

Article

Spatial Patterns and Associated Factors of Ecological Resilience Across Urban–Rural Catchments in the Urumqi Metropolitan Area

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Abstract

Understanding ecological resilience (ER) across urban–rural gradients is important for differentiated management in arid metropolitan areas. Using 2 km grid data for 2013, 2018, and 2023, this study delineated travel-time-based urban–rural catchments in the Urumqi Metropolitan Area. The optimal-parameter Geodetector and multiscale geographically weighted regression were used to examine global explanatory patterns and local ER–factor associations, while spatially constrained clustering identified management types. The results showed that (1) mean ER values were 0.49, 0.50, and 0.48, respectively. ER was lower in urban centers and higher in rural areas and hinterlands. Compared with 2013, ER in 2023 was higher in urban centers and peri-urban regions but lower in rural areas and hinterlands. (2) Socioeconomic factors were more prominent in urban centers and peri-urban regions, whereas rural areas exhibited temporally variable natural and socioeconomic patterns. Elevation and soil organic matter were more prominent in hinterlands, and factor interactions were predominantly characterized by bi-factor or nonlinear enhancement. (3) Local ER–factor associations varied in direction, magnitude, and spatial scale. Negative associations with nighttime light intensity, road density, and built-up land proportion were concentrated in more urbanized areas. (4) Overlaying four spatial clusters with four catchment categories produced 16 integrated management types. These units provide a spatial basis for differentiated ecological management and regional planning in the Urumqi Metropolitan Area.

Keywords: urban–rural systems; arid regions; mountain–oasis–desert gradient; spatial heterogeneity; ecological management zoning

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1. Introduction

Rapid urbanization is increasing pressure on arid metropolitan ecosystems [1], where water scarcity [2] and ecological fragility [3] already constrain ecological processes and regional development. Urban expansion, infrastructure construction, and intensified resource use alter land-cover patterns [4], fragment habitats [5], and disrupt ecological connectivity [6]. These pressures vary across urban centers, peri-urban regions, rural areas, and hinterlands, and regional averages may therefore conceal variation in ecological conditions and resilience [7]. Examining ecological resilience along the urban–rural

gradient can clarify this intra-regional variation and inform differentiated ecological management in arid metropolitan regions.

Ecological resilience refers to the capacity of ecosystems to absorb disturbance, reorganize under changing conditions, and retain essential structures, functions, and feedbacks [8]. Accordingly, the concept emphasizes the persistence of ecological systems under disturbance [9] and their capacity to accommodate change without losing the organization and processes that sustain essential functions [10,11]. This focus distinguishes ecological resilience from ecosystem health, ecological risk, and landscape ecological security, which primarily concern current ecological condition [12], potential threats and losses [13], and the spatial maintenance of ecological processes [14], respectively. Empirical studies have operationalized this concept through multidimensional indicators to assess spatial patterns of ER and examine its associations with natural and socioeconomic factors at provincial [15], municipal [16], and county scales [17].

Despite these advances, existing studies provide limited understanding of how ER and its associated factors vary within functionally connected urban–rural systems. Most assessments rely on administrative units [18] or binary urban–rural classifications [19], which may overlook ecological variation associated with accessibility to urban centers and with the distribution of land development, infrastructure, and human activity [20–22]. Many global analyses summarize average factor relationships, providing limited insight into interactions, local differences in association direction and magnitude, and factor-specific spatial scales [23]. In addition, local association patterns are rarely translated into spatially contiguous management units [24]. The Urumqi Metropolitan Area (UMA) extends from the northern foothills of the Tianshan Mountains through oasis areas to the southern margin of the Gurbantunggut Desert. Across this mountain–oasis–desert transition, urban expansion and infrastructure development are unevenly distributed across urban centers, peri-urban regions, rural areas, and hinterlands.

Accordingly, this study addresses three questions: how ER levels and observed changes differ across urban centers, peri-urban regions, rural areas, and hinterlands; how the explanatory power, interactions, direction, magnitude, and spatial scales of ER–factor associations vary across these catchments; and how such heterogeneity can be translated into spatially contiguous ecological management units. Using 2 km grid data for 2013, 2018, and 2023, we delineate travel-time-based urban–rural catchments and combine the optimal-parameter Geodetector, multiscale geographically weighted regression, and spatially constrained multivariate clustering. The results reveal contrasting ER changes across the urban–rural gradient, differences in factor importance among catchments, spatially and scale-dependent ER–factor associations, and 16 integrated management types derived from four spatial clusters and four catchment categories. By linking functional urban–rural differentiation, multiscale ER–factor associations, and spatially contiguous zoning, this study provides a spatially explicit basis for differentiated ecological management in the UMA and an analytical framework applicable to comparable arid metropolitan settings.

2. Materials and Methods

2.1. Study Area

The Urumqi Metropolitan Area (UMA) is situated in northeastern Xinjiang (Figure 1), within the oasis belt on the northern foothills of the Tianshan Mountains. The UMA was selected because it contains a pronounced mountain–oasis–desert gradient within a rapidly urbanizing metropolitan region. This combination provides an informative setting for examining ecological resilience and its associated factors across functionally connected urban centers, peri-urban regions, rural areas, and hinterlands under strong water constraints and uneven human pressure.

The southern part of the UMA is bordered by the Tianshan Mountains, while the northern part adjoins the Gurbantunggut Desert, resulting in a terrain that slopes downward from south to north, characterized by a combination of mountains, oases, and desert landscapes. The region experiences low annual precipitation coupled with high annual evaporation rates. With the rapid advancement of urbanization, the ecosystem within the UMA is under increasing pressure, particularly in urban centers. The intense human activities and ecological fragility have led to frequent ecological and environmental issues, including air pollution, soil erosion, and habitat degradation. These conditions make the UMA an informative case for examining spatial differences in ecological resilience across an arid mountain–oasis–desert urban–rural system.

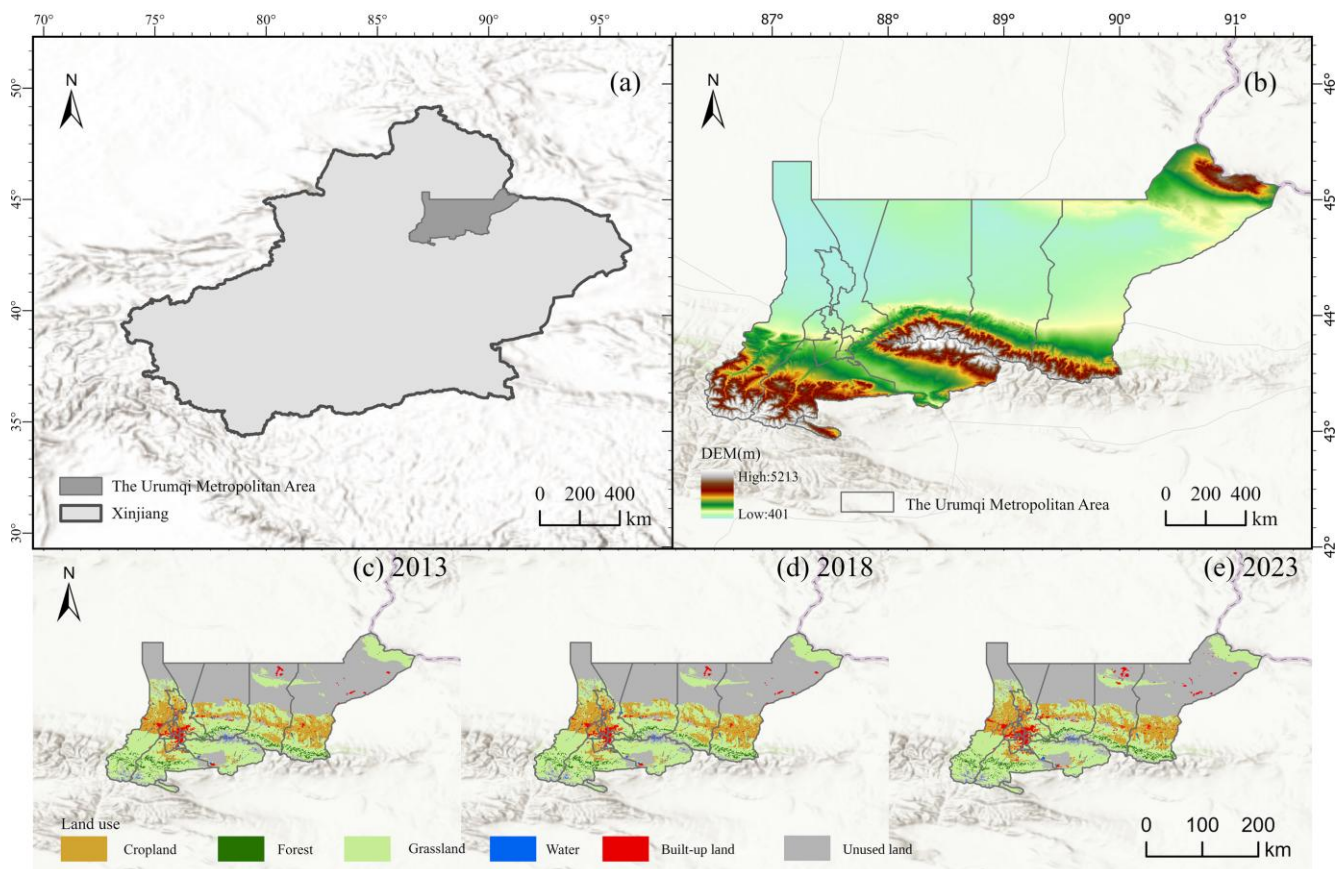


Figure 1. Maps of the study area. (a) Location of the Urumqi Metropolitan Area, (b) Elevation of the study area, and (c–e) Land use data of the study area in 2013, 2018, and 2023, respectively. Data sources: The boundary, elevation, and land-use datasets described in Section 2.2.

2.2. Data Sources and Preprocessing

The land use data utilized in this study, with a spatial resolution of 1 km, were obtained from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, for the years 2013, 2018, and 2023. Based on previous studies [25,26], the following variables were selected as explanatory factors: potential evapotranspiration (PET), soil organic matter (OM), elevation (DEM), distance to water systems (DWS), nighttime light index (NLI), road density (RD), and proportion of built-up land (POB). The PET data were obtained from the MODIS/Terra MOD16A3GF Version 6.1 dataset, which is distributed by the NASA Land Processes Distributed Active Archive Center (LP DAAC, Sioux Falls, SD, USA). The OM data were obtained from the National Tibetan Plateau Data Center with a spatial resolution of 1 km. The DEM data were obtained from the General Bathymetric Chart of the Oceans (GEBCO) dataset with a spatial resolution of

1 km. Water system and road network data for 2013, 2018, and 2023 were obtained from OpenStreetMap (OSM), an open geospatial database. The NLI data were provided by the Earth Observation Group and have a spatial resolution of 1 km. The population data were obtained from LandScan with a spatial resolution of 1 km. Year-specific PET, land-use, NLI, population, road-network, urban-boundary, and water-system data corresponding to 2013, 2018, and 2023 were used for each observation year, whereas OM and DEM were treated as time-invariant background variables. Annual net primary productivity (NPP) data for 2013, 2018, and 2023 were obtained from MODIS.

2.3. Research Methods

2.3.1. Ecological Resilience Evaluation Model

In this study, ecological resilience was evaluated using a landscape-based resistance–adaptation–recovery framework. The framework characterizes landscape conditions associated with the capacity to maintain ecological structure and functions under external pressure, adjust to changing environmental conditions, and support ecological restoration following disturbance [27]. Resistance, adaptation, and recovery were quantified separately and integrated into a composite index. The index was used to compare relative spatial differences in ER across grid cells and observation years and does not represent directly observed post-disturbance recovery [28].

Resistance (P) represents landscape conditions related to the maintenance of ecological structure and functions under external pressure [29]. Habitat quality estimated using the InVEST Habitat Quality model was used to characterize resistance. The model evaluates habitat condition by integrating land-cover suitability with the intensity, distance, weight, and spatial decay of surrounding threats. Higher habitat-quality values indicate lower estimated habitat degradation and more favorable conditions for maintaining ecological functions under pressure. The threat factors, maximum influence distances, relative weights, decay functions, habitat suitability values, and sensitivity coefficients were determined with reference to previous InVEST-based research [30] and are reported in Appendix A Tables A2 and A3. The adaptation weights and recovery coefficients are cited in their respective descriptions below.

Adaptation (A) represents landscape structural conditions that facilitate ecological adjustment under anthropogenic pressure and natural disturbance [31]. It was evaluated using the Shannon diversity index ($SHDI$), landscape splitting index ($SPLIT$), and landscape division index ($DIVISION$). $SHDI$ reflects the diversity of land-cover composition and was treated as a positive indicator because greater landscape diversity can support multiple ecological functions and adjustment pathways [32]. $SPLIT$ and $DIVISION$ reflect landscape subdivision and separation. Higher values indicate greater fragmentation and weaker structural continuity and were therefore treated as negative indicators [33]. $SHDI$ was normalized using positive min–max normalization, whereas $SPLIT$ and $DIVISION$ were reverse normalized so that higher standardized values consistently represented more favorable adaptation conditions. The standardized indicators were assigned weights of 0.5, 0.3, and 0.2, respectively [34], and integrated using Equation (1).

$$A = 0.5SHDI + 0.3SPLIT + 0.2DIVISION \quad (1)$$

Recovery (R) represents landscape conditions related to the restoration of ecological structure and functions following disturbance [35]. It was evaluated using land-cover composition and category-specific ecological recovery coefficients. The coefficients reflect differences in the relative ecological functions and recovery potential of farmland, woodland, grassland, water bodies, built-up land, and unused land [36]. Recovery coefficients of 0.5, 0.9, 0.7, 0.8, 0.4, and 0.1 were assigned to these land-cover categories, respectively [37]. Recovery was calculated as the area-weighted sum of the land-cover coefficients

using Equation (2). The recovery component therefore represents relative potential ecological recovery inferred from land-cover composition and category-specific coefficients, rather than actual recovery observed after a specific disturbance.

$$R = \sum L_k \times RC_k \quad (2)$$

Resistance, adaptation, and recovery were calculated separately and then normalized to a common scale from 0 to 1. To ensure comparability across observation years, the minimum and maximum values were derived from the pooled grid observations for 2013, 2018, and 2023 and applied consistently to all three years. The normalized dimensions were integrated using the geometric mean. This aggregation approach limits complete compensation among dimensions, so a low value in any dimension constrains the overall ER value [38]. The index was calculated using Equation (3).

$$ER = \sqrt[3]{P \times A \times R} \quad (3)$$

where ER denotes the ecological resilience index, and P , A , and R denote the normalized resistance, adaptation, and recovery, respectively. $SHDI$ is the Shannon diversity index, $SPLIT$ is the landscape splitting index, $DIVISION$ is the landscape division index, L_k is the area proportion of land-cover category k , and RC_k is the ecological recovery coefficient assigned to land-cover category k . Detailed definitions and calculations of the component indicators are provided in Appendix A Table A1. For descriptive mapping and interannual comparison, ER values were classified into five fixed equal-width levels within the normalized range [0, 1]: Weak [0.00, 0.20), Relatively weak [0.20, 0.40), Ordinary [0.40, 0.60), Relatively well [0.60, 0.80), and Well [0.80, 1.00]. Identical classification thresholds were applied to 2013, 2018, and 2023 to ensure direct temporal comparability. These levels were used for descriptive mapping and comparison and do not represent empirically derived ecological thresholds.

To assess the sensitivity of the ER index to its literature-based parameterization, a set of alternative adaptation-weight and recovery-coefficient scenarios was examined. For the adaptation component, the baseline weights of 0.50, 0.30, and 0.20 assigned to $SHDI$, reverse-normalized $SPLIT$, and reverse-normalized $DIVISION$, respectively, were derived from the weighting scheme used in previous research [34]. These baseline weights were compared with an equal-weight scheme assigning one-third to each indicator, an $SHDI$ -enhanced scheme of 0.60, 0.25, and 0.15, and a $SPLIT/DIVISION$ -enhanced scheme of 0.40, 0.35, and 0.25. For the recovery component, the baseline coefficients of 0.50, 0.90, 0.70, 0.80, 0.40, and 0.10 assigned to farmland, woodland, grassland, water bodies, built-up land, and unused land, respectively, were adopted from previous research [37]. Each coefficient was separately increased and decreased by 10%, yielding 12 one-at-a-time perturbation scenarios. The remaining coefficients were held constant, and all adjusted values were constrained to the interval from 0 to 1. Under each scenario, the affected component was recalculated using the same pooled normalization procedure as the baseline analysis, while the other two ER dimensions were held constant. The alternative ER estimates were compared with the baseline results separately for 2013, 2018, and 2023 using Spearman rank correlation, mean absolute difference, and agreement in the five fixed ER classes.

To assess the external consistency of the ER index, NPP was used as an independent indicator of ecosystem functioning. Grid-level Pearson correlations between ER and NPP were calculated separately for 2013, 2018, and 2023. Because NPP mainly represents ecosystem productivity, this assessment provides only partial external consistency evidence for the ecological relevance of the ER index and does not constitute comprehensive validation. Given the spatial dependence among neighboring grid cells, the Pearson coefficients were interpreted descriptively, and conventional p values were not used for substantive inference.

2.3.2. Delineation of Urban–Rural Catchments

Urban–rural catchments were delineated using a travel-time-based framework that combines the population hierarchy of urban centers with least-cost accessibility [39]. This approach represents functional connections shaped by access to urban centers beyond administrative boundaries and fixed-distance buffers [40]. The population classes and travel-time intervals were applied consistently across the three observation years.

First, urban centers were identified using urban-boundary and population data. Based on the population thresholds proposed by Chen et al. [41] and the population structure of the UMA, urban centers were classified into four categories: large cities with 1–5 million inhabitants, intermediate cities with 0.5–1 million inhabitants, small cities with 50,000–500,000 inhabitants, and towns with 20,000–50,000 inhabitants. Second, a regional travel-cost surface was constructed by integrating road and railway networks, transport barriers, land-cover-specific movement speeds, and slope-adjusted travel costs. The transport speeds, off-road movement speeds, barrier rules, population thresholds, travel-time intervals, and overlay procedures are reported in Appendix A Tables A4–A7.

The minimum cumulative travel time from each grid cell to the nearest urban center was then calculated. Travel time was divided into six intervals: 0 h, 0–0.5 h, 0.5–1 h, 1–2 h, 2–3 h, and more than 3 h. These intervals were aggregated into four urban–rural catchment categories. Grid cells within identified urban boundaries were classified as urban centers, areas within 1 h of an urban center were classified as peri-urban regions, areas located 1–3 h from an urban center were classified as rural areas, and areas located more than 3 h from any urban center were classified as hinterlands. Where catchments associated with urban centers of different population sizes overlapped, priority was assigned to the larger urban center within the same travel-time interval. The same delineation procedure was applied to all three observation years. The transport speeds and barrier settings used in the baseline analysis were directly adopted from the accessibility framework of Chen et al. [41]. The 1 km/h value represents an imposed low movement speed within a 1 km buffer on both sides of expressways and railways and was used to approximate their restricted permeability, rather than observed travel speed. To evaluate whether the catchment delineation depended strongly on this assumption, two alternative barrier scenarios were examined. The first scenario retained the 1 km buffer but increased the movement speed within it from 1 to 3 km/h, while the second removed the low-speed buffer. All other network speeds, off-road movement speeds, population thresholds, travel-time intervals, and overlay rules were held constant. The alternative catchment classifications were compared with the baseline separately for 2013, 2018, and 2023 using category-specific area changes, overall grid-cell agreement, and Cohen’s kappa.

2.3.3. Optimal-Parameter Geodetector (OPGD) Model

The optimal-parameter Geodetector (OPGD) was used to examine the explanatory power of selected natural and socioeconomic factors for the spatial differentiation of ecological resilience [42]. Compared with the conventional Geodetector, OPGD reduces dependence on a predetermined discretization scheme by identifying the combination of classification method and number of intervals that maximizes the explanatory power of each continuous variable [43].

Before factor detection, continuous explanatory variables were discretized using five classification methods, including equal interval, natural breaks, quantile, geometric interval, and standard deviation, with the number of intervals ranging from three to six. For each variable, the method–interval combination yielding the highest q value was retained as the optimal discretization scheme. The factor detector was then used to quantify the explanatory power of each factor for the spatial differentiation of ER, and the interaction detector was used to evaluate changes in explanatory power when two factors were

considered jointly. Bi-factor enhancement was identified when the joint q value exceeded both individual q values but remained lower than their sum, whereas nonlinear enhancement was identified when the joint q value exceeded their sum.

Factor and interaction detection were conducted for the entire study area and separately for urban centers, peri-urban regions, rural areas, and hinterlands in each observation year. To assess potential circularity arising from the shared land-cover information between POB and the ER index, both detectors were repeated after excluding POB for the entire study area and each urban–rural catchment in 2013, 2018, and 2023. The rankings of the remaining factors and the strongest interactions not involving POB were compared with the corresponding results obtained from the full set of explanatory factors.

All OPGD analyses were implemented in R using the GD package. Given the spatial dependence among neighboring grid cells, conventional factor-detector p values were not used for substantive inference. Interpretation focused on q -statistic magnitudes, factor rankings, interaction patterns, and their consistency after POB exclusion. The explanatory power of each factor was measured using the q statistic, expressed as Equation (4).

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^L N_h \sigma_h^2 \quad (4)$$

where q denotes the explanatory power of factor X . N and N_h denote the numbers of grid cells in the entire study area and in stratum h , respectively. σ_h and σ^2 represent the variance of the entire region and the h -th stratum, respectively. The q statistic ranges from 0 to 1, with a higher value indicating that the spatial stratification of the factor corresponds more closely to the spatial differentiation of ER.

2.3.4. Multiscale Geographically Weighted Regression (MGWR) Model

Multiscale geographically weighted regression was used to examine spatial variation in the associations between ecological resilience and the selected explanatory factors [44]. Unlike global regression, which estimates a single coefficient for each explanatory variable across the study area, MGWR allows local coefficients to vary across locations and estimates a variable-specific bandwidth for each explanatory factor [45]. A larger bandwidth indicates that the local coefficient is estimated using a broader spatial neighborhood and generally exhibits smoother spatial variation, whereas a smaller bandwidth indicates stronger spatial nonstationarity and more localized variation.

Before model estimation, global multicollinearity was assessed using pairwise Pearson correlation coefficients and variance inflation factors, and ER and all explanatory variables were standardized using the z -score method. Separate MGWR models were estimated for 2013, 2018, and 2023 and compared with OLS and GWR using AICc, R^2 , and adjusted R^2 , while residual spatial dependence was assessed using global Moran's I . Local multicollinearity was evaluated using local condition numbers, and the proportion of grid cells with values greater than 30 was summarized by observation year. Coefficient uncertainty was characterized using pseudo- t statistics derived from the local coefficients and their standard errors, and the proportion of grid cells with absolute pseudo- t values greater than 1.96 was reported for each explanatory factor and observation year. Variable-specific bandwidths were used to characterize the spatial scales of the ER–factor associations. To assess sensitivity to POB, the MGWR models were re-estimated without POB under identical settings, and changes in model fit, bandwidths, Pearson correlations between corresponding coefficient surfaces, and coefficient-sign agreement were compared. The MGWR model is expressed in Equation (5).

$$y_i = \sum_{j=1}^k \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i \quad (5)$$

where y_i denotes the standardized ER value at location i , (u_i, v_i) denotes the spatial coordinates of location i , $\beta_{bwj}(u_i, v_i)$ denotes the local coefficient of explanatory variable j at location i , and bw_j denotes the variable-specific bandwidth. x_{ij} denotes the standardized value of explanatory variable j at location i , and ε_i represents the random error term.

2.3.5. Spatially Constrained Multivariate Clustering Analysis (SCMCA)

Spatially constrained multivariate clustering analysis was used to identify spatially contiguous areas with similar local ER–factor association patterns. By incorporating spatial adjacency into multivariate clustering, the method reduces the spatial fragmentation that may occur when clustering is based solely on attribute similarity. The local MGWR coefficient surfaces for PET, OM, DEM, DWS, NLI, RD, and POB in 2023 were used as clustering variables. Before clustering, each coefficient surface was standardized using the z-score method to place the local coefficients of different explanatory factors on a comparable scale. Because the number of clusters was not specified a priori, ArcGIS Pro 3.0.2 evaluated solutions ranging from 2 to 30 clusters using the Calinski–Harabasz pseudo F-statistic. The four-cluster solution with the highest pseudo F-statistic was retained, and the neighboring three- and five-cluster solutions were compared to assess sensitivity to the selected cluster number.

To assess whether the clustering results depended strongly on the inclusion of POB, the spatially constrained clustering was repeated using the six local coefficient surfaces for PET, OM, DEM, DWS, NLI, and RD obtained from the POB-excluded MGWR model. The same z-score standardization, four-cluster specification, and spatial-contiguity setting were applied. Spatial contiguity was defined using the contiguity–edges–corners criterion, under which grid cells sharing an edge or vertex were treated as neighbors. Because cluster labels are arbitrary, the clusters from the alternative solution were matched to the baseline clusters according to maximum spatial overlap before calculating grid-cell agreement. Similarity between the two solutions was evaluated using the adjusted Rand index, grid-cell agreement, and agreement in the 16 integrated management types. The baseline four spatial clusters were subsequently overlaid with the four urban–rural catchment categories to produce the 16 management types.

3. Results

3.1. Spatiotemporal Characteristics of Ecological Resilience in Urban–Rural Catchments

ER exhibited pronounced spatial differentiation across urban–rural catchments (Figure 2). The mean ER values were 0.49 in 2013, 0.50 in 2018, and 0.48 in 2023. Between 2013 and 2023, the areas classified as urban centers, peri-urban regions, and rural areas increased from 936 km², 2488 km², and 1049 km² to 2695 km², 6756 km², and 2418 km², respectively, while the area classified as hinterlands decreased from 52,222 km² to 44,826 km².

Spatially, ER exhibited a clear center-to-periphery pattern, with values generally increasing from urban centers toward rural areas and hinterlands. Areas classified as Weak and Relatively weak were concentrated mainly in urban centers, whereas areas classified as Relatively well and Well occurred predominantly in rural areas and hinterlands. Compared with 2013, ER in 2023 was generally higher in urban centers and peri-urban regions but lower in rural areas and hinterlands. The Pearson correlation coefficients between ER and annual NPP were 0.31, 0.35, and 0.29 in 2013, 2018, and 2023, respectively. Their consistently positive direction across the three observation years provides partial external

consistency evidence for the ecological relevance of the ER index, although these descriptive associations do not constitute comprehensive validation.

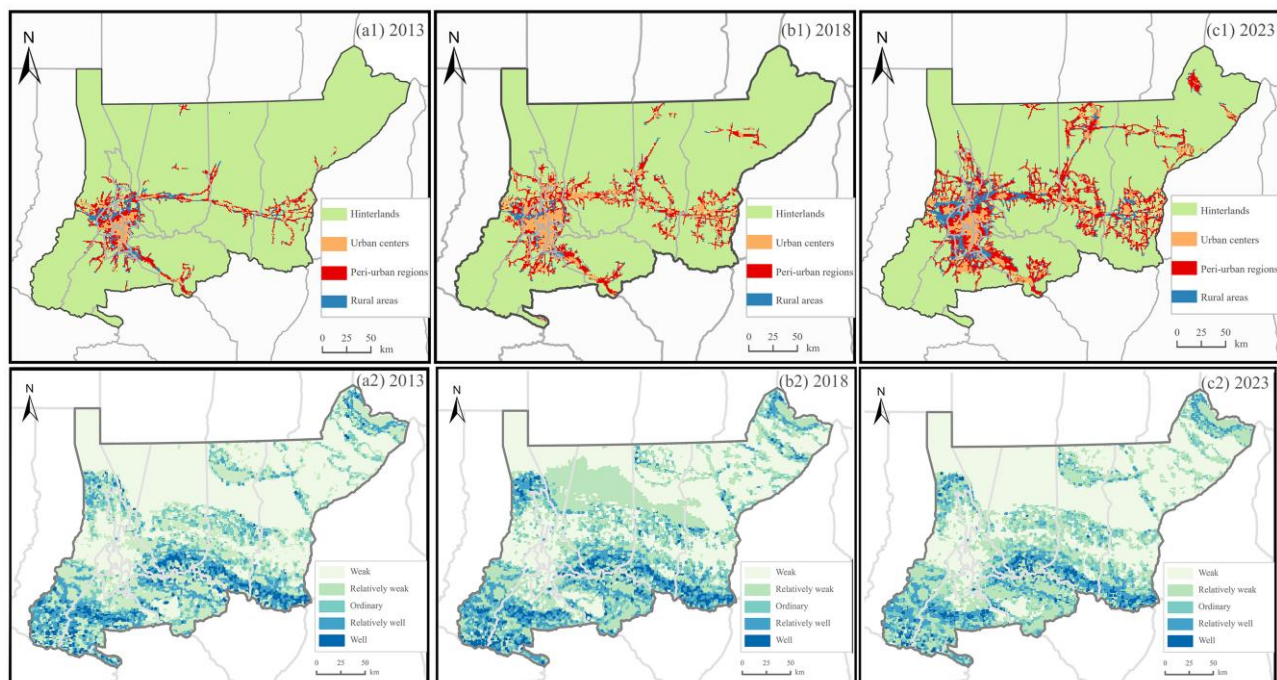


Figure 2. Spatial patterns and changes in ER across urban–rural catchments in 2013, 2018, and 2023. Panels (a1–c1) show the spatial patterns of urban–rural catchments; panels (a2–c2) show the spatial patterns of ER. Source: Authors’ analysis based on the datasets described in Section 2.2.

The sensitivity analysis supported the broad stability of the ER estimates under the examined alternative parameter settings. Across the three adaptation-weight scenarios and observation years, Spearman correlations between the alternative and baseline ER estimates ranged from 0.993 to 0.998, mean absolute differences ranged from 0.014 to 0.020, and agreement in the five fixed ER classes ranged from 97.3% to 98.5%. Across the recovery-coefficient scenarios, Spearman correlations ranged from 0.996 to 1.000 and mean absolute differences did not exceed 0.007, while class agreement remained at or above 97.2% in all scenarios and observation years. Together, these results support the stability of the broad ER rankings and five-class spatial patterns under the examined parameter settings (Appendix A Tables A16 and A17). The four urban–rural catchment categories also remained broadly stable under the alternative barrier settings. When the movement speed within the 1 km buffer was increased from 1 to 3 km/h, overall grid-cell agreement with the baseline classification ranged from 98.8% to 99.4%, and Cohen’s kappa ranged from 0.962 to 0.968. After the low-speed buffer was removed, grid-cell agreement remained between 97.4% and 98.7%, with kappa values ranging from 0.917 to 0.930. Urban-center areas remained unchanged because they were defined using year-specific urban boundaries. The alternative settings mainly expanded peri-urban and rural areas and reduced hinterland areas. The largest differences occurred in 2023 under the buffer-removed scenario, when peri-urban and rural areas increased by 568 km² and 332 km², respectively, and hinterlands decreased by 900 km². These results support the broad spatial stability of the four catchment categories under the examined barrier assumptions (Appendix A Tables A18 and A19).

3.2. Global Patterns of Factor Explanatory Power for ER

The OPGD model was used to assess the explanatory power of individual factors and factor interactions for the spatial differentiation of ER across the three observation years. Before factor detection, all continuous variables underwent optimal discretization, with the selected classification methods and numbers of intervals reported in Appendix A Table A8.

Across the entire study area, DEM, OM, and POB had the highest mean q values across the three observation years, at 0.26, 0.22, and 0.18, respectively (Figure 3). The relative explanatory power of socioeconomic and natural factors also varied among the observation years. Socioeconomic factors generally had higher q values in 2018 and 2023 than in 2013, whereas several natural factors had lower q values.

The OPGD analysis was further conducted separately for urban centers, peri-urban regions, rural areas, and hinterlands. Socioeconomic factors were generally more prominent in urban centers and peri-urban regions, whereas rural areas exhibited greater temporal variation in the relative importance of natural and socioeconomic factors. In hinterlands, DEM and OM consistently showed greater explanatory power, while socioeconomic factors played a more limited role.

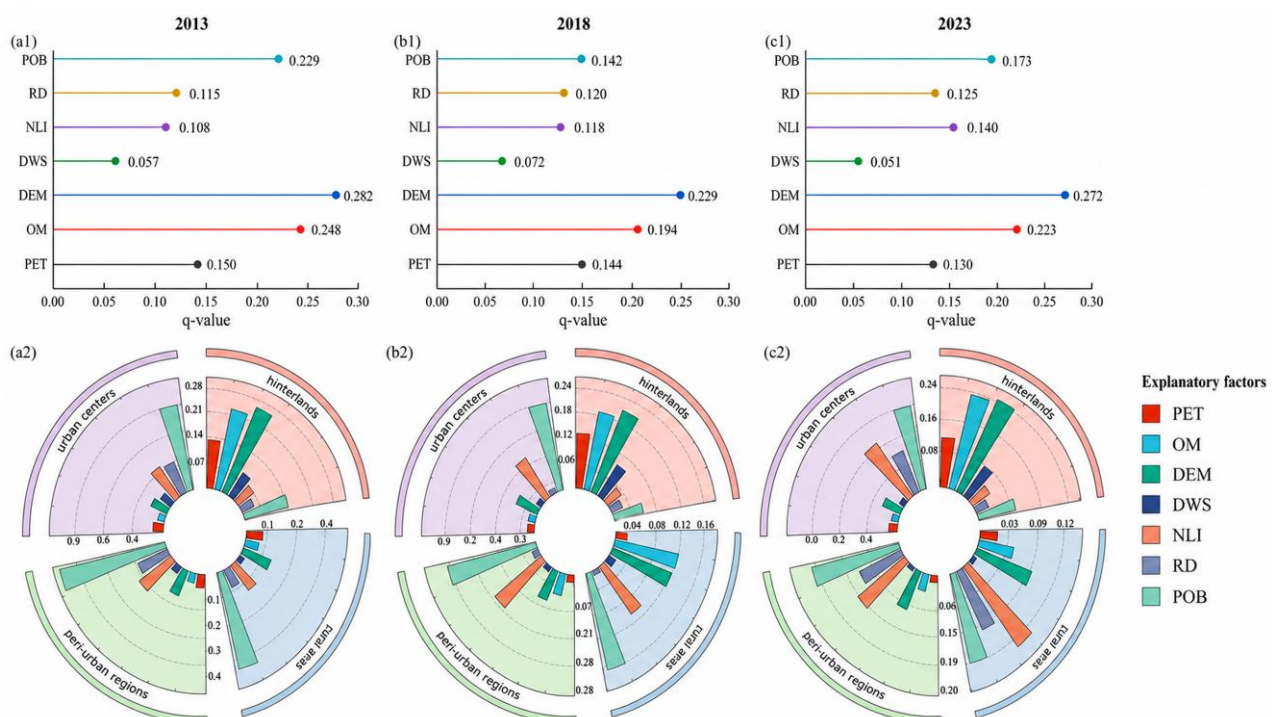


Figure 3. Single-factor detection results of the OPGD model in 2013, 2018, and 2023. (a1–c1) show the detection results at the global scale for the three time points, (a2–c2) show the corresponding results across urban–rural catchments. Source: Authors’ analysis based on the datasets described in Section 2.2.

Interaction detection was further used to assess the joint explanatory power of factor pairs (Figure 4). Across the three observation years, factor interactions were predominantly characterized by bi-factor or nonlinear enhancement. For the entire study area, DEM $\cap$ POB had the highest mean joint q value of 0.39, approximately 1.51 times the mean q value of DEM alone. It was followed by OM $\cap$ POB (0.38), DEM $\cap$ NLI (0.35), DEM $\cap$ RD (0.34), OM $\cap$ RD (0.33), and OM $\cap$ NLI (0.33). The mean joint q values of all six factor pairs exceeded 0.30, placing interactions involving DEM, OM, POB, NLI, and RD among the strongest associations with the spatial differentiation of ER. Joint explanatory patterns also differed across urban–rural catchments. Across the three observation years, the highest

mean joint q values in urban centers and peri-urban regions generally occurred among socioeconomic factors or between socioeconomic and natural factors. $POB \cap DEM$ (0.41), $POB \cap NLI$ (0.40), and $POB \cap RD$ (0.39) had the highest mean joint q values. In rural areas and hinterlands, interactions involving natural factors generally had greater joint explanatory power, with $DEM \cap OM$ recording the highest mean joint q value of 0.34. After POB was excluded, NLI ranked first in urban centers and peri-urban regions across all three observation years, while DEM and OM remained the two leading factors in hinterlands. The leading factor in rural areas varied among DEM , OM , and NLI , and the strongest interactions not involving POB mainly combined DEM or OM with NLI or RD (Appendix A Table A9).

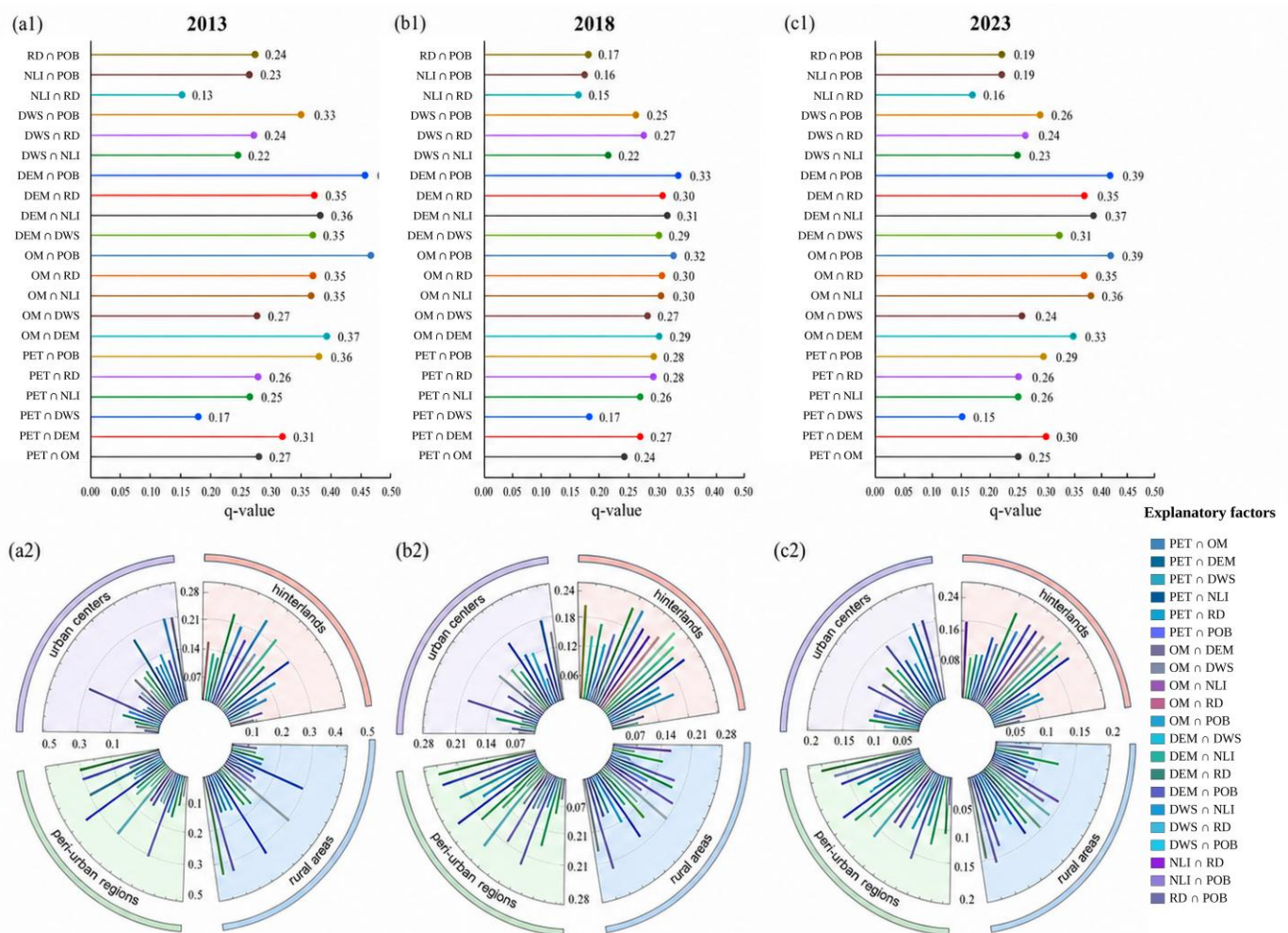


Figure 4. Interaction detection results of the OPGD model in 2013, 2018, and 2023. (a1–c1) show the interaction detection results at the global scale for the three time points, (a2–c2) show the corresponding results for urban–rural catchments. Source: Authors’ analysis based on the datasets described in Section 2.2.

3.3. Local Patterns of Factor Associations with ER

The same explanatory variables were used in the OPGD and MGWR analyses. Before MGWR estimation, global multicollinearity was assessed using pairwise Pearson correlations and variance inflation factors. The mean VIF was 3.74, all VIF values were below 5, and all pairwise correlation coefficients were below 0.7, suggesting that severe global multicollinearity was not evident among the selected explanatory variables. MGWR was then used to estimate spatially varying ER–factor associations. Across all three observation

years, MGWR produced lower AICc values and higher R^2 and adjusted R^2 values than OLS and GWR, indicating better relative fit for the data used in this study (Appendix A Table A10). Residual Moran's I was also lower for GWR and MGWR than for OLS in each year, with MGWR yielding the lowest values (Appendix A Table A11). Median local condition numbers ranged from 12.8 to 14.2 across the three observation years, and only 1.8–2.7% of grid cells exceeded 30, suggesting that severe local multicollinearity was limited to a small proportion of the study area (Appendix A Table A12). The proportion of local coefficients with absolute pseudo-t values greater than 1.96 ranged from 43.7% to 75.1% across factors and observation years. OM and DEM generally exhibited relatively broad coefficient support, while the corresponding proportion for NLI increased over time (Appendix A Table A13).

Spatial variation in ER–factor associations was examined using the variable-specific bandwidths and local regression coefficients derived from MGWR (Figures 5 and 6). Across urban–rural catchments, the estimated associations varied substantially in both direction and magnitude.

Regarding the natural factors, the local coefficients of DEM and OM generally became more positive from urban centers toward hinterlands. Their coefficients showed greater spatial variation in urban centers and peri-urban regions, whereas predominantly positive coefficients were observed in rural areas and hinterlands. DWS showed both positive and negative coefficients across the study area, with relatively strong negative associations in parts of the peri-urban regions. The coefficients of PET became less positive toward urban centers and were negative in some locations. These results indicate substantial spatial heterogeneity in the associations of ER with topography, soil conditions, water-system proximity, and potential evapotranspiration.

Among the socioeconomic factors, negative NLI coefficients became more widely distributed between 2013 and 2023, particularly in peri-urban regions and rural areas. RD coefficients were relatively weak in 2013, whereas stronger negative associations became increasingly concentrated along major transportation corridors in 2018 and 2023. Negative POB coefficients became more spatially concentrated in densely urbanized areas by 2023. These results show that the direction and spatial distribution of socioeconomic associations with ER varied across factors, locations, and observation years.

In addition to variation in coefficient direction and magnitude, the variable-specific bandwidths differed across explanatory factors and observation years. PET operated at progressively broader estimation scales, with bandwidths increasing from 5513 neighbors in 2013 to 7607 in 2018 and 8101 in 2023. OM and DEM exhibited comparatively smaller bandwidths that varied among observation years. DWS shifted from a relatively localized scale in 2013 to much broader scales in 2018 and 2023, with its bandwidth increasing from 4218 to 13,090 and 14,384 neighbors. By contrast, the bandwidth of NLI declined from 3419 in 2013 to 1747 in 2018 and 569 in 2023, indicating increasingly localized associations with ER. RD retained a bandwidth of 14,384 neighbors in all three years, suggesting an association operating at an approximately global scale. POB exhibited the smallest bandwidth in 2013, increased in 2018, and declined again in 2023. Overall, the estimation scales of ER–factor associations were factor-specific and temporally variable.

The MGWR models were re-estimated after excluding POB. AICc increased by 5.94–9.37, while R^2 and adjusted R^2 decreased by 0.026–0.042 and 0.023–0.040, respectively. Overall model fit therefore declined modestly after POB exclusion. The variable-specific bandwidths of the six remaining factors were broadly comparable between the two model specifications. Pearson correlations between the corresponding local coefficient surfaces ranged from 0.882 to 0.986, while coefficient-sign agreement ranged from 87.6% to 99.1%. Relatively greater changes occurred for PET in 2013 and DEM in 2023, although their

broad spatial patterns remained comparable. Overall, most broad local association patterns were retained after POB exclusion (Appendix A Tables A14 and A15).

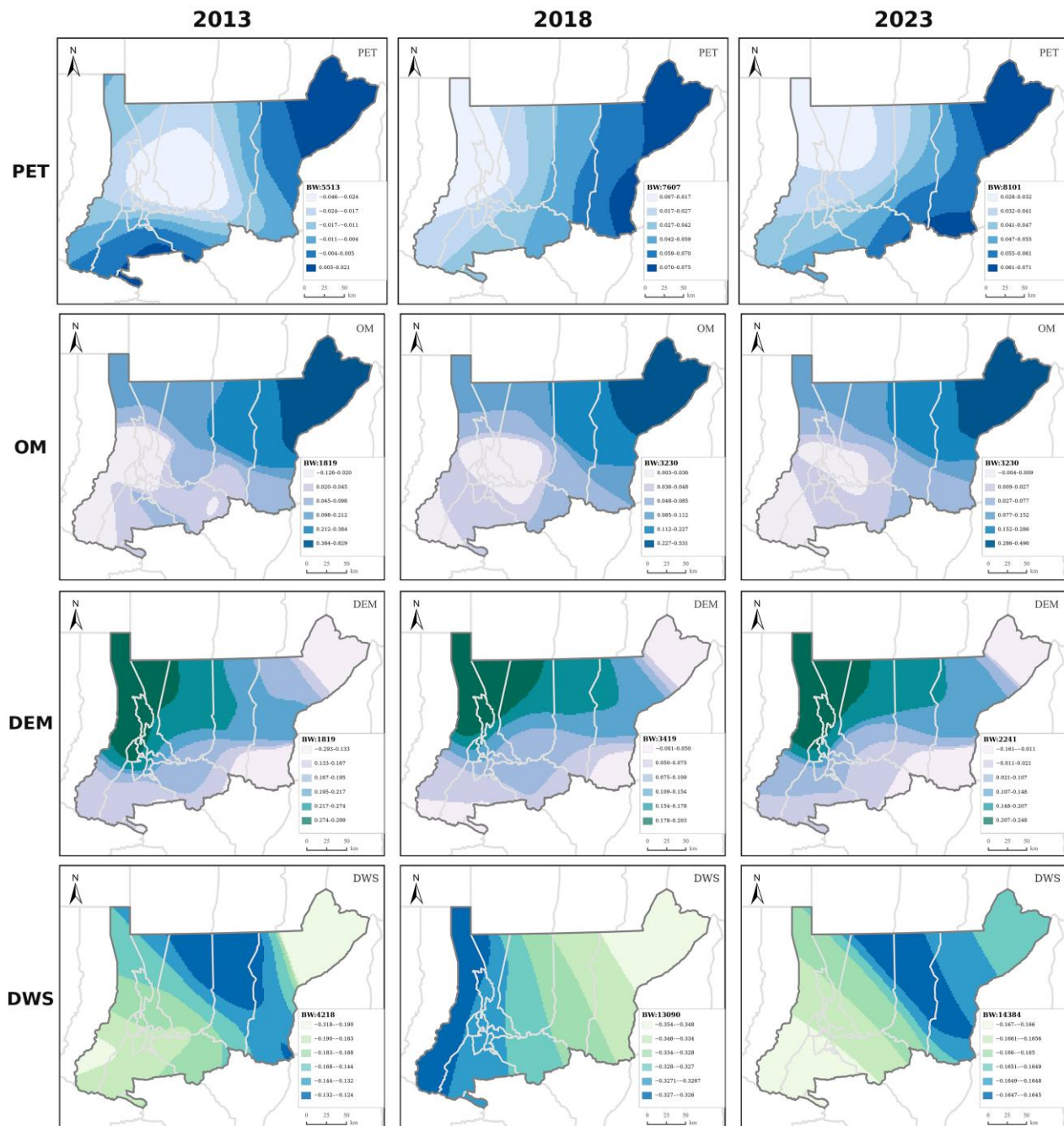


Figure 5. Spatial distributions of local MGWR coefficients and variable-specific bandwidths for natural factors in 2013, 2018, and 2023. The columns correspond to the three observation years, and the rows show the local coefficients for potential evapotranspiration (PET), soil organic matter (OM), elevation (DEM), and distance to water systems (DWS). BW in each legend denotes the corresponding variable-specific bandwidth expressed as the number of nearest neighbors. Source: Authors' analysis based on the datasets described in Section 2.2.

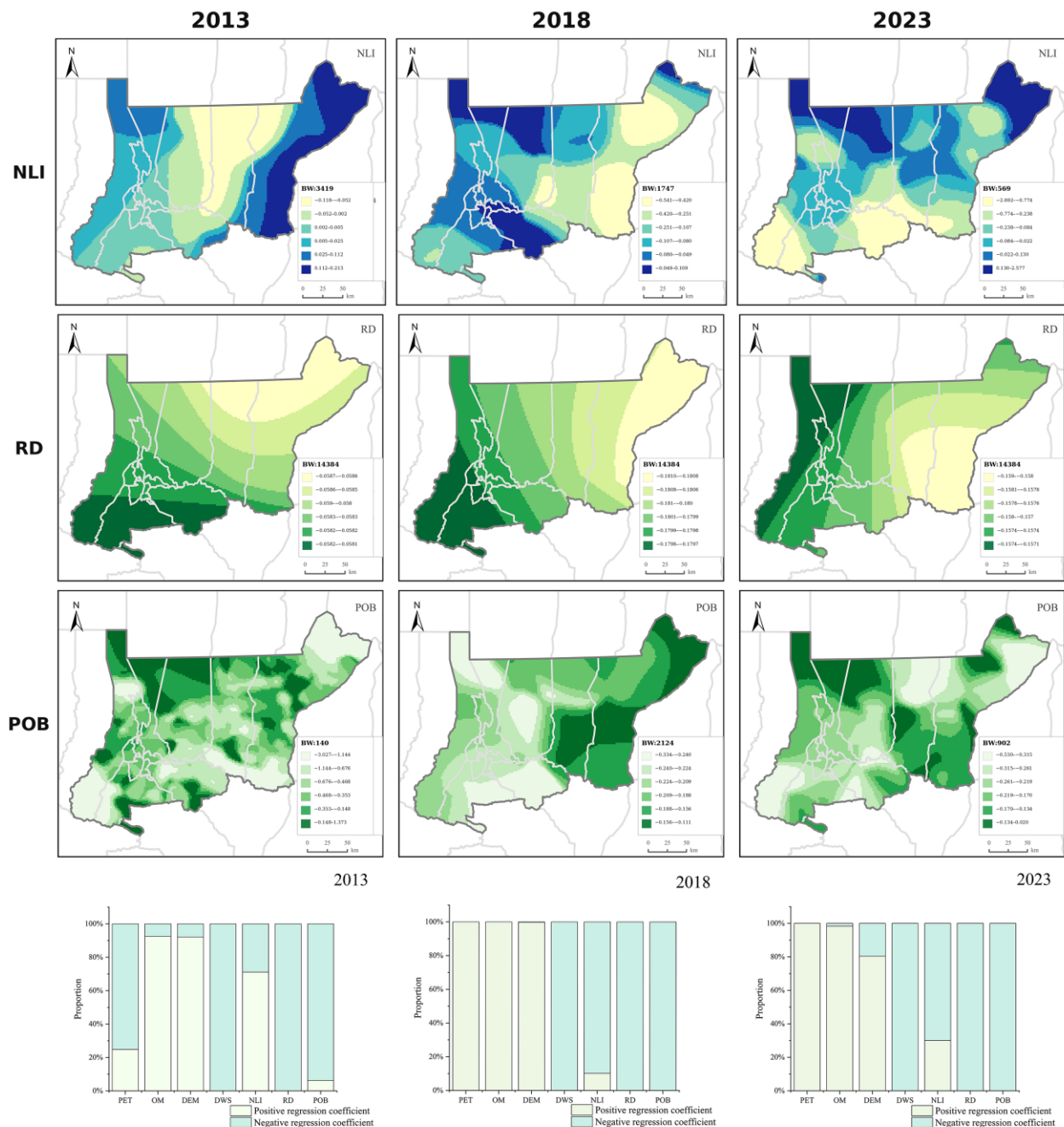


Figure 6. Spatial distributions of local MGWR coefficients for socioeconomic factors and proportions of positive and negative local coefficients in 2013, 2018, and 2023. The maps show the local coefficients and corresponding variable-specific bandwidths for nighttime light index (NLI), road density (RD), and proportion of built-up land (POB). The bar charts summarize the proportions of positive and negative local coefficients for all seven explanatory factors in each observation year. Source: Authors' analysis based on the datasets described in Section 2.2.

3.4. Ecological Management Zoning Across Urban–Rural Catchments

To identify spatially differentiated ecological management units, the four spatial clusters derived from the local MGWR coefficients for 2023 were overlaid with the four urban–rural catchment categories. This procedure produced 16 integrated ecological management types (Figure 7). The four-cluster solution produced a Calinski–Harabasz pseudo F-statistic of 512.8, compared with 438.6 for the three-cluster solution and 476.4 for the five-cluster solution. The four-cluster solution also had the highest pseudo F-statistic among the solutions evaluated from 2 to 30 clusters. After POB was excluded from the

MGWR model, the resulting four-cluster solution retained an adjusted Rand index of 0.846 and a grid-cell agreement rate of 92.7% relative to the baseline solution. Because the same urban–rural catchment classification was used in both overlays, agreement in the 16 integrated management types was also 92.7%. These results support the broad stability of the four-cluster structure and the resulting management types under the examined cluster-number and variable-set specifications (Appendix A Tables A20 and A21). The resulting types differed in ER levels, land-cover characteristics, and local ER–factor association profiles. Three-dimensional surface plots of ER and the key factors characterizing the spatial clusters are presented in Appendix A Figure A1.

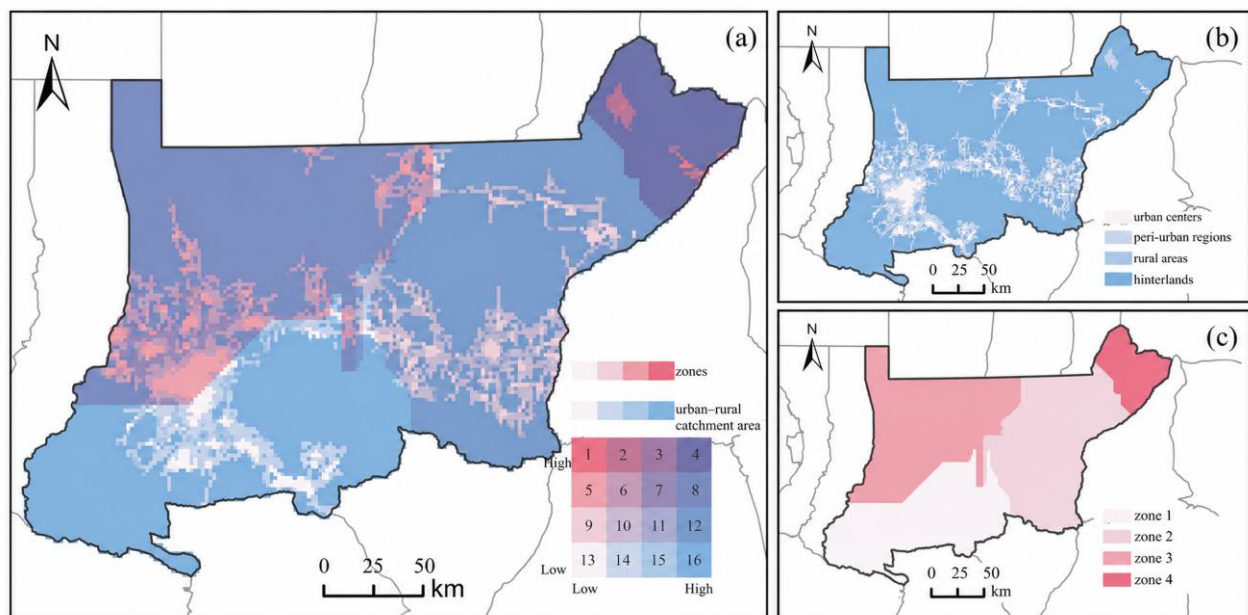


Figure 7. Integrated ecological management zoning across urban–rural catchments. Panel (a) shows the 16 management types generated by overlaying the four urban–rural catchment categories with the four spatial clusters of local ER–factor associations in 2023. The inset matrix shows the correspondence among urban–rural catchment categories, spatial clusters, and management-type numbers. Panels (b,c) show the urban–rural catchments and spatial clusters, respectively. Source: Authors’ analysis based on the datasets described in Section 2.2.

Urban centers exhibited the lowest overall ER and were mainly associated with Types 5 and 13. The mean local coefficients of NLI, RD, and POB were more negative in these areas than in the other catchments, with NLI showing the largest negative mean coefficient. Urban-center types were therefore characterized by relatively low ER and comparatively strong negative associations with socioeconomic factors.

Peri-urban regions showed greater heterogeneity in both spatial types and local association profiles. The eastern sector was mainly associated with Type 10 and was characterized by cropland, forest, and grassland, together with positive PET coefficients and negative RD coefficients. The southern sector was mainly associated with Type 14 and exhibited relatively high NLI, RD, and POB values. The northern sector was associated primarily with Types 4, 8, and 10 and showed comparatively strong PET-related association patterns.

Rural areas, which were mainly distributed adjacent to peri-urban regions, were predominantly associated with Type 7. These areas showed positive mean coefficients for NLI and RD and a negative mean coefficient for PET, forming a distinct local association profile relative to urban centers and peri-urban regions.

Hinterlands accounted for the largest proportion of the study area and were mainly associated with Types 8, 12, and 16. Natural factors retained greater explanatory importance in these areas, with PET showing the highest mean local coefficient. Socioeconomic coefficients were generally less pronounced than those observed in urban centers and peri-urban regions.

4. Discussion

4.1. Urban–Rural Differentiation and Divergent Changes in Ecological Resilience

The limited variation in mean ER across the UMA concealed a persistent urban–rural gradient and contrasting changes across the four catchment categories. Urban centers consistently exhibited lower ER than rural areas and hinterlands, which may be related to concentrated built-up land, transport infrastructure, and human activity that reduce habitat quality and landscape continuity [46,47]. Rural areas and hinterlands retained more natural and semi-natural land cover and generally showed higher ER, although these advantages remained constrained by aridity [48], water limitation [49], and ecological sensitivity [50]. Compared with 2013, ER in 2023 was higher in urban centers and peri-urban regions but lower in rural areas and hinterlands, indicating that the relatively stable regional mean masked contrasting changes across the metropolitan system [51].

The divergent trajectories may reflect the uneven distribution of ecological improvement and disturbance along the urban–rural gradient. Increased ER in urban centers and peri-urban regions may be associated with localized improvements in habitat condition and landscape configuration under ecological restoration, green-space development, and environmental management [52,53]. The decline in rural areas and hinterlands may correspond to land-cover conversion, landscape fragmentation, and disturbance around agricultural areas, transport corridors, and desert margins [54]. By distinguishing functionally connected urban–rural catchments, this study reveals ecological differences that may be obscured by regional averages, administrative units, or binary urban–rural classifications. The findings further show that current ER levels and changes across the three observation years should be evaluated jointly, as urban areas with low but improving ER and peripheral areas with higher but declining ER require different management priorities.

4.2. Urban–Rural Differences in Factors Associated with ER

The relative importance of natural and socioeconomic factors differed across urban–rural catchments [55]. Socioeconomic factors were more prominent in urban centers and peri-urban regions, whereas rural areas exhibited greater temporal variation in the relative importance of natural and socioeconomic factors. DEM and OM were more prominent in hinterlands, corresponding to the greater role of topographic and soil conditions under lower development intensity. These differences are consistent with the mountain–oasis–desert setting of the UMA: ecological conditions around urban and oasis areas are associated with both development intensity and environmental constraints [56], while those in hinterlands remain more closely related to natural background conditions [57]. After POB was excluded, NLI remained the leading factor in urban centers and peri-urban regions, while DEM and OM remained the two leading factors in hinterlands. Interactions combining DEM or OM with NLI or RD generally had higher joint q values, consistent with the combined influence of natural and socioeconomic conditions on ER differentiation.

The MGWR results further showed that ER–factor associations differed in direction and estimation scale [58]. DEM and OM became more positively associated with ER toward hinterlands, whereas negative associations with NLI, RD, and POB were

concentrated in more urbanized areas. The association of a socioeconomic factor with ER may therefore vary with development intensity and local environmental conditions [59]. PET and DWS operated over broader scales in the later observation years, RD approximated a global scale throughout, and NLI became increasingly localized. OM, DEM, and POB showed comparatively smaller or more year-specific bandwidths. These differences demonstrate that global factor importance alone cannot fully represent ER differentiation because local association direction and estimation scale also vary among factors and locations [60]. The limited changes in model fit, bandwidths, and coefficient surfaces after POB exclusion support interpretation of the broad association patterns, while individual local coefficients should still be interpreted cautiously.

4.3. From Urban–Rural Heterogeneity to Differentiated Ecological Management

The results indicate that differentiated ecological management should consider both the functional position of each area within the urban–rural system and its local ER–factor association profile. The four urban–rural catchments distinguish broad differences in ER levels, changes across the three observation years, and development conditions, while the four spatial clusters identify local variation that remains within each catchment. Their overlay therefore provides a two-level basis for management zoning. The catchment categories define the general management direction, and the spatial clusters refine priorities according to local environmental and socioeconomic associations. The high grid-cell agreement and kappa values obtained under the alternative barrier settings further support the use of the four catchment categories as broad management units, although their local boundaries should still be interpreted as approximate. The clustering checks provided additional support for the second level of the zoning framework. The four-cluster solution had the highest Calinski–Harabasz pseudo F-statistic among the tested cluster numbers, and the POB-excluded solution retained an adjusted Rand index of 0.846 and 92.7% grid-cell agreement with the baseline clustering. The spatial clusters and integrated management types can therefore be used as broad reference units, while their local boundaries still require verification through ecological monitoring and planning practice. This refinement is particularly relevant in peri-urban regions, where urban expansion, oasis agriculture, transport development, and desert-edge processes produce substantial internal variation [61]. The 16 integrated types therefore provide a more detailed spatial reference for differentiating management priorities within the broader urban–rural framework.

Urban centers require continued attention because their ER remained lower than that of the other catchment categories, although it was higher in 2023 than in 2013. The negative associations with NLI, RD, and POB support priorities related to controlling construction intensity, reducing road-related landscape fragmentation, and improving ecological connectivity through water-efficient green infrastructure [62]. In peri-urban regions, management should respond to differences among spatial clusters. Oasis agricultural and semi-natural landscapes require protection from fragmented expansion [63], while areas with relatively high development intensity should prioritize compact land-use patterns and the control of further fragmentation [64]. Rural areas retained relatively high ER, but their ER was lower in 2023 than in 2013, indicating the need to maintain farmland, forest, and grassland continuity and coordinate infrastructure development with water availability [65]. In hinterlands, where natural factors were more prominent, water conservation, soil and natural vegetation protection, and restrictions on disturbance should remain the main priorities [66]. These management directions are derived from the observed spatial associations and require further adjustment through ecological monitoring, water resource constraints, and local planning practice.

4.4. Limitations

Several limitations should be acknowledged. First, the ER index represents landscape conditions associated with resistance, adaptation, and recovery rather than observed responses to a specific disturbance. The recovery component represents relative potential ecological recovery inferred from land-cover composition and category-specific coefficients. Although the sensitivity analysis supported the broad stability of ER rankings and class patterns under the examined alternative weights and recovery coefficients, the baseline parameters were adopted from previous studies and were not locally calibrated for the UMA. The correlations with NPP provide only partial external support and do not constitute a comprehensive validation of the ER index. Future studies should extend the examined parameter ranges, strengthen local parameter calibration, and validate the index using multiple independent ecological indicators, including field observations, biodiversity metrics, remote-sensing indices, and post-disturbance monitoring.

Second, the three observation years cannot capture continuous ecological dynamics, and the OPGD and MGWR results represent spatial associations rather than causal effects. Although model comparisons and residual Moran's *I* suggest that MGWR reduced the remaining spatial dependence, neighboring grid cells remain spatially correlated and cannot be regarded as fully independent observations. Conventional factor-detector *p* values should therefore be interpreted cautiously. Although local multicollinearity and coefficient uncertainty were evaluated using local condition numbers and pseudo-*t* statistics, these diagnostics do not account for spatial dependence or multiple local comparisons. Individual local coefficients should therefore be interpreted cautiously, particularly where coefficient magnitudes were close to zero. The catchment classifications remained highly consistent under the examined barrier scenarios, although local boundaries may still vary with untested network-speed assumptions, transfer rules, and grid resolution. Although excluding POB reduced concern about shared land-cover information, its comparatively high explanatory power in the full-factor analysis should still be interpreted cautiously.

Third, the management zoning was based on the 2023 MGWR coefficients. Although the four-cluster solution had the highest Calinski–Harabasz pseudo *F*-statistic among the tested cluster numbers and remained broadly consistent after POB exclusion, the sensitivity of the zoning to alternative spatial-contiguity definitions, coefficient-standardization procedures, and data from other observation years was not fully examined. The integrated types should therefore be treated as spatial reference units rather than definitive planning boundaries and should be further evaluated using ecological monitoring, water-resource constraints, field evidence, and local planning objectives.

5. Conclusions

By integrating urban–rural catchments with global and local factor analyses and spatially constrained clustering, this study connects ER differentiation with ecological management zoning in the Urumqi Metropolitan Area. The main findings are as follows.

- (1) Mean ER values were 0.49, 0.50, and 0.48 in 2013, 2018, and 2023, respectively. Lower ER was concentrated in urban centers, whereas higher ER occurred mainly in rural areas and hinterlands. Compared with 2013, ER in 2023 was higher in urban centers and peri-urban regions but lower in rural areas and hinterlands.
- (2) Socioeconomic factors were more prominent in urban centers and peri-urban regions, whereas rural areas exhibited temporally variable natural and socioeconomic patterns. Elevation and soil organic matter were more prominent in hinterlands. Factor interactions were predominantly characterized by bi-factor or nonlinear enhancement.

- (3) Local ER–factor associations varied in direction, magnitude, and spatial scale across locations and observation years. Associations with elevation and soil organic matter became more positive toward hinterlands. Negative associations with nighttime light intensity, road density, and the proportion of built-up land were concentrated in peri-urban and rural areas, along major transport corridors, and in densely urbanized areas, respectively. The nighttime light index became increasingly localized, whereas road density operated at an approximately global scale.
- (4) Four spatial clusters derived from the 2023 local ER–factor association patterns were overlaid with four urban–rural catchment categories to produce 16 integrated ecological management types. By combining catchment position with local association patterns, the zoning provides spatially explicit units for differentiated ecological management and regional planning.

Given the landscape-based ER measure and the three observation years, these findings should be interpreted as relative spatial evidence for the UMA. Future research should extend the parameter ranges examined in this study, strengthen local calibration, and evaluate the transferability of the analytical framework using field and post-disturbance observations and comparative applications in other arid metropolitan regions.

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

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Abbreviations

The following abbreviations are used in this manuscript:

ER	Ecological Resilience
PET	Potential Evapotranspiration
OM	Soil Organic Matter
DEM	Elevation (Digital Elevation Model)
DWS	Distance to Water Systems
NLI	Nighttime Light Index
RD	Road Density
POB	Proportion of Built-Up Land
NPP	Net Primary Productivity
UMA	Urumqi Metropolitan Area
HQ	Habitat Quality
SHDI	Shannon Diversity Index
SPLIT	Landscape Splitting Index
DIVISION	Landscape Division Index
NASA	National Aeronautics and Space Administration
MODIS	Moderate Resolution Imaging Spectroradiometer
GEBCO	General Bathymetric Chart of the Oceans
OPGD	Optimal-Parameter Geodetector
MGWR	Multiscale Geographically Weighted Regression
SCMCA	Spatially Constrained Multivariate Clustering Analysis
GWR	Geographically Weighted Regression

AICc	Corrected Akaike Information Criterion
VIF	Variance Inflation Factor
BW	Bandwidth

Appendix A

Appendix A.1. Ecological Resilience Indicators and InVEST Parameter Settings

Ecological resilience was evaluated using a landscape-based resistance–adaptation–recovery framework. Resistance was characterized by habitat quality, adaptation by landscape diversity and fragmentation, and recovery by land-cover composition and category-specific ecological recovery coefficients. The three dimensions were calculated separately and normalized to a common scale from 0 to 1. To ensure comparability across observation years, the minimum and maximum values were derived from the pooled grid observations for 2013, 2018, and 2023 and applied consistently to all three years. The normalized dimensions were then integrated using the geometric mean.

Table A1. Indicators and corresponding formulas.

Indicator	Formula	Meaning
<i>SHDI</i>	$SHDI = -\sum_{i=1}^m P_i \ln(P_i)$	Where m denotes the number of landscape types, and P_i denotes the proportional area of landscape type i . $SHDI \geq 0$; higher values indicate greater land-cover diversity and evenness.
<i>SPLIT</i>	$SPLIT = \frac{A^2}{\sum_{i=1}^m \sum_{j=1}^n a_{ij}^2}$	Where A denotes the total landscape area, and a_{ij} denotes the area of patch j within landscape type i ; and m and n represent the total number of patch types and the number of patches in each type, respectively. $SPLIT \geq 1$; higher original values indicate greater subdivision of the landscape.
<i>DIVISION</i>	$DIVISION = 1 - \sum_{i=1}^m \sum_{j=1}^n \left(\frac{a_{ij}}{A} \right)^2$	Where A denotes the total landscape area, and a_{ij} denotes the area of patch j within landscape type i ; and m and n represent the total number of patch types and the number of patches in each type, respectively. Higher original values indicate greater landscape division and weaker structural connectivity.
<i>HQ</i>	$Q_{xy} = H_j \left(1 - \frac{D_{xy}^z}{D_j^z + k^z} \right)$	Where Q_{xy} denotes the habitat quality index of grid cell x in habitat type j , ranging from 0 to 1; H_j denotes the habitat suitability of habitat type j ; D_{xy} denotes the habitat degradation level of grid cell x in habitat type j ; k denotes the half-saturation constant, which is usually set to half of the maximum degradation value; and z denotes a normalization constant, which is a default model parameter and is generally set to 2.5. Higher habitat quality indicates lower habitat degradation and a greater capacity to maintain ecological structure and functions under external pressure.

Resistance was estimated using the InVEST Habitat Quality model version 3.14.2. Five land-cover-related threats were considered. The scaling parameter z was fixed by the

model at 2.5. A preliminary model run yielded a maximum grid-cell degradation value of 0.10. The half-saturation constant k was set to one-half of this maximum value, resulting in $k = 0.05$. The same calibrated k value, threat settings, habitat suitability values, and sensitivity coefficients were applied consistently to 2013, 2018, and 2023.

Table A2. Threat-factor settings used in the InVEST Habitat Quality model.

Threat Factor	Maximum Influence Distance (km)	Weight	Decay Type
Cultivated land	4	0.6	Linear
Urban land	6	1.0	Exponential
Rural residential land	8	0.8	Exponential
Other construction land	7	0.7	Exponential
Unused land	4	0.4	Linear

Table A3. Habitat suitability and sensitivity parameters used in the InVEST Habitat Quality model.

LULC Code	Land-Cover Category	Habitat Suitability	Cultivated Land	Urban Land	Rural Residential Land	Other Construction Land	Unused Land
11	Paddy field	0.5	0.0	0.8	0.6	0.7	0.4
12	Dry land	0.5	0.0	0.8	0.6	0.7	0.4
21	Forestland	1.0	0.7	0.9	0.8	0.8	0.5
22	Shrubland	0.9	0.6	0.8	0.7	0.7	0.4
23	Sparse forestland	0.8	0.7	0.9	0.8	0.8	0.5
24	Other forestland	0.6	0.7	0.9	0.8	0.8	0.5
31	High-coverage grassland	0.9	0.6	0.7	0.7	0.7	0.7
32	Medium-coverage grassland	0.8	0.7	0.8	0.8	0.8	0.7
33	Low-coverage grassland	0.7	0.7	0.8	0.8	0.8	0.7
41	Rivers and canals	0.9	0.4	0.7	0.6	0.7	0.4
42	Lakes	0.9	0.4	0.7	0.6	0.7	0.4
43	Reservoirs and ponds	0.9	0.4	0.7	0.6	0.7	0.4
44	Permanent glaciers and snow	0.9	0.4	0.7	0.6	0.7	0.4
45	Tidal flats	0.9	0.4	0.7	0.6	0.7	0.4
46	Bottomland	0.9	0.4	0.7	0.6	0.7	0.4
51	Urban land	0.0	0.0	0.0	0.0	0.0	0.0
52	Rural residential land	0.0	0.0	0.0	0.0	0.0	0.0
53	Other construction land	0.0	0.0	0.0	0.0	0.0	0.0
61	Sandy land	0.3	0.4	0.6	0.5	0.6	0.0
62	Gobi	0.3	0.4	0.6	0.5	0.6	0.0
63	Saline-alkali land	0.3	0.4	0.6	0.5	0.6	0.0
64	Marshland	0.3	0.4	0.6	0.5	0.6	0.0
65	Bare land	0.3	0.4	0.6	0.5	0.6	0.0
66	Bare rock and gravel	0.3	0.4	0.6	0.5	0.6	0.0
67	Other unused land	0.3	0.4	0.6	0.5	0.6	0.0

Notes: The threat-factor settings, habitat suitability values, and sensitivity coefficients were determined with reference to previous InVEST-based research [30] and adapted to the land-cover classification used in this study. Maximum influence distance is expressed in kilometers. Threat weights represent relative importance and are normalized internally by the model. Habitat suitability and sensitivity values range from 0 to 1. A habitat suitability value of 0 indicates non-habitat, whereas 1 indicates the highest habitat suitability. A sensitivity value of 0 indicates no sensitivity to the corresponding threat, whereas 1 indicates the highest sensitivity. The scaling parameter z was fixed by the model at 2.5. A preliminary model run yielded a maximum degradation value of 0.10, and the half-saturation constant k was therefore set to one-half of this value, resulting in $k = 0.05$. Identical parameter settings were applied to 2013, 2018, and 2023.

Appendix A.2. Parameter Settings for Urban–Rural Catchment Delineation

Urban–rural catchments were delineated using urban-center population classes and minimum cumulative travel time. The travel-cost surface integrated transport-network speeds, transport barriers, land-cover-specific movement speeds, and slope-adjusted travel costs. The parameter settings are summarized in Tables A4–A7.

Table A4. Transport-network and barrier speeds used to delineate urban–rural catchments.

Component	Category	Speed or Rule
Road	Expressway	120 km/h
Road	Trunk road	90 km/h
Road	Primary road	80 km/h
Road	Secondary road	60 km/h
Road	Tertiary road	40 km/h
Road	Minor road	20 km/h
Railway	Railway	250 km/h
Barrier	Buffers on both sides of railways and express-ways	1 km/h within a 1 km buffer

Table A5. Off-road movement speeds used to delineate urban–rural catchments.

Land-Cover Category	Speed	Land-Cover Category	Speed
Built-up land	5.00 km/h	Permanent wetlands	2.00 km/h
Cropland	2.50 km/h	Snow and ice	1.62 km/h
Cropland–natural vegetation mosaic	3.24 km/h	Bare land	3.00 km/h
Savanna	4.86 km/h	Water bodies	1.00 km/h
Grassland	4.86 km/h	Mixed forest	3.24 km/h
Evergreen broadleaf forest	1.62 km/h	Deciduous needleleaf forest	3.24 km/h
Deciduous broadleaf forest	4.00 km/h		

Table A6. Urban-center population classes used to delineate urban–rural catchments.

Urban-Center Class	Population Threshold
Large cities	1–5 million
Intermediate cities	0.5–1 million
Small cities	50,000–500,000
Towns	20,000–50,000

Table A7. Urban–rural catchment classification rules.

Catchment Category	Classification Rule
Urban centers	Grid cells within identified urban boundaries
Peri-urban regions	Travel time of 0–1 h
Rural areas	Travel time of more than 1 h and no more than 3 h
Hinterlands	Travel time of more than 3 h from any urban center
Overlapping catchments	Assigned to the larger urban center within the same travel-time interval

Notes: Travel time was initially divided into 0 h, 0–0.5 h, 0.5–1 h, 1–2 h, 2–3 h, and more than 3 h. Travel costs were adjusted for slope before the layers were integrated. The overlay priority was road network, transport barrier, land cover, and slope. The same parameter settings and classification rules were applied to 2013, 2018, and 2023.

Appendix A.3. OPGD Discretization and Results Excluding POB

Continuous explanatory variables were discretized using equal interval, natural breaks, quantile, geometric interval, and standard deviation methods, with the number of intervals ranging from three to six. For each factor, the classification method and number of intervals yielding the highest q value were retained. The selected discretization schemes are reported in Table A8. To examine whether the principal factor patterns depended on the inclusion of POB, the factor and interaction detection results were further summarized after POB was excluded. Table A9 reports the three leading factors and the strongest interaction not involving POB for each observation year and spatial unit.

Table A8. Selected discretization methods and numbers of intervals for the OPGD analysis.

Region	Factor	2013	2018	2023
Entire study area	PET	SD-3	SD-3	SD-3
Entire study area	OM	GI-6	Q-6	Q-6
Entire study area	DEM	SD-6	SD-5	SD-5
Entire study area	DWS	Q-6	EI-6	Q-6
Entire study area	NLI	SD-6	SD-6	SD-6
Entire study area	RD	NB-6	NB-6	GI-6
Entire study area	POB	Q-6	NB-6	Q-6
Hinterlands	PET	Q-5	SD-3	SD-3
Hinterlands	OM	Q-6	Q-6	Q-6
Hinterlands	DEM	SD-5	SD-5	SD-5
Hinterlands	DWS	SD-6	EI-6	Q-6
Hinterlands	NLI	SD-6	Q-6	SD-6
Hinterlands	RD	SD-4	SD-4	SD-6
Hinterlands	POB	EI-5	SD-5	Q-6
Rural areas	PET	Q-5	Q-6	Q-6
Rural areas	OM	Q-6	Q-6	Q-6
Rural areas	DEM	SD-6	EI-4	NB-5
Rural areas	DWS	Q-6	EI-6	NB-6
Rural areas	NLI	NB-6	Q-6	SD-6
Rural areas	RD	NB-6	Q-4	NB-6
Rural areas	POB	SD-6	NB-4	GI-6
Peri-urban regions	PET	Q-6	Q-5	Q-5
Peri-urban regions	OM	SD-5	Q-6	Q-5
Peri-urban regions	DEM	GI-5	EI-4	NB-6
Peri-urban regions	DWS	Q-5	NB-6	EI-6
Peri-urban regions	NLI	Q-6	SD-6	SD-6
Peri-urban regions	RD	NB-6	EI-5	NB-6
Peri-urban regions	POB	Q-6	Q-6	EI-6
Urban centers	PET	Q-5	Q-4	SD-3
Urban centers	OM	NB-6	SD-5	Q-5
Urban centers	DEM	SD-5	NB-6	SD-6
Urban centers	DWS	Q-6	NB-6	Q-6
Urban centers	NLI	GI-6	GI-6	GI-6
Urban centers	RD	Q-6	SD-4	GI-6
Urban centers	POB	SD-5	EI-4	EI-6

Note: EI, NB, Q, GI, and SD denote equal interval, natural breaks, quantile, geometric interval, and standard deviation, respectively. The numeral following the hyphen denotes the selected number of intervals.

Table A9. Leading OPGD factors and strongest interactions not involving POB.

Year	Spatial Unit	Three Leading Factors (q)	Strongest Interaction Not Involving POB (Joint q)
2013	Entire study area	DEM (0.282); OM (0.248); PET (0.150)	OM $\cap$ RD (0.354)
2013	Urban centers	NLI (0.237); RD (0.220); DEM (0.122)	DEM $\cap$ RD (0.345)
2013	Peri-urban regions	NLI (0.158); RD (0.133); DEM (0.105)	DEM $\cap$ NLI (0.242)
2013	Rural areas	DEM (0.135); NLI (0.123); RD (0.085)	DEM $\cap$ NLI (0.257)
2013	Hinterlands	DEM (0.284); OM (0.253); PET (0.150)	OM $\cap$ DEM (0.356)
2018	Entire study area	DEM (0.229); OM (0.194); PET (0.144)	DEM $\cap$ NLI (0.308)
2018	Urban centers	NLI (0.090); DEM (0.046); OM (0.013)	DEM $\cap$ NLI (0.131)
2018	Peri-urban regions	NLI (0.190); DEM (0.096); OM (0.073)	OM $\cap$ NLI (0.258)
2018	Rural areas	OM (0.131); DEM (0.125); NLI (0.107)	OM $\cap$ NLI (0.249)
2018	Hinterlands	DEM (0.235); OM (0.211); PET (0.149)	DEM $\cap$ DWS (0.307)
2023	Entire study area	DEM (0.272); OM (0.223); NLI (0.140)	DEM $\cap$ NLI (0.366)
2023	Urban centers	NLI (0.277); RD (0.199); DEM (0.088)	DEM $\cap$ NLI (0.316)
2023	Peri-urban regions	NLI (0.124); RD (0.103); DEM (0.087)	DEM $\cap$ NLI (0.200)
2023	Rural areas	NLI (0.126); RD (0.078); DEM (0.077)	OM $\cap$ NLI (0.204)
2023	Hinterlands	DEM (0.286); OM (0.274); PET (0.149)	OM $\cap$ DEM (0.365)

Note: Values in parentheses are OPGD q statistics. Factors are listed in descending order of q. The strongest interaction refers to the factor pair with the highest joint q value among interactions not involving POB. POB was omitted because it shares land-cover information with the ER index.

Appendix A.4. Clustering Settings, Model Performance, and MGWR Diagnostics

The local MGWR coefficient surfaces for PET, OM, DEM, DWS, NLI, RD, and POB in 2023 were used as clustering variables and standardized using the z-score method to ensure comparability across factors. ArcGIS Pro evaluated solutions ranging from 2 to 30 clusters using the Calinski–Harabasz pseudo F-statistic. The four-cluster solution was identified as optimal and retained for the spatially constrained multivariate clustering analysis. Spatial adjacency was defined using the default contiguity–edges–corners criterion, under which grid cells sharing an edge or vertex were treated as neighbors. Model-performance statistics for the OLS, GWR, and MGWR models and the corresponding residual spatial autocorrelation are summarized in Tables A10 and A11.

Table A10. Year-specific performance comparison of the OLS, GWR, and MGWR models.

Year	Model	AICc	R ²	Adjusted R ²
2013	OLS	570.62	0.525	0.515
2013	GWR	515.44	0.688	0.628
2013	MGWR	466.28	0.787	0.751
2018	OLS	598.47	0.498	0.488
2018	GWR	543.82	0.657	0.596
2018	MGWR	491.63	0.749	0.705
2023	OLS	583.93	0.507	0.497
2023	GWR	528.85	0.665	0.606
2023	MGWR	481.52	0.744	0.710

Note: Lower AICc values and higher R² and adjusted R² values indicate better relative model fit. Model-performance statistics are reported separately for 2013, 2018, and 2023.

Table A11. Global Moran's I for ER and model residuals.

Year	ER	OLS Residuals	GWR Residuals	MGWR Residuals
2013	0.680	0.290	0.120	0.045
2018	0.720	0.320	0.140	0.052

2023 0.690 0.300 0.110 0.041

Note: Global Moran's I was calculated using the same spatial-weights specification for ER and the residuals of the OLS, GWR, and MGWR models. Lower residual Moran's I values indicate weaker remaining spatial dependence.

Local condition numbers and pseudo-t statistics were further summarized to evaluate local multicollinearity and coefficient uncertainty in the MGWR estimates.

Table A12. Local multicollinearity diagnostics for the MGWR models.

Year	Median Local Condition Number	95th Percentile	Maximum	Grid Cells with Condition Number > 30 (%)
2013	14.2	27.6	41.6	2.7
2018	12.8	24.9	37.4	1.8
2023	13.5	26.3	39.2	2.2

Note: Local condition numbers were used to assess local multicollinearity. Values greater than 30 were treated as evidence of potentially unstable local coefficient estimation. The reported percentages represent the proportions of all valid grid cells exceeding this threshold.

Table A13. Coefficient-uncertainty diagnostics for the MGWR models.

Year	Factor	Grid Cells with Pseudo-t > 1.96 (%)
2013	PET	46.8
2013	OM	69.4
2013	DEM	72.1
2013	DWS	52.6
2013	NLI	58.3
2013	RD	43.7
2013	POB	66.2
2018	PET	54.1
2018	OM	73.8
2018	DEM	70.5
2018	DWS	61.7
2018	NLI	68.9
2018	RD	49.5
2018	POB	60.4
2023	PET	57.2
2023	OM	71.6
2023	DEM	67.3
2023	DWS	63.5
2023	NLI	75.1
2023	RD	52.4
2023	POB	64.8

Note: Coefficient uncertainty was summarized using local pseudo-t statistics. The reported percentages represent the proportions of grid cells with absolute pseudo-t values greater than 1.96 and were used as descriptive diagnostics of the spatial support for the estimated local coefficients.

The MGWR models were further re-estimated after excluding POB. Changes in AICc, R², adjusted R², variable-specific bandwidths, Pearson correlations between corresponding local coefficient surfaces, and coefficient-sign agreement were used to compare the full and POB-excluded model specifications.

Table A14. Changes in MGWR model fit after excluding POB.

Year	Metric	Full Model	POB-Excluded Model	Change
2013	AICc	466.28	475.65	+9.37
2013	R ²	0.787	0.745	−0.042
2013	Adjusted R ²	0.751	0.711	−0.040
2018	AICc	491.63	497.57	+5.94
2018	R ²	0.749	0.723	−0.026
2018	Adjusted R ²	0.705	0.682	−0.023
2023	AICc	481.52	488.23	+6.71
2023	R ²	0.744	0.717	−0.027
2023	Adjusted R ²	0.710	0.684	−0.026

Table A15. Changes in variable-specific bandwidths and local coefficient patterns after excluding POB.

Year	Factor	Bandwidth with POB	Bandwidth Without POB	Pearson Correlation Between Local Coefficient Surfaces	Grid Cells Retaining the Same Coefficient Sign (%)
2013	PET	5513	5078	0.882	87.6
2013	OM	1819	1964	0.981	97.8
2013	DEM	1819	2058	0.973	95.4
2013	DWS	4218	4486	0.948	96.7
2013	NLI	3419	2896	0.906	90.8
2013	RD	14384	13762	0.956	97.1
2018	PET	7607	7394	0.972	98.4
2018	OM	3230	3378	0.986	99.1
2018	DEM	3419	3566	0.964	96.5
2018	DWS	13090	12784	0.961	98.7
2018	NLI	1747	1896	0.979	97.3
2018	RD	14384	14012	0.968	98.9
2023	PET	8101	7864	0.951	97.6
2023	OM	3230	3448	0.982	96.9
2023	DEM	2241	2586	0.918	88.7
2023	DWS	14384	13946	0.958	98.1
2023	NLI	569	648	0.961	95.8
2023	RD	14384	14108	0.969	98.6

Note: The full model included PET, OM, DEM, DWS, NLI, RD, and POB, whereas the POB-excluded model retained the other six explanatory variables. Both model specifications used the same observations, data standardization, kernel function, and bandwidth-selection procedure. Change was calculated as the value of the POB-excluded model minus that of the full model. Bandwidths represent the number of nearest neighbors selected for each explanatory factor. Pearson correlation coefficients describe the similarity between corresponding local coefficient surfaces. Sign agreement represents the percentage of grid cells in which the corresponding local coefficients retained the same positive or negative sign after POB was excluded.

Appendix A.5. Sensitivity Analysis of the ER Index

Sensitivity analyses were conducted to examine whether the ER estimates depended strongly on the literature-based adaptation weights and land-cover-specific recovery coefficients. Three alternative adaptation-weighting schemes were compared with the baseline scheme. Recovery sensitivity was assessed by separately increasing and decreasing each recovery coefficient by 10%. The alternative ER estimates were evaluated using grid-level rank correlation, mean absolute difference, and agreement in the five fixed ER classes.

Table A16. Sensitivity of ecological resilience to alternative adaptation-weighting schemes.

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Scenario	Year	Spearman Correlation	Mean Absolute Difference	Class Agreement (%)
Equal weights	2013	0.998	0.014	98.3
Equal weights	2018	0.998	0.015	97.9
Equal weights	2023	0.998	0.014	98.2
SHDI-enhanced weights	2013	0.994	0.019	97.8
SHDI-enhanced weights	2018	0.993	0.020	97.3
SHDI-enhanced weights	2023	0.993	0.020	97.6
SPLIT/DIVISION-enhanced weights	2013	0.995	0.017	98.5
SPLIT/DIVISION-enhanced weights	2018	0.994	0.018	98.0
SPLIT/DIVISION-enhanced weights	2023	0.994	0.018	98.4

Table A17. Sensitivity of ecological resilience to perturbations of land-cover-specific recovery coefficients.

Year	Spearman Correlation Range	Maximum Mean Absolute Difference	Minimum Class Agreement (%)
2013	0.998–1.000	0.003	98.8
2018	0.996–1.000	0.007	97.2
2023	0.999–1.000	0.003	97.9

Note: The equal-weight scheme assigned one-third of the total weight to each of SHDI, reverse-normalized SPLIT, and reverse-normalized DIVISION. The SHDI-enhanced scheme used weights of 0.60, 0.25, and 0.15, and the SPLIT/DIVISION-enhanced scheme used weights of 0.40, 0.35, and 0.25. Recovery sensitivity was assessed using 12 one-at-a-time scenarios generated by separately increasing and decreasing each of the six land-cover-specific recovery coefficients by 10%. For each observation year, Table A17 reports the range of Spearman correlations, the maximum mean absolute difference, and the minimum class agreement across the 12 scenarios. Spearman correlation measures consistency in grid-cell ranking, mean absolute difference measures the average numerical change in ER, and class agreement represents the percentage of grid cells assigned to the same fixed ER class as under the baseline setting.

Appendix A.6. Sensitivity of Urban–Rural Catchment Delineation

Sensitivity analysis was conducted to evaluate whether the four urban–rural catchment categories depended strongly on the low-speed barrier setting applied around expressways and railways. The baseline scenario assigned a movement speed of 1 km/h within a 1 km buffer. Two alternative scenarios were tested by increasing the buffer speed to 3 km/h and removing the low-speed buffer, respectively. All other travel-cost parameters and classification rules were held constant. The alternative classifications were evaluated using changes in the area of each catchment category, overall grid-cell agreement, and Cohen’s kappa.

Table A18. Changes in catchment area under alternative barrier settings relative to the baseline scenario.

Year	Scenario	Change in Urban-Center Area (km ²)	Change in Peri-Urban Area (km ²)	Change in Rural Area (km ²)	Change in Hinterland Area (km ²)
2013	3 km/h buffer	0	+120	+88	−208
2013	Buffer removed	0	+284	+164	−448
2018	3 km/h buffer	0	+192	+128	−320
2018	Buffer removed	0	+420	+252	−672
2023	3 km/h buffer	0	+248	+156	−404
2023	Buffer removed	0	+568	+332	−900

Table A19. Agreement between alternative and baseline catchment classifications.

Year	Scenario	Grid-Cell Agreement (%)	Cohen's Kappa
2013	3 km/h buffer	99.4	0.962
2013	Buffer removed	98.7	0.917
2018	3 km/h buffer	99.1	0.965
2018	Buffer removed	98.1	0.926
2023	3 km/h buffer	98.8	0.968
2023	Buffer removed	97.4	0.930

Note: The baseline scenario assigned a movement speed of 1 km/h within a 1 km buffer on both sides of expressways and railways. The 3 km/h buffer scenario retained the same buffer width but increased the movement speed to 3 km/h. The buffer-removed scenario excluded the low-speed buffer while retaining all other travel-cost parameters and classification rules. Positive area changes represent category expansion relative to the baseline, and negative values represent contraction. Grid-cell agreement represents the percentage of grid cells assigned to the same catchment category as under the baseline scenario. Cohen's kappa measures classification agreement after accounting for agreement expected by chance.

Appendix A.7. Stability of Spatial Clustering and Integrated Management Types

Cluster stability was assessed from two complementary perspectives. First, the Calinski–Harabasz pseudo F-statistics of the neighboring three-, four-, and five-cluster solutions were compared to evaluate sensitivity to the selected number of clusters. Second, the four-cluster analysis was repeated using the six local coefficient surfaces obtained from the POB-excluded MGWR model. The alternative cluster labels were matched to the baseline labels according to maximum spatial overlap. Similarity was evaluated using the adjusted Rand index, grid-cell agreement, and agreement in the 16 integrated management types.

Table A20. Comparison of neighboring cluster-number solutions.

Number of Clusters	Calinski–Harabasz Pseudo F-statistic	Treatment
3	438.6	Alternative solution
4	512.8	Retained solution
5	476.4	Alternative solution

Table A21. Comparison of the baseline and POB-excluded four-cluster solutions.

Comparison	Number of Clusters	Adjusted Rand Index	Grid-Cell Agreement (%)	Management-Type Agreement (%)
POB-excluded versus baseline solution	4	0.846	92.7	92.7

Note: The baseline clustering used the 2023 local MGWR coefficient surfaces for PET, OM, DEM, DWS, NLI, RD, and POB. The POB-excluded clustering used the corresponding six coefficient surfaces for PET, OM, DEM, DWS, NLI, and RD, while retaining the same four-cluster specification, z-score standardization, and contiguity–edges–corners setting. Table A20 reports the three solutions neighboring the retained cluster number; the four-cluster solution had the highest Calinski–Harabasz pseudo F-statistic among all solutions evaluated from 2 to 30 clusters. Cluster labels in the POB-excluded solution were matched to the baseline labels according to maximum spatial overlap. The adjusted Rand index measures similarity between the two complete cluster partitions, while grid-cell agreement represents the percentage of grid cells retaining the same matched cluster assignment. Because the same urban–rural catchment categories were used in both overlays, management-type agreement was equal to cluster-level grid-cell agreement.

Appendix A.8. Three-Dimensional Surface Visualization

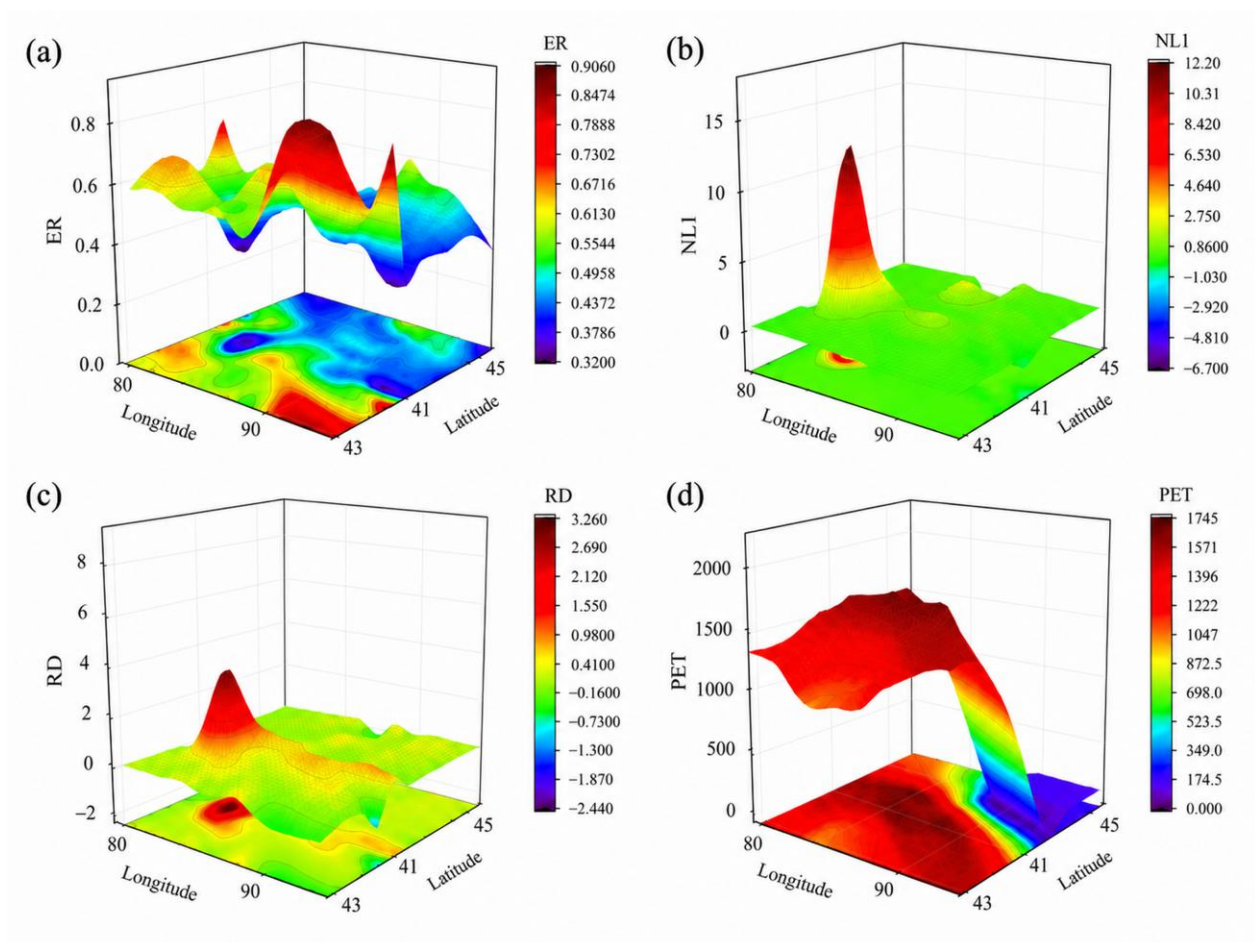


Figure A1. Three-dimensional surface distributions of ecological resilience and selected factors in 2023. Panels (a–d) show ecological resilience (ER), nighttime light index (NLI), road density (RD), and potential evapotranspiration (PET), respectively. Source: Authors’ analysis based on the datasets described in Section 2.2.

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