

Original Research

Spatiotemporal Heterogeneity and Future Trajectories of Landscape Ecological Risks in the Danjiangkou Reservoir Area, China

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Abstract

As a pivotal node of China's national ecological network, the Danjiangkou reservoir area has long been a focal point for ecological security due to its complex human–land interactions and high ecological vulnerability. Optimizing land use patterns is therefore essential for supporting sustainable ecosystem growth in this area. Utilizing the Landscape Ecological Risk Index (LERI), this study characterized the historical evolution of ecological risks (2000–2020). To explore future risks, the PLUS model was employed to project future land use patterns across various scenarios for 2030, and the related risks were evaluated in the reservoir area. The findings reveal that (1) From 2000 to 2020, land use structure underwent substantial reconfiguration, with forest and water expansion contrasting with declines in cultivated land and grassland, driven primarily by ecological restoration and reservoir construction; (2) The Landscape Ecological Risk (LER) exhibited strong positive spatial autocorrelation, with high-risk clusters concentrated in central zones with intensive human activity, while low-risk areas remained in mountainous regions with minimal disturbance; (3) Scenario simulations reveal that under the natural development (ND) and cultivated land preservation (CP) scenarios, urban expansion and agricultural encroachment further increase the aggregation of high-risk patches. Conversely, the ecological protection (EP) scenario – prioritizing restoration and spatial regulation – effectively mitigates risk and expands low-risk areas; (4) To guarantee long-term ecological stability, territorial spatial planning must prioritize ecological protection pathways, complemented by targeted restoration in high-risk zones and cross-administrative synergistic management. These insights provide critical evidence for adaptive management and the pursuit of regional sustainability within the reservoir area.

Keywords: LER, PLUS model, land use transitions, future trajectories, Danjiangkou reservoir area

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Introduction

Climate change, coupled with intensified anthropogenic disturbances, is continuously reshaping the structure and functioning of natural ecosystems [1-3]. Among the primary causes of environmental change worldwide, land use transitions represent a primary driver, as modifications in land use patterns directly influence ecosystem structure, processes, and stability [4, 5]. The term “Landscape Ecological Risk (LER)” emphasizes the potential for degradation in ecosystem stability and human well-being, stemming from anthropogenic or natural alterations to landscape patterns and processes [6]. Together with rapid urban expansion, irrational exploitation of land resources has grown more prevalent, especially in ecologically sensitive and vulnerable regions, where the LER is expected to intensify [7].

The LER originates from the complex interplay between spontaneous natural successions and anthropogenic disturbances, ultimately manifesting as functional degradation of ecosystems [8]. Current approaches for evaluating the LER are principally divided into two frameworks: the landscape index method and the comprehensive index method [9-11]. The comprehensive index method typically constructs multidimensional evaluation frameworks, including the pressure–state–response (PSR) model or ecosystem service-based indicator systems, to achieve an integrated assessment of ecological risk [12, 13]. However, this approach often involves complex indicator selection and subjective weighting, which may introduce uncertainty and reduce the transparency and comparability of results. In contrast, the landscape index method establishes ecological risk models by selecting a series of quantitative metrics that characterize landscape pattern features – such as fragmentation, isolation, and dominance – thereby directly reflecting the structural attributes of landscapes and their spatial heterogeneity [14, 15]. Owing to its capacity to explicitly depict spatial pattern variations, the landscape index method has been frequently employed in empirical studies [16, 17]. Land use transitions function as a primary driver of LER evolution. Consequently, simulating and predicting landscape risk trajectories under divergent land use scenarios have become essential areas of research [18-20]. A variety of modeling approaches have been established to simulate land use dynamics, typified by the Cellular Automata and Markov chain (CA-Markov) model, the Future Land Use Simulation (FLUS) model, and the Patch-generating Land Use Simulation (PLUS) model [21-23]. Notably, the PLUS model demonstrates enhanced efficacy in capturing patch-level land use transitions and identifying driving mechanisms, making it particularly suitable for analyzing complex land system changes and leading to its widespread application in recent studies [24, 25].

As the core headwater region of the South-to-North Water Diversion Project (SNWDP) (Middle

Route), the Danjiangkou reservoir area represents a critical ecological functional zone in China [26]. In recent decades, intensified human activities have driven increasingly frequent and complex land use transitions within the reservoir catchment, exerting substantial pressure on its ecological environment [27]. Hence, a robust investigation into the LER within this region is indispensable for safeguarding ecological security and advancing ecological sustainability. While extant literature has extensively explored land use dynamics and their environmental implications, the spatiotemporal progression and future trajectories of the LER in this region, especially within critical national ecological functional zones, remain insufficiently addressed [28, 29].

Based on the above analysis, the LERI was employed to examine the spatiotemporal heterogeneity of ecological risks in the Danjiangkou reservoir area (2000–2020). Subsequently, the land use patterns under various scenarios (the ND, CP, and EP scenarios) for 2030 were projected utilizing the PLUS model, which also predicted the associated LER in this area. Specifically, this study attempts to (1) characterize the features of land use transitions; (2) elucidate the spatiotemporal heterogeneity of the LER; and (3) project future risk trajectories under different scenarios for 2030 in the reservoir area, thereby providing indispensable empirical insights for the long-term ecological integrity of the reservoir area.

Materials and Methods

Study Area

As a critical ecological functional zone, the study region (32°12′–33°49′N, 109°27′–111°52′E) spans approximately 17,900 km². It encompasses a cross-provincial area that includes Danjiangkou City, the districts of Yunyang, Zhangwan, and Maojian, and Yunxi County in Hubei, as well as Xichuan and Xixia counties in Henan [30] (Fig. 1). The topography of the reservoir area is remarkably complex, exhibiting a general gradient descending from northwest to southeast and encompassing diverse geomorphic types. The regional climate is dictated by a subtropical monsoonal system, leading to a well-defined dry and wet seasonality. The regional economy is primarily oriented toward an eco-friendly and sustainable development model. In recent years, ecological agriculture, ecological tourism, and other sectors have developed rapidly in the reservoir area [31].

Data Sources

The core dataset in this research comprises fine-resolution (30 m) land use products at 10-year intervals from 2000 to 2020, supplemented by a diverse array of determinant factors relevant to land cover transformations. The land cover categories were

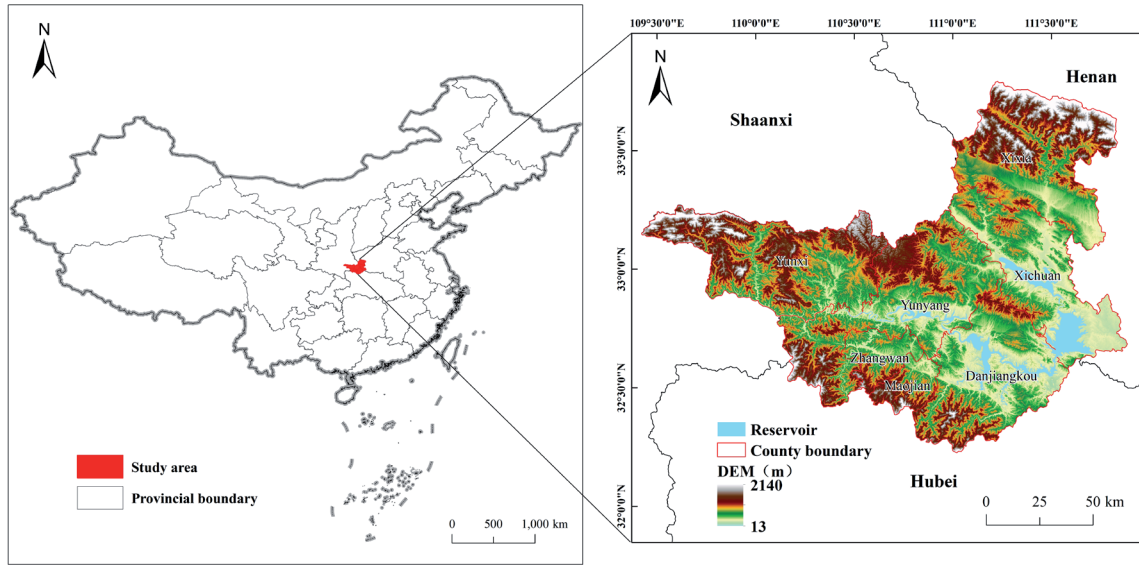


Fig.1. Spatial scope of the reservoir area.

retrieved via the Resource and Environmental Science and Data Center (RESDC) platform (<https://www.resdc.cn>). For the convenience of analysis, we consolidated the land cover information into six major typologies (i.e., cultivated, forest, grassland, water, construction, and unused land). Drawing upon previous investigations, the determinants of land use transitions were categorized into three groups: natural, economic, and social variables. Natural drivers included topographic features (elevation and slope), climatic variables, soil types, and water accessibility. Economic drivers comprised GDP, night light data, and the influence of township centers. Social drivers included accessibility to transportation infrastructure, including railways and various tiers of the road system. Among them, topographic variables, including elevation and slope, were extracted from the Geospatial Data Cloud (<https://www.gscloud.cn>). Meteorological, pedological, and socioeconomic indicators were retrieved from the RESDC platform. Road networks and water systems were retrieved from OpenStreetMap (OSM) (<https://www.openstreetmap.org>). To facilitate multi-source data integration, ArcGIS 10.8 was utilized for spatial preprocessing. All gridded variables were subsequently rescaled to a uniform 30 m spatial resolution. For spatial consistency, the resampling was based on the nearest-neighbor method to match the primary land use baseline. Temporally, socio-economic and environmental datasets were selected from the years closest to the study time points to minimize alignment errors.

Methods

Transitions in Land Use

To effectively evaluate the evolutionary process of regional land patterns, the land use transition map was

utilized as a robust analytical tool [32]. By implementing a spatial overlay of multitemporal datasets, this research obtained the specific trajectories and spatial distributions of land cover shifts at various stages. The computational formula is defined as follows:

$$C = 10 \times A + B \quad (1)$$

Where C is the map unit's grid value, which reflects the land use change process at a certain stage; A is the map unit's grid value in the previous period; B is the grid value for the later period. For computational efficiency, the land use typologies were labeled with corresponding numeric codes (1-6) (representing cultivated, forest, grassland, water, construction, and unused land, respectively). Through the superposition of multitemporal layers, we generated land use change maps for three distinct intervals: 2000-2010, 2010-2020, and 2000-2020.

Assessment of the LER

To elevate the accuracy of the LER metrics, the assessment-unit size was determined based on the established criterion that the analytical grid size should be two to five times the mean patch size [33]. Thus, a 3 km × 3 km equidistant sampling scheme was implemented, partitioning the Danjiangkou reservoir area into 2,194 risk assessment units. The LERI for each risk assessment unit was determined utilizing Fragstats 4.8 software. To visualize the LERI, spatial interpolation analysis was performed using the standard Kriging interpolation approach. Within this framework, the Landscape Disturbance Index (LDI) was evaluated using a composite framework incorporating the Landscape Advantage (LAI), Landscape Separation (LSI), and Landscape Fragmentation (LFI) indices, with

their specific weights and integration methods detailed in Table 1. This approach was intended to elucidate the relationship between landscape structure and its associated ecological vulnerability. Subsequently, by integrating the LDI with the Landscape Vulnerability Index (LVI), the Landscape Loss Index (LLI) was calculated. Building upon this, the LERI of each risk assessment unit was quantified based on the LLI. The specific computational procedures and ecological implications of these indices are summarized in Table 1 [34, 35].

Spatial Autocorrelation Analysis

Spatial autocorrelation, an essential geostatistical approach, was implemented to ascertain the spatial dependencies of variables and delineate their clustering patterns [36]. In the present study, global spatial autocorrelation was utilized to quantitatively assess the overall spatial dependence of the LER. In contrast, local spatial autocorrelation was implemented to detect spatial heterogeneity and identify specific clustering patterns of risk at a finer scale. Specifically, it identifies four modes of spatial clustering: High–High (H–H), High–Low (H–L), Low–High (L–H), and Low–Low (L–L) [37, 38]. The corresponding calculation methods are provided below:

$$Global\ Moran's\ I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (2)$$

$$Local\ Moran's\ I = \frac{n(x_i - \bar{x}) \sum_{j=1}^n w_{ij} (x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (3)$$

Where n signifies the aggregate count of spatial units; x_i and x_j denote the respective attribute values for elements i and j ; $\bar{x}$ serves as the corresponding average; and w_{ij} indicates the weighting factor between elements i and j . The value of *Global Moran's I* (GMI) ranges from -1 to 1. $I > 0$ suggests positive spatial autocorrelation, indicating a clustered spatial pattern, while $I < 0$ implies negative spatial autocorrelation, reflecting a dispersed spatial pattern. When the index approaches 0, it suggests a lack of spatial autocorrelation, indicating a random distribution. For *Local Moran's I* (LMI), positive signs signify similar spatial clustering (H–H or L–L), while negative values reveal different spatial clustering (H–L or L–H).

PLUS Model

As a patch-based simulation framework, the PLUS model combines rule extraction, underpinned by the Land Expansion Analysis Strategy (LEAS), with a Cellular Automata module driven by multi-type Random Seeds (CARS) to simulate land use dynamics [24, 39]. This model demonstrates strong capability in uncovering the underlying mechanisms of spatial expansion and projecting future pattern evolution. Consequently, the simulation process in this study was conducted through the following steps. First,

Table 1. Calculation formulas and significance of landscape indices.

Landscape Index	Calculation Formula	Parameter Description
LFI	$C_i = \frac{n_i}{A_i}$	A_i denotes the total area of landscape type i , and n_i represents the number of patches belonging to that specific type.
LSI	$N_i = \frac{A}{2A_i} \sqrt{\frac{n_i}{A}}$	A_i represents the total area of landscape type i , n_i denotes the number of patches of that type, and A is the total area of the specific assessment unit.
LAI	$D_i = \frac{Q_i + M_i + 2L_i}{4}$	Q_i represents the patch density, which is the percentage of the total patch count represented by landscape type i ; M_i denotes the patch frequency, which is the percentage of the total number of sample areas represented by landscape type i ; L_i represents the patch proportion, which is the ratio of the area of landscape type i to the total area.
LDI	$E_i = aC_i + bN_i + cD_i$	C_i , N_i , and D_i denote the LFI, LSI, and LAI, respectively; a , b , and c represent the weights assigned to the corresponding indices, which were set at 0.5, 0.3, and 0.2 according to established research.
LVI	$V_i = \frac{Z_i}{Z}$	Z_i denotes the value assigned to the vulnerability level of patch i , and Z represents the total value assigned to the vulnerability level. Based on the characteristics of the study area, the land use types were assigned vulnerability values as follows: construction land (1), forest land (2), grassland (3), cultivated land (4), water bodies (5), and unused land (6).
LLI	$R_i = E_i \times V_i$	E_i and V_i are the LDI and LVI, respectively.
LERI	$LERI_k = \sum_{i=1}^n \frac{A_{ki} R_i}{A_k}$	n represents the number of landscape types; A_k denotes the total area of evaluation unit k ; A_{ki} is the area of landscape type i within evaluation unit k ; and R_i indicates the LLI for landscape type i .

the expanded patches of land use across the Danjiangkou reservoir area were extracted by performing a spatiotemporal overlay of the thematic layers across a ten-year interval (2010–2020). Second, within the LEAS module, a Random Forest (RF) approach was utilized to establish the probabilistic link between land expansion and diverse driving forces, including natural, economic, and social variables, thereby estimating the expansion potential for each land use category. Finally, the Markov Chain (MC) module was employed to derive transition probabilities among land use categories for 2030. Building upon these probabilistic estimates, the CARS module was implemented to project land use configurations for 2030 across multiple scenarios by incorporating land use demand, transition matrices, and neighborhood weighting.

To harmonize with the multifaceted growth blueprints of the reservoir area, three distinct simulation scenarios were formulated to project land use distributions for 2030 [18, 40]. Under the ND scenario, reservoir construction and operation were taken into account. The conversion probabilities from 2010 to 2020 served as the baseline. Given that the major expansion phase of the SNWDP concluded around 2014, the rapid expansion of water area observed in the previous decade is expected to stabilize. Consequently, the conversion potentials into water bodies were curtailed by 60% to reflect this post-construction stabilization, drawing on historical deceleration trends. Building upon the ND scenario, the CP scenario integrates strict protection mandates for cultivated land in the reservoir area. To align with China's strict "redline" policy for permanent basic farmland protection, which strictly prohibits the non-agriculturalization of high-quality cropland, the transition probabilities from cultivated land to other types were reduced by 50%. This 50% restriction reflects the localized farmland conservation targets outlined in regional land use master plans. For the EP scenario, policy constraints and ecological restoration requirements outlined in the "Danjiangkou Reservoir Area and Upstream Water Pollution Prevention and

Soil Conservation Plan" were considered. Concretely, the conversion probabilities from forest land, grassland, and water to construction land were constrained by 40%, while those from cultivated land were reduced by 20% to curb urban expansion. These specific reduction thresholds (40% and 20%) were determined based on the aggressive urban growth boundaries and ecological redlines delineated in local spatial planning. Conversely, the conversion potentials from cultivated land and grassland to forest land were enhanced by 20% to prioritize reforestation, aligning with the Grain for Green Program (GGP) targets specified for the upstream catchment areas [27]. Based on the above adjusted probabilities, the MC model was executed to derive the quantitative land use requirement for 2030 under the three scenarios.

Considering the distinct development characteristics of each scenario and drawing on relevant literature, three distinct land use transition cost matrices were configured to reflect the unique constraints under the ND, CP, and EP scenarios [41] (Table 2). Local weights were applied to represent the growth potential of various land cover classes. Furthermore, variations in the Total Area (TA) of each land use type across scenarios were calculated using the following equation:

$$X_i = \frac{\Delta TA_i - \Delta TA_{min}}{\Delta TA_{max} - \Delta TA_{min}} \quad (4)$$

Where X_i represents the weight assigned to land type i ; ΔTA_i denotes the variation in total area for land use type i throughout the investigation; and ΔTA_{max} and ΔTA_{min} indicate the extreme values of TA fluctuations recorded during the same interval.

To examine the performance of the simulation model, the Kappa Coefficient (KC) and Overall Accuracy (OA) were employed as critical criteria for validating the accuracy of simulated land use dynamics against empirical data. Previous studies suggest that values exceeding 0.80 indicate satisfactory model performance [42].

Table 2. Land use transition cost matrix under multiple scenarios (2020–2030).

Land use type	ND						CP						EP					
	L ₁	L ₂	L ₃	L ₄	L ₅	L ₆	L ₁	L ₂	L ₃	L ₄	L ₅	L ₆	L ₁	L ₂	L ₃	L ₄	L ₅	L ₆
L ₁	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	1
L ₂	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	0	0	0
L ₃	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0
L ₄	1	1	1	1	1	1	1	0	1	1	1	1	0	0	0	1	0	0
L ₅	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0
L ₆	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Note: A value of 0 signifies that land use conversion is prohibited, whereas 1 denotes that conversion is permitted; L₁–L₆ correspond to cultivated land, forest land, grassland, water, construction land, and unused land. Rows in the matrix represent transfers out, while columns represent transfers in.

Results and Discussion

Characteristics of Land Use Dynamics

Land use dynamics within the Danjiangkou reservoir area were systematically analyzed for the 2000-2020 period. Spatially (Fig. 2), forest land was the predominant land cover category, constituting over 65% of the total territory, while cultivated land comprised more than 22%. Forest land exhibited the most significant increase throughout the study period, expanding by 762.07 km² (4.25% of the total area). Water bodies also showed a notable increase of 321.91 km², representing 1.82% of the total area. Conversely, cultivated land experienced the largest decline, decreasing by 659.10 km² (3.68%), followed by grassland, which decreased by 551.58 km² (3.08%). These shifts were primarily policy-driven and hydrologically induced. Specifically, the expansion of forest and the contraction of cultivated land and grassland were largely driven by ecological restoration policies, such as the GGP. Meanwhile, the increase in water area was directly induced by the expansion of the Danjiangkou Dam and subsequent reservoir filling for the SNWDP.

Land use dynamics in the reservoir area were further examined using a map-based analytical approach for the 2000-2020 period. During the 2000-2010 period, the primary land use dynamics were defined by the bi-directional exchange between cultivated and forest lands (34.94% and 29.64%, respectively), alongside a significant conversion from grassland to cultivated land (15.62%). In the subsequent period (2010-2020), the conversions from cultivated land to forest land became more pronounced (44.56%), followed by conversions from forest land to cultivated land (17.62%) and from cultivated land to water (12.39%). Considering the full study period (2000-2020), the principal transition types included cultivated land to forest land (38.80%), forest land to cultivated land (19.04%), grassland to cultivated land (10.87%), grassland to forest land (10.45%), and cultivated land to water (9.63%). Overall, ecological conservation policies implemented over the past two decades have driven frequent interconversions among

forest land, grassland, and cultivated land, while reservoir construction has played a critical role in the conversion of cultivated land to water (Fig. 3).

Spatiotemporal Heterogeneity of the LER

Spatiotemporal Distribution of the LER

Using the natural breaks classification method, the LERI of the Danjiangkou reservoir area for 2000, 2010, and 2020 was classified into five risk categories: low, medium-low, medium, medium-high, and high (Fig. 4). Spatially, the various levels of risk exhibited clear clustering characteristics throughout 2000-2020. Notably, the mountainous regions consistently exhibited low and medium-low risk levels. This pattern is primarily driven by elevation constraints and steep slopes that limit human accessibility, resulting in lower agricultural and urban development intensity. Furthermore, these high-elevation zones are dominated by stable forest cover, which inherently possesses high ecological resilience and minimizes landscape fragmentation. In terms of area, in 2000, low-risk and medium-low-risk areas dominated, representing 52.87% of the total areal extent and indicating a relatively favorable ecological state with low overall risk levels at that time. High-risk areas constituted the smallest proportion, at only 3.74%. By 2010, medium-low-risk areas remained predominant; however, the coverage of low-risk areas contracted, while the proportion of high-risk areas increased markedly to 5.19%, reflecting a rise in ecological risk in certain regions over this interval. By 2020, the coverage of low-risk areas recovered, while medium-low-risk areas underwent a significant contraction. Concurrently, medium-high-risk areas occupied a relatively larger share, and although the coverage of high-risk areas decreased compared to 2010, it remained higher than that in 2000. These results indicate a degree of adjustment in the LER during the 2010-2020 interval.

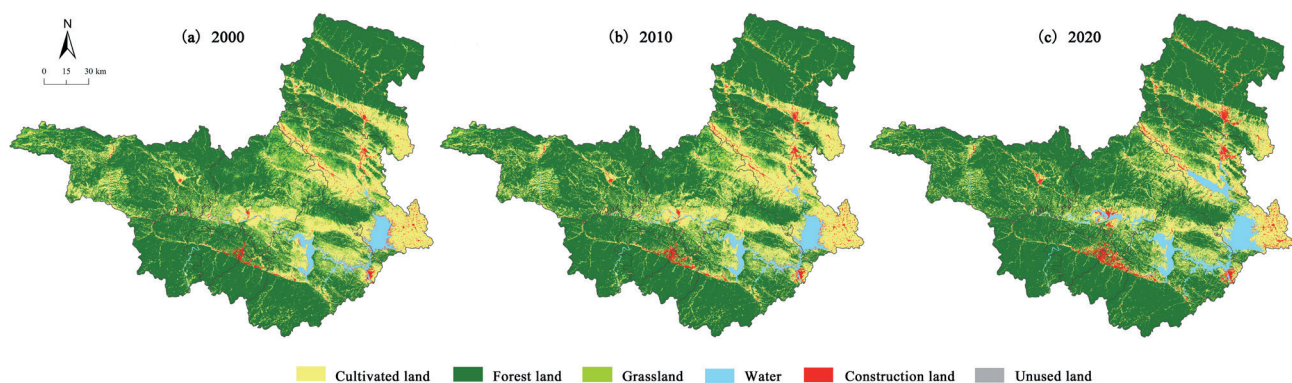


Fig. 2. Spatial pattern of land use in the reservoir area (2000-2020).

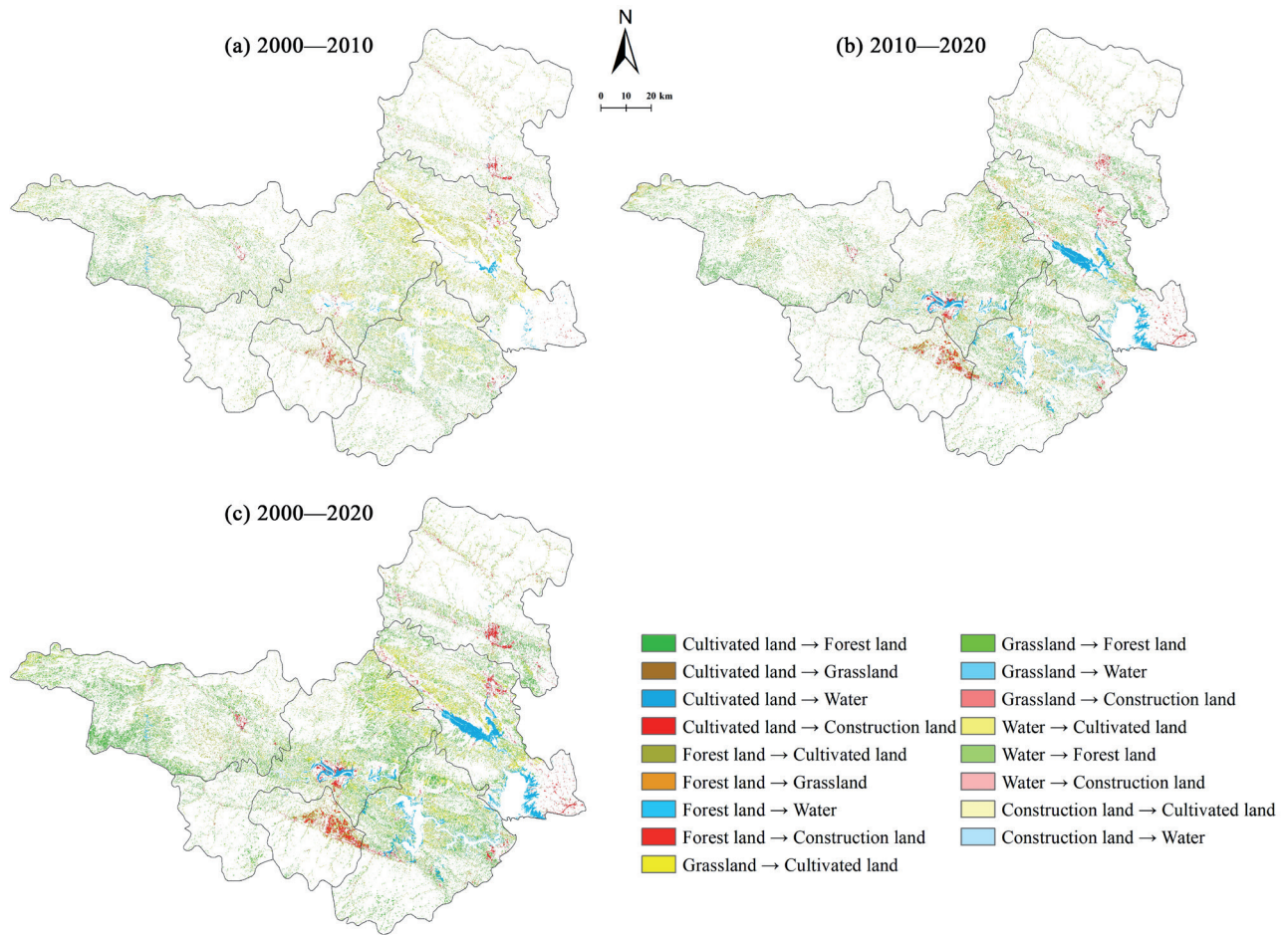


Fig. 3. Spatial changes of land use in reservoir area at different stages (2000–2020).

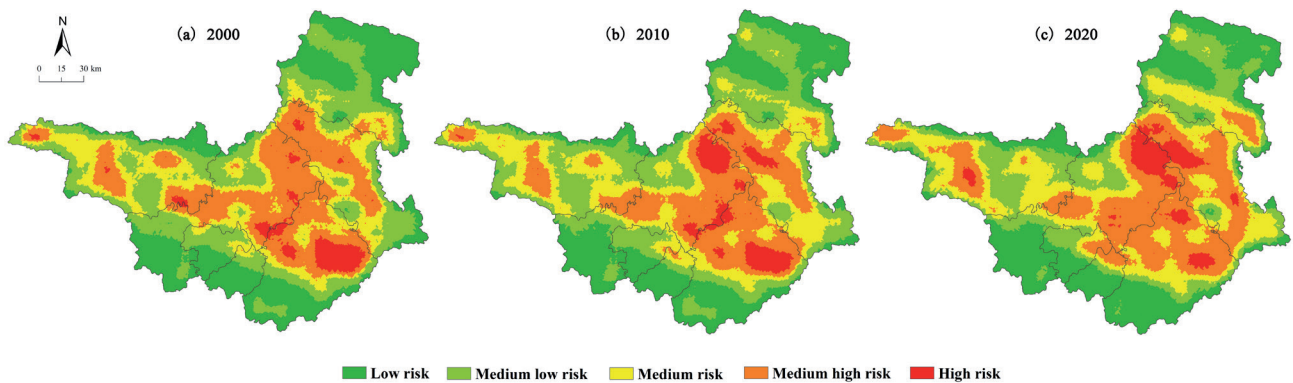


Fig. 4. Spatial distribution of the LER in the reservoir area (2000–2020).

Transitions of the LER

The transitions of the LER were further analyzed in the Danjiangkou reservoir area (2000–2020) (Fig. 5). During 2000–2010, the most prominent transition occurred from low-risk areas to medium-low-risk areas, covering 517.86 km² (11.46%), while no direct transitions from low to higher-risk areas (medium, medium-high, or high) were detected. Medium-low-risk areas

exhibited bidirectional transitions, with 204.38 km² (4.13%) reverting to low-risk areas and 687.61 km² (13.88%) increasing to medium risk, whereas only negligible areas shifted to medium-high risk. Medium-risk areas showed comparable exchanges with adjacent levels, decreasing to medium-low risk (390.96 km², 11.57%) and increasing to medium-high risk (471.64 km², 13.95%). Transitions from medium-high-risk areas to lower levels were limited, whereas transitions to high-

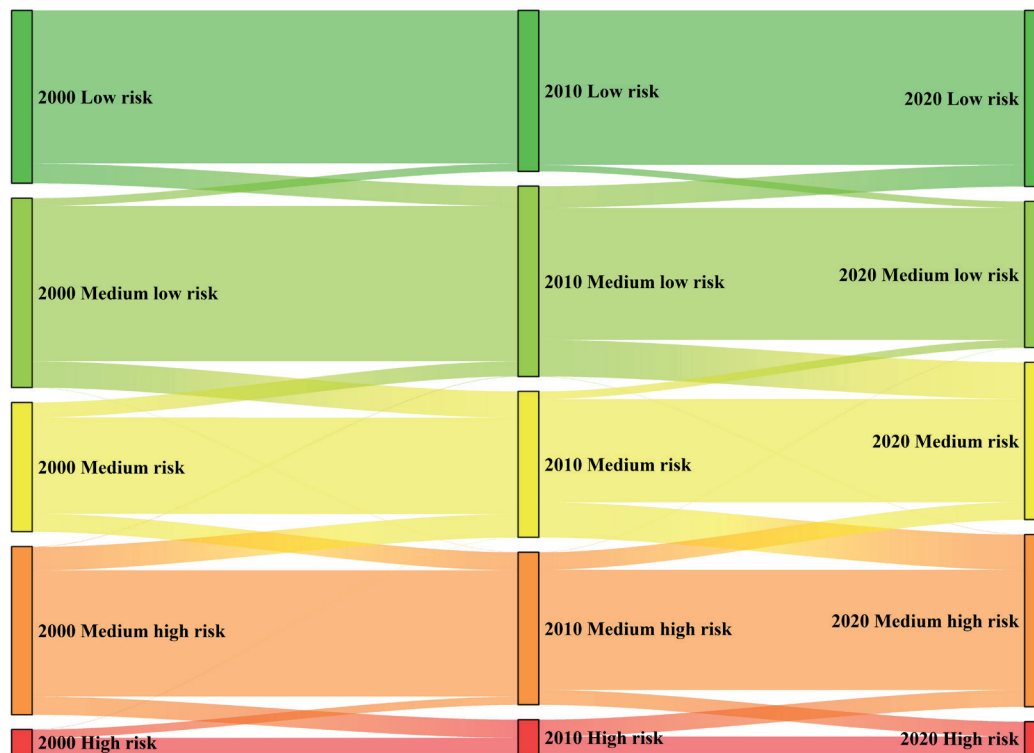


Fig. 5. Transitions of the LER in the reservoir area (2000-2020).

risk areas were more pronounced (471.80 km², 10.73%). High-risk areas displayed slight reductions, with a small proportion shifting to medium risk and a more substantial portion (213.26 km², 31.80%) declining to medium-high risk. During 2010-2020, transitions between adjacent risk levels became more active. The transition from low-risk areas to medium-low-risk areas decreased to 169.96 km² (4.04%). Conversely, medium-low-risk areas exhibited increased dynamics, with 566.18 km² (11.38%) converting to low-risk areas and 954.61 km² (19.18%) transitioning to medium risk. Medium-risk areas predominantly shifted toward higher risk levels, with 918.47 km² (24.06%) converting to medium-high risk, compared to 199.38 km² (5.22%) declining to medium-low risk. Medium-high-risk areas continued to expand toward high-risk areas (390.08 km², 9.78%), while nearly half of the high-risk areas (441.88 km², 47.56%) transitioned to medium-high risk. Overall, low-risk areas maintained relative stability, with limited transitions mainly to adjacent levels throughout the investigation. Conversely, medium-low, medium, and medium-high-risk areas underwent more marked bidirectional exchanges with neighboring levels. High-risk areas showed partial persistence, while a considerable proportion shifted toward medium-high-risk areas, indicating localized risk mitigation.

Spatial Aggregation of the LER

The values of GMI in 2000, 2010, and 2020 were 0.647, 0.649, and 0.626 for the Danjiangkou reservoir

area, respectively (Fig. 6). All values are positive and relatively high, signifying a strong positive spatial autocorrelation in the LER throughout the study period. From the overall changes (2000-2020), although the GMI values fluctuated, they remained at a high level, suggesting persistent spatial clustering of the *LER* in the area.

With respect to spatial clustering (Fig. 6), during the 2000–2020 period, the LER in the reservoir area was characterized by the H–H and L–L clusters, both exhibiting relatively concentrated and stable spatial patterns. In contrast, the L–H and H–L clusters were limited in extent and more spatially dispersed. The H–H clusters were predominantly concentrated in the central part of the reservoir area. This spatial convergence is fundamentally driven by specific socio-economic pressures and topographic conduits. Centered around major towns and riparian plains, rapid urbanization and infrastructure development tied to the SNWDP have severely fragmented the landscape. Furthermore, driven by local economic demands, intensive agricultural expansion – characterized by large-scale citrus orchard conversion on gentle slopes and chemically intensive farming – has accelerated soil erosion and nutrient runoff. In contrast, the L–L clusters were largely distributed in mountainous regions characterized by complex terrain, lower levels of human disturbance, and relatively well-preserved ecosystems, leading to consistently minimal ecological risk.

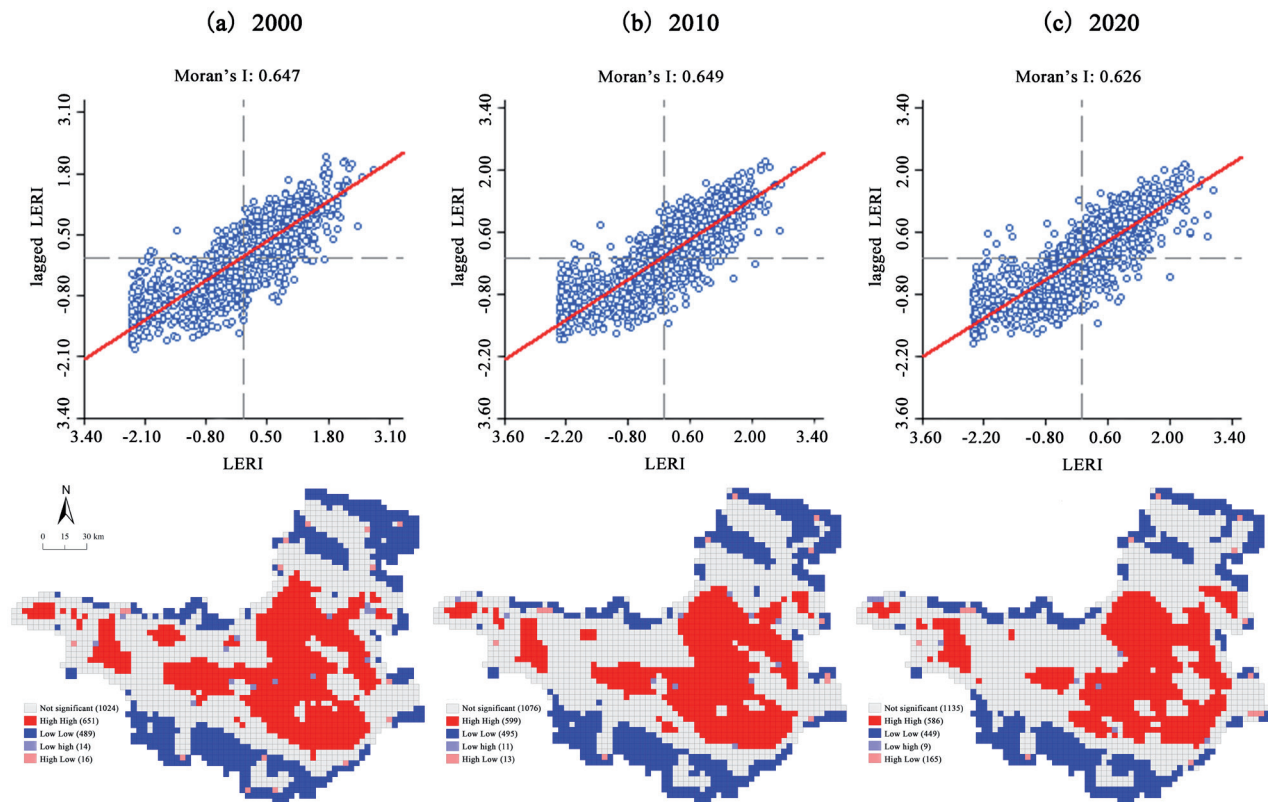


Fig. 6. Moran Index and LISA cluster diagrams of the LERI in the reservoir area (2000-2020).

Multi-scenario Simulation of the LER

Using land cover datasets and multiple drivers for the Danjiangkou reservoir area, we simulated the 2020 land use configuration with the PLUS model. The model's simulation performance was validated against the observed 2020 data, achieving an OA of 0.932 and a KC of 0.916. These results imply a high level of predictive precision, validating the model's efficacy for regional land use simulation (Fig. 7a). Subsequently, taking the 2020 land use conditions as the reference, we projected the land use distribution for 2030 under three scenarios based on different regional development objectives. Under the ND scenario (Fig. 7b), cultivated land and grassland diminished by 133.44 km² and 14.35 km², respectively, whereas forest land, construction land, and water area expanded by 128.67 km², 13.24 km², and 5.91 km². Changes in unused land were minimal, suggesting that without stringent policy constraints, the growth of forest and construction land is marked, exerting pressure on cultivated land and potentially threatening regional food security. Under the CP scenario (Fig. 7c), cultivated land expanded by 164.57 km², while forest land and grassland diminished by 136.57 km² and 28.44 km², respectively. Other land use types showed only minor changes, reflecting effective maintenance of agricultural land and food security. Under the EP scenario (Fig. 7d), forest land, water area, and construction land expanded by 246.77 km², 6.70 km², and 3.10 km², respectively. Conversely, a substantial

decline was observed in cultivated land (230.79 km²) and grassland (25.80 km²), while unused land remained relatively stable. These outcomes demonstrate that the EP scenario effectively facilitates regional ecological restoration and strengthens conservation efforts.

Scenario-based simulations reveal pronounced spatiotemporal variability of the LER in the reservoir area (Fig. 8). Under the ND scenario, medium-high-risk and high-risk areas exhibit a notable geographic concentration within the central region, encompassing 26.04% and 4.70% of the entire study area, respectively. These regions are likely associated with intensive human activities or ecologically sensitive environments. In contrast, low-risk and medium-low-risk areas are largely clustered in the peripheral parts of the reservoir area, representing 25.41% and 21.21%, respectively, and are characterized by lower anthropogenic disturbance and more stable ecosystems. Under the CP scenario, adjustments in land use aimed at preserving cultivated land lead to an expansion of higher-risk areas. Compared with the ND scenario, high-risk and medium-high-risk areas increase by 176.04 km² and 13.39 km², respectively. This pattern suggests that constraints on the expansion of ecological land may elevate ecological risk in certain areas. Meanwhile, the increase in low-risk areas indicates localized improvements in ecological conditions under cultivated land protection measures. Conversely, the EP scenario shows a marked decline in medium-high-risk and high-risk areas, accompanied by a substantial expansion of low-risk areas to

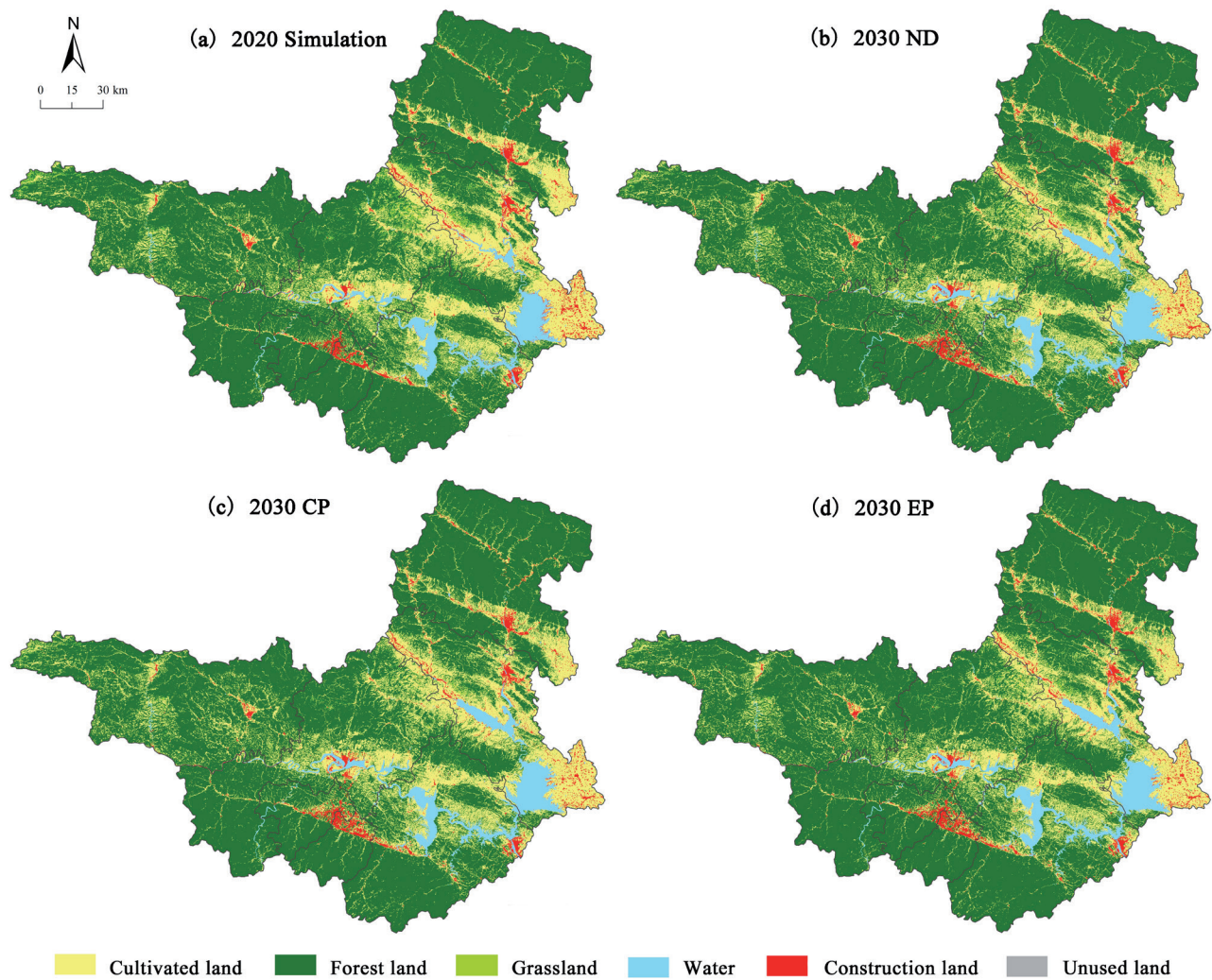


Fig. 7. Spatial distribution of land use in the reservoir area under various scenarios in 2030.

4,825.65 km². This indicates that ecological conservation and restoration measures – such as afforestation and wetland protection – are effective in mitigating the LER and enhancing overall ecosystem stability.

Discussion

This study investigates a range of potential evolutionary trajectories for the LER in the Danjiangkou reservoir area by constructing three scenarios (the ND, CP, and EP scenarios). Under the 2030 ND scenario, high-risk clusters significantly overlap with regions of intensive anthropogenic activity and ecological fragility, indicating that the land use evolution is likely to maintain its historical trajectory in the absence of effective external intervention. Processes such as urban sprawl, infrastructure development, and agricultural intensification may further exacerbate habitat fragmentation and the erosion of critical ecosystem services. In the 2030 CP scenario, although low-risk areas show a slight increase, medium-high-risk and

high-risk areas expand markedly. This outcome can be attributed to policy-driven land use adjustments aimed at safeguarding cultivated land [43, 44]. Conversely, the 2030 EP scenario yields the most favorable outcomes, characterized by a substantial reduction in high-risk clusters and the formation of extensive, contiguous low-risk landscapes. This optimized pattern highlights the efficacy of proactive conservation, which is inherently tied to the timing and intensity of regional eco-policies and reservoir engineering. Historically, the large-scale conversion of cultivated land to forest was catalyzed by the high-intensity implementation of the GGP (since the early 2000s) and the multi-phase Danjiangkou Eco-environmental Protection Plans. Meanwhile, the expansion of water bodies directly reflects the critical milestones of the SNWDP, particularly the dam heightening in 2013 and the subsequent multi-stage water impoundment. The EP scenario demonstrates that sustaining these high-intensity, policy-driven transitions after 2020 is vital for mitigating cumulative ecological risks. However, implementing such intensive ecological preservation inevitably introduces critical

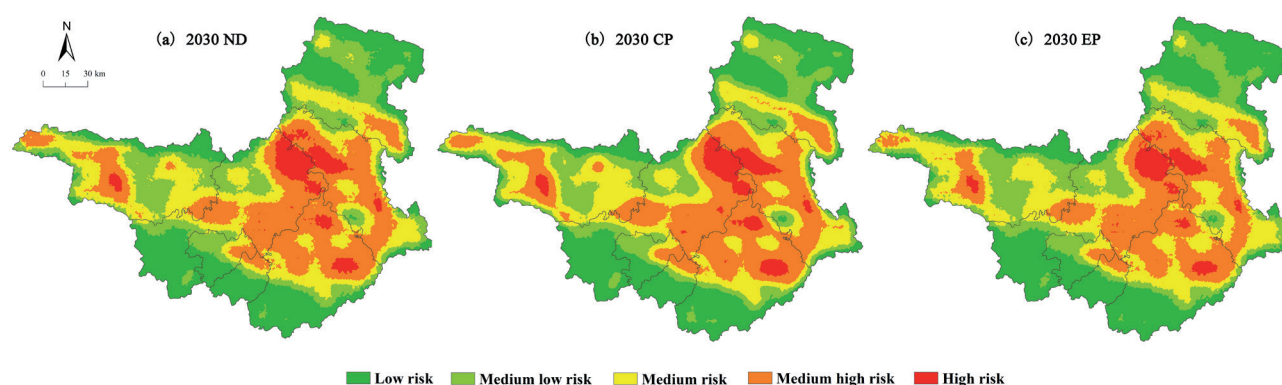


Fig. 8. Spatial distribution of the LER in the reservoir area under various scenarios in 2030.

trade-offs, as the expansion of ecological spaces may restrict agricultural productivity and constrain the spatial footprint required for urban development. Overall, transitioning toward a sustainable development pathway centered on ecological restoration and spatial optimization while balancing these multi-sectoral trade-offs is essential for enhancing long-term ecological security in the reservoir area [45, 46].

This work offers pivotal practical implications for refining ecological conservation strategies and advancing sustainable regional development within the Danjiangkou Reservoir area, providing a robust empirical basis for future spatial planning. Land use management should move beyond a single-objective approach toward integrated territorial spatial governance informed by the LER assessments. In the formulation of territorial spatial planning, multi-scenario simulation outcomes should be fully incorporated, with priority given to ecological protection strategies. Low-risk areas should be strictly conserved, while medium-risk and high-risk areas require targeted restoration and management interventions. Furthermore, as the core headwater region of the SNWDP (Middle Route), the ecological integrity of the reservoir area critically impacts national security frameworks. Given that the reservoir and its upstream regions span multiple administrative jurisdictions, it is essential to overcome administrative fragmentation and implement basin-oriented governance, supported by differentiated ecological conservation and industrial growth policies. Additionally, while the Kriging interpolation used in this study effectively captures spatial risk gradients, future research should incorporate alternative spatial interpolation methods and validation metrics to further quantify the potential uncertainties introduced by spatial smoothing. Furthermore, while our 2030 projections capture major macro-scenarios, future LER trajectories may still diverge due to abrupt policy shifts, macro-economic fluctuations, or climate variability that are inherently difficult for statistical models to fully anticipate.

Conclusions

In the study, the LERI was utilized to examine the spatiotemporal heterogeneity of ecological risks in the Danjiangkou reservoir area (2000-2020). Furthermore, the land use patterns under various scenarios for 2030 were projected utilizing the PLUS model, which also predicted the associated LER in this area. The core insights are as follows:

(1) For the 2000-2020 period, the land use composition of the reservoir area underwent substantial changes, characterized by marked expansions of forest land and water bodies and steady declines in cultivated land and grassland. Land use transitions were dominated by reciprocal conversions between cultivated and forest lands, as well as the transition of grassland into both categories. These patterns indicate that ecological restoration initiatives and reservoir construction have been key drivers of land use change, which has in turn reshaped landscape patterns and driven the spatiotemporal configuration of ecological risk.

(2) The LER manifested strong positive spatial autocorrelation and pronounced clustering over the study period. High-risk areas were largely clustered in central areas characterized by high-intensity anthropogenic disturbances, whereas low-risk areas were mainly distributed within mountainous regions characterized by complex terrain and limited anthropogenic disturbance. Frequent transitions across intermediate risk levels highlight the dynamic nature of the LER, largely dictated by land use change and human activities.

(3) Development scenarios profoundly influence the spatial pattern of the LER. Under the ND scenario, the growth of construction land drives further aggregation of medium-high-risk areas. While cultivated land protection enhances food security, it may inadvertently intensify ecological risk through encroachment on ecological land. In contrast, the EP scenario – characterized by strengthened restoration efforts and spatial regulation – effectively reduces high-risk areas and expands low-risk areas, thereby lowering overall ecological risk.

(4) To guarantee the long-term ecological resilience of the reservoir area, it is essential to adopt an ecological-priority principle in territorial spatial planning. Priority should be given to ecological protection pathways, complemented by targeted restoration and adaptive management within medium-high-risk and high-risk areas. In addition, establishing cross-administrative, basin-oriented collaborative governance mechanisms is critical for implementing differentiated ecological protection policies, balancing cultivated land conservation with ecological restoration, and enhancing ecosystem service provision and landscape resilience.

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AI Usage Disclosure Statement

The authors solely employed the Gemini for grammatical revision and readability improvement of partial sentences in the manuscript. AI was not involved in research data generation, figure plotting, or result analysis

Conflict of Interest

The authors declare no conflict of interest.

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