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Risk-service mismatches reveal conservation and restoration priorities in China's major urban agglomerations

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Abstract

Rapid urbanization can expose high-value ecosystems to disturbance while leaving other landscapes degraded and vulnerable. This study develops a risk-service mismatch framework that integrates the landscape ecological risk index (LERI), ecosystem service value (ESV), performance-screened machine-learning diagnosis, and bivariate ecological zoning. The framework was applied to the Beijing-Tianjin-Hebei region (BTH), Yangtze River Delta (YRD), and Guangdong-Hong Kong-Macao Greater Bay Area (GBA) for five years between 2000 and 2020. Mean LERI declined and ESV increased in all three regions, but their trajectories and spatial configurations differed. The YRD showed the largest LERI reduction yet retained relatively high risk, whereas the GBA combined the lowest mean risk with concentrated high-risk patches. Regulating services dominated ESV growth, and water bodies and forestland were persistent contributors. Driver importance was interpreted only for models with adequate test-set performance. Ecological advantage zones expanded in all regions, but vulnerable zones persisted in the BTH plains and sensitivity zones increased in the YRD and GBA. By distinguishing high-value ecosystems requiring risk control from low-value landscapes requiring functional restoration, the framework converts joint assessment into region-specific conservation and restoration priorities.

Keywords: landscape ecological risk; ecosystem service value; risk-service mismatch; ecological zoning; machine learning; urban agglomerations

Introduction

Rapid urbanization changes land-use composition, fragments ecological space, and increases pressure on ecosystems within and around urban agglomerations [1]. These effects are often concentrated along expansion fronts and transport corridors, where landscape connectivity declines as built-up land increases [2]. China's Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), and Guangdong-Hong Kong-Macao Greater Bay Area (GBA) represent three highly urbanized regions with contrasting climates, landscape structures, and development trajectories. A comparison of these regions can therefore reveal both shared and region-specific ecological priorities.

Landscape ecological risk and ecosystem services provide complementary perspectives on regional ecological security. Landscape ecological risk, commonly represented by the landscape ecological risk index (LERI), characterizes the potential for ecological loss arising from landscape disturbance and land-type vulnerability [3,4]. Ecosystem service value (ESV) estimates the benefits that ecosystems provide through provisioning, regulating, supporting, and cultural services [5,6]. LERI identifies where ecological systems are vulnerable to disturbance, whereas ESV identifies where ecological functions are concentrated. Considering either indicator alone may therefore produce incomplete management priorities.

Recent research has increasingly integrated ecological risk and ecosystem services to support spatial planning. Joint assessments have been used to identify ecological security patterns and management zones at city and urban-agglomeration scales [7,8]. Bivariate zoning has further distinguished areas with different combinations of ecological risk and service value [9,10]. Applications in the YRD and other rapidly urbanizing regions show that this approach can translate ecological indicators into spatially differentiated management categories [11,12]. However, most studies focus on a single city, watershed, mountain region, or urban agglomeration, which limits evaluation of whether the same zoning logic remains consistent across different metropolitan contexts [13,14].

Existing integrated assessments also tend to treat LERI-ESV zoning as an indicator overlay rather than as a diagnosis of risk-service mismatch. This distinction has direct management implications. High ESV combined with high LERI identifies valuable ecosystems that require risk control, whereas low ESV combined with high LERI identifies degraded landscapes that require ecological restoration [15,16]. Studies of mountain and urban systems have recognized similar contrasts, but they rarely compare how these categories change among regions with different hydrological conditions and development intensities [14,17]. Consequently, the spatial distinction between protecting existing services and rebuilding impaired services remains insufficiently tested.

A further limitation concerns the explanation of spatial variation in ESV. Machine-learning models can identify nonlinear associations between ESV and land cover, vegetation, climate, terrain, and socioeconomic conditions [18,19]. Related studies show that anthropogenic and landscape-pattern variables can have region-specific effects on ecosystem services [20,21]. However, variable importance is not equally reliable when predictive performance differs among regions or years. Interpreting weak models as ecological mechanisms can therefore overstate the evidence. A comparative framework should link driver interpretation to explicit model-performance thresholds.

This study evaluates BTH, YRD, and GBA from 2000 to 2020 under a consistent analytical protocol. Three questions are addressed: how LERI and ESV changed across contrasting urban agglomerations, which ESV drivers remained interpretable after model-performance screening, and how risk-service mismatches separated conservation from restoration priorities. The contribution is threefold. First, the cross-regional design tests whether a common zoning logic remains informative across water-constrained, river-network, and estuarine metropolitan systems. Second, the mismatch framework distinguishes high-value ecosystems exposed to risk from low-value landscapes requiring functional recovery. Third, driver attribution is conditioned on out-of-sample model performance, preventing weak predictions from being presented as ecological mechanisms. The resulting framework supports comparative diagnosis rather than direct causal inference.

Materials and methods

Study area

BTH lies in northern China and includes Beijing, Tianjin, and prefecture-level cities in Hebei, covering approximately 217,000 km². It spans the North China Plain, Yanshan Mountains, and Taihang Mountains and has a temperate monsoon climate with limited water resources. Intensive urban expansion, industrial development, and resource constraints make the region sensitive to ecological disturbance [22,13,23] (Fig 1).

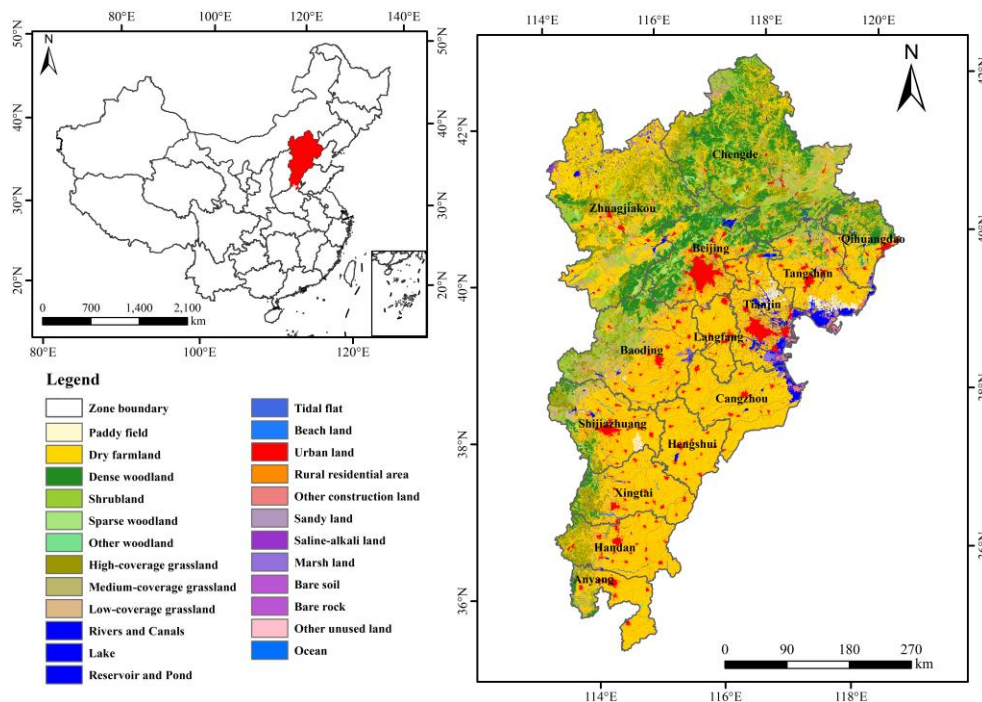


Fig. 1 Overview of the study area in the Beijing-Tianjin-Hebei region.

The YRD lies on China's eastern coast, with Shanghai as its core and selected cities in Jiangsu, Zhejiang, and Anhui, covering approximately 225,000 km². Its subtropical monsoon climate, dense river network, and complex land-use mosaic coexist with rapid urbanization and industrial integration that have compressed ecological space [24,25,26] (Fig 2).

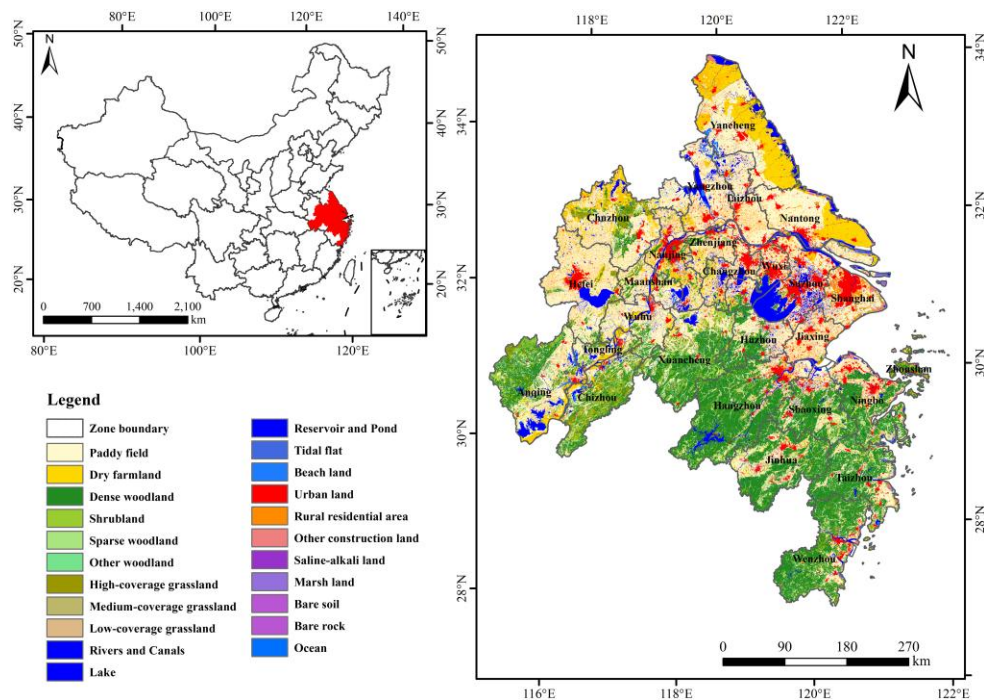


Fig. 2 Overview of the study area in the Yangtze river delta region.

The GBA occupies the lower Pearl River Basin and includes nine Pearl River Delta cities plus Hong Kong and Macao, covering approximately 55,000 km². Its mountain-sea setting, dense river network, and subtropical monsoon climate support substantial ecosystem service provision, but industrialization and built-up land expansion have fragmented ecological space [27,28,29] (Fig. 3).

Together, the regions represent contrasting urban ecological transitions. BTH is a water-constrained mountain-plain system, the YRD contains river-lake-plain industrial corridors, and the GBA is a coastal bay system. In the GBA, mountains, estuaries, river networks, and reclaimed landscapes are tightly connected [30].

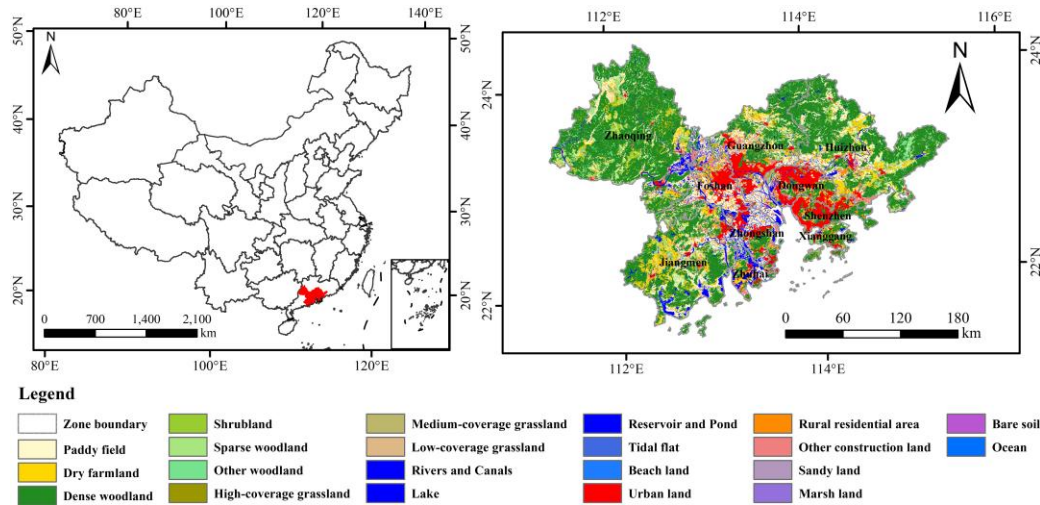


Fig. 3 Overview of the study area in Guangdong-Hong Kong-Macao region.

Data sources

This study selected 2000, 2005, 2010, 2015, and 2020 as time nodes. Land-use data were obtained from GlobeLand30 (<http://globeland30.org>) at a spatial resolution of 30 m. Based on the land-use characteristics of the study area, land-use types were reclassified into six categories: cropland, forestland, grassland, water bodies, built-up land, and unused land. NDVI, meteorological variables, GDP, population density, and net primary productivity (NPP) were obtained from the Resource and Environmental Science Data Center (<https://www.resdc.cn>). Digital elevation model (DEM) data were obtained from the Geospatial Data Cloud (<https://www.gscloud.cn>). All datasets were projected, spatially aligned, and resampled before the subsequent LERI, ESV, and driving factor analyses. The five-year interval was selected to balance data consistency, long-term comparability, and the need to capture major phases of urban expansion and ecological restoration. Before analysis, all spatial layers were harmonized to the same coordinate system and grid framework to reduce errors caused by projection, resolution, and boundary inconsistencies. This preprocessing step was essential because both LERI and ESV are sensitive to land-use classification and spatial aggregation.

Analytical methods

1 Landscape ecological risk assessment

Landscape ecological risk assessment combines landscape-pattern indicators with the ecological vulnerability of land-use types [4,31,32]. LERI was calculated for each grid cell to compare spatial variation among years and urban agglomerations. The risk value of land-use type i was defined as:

$$LERI = \sum_{i=1}^n \frac{A_i}{A} \times R_i \quad (1)$$

The grid-cell approach was used because it allows ecological risk to be compared within and among urban agglomerations without being constrained by administrative boundaries. It also makes it possible to identify localized high-risk patches that may be obscured by city-level or regional averages. This is particularly important in urban agglomerations, where high-risk areas often occur along transport corridors, urban expansion fronts, and fragmented agricultural landscapes.

LERI denotes the landscape ecological risk index. A_i is the area of landscape type i , A is the total study-area extent, and R_i is the corresponding risk value. The number of landscape types is denoted by n . R_i combines landscape disturbance (D_i) and ecological fragility (F_i):

$$R_i = D_i \times F_i \quad (2)$$

Landscape disturbance (D_i) was characterized using fractal dimension, aggregation, and dispersion indices [33]. It was calculated as [16,14,34]:

$$\Phi D_i = \alpha C_i + \beta S_i + \gamma D_i \quad (3)$$

To improve reproducibility, the landscape disturbance index (D_i) was calculated from three normalized components: fragmentation (C_i), separation (S_i), and dominance (N_i). Fragmentation reflects the degree of patch subdivision, separation describes the spatial dispersion of patches, and dominance represents the relative control of each land-use type within the landscape. Following commonly used LERI studies, the weights of C_i , S_i , and N_i were set to 0.5, 0.3, and 0.2, respectively, because fragmentation is generally the most direct indicator of landscape disturbance.

The ecological fragility coefficient (F_i) was assigned according to the sensitivity and recovery capacity of each land-use type. Initial scores were assigned as follows: built-up land, 1; forestland, 2; grassland, 3; cropland, 4; water bodies, 5; and unused land, 6. The scores were normalized by their sum. For grid cell j , A_{ij} is the area of land-use type i and A_j is the total grid-cell area. The risk value for land-use type i was calculated as $R_i = D_i \times F_i$, and grid-level LERI was calculated as the area-weighted sum of all land-use risk values. The same weights, fragility coefficients, grid size, and classification rules were used for all years and regions.

$$LERI_j = \sum_{i=1}^n \frac{A_{ij}}{A_j} \times R_i \quad (4)$$

$$LERI_{region} = \frac{1}{m} \sum_{j=1}^m \frac{A_j}{A_j} LERI_j \quad (5)$$

All LERI values were calculated using consistent land-use classes, grid units and classification rules across the five study years to ensure temporal comparability.

2 Ecosystem service valuation

Ecosystem service value (ESV) was estimated using the value-equivalent factor method proposed by Xie et al.

Ecosystem services were grouped into provisioning, regulating, supporting, and cultural services, including food production, raw material production, water supply, gas regulation, climate regulation, environmental purification, hydrological regulation, soil retention, nutrient cycling, biodiversity maintenance, and recreation. The total ESV was calculated by combining the area of each land-use type with the corresponding equivalent factor and the economic value of one standard equivalent factor:

$$ESV = \sum_{i=1}^n A_i \times VC_i \quad (6)$$

In this equation, V denotes total ESV and e_{ij} denotes the equivalent factor for ecosystem service i and land-use type j . E_a is the economic value of one standard equivalent factor (yuan ha^{-1}), and A_j is the area of land-use type j . E_a was calculated from the net economic value of grain production per unit area using the main crops in each region. Values were converted to comparable prices using the consumer price index. Region- and year-specific E_a values represented differences in grain-production value (Table 1). Equivalent factors and land-use classes remained consistent across regions and years.

Table 1 Economic value of one standard equivalent factor (E_a , yuan ha^{-1}).

Region	2000	2005	2010	2015	2020
BTH	1216.93	1269.70	1845.88	1882.14	2027.83
YRD	1323.22	1646.79	2239.22	2415.58	2249.74
GBA	1215.81	1536.99	2180.95	2195.41	2150.55

ESV is total ecosystem service value; A_i is the area of land-use type i ; V_{Ci} is its unit-area service-value coefficient (yuan $\text{ha}^{-1} \text{yr}^{-1}$); and n is the number of land-use types. The grain-production equivalent provides the benchmark used to convert land-use-specific coefficients into a common equivalent factor value (EFV):

$$V_{Ci} = EFV_i \times P \quad (7)$$

EFV_i is the equivalent factor for service type i , and PPP is the benchmark monetary value corresponding to one equivalent value, derived from regional grain production and market price.

3 Machine-learning analysis of ESV drivers

After LERI and ESV were mapped, machine-learning and baseline regression models were fitted to diagnose the spatial drivers of ESV. Candidate models comprised linear regression, k-nearest neighbors, support vector regression, random forest, gradient boosting decision trees, XGBoost, LightGBM, AdaBoost, CatBoost, and back-propagation neural networks. Explanatory variables represented land-use composition, LERI, NDVI, topography, climate, and socioeconomic conditions [18,19]. Grid cells were randomly divided into training and testing subsets before model fitting. The training set supported calibration and hyperparameter tuning, whereas the testing set was reserved for final evaluation. A fixed random seed ensured repeatable data splitting and model comparison. Performance was evaluated using test-set R^2 , root mean square error (RMSE), and mean absolute error (MAE). Test-set R^2 was the primary selection criterion; RMSE and MAE resolved comparisons between similarly performing models.

For tree-based models with acceptable predictive performance, variable importance was extracted from the fitted model and normalized to compare the relative contribution of different drivers. Driver importance was interpreted only when test-set R^2 was ≥ 0.50 . Models with $0.30 \leq R^2 < 0.50$ were treated as weak supplementary evidence, whereas models with $R^2 < 0.30$ were not used for ecological interpretation. Because the grid cells were randomly split, potential spatial autocorrelation may remain between training and testing samples. Therefore, the machine-learning results were interpreted as diagnostic associations rather than causal mechanisms.

Comparison across candidate models reduced dependence on a single algorithm and covered linear, nonlinear, instance-based, and ensemble approaches. Variable importance was emphasized only when tree-based models achieved adequate test-set performance. Weakly explained years were treated as evidence of missing processes rather than robust driver diagnoses.

4 Ecological zoning

Each grid cell was assigned to one of four ecological zones after LERI and ESV were calculated. High ESV and low LERI defined ecological advantage zones. High ESV and high LERI defined ecological sensitivity zones. Low ESV and low LERI defined ecological potential zones, whereas low ESV and high LERI defined ecological vulnerability zones.

Pooled medians avoided the instability of redefining high and low categories in each year. Consequently, changes in zoning reflected shifts relative to each urban agglomeration's long-term distribution rather than annual threshold adjustment.

Cells above the long-term ESV median and below the long-term LERI median were assigned to advantage zones.

Cells above both medians were assigned to sensitivity zones, and cells below both medians to potential zones. Cells below the ESV median but above the LERI median were assigned to vulnerability zones.

5 Statistical analysis

Statistical analyses were used to compare regional and temporal differences in LERI and to examine the association between ESV and LERI. Kruskal-Wallis tests were applied because LERI values were not assumed to follow a normal distribution. When significant differences were detected, pairwise comparisons were conducted with p-value adjustment for multiple testing. Pearson correlation coefficients were used to quantify linear associations between normalized ESV and LERI, whereas Spearman rank correlation coefficients were used to assess monotonic associations that were less sensitive to non-normal distributions. For each test, the test statistic, sample size, and p-value were reported in the corresponding result tables or supplementary materials. Statistical significance was assessed at $p < 0.05$.

Results

Spatiotemporal evolution of LERI

A total of 107,941 valid grid cells were analyzed across the five study years using a common risk classification.

Mean LERI declined in all three regions from 2000 to 2020. The largest decline occurred in the YRD (8.32%), followed by the GBA (6.48%) and BTH (2.25%). The YRD had the highest mean risk and the largest proportion of high-risk area in most years. BTH had intermediate and comparatively stable risk, whereas the GBA combined the lowest regional mean with concentrated high-risk patches. LERI differed among regions in every study year and among years within each region (Kruskal-Wallis tests, all $p < 0.001$; Table 2).

Table 2 Kruskal-Wallis test results for differences in LERI among regions and years.

Comparison	df	H statistic	n	p-value
Among regions, 2000	2	881.960	21516	<0.001
Among regions, 2005	2	415.357	21482	<0.001
Among regions, 2010	2	293.171	21600	<0.001
Among regions, 2015	2	324.649	21547	<0.001
Among regions, 2020	2	277.951	21590	<0.001
Among years, BTH	4	464.685	46991	<0.001
Among years, YRD	4	830.596	48024	<0.001
Among years, GBA	4	141.890	12720	<0.001

1 Cross-regional comparison of LERI spatial patterns

Fig 4 shows the spatial distribution of LERI across the five study periods. In BTH, high-risk areas were concentrated in the central and southern plains, the Beijing-Tianjin-Tangshan development belt, and major transport corridors, whereas northern and western mountains showed lower risk. In the YRD, high-risk grid cells were denser along the Shanghai-Nanjing-Hangzhou-Ningbo corridor, Suzhou-Wuxi-Changzhou region, and riverine and coastal development zones. In the GBA, the regional mean risk was low, but high-risk patches clustered along the Pearl River Estuary and the Guangzhou-Foshan-Dongguan-Shenzhen development axis.

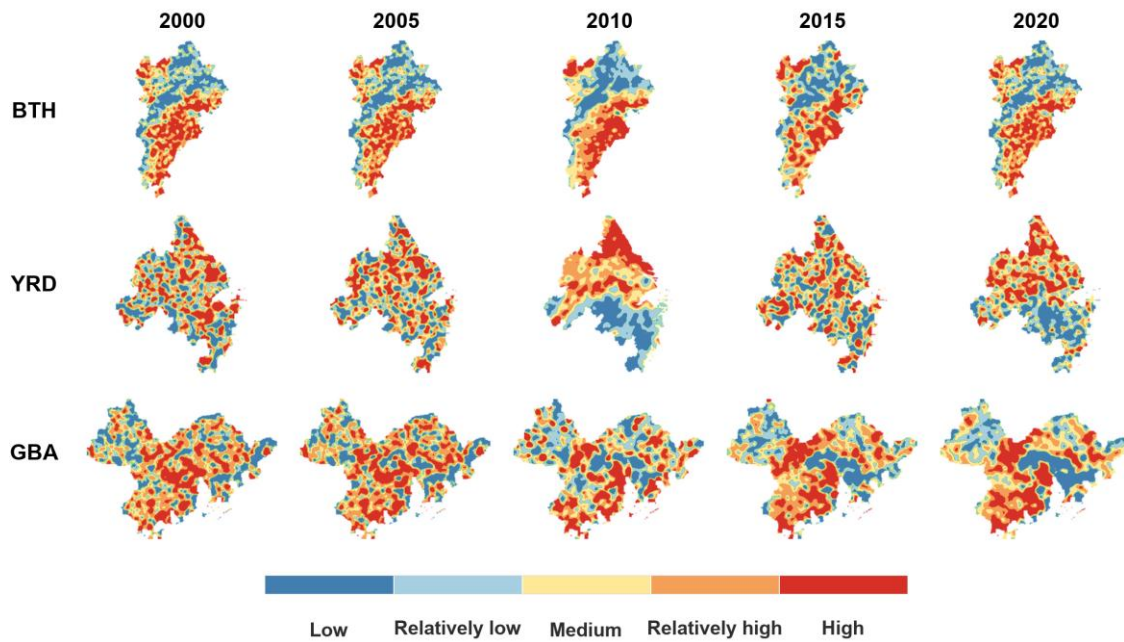


Fig .4 Evolution of LERI spatial pattern in three urban agglomerations from 2000 to 2020.

The YRD retained the highest mean LERI in 2000 and 2020 despite its largest overall decline. BTH showed a clear mountain-plain gradient, whereas the GBA combined low regional mean risk with highly concentrated local hotspots.

The high baseline in the YRD was consistent with persistent ecological pressure in a mature urban agglomeration. In the GBA, the low regional mean concealed a sharp contrast between peripheral ecological areas and the urbanized bay core. The modest decline in BTH indicated continued fragmentation in the plains despite relatively stable mountain barriers.

2 Temporal evolution of mean LERI

Mean LERI declined in all three regions from 2000 to 2020, although the trajectories differed (Fig 5). BTH increased slightly before 2005 and then declined and stabilized, resulting in an overall decrease of 2.25%. The YRD declined continuously from 0.016737 to 0.015344, an 8.32% reduction. The GBA declined slightly before 2005, increased in 2010, and then reached the lowest mean risk among the three regions in 2020.

The trajectories are consistent with path-dependent risk mitigation [35,36,17]. Areas with high initial fragmentation may require prolonged restoration before mean risk declines, while regions with strong ecological barriers can retain low averages alongside localized development hotspots.

Risk reduction should therefore be evaluated through both magnitude and spatial configuration. Declining mean LERI does not ensure ecological security where remaining high-risk patches lie adjacent to high-value ecosystems.

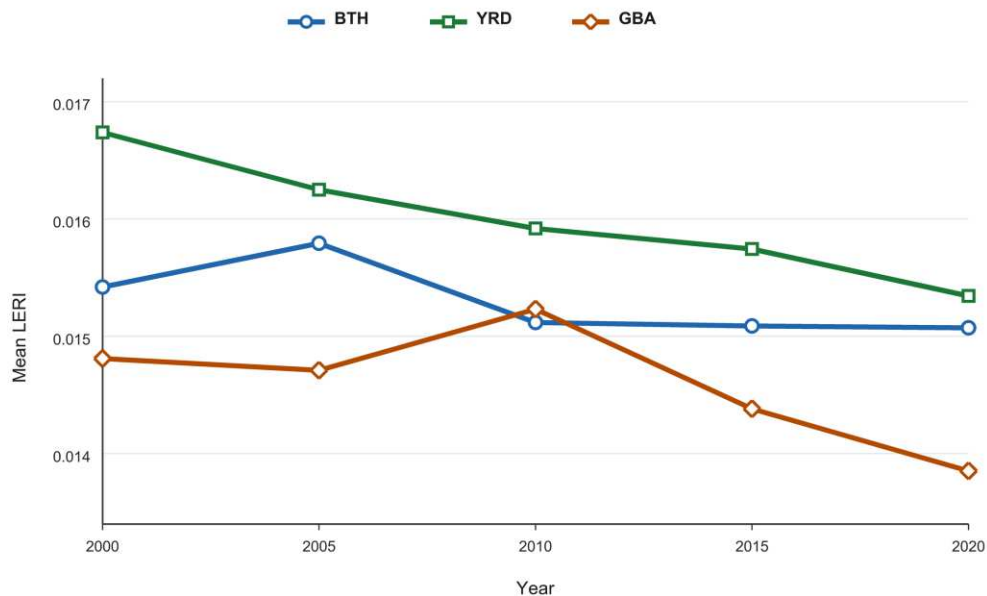


Fig. 5 Change trend and interquartile range of LERI mean values in the three urban agglomerations.

BTH showed a temporary increase before 2005, and the GBA showed a temporary increase around 2010. Both regions declined more consistently after 2010 (Table 3).

Table 3 Temporal change in mean LERI across the three urban agglomerations.

urban agglomeration	2000	2020	absolute change	rate of change	Linear slope every 5 years
BTH	0.015419	0.015072	-0.000347	-2.25%	-0.000140
YRD	0.016737	0.015344	-0.001393	-8.32%	-0.000329
GBA	0.014811	0.013852	-0.000959	-6.48%	-0.000225

3 Dispersion and changes in risk-level structure

Distributional indicators showed that declining mean LERI did not necessarily imply reduced internal heterogeneity. The coefficients of variation increased in both the YRD and GBA, suggesting stronger spatial differentiation and persistent local high-risk patches, whereas BTH maintained a relatively stable distributional width. Risk-class composition also shifted from high-risk to low-risk grid cells (Fig 6; Table 4). In the YRD, medium-high and high-risk areas decreased from 54.77% to 40.80%, whereas low and relatively low-risk areas increased from

32.53% to 41.61%. BTH showed a slower reduction in high-risk cells. The GBA had the most favorable overall risk structure but retained high-risk clusters in the bay core.

Table 4 Change in the LERI risk-level structure of the three urban agglomerations.

urban agglomeration	2000 higher+high risk	2020 Higher+High Risk	Change (percentage points)	2000 low+lower risk	2020 Low+lower risk
Beijing-Tianjin-Hebei	40.04%	34.52%	-5.52	38.29%	40.21%
Yangtze River Delta	54.77%	40.80%	-13.97	32.53%	41.61%
Guangdong-Hong Kong- Macao Greater Bay Area	16.99%	11.89%	-5.10	53.20%	62.18%

This pattern is important for management because mean LERI alone may underestimate localized ecological pressure. A region can show declining average risk while still retaining high-risk clusters along urban expansion frontiers, port zones, transport corridors, or fragmented agricultural landscapes. Therefore, both mean trends and distributional structure were used to interpret risk evolution in this study.

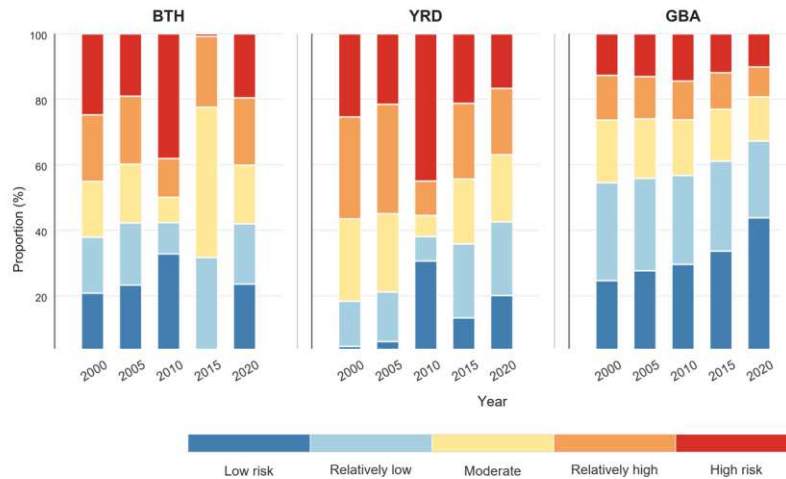


Fig. 6 Evolution of LERI risk-level structure under the unified threshold system.

Spatiotemporal evolution of ESV

1 Temporal and spatial patterns of ESV

Total ESV increased in all three regions, but the temporal trajectories differed. In BTH, ESV increased around 2010 and reached approximately 5.36×10^{11} yuan in 2020. In the YRD, ESV increased from 5.38×10^{11} yuan in 2000 to 10.2818×10^{11} yuan in 2015, then declined to 9.34×10^{11} yuan in 2020. In the GBA, ESV increased most rapidly between 2000 and 2010 and then stabilized at approximately 2.49×10^{11} yuan in 2020. Regulating services

accounted for more than 70% of total ESV in every region, followed by supporting services. Forestland and water bodies made the largest contributions.

High-ESV areas concentrated in ecological barriers and water-related landscapes (Fig. 7). In BTH, these areas included the Yanshan-Taihang Mountains and coastal wetlands. In the YRD, they included the mountains of western Zhejiang and southern Anhui, Taihu Lake, the Yangtze River Estuary, and Hangzhou Bay. In the GBA, they formed mountain-reservoir-estuary corridors.

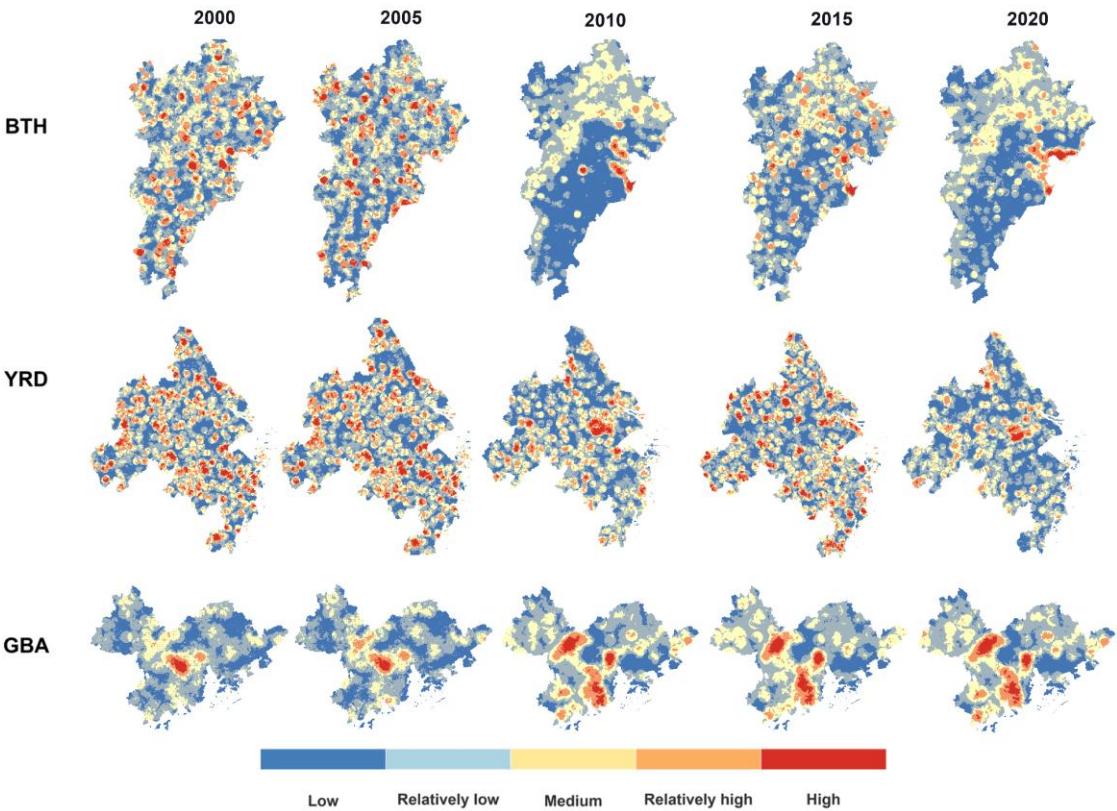


Fig. 7 Changes in spatial distribution of ESV in three urban agglomerations from 2000 to 2020.

2 Changes in ESV per unit area

ESV per unit area was calculated to compare regions of different sizes. It increased overall from 2000 to 2020, although the magnitude and trajectory differed among regions (Fig 8; Table 5). The GBA retained the highest value, increasing from 2.72 to 4.5076 million yuan km⁻². The YRD increased from 2.4365 to 4.2032 million yuan km⁻², and BTH increased from 1.4224 to 2.3966 million yuan km⁻².

Table 5 ESV per unit area across the three urban agglomerations (10,000 yuan km⁻²).

urban agglomeration	2000	2005	2010	2015	2020
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Beijing-Tianjin-Hebei	142.24	146.71	205.87	206.82	239.66
Yangtze River Delta	243.65	305.11	443.45	459.08	420.32
Guangdong-Hong Kong-Macao Greater Bay Area	272.00	333.93	463.87	463.67	450.76

All three regions showed a marked increase around 2010. After 2010, BTH remained broadly stable and increased again by 2020, whereas the YRD and GBA declined slightly after 2015. ESV per unit area therefore provided a direct comparison of service value relative to territorial extent.

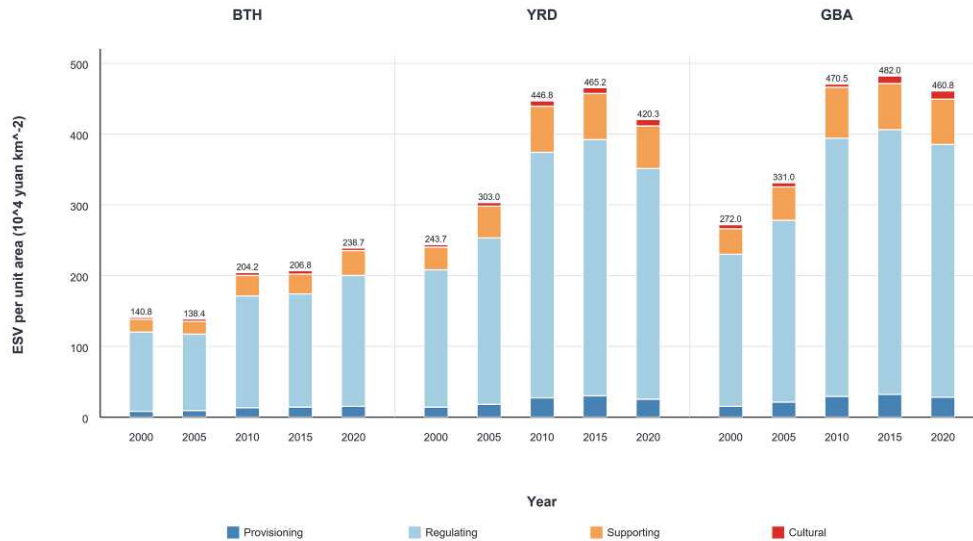


Fig. 8 Composition of ESV per unit area by service category in 2020.

Service-category decomposition showed that regulating services consistently formed the dominant component of ESV per unit area (Fig 8). Provisioning, supporting, and cultural services contributed less on a per-unit-area basis, although their relative importance varied by region. The GBA and YRD generally had higher regulating and supporting service values per unit area than BTH, indicating stronger ecosystem service concentration within unit land space.

The dominance of regulating services suggests that changes in ESV were driven less by direct provisioning benefits than by climate regulation, hydrological regulation, soil retention, habitat maintenance, and related ecological functions. This result is consistent with the role of forests and water bodies as the main ecological carriers in rapidly urbanizing landscapes [20]. It also indicates that restoration policies targeting wetland protection, forest conservation, river-lake connectivity, and blue-green network construction can generate substantial service-value gains at the regional scale.

3 Drivers of ESV

Test-set R^2 was the primary model-selection criterion, and RMSE and MAE were secondary criteria. The selected model was the best-performing candidate for each region and year, but it did not necessarily have sufficient explanatory power. Driver importance was interpreted only for models with moderate or high explanatory power. Weak models were treated as supplementary evidence, and models with insufficient performance were not used for driver interpretation (Fig 9).

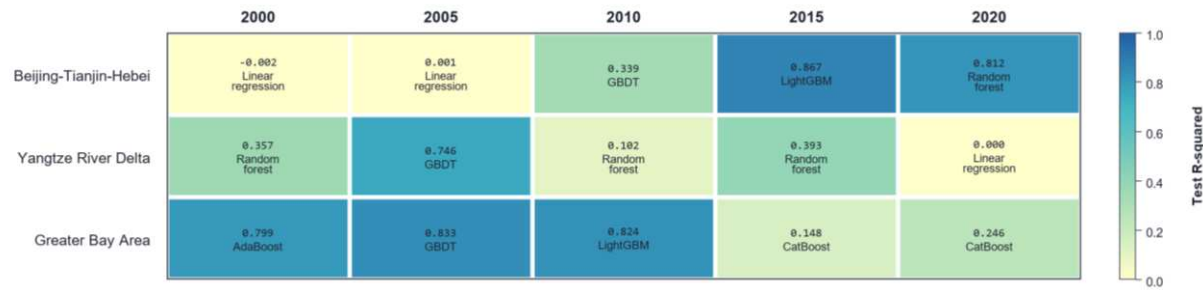


Fig. 9 Heat map of optimal model test-set R^2 for the three urban agglomerations by year.

Model performance varied among regions and years (Fig 10). The GBA models had high explanatory power in 2000, 2005, and 2010 ($R^2 = 0.799, 0.833$, and 0.824 , respectively). BTH models had insufficient explanatory power in 2000 and 2005 but improved in 2015 and 2020 ($R^2 = 0.867$ and 0.812 , respectively). Performance fluctuated most strongly in the YRD, where the 2005 model reached moderate-to-high explanatory power but most other years were weak or insufficient.

The temporal variation in model performance shows that ESV drivers were not stationary. High explanatory power occurred when the selected land-cover, hydrological, risk, and socioeconomic variables aligned with ESV spatial patterns. Low or negative R^2 values indicated that static variables did not capture all relevant processes.

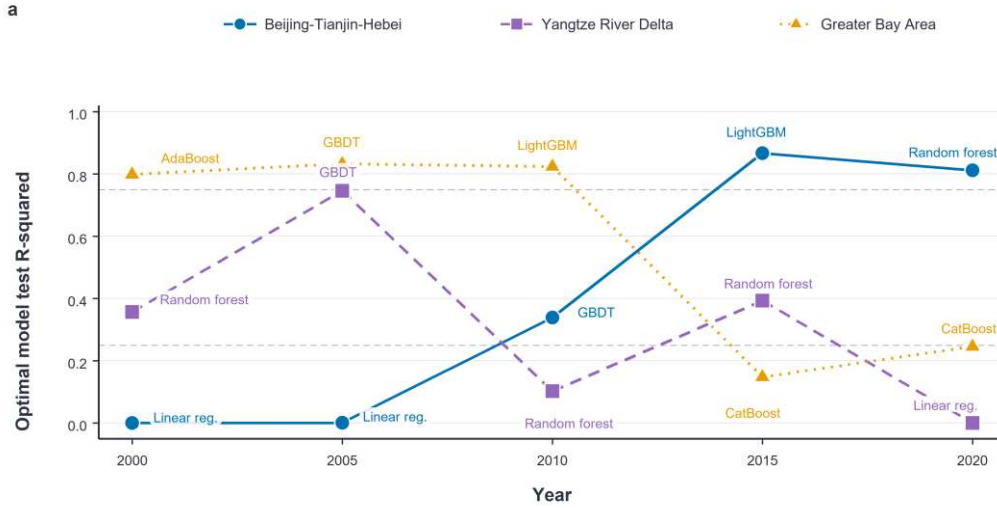


Fig. 10 Temporal changes in optimal model test-set R^2 . Dotted lines indicate thresholds for high, moderate, and weak explanatory power.

The optimal algorithm varied by region and year. Ensemble tree models performed well in several cases, implying nonlinear thresholds and variable interactions; however, algorithm choice was interpreted jointly with test-set R^2 . When R^2 was close to zero, the algorithm type was not used to infer a dominant ecological mechanism. Outperforming other candidates does not ensure that a model explains substantial variation. Algorithm labels and variable importance were therefore not interpreted as ecological mechanisms when test-set R^2 approached zero. Secondary drivers varied among regions. Forestland, built-up land, and socioeconomic factors were more evident in BTH. Water-network and climatic variables were more prominent in the YRD. In the GBA, water bodies, forestland, built-up land, and night-time light were relevant during years with stronger model performance. The ecological role of water bodies differed among regions. In BTH, rivers, reservoirs, and wetlands were important under water-scarce conditions. In the YRD, river-lake networks and coastal wetlands provided high service value but were close to development corridors [37]. In the GBA, the Pearl River Estuary, river networks, reservoirs, and mountain water-conservation areas created a pattern in which high ecological value frequently overlapped with risk [38]. Secondary drivers were interpreted only for models with adequate performance (Figs 11 and 12). Forestland, built-up land, and socioeconomic indicators were most evident in BTH. Climatic and water-network variables contributed in some YRD years, whereas forestland, built-up land, night-time light, and topography contributed in the GBA.

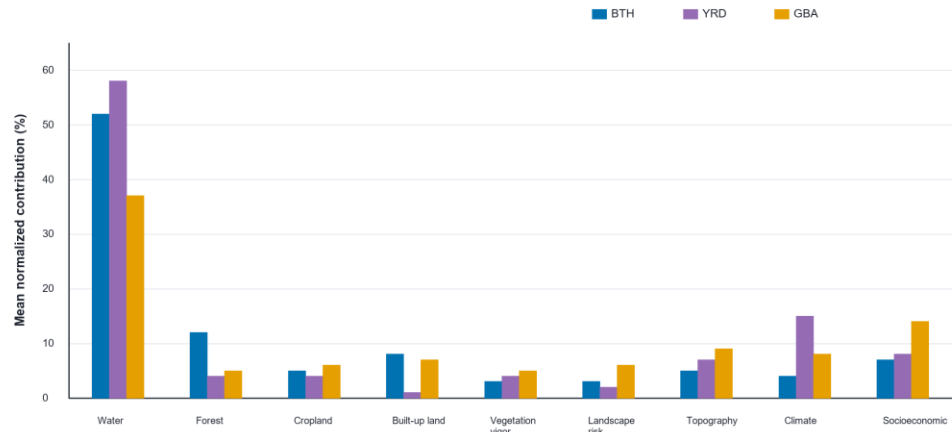


Fig. 11 Average contributions of the main driving-factor categories in the three urban agglomerations.

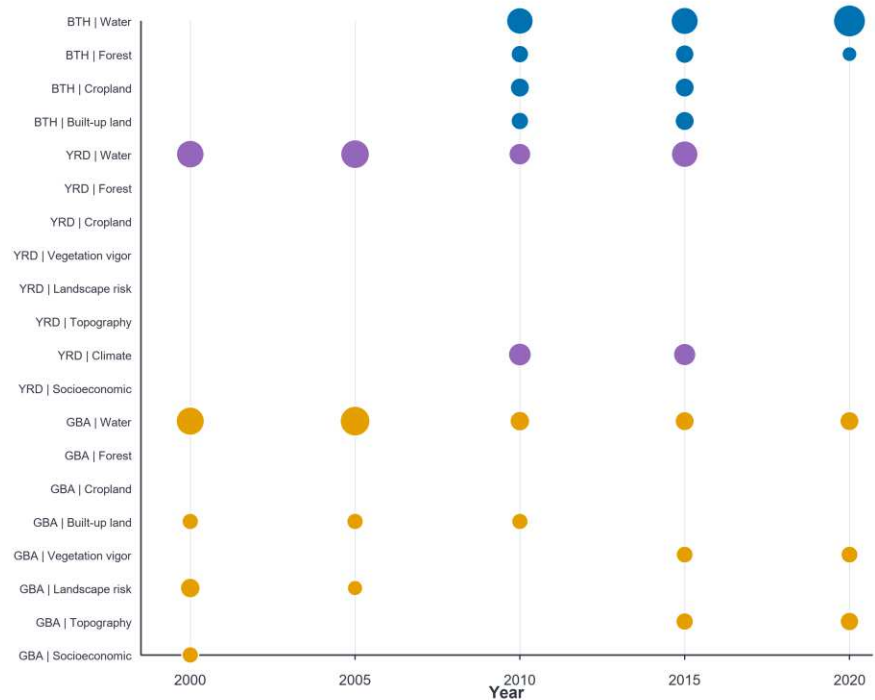


Fig. 12 Spatial location and intensity of key driving factors in the optimal model.

Ecological zoning

1 Spatial pattern of bivariate ecological zoning

Fig 13 illustrates the discriminative meaning of the four zoning types. Ecologically advantageous areas indicate high ESV and low LERI, representing stable high-value spaces within the regional ecological security pattern. Ecologically sensitive zones indicate high ecological value coupled with high risk, where strong service supply

overlaps with elevated risk exposure. Ecological potential zones indicate low risk but insufficient service value, whereas ecologically vulnerable zones indicate low service value and high risk. The three urban agglomerations showed distinct temporal reorganizations. BTH shifted from a mixed pattern in 2000 toward a larger share of advantage zones and fewer potential zones. Advantage zones expanded and vulnerability zones contracted in the YRD. The GBA changed most strongly, with substantial increases in both advantage and sensitivity zones after 2010.

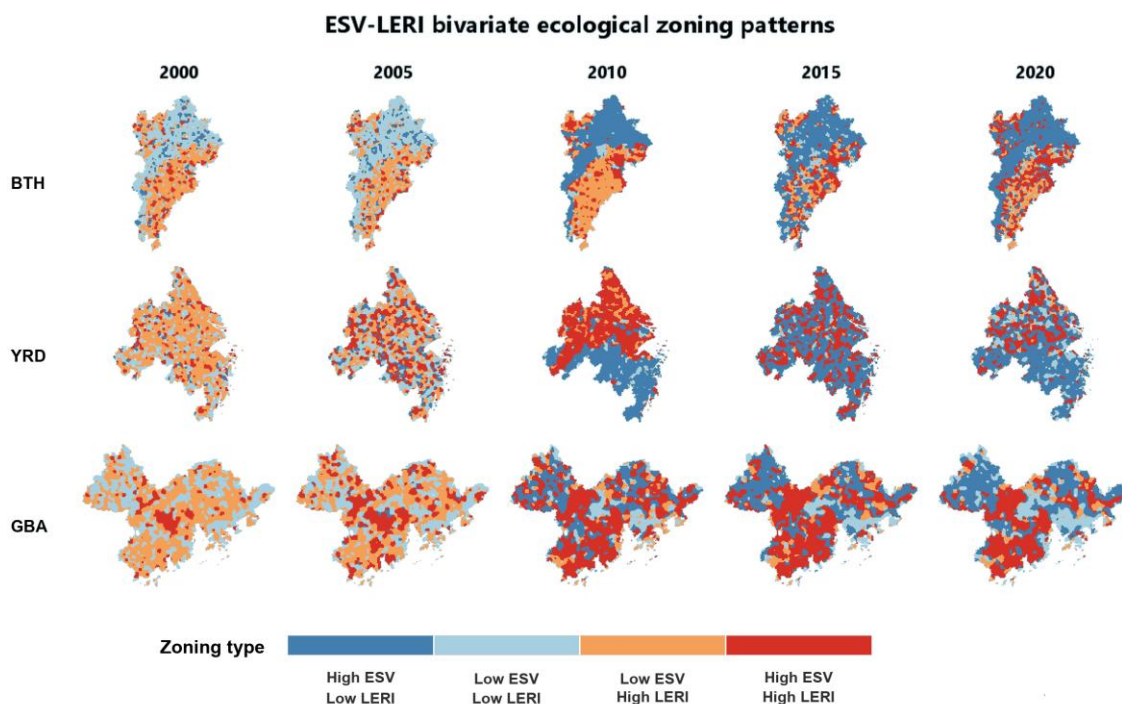


Fig. 13 Evolution of ESV-LERI dual-value ecological zoning in the three urban agglomerations.

Advantage zones generally aligned with mountain forests, water-source conservation areas, wetlands, and ecological barriers. Sensitivity zones occurred where high-value ecological spaces intersected with development pressure, including urban-fringe wetlands, piedmont transitions, river- and lake-adjacent areas, and estuarine bays. Vulnerability zones represented the overlap between low ESV and high LERI (Fig 13).

2 Temporal evolution of zoning structure

Figures 14 and 15 show the temporal changes in the proportions of the four zoning types. The most consistent trend was the expansion of ecologically advantageous areas, indicating that high-service low-risk spaces increased across all three urban agglomerations from 2000 to 2020.

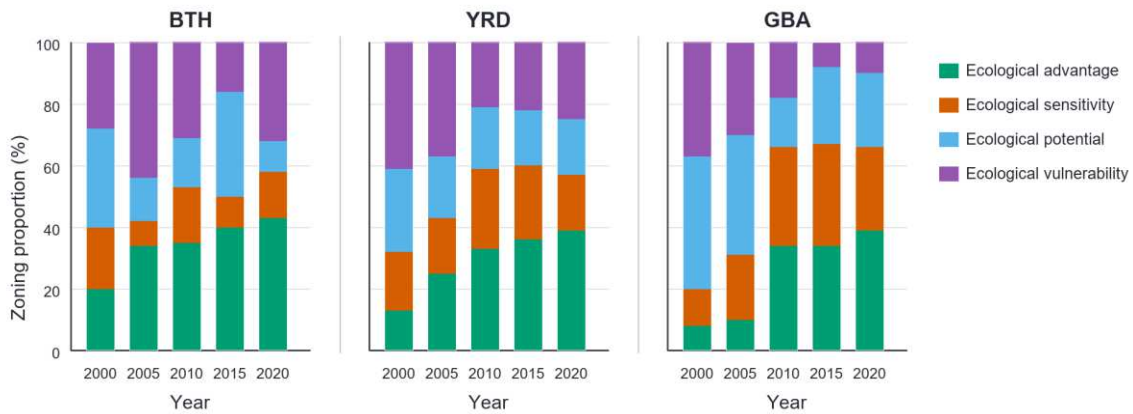


Fig. 14 Evolution of ESV-LERI dual-value ecological zoning structure in the three urban agglomerations.

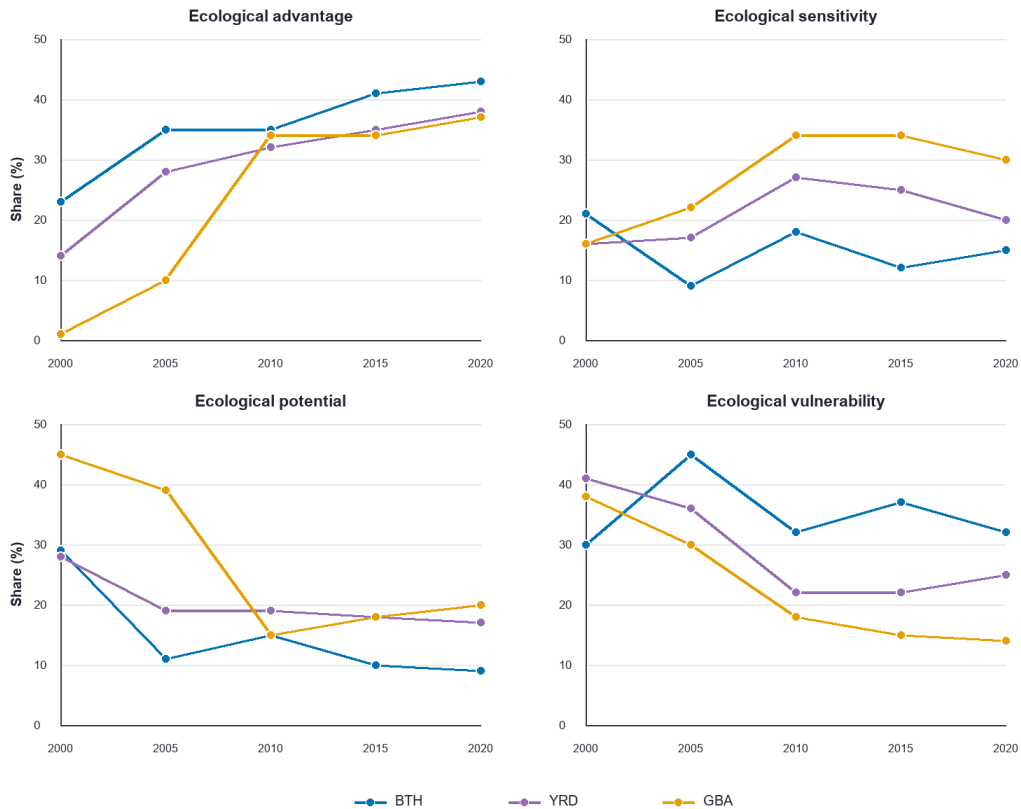


Fig. 15 Comparison of the proportions of the four ecological zoning types among urban agglomerations.

In BTH, ecologically advantageous areas increased from 21.54% to 42.96%, but ecologically vulnerable areas also increased from 28.97% to 32.32%, indicating persistent management challenges in the plains. In the YRD, ecologically advantageous areas increased from 13.29% to 38.04% and ecologically vulnerable areas declined from 41.14% to 25.32%, although ecologically sensitive areas increased from 15.60% to 19.16%. The GBA changed most

markedly: advantageous areas increased from 0.94% to 36.80%, vulnerable areas declined from 37.35% to 13.61%, and sensitive areas increased from 16.32% to 29.78%.

The 2020 zoning structure revealed distinct management needs. BTH combined the largest advantage-zone share with a substantial vulnerability-zone share. The YRD combined ecological advantages with growing sensitivity, while the GBA showed rapid vulnerability-zone contraction alongside a marked increase in high-ESV, high-LERI sensitivity zones (Fig 16).

Ecological improvement and residual risk therefore coexisted. Increasing advantage-zone area did not remove the need to manage vulnerability in BTH or sensitivity in the YRD and GBA.

The four zones imply distinct interventions. Advantage zones require protection from fragmentation, whereas sensitivity zones require risk buffering and development restrictions. Potential zones require ecological-function enhancement. Vulnerability zones require priority restoration and connectivity reconstruction.

The classification prevents a one-size-fits-all approach. High-ESV, high-LERI areas require risk control to retain existing services, whereas low-ESV, high-LERI areas require ecological improvement to rebuild service capacity.

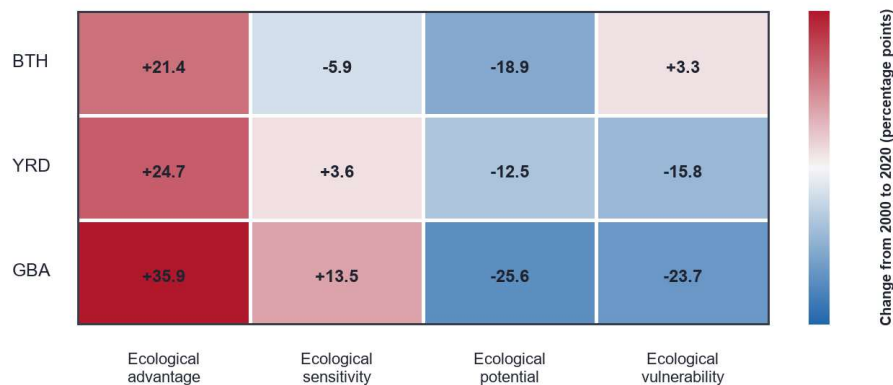


Fig. 16 Comparison of changes in the proportions of ecological zoning types from 2000 to 2020 (percentage points).

3 ESV-LERI relationships

Fig 17 shows the two-dimensional coupling relationship between normalized ESV and normalized LERI. In BTH, ESV and LERI showed a negative correlation in some years, suggesting that high-service-value spaces tended to be associated with lower ecological risk. In the GBA, positive or weakly positive correlations in most years indicated

that some high-service-value spaces were also exposed to elevated risk. In the YRD, weak correlations reflected more complex risk-service spatial combinations.

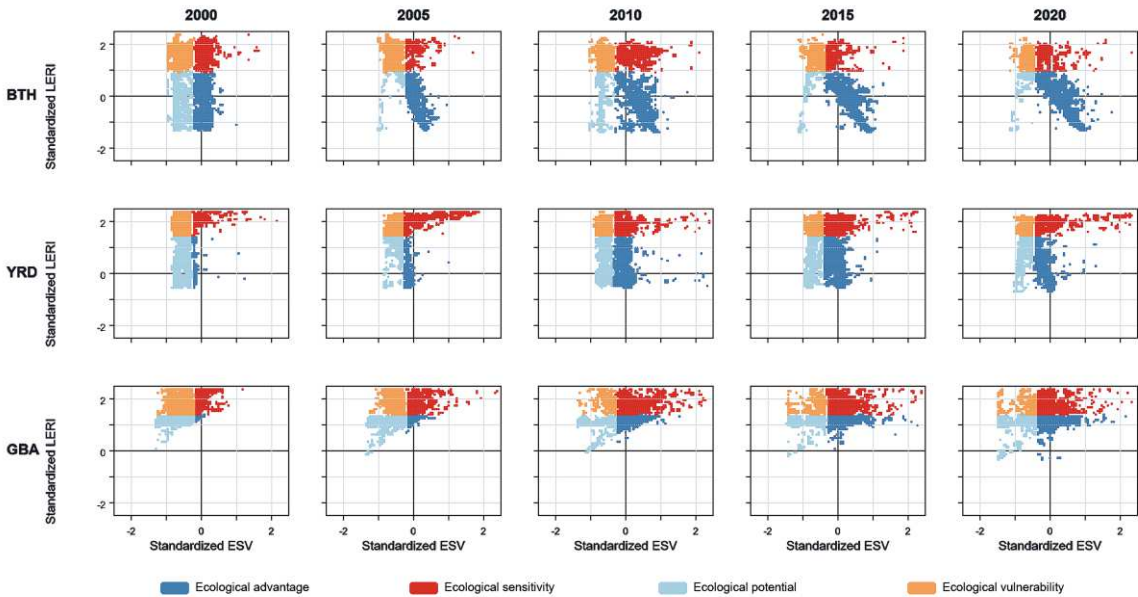


Fig. 17 ESV-LERI two-dimensional coupling relationship and ecological zoning identification.

Correlation analysis confirmed this regional heterogeneity. Pearson coefficients for the GBA were 0.364 in 2000 and 0.348 in 2005, indicating overlap between high ESV and high risk. Spearman coefficients for BTH were -0.463 , -0.400 , and -0.397 in 2000, 2005, 2015, and 2020, respectively. These values indicated that high-ESV areas in BTH were more likely to have low risk. Correlations were weak in the YRD, where a single risk-service gradient did not describe the zoning pattern.

The two-dimensional coupling analysis therefore provides information that simple univariate maps cannot offer [15]. Negative ESV-LERI relationships identify regions where high ecological value is relatively secure, while positive relationships highlight spaces where valuable ecosystems are exposed to disturbance. Weak relationships, as observed in the YRD, indicate that ecological zoning may be shaped by multiple interacting factors rather than by a single risk-service gradient.

Discussion

Causes of spatiotemporal variation in LERI and ESV

Differences in LERI and ESV among the three urban agglomerations reflect development stage, ecological governance, physical geography, and climatic-hydrological conditions. Previous comparative studies have similarly

shown that natural and human drivers of ecosystem services vary among China's developed regions [6,19]. Declining LERI and rising ESV are therefore not necessarily synchronous indicators of reduced ecological pressure; they can result from different combinations of development intensity, ecological engineering, and spatial governance.

The Kruskal-Wallis results confirm that LERI differences were not only reflected in mean values but also in the overall distribution of grid-level risk across regions and years. The same numerical trend can therefore imply different planning needs. Declining LERI in the YRD does not remove the need for risk control because its baseline remains high. Low mean LERI in the GBA does not imply region-wide security because high-risk patches cluster in the bay core. Likewise, expanding advantage zones in BTH must be read alongside persistent vulnerable plains. In BTH, stable mountain and water-conservation barriers coexist with persistent plain-area pressure from population concentration, transport infrastructure, industrial activity, and cropland fragmentation [22,23]. In the YRD, dense river networks and governance interventions have supported ecological improvement, while urban expansion, riverside development, and land-use change continue to compress ecological space [24,25]. In the GBA, peripheral mountains and estuarine wetlands support high ESV, whereas development around the Pearl River Estuary and coastal zones maintains localized risk exposure [27,29].

Climate and hydrology reinforced these regional differences. Water scarcity increases the ecological importance of rivers, reservoirs, and wetlands in BTH [22]. River-lake networks and subtropical vegetation support strong regulating services in the YRD [25]. In the GBA, estuarine and coastal ecosystems provide substantial services but remain closely coupled with intensive urban development [27,28]. These contrasts explain why joint analysis of LERI and ESV revealed priorities that were not apparent from either indicator alone.

This interpretation helps explain why high-value ecological spaces do not always correspond to low-risk spaces. Wetlands, rivers, lakes, reservoirs, and estuarine ecosystems provide hydrological, habitat, and other regulating services, but many are located close to dense development corridors [27,38]. In highly urbanized regions, these landscapes can therefore function as ecological assets and risk-bearing frontiers at the same time.

Interpretation of ESV drivers

The principal contribution is not another overlay of LERI and ESV, but a comparative diagnosis of where ecological value and risk diverge. Three advances support this distinction. A common protocol enables direct comparison across contrasting metropolitan systems. Mismatch classes separate the protection of exposed high-value ecosystems

from the restoration of degraded low-value landscapes. Machine-learning evidence is retained only when out-of-sample performance supports interpretation. Together, these advances link zoning outcomes to both management purpose and evidential strength.

ESV was associated with land cover, water bodies, vegetation, topography, climate, and socioeconomic variables, consistent with previous studies that identified interacting natural and anthropogenic controls on ESV [18,19].

However, the strength of these associations varied substantially among regions and years. Water bodies were the most stable interpretable driver, although their ecological roles differed among water-scarce, river-network, and estuarine settings.

Water bodies were the most stable interpretable driver in models with moderate or high explanatory power. In BTH, rivers, reservoirs, and wetlands showed a scarcity effect under water-resource constraints, consistent with regional ecosystem-service assessments [22]. In the YRD, dense river-lake networks and coastal wetlands provided high service value but were also adjacent to development corridors [24,25]. In the GBA, the Pearl River Estuary, river networks, reservoirs, and mountain water-conservation areas jointly shaped the ESV pattern [27,29]. These differences indicate that the same driver category can have different ecological meanings across urban agglomerations.

Temporal variation in model explanatory power should be interpreted as a substantive finding rather than only a technical limitation. Interpretable machine-learning studies of ESV similarly emphasize that driver attribution depends on adequate predictive performance and model transparency [18]. Higher R^2 values identify periods when the selected variables captured the main spatial gradients of ESV, whereas low R^2 values indicate that additional process variables are needed. Future research should incorporate land-use transitions, restoration intensity, policy implementation, shoreline change, spatial spillovers, cross-boundary hydrological connectivity, and extreme climate events.

Machine learning should thus be treated as a diagnostic layer rather than a substitute for ecological interpretation. It can identify nonlinear associations and rank candidate drivers, but these outputs do not by themselves establish causal mechanisms [18,21]. The weakly explained years in this study therefore indicate where policy interventions, engineering projects, and cross-boundary water management require additional process-based evidence.

Ecological zoning and management implications

The zoning results support differentiated management [39,40,41]. Advantage zones require strict protection and monitoring. Priorities include the Yanshan-Taihang Mountains and water-conservation areas in BTH; the western Zhejiang-southern Anhui mountains, Taihu Lake, and estuarine wetlands in the YRD; and peripheral mountains, reservoirs, river-source areas, and estuarine wetlands in the GBA.

Sensitivity zones, where high ESV overlaps with high LERI, should be prioritized in ecological red lines, land-use regulation, buffer-zone design, and project-access review [42,43,44]. Vulnerability zones require restoration through built-up land boundary control, fragmented-patch repair, and ecological corridor reconstruction, particularly in the BTH plains and remaining high-risk areas of the YRD and GBA.

Dual-value zoning should integrate risk reduction, value enhancement, and connectivity improvement [15,34,45]. High-value, high-risk spaces require buffering and land-use regulation; low-value, high-risk spaces require restoration and connectivity; low-risk, low-value spaces require service-function enhancement; and high-value, low-risk spaces require long-term protection.

Operationally, the framework informs decisions at regional, intra-regional, and project scales. It locates areas requiring risk buffering, value enhancement, connectivity improvement, protection, restoration, or monitoring. Interpretable drivers can also support blue-green corridor design, ecological red-line management, and restoration-project allocation [38,46].

This study has three limitations. First, ESV estimates rely on land-use-based equivalent coefficients, which support regional comparison but do not fully represent local ecological processes or service demand [5,35]. Second, the machine-learning analysis used available static spatial variables and could not directly represent policy intensity, restoration investment, shoreline engineering, or extreme climate events. Third, management decisions require finer-scale field verification and stakeholder-based planning despite the use of a unified urban-agglomeration framework.

Future work should combine scenario simulation with service supply-demand matching [47]. These additions could test how zoning responds to alternative urban-growth, restoration, and climate-risk pathways [48] and whether high-service spaces coincide with human demand.

Conclusions

This study establishes a risk-service mismatch framework that combines LERI, ESV, performance-screened machine learning, and bivariate zoning. Its central advance is to separate exposed high-value ecosystems requiring

risk control from degraded low-value landscapes requiring functional restoration under a consistent cross-regional protocol.

From 2000 to 2020, LERI declined and ESV increased across BTH, YRD, and GBA, but regional trajectories remained distinct. The YRD achieved the largest risk reduction while retaining a high risk baseline. The GBA combined low mean risk with concentrated hotspots, whereas BTH changed more modestly. Advantage zones expanded from 21.54% to 42.96% in BTH, from 13.29% to 38.04% in the YRD, and from 0.94% to 36.80% in the GBA. Nevertheless, vulnerable zones persisted in BTH and sensitivity zones increased in the YRD and GBA. These contrasts require region-specific intervention. BTH needs restoration of vulnerable plains and protection of mountain barriers. The YRD requires risk management in river-lake wetlands, mountain margins, and urban expansion zones. The GBA requires stronger protection and connectivity for estuarine, wetland, mountain, and coastal ecosystems. The framework can inform territorial planning and restoration prioritization, but its interpretation remains bounded by land-use-based ESV coefficients and the non-causal nature of machine-learning associations.

Author contributions

Conceptualization: Siyuan Liu and Yanfei Sun. Methodology: Siyuan Liu and Yanfei Sun. Software: Siyuan Liu. Validation: Siyuan Liu and Yanfei Sun. Formal analysis: Siyuan Liu, Yanfei Sun, Ke Liu, Zixi Tan, and Wen Pan. Investigation: Siyuan Liu and Yanfei Sun. Resources: Yanfei Sun. Data curation: Siyuan Liu, Ke Liu, Zixi Tan, and Wen Pan. Writing – original draft: Siyuan Liu. Writing – review and editing: Siyuan Liu, Yanfei Sun, Ke Liu, Zixi Tan, and Wen Pan. Visualization: Siyuan Liu, Ke Liu, Zixi Tan, and Wen Pan. Supervision: Yanfei Sun. Project administration: Siyuan Liu and Yanfei Sun.

as the first and corresponding author, led the study design, methodological development, data analysis, interpretation, and manuscript preparation. Yanfei Sun made substantial contributions to the study design, research supervision, interpretation of the results, and manuscript revision. All authors read and approved the final manuscript.

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Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Competing interests

The authors declare no competing interests.

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