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Impact of land use on macroinvertebrates from a multiscale perspective: enhancing structural equation models with inverse distance-weighted metrics

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Effective riverine ecosystem management and restoration are predicated upon comprehending the relationship between land use patterns, the aquatic environment, and macroinvertebrates. However, the processes by which land use affects riverine ecosystems are exceedingly complex, influenced by factors across varying special scales. To explore these multi-scale relationships, we centered our study on the Taizi River Basin (TRB) in northeastern China, encompassing data on land use, macroinvertebrates, physical habitats, and water quality. We employed a synergy of correlation analysis, multiple stepwise regression, and redundant analysis techniques to discern these relationships at diverse spatial extents. This approach led to the development of 24 structural equation models (SEMs) that delineate the pathways bridging land use patterns to various biological indices. Remarkably, the interpretive capacity of SEM-Benthic Index of Biotic Integrity (SEM-BIBI), SEM-Shannon Wiener index (SEM-H'), and SEM-Average Score Per Taxon (SEM-ASPT) models was 76%, 70%, and 66% respectively. Within the TRB, the primary pathway from land use pattern to biological index consisted of: land use (predominantly rural and agricultural) feeding into physical habitat (habitat complexity, combined characteristic of speed and depth), which in turn affected benthic indicators. A secondary pathway charts a course from land use, through water quality (electrical conductivity and total dissolved solids) and culminating in benthic variations. Furthermore, our findings indicated that inverse-distance-weighted (IDW) metrics, specifically the IDW distance based on flow length to the stream outlet and the nearest stream (iFLO_m and iFLS_m, respectively) could provide more accurate

interpretations of the river's ecological health status. Given the effects of rural areas and agriculture on macroinvertebrates, we recommend establishing 100-m wide riparian buffers. The optimal buffer range should be determined by evaluating various biological needs and considerations.

KEYWORDS

land use pattern, macroinvertebrate, structural equation models, IDW, multiple pathways

1 Introduction

Land use change is intimately associated with regional hydrological processes, including evapotranspiration and base flow formation. These processes in turn influence the water balance (Schilling et al., 2008; Li et al., 2020), riparian vegetation (Palt et al., 2022), and biodiversity (Fierro et al., 2017; Luo et al., 2021) of rivers. Urbanization and agriculture have reduced water yield and deteriorated water quality. (Atasoy et al., 2006; Chen et al., 2016; Fan et al., 2022; Kaufmann et al., 2022; Feio et al., 2023). These shifts subsequently alter the composition and diversity of aquatic organisms such as fish, algae, and macroinvertebrates in rivers, lakes, and other water bodies (Liu et al., 2023).

Among these affected aquatic organisms, macroinvertebrate assemblages serve as optimal indicators of river ecosystem alterations. Macroinvertebrates exhibit inherent sensitivity to changes in riverine health, exist in diverse groupings, have broad life-history requirements, and can be readily collected (Wallace and Webster, 1996; O'Brien et al., 2016). Therefore, macroinvertebrates have been widely employed in water ecological monitoring in Australia (Kefford et al., 2020), the United States (Carlisle and Hawkins, 2008; Wilkins et al., 2015), and many other regions (Eriksen et al., 2021).

The reactions of macroinvertebrates to land use patterns are intricate and influenced by various factors at different spatial extents. According to the hierarchical framework proposed by Frissell et al. (1986), smaller-scale systems are shaped within the constraints delineated by the larger-scale systems they are a part of. Various factors, including the climate, geology, and vegetation at the basin level significantly affect the water environment and physical habitats, thereby directly affecting macroinvertebrates. Numerous studies have explored the effects of environmental factors on macroinvertebrates at different spatial extents, such as land use (Hettetronquart et al., 2017; Dalu et al., 2022) and riparian vegetation (Palt et al., 2022). However, varied key influential factors have been identified according to the choice of scale in the analysis (Gove et al., 2010; Colas et al., 2017). Earlier work by Kaufmann et al. (1999) laid foundational methodologies for quantifying the physical habitats in wadable streams, presenting a crucial reference for contemporary aquatic research. Typically, at larger spatial extents, land use changes exert long-term, comprehensive effects on macroinvertebrates. However, at the reach scale, factors such as the riparian zone, water quality, and sediment significantly affect

the ecology of macroinvertebrates (Hettetronquart et al., 2017; Luo et al., 2018; He et al., 2020). Many studies have investigated how land use and environmental factors affect macroinvertebrates in specific regions in the Americas and in South America (Macedo et al., 2014; Chen et al., 2019; Herlihy et al., 2020; Hughes et al., 2023). However, there is a lack of comprehensive research in China examining land use patterns and their impact pathways at multiple spatial scales. This multiscale perspective is required to obtain global insight on these associations and offer practical guiding significance for effective management.

Basin conditions are typically characterized according to lumped attributes, such as the percentage of land use, as a lumped method offers operational advantages for ecosystem research. In particular, lumped attributes can be readily obtained through a geographic information system (GIS); however, this comes at a cost of losing spatially explicit information. Several GIS-based methods are more suited to explain the ecological processes of regions affected by land use changes, but cannot reveal crucial information on the spatial distribution of distinct land use activities. For instance, Lorion and Kennedy (2010) discovered that riparian forest buffers significantly influence macroinvertebrate diversity in neotropical headwater streams. An alternative method to lumped metrics is a distance-weighted approach with the advantage of a spatially explicit analysis that can better reflect macroinvertebrates as indicators of aquatic system health. A distance-weighted approach also improves the predictive power of the relationship between land use and benthic characteristics (Peterson et al., 2011; Zhang et al., 2015; Meyer et al., 2022). Taking these considerations into account, we compared the effectiveness of lumped metrics, Euclidean distance buffer metrics, and inverse distance-weighted (IDW) metrics in determining the impacts of land use on macroinvertebrate assemblages at multiple key spatial extents.

Structural equation models (SEMs) have been widely used in psychology and social science (MacCallum and Austin, 2000), and their application in ecological research has been expanding in recent years (Capmourteres and Anand, 2016; Villeneuve et al., 2018; Jia et al., 2023). SEMs are instrumental in the modeling and testing of causal relationships among factors, leveraging the covariance structure between variables (Shipley, 2002). Thus, SEMs show promising applications in various studies of the natural environment, including those focused on soil, biology (Eisenhauer et al., 2015; Beaumelle et al., 2016; Fan et al., 2016; Cui et al., 2022),

and freshwater ecosystems (Leitão et al., 2018; Alvarenga et al., 2021).

Recognizing the influence of environmental factors on macroinvertebrates via diverse pathways, we employed SEMs to identify the pivotal factors shaping these relationships. We further explored the intricate and variable nature of the ecological pathways across different spatial extents. Toward this end, we established SEMs of land use patterns related to macroinvertebrates in the Taizi River Basin (TRB) of China. The goals of our research were to (i) evaluate the influence of land use metrics on macroinvertebrates and (ii) discern the primary ecological pathways concerning land use patterns, the water environment and physical habitat, and macroinvertebrates. Notably, the multiscale approach adopted herein enabled identification of impacts at various spatial extents. Elucidation of these impact pathways will serve as a baseline and foundation for regional land use planning and river ecological management.

2 Materials and methods

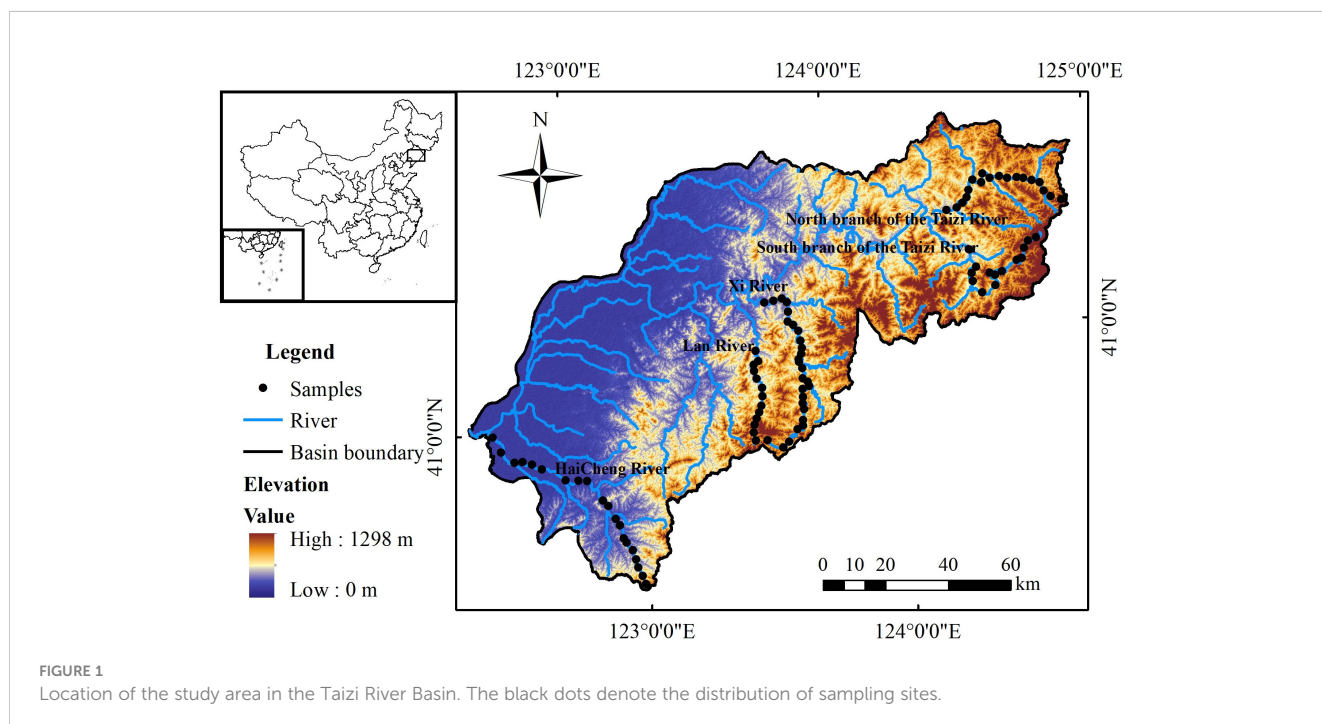
2.1 Study area

The Taizi River (122°25' E–124°56' E, 40°28' N–41°40'N) is located in the southeastern part of Liaoning Province in northeastern China. This river serves as a key tributary of the Liaohe River upstream, spanning a total length of 413 km with coverage of $1.4 \times 10^4 \text{ km}^2$ (Figure 1). The TRB is characterized by a complex terrain with increasing elevation and human activities from east to west. The upper reaches are mainly low hills with high vegetation cover and limited human interventions, while the middle and lower reaches are marked by hilly and plain terrains. Flow paths

through Benxi, Liaoyang, and Anshan reveal a dominantly industrial landscape. The lower reach underpins the agricultural economy of Liaoning Province. The diversity in climatic conditions and topography across different geographical regions results in a differential distribution of land use changes across the TRB.

2.2 Macroinvertebrate sampling

We selected 92 sampling locations spread across the TRB (Figure 1), encompassing the Haicheng River, Lanhe River, Xihe River, and southern and northern tributaries flowing into the Taizi River. Macroinvertebrate samples were collected with a Surber net ($30 \times 30 \text{ cm}$, 0.4mm). At locations where wading was possible, we gathered three replicate samples from two riffles and a shallow pool. For sites where wading was not feasible, three replicates samples were collected from shallow waters along the river bank using the same method. All specimens were passed through a 0.4-mm mesh sieve. The remaining organisms were fixed, preserved using 70% alcohol, and brought back to the laboratory for identification under a stereomicroscope (Olympus SZ511), according to the identification keys of Merritt and Cummins (1996) and Morse et al. (1984). A total of 76 families were determined, enabling establishment of assemblage indicators. The overall sample was largely dominated by insects, crustaceans, and gastropods, comprising 90.8%, 2.0%, and 1.7% of the total sample, respectively. Among the identified taxa, *Orthocladinae*, *Chironomidae*, and *Baetidae* are density-predominant species, contributing to 25.6%, 13.9%, and 9.3% respectively (see the Appendix for details). To adequately characterize the macroinvertebrate assemblages within the TRB, each sample was evaluated using the benthic index of biotic integrity (B-IBI), average



score per taxon (ASPT), and Shannon–Wiener index (H'). The evaluation of B-IBI was based on reported river health assessment indicators from North America and Europe. Through distribution tests, sensitivity analysis, and correlation tests, the following core parameters of B-IBI for the study area were determined: total taxa, Plecoptera taxa, Trichoptera%, EPT% (total *Ephemeroptera*, *Plecoptera*, and *Trichoptera* individuals divided by the total number of macroinvertebrates of all taxa), tolerant taxa%, dominant taxa%, filterers%, and predators%. The B-IBI was then computed using a standardized method, as described by Qu et al. (2012). The formulas for calculating B-IBI, ASPT, and H' are provided in Table S1 and Text S1.

2.3 Water environment and physical habitat variables

Across the 92 sampling sites, we identified 14 variables emblematic of the physical habitat and water environment (Table 1). River width measurements were based on three random transects per sampling station, while the water depth was measured only at the macroinvertebrate sampling locations. A multiparameter water quality probe (YSI-Pro Plus, YSI Inc., USA) was utilized to measure the water temperature, electrical conductivity (EC), dissolved oxygen (DO), total dissolved solids (TDS), and pH. The total phosphorus (TP), total nitrogen (TN), ammonia nitrogen ($\text{NH}_3\text{-N}$), nitrate-nitrogen ($\text{NO}_3\text{-N}$), and chemical oxygen demand (COD) were evaluated in the laboratory per the “Environmental quality standards for surface water” standard of China (GB3838-2002). Water samples were collected in sterilized polyethylene bottles and immediately acidified to $\text{pH} < 2$

TABLE 1 Descriptions and codes of water environmental and habitat variables.

Variable group		Code	Unit
Physical Habitat	Water depth	DEPTH	m
	River width	WIDTH	m
	Discharge	VELOCITY	m/s
Basic Water Quality	Temperature	T	°C
	Suspended solid	SS	mg/L
	Electrical conductivity	EC	$\mu\text{S}/\text{cm}$
	Dissolved oxygen	DO	mg/L
	Total dissolved solids	TDS	mg/L
	pH	pH	–
Nutrient and Organic Pollution	Total phosphorus	TP	mg/L
	Total nitrogen	TN	mg/L
	Nitrate-nitrogen	$\text{NO}_3\text{-N}$	mg/L
	Ammonia nitrogen	$\text{NH}_4\text{-N}$	mg/L
	Chemical oxygen demand	$\text{COD}_{\text{Cr}}/\text{COD}_{\text{Mn}}$	mg/L

for preservation. The samples were stored in a cooler with ice packs to maintain a temperature below 4°C during transport. In the lab, samples were maintained at 4°C and analyzed within 48 h. Suspended solids (SS) were quantified via filtration through pre-dried cellulose acetate membranes (0.45 μm) per the Chinese standard (GB11901-89).

Our analysis approach involved the adoption of 10 quality indicators for river habitat, as detailed in Table S2: substrate, habitat complexity, comprehensive depth and flow velocity, embankment stability, channel change, river flow, vegetation diversity, water quality, human activities, and riparian land use. Together, these indicators provide a comprehensive perspective on water quality, water yield, human activity, and the physical structure of the river habitat. The rating system used in the Liaohe Basin (Zheng et al., 2007) served as our primary criteria for evaluation, which was complemented by methods from Hughes et al. (2010) on agricultural stream habitats.

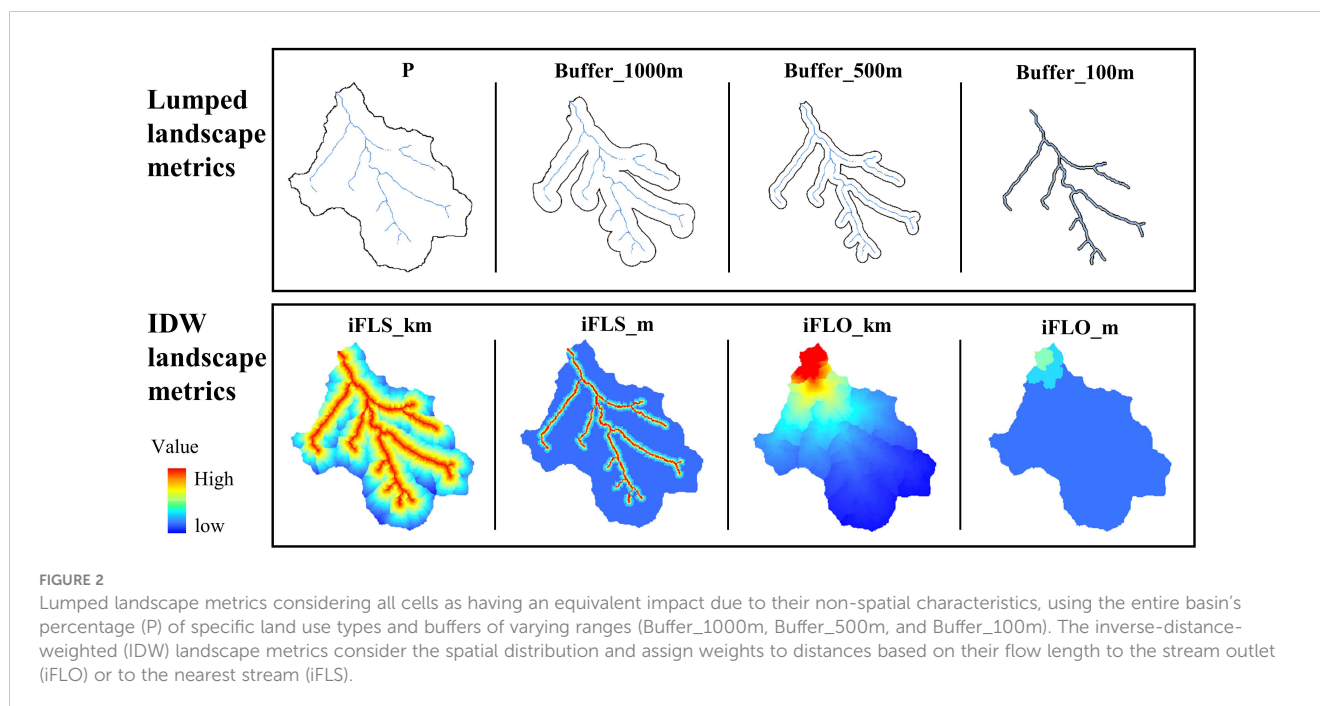
2.4 Landscape pattern and metrics

Land use classification was conducted based on the 2010 Landsat Thematic Mapper data with a spatial resolution of 30 m. We utilized a supervised classification approach in ERDAS IMAGINE, defining training areas for each land use type to interpret the imagery. The resulting land use map was divided into five categories: rural area, urban area, forest, grassland, and agricultural land. Although rural areas might also contain forests, grasslands, and agricultural lands, these terms primarily describe types of landscapes or land uses rather than the human settlement patterns characterizing rural areas. We utilized both lumped metrics and IDW metrics for comparison (Figure 2). The former quantifies the percentage values of different land uses at the watershed or buffer scales. The latter involves the use of spatial weight layers, giving higher importance to landscape cells closer to streams or monitoring sites. We calculated the IDW metrics by superimposing land use layers and spatial weight layers via a distance-decay function. The IDW metrics calculated based on their flow length to the stream outlet (iFLO) and the flow length to nearest stream (iFLS) were used to represent the distance in spatial weight layers. This approach results in higher weight values for areas closer to streams or monitoring sites (Peterson et al., 2011; Walsh and Webb, 2014).

3 Statistical analysis

3.1 Data preprocessing

Redundancy analysis (RDA) was employed to discern water environment and physical habitat factors that significantly affect the structural characteristics of macroinvertebrates. The species data used for the RDA were the absolute numbers for each species. The eigenvalues for each axis were deduced through a detrending analysis performed prior to the RDA, with a maximum value of 3.38 (range: 3–4). Subsequently, RDA was utilized to delve deeper



into the association between environmental factors and macroinvertebrates. We determined the variables using abundance data, conducted significance tests, and then screened the key environmental factors through the pre-selection process. Environmental factors contributing significantly ($p < 0.05$) to species variation were evaluated using the Monte Carlo permutation test with 999 permutations. Variables with a variance inflation factor less than 5 were selected for inclusion in the model.

RDA offers a descriptive global view of the relationships among all variables. Therefore, to ascertain which variables have the greatest predictive importance, we employed multivariate stepwise regression models to investigate the influence of land use patterns on river chemistry, physical parameters, and macroinvertebrates. The adjusted R^2 value from the regression model quantifies the explanatory power of these metrics, helping to elucidate the impacts of land use under various landscape metrics from a predictive modeling perspective. Finally, we developed SEMs to examine the pathways between land use pattern, water environment, physical habitat, and macroinvertebrates. RDA and multivariate stepwise regression were performed using CANOCO4.5 and STATISTICA7.0 software, respectively. To ensure adherence to normality assumptions, all environmental data and evaluation indicators (S1–S10), with the exception of pH, were subjected to $\log(x + 1)$ transformation and standardization prior to RDA; pH was not log-transformed given its inherent logarithmic nature.

3.2 SEM construction

SEMs were implemented using AMOS 7.0 software (Arbuckle, 2006) to examine the pathway and assess the pathway coefficient (Pc) of the influence of human activities on river ecosystems across

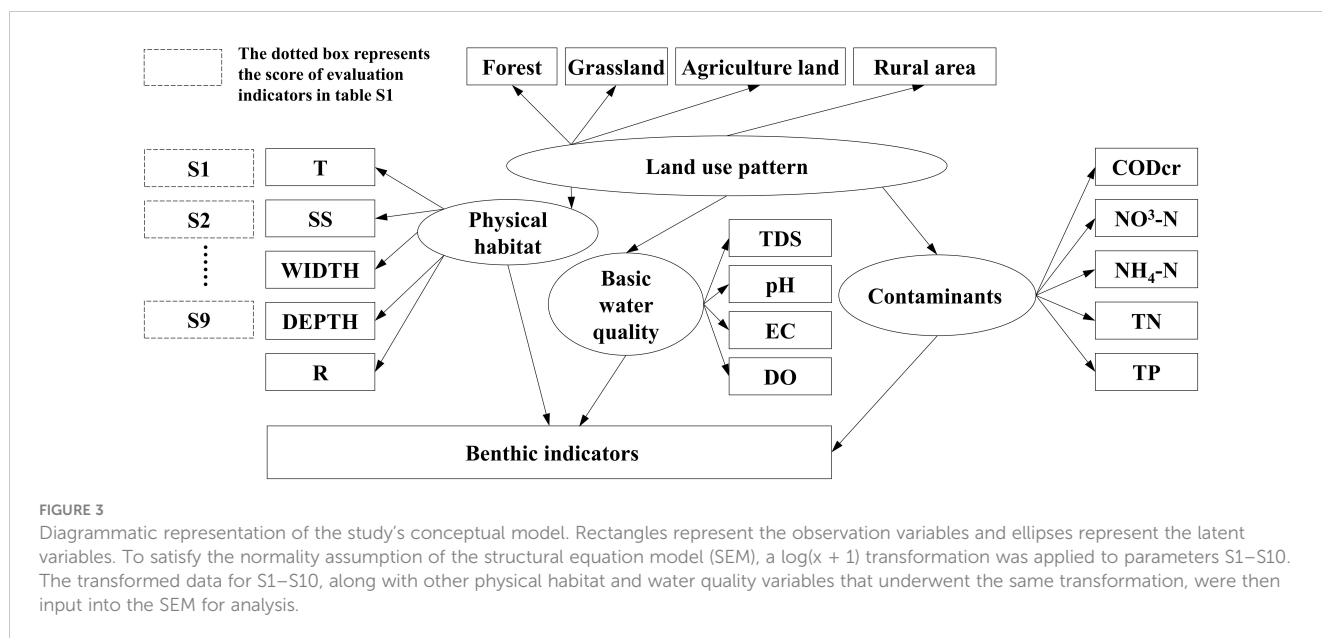
diverse spatial extents. Prior to model construction, a conceptual model of the regional river ecosystem was required. The conceptual model was informed by the fundamental theory and associated findings from prior Taizi River ecosystem studies (Figure 3).

Following creation of the conceptual model, observational data were incorporated into the models. Model refinement was achieved by adjusting the Modified Index (MI) by adding or removing variables to better align the theoretical models with the observational data. The models' reliability was verified using Chi-square (χ^2), root mean square error of approximation (RMSEA), non-centrality parameter (NC), adjusted goodness-of-fit index (AGFI), and comparative fit index (CFI) (Bentler and Bonett, 1980; Browne and Cudeck, 1992). R^2 is used to interpret the macroinvertebrate index, while Pc delineates the impact of different paths. Common grounds for model adjustments include insufficient ecological data, non-compliance with normality assumptions, autocorrelation between different environmental factors, and model definition inconsistency with the actual situation.

4 Results

4.1 Identification of environment and physical habitat impacts

At the spatial extent of the river, we predominantly focused on the impacts of the water environment and physical habitat on macroinvertebrate assemblages. Among the correlations between land use and water quality, temperature exhibited significant correlations with iFLS_km_agriculture% ($R = 0.575$, $p < 0.01$), iFLS_km_rural% ($R = 0.597$, $p < 0.01$), iFLO_km_rural% ($R = 0.541$, $p < 0.01$), and iFLO_m_rural% ($R = 0.526$, $p < 0.01$).



Moreover, EC exhibited strong associations with iFLO_km_rural% ($R = 0.520, p < 0.01$) and iFLO_m_rural% ($R = 0.52, p < 0.01$). Furthermore, TDS demonstrated significant correlations with iFLO_km_rural% ($R = 0.474, p < 0.01$) and iFLO_m_rural% ($R = 0.425, p < 0.01$).

Informed by the correlation analysis between water environment and physical habitat, the preliminary findings showed a close correlation between TDS and T ($R = 0.669, p < 0.01$), EC ($R = 0.837, p < 0.01$), and TN ($R = 0.515, p < 0.01$), prompting its exclusion in the RDA. Additionally, macroinvertebrate species with a low frequency of occurrence (less than 5%) were omitted at each site. The RDA results indicated substantial eigenvalues on the first and second axes (values of 0.205 and 0.065 respectively) (Table 2), accounting for 30.7% of the total variation in accumulated species variance. The arrows in Figure 4 represent the significant water environmental and physical habitat factors with an impact on macroinvertebrate communities.

The Monte Carlo test demonstrated that all axis interpretation rates were significant ($F = 2.873, p < 0.001$). Major contributors to the first axis were S2 (habitat complexity) ($F = 2.735, p < 0.001$). The second axis was significantly influenced by temperature ($F = 7.838, p < 0.001$), EC ($F = 2.364, p < 0.01$), and TN ($F = 2.033, p < 0.01$).

Therefore, our results demonstrated that variations in the macroinvertebrate community are primarily driven by environmental differences and human impacts in the tributaries

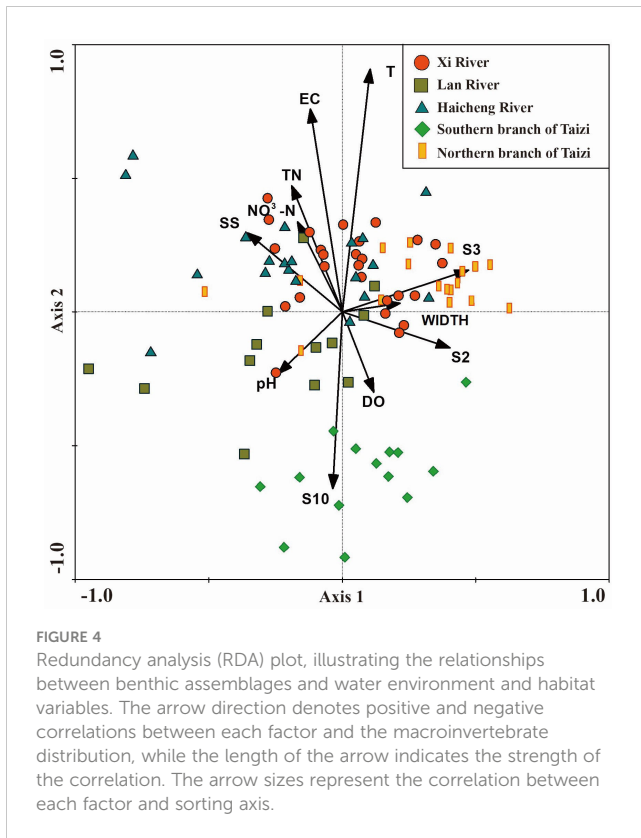
(Figure 4). A clear divergence was noted in the macroinvertebrate assemblage distribution across spatial extents. In the northern branch of the Taizi River, the distribution focused in the first quadrant, primarily influenced by S2, whereas in the southern section, the distribution was concentrated in the third and fourth quadrants. In the Xi and Haicheng rivers, the macroinvertebrate assemblage distribution was focused in the first and second quadrants, with a greater influence from T, EC, and TN. However, in the Lan River, the distribution was primarily in the third quadrant, largely influenced by pH. Overall, the RDA findings indicated that habitat complexity constituted the main physical habitat factor directly affecting the macroinvertebrate distribution. Temperature, EC, and TN were the major water quality factors influencing the macroinvertebrate distribution.

4.2 Impact of landscape metrics on macroinvertebrate indices

Multiple linear stepwise regression was employed with land use landscape metrics and macroinvertebrate biological indices. We utilized a diverse set of landscape indicators to better understand how different land use patterns influence the macroinvertebrate distribution along river pathway distance gradients (Table 3). The

TABLE 2 Summary of the redundancy analysis.

Axes	Eigenvalues	Species-environment correlations	Species-environment correlations of species data (%)	Species-environment correlations of species-environment (%)
1	0.205	0.804	22.4	56.2
2	0.065	0.768	30.7	81.5
3	0.029	0.663	33.5	87.1
4	0.016	0.629	35.4	90.3



B_m metric underscores the prominence of agriculture, highlighting its protective zones and interactions around water bodies. As we shifted our focus to iFLO and iFLS, which measure the distance gradients to the stream outlet and nearest stream, respectively, the influence of rural landscapes became increasingly evident. In contrast, the P_m metric offers a more holistic perspective on the overall pattern, which recognizes the influence of rural landscapes while simultaneously capturing the impact of forested areas.

Macroinvertebrate indices also highlight differences among tributaries. The B-IBI showed that the north and south branches exhibit good biological integrity, suggesting a healthy river state. However, as the river flows downstream, with the expansion of urbanized areas and agricultural land use, the health status of the sampling sites progressively deteriorated. The Haicheng River comprised the poorest assessment indicators, which further corroborated the RDA findings.

In evaluating the relationship between landscape metrics and bioindicators, it became evident that certain metrics played a pivotal role in explaining macroinvertebrate biological indices. The optimal land use landscape metrics varied among the indices B-IBI, ASPT, and H'. Specifically, iFLO_{km} had the highest explanatory power for B-IBI ($R^2 = 0.382$, $p < 0.001$). For ASPT, both iFLO_{km} and P had similar explanatory power ($R^2 = 0.371$, $p < 0.001$). The optimal landscape metric for H' was the lumped land use percentage (P), with an R^2 value of 0.172, which was significant at $p < 0.0011$. However, this explanatory power was notably weaker compared to that for B-IBI and ASPT. Additionally, under the optimal landscape for B-IBI, ASPT, and H', the predictive variables were predominantly rural.

4.3 Multi-scale pathways identified by SEMs

Based on the RDA and regression analysis results, 24 SEMs of B_{IBI}, ASPT, and H' were developed; these models and their adaptability indicators are presented in Table 4. Of the 24 models, 11 exhibited a good fit ($p > 0.05$). The errors in these models were all below 0.06, indicating that the latent variables in the models were properly fitted and explained. The most interpretable models for B_{IBI}, ASPT, and H' were then selected for more detailed analysis. The SEM-BIBI, SEM-ASPT, and SEM-H' models, along with the standardized Pc, are depicted in Figure 5. The landscape pattern metric with the highest interpretability for macroinvertebrate indices was iFLO_m.

The SEM-BIBI model accounted for 76% of the variation in B-IBI. From the viewpoint of impact pathways, land use patterns primarily affect macroinvertebrates by modifying their physical habitat conditions ($P_c = -0.41$), largely focusing on habitat complexity (0.53), combined speed-depth characteristics (0.24), and water depth (0.21). The main influence of land use patterns depends on the river's basic water quality ($P_c = 0.53$), which further impacts the B-IBI ($P_c = -0.33$). Nutrient and organic pollution factors, such as NO₃-N and TN, were mainly influenced by land use ($P_c = -0.24$), but exert a limited impact on B-IBI ($P_c = -0.01$). With respect to land use pattern metrics, the rural area showed the largest contribution to the land use pattern based on the iFLO_m metric (0.92), followed by agricultural land (0.46) and grassland (-0.33).

The SEM-H' model explained 70% of the variance in the Shannon–Wiener index. Land use has a major impact on the physical habitat ($P_c = -0.28$), thereby affecting macroinvertebrates. The primary areas of influence include habitat complexity (0.65), water depth (0.36), and the combined characteristic of speed and depth (0.41). Land use patterns primarily influence the river's basic water quality ($P_c = 0.61$), whereas water quality deterioration only demonstrated a minor effect on the biological index ($P_c = -0.14$). Nutrient and organic pollution were also influenced by land use patterns ($P_c = -0.30$), although their impact on the Shannon–Wiener index was minimal ($P_c = 0.07$). Using the iFLO_m metric, the largest contribution from the land use pattern was derived from the rural residential area (0.84), followed by agricultural land (0.51) and grassland (-0.23).

Overall, the SEM-ASPT model accounted for 66% of the variation in the ASPT. Consistently, land use patterns mainly impact macroinvertebrates through modifications to physical habitat conditions ($P_c = -0.51$), primarily emphasizing habitat complexity (0.41), water depth (0.15), and the combined characteristic of speed and depth (0.15). Land use also showed an influence on the river's basic water quality ($P_c = 0.52$), with EC (0.93) and TDS (0.90) being the most significant contributors. Nutrient and organic pollution, influenced by land use patterns ($P_c = -0.24$), exert minimal impacts on the ASPT ($P_c = -0.07$). According to the iFLO_m metric, the rural residential area demonstrated the highest contribution to the land use pattern (0.94), followed by agricultural land (0.46) and grassland (-0.29).

TABLE 3 Multiple linear stepwise regression of landscape metrics and macroinvertebrate indices.

Macroinvertebrate indices	Landscape metrics	Predictive variable	R ²	Adjust-R ²	Significance	
B-IBI	P	(-)rural** forest*** (-)agriculture*	0.363	0.341	0	***
	B_1000m	(-)agriculture***	0.156	0.174	0	***
	B_500m	(-)agriculture*	0.098	0.088	0.05	*
	B_100m		ns			
	iFLS_km	(-)rural*** grass*	0.358	0.343	0	***
	iFLS_m		ns			
	iFLO_km	(-)rural*** grass**	0.395	0.382	0	***
	iFLO_m	(-)rural***	0.284	0.276	0	***
H'	P	(-)rural*** forest***	0.191	0.172	0	***
	B_1000m		ns			
	B_500m		ns			
	B_100m		ns			
	iFLS_km	(-)rural*	0.085	0.075	0.05	*
	iFLS_m		ns			
	iFLO_km	(-)rural***	0.150	0.140	0	***
	iFLO_m	(-)rural**	0.108	0.099	0	***
ASPT	P	forest*** (-)agriculture***	0.385	0.371	0	***
	B_1000m	(-)agriculture***	0.139	0.129	0	***
	B_500m	(-)agriculture*	0.084	0.074	0.05	*
	B_100m		ns			
	iFLS_km	(-)rural***	0.292	0.284	0	***
	iFLS_m		ns			
	iFLO_km	(-)rural*** forest*	0.385	0.371	0	***
	iFLO_m	(-)rural***	0.344	0.33	0	***

***p < 0.001, **p < 0.01, *p < 0.05, ns means not significant, (-) means negative correlation. Bold the highest Adjusted-R² values of Landscape metrics for each Macroinvertebrate index.

5 Discussion

5.1 Land use pattern metrics

This study utilized lumped and IDW metrics to examine the influence of land use on environmental and physical factors affecting macroinvertebrate communities at various river ecosystem spatial scales. The findings were particularly notable in comparing the explanatory power (R²) of multiple stepwise regression (Table 3) with that of SEM (Table 4). The results from multivariate stepwise regression highlighted P and iFLO_km as the most explanatory metrics. However, SEM analysis revealed iFLO_m and iFLO_km as the top predictors, followed by iFLS_m, iFLS_km, Buffer metrics, with P showing the lowest explanatory strength.

The landscape metrics (iFLO_m and iFLO_km) with inverse distance weights showed commendable explanatory ability, whereas the lumped attribute P showed a divergence according to the model used for evaluation. As a fundamental and widely used landscape

descriptor, P metrics concentrate on analyzing the proportions of different land use types. This analysis is crucial for understanding ecological processes and for identifying the specific effects of various land use types on related factors. (Mello et al., 2018). According to Table 3, P metrics exhibit robust explanatory capacity for H' (0.172) and ASPT (0.371). Moreover, the capability of P metrics to interpret B-IBI (0.363) is only slightly less effective than that of IDW metrics (0.382), underscoring the broad applicability of P.

However, P metrics exhibited a substantial difference in predictive ability according to the various indices in SEMs. The explanatory capacity of P for the biological index B-IBI did not show improvement in the SEM (0.35) compared to multiple regression results (0.363); a similar effect was observed for the ASPT and H' indices. This implies a low upper limit for the explanatory ability of P, indicating that an SEM cannot further enhance this ability of P metrics. Conversely, SEM analysis revealed an improved explanatory capacity for the 'Buffer' attribute, suggesting its greater importance for benthic organisms compared

TABLE 4 Evaluation indicators and significance of all structural equation models (SEMs).

Macroinvertebrate indices	landscape metrics	R ²	χ ²	Degree of freedom	p	Fitness	RMSEA	GFI	CFI
B-IBI	P	0.34	71.641	57	0.053	Good	0.053	0.901	0.974
	B_1000m	0.51	77.851	60	0.06	Good	0.057	0.892	0.966
	B_500m	0.49	90.052	62	0.008	/	0.073	0.886	0.93
	B_100m	ns	/	/	/	/	/	/	/
	iFLS_km	0.75	90.371	59	0.001	/	0.069	0.829	0.92
	iFLS_m	0.62	72.073	62	0.029	/	0.058	0.841	0.938
	iFLO_km	0.73	81.155	63	0.033	/	0.061	0.886	0.969
	iFLO_m	0.76	84.842	65	0.15	Good	0.043	0.9	0.954
H'	P	0.54	68.357	57	0.144	Good	0.047	0.907	0.979
	B_1000m	0.62	70.798	60	0.161	Good	0.044	0.905	0.969
	B_500m	0.68	84.287	62	0.031	/	0.063	0.895	0.947
	B_100m	ns	/	/	/	/	/	/	/
	iFLS_km	0.69	84.601	60	0.012	/	0.057	0.851	0.95
	iFLS_m	0.69	77.984	62	0.083	Good	0.053	0.9	0.968
	iFLO_km	0.76	82.187	63	0.041	/	0.061	0.87	0.953
	iFLO_m	0.7	99.867	65	0.158	Good	0.061	0.889	0.926
ASPT	P	0.44	67.605	56	0.138	Good	0.048	0.907	0.979
	B_1000m	0.31	79.113	60	0.051	Good	0.059	0.889	0.962
	B_500m	ns	/	/	/	/	/	/	/
	B_100m	0.46	77.555	62	0.088	/	0.053	0.896	0.96
	iFLS_km	0.54	80.832	59	0.031	/	0.064	0.891	0.963
	iFLS_m	0.51	85.243	63	0.012	/	0.071	0.87.9	0.927
	iFLO_km	0.64	80.291	64	0.107	Good	0.067	0.882	0.951
	iFLO_m	0.66	84.582	65	0.052	Good	0.058	0.897	0.953

ns means not significant.

Bold the highest R² values of Landscape metrics for each Macroinvertebrate index.

to the broader impact of the entire basin. However, determining the most crucial range of the buffer zone still requires further investigation.

While the efficacy of iFLO_km and iFLO_m metrics differed among methods, they were generally more effective than other landscape metrics in elucidating biological indices. Multiple regression analysis indicated that iFLO_km had the highest interpretative strength for B-IBI (0.382) and ASPT (0.371). In SEMs, however, iFLO_m models exhibited slightly better performance than iFLO_km, albeit not significantly so. In SEMs, iFLO_m and iFLO_km's explanatory abilities were 47–63% greater compared to multiple regression, demonstrating their substantial benefits. Of all eight landscape metrics tested, only the SEM using iFLS_m metrics demonstrated a high level of fitness, with its capacity to interpret H' being strong (0.70), closely followed by iFLO_m (0.69). Hence, selecting the most suitable landscape metrics for accurate ecological description in a specific area requires thorough verification and comparison using diverse methodologies.

By integrating the statistical results with existing research theories, SEM can precisely describe ecological conditions. This method underscores the comparative advantage of improved landscape metrics. Peterson et al. (2011) corroborate that the use of ameliorated land use landscape metrics can amplify the description ability for river habitats. This is congruent with our original intent to perpetually enhance landscape metrics. Consequently, employing SEM brings analytical approaches and systems closer to the dynamics of natural ecology, thereby enhancing the accuracy and reliability of ecological description.

5.2 Multiple pathways of the SEMs and management recommendations

This research utilized SEM to explore the relationship between macroinvertebrates and environmental variables at different spatial

extents (Figure 5). In the TRB, the main pathway from land use (rural and agriculture) to biological indices was through physical habitat factors (habitat complexity, speed and depth) to benthic indicators. A secondary pathway connected these land use types to water quality parameters (electrical conductivity and total dissolved solids), impacting benthic indicators.

In the context of basin-wide spatial extents, the presence of rural and agricultural lands plays a crucial role in shaping macroinvertebrate populations. It predominantly influences their distribution by modifying the river channel, physical habitat, and water quality in riparian zones. The influence of rural areas and agricultural land on macroinvertebrates has been widely

investigated across different regions. Among various environmental factors examined, Zhang et al. (2018) found that escalating agriculture activities led to a decrease in richness and diversity of pollution-sensitive macroinvertebrate species. Probst et al. (2005) concluded that agricultural runoff significantly contributes to biological assemblage variations. They noted that increased agricultural land often leads to reduced vegetation cover, which affects the runoff process. This change typically results in expanded shallow water areas in the river's biological habitat, thereby simplifying the habitat structure (Allan, 2004). The influence of rural areas on macroinvertebrates is largely due to human activities, as pollution from these activities significantly

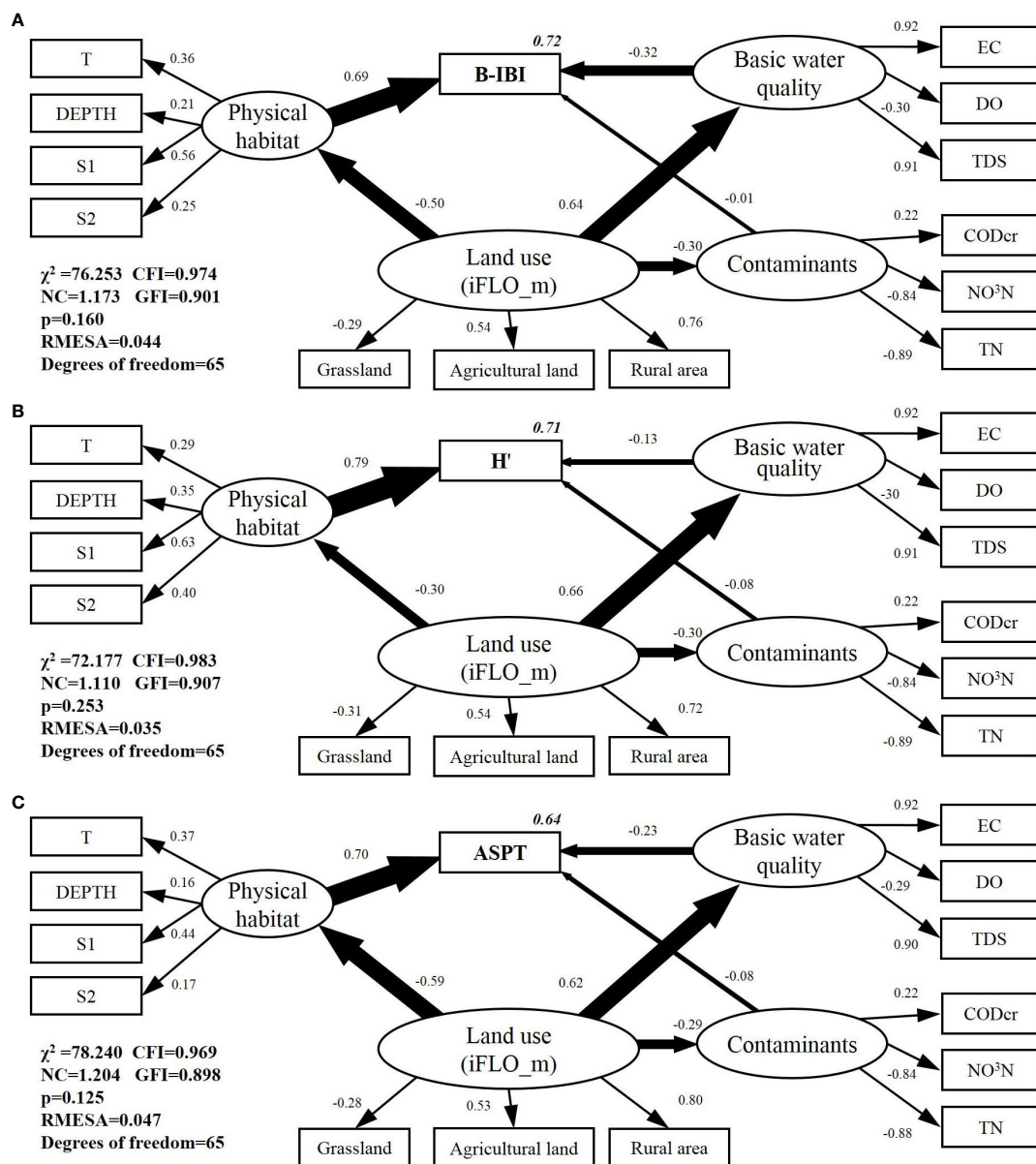


FIGURE 5 Structural equation models (SEMs) for biological indicators: (A) SEM-BIBI, (B) SEM-H', (C) SEM-ASPT. (Rectangles represent the observation variables, ellipses represent the latent variables, and circles represent the error term for each variable. The number on the single arrow indicates the path coefficient, with + and - representing a positive and negative correlation, respectively. The number on the box represents the explain ability of the model (R²). S1 and S2 represent substrate and habitat complexity parameters, respectively, defined in Table S1.

alters water quality. Water pollution therefore leads to changes in physical and chemical variables like conductivity, turbidity, and total suspended solids, which in turn affect benthic organism assemblages. Similar responses of benthic assemblages to pollution and habitat alterations have been observed in various studies (Minaya et al., 2013; Boehme et al., 2016), which align with our results.

We employed data related to water quality, nutrient and organic pollution, habitat, and biological indicators to investigate the characteristics of the five tributaries on the Taizi River. The RDA results illustrated that physical habitat factors (S2, S3, S10) primarily govern the macroinvertebrate assemblage distribution. Following a substantial period of evolution, the riverbeds manifest diverse geological characteristics across the five rivers. Aquatic vegetation, litter, fallen wood, inverted embankments, and boulders enrich a variety of habitats. The absence of arable land, coupled with nutrient interception and high nutrient content, creates ideal conditions for benthic habitats. This is particularly evident in the northern and southern branches of the Taizi River, near the Dadi Forest Park, an area characterized by lush vegetation and excellent water quality.

However, analysis of the correlation between land use patterns and water quality has inherent limitations. Water quality is influenced by the instantaneous effects of point-source emissions and the combined effects of both point and non-point sources; these often demonstrate a non-linear relationship with static land use patterns and singular water quality test data (Wu et al., 2012). Within the TRB, conductivity and TN emerged as the principal water quality factors affecting macroinvertebrates, notably in the Xi River and Haicheng River. This effect is largely attributed to urban and industrial activities within the region, particularly the presence of petrochemical, electroplating, and mining factories near the city spanning the middle and lower reaches of the Taizi River (Qu et al., 2017; Wang et al., 2018). Metal mines and heavy industries are significant sources of pollution. The chemicals from these industries, released through wastewater discharge, affect the distribution of macroinvertebrate communities in the river.

The comparison of landscape metrics underscored that rural and agricultural areas closer to the river more significantly influence river water quality and biological habitats. This influence is especially pronounced in terms of benthic biodiversity. This indicates that the efficacious management of riparian areas within rural and agricultural lands forms the key to reviving the health of river ecosystems. A judicious approach to management could balance the dual goals of pollution control and biodiversity conservation. For instance, a study by McCracken et al. (2012) in the United Kingdom suggested that when the farm fence set aside for river protection is wider than 5.4 m, there is a marked increase in aquatic invertebrate diversity. Similarly, Hughes and Vadas (2021) highlighted the influence of agriculture on the quality of streams and rivers in the western United States. Accordingly, they proposed that policies encouraging the preservation and restoration of riparian zones would increase the chances of improved biological conditions in streams. Sweeney and Newbold (2014) proposed that the ideal buffer zone width could vary based on the location; they

recommended a buffer width of at least 30 m to optimally protect the water quality and ecological health of small streams. However, in the TRB and northern China, farmlands are typically less than 5.4 meters from rivers, a practice stemming from traditional farming habits. This proximity, along with the characteristics of the surrounding landscape, notably affects riparian zones in agricultural and residential areas (Zhang et al., 2013). Consequently, it is recommended that the government and agricultural management department establish a buffer protection zone along the riverbanks of agricultural lands to enhance the water quality and ecological health of the TRB. Given the effects of large-scale agriculture and proximity of rural areas to rivers on benthic organisms, we recommend establishing 100-m wide riparian buffers. However, when implementing these measures, the impacts on other regional wildlife, such as fish and wild animals, should be considered to determine the optimal buffer range.

6 Summary and conclusions

Utilizing a comprehensive dataset from the TRB, including macroinvertebrates, water environmental factors, and physical habitat, this study effectively used SEMs to examine land use effects on macroinvertebrates across multiple scales. The findings provide several key insights with practical implications for enhanced management.

Along the spatial extent of the river, macroinvertebrate assemblages were significantly influenced by water and habitat parameters. In particular, temperature, EC, TN, and habitat complexity emerged as dominant influencers across different river reaches. Correlation and regression analyses in this study showed that land use landscape metrics, especially those related to rural areas, have a significant impact on macroinvertebrate biological indices along river pathways. These metrics varied in their explanatory power for different indices like B-IBI, ASPT, and H'.

Of the 24 structured SEMs, 11 exhibited an exemplary model fit. Collectively, these models articulate a narrative where land use, especially in rural areas, affects macroinvertebrates by altering physical habitats and water quality. In this analysis, the iFLO_m metric proved particularly effective, exhibiting strong interpretative capabilities in our refined SEM models. Its explanatory power for SEM-BIBI, SEM-H', and SEM-ASPT was observed to be 76%, 70%, and 66%, respectively. The primary pathway of influence within the TRB is delineated as: land use (predominantly rural and agricultural) feeding into physical habitat (habitat complexity, combined characteristic of speed and depth), which in turn affects benthic indicators. A secondary pathway charts a course from land use through water quality (electrical conductivity and total dissolved solids), culminating in benthic variations.

SEMs have proven to be invaluable in discerning the complex relationships between land use and macroinvertebrates. These diverse land use descriptions underscore that IDW metrics, especially iFLO_m and iFLS_m, offer substantial advantages in deciphering the ecological status of river health under various impact pathways. Moreover, the present findings further

emphasize the need for verification of diverse landscape metrics, demonstrating the benefits of structural equation modeling in delivering a refined ecological understanding.

Overall, our results demonstrate that close-proximity rural and agricultural land use in the TRB significantly shape macroinvertebrate distributions by altering river habitats and water quality. This highlights the need for the construction of strategic riparian buffer zones. Specifically, from the perspective of macroinvertebrates in the TRB, we recommend establishing 100-m wide riparian buffers. Buffer zones that take into account a broader range of biological needs will further enhance the ecosystem health of the river basin.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

KM: Conceptualization, Data curation, Investigation, Methodology, Software, Visualization, Writing – original draft. HZ: Funding acquisition, Methodology, Supervision, Writing – review & editing. MZ: Writing – review & editing. XQ: Resources, Supervision, Writing – review & editing. NW: Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fevo.2023.1292721/full#supplementary-material>

TEXT S1

The formulas for calculating ASPT and H'.

SUPPLEMENTARY TABLE 1

Formula for calculating of the core attributes of B-IBI.

SUPPLEMENTARY TABLE 2

The evaluation indicators and evaluation criteria of river habitat.

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