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SPATIOTEMPORAL EVOLUTION AND REGIONAL DIFFERENCES OF URBAN ECOLOGICAL RESILIENCE IN THE MIDDLE YANGTZE RIVER CITY CLUSTER

Abstract: This study evaluates the spatio-temporal evolution and regional disparities of urban ecological resilience (UER) in the middle Yangtze River city cluster (MYR city cluster) from 2010 to 2022. Based on a “resistance-adaptability-restoration” framework, we construct a multi-indicator evaluation model and apply the entropy weight method to measure resilience levels. Spatial autocorrelation analysis (*Moran’s I* and LISA) identifies clustering patterns, while Markov chains and Dagum’s Gini coefficient reveal dynamic transitions and regional differences. Finally, the geodetector method is used to explore influencing factors. Results show that overall UER has improved, with restoration surpassing resistance and adaptability, though fluctuations remain. Spatially, high-value clusters are concentrated in the Poyang Lake area, while low-value clusters are located in the Wuhan City Circle, with evident “club convergence” and path dependence. Regional disparities in UER are narrowing, but intra-regional imbalance persists, especially in the Wuhan City Circle and Changzhutan City Cluster. Precipitation, topographic relief, and investment in pollution control emerge as the dominant drivers, with interactive effects stronger than single-factor influences. Policy recommendations include strengthening ecological compensation, tailoring resilience-building strategies to geographic conditions, and enhancing cross-regional governance. These findings offer direct scientific support for ecological engineering decisions and pollution-control planning in the MYR city cluster, thereby contributing to sustainable development and ecological management in the Yangtze River Economic Belt.

Keywords: urban ecological resilience, influencing factors, geodetector, regional differences

Introduction

Amidst rapid industrialisation and urbanisation, urban development faces mounting pressures from environmental pollution, resource scarcity, and ecological degradation [1]. Enhancing urban ecological resilience (UER) is thus central to achieving sustainable development [2]. As a core area for implementing the Yangtze River Economic Belt’s strategy of “stepping up conservation of the Yangtze River and stopping its overdevelopment”, improving UER in the middle Yangtze River city cluster (MYR city cluster) is crucial for safeguarding regional ecological security and fostering coordinated development.

The concept of resilience was initially introduced in ecology by ecologist Holling, who posited that ecological resilience is the dynamic capacity of an ecosystem to autonomously

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absorb, maintain, and restore equilibrium following a transient or abrupt disturbance [3]. Research has since expanded, refining definitions, assessment methods, and enhancement strategies [4-6]. Chinese scholars have gradually expanded their research from theoretical discussions [7-9] to empirical analyses [10-12]. However, focused research on the MYR city cluster remains limited and lacks an integrated methodology. For instance, while Lu et al. [13] assessed the spatiotemporal evolution of UER in the Yellow River Basin, they did not quantify the interactive effects among driving factors. Similarly, Huang et al. [9] examined UER dynamics within the Shandong peninsula urban agglomeration, but neither adopted a cross-provincial cluster perspective nor explored driver interactions. Though recent integrated frameworks represent progress [12, 14], a systematic study of the multi-provincial MYR city cluster - combining spatial pattern analysis, dynamic transition modelling, inequality measurement, and interactive factor detection - is still needed.

Therefore, this study constructs a UER evaluation model for the MYR city cluster based on a “resistance-adaptability-restoration” framework. We systematically analyse the spatio-temporal evolution, regional differences, and influencing factors of UER using spatial autocorrelation, Markov chains, Dagum’s Gini coefficient, and Geodetector. This integrated approach yields scientific insights that transcend a mere regional case study, as it separates the spatial, temporal, and structural dimensions of resilience while quantifying how drivers interact to shape these outcomes. By shifting from descriptive assessment to diagnostic analysis, this study identifies precise intervention points, thereby offering an evidence-based foundation for targeted ecological engineering and pollution-control planning in the region.

Theoretical elaboration and research methods

Research area

The MYR city cluster spans around 317,000 km², comprising three principal regions: the Wuhan City Circle, the Changzhutan City Cluster, and the Poyang Lake City Cluster, which was the first giant cross-provincial state-level city cluster sanctioned by China in 2015. The Wuhan City Circle comprises Wuhan, Huangshi, Ezhou, Huanggang, Xiaogan, Xianning, Xiangyang, Yichang, Jingzhou, Jingmen, Xiantao, Qianjiang, and Tianmen. The Changzhutan City Cluster includes Changsha, Zhuzhou, Xiangtan, Yueyang, Yiyang, Changde, Hengyang, and Loudi. The Poyang Lake City Cluster consists of Nanchang, Jiujiang, Yichun, Pingxiang, Shangrao, Jingdezhen, Yingtan, Xinyu, Fuzhou, and Ji’an (Fig. 1). As a significant component of the Yangtze River Economic Belt, the MYR city cluster, is strategically situated to evolve into a highly influential ecological city cluster, characterised by its intricate terrain and over 80 % vegetation cover. To further this objective, the Chinese government has implemented various initiatives, including the ‘Plan for the Development of the MYR City Cluster’ and the ‘14th Five-Year Plan for the Development of the MYR City Cluster’. The application of these policies has enabled the MYR city cluster to achieve significant advancements in UER, thereby establishing a robust foundation for sustainable development in the region.

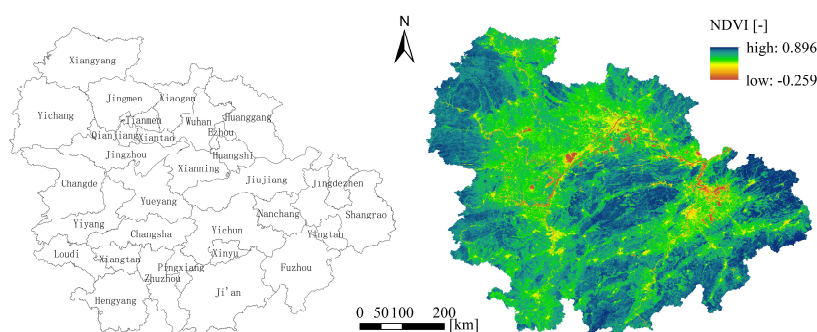


Fig. 1. Overview of the study area

Scientific content and indicator system

Theoretical logic of UER

UER extends from the concept of ecological resilience [3], which has since evolved within social-ecological systems to encompass three core capacities: the ability to resist (withstand initial disturbances), adapt (adjust to ongoing stresses), and restore (recover functionality after shocks) [6]. Synthesising this view, we conceptualise UER as the synergistic integration of these three dimensions, encapsulating the overall capacity of urban ecosystems to withstand and recuperate from external threats and disruptions [15]. This framing acknowledges that UER varies spatially due to differences in cities' ecological resource endowments and manifests through complex spatio-temporal patterns influenced by multiple drivers. Consequently, capturing such complexity necessitates a multi-dimensional assessment approach, where evaluating resilience through structured, multi-indicator systems becomes essential not only for measurement but also for informing urban sustainability planning [16].

An evaluation model for UER

Building upon the theoretical framework outlined above, this study operationalises UER by focusing on environmental indicators, supported by key socioeconomic proxies. This scoping choice serves to prioritise the foundational ecological constraints and carrying capacity of the MYR city cluster, aligning with its conservation goals. Guided by the “resistance-adaptability-restoration” framework and the principles of objectivity, representativeness, and data availability, this study constructs a multidimensional evaluation system comprising 14 indicators (see Table S1 in the Supplementary Materials). The resistance dimension employs pressure-based proxies, measured by population density, construction land area per unit gross domestic product (GDP) [17], and the emissions of industrial ‘three wastes’ per unit of GDP [13]. These three industrial waste metrics are retained as separate indicators to preserve their distinct pollution pathways and potential differential impacts on ecosystem stress, thereby avoiding the loss of diagnostic specificity. The adaptability dimension is evaluated through management-efficiency metrics: the air quality excellence rate [18], alongside the treatment rates of domestic waste and sewage, and the comprehensive utilisation rate of general industrial solid waste [19]. The restoration

dimension is assessed via ecological endowment and investment, including per capita water resources, per capita park green space [20], the ratio of energy conservation and environmental protection expenditure [21], and two complementary green space metrics - the green coverage rate (for climate regulation) and the green space ratio (for biodiverse infrastructure) of built-up areas [9].

Data sources and processing

This study focuses on the 28 prefecture-level cities in the MYR city cluster, excluding Xiantao, Tianmen, and Qianjiang due to their significant data deficiencies, covering the period from 2010 to 2022. The data primarily originates from the 2010-2023 China Statistical Yearbook, the China Environmental Statistical Yearbook, and the statistical yearbooks of individual municipal governments, etc. Some missing data in the study are supplemented by employing the method of approximating the difference between adjacent years.

Research methods

Entropy weight method

This study uses the entropy weight approach to assess UER in the MYR city cluster. This method objectively determines indicator weights based on information entropy, thereby mitigating the subjective bias of traditional methods and enhancing the objectivity of the results [22]. The procedure consists of data normalisation, entropy calculation, and weight determination. First, raw indicator values were normalised to a comparable scale [0,1]. For a positive indicator (where a larger value indicates better resilience) and a negative indicator (e.g., industrial waste emissions per unit GDP, where a larger value is worse), the normalised values r_{ij} are calculated using min-max normalisation. For a positive indicator:

$$r_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (1)$$

and for a negative indicator:

$$r_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (2)$$

where x_{ij} is the original value of indicator j for city i , and $\max(x_j)$ and $\min(x_j)$ are the maximum and minimum value of indicator j across all cities, respectively.

Subsequently, the information entropy e_j and final weight w_j for each indicator j are calculated:

$$e_j = -\frac{\sum_{i=1}^m p_{ij} \ln p_{ij}}{\ln m}, \text{ with } p_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}} \quad (3)$$

$$w_j = \frac{1 - e_j}{\sum_{j=1}^n (1 - e_j)} \quad (4)$$

Where $m = 28$ (cities) and $n = 14$ (indicators). A smaller entropy e_j yields a larger weight w_j , reflecting the indicator's greater discriminatory power in the evaluation.

Spatial autocorrelation

Spatial autocorrelation is analysed using both *Global Moran's I* and *Local Moran's I*. *Global Moran's I* is calculated as:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (5)$$

and *Local Moran's I* for unit i is:

$$I_i = \frac{(x_i - \bar{x})}{\frac{1}{n} \sum_i (x_i - \bar{x})^2} \sum_j w_{ij} (x_j - \bar{x}) \quad (6)$$

where $n = 28$ (cities), x_i and x_j represent the UER values for cities i and j respectively, $\bar{x}$ is the mean of UER, and w_{ij} is the spatial weight. In this study, *Global Moran's I* assessed the overall spatial dependence of UER in the MYR city cluster, while *Local Moran's I* identified local spatial clusters and outliers. A row-standardised rook contiguity weight matrix was constructed (neighbouring cities = 1, otherwise 0). Robustness was confirmed using an alternative queen matrix. The calculations follow the established methodology in [23].

Markov chains

The dynamics of UER are analysed using Markov chains. Utilising this method models the probability of a city's UER state transitioning between discrete types over time. Under the Markov assumption that the future state depends only on the present state. The resulting transition probability matrix was used to identify stability and "club convergence" patterns within the MYR city cluster. An upward (or downward) transfer is defined as an increase (or decrease) in a city's UER type between two time points. The specific calculation of transition probabilities follows the established methodology in reference [24].

Dagum's Gini coefficient

This study employed the Dagum Gini coefficient decomposition to examine the spatial disparities in UER across the three major sub-regions of the MYR city cluster: the Wuhan City Circle, Changzhutan City Cluster, and Poyang Lake City Cluster. As a traditional yet robust approach for analysing the origins of spatial differentiation, this method effectively decomposes the overall disparity into contributions from intra-regional differences, inter-regional differences, and transvariation intensity, while rigorously addressing the issue of overlapping samples between subgroups. The detailed calculations follow the established methodology in reference [25].

Geodetector

We applied the Geodetector model, a statistical tool based on the principle of spatial stratification heterogeneity, to identify the driving factors of UER in the MYR city cluster. This method assesses the similarity of spatial distributions between dependent and independent variables. We utilised its factor detector to quantify the individual explanatory power (q -value) of each determinant, and the interaction detector to reveal the interplay between factor pairs. The detailed computational procedures are provided in reference [26].

Methodological comparison

A systematic comparison of the four methods is presented (Table 1) to enhance the clarity and rigour of the methodological approach.

Table 1
Summary and comparison of the research methods

Methods	Core function	Rationale	Exemplary applications
Spatial autocorrelation	Identifies spatial clustering patterns of UER	Serves as a diagnostic tool to reveal both global spatial dependence and local clusters (e.g., HH, LL)	[27]
Markov chains	Reveals dynamic transitions and evolution trends of UER	Captures the stability and transition probabilities of resilience states, dynamics that traditional time-series models may not fully capture	[28]
Dagum's Gini coefficient	Decomposes sources of regional disparity in UER	Attributes disparity to its sources (intra-regional, inter-regional, transvariation), solving the overlapping subgroup contributions issue present in the traditional Gini	[29]
Geodetector	Detects drivers and their interactions on UER heterogeneity	Identifies key influencing factors and quantifies their interactive effects, operating without the linearity assumptions required by many conventional models	[30]

The multi-method approach forms a complementary analytical framework, leveraging spatial autocorrelation and Markov chains to decipher the spatiotemporal evolution of UER. At the same time, Dagum's Gini coefficient and Geodetector quantify regional disparities and underlying drivers, respectively. This integrated method effectively connects spatial patterns with their underlying mechanisms.

Assessment and evaluation of UER in the MYR city cluster

Assessment of resilience levels

UER in the MYR city cluster, assessed using the entropy weight method, exhibited a dynamic "fluctuation-rebound" trajectory from 2010 to 2022, with a net increase of 8.50 % over the study period (Fig. 2; for detailed annual values, see Table S2 in the Supplementary Materials).

Analysis of the three underlying dimensions reveals divergent trends that explain the overall trajectory (Fig. 2). The resistance dimension demonstrated a consistent, monotonic increase, reflecting the cumulative benefits of long-term environmental governance. In contrast, the restoration capacity was the most volatile component, whose fluctuations closely mirrored those of the composite UER index. This strong correlation suggests that restoration is the primary driver of the short-term dynamics in overall resilience. Meanwhile, the adaptability dimension experienced a gradual decline, indicating persistent challenges in adjusting socio-economic structures to mitigate environmental pressures. The convergence of these trends—specifically, the robust growth in resistance and the overall recovery of restoration—ultimately resulted in the observed net increase in the composite UER index, despite the headwind from declining adaptability.

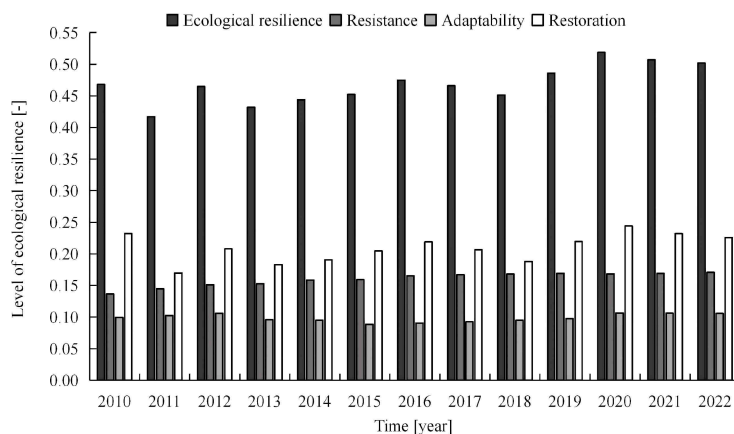


Fig. 2. UER and three-dimensional temporal evolution in the MYR city cluster

Spatio-temporal evolutionary features

Global spatial autocorrelation analysis reveals a significant and strengthening clustering pattern of UER in the MYR city cluster from 2010 to 2022. As shown in Table 2, all *Moran's I* values are statistically significant ($p < 0.05$), confirming a non-random distribution. The index increased substantially from 0.354 in 2010 to 0.587 in 2022, indicating a considerable reinforcement of spatial dependence. This upward trend signifies that spatial interactions in ecological resilience among cities have become progressively more pronounced.

Table 2

Global Moran's index of UER in the MYR city cluster

Years	<i>Moran's I</i>	z-value	p-value
2010	0.354	3.114	0.001
2011	0.243	2.237	0.013
2012	0.412	3.627	0.000
2013	0.385	3.393	0.000
2014	0.361	3.210	0.001
2015	0.384	3.385	0.000
2016	0.241	2.230	0.013
2017	0.229	2.138	0.016
2018	0.302	2.705	0.003
2019	0.534	4.601	0.000
2020	0.315	2.813	0.002
2021	0.510	4.370	0.000
2022	0.587	4.980	0.000

This trend manifests at the local scale as a distinct spatial polarisation pattern, as shown in the LISA cluster maps (Fig. 3). The results delineate a clear core-periphery structure: the Poyang Lake City Cluster exhibits a persistent High-High (H-H) agglomeration, while the core area of the Wuhan City Circle is characterised by a concentrated Low-Low (L-L) agglomeration. In the long term, the most significant spatial

change primarily occurred within sections of the Changzhutan City Cluster, where the spatial extent of the L-L agglomeration expanded noticeably by 2022 compared to its 2010 baseline.

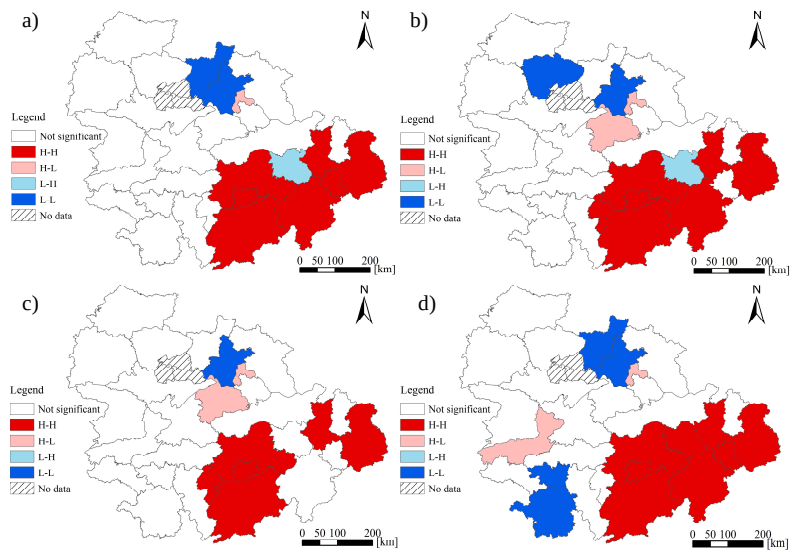


Fig. 3. Spatial agglomeration patterns of UER in the MYR city cluster in: a) 2010, b) 2014, c) 2018, and d) 2022

The coexistence of strengthening global autocorrelation and persistent local clustering patterns signifies an ongoing process of spatial polarisation. The dominance and spatial evolution of the H-H and L-L clusters suggest that positive spatial spillover effects occur primarily among cities with similar resilience levels, thereby exacerbating regional disparities. This polarisation underscores that UER management necessitates regional coordination to address both the self-reinforcing advantages of high-resilience cores and the developmental constraints within low-resilience areas, highlighting the critical need for targeted governance strategies that transcend individual city boundaries.

Dynamic evolutionary pattern

This study employs Markov chain analysis to examine the dynamic evolution of UER in the MYR city cluster. The period was segmented into three successive sub-periods, and UER was categorised into four types using the quartile method: lower level (Type I), low level (Type II), high level (Type III), higher level (Type IV), an approach that ensures balanced group sizes and clarifies distributional tails (Table 3). This design allows us to trace resilience trajectories and transition pathways. Given the limited sample size within transition cells, the derived probabilities are best interpreted as indicative of general patterns of stability and change, rather than precise point estimates.

The results point to three defining features of UER evolution in the MYR city cluster. First, the system exhibits marked stability and a robust pattern of club convergence. This is evidenced not only by the high diagonal probabilities (81.61 % for Type I and 74.07 % for

Type IV) in the full-period matrix, but also by the consistent concentration of cities in similar state distributions across the three sub-periods (see Table 3), indicating strong self-reinforcement at both resilience extremes. Second, a clear path dependence is observed, with transitions occurring almost exclusively between adjacent types and no direct leaps across resilience tiers. Third, despite the prevailing upward trend, non-negligible downward transition probabilities (e.g., 13.10 % from Type II to I) persist throughout the study period and across sub-periods, revealing lingering internal transition risks. These findings underscore that effective resilience management requires targeted interventions to mitigate localised vulnerabilities and reinforce the observed positive regional trajectory.

Table 3

Markov transfer probability matrix for UER in the MYR city cluster [%]

	2010-2014				2014-2018			
Classification	Type I	Type II	Type III	Type IV	Type I	Type II	Type III	Type IV
Type I	90.24	7.32	2.44	0	78.13	21.88	0	0
Type II	20.83	58.33	16.67	4.17	10.34	72.41	17.24	0
Type III	0	22.22	55.56	22.22	0	19.23	61.54	19.23
Type IV	0	10.00	40.00	50.00	0	0	20.00	80.00
	2018-2022				2010-2022			
Classification	Type I	Type II	Type III	Type IV	Type I	Type II	Type III	Type IV
Type I	64.29	28.57	7.14	0	81.61	16.09	2.30	0
Type II	9.68	58.06	32.26	0	13.10	63.10	22.62	1.19
Type III	0	19.35	48.39	32.26	0	20.24	54.76	25.00
Type IV	0	0	11.11	88.89	0	2.47	23.46	74.07

Regional variance analysis

Analysis using Dagum's Gini coefficient decomposition reveals a narrowing of spatial disparities in UER across the MYR city cluster between 2010 and 2022. The overall Gini coefficient declined from 0.113 to 0.096, representing a relative decrease of 15.04 % (Fig. 4). While these absolute values indicate a modest level of inequality, the relative change highlights a meaningful trend toward convergence. This trend is likely attributable to coordinated regional initiatives in resource conservation and environmental management, which have helped mitigate spatial imbalances in ecological resilience.

At the intra-regional level, all three major sub-regions - Wuhan City Circle, Changzhutan City Cluster, and Poyang Lake City Cluster - exhibited declining internal disparities over the study period (Fig. 4). The Poyang Lake City Cluster not only maintained the lowest average Gini coefficient (0.065) but also achieved the most substantial relative decline (45.39 %), indicating significant progress toward balanced internal development. The Wuhan City Circle, while showing improvement (23.30 % decline), retained the highest level of internal inequality (0.085), suggesting a need for continued focus on harmonised development within this sub-region. In this context, regional coordinated development strategies must be reinforced, and inter-city collaboration in the city cluster should be promoted to facilitate the balanced improvement of ecological resilience throughout the cluster, ultimately achieving a comprehensive enhancement of UER in the MYR city cluster.

The Dagum Gini decomposition quantitatively confirms that inter-regional differences are the dominant source of total inequality, contributing 59.59 % - significantly higher than

the contributions from intra-regional differences (23.84 %) and hypervariable density (16.57 %) (Fig. 5). The term “hypervariable density” here refers to the overlapping component of inequality arising from the distributional overlap between regions. This decomposition, alongside the notable disparities in ecological resources, socio-economic context, and growth trajectories among the three principal regions, underpins the observed variations in UER. Consequently, the ecological resilience of each region in the MYR city cluster exhibits a pronounced “gradation” distribution, with the most pronounced inter-regional gap existing between the Wuhan City Circle and the Poyang Lake City Cluster. Addressing these cross-regional disparities should therefore be the priority for achieving coordinated ecological resilience enhancement across the MYR city cluster.

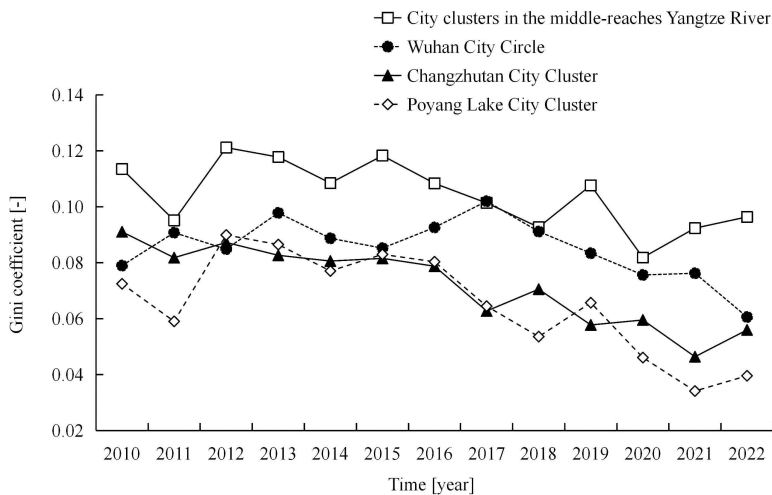


Fig. 4. Temporal trends and intra-regional decomposition of UER disparity in the MYR city cluster

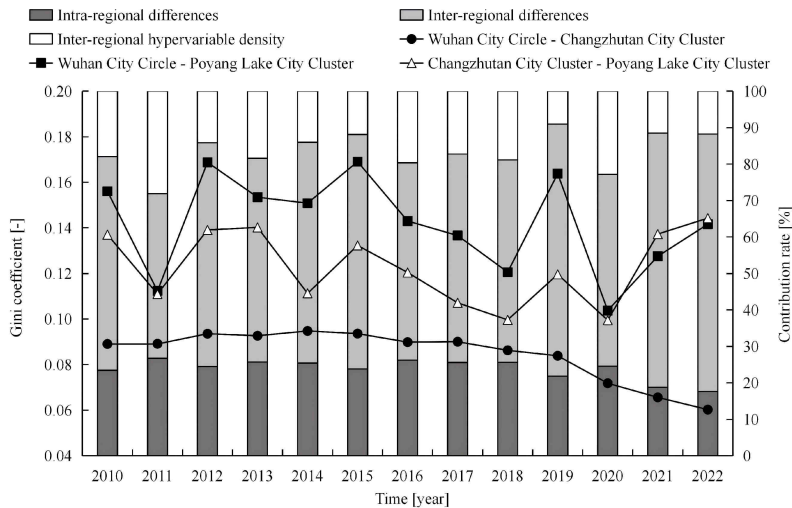


Fig. 5. Dagum's Gini coefficient decomposition of UER inequality in the MYR city cluster

Detection of factors influencing UER in the MYR city cluster

Influencing factor selection

The city is a multifaceted coupled system that integrates natural ecology, human society, economic activities, and additional systems. The ecological subsystem, as the foundation of the urban system, is the initial entity affected by risk. Simultaneously, the feedback loop between ecological subsystems and the interaction of internal elements collectively establish UER, enabling adaptation to and resistance against disturbances [31]. Consequently, based on the study area context and previous research [32, 33], nine indicators were chosen as influencing factors based on geographic, economic, and social dimensions (Table 4).

Table 4

Selected indicators for analysing UER influencing factors in the MYR city cluster

Factor classification	Variable name	Indicator meaning
Geography	Topographical factors	Degree of terrain relief (V_1)
	Vegetation cover	Normalised vegetation index (V_2)
	Water conditions	Annual precipitation (V_3)
Economy	Economic development	Per capita GDP (V_4)
	Open to the outside world	Actual utilisation of foreign capital as a percentage of GDP (V_5)
	Industrial structure	Advanced industrialisation (V_6)
Society	Population size	Total population of the region at the end of the year (V_7)
	Environmental regulation	Investment in environmental pollution control as a share of GDP (V_8)
	Scientific and educational inputs	The sum of fiscal expenditures on science and education (V_9)

Among the influential factor indicators: (1) The geographic dimension is represented by terrain relief, annual precipitation, and the normalised difference vegetation index (NDVI), reflecting topographic constraints, water resource availability, and vegetation cover that directly shape the spatial foundation of UER [32, 34]. (2) The economic dimension includes per capita GDP, foreign capital utilisation, and advanced industrialisation, which furnish the material basis and developmental impetus for urban ecosystem regulation [35]. (3) The social dimension comprises population size, the share of environmental pollution control investment in GDP, and investment in the environment, science, and education. Population size pressures ecological carrying capacity, while strategic investments are pivotal for enhancing resilience through environmental improvement and ecological capital optimisation [36].

Factor detection analysis

Prior to analysis, all continuous influencing factors were discretised using the natural breaks (Jenks) method. We systematically tested stratification levels from $k = 2$ to $k = 8$ for each factor and selected the optimal classification to maximise its q -value, ensuring an effective representation of spatial heterogeneity. This optimised discretisation for factor detection found that annual precipitation (V_3), degree of terrain relief (V_1), and investment in environmental pollution control as a share of GDP (V_8) are the main causes of UER spatial heterogeneity in the MYR city cluster during the study period (see Table S3 in the Supplementary Materials for yearly statistics). These factors consistently demonstrated the

highest q -value, with V_8 showing a fluctuating upward trend in its influence. To assess robustness, a sensitivity analysis using an alternative discretisation method (quantile classification) was conducted. The core results - the dominance of V_1 , V_3 , and V_8 - remained consistent, supporting the reliability of our conclusions despite the sensitivity of high q -values to the limited sample size ($n = 28$ cities).

Interaction detection analysis

To further investigate the synergistic effects among driving factors, we employed interaction detection to evaluate the combined q -value of factor pairs (see Fig. 6).

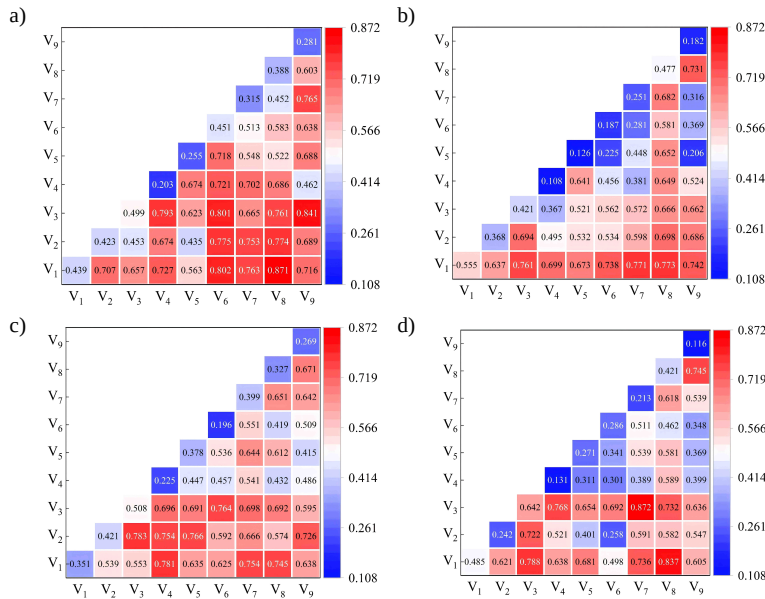


Fig. 6. Factor interaction detection results for UER in the MYR city cluster in: a) 2010, b) 2014, c) 2018, and d) 2022

The results revealed that factor interactions predominantly exhibited two-factor and nonlinear enhancement effects (Fig. 6). Throughout the study period, the degree of terrain relief (V_1) and investment in environmental pollution control as a share of GDP (V_8) emerged as particularly influential, often yielding high joint q -value (e.g., $V_1 \cap V_8$ reached a q -value of 0.837 in 2022). Similarly, annual precipitation (V_3) frequently formed strong interactive effects with other socio-economic factors, such as $V_3 \cap V_7$ ($q = 0.872$ in 2022). These exceptionally high interaction q -values suggest strong synergistic mechanisms; however, as with the single-factor results, their precise magnitude should be considered indicative due to sample size constraints. Overall, these findings underscore that the evolution of UER is not governed by single factors but by complex synergistic interactions, where the combination of geographic constraints and socio-economic investments creates amplified effects on ecological resilience outcomes.

Conclusion

This study developed a multi-indicator evaluation model of UER in the MYR city cluster, covering the period 2010-2022. By integrating entropy weight evaluation, spatial autocorrelation analysis, Markov chain transitions, Dagum's Gini decomposition, and geodetector analysis, we revealed both the temporal dynamics and the spatial heterogeneity of UER in this region. The results indicate that: (1) A developmental asymmetry, where overall UER increased, with the restoration capacity consistently outpacing the resistance and adaptability; (2) A stable spatial stratification with defined inequality sources, characterised by a "club convergence" pattern with strong path dependence that concentrates high-value areas in the Poyang Lake city cluster and low-value areas within the Wuhan City Circle, and where inter-regional differences remain the dominant source of disparity; (3) The dominance of interactive drivers, where factor detection highlights annual precipitation, terrain relief, and environmental pollution control investment as the most influential determinants. Moreover, interaction effects between natural and socio-economic variables are stronger than single-factor effects, indicating UER is shaped by multiple coupled drivers.

These diagnostic insights directly inform spatially targeted ecological management. For low-resilience cores in the Wuhan City Circle, where high industrial wastewater and SO₂ emissions correlate with weak resistance, policy must prioritise upgrading municipal wastewater treatment plants and deploying industrial flue-gas desulphurisation technologies, supported by ecological compensation. For the stable, high-resilience Poyang Lake cluster, the strategy should leverage its status as a regional "ecological anchor" to pilot advanced wetland and basin-scale restoration. Furthermore, given the high *q-value* and strong interactions of environmental pollution-control investment (V_8), cross-regional funds should be directed toward integrated projects in high-precipitation mountainous areas, such as coupling forestry restoration with agricultural non-point source pollution control, to maximise synergistic resilience gains. These measures align with the broader goals of ecological civilisation construction and sustainable development in the Yangtze River Economic Belt.

This study has limitations that chart directions for future research. The indicator system focuses primarily on the environmental dimension and does not fully capture socioeconomic resilience facets like governance or community adaptation. Data constraints included the imputation of minor gaps and the exclusion of three cities. Methodologically, Geodetector results, while robust, are sensitive to discretisation methods and the city-level sample size. Moreover, the UER index lacks direct validation against independent ecological outcome data (e.g., water quality trends, biodiversity indices). Future work should: (1) integrate social and economic resilience indicators to construct a holistic social-ecological framework; (2) extend the temporal scope and incorporate high-resolution data (e.g., remote sensing, real-time emissions) to improve dynamic monitoring and causal inference; and (3) validate the resilience index against observed recovery rates from specific disturbances, thereby strengthening its practical utility for ecological engineering.

References

- [1] Liang L, Wang Z, Li J. The effect of urbanisation on environmental pollution in rapidly developing urban agglomerations. *J Cleaner Prod.* 2019;237:117649. DOI: 10.1016/j.jclepro.2019.117649.

- [2] Perchinunno P, Massari A, L'Abbate S, Mongelli L. Ecological transition and sustainable development, a multivariate statistical analysis to guide the policies of the national recovery and resilience plan. *Social Indicators Res.* 2024;175:763-77. DOI: 10.1007/s11205-023-03078-w.
- [3] Holling CS. Resilience and stability of ecological systems. *Annual Rev Ecol Systematics.* 1973;4:1-23. DOI: 10.1146/annurev.es.04.110173.000245.
- [4] Cheung P, Nozawa Y, Miki T. Ecosystem engineering structures facilitate ecological resilience: A coral reef model. *Ecol Res.* 2021;36:673-85. DOI: 10.1111/1440-1703.12230.
- [5] Botequilha-Leitão A, Díaz-Varela ER. Performance based planning of complex urban social-ecological systems: The quest for sustainability through the promotion of resilience. *Sust Cities Society.* 2020;56:102089. DOI: 10.1016/j.scs.2020.102089.
- [6] Folke C. Resilience: The emergence of a perspective for social-ecological systems analyses. *Global Environ Change.* 2006;16:253-67. DOI: 10.1016/j.gloenvcha.2006.04.002.
- [7] Feng X, Zeng F, Loo BPY, Zhong Y. The evolution of urban ecological resilience: An evaluation framework based on vulnerability, sensitivity and self-organization. *Sust Cities Society.* 2024;116:105933. DOI: 10.1016/j.scs.2024.105933.
- [8] Zhang T, Sun Y, Zhang X, Yin L, Zhang B. Potential heterogeneity of urban ecological resilience and urbanization in multiple urban agglomerations from a landscape perspective. *J Environ Manage.* 2023;342:118129. DOI: 10.1016/j.jenvman.2023.118129.
- [9] Huang L, Wang J, Cheng H. Spatiotemporal changes in ecological network resilience in the Shandong Peninsula urban agglomeration. *J Cleaner Prod.* 2022;339:130681. DOI: 10.1016/j.jclepro.2022.130681.
- [10] Wang Y, Cai Y, Xie Y, Chen L, Zhang P. An integrated approach for evaluating dynamics of urban eco-resilience in urban agglomerations of China. *Ecol Indicators.* 2023;146:109859. DOI: 10.1016/j.ecolind.2023.109859.
- [11] Sun J, Zhai N, Mu H, Miao J, Li W, Li M. Assessment of urban resilience and subsystem coupling coordination in the Beijing-Tianjin-Hebei urban agglomeration. *Sust Cities Society.* 2024;100:105058. DOI: 10.1016/j.scs.2023.105058.
- [12] Yang Z, Cui X, Dong Y, Guan J, Wang J, Xi Z, et al. Spatio-temporal heterogeneity and influencing factors in the synergistic enhancement of urban ecological resilience: Evidence from the Yellow River Basin of China. *Appl Geography.* 2024;173:103459. DOI: 10.1016/j.apgeog.2024.103459.
- [13] Lu F, Liu Q, Wang P. Spatiotemporal characteristics of ecological resilience and its influencing factors in the Yellow River Basin of China. *Scientific Rep.* 2024;14:16988. DOI: 10.1038/s41598-024-67628-z.
- [14] Lee CC, Yan J, Li T. Ecological resilience of city clusters in the middle reaches of Yangtze River. *J Cleaner Prod.* 2024;443:141082. DOI: 10.1016/j.jclepro.2024.141082.
- [15] Tong Y, Lei J, Zhang S, Zhang X, Rong T, Fan L, et al. Analysis of the spatial and temporal variability and factors influencing the ecological resilience in the urban agglomeration on the northern slope of Tianshan Mountain. *Sustainability.* 2023;15(6):4828. DOI: 10.3390/su15064828.
- [16] Cao S, Pang C. Comprehensive assessment of urban ecological environment based on multisource data integration analysis. *Ecol Chem Eng S.* 2025;32(4):501-14. DOI: 10.2478/eces-2025-0026.
- [17] Wang K, Ma H, Fang C. The relationship evolution between urbanization and urban ecological resilience in the Northern Slope Economic Belt of Tianshan Mountains, China. *Sust Cities Society.* 2023; 97:104783. DOI: 10.1016/j.scs.2023.104783.
- [18] Zou C, Zhu J, Lou K, Yang L. Coupling coordination and spatiotemporal heterogeneity between urbanization and ecological environment in Shaanxi Province, China. *Ecol Indicators.* 2022;141:109152. DOI: 10.1016/j.ecolind.2022.109152.
- [19] Chang Q, Sha Y, Chen Y. The coupling coordination and influencing factors of urbanization and ecological resilience in the Yangtze River Delta urban agglomeration, China. *Land.* 2024;13(1):111. DOI: 10.3390/land13010111.
- [20] Feng S. Implementation of decision support system for ecological environment planning of urban green space. *Ecol Chem Eng S.* 2024;31(2):177-92. DOI: 10.2478/eces-2024-0012.
- [21] Ying Z, Yuan C, Zhuolu L, Weiling J. Ecological resilience assessment of an emerging urban agglomeration: A case study of Chengdu-Chongqing Economic circle, China. *Polish J Environ Stud.* 2022;31:2381-95. DOI: 10.15244/pjoes/144098.
- [22] Xu H, Jiao M. City size, industrial structure and urbanization quality - A case study of the Yangtze River Delta urban agglomeration in China. *Land Use Policy.* 2021;111:105735. DOI: 10.1016/j.landusepol.2021.105735.
- [23] Anselin L. Local Indicators of Spatial Association - LISA. *Geographical Analysis.* 1995;27:93-115. DOI: 10.1111/j.1538-4632.1995.tb00338.x.
- [24] Rey SJ. Spatial empirics for economic growth and convergence. *Geographical Analysis.* 2001;33:195-214. DOI: 10.1111/j.1538-4632.2001.tb00444.x.

- [25] Dagum C. A new approach to the decomposition of the Gini income inequality ratio. *Empirical Economics*. 1997;22:515-31. DOI: 10.1007/BF01205777.
- [26] Wang JF, Zhang TL, Fu BJ. A measure of spatial stratified heterogeneity. *Ecol Indicators*. 2016;67:250-56. DOI: 10.1016/j.ecolind.2016.02.052.
- [27] Barnett L, Ward EJ, Jannot JE, Shelton AO. Dynamic spatial heterogeneity reveals interdependence of marine faunal density and fishery removals. *Eco Indicators*. 2019;107:105585. DOI: 10.1016/j.ecolind.2019.105585.
- [28] Saba CS, David OO. Convergence patterns in global ICT: Fresh insights from a club clustering algorithm. *Telecommunications Policy*. 2020;44:102010. DOI: 10.1016/j.telpol.2020.102010.
- [29] Zhou S, Geng X, Jia W, Xu H, Xu X, Chen H, et al. Towards climate-adaptive equality in coastal megacities: Assessing urban flooding risk disparities and nonlinear effect of multidimensional indicators through an interpretable Light-SHAP framework. *Sust Cities Society*. 2025;132:106809. DOI: 10.1016/j.scs.2025.106809.
- [30] Li F, Nan T, Zhang H, Luo K, Xiang K, Peng Y. Evaluating ecological vulnerability and its driving mechanisms in the Dongting Lake Region from a multi-method integrated perspective: Based on geodetector and explainable machine learning. *Land*. 2025;14(7):1435. DOI: 10.3390/land14071435.
- [31] Ying C, Liu Y, Li J, Zhong J, Chen Y, Ai S, et al. Evolution and influencing factors of coastal resilience in the East China Sea. *Sci Total Environ*. 2024;944:173841. DOI: 10.1016/j.scitotenv.2024.173841.
- [32] Yang H, Nie S, Zhou H, Zhou X, Wang Y. Ecological sensitivity and its driving factors in the Yangtze River Delta, China. *Environ Eng Manage J*. 2024;23(7):1475-94. DOI: 10.30638/eemj.2024.121.
- [33] Zheng J, Wang J, Liu C. Response of habitat quality to temporal and spatial land use change and its driving factors: a case study of ganjiang river basin. *Environ Eng Manage J*. 2024;23(6):1231-46. DOI: 10.30638/eemj.2024.100.
- [34] Xu C, Li B, Kong F, He T. Spatial-temporal variation, driving mechanism and management zoning of ecological resilience based on RSEI in a coastal metropolitan area. *Ecol Indicators*. 2024;158:111447. DOI: 10.1016/j.ecolind.2023.111447.
- [35] Wang C, Gong W, Zhao M, Zhou Y, Zhao Y. Spatio-temporal evolution characteristics of eco-efficiency in the Yellow River Basin of China based on the super-efficient SBM model. *Environ Sci Pollut Res*. 2023;30:72236-47. DOI: 10.1007/s11356-023-27363-w.
- [36] Luo D, Liang L, Wang Z, Chen L, Zhang F. Exploration of coupling effects in the economy-society-environment system in urban areas: Case study of the Yangtze River Delta urban agglomeration. *Ecol Indicators*. 2021;128:107858. DOI: 10.1016/j.ecolind.2021.107858.