GDP, industrial output, fiscal revenue, employment, etc.	2018–2023	County level	Xi'an Statistical Yearbook; Statistical Bulletins of National Economic and Social Development of each district/county
Land Use Data	Annual land cover classification data, CLCD)	2018–2023	30 m	Earth System Science Data platform https://zenodo.org/records/12779975 (accessed on 5 March 2025)
Remote Sensing Data	Normalized Difference Vegetation Index (NDVI), MOD13A3)	2018–2023	1 km	NASA Earthdata platform: https://search.earthdata.nasa.gov/search (accessed on 5 March 2025)

Ecologic al Productivity Data	Net Primary Produc-tivity (NPP), MOD17A3HG F	2018–2023	500 m	NASA Earthdata platform https://lpdaac.usgs.gov/products/mod17a3hgv061/ (accessed on 5 March 2025)
Road Network Data	Vector road net-works at multiple levels: expressways, arterials collector s, etc.	2018–2023	1:10,000 vector	OpenStreetMap
POI Data	Spatial locations and attributes of emer-gency shelters and heat-relief facilities	2018–2023	Coordinates	Collected via Amap API
Basic Geo-graphic Infor-mation	Administrative boundaries of Xi'an and district bounda-ries	2024 revised	1:1000,000	National Geomatics Center of China (Tianditu): https://www.tianditu.gov.cn/ (accessed on 8 October 2025)

Table A6. Summary of data-processing methods and key parameters.

Data Dimension	Indicator/Metric	Method & Tool	Parameters & Logic
Socioeconomic	Industrial Diversity (HHI)	Index calculation	$HHI = \sum (x_i/X)^2$
	Employment Market Resilience	Statistical ratio calcu-lation	$(E_t - E_{t-1})/E_{t-1}$ (E: New employment)
Landscape Ecology	Proportion of Landscape (PLAND)	Fragstats 4.2	Patch area/total landscape area
	Physical Connectivity (CONNECT)	Fragstats 4.2	Number of actual connec-tions/number of possible connections
	Landscape Heterogeneity (SHDI))	Fragstats 4.2	Shannon diversity index for-mula
Spatial Networks (POI & OSM)	Ecological Recovery Efficiency	Remote sensing sta-tistical ratio	$(V_t - V_{t-1})/V_{t-1}$ (V:FVC/NPP)
	Healthcare Accessibility	GIS network analysis (Drive time)	Summary of data-processing methods and key parameters
	Fire Service Responsiveness	GIS network analysis (Drive time)	Thresholds: 4, 8, and 12 min; Speeds: 100/70/25 km·h ⁻¹
	Heat-Relief Facility Accessibility	GIS network analysis (Walk time)	Thresholds: 5, 10, and 15 min; Speed: 1.3 m·s ⁻¹
	Emergency Shelter Accessibility	GIS network analysis (Walk time)	Thresholds: 10 and 20 min; Speed: 1.5 m·s ⁻¹

Table A7. Comparison of annual resilience scores for the 13 districts and counties of Xi'an under the CRITIC and EWM methods.

District/County	Weighting Method	2018	2019	2020	2021	2022	2023	Average
Xincheng	CRITIC	0.515	0.457	0.510	0.609	0.528	0.513	0.522
	EWM	0.512	0.443	0.505	0.598	0.521	0.515	0.516
Beilin	CRITIC	0.616	0.575	0.526	0.606	0.596	0.580	0.583
	EWM	0.608	0.552	0.518	0.592	0.585	0.572	0.571
Lianhu	CRITIC	0.495	0.498	0.446	0.501	0.452	0.449	0.474
	EWM	0.491	0.485	0.432	0.496	0.444	0.455	0.467
Baqiao	CRITIC	0.455	0.425	0.311	0.403	0.361	0.383	0.390

Weiyang	EWM	0.461	0.418	0.302	0.395	0.355	0.391	0.387
	CRITIC	0.462	0.466	0.376	0.408	0.379	0.482	0.429
Yanta	EWM	0.455	0.458	0.365	0.398	0.368	0.476	0.420
	CRITIC	0.497	0.466	0.450	0.566	0.519	0.515	0.502
Yanliang	EWM	0.488	0.452	0.438	0.551	0.505	0.509	0.491
	CRITIC	0.405	0.384	0.428	0.395	0.414	0.406	0.405
Lintong	EWM	0.395	0.371	0.415	0.380	0.402	0.398	0.394
	CRITIC	0.468	0.412	0.477	0.425	0.388	0.417	0.431
Changan	EWM	0.472	0.405	0.485	0.431	0.395	0.428	0.436
	CRITIC	0.427	0.384	0.294	0.348	0.304	0.319	0.346
Gaoling	EWM	0.435	0.391	0.285	0.342	0.315	0.320	0.348
	CRITIC	0.358	0.357	0.409	0.355	0.352	0.354	0.364
Huyi	EWM	0.342	0.341	0.398	0.342	0.338	0.342	0.351
	CRITIC	0.335	0.318	0.331	0.304	0.310	0.346	0.324
Lantian	EWM	0.328	0.310	0.325	0.298	0.305	0.338	0.317
	CRITIC	0.426	0.365	0.405	0.410	0.364	0.430	0.400
Zhouzhi	EWM	0.418	0.355	0.398	0.402	0.358	0.422	0.392
	CRITIC	0.329	0.336	0.346	0.347	0.365	0.363	0.348
Citywide Average	EWM	0.320	0.325	0.335	0.338	0.352	0.355	0.338
	CRITIC	0.443	0.416	0.409	0.449	0.422	0.435	0.429
	EWM	0.435	0.402	0.398	0.441	0.415	0.428	0.420

Note: Correlation analysis shows that the resilience ranking results derived from the two weighting methods demonstrate strong consistency (Spearman's rank correlation coefficient $\rho = 0.941$, $p < 0.001$).

Appendix B

Table A8. Sources and decomposition of differences.

Year	Overall Gin	Intra-Group Gini (Gw)	Inter-Group Gini (Gb)	Transvariation Component (Gt)	Intra-Group Contribution (%)	Inter-Group Contribution (%)	Transvariation Contribution (%)
2018	0.095	0.02	0.072	0.003	21.138%	75.850%	3.012%
2019	0.093	0.016	0.076	0.001	17.286%	82.469%	0.246%
2020	0.1	0.032	0.039	0.029	31.887%	38.927%	29.186%
2021	0.122	0.029	0.088	0.005	24.112%	71.886%	4.002%
2022	0.113	0.031	0.073	0.008	27.709%	65.035%	7.256%
2023	0.099	0.024	0.065	0.009	24.244%	66.317%	9.439%
Average	0.104	0.025	0.069	0.009	24.396%	66.747%	8.857%

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