Spatiotemporal Evolution Characteristics and Development Trend Prediction of Urban Resilience in the Urban Agglomeration on the Northern Slope of the Tianshan Mountains: Postprint

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Abstract

Urban resilience construction in urban agglomerations has emerged as a focal topic in urban risk governance research. Employing panel data from 15 cities in the Tianshan North Slope Urban Agglomeration for the period 2010–2022, this study constructs an urban resilience evaluation index system based on the DPSR model from a dynamic perspective, encompassing four dimensions: "driving force-pressure-state-response". The entropy method and kernel density analysis are utilized to examine spatio-temporal evolution characteristics of urban resilience, the geographical detector is applied to identify key influencing factors, and a grey prediction model is employed to forecast future development trends. The findings reveal that: (1) Urban resilience in the Tianshan North Slope Urban Agglomeration exhibited significant improvement from 2010 to 2022, establishing a "core-periphery" spatial pattern with western Urumqi City as a high-resilience core and the urban agglomeration periphery as low-resilience areas; (2) Disturbance response capability represents the most significant determinant of urban resilience, with the influence of environmental regulation and ecological pollution gradually intensifying over time; (3) The "core-periphery" spatial distribution pattern of urban resilience in the Tianshan North Slope Urban Agglomeration will be further consolidated during 2023–2027, exacerbating inter-regional development imbalances. These research findings can provide theoretical guidance for development planning and resilience enhancement in the Tianshan North Slope Urban Agglomeration, thereby strengthening urban adaptive capacity, recovery capacity, and sustainable development capability in the face of various disturbances.

Full Text

Spatio-temporal Evolution Characteristics and Development Trend Prediction of Urban Resilience in the Urban Agglomeration on the Northern Slope of the Tianshan Mountains

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Abstract: The construction of urban resilience in urban agglomerations has emerged as a critical focus in urban risk governance research. This study employs panel data from 15 cities within the urban agglomeration on the northern slope of the Tianshan Mountains in Xinjiang, China, spanning 2010 to 2022. Grounded in the DPSR (Driving force-Pressure-State-Response) model, we construct a dynamic urban resilience evaluation index system encompassing four dimensions. The entropy method and kernel density estimation are utilized to analyze the spatio-temporal evolution characteristics of urban resilience. Geographical detectors are employed to explore the primary influencing factors, while a grey prediction model forecasts future development trends. The results reveal that: (1) From 2010 to 2022, urban resilience in the Tianshan Mountains northern slope urban agglomeration improved significantly, forming a distinct "core-edge" spatial pattern. The western region of Urumqi City has evolved into a high-resilience zone, while peripheral areas exhibit lower resilience. (2) The response system consistently demonstrates the most substantial influence on urban resilience. Over time, the impact of environmental regulation and ecological pollution indicators has gradually intensified. Specifically, the total production value of large-scale industrial enterprises, carbon dioxide emissions, the number of utility model patents, the digital financial inclusion index, and general public budget expenditures exert strong long-term effects on urban resilience. (3) Dynamic predictions for 2027 indicate that urban resilience will continue to improve significantly, with steady growth across all cities in the agglomeration. Spatially, Urumqi will maintain its leading position, further widening regional disparities and reinforcing the "core-edge" pattern. These findings provide theoretical references for development planning and resilience enhancement in the Tianshan Mountains northern slope urban agglomeration, thereby strengthening cities' capacities to adapt to, recover from, and sustainably develop in the face of various disturbances.

Keywords: urban resilience; DPSR model; spatio-temporal evolution; grey prediction model; urban agglomeration on the northern slope of the Tianshan Mountains

1 Study Area Overview

The urban agglomeration on the northern slope of the Tianshan Mountains is located in the hinterland of the Eurasian continent, along the southern margin of the Junggar Basin. It covers approximately 25% of Xinjiang' s total area and houses over half of the region' s urban population. As Xinjiang' s most economically developed area, it generates more than 50% of the region' s GDP. Currently, supported by favorable policies and geographical advantages, cities within this agglomeration are accelerating development, with continuous improvements in transportation infrastructure, optimized industrial chains, and advancing ecological governance, playing a crucial role in driving, radiating, and demonstrating development across Xinjiang.

Based on data availability, this study encompasses 15 cities and counties: Urumqi City, Shihezi City, Kuitun City, Wusu City, Shawan City, Karamay City, Turpan City, Changji City, Fukang City, Mori Kazakh Autonomous County, Hutubi County, Wujiaqu City, Manas County, Qitai County, and Jimsar County [Figure 1: see original paper].

2 Data and Methods

2.1 Indicator System Construction

Drawing upon existing research and considering the actual development conditions of the Tianshan Mountains northern slope urban agglomeration, we construct an urban resilience evaluation index system from four DPSR dimensions: Driving force, Pressure, State, and Response. Driving force represents the fundamental factors that generate disturbances in urban systems, primarily related to urban development indicators. We examine this dimension through economic growth, infrastructure development, and population dynamics. Pressure refers to direct threats and negative impacts on urban systems and functions. Given that this urban agglomeration lies in arid and semi-arid regions with fragile ecological environments, we assess pressure from ecological, resource, and population perspectives. State reflects the current condition of urban systems, encompassing economic, social, ecological, and infrastructure aspects, evaluated through industrial structure, social status, and ecological conditions. Response indicates the capacity of urban systems to cope with disturbances, examined through environmental governance and social governance capabilities. The complete indicator system comprises 24 specific metrics across the four dimensions .

2.2 Data Sources

Economic, infrastructure, and population panel data were primarily obtained from the *Xinjiang Statistical Yearbook* (2011-2023), *China County Construction Statistical Yearbook* (2011-2023), *China County Statistical Yearbook* (2011-2023), *National Economic and Social Development Statistical Bulletin* (2010-

2022), and *Xinjiang Survey Yearbook* (2011-2023). Normalized Difference Vegetation Index (NDVI) data were sourced from the National Earth System Science Data Center. Annual average precipitation data were obtained from the European Centre for Medium-Range Weather Forecasts. PM2.5 data were acquired from the Atmospheric Composition Analysis Group at Washington University in St. Louis. Digital financial inclusion index data came from the Peking University Digital Finance Research Center. Missing data were supplemented using linear interpolation and adjacent point linear trend methods, with raw data accounting for 92% of the total dataset.

2.3 Research Methods

2.3.1 Entropy Method The entropy method avoids subjective bias in weight assignment while improving evaluation accuracy through correlation analysis. We employ this method to calculate indicator weights for urban resilience in the study area.

First, indicators undergo range standardization:

For positive indicators:

$$y_{ij} = \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})} + 0.0001$$

For negative indicators:

$$y_{ij} = \frac{\max(X_{ij}) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})} + 0.0001$$

where y_{ij} is the standardized value, i represents the year ($i = 2010, 2011, \cdots, 2022$), j represents the j-th indicator ($j = 1, 2, 3, \cdots, 24$), and X_{ij} is the original data for indicator j in year i.

Next, calculate the proportion of indicator j in region i:

$$Z_{ij} = \frac{y_{ij}}{\sum_{i=1}^{n} y_{ij}}$$

Then compute the information entropy e_j:

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} Z_{ij} \times \ln(Z_{ij})$$

Calculate information entropy redundancy d_j:

$$d_j = 1 - e_j$$

Determine indicator weights W_j:

$$W_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$$

Finally, measure the comprehensive urban resilience evaluation value Y:

$$Y = \sum_{j=1}^{m} W_j \times y_{ij}$$

2.3.2 Kernel Density Analysis Kernel density estimation effectively reflects the distance decay effect of geographical phenomena in space. We employ this method to analyze the spatial distribution and aggregation patterns of urban resilience evaluation values [Figure 5: see original paper].

The kernel density estimator is calculated as:

$$f_n(x) = \frac{1}{nh_n} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h_n}\right)$$

where $f_n(x)$ is the kernel density estimate, n is the number of basic research units, h_n is the bandwidth (ArcGIS software default), K is the kernel function, and x_i is the distance from the estimation point to point i within the bandwidth range.

2.3.3 Geographical Detector We utilize the optimal geographical detector model to explore the internal driving factors influencing urban resilience. The factor detection formula is:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

where q measures the influence strength of factors on urban resilience spatial distribution (range [0,1]), with larger values indicating greater impact. Y represents the urban resilience evaluation value, h is the indicator classification ($h = 1, 2, 3, \cdots, L$, with optimal geographical parameter methods used for classification), N_h is the number of urban resilience evaluation indicators in class h, σ_h^2 is the variance of class h, N is the total number of research units, and σ^2 is the variance of Y.

2.3.4 Grey Prediction Model The GM(1,1) grey prediction model is suitable for small-sample, information-poor datasets, requiring no specific distribution assumptions while offering high prediction accuracy and broad applicability, though its long-term predictive capacity is limited. We predict urban resilience trends for 2027 using this model, which involves constructing non-negative sequences, calculating grade ratios, building data matrices, solving for development coefficients and grey action quantities, and generating predictions.

Model accuracy is validated through posterior variance ratio (C) and average relative error tests. All C values are less than 0.5, indicating high prediction precision, while average relative errors below 0.3 demonstrate good model fit .

3 Results and Analysis

3.1 Urban Resilience Evaluation Results

Urban resilience evaluation values in the Tianshan Mountains northern slope urban agglomeration range from 0.23 to 0.61, showing an overall "ascending-fluctuating-ascending" trend with a peak in 2021 [Figure 2: see original paper]. The COVID-19 outbreak in early 2020 significantly impacted the region, disrupting metabolic flows, governance networks, infrastructure, and capital flows, causing a temporary resilience decline. However, subsequent recovery demonstrates considerable self-restoration capacity when facing public health emergencies.

The coefficient of variation remains relatively stable, indicating consistent inter-city resilience differences throughout the study period. Skewness coefficients between 1.41 and 3.26 reveal substantial fluctuations in high-resilience areas, with numbers first decreasing then increasing. Kurtosis coefficients ranging from 1.48 to 11.68 show that extreme differences were pronounced in 2010 and 2015, with similar resilience values clustering spatially, a pattern that only gradually diminished after 2020.

Urumqi City exhibits significantly higher resilience than other cities, reflecting its polarizing status as Xinjiang' s capital with strong resource aggregation capacity. Other cities show resilience values between 0.23 and 0.45, substantially lagging behind Urumqi. All cities demonstrated noticeable growth from 2010 to 2022, with Urumqi recording the largest increase (114.75%) and Wujiaqu City the smallest (27.86%), highlighting uneven development and substantial regional disparities [Figure 3: see original paper].

3.2 Temporal Evolution Characteristics of Urban Resilience Subsystems

Box plots illustrate temporal trends across four subsystems. For driving force [Figure 4a: see original paper], median values consistently fall below means with high outliers in most years, indicating an unbalanced "low-value cluster" characteristic. Although the box gradually rises, suggesting slow improvement, the 2020 COVID-19 shock abruptly shortened the box and lowered medians and means, particularly affecting high-driving-force cities.

For pressure [Figure 4b: see original paper], means remain near medians with minimal change, showing no significant pressure intensification. The box first narrows then widens, indicating pressure data follows a normal distribution with differences first decreasing then increasing, likely related to varying pressure sources and development plans across cities.

For state [Figure 4c: see original paper], the box shows small size variations, indicating reduced data dispersion over time. The median exhibits stage-wise improvement, demonstrating gradual enhancement of urban conditions. For response [Figure 4d: see original paper], the box shows stage-wise growth with medians in the lower-middle portion and means substantially higher than medians, indicating overall improvement in disturbance response capacity but increasing data dispersion and widening gaps between cities' disaster response capabilities.

Overall urban resilience [Figure 4e: see original paper] shows medians consistently in the lower-middle position, confirming that low-resilience cities dominate the agglomeration—a characteristic unchanged by development. The persistence of outliers in most years reflects unbalanced and uncoordinated development, with Urumqi and a few high-resilience cities holding important positions in regional planning.

3.3 Spatial Evolution Characteristics of Urban Resilience

Kernel density maps generated from 2010, 2015, 2020, and 2022 data reveal a clear "core-edge" macro-pattern [Figure 5: see original paper]. High-value zones concentrate in the central-western region, diffusing outward in wave-like patterns with significant regional differences. Low-value zones distribute around the periphery, forming a "west-high-east-low" pattern, with Turpan City consistently in low-value areas.

From 2010 to 2022, spatial patterns show stage-wise convergence, with high-resilience areas increasingly concentrating in Urumqi before gradually diffusing after 2015. Urumqi and Shihezi City, as high-resilience centers, radiate outward in concentric circles, while low-resilience areas remain widespread at the edges. These spatial disparities primarily stem from locational differences—Urumqi and Shihezi possess strong resource aggregation, developed industrial chains, and abundant resources, establishing them as Xinjiang' s economic core with relatively robust resilience.

3.4 Influencing Factors of Urban Resilience

Geographical detector analysis identifies key driving factors . The response system consistently shows the strongest influence, with its impact concentrating over time. By 2022, environmental regulation and ecological pollution indicators' influence began strengthening. Specifically, total production value of large-scale industrial enterprises, carbon dioxide emissions, utility model patents, digital financial inclusion index, and general public budget expenditures demonstrate strong long-term effects.

In 2010 and 2015, the top ten influencing factors showed similar impact levels.

By 2020, influence began concentrating in the response system. By 2022, impact was no longer limited to the response system alone, with environmental regulation and ecological pollution indicators gaining prominence. This shift likely reflects increasing environmental pressures and resource constraints in this arid/semi-arid region as urban development progresses.

3.5 Predictive Analysis of Urban Resilience Development

Grey model predictions indicate that by 2027, urban resilience across the agglomeration will show significant improvement with steady growth in all cities . Spatially, Urumqi will maintain its leading position, with regional disparities further widening. The "core-edge" pattern will become more entrenched, and the "polarization" effect will intensify [Figure 6: see original paper].

While enhanced resilience strengthens individual cities' disaster resistance, excessive inter-regional disparities may weaken collaborative risk resistance capacity. Therefore, strengthening inter-regional connections and leveraging Urumqi' s radiating leadership will be crucial for future resilience enhancement.

4 Discussion

Urban resilience theory has evolved from single equilibrium to multiple equilibrium and finally to dynamic non-equilibrium states, moving beyond the concept of resilience as mere "bouncing back." While some scholars emphasize "specific resilience" to known risks, ecological researchers highlight the importance of "general resilience" to unforeseen threats—both being equally important without sacrificing one for the other.

This study measures urban resilience through the dynamic DPSR framework, considering the ecological characteristics of the Tianshan Mountains northern slope urban agglomeration and its ten major industrial clusters. This approach advances resilience measurement but remains imperfect. The current "core-edge" spatial pattern with unbalanced development aligns with findings from other Chinese urban agglomerations. As a metropolitan region union, this agglomeration should avoid "short-board effects" that undermine overall resilience. Learning from international experiences—such as promoting inter-city division of labor, upgrading transportation networks, and enhancing central city' s radiating effects—can improve overall development and resilience.

The strengthening influence of environmental regulation and ecological pollution indicators likely reflects development pressures exceeding environmental carrying capacity. Future planning should incorporate more environmental factors to achieve sustainable development. While the DPSR-based evaluation offers innovation over traditional static assessments, limitations remain in fully capturing historical change patterns and resilience evolution laws.

5 Conclusions

This study reveals three key findings: (1) From 2010 to 2022, urban resilience in the Tianshan Mountains northern slope urban agglomeration improved significantly but with substantial regional disparities. The "core-edge" pattern is pronounced, with Urumqi in a persistent polarizing position and low-resilience areas widespread. Subsystem analysis shows slowly improving but highly variable driving forces; pressure levels remain stable but with increasing inter-city differences; states show stable, gradual improvement; and response capacities have improved overall but with widening gaps between cities.

(2) The response system consistently exerts the strongest influence on resilience, with environmental regulation and ecological pollution indicators gaining importance over time. Key metrics including industrial production value, CO_2 emissions, patents, digital financial inclusion, and public budget expenditures strongly affect resilience.

(3) Predictions for 2027 indicate continued robust growth in urban resilience across the agglomeration. Spatially, Urumqi' s dominance will persist, regional disparities will widen, and the "core-edge" pattern will strengthen. Enhancing inter-regional connectivity and leveraging Urumqi's leading role will be essential for balanced resilience improvement.

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Note: Figure translations are in progress. See original paper for figures.