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Unraveling the Complex Relationship between Urbanization and Landscape Ecological Risk: Insights from Chinese Cities

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Highly urbanized cities have undergone substantial land use changes driven by intensive human activities, leading to increasingly prominent ecological security challenges. This study employed landscape pattern indices to evaluate the landscape ecological risk (LER) across 275 prefecture-level cities in China from 2011 to 2019. We hypothesized that the mechanisms influencing LER vary according to the level of urbanization. An integrated panel threshold regression model was applied to examine this hierarchical influence and identify potential thresholds in the urbanization rate (UR). In addition, the spatial spillover effects of LER were investigated using a spatial panel econometric model. Our findings revealed an initial increase in LER from 2011 to 2013, followed by a notable stabilization between 2015 and 2019, with evident spatial heterogeneity. Using UR as the threshold variable, the normalized difference vegetation index, population density, and per-capita gross domestic product (PGDP) were found to exert nonlinear impacts on LER, which were consistent across multiple model specifications. A critical threshold was identified at a UR of 62.1%, beyond which the influence of PGDP on LER altered substantially. Spatial spillover effects of LER were also stronger in cities below this UR threshold, implying that highly urbanized cities may possess self-regulatory ecosystem mechanisms that mitigate LER. Based on the results, the development of secondary and tertiary industries, alongside the construction of infrastructure, could mitigate LER for low-urbanization cities. In highly urbanized cities, blue-green space planning should be strategically aligned with industrial transformation and upgrading, thereby bolstering urban ecological protection and contributing to long-term environmental sustainability.

Introduction

The world is undergoing a profound phase of urbanization [1]. Rapid population influx into cities and high-intensity land development have imposed potentially negative impacts on ecosystem structure, ecological functions and stability [2], which significantly undermines the capacity of urban ecosystems to recover from disturbances and exacerbates ecological risks in many urban contexts [3]. In China, for instance, the land development intensity has greatly exceeded the 15% threshold, a critical value for ecological security in international standards. Concurrently, the rapid expansion of transportation networks has led to increased landscape fragmentation. These changes have resulted in habitat loss, urban air pollution, elevated risks of urban flooding, urban heat island effects, and other environmental challenges [4], thereby threatening the well-being of urban residents. Understanding how urbanization influences ecological risks has then become a pressing issue [5], given its long-term implications for sustainable development both in China and worldwide.

The concept of ecological risk emerged in the 1990s [6], building on the risk management framework that incorporates hazard, exposure, and vulnerability. In general, ecological risk refers to threats to the health and productivity of species and ecosystems [7], reflecting the adverse effects of human activities and environmental changes on ecosystem components [8]. The rise and widespread adoption of landscape ecological risk (LER) are largely attributed to rapid land use changes in urban areas and empirical evidence linking landscape patterns with ecological outcomes [9]. LER captures the combined impacts of human activities and natural disasters on landscape structure and function [10]. As an ecological management tool, LER assessment offers valuable references for planners, managers, and policymakers. Common assessment approaches include the landscape pattern method based on land use/cover change [10], the source–sink analysis method [11], and the Pressure–State–Response model [12]. Previous studies have applied LER assessments in coastal zones, river basins, mining areas [8,11], and particularly in cities [13]. Considering the relationship between urbanization and ecological risk, earlier studies have generally shown that LER increases as rapid urbanization progresses, largely due to the fragmentation of ecological land and cultivated areas during the urbanization process [14]. However, in highly urbanized cities, the active and intensive utilization of land, which leads to the spatial agglomeration of built-up landscapes, may interact and mitigate certain urban ecological risks. LER will also typically show a gradual downward trend when efficient land use and ecological protection policies are implemented [15]. It has been demonstrated that the relationship between urbanization and LER could be nonlinear [15]. When exploring the influences of external factors on LER during the urbanization process, approaches such as the geographical detector model [5], geographically weighted regression approach [16], and correlation analysis [9] have been widely applied. Spatial results showed that socioeconomic activities, represented by population density (PD) and the proximity to the center of urban development, tend to increase ecological risks [17], and the reduction of natural resources as well as the severity of environmental pollution had a direct enhancement on the ecological risk [18]. Meanwhile, it is also notable that the spatial spillover effect of LER among cities would affect regional ecological patterns. Factors influencing LER, such as the ecological environment, production factors, and industrial structure in neighboring regions, can also generate spatial spillover effects. This is consistent with the broader principle that spatial effects arise from interactions across cities, which are notably observed in urbanization processes and the configuration of landscape patterns.

Although ecological problems have garnered widespread attention in the urbanized world, the complex relationship between LER and urbanization has not been systematically explored, particularly when tremendous heterogeneity exists in the interactions among landscape change and socioeconomic development. It is crucial to understand all these interactions, as the impact of urbanization on LER may vary across different developmental stages. Further, identifying potential thresholds in the urbanization–LER relationship is essential for implementing hierarchical control and risk management in cities, yet this aspect remains underexplored in the existing literature. In addition, current studies still exhibit limitations in addressing the spatial correlation of LER. Therefore, our research specifically aims to fill the research gaps by systematically examining the underexplored relationships and mechanisms between LER and urbanization. The research objectives are guided by the following research questions: (a) Is there a nonlinear correlation relationship between urbanization and LER in Chinese cities? (b) Do the variations of LER exhibit spatial correlations in Chinese cities, and what form does this take?

Hence, we developed a framework to unravel the complex relationship between urbanization and LER, and reveal the spatial interactions in Chinese cities. Alterations in socioeconomic dynamics—such as shifts in PD, variations in per capita GDP, developments in infrastructure, and changes in industrial composition—can induce transformations in regional land use and concurrently give rise to pollutant generation. However, their effects on LER may differ depending on the nature of the interaction between LER and urbanization. We therefore hypothesized that cities at different urbanization levels exhibit distinct driving mechanisms behind LER changes and that socioeconomic factors exert threshold effects on LER. In highly urbanized settings, it exacerbates population and resource pressures, resulting in natural landscape loss, ecological deterioration, and, consequently, higher LER. In contrast, at incipient stages, urbanization functions primarily through population concentration that intensifies existing built-up areas, thereby mitigating pressures on ecological security. These observations support our hypothesis that the influence of socioeconomic factors on LER exhibits stage-specific heterogeneity under different urbanization levels. Spatial spillover effects of LER are also expected to vary accordingly. In this study, we employed a panel threshold model to explore the socioeconomic effects on LER, and the spatial regression model was used to diagnose the spatial spillover effect during the period when there was change in LER.

Materials and Methods

Materials

Study area

We selected 275 prefecture-level cities in China as the study area, with 36.36%, 34.91%, and 28.73% located in Eastern, Central, and Western China, respectively (Fig. 1). Several cities were excluded due to unavailability of datasets. The study period spans from 2011 to 2019, a phase marked by China's transition in urbanization following the introduction of the new urbanization strategies, which imposed more stringent requirements for urban spatial construction and development. During this period, the concept of ecological civilization was also emphasized to enhance regional environmental protection. The formal inclusion of ecological civilization into the Constitution in 2018 signified a paramount national strategy aimed at reinforcing environmental protection, upgrading ecosystem integrity, and aligning with LER development objectives.

From 2011 to 2019, the urbanization rate (UR) in the study area exhibited continuous growth. Spatially, cities with a UR exceeding 80% were widely distributed. Economic development progressed favorably, and per-capita GDP increased by 67.55% over the study period. Concurrently, the industrial structure underwent significant changes: the proportions of primary and secondary industries decreased by 1.90% and 11.62%, respectively, while tertiary industry increased by 13.52%. These socioeconomic developments reshaped land use structure, thereby influencing the ecological environment. Between 2011 and 2019, built-up land expanded most markedly, followed by forest land. In contrast, grassland and cropland decreased substantially, with water areas, unutilized land, and wetlands also showing notable declining trends. The reduction in key ecological lands, such as water bodies, wetlands, and cropland, may impair ecosystem functions and potentially threaten regional ecological security and food security.

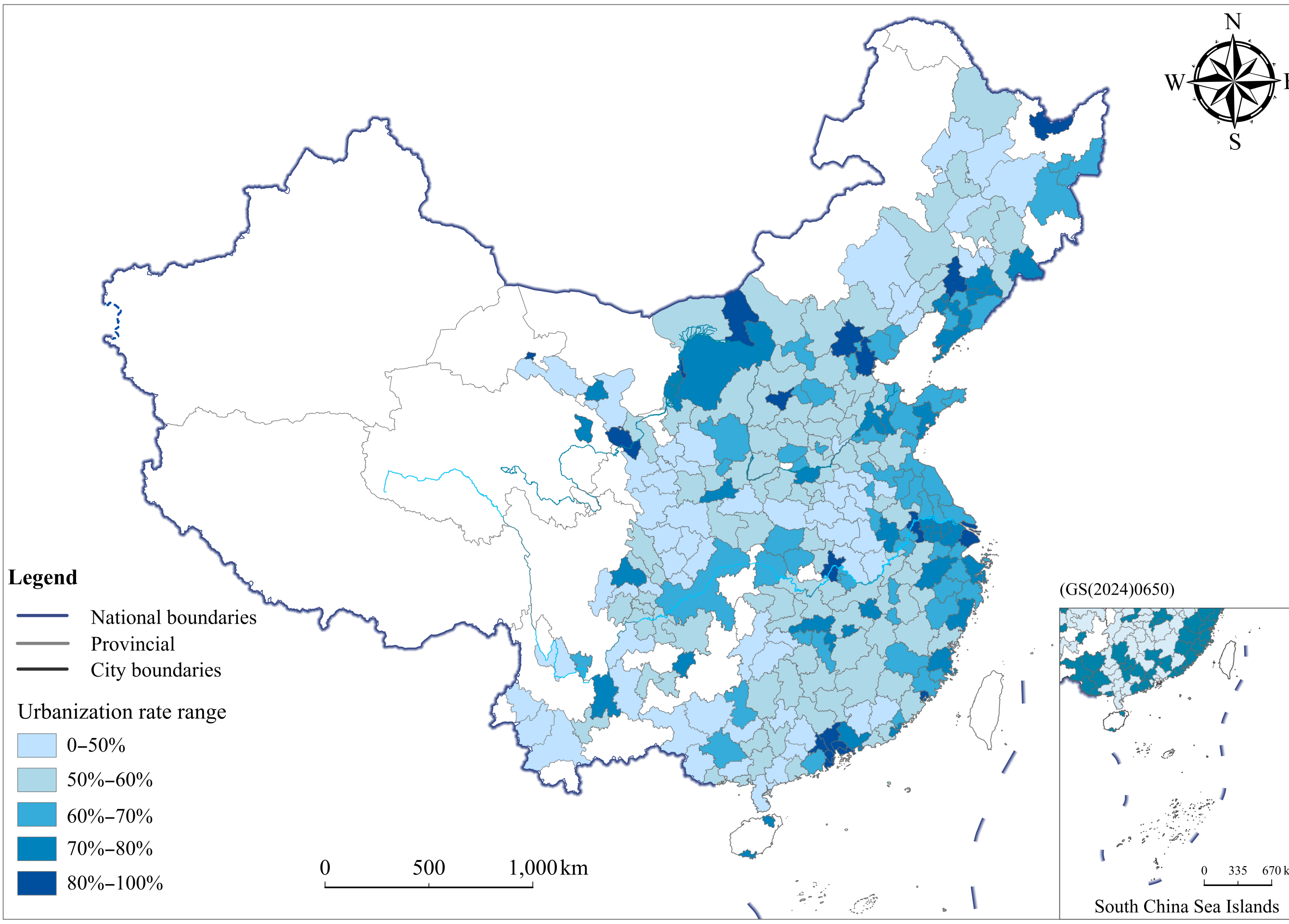

Fig. 1. Map of China showing the urbanization rate in 2019 of cities investigated within this study.

Data sources

Our study utilized 4 main categories of data: geographic data, land cover data, socioeconomic statistics, and natural environment data. Geographic data comprised administrative boundaries and the distribution of rivers and lakes across China, which was obtained from the National Geographic Information Resources Catalog Service System (http://www.webmap.cn). Land cover data from 2011 to 2019 were derived from the China A Land Cover Dataset developed by Yang and Huang [19], with a spatial resolution of 30 m × 30 m. The original land cover types were reclassified into 7 categories: cropland, forest, grassland, water, unused land, built-up land, and wetland. Snow cover and shrubland were reclassified as water and forest, respectively, due to their analogous characteristics in the Chinese urban context. Socioeconomic statistics were collected from the China City Statistical Yearbook (2012 to 2020), the China City Construction Statistical Yearbook (2012 to 2020), municipal statistical yearbooks, and statistical bulletins on national economic and social development. Natural environmental datasets included annual mean temperature, annual accumulated precipitation, and the normalized difference vegetation index (NDVI) for the years 2011, 2013, 2015, 2017, and 2019. These datasets were sourced from the National Center for Environmental Information of the National Oceanic and Atmospheric Administration (https://www.ncei.noaa.gov) and the MOD13A3 product distributed by NASA (https://search.earthdata.nasa.gov/search).

Methods

Figure 2 illustrates the theoretical framework of this study. We aimed to investigate the threshold and spatial spillover effects of LER throughout China's rapid urbanization process. The evaluation of LER was implemented with the considerations of both disturbance and vulnerability within the land use system. Given the considerable discrepancies in socioeconomic and ecological attributes among cities at different urbanization levels, we hypothesized that the mechanisms influencing LER differ between highly urbanized and less-urbanized cities.

Assessment of LER

LER is an integrated concept that describes the interaction between landscape patterns and ecological processes based on the pattern-process correlation theory [20]. Land use is intricately related to ecological risk because it reflects the intensity and manner of human impact on natural ecosystems. In recent years, hazards causing ecological risk have evolved from single pollutants [21] to the spatial mosaic of multiple ecosystems, which necessitate the extension of analysis to the landscape scale [22]. Metrics of landscape patterns not only reflect the spatial distribution of landscape components, but also indicate the vulnerability of an ecosystem, as determined by the combination of different land use types and their exposure to significant climatic or other risk variations [23]. As a result, the concept of LER has gained increasing popularity by emphasizing the

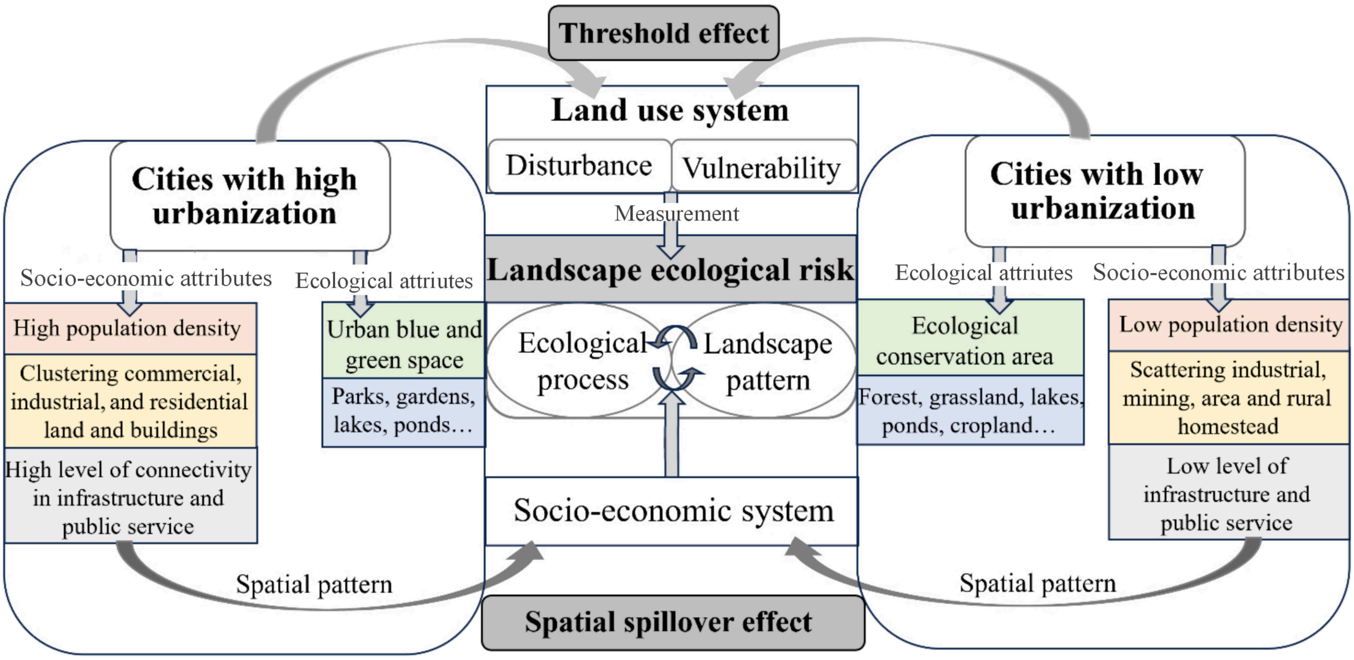

Fig. 2. Theoretical framework.

interaction and coupling between landscape patterns and ecological processes. Referring to relevant landscape pattern-based approaches to evaluate LER in existing studies [10,16], our study used the landscape disturbance index (D_k) and landscape vulnerability index (V_k) to calculate LER. D_k characterizes the extent of human interference that different landscape components may experience in the process of urbanization [24], and V_k illustrates the sensitivity and the lack of adaptive capacity of different landscape types to withstand external disturbances [15]. When combined, they provide a comprehensive assessment of how landscape patterns will interact with ecological processes under the impacts of multiple risk events in a region. Given that urbanized cities are threatened by multiple risk sources that are difficult to quantify at an individual level, LER was evaluated through an integrated analysis of landscape pattern changes; this approach also aids in guiding land use spatial planning for risk management. The grid scale applied in our analysis is consistent with the spatial resolution of the base land use data (30 m × 30 m). The formula for calculating LER is as follows:

$$\mathrm{LER}_i = \sum_{k=1}^{n} \frac{A_{ki}}{A_i} \left(D_k \times V_k\right) \tag{1}$$

where LER_i denotes the ecological risk index of the ith sample area; n is the number of land cover types; A_{ki} represents the total area of landscape type k in the ith sample area; A_i indicates the total area of sample i; and D_k and V_k are the landscape disturbance and vulnerability index of landscape type k, respectively.

The lower the disturbance index, the more favorable it is to the survival of organisms. The general form of D_k equation is as follows [10]:

$$D_k = aF_k + bS_k + cO_k \tag{2}$$

where F_k, S_k, and O_k are the landscape fragmentation index, landscape separation index, and landscape dominance index of the kth landscape type, respectively. F_k indicates the reduced ability of the ecosystem to resist external interference from the surrounding environment. S_k denotes the landscape separation index, reflecting the degree of separation of individual patches within each landscape type. O_k is the landscape dominance index, typically referred to the dominance of patches within a specific landscape type. a, b, and c are corresponding weights, with $a + b + c = 1$. The landscape fragmentation index directly indicates the degree of landscape division caused primarily by human activities (e.g., urban expansion, infrastructure development, and agriculture production), and serves as the foundation for the occurrence and propagation of disturbances [25]. This index exhibits high relevance to the connotation of LER and exerts the most significant influence. The splitting index characterizes the dispersion of homogeneous patches, which indirectly exacerbates disturbance propagation; while the dominance index reflects ecosystem stability through landscape dominance [24]. Both indices also capture the influence of human activities on ecosystems. Based on theoretical implications and empirical studies conducted in cities across western and eastern China [13], we ultimately determined the weights in the calculation of landscape disturbance as 0.5, 0.3, and 0.2 for F_k, S_k, and O_k, respectively.

The general form of F_k, S_k, and O_k expressions are as follows:

$$F_k = \frac{n_k}{A_k} \tag{3}$$

$$S_k = \frac{A}{2A_k}\sqrt{\frac{n_k}{A}} \tag{4}$$

$$O_k = d\frac{n_k}{N} + \frac{A_k}{A} \tag{5}$$

where n_k is the number of patches of the kth landscape type and A_k is the total area of the kth landscape type. N and A represent the total number and total area of patches of all landscape types, respectively. Relative coverage of certain landscape type was considered more important in the calculation of landscape dominance than relative density, with the consideration of resource control and functional contribution factors. Based on the rationale, weights of d and e were set as 0.6 and 0.4, respectively [26].

According to empirical studies in China with similar case study areas [10,16], V_k was assigned by diverse vulnerability of different landscape types as follows: unused land = 7, wetland = 6, water = 5, cropland = 4, grassland = 3, forest = 2, and impervious = 1. The Landscape Vulnerability Index represents the vulnerability and sensitivity of ecosystems represented by different landscape types when disturbed [27]. The vulnerability scoring reflects the magnitude of anthropogenic development impact on different land use types [28]. Specifically, unused land exhibits extreme sensitivity owing to high development pressure in the absence of legal protection, which often leads to irreversible conversion; wetlands and water bodies face moderate-to-high risks from reclamation and pollution, which is exacerbated by slow recovery rates despite partial regulatory safeguards; cropland demonstrates reduced vulnerability under China's stringent farmland protection policies that prohibit development; forests and grasslands maintain inherent resilience through conservation management practices; and impervious surfaces, similar to built-up areas, show minimal response to ecological disturbance due to their engineered inertness [29]. Based on the theoretical framework of the landscape vulnerability index and supporting empirical studies, specific values were assigned to each land use type.

The threshold effects of UR on LER under different schemes

According to the hypothesis, we proposed an integrated research framework (illustrated in Fig. 3). The panel threshold model was applied to investigate the temporal heterogeneity in how UR could influence LER under different schemes. The threshold regression model was proposed by Hansen (1999) and has been widely utilized in exploring nonlinear effects of attributes, such as the influence of natural and anthropogenic drivers on ecosystem services [30]. Thus, we adopted the panel threshold regression method to explore whether UR has a phased effect on LER, as well as to obtain the threshold (Eq. 6).

$$\mathrm{LER}_{it} = \alpha_0 + \beta_0 \mathrm{CO}_{it} \times I\left(\mathrm{UR}_{it} \le \varphi_1\right) + \beta_1 \mathrm{CO}_{it} \times I\left(\varphi_1 < \mathrm{UR}_{it} \le \varphi_2\right) + \ldots + \beta_m \mathrm{CO}_{it} \times I\left(\mathrm{UR}_{it} > \varphi_m\right) + \lambda X_{it} + \varepsilon_{it} \tag{6}$$

where β_m is the regression coefficient of the core explanatory variable; $I(\cdot)$ is the indicative function; UR_{it} is the threshold variable; φ_m is the unknown threshold value, obtained through 300 rounds of repeated bootstrap sampling; m is the number of thresholds; i represents city; t represents period (in years); LER_{it} denotes the landscape ecological risk index of city i in period t; CO_{it} is the value of the potential core explanatory variable of city i in period t; X_{it} represents the control variable; α_0 is a constant; λ represents the regression coefficient of the control variable; and ε_{it} is a random perturbation term (considered as error).

Based on the hypothesis of stage-specific heterogeneity in how socioeconomic factors could influence LER at different urbanization levels, 2 analytical schemes were established by introducing a core explanatory variable for the social and economic domains, respectively (Fig. 3). In the social domain, PD served as the factor that exhibits a nonlinear relationship with LER. In the economic domain, per-capita GDP (PGDP) was selected as the factor that differentiates its influence on LER across varying URs.

Scheme 1: Social and public-oriented scheme

Social development conditions influence LER from 2 aspects: one is the disturbance to the landscape ecology of residential areas and their surroundings caused by frequent and intense

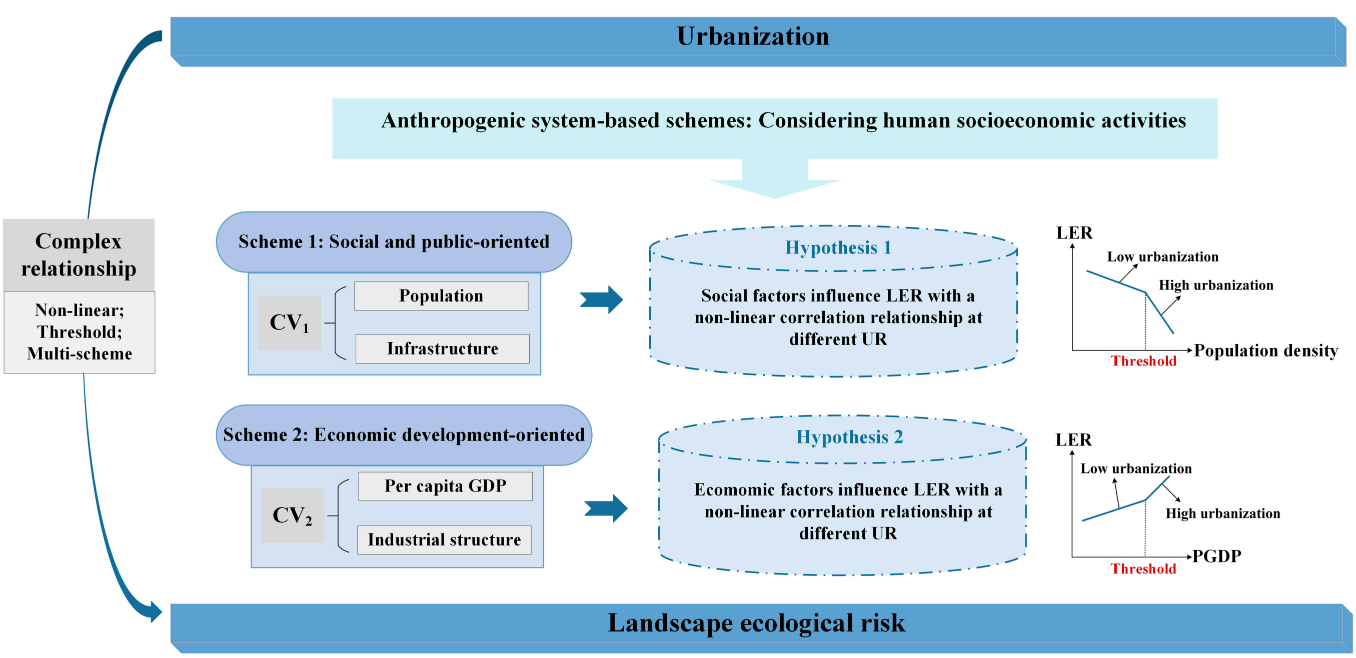

Fig. 3. Threshold effects and research hypotheses of UR on LER under different schemes. CV_i, core explanatory variable; UR, urbanization rate; LER, landscape ecological risk; GDP, gross demestic product; PGDP, per-capita GDP.

land use changes due to anthropogenic activities [31], while another is the inevitability of built-up land expansion and the centralization of landscape patches resulting from agglomeration effects. PD represents the degree of urban population agglomeration and is a key factor that reflects the intensity of human and social development. Empirical studies indicated that areas with higher PD were typically characterized by elevated ecological risk [32]. Therefore, PD was selected as the core explanatory variable in Scheme 1.

Scheme 2: Economic development-oriented scheme
Economic growth is closely related to industrial structure and land use patterns. The uncontrolled expansion of built-up land for urban development induces landscape fragmentation, thereby adversely affecting ecosystem structure and functioning. As the industrial structure reflects the pattern of regional economic development, and PGDP is a common indicator of regional economic development status [20], it was selected as the core explanatory variable in Scheme 2.

Exploration of the spatial spillover effect on LER

LER is driven by spatial spillover effects that transcend administrative boundaries, which reflect the continuity of natural geographic units and the mobility inherent in socioeconomic development. A thorough investigation must account for the heterogeneity of these spatial influences across cities at different urbanization levels, particularly when one attempts to validate the hypothesis that the driving mechanisms of LER vary above and below specific urbanization thresholds. Changes in land use patterns, especially increasing urban density, tend to raise land demand in peripheral areas, creating potential for land use conflicts [32]. Ecosystem degradation originated in one city may extend to neighboring regions, diminish overall ecosystem service capacity, and thereby threaten regional ecological security. Conversely, the implementation of spatial coordination strategies, such as the development of intercity transportation networks, has accelerated the flow of labor, technology, services, and resources in recent years, which effectively shorten the spatial distance between cities within urban agglomerations [33]. Variations in PD and industrial structure further influence land use composition, spatial configuration, and pollutant emissions, which collectively shape the LER profile of cities. Moreover, differences in the strength of intercity linkages and the intensity of production factor mobility suggest that changes in landscape patterns may also exhibit regional variations. Consequently, the spatial spillover effects of LER are likely to vary significantly across cities with different URs.

The spatial regression model is a statistical approach capable of accounting for spatial dependence and heterogeneity [34] and has been widely applied in geographical studies that analyze the spatial spillover effects of environmental pollution [35] and ecosystem services [36]. Conventional spatial econometric models include the spatial error model (SEM) and the spatial lag model (SLM), with SEM capturing the spatial dependence of error terms, whereas SLM directly incorporating it in the dependent variable. In this study, Moran's *I* was first employed to test whether spatial autocorrelation in LER exists across cities. Subsequently, the Lagrange multiplier (LM) and robust Lagrange multiplier (robust LM) tests were used to determine the appropriate form of the model. The formula for SEM and SLM are specified as in Eqs. 7 and 8, respectively.

$$\mathrm{LER}_{it} = \beta X_{it} + \theta_{it}\left(\text{where } \theta_{it} = \omega \sum_{j=1}^{N} w_{ij}\theta_{jt} + \varepsilon_{it}\right) \tag{7}$$

$$\mathrm{LER}_{it} = \rho \sum_{j=1}^{N} w_{ij}\mathrm{LER}_{jt} + \beta X_{it} + \varepsilon_{it} \tag{8}$$

where LER_{it} denotes the landscape ecological risk of city i in period t; X_{it} represents the influencing factors on the LER of city i in period t; β is the spatial regression coefficient of the explanatory variables; θ_{it} is the residual term of spatial autocorrelation; ω is the spatial autoregressive coefficient of the spatial error term; w_{ij} is the (i,j)th element of the spatial weight matrix W, which is defined as the inverse distance matrix processed with row standardization, and alternative matrices such as continuity and economic ties are also introduced for comparison; ε_{it} is the independent and identically distributed random disturbance term; ρ is the coefficient of the spatial lag term of LER; and LER_{jt} denotes the endogenous dependent variable of the area adjacent to city i, with j ranging from 1 to N.

Results

Spatiotemporal dynamics of LER

From 2011 to 2019, LER in the study area was generally low but exhibited distinct spatial heterogeneity. The average LER values were 0.0217, 0.0219, 0.0219, 0.0219, and 0.0219 in 2011, 2013, 2015, 2017, and 2019, respectively. A slight increase in LER was observed from 2011 to 2013, after which it remained stable until 2019. During the initial period (2011 to 2013), increased landscape fragmentation and separation of grassland, unused land, and wetland led to a notable rise in landscape disturbance. These changes impaired the structural integrity of grassland, unused land, and wetland ecosystems, diminished their service functions and consequently elevated regional ecological risks.

The spatiotemporal pattern of LER in the study area from 2011 to 2019 is shown in Fig. 4A to C, and the change of LER is exhibited in Fig. 4D to F. The magnitude of change in LER was not obvious from 2011 to 2019, but spatial disparities were apparent. The majority of cities had middle or low LER, while the cities with the highest LER constituted the smallest proportion, staying at 4.00% during the entire study period. The spatial pattern of cities in the middle-risk category experienced significant changes during the study period, while others remained stable. Lowest-level cities were mainly distributed in eastern, southern, and northeastern China. The LERs of cities in central China were in the lower-risk category, cities in the middle- and higher-risk categories were primarily distributed in northern and northwestern China, while a minority were distributed in eastern areas and southwestern regions. In Jiangsu Province, LER increased from 2011 to 2015, with cities such as Yancheng, Yangzhou, Zhenjiang, and Taizhou shifting from the lowest- to the middle-risk category. From 2015 to 2019, LER in Taizhou City continued to rise, reaching the higher-risk level by 2019. The dominant land cover types in Taizhou were cropland, built-up land, and water. Landscape fragmentation in the city increased consistently, with the corresponding index rising from 0.25 in 2011 to 0.50 in 2019. Cities in the highest-risk category were spatially decentralized.

Between 2011 and 2015, 65.45% of cities experienced LER growth, predominantly located in eastern and northern China.

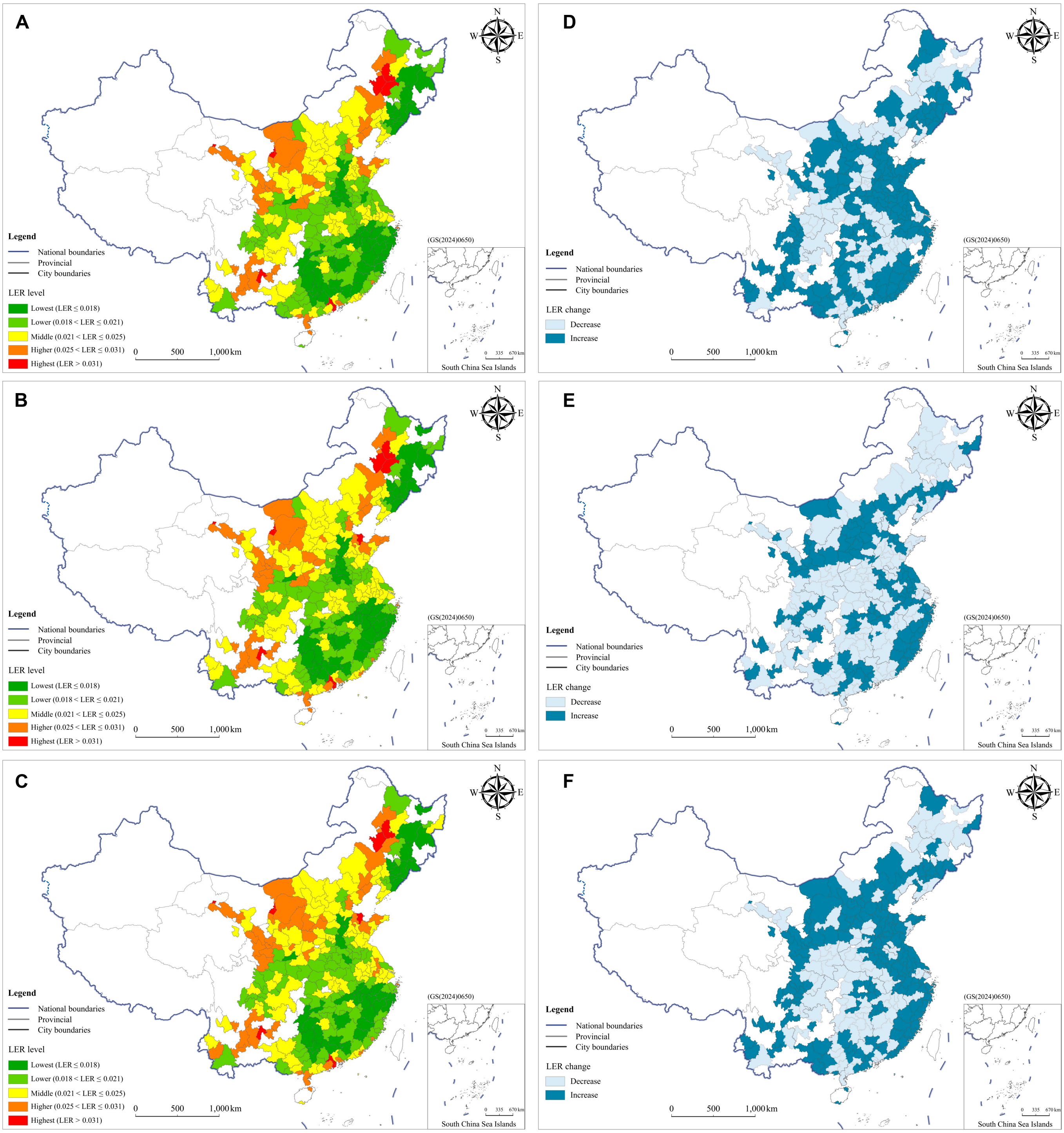

Fig. 4. Spatiotemporal pattern of LER in China in 2011 (A), 2015 (B), and 2019 (C) and its changes [2011 to 2015 (D), 2015 to 2019 (E), and 2011 to 2019 (F)].

From 2015 to 2019, the proportion of cities with declining LER increased significantly to 56.36%, mainly concentrated in northeastern, central, and southern China. Conversely, cities with rising LER decreased to 43.64%, mostly in northern China. Overall, 59.27% of cities witnessed an increase in LER from 2011 to 2019, with the most pronounced growth occurring in northern and eastern China, while central and northeastern China experienced a notable decrease.

As illustrated in Figs. 4A to C and 5, which present the distribution of LER classes across different urbanization levels from 2011 to 2019, cities with a UR below 50% in 2011 displayed diverse risk levels, dominated by the lower-risk (20.73%) and middle-risk (17.09%) categories, while 9.82% fell into the higher- and highest-risk tiers. The highest-risk cities were primarily found in the 50% to 80% UR range (1.45% to 1.82%), whereas the lowest-risk cities were concentrated in areas with UR below 50% (12.73%). Between 2011 and 2015, UR increased significantly, leading to shifts in LER distribution: cities with UR < 50% experienced a decline across all risk levels, but remained predominantly lower and middle risks. In contrast,

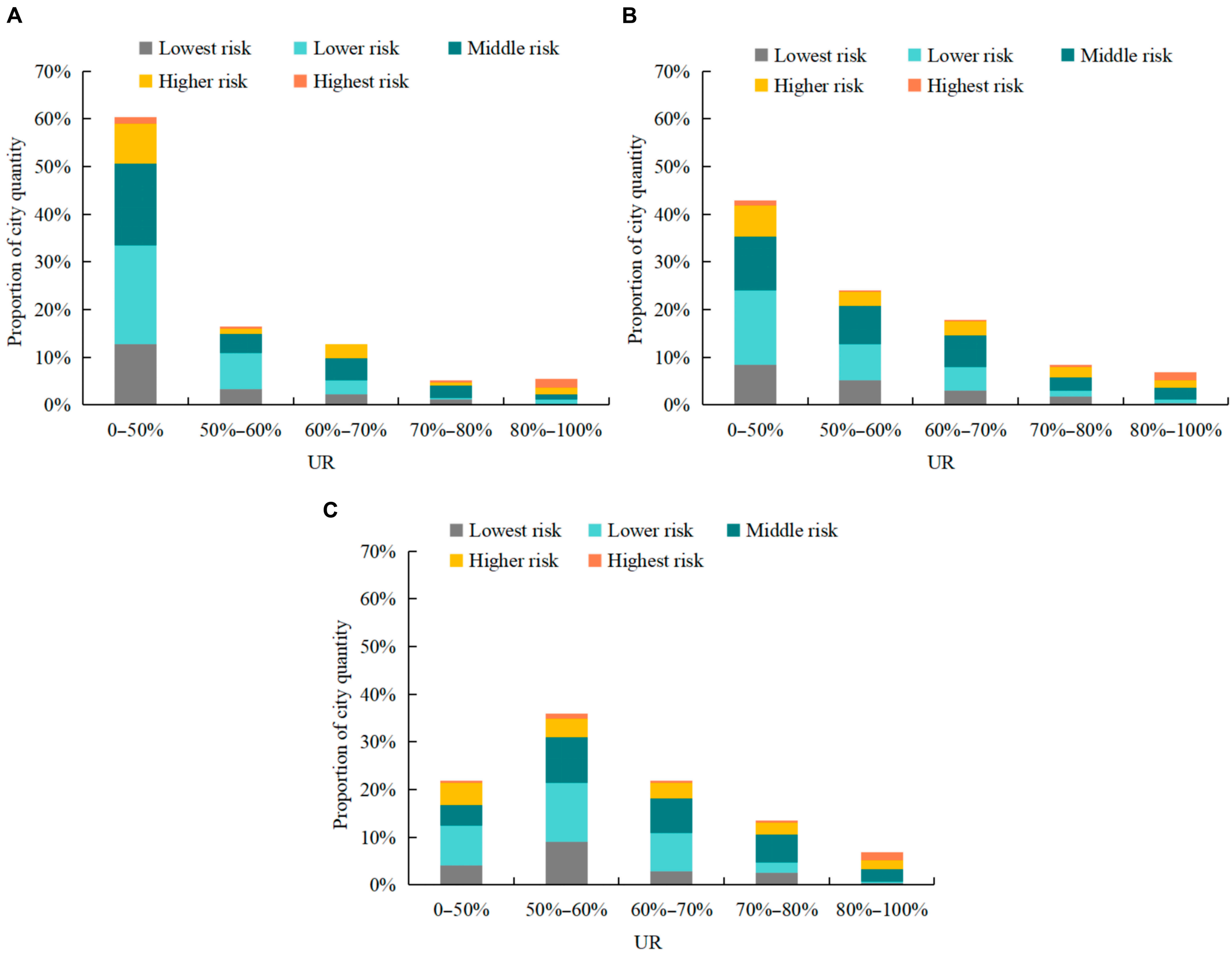

Fig. 5. Distribution of LER classes under different urbanization levels in 2011 (A), 2015 (B), and 2019 (C).

LER rose notably among cities with UR > 50%, particularly within the 50% to 60% UR bracket, where the proportion of middle- to highest-risk cities increased by 5.82% (reaching 11.27%). By 2019, the lowest- and lower-risk cities were mostly concentrated in the 50% to 60% UR range (9.09% and 12.36%, respectively), whereas areas with UR < 50% or 60% to 70% UR were dominated by lower-risk cities (8.36% and 8.00%). Middle-risk cities clustered mainly within the 50% to 80% UR interval, and higher-risk cities were mostly found below 70% UR. Notably, the number of higher-risk cities with UR > 80% increased by one, that is, Lanzhou in Gansu Province, attributed to landscape changes during the 2015 to 2019 period, in which grassland decreased by 24,080.58 ha, built-up land expanded by 747.18 ha, and heightened fragmentation of farmland and forest contributed to elevated LER.

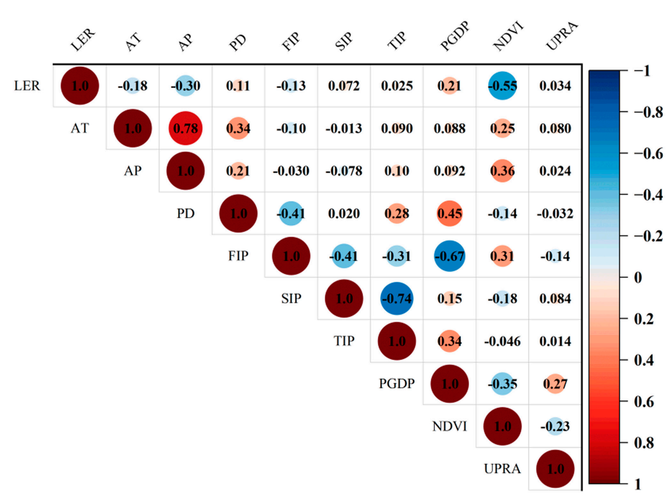

Fig. 6. Correlation coefficient of LER and core explanatory variables. Note: AT, average annual temperature; AP, accumulated annual precipitation; PD, population density; FIP, proportion of primary industry; SIP, proportion of secondary industry; TIP, proportion of tertiary industry; PGDP, per-capita GDP; NDVI, normalized difference vegetation index; UPRA, urban per capita road area.

The heterogeneity of the influence of urbanization on LER

Identification of the influencing factors

Figure 6 indicates the correlation coefficients between LER and several influencing factors in socioeconomic and natural

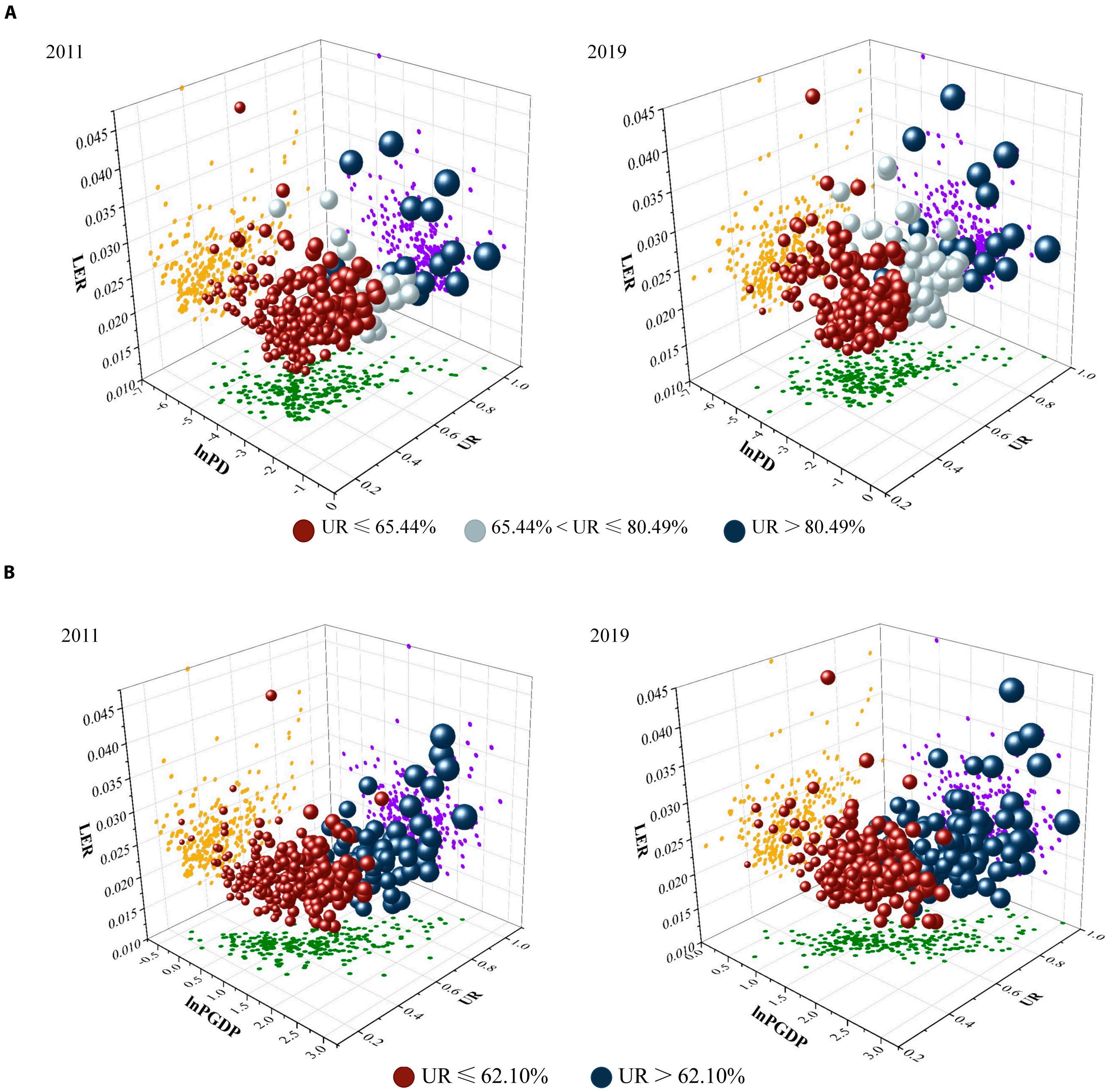

Fig. 7. The threshold effect of UR on LER under the social and public-oriented scheme (A) and the economic development-oriented scheme (B). Note: The higher the urbanization rate, the larger the sphere. UR, urbanization rate; LER, landscape ecological risk; PD, population density; PGDP, per-capita GDP.

domains. NDVI had a significant negative impact on LER, whereas PD and PGDP were positively correlated. Referring to related studies and taking into account the analysis of potential core factors, and the diagnosis of correlation, PD and PGDP were the potential core explanatory variables under different schemes, so as to explore the nonlinear influence on LER under the effects of urbanization.

Based on data accessibility and multicollinearity considerations, the following control variables were ultimately selected: average annual temperature (AT), accumulated annual precipitation (AP), urban per-capita road area (UPRA), proportion of primary industry (PIP), proportion of secondary industry (SIP), and proportion of tertiary industry (TIP). Climate variables are key factors that affect regional ecological sensitivity. Temperature and precipitation [37], which often exhibit variability across cities, serve as important indicators of climate change, with regional average temperature exerting multifaceted impacts on urban landscapes. In the process of social development, road construction can fragment preexisting landscapes [38], potentially increasing urban ecological risks. Industrial structure reflects regional economic development patterns and can readily induce changes in land use structure [39]. When constructing models with one of the potential core variables, namely, PD or PGDP, as the core explanatory variable, the other 2 were included as control variables to ensure the scientific validity of the results. To stabilize the data and mitigate heteroskedasticity, logarithmic transformations were applied to some variables. Although pollution and policy are relevant factors when exploring the driving mechanisms of LER, preliminary diagnostics indicated that pollution indicators such as industrial wastewater discharge and industrial dust emissions showed no significant correlation with LER, as reviewed from the Pearson and rank correlation tests at the 5% significance level. Meanwhile, accurately determining the timing and lag effects of various policies remains challenging. Some of these factors were excluded from the current study, but may be reconsidered in future research as data availability improves.

The threshold effect of UR on LER

A panel threshold regression model was employed to examine whether UR exerts a threshold effect on LER based on different modeling schemes. In the social and public-oriented scheme with PD as the core explanatory variable, a single threshold was identified at 5% significance level (F statistic = 32.75). The model passed the double threshold test ($P < 0.1$) but not the triple threshold test. In the economic development-oriented scheme, a single threshold effect of PGDP on LER was also observed ($P < 0.1$). These results indicate that both PD and PGDP exhibited nonlinear influences on LER, moderated by urbanization levels. Based on the threshold effect tests, specific threshold values of UR corresponding to PD and PGDP were estimated and are shown in Fig. 7.

In the social development-oriented scheme with PD as the core variable, double thresholds of UR were identified at 65.44% and 80.49%. The coefficient of PD was insignificant when UR was below 65.44% or between 65.44% and 80.49%, but became significantly negative (−0.018, $P < 0.05$) once UR exceeded 80.49%. This suggests that in cities with UR > 80.49%, an increase in PD will help mitigate LER, unlike in cities with a lower UR.

In the economic development-oriented scheme with PGDP as the core variable, a UR threshold was identified at 62.10%, with a 95% confidence interval of [61.82%, 62.20%]. The coefficient of PGDP increased from 0.006 ($P < 0.1$) to 0.014 ($P < 0.01$) after UR exceeded 62.10%, indicating that the promoting effect of PGDP on LER strengthened at higher urbanization levels. These findings support our research hypothesis.

In terms of urbanization effects, the influences of PD and PGDP on LER exhibited stage heterogeneity. Specifically, an increase in PD suppressed the rise in regional LER, and this suppressive effect became more pronounced as UR increased. This pattern may be attributed to the fact that higher UR promotes greater urban population agglomeration, spatial concentration of built-up land, and increased green coverage. Concurrently, rural natural ecosystems experienced reduced human interference, leading to improved vegetation cover and enhanced ecosystem stability. The establishment and reinforcement of ecological barriers further contributed to maintain regional ecological security, thereby mitigating ecological risks. In contrast, PGDP exerted a significant positive influence on LER, and this effect was further amplified by rising UR. In the early stages of urbanization, extensive economic growth patterns often lead to pollution and degradation of preexisting ecosystem functioning, thereby elevating ecological risks. As urbanization accelerates, economic expansion drives large-scale built-up land sprawl, resulting in the shrinkage and fragmentation of ecological land. Pollutants emitted by industries and transportation are likely to exceed environmental carrying capacity, causing irreversible damages to ecosystem structure and functioning, and ultimately posing greater threats to regional ecological security.

The integrated influence on LER based on the spatial panel econometric model

A spatial panel econometric model was employed to examine the heterogeneity in spatial spillover effects of LER across cities at different stages of urbanization. As identified in this study, the influence of PD and PGDP on LER exhibited nonlinear characteristics under the moderating effect of urbanization, with a threshold UR value of 62.10% observed for the impact of PGDP on LER. Considering the quantitative disparities between city groups above and below this threshold, as well as the complexity of mechanism identification and anthropogenic intervention, the economic development-oriented scheme was selected for further analysis. This scheme provides a suitable basis for deriving subsequent management recommendations. Within this framework, cities were categorized into 2 groups based on whether their average UR from 2011 to 2019 was above or below the threshold value of 62.10%. This classification resulted in 198 cities with UR ≤ 62.10% and 77 cities with UR > 62.10%.

Spatial autocorrelation of LER and UR in low- and high-urbanization cities

To examine the spatial correlation between LER and UR across cities at different urbanization levels, univariate and bivariate Moran's I values were calculated for each variable. In cities with UR below 62.10%, both LER and UR exhibited significant positive spatial autocorrelation ($P < 0.1$). However, the bivariate Moran's I value between LER and UR in these cities was negative and increased gradually over the study period, which was statistically significant at the 1% level. This indicates a significant negative spatial correlation between LER and UR in low-urbanization cities, which weakened over time. For cities with UR above 62.10%, the univariate Moran's I value for LER increased and was significant at the 1% level, whereas no significant spatial dependence was observed for UR. Meanwhile, the bivariate Moran's I value between UR and LER showed a steady increase and was significant at the 1% level from 2011 to 2019, revealing significant spatial interdependence between the 2 variables in highly urbanized cities. Compared to cities below the UR threshold, those above it exhibited stronger spatial aggregation in both univariate LER and bivariate LER–UR associations, though UR itself displayed a lower geographical proximity. Given the spatial correlations observed in both city groups, spatial effects were incorporated into the econometric modeling framework. A spatial panel econometric model was then applied to investigate spatial spillover effects.

Spatial spillover effect of LER in low- and high-urbanization cities

To select an appropriate spatial econometric model for analyzing LER spillover effects, LM and robust LM tests were conducted. For both city groups, the SEM was identified as the most suitable approach for capturing LER spillovers. In addition, results obtained using an inverse distance spatial weight matrix were consistent with those based on contiguity and economic tie matrices, supporting the robustness of the spatial model selection. The SEM regression results are summarized in Table 1.

Table 1. Regression results based on the spatial panel error model. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Cities (UR ≤ 62.10%)		Cities (UR > 62.10%)	
Variables	Coefficient	$P > z$	Coefficient	$P > z$
ln UR	−0.148***	0.000	0.142	0.101
ln AT	0.053*	0.071	0.172***	0.000
ln AP	−0.012	0.608	−0.103***	0.000
NDVI	−0.826***	0.000	−0.788***	0.000
ln PD	0.011	0.184	0.054***	0.000
ln UPRA	−0.026**	0.024	−0.009	0.666
ln FIP	−0.099***	0.000	0.038***	0.005
ln SIP	−0.187***	0.000	−0.116**	0.025
ln TIP	−0.162***	0.000	−0.159***	0.007
ln PGDP	0.012	0.492	−0.011	0.639
λ	2.826***	0.000	0.800***	0.000

UR, urbanization rate; AT, average temperature; AP, accumulated precipitation; NDVI, normalized difference vegetation index; PD, population density; UPRA, urban per capita road area; FIP, proportion of primary industry; SIP, proportion of secondary industry; TIP, proportion of tertiary industry; PGDP, per-capita GDP

For low-urbanization cities, the spatial error term coefficient (λ) was 2.826 ($P < 0.01$), indicating a significant positive spatial dependence of LER in cities with UR below 62.10%. This implies that a city's LER is influenced not only by its own factors, but also by random disturbances and the LER levels of neighboring cities. Among the explanatory variables, average temperature exhibited a positive effect on LER ($P < 0.1$), suggesting that a 1% increase in temperature can lead to a 0.053% rise in LER. Elevated temperatures contribute to more frequent extreme weather events (e.g., droughts and heavy rainfall) and ecosystem disruptions, which alter regional landscape patterns and elevate LER. In contrast, UR, NDVI, and the proportions of primary, secondary, and tertiary industries all exerted negative effects on LER ($P < 0.1$). Urban road area per capita also had a suppressive influence on LER ($P < 0.5$). Among these inhibiting factors, NDVI showed the strongest effect. Increased vegetation coverage helps improving ecosystem structure, mitigating soil erosion, and enhancing biodiversity, which eventually reduces LER effectively. In terms of the role of urbanization, cities at lower UR levels experienced population concentration that promotes the reorganization of disordered and fragmented urban spaces into more compact and organized structures, which reduces built-up land fragmentation and consequently lowers LER. A comparison of explanatory variables and spatial factors reveals that LER in these cities was spatially driven, with spatial effects outweighing local factors.

For high-urbanization cities, the spatial autoregressive coefficient (λ) for LER was 0.800 ($P < 0.1$), reflecting a positive spatial spillover effect. Among intrinsic influencing factors, AT, PD, and the FIP positively affected LER ($P < 0.1$). Temperature had the largest effect, with each unit increase corresponding to a 0.172-unit rise in LER. In highly urbanized areas, increased PD can intensify land use conflicts and reduce landscape connectivity, leading to ecological imbalance and compromising regional ecological security. Expansion of primary industries, coupled with pesticide and fertilizer use, adversely affect ecological lands and water bodies, which further elevates LER. On the other hand, NDVI, accumulated precipitation, and the proportions of secondary and tertiary industries suppressed LER. NDVI again exhibited a strong inhibitory effect. An increase in green space coverage and the optimization of park system layouts help in alleviating landscape fragmentation, promoting patch-corridor green distribution, and forming ecological green networks. Higher rainfall can expand water areas, raise humidity levels, and improve vegetation coverage. Enhancements in blue-green infrastructure, such as urban river corridors integrated with green spaces, can bolster ecosystem stability and reduce LER. Optimization of the industrial structure, as characterized by a smaller primary sector, a high-quality secondary industry, and an expanded tertiary sector, curbs the ecological footprint and supports sustainable economic–environmental coordination. As for low-UR cities, spatial drivers of LER outweighed local factors. Notably, the spatial error coefficients were smaller for cities above the UR threshold than below it, indicating stronger spatial spillover effects in cities with UR < 62.10%. Regions such as north and northeast China exhibited high–high LER clustering due to similar natural endowments and resource-dependent industries; while central and eastern China, characterized by flat terrain, minimal disturbance, shared resources, and regional development policies, showed low–low clustering [40]. In highly urbanized cities like Shanghai, fragmentation of construction land weakened LER spatial correlation. The specific clustering patterns of LER under different UR levels are provided in the Appendix.

Discussion

Spatiotemporal heterogeneity of LER was illustrated in this study, and its influencing mechanisms varied in different cities. The novelty of our study lies in our exploration of this heterogeneity and the identification of thresholds at which UR determines the differentiated interactions between LER and critical factors in multiple schemes under multiple hypotheses. By the end of 2022, China's rapid urbanization had reached 65.22%; however, significant regional disparities persisted, with eastern China exhibiting higher UR than central and western regions, which was closely linked to their respective stages of economic development. Our results confirm that PD and PGDP exert nonlinear effects on LER under the moderating roles of UR, thereby validating Hypothesis 1.

Furthermore, this study examined the correlation between UR and LER, and the spatial spillover effects of LER at a macro level, which can provide clearer insights regarding its influencing mechanisms. We found that LER was affected by neighboring cities, which was consistent with findings by Lee et al. [41] and Chen and Chi [42]. More importantly, we further investigated whether differences existed in the spatial spillover effects of LER between cities below and above the UR threshold. The results showed that there were spatial spillover effects in LER for both types of cities and that the spatial driver of ecological risk was stronger than the local driver; thus the Hypothesis 2 was formulated. This can be attributed to high levels of socioeconomic development, technological advancement, and strong interregional economic linkages between these cities. In addition, the implementation of regional coordinated development strategies (e.g., the Yangtze River Delta integration strategy) has facilitated cross-regional collaboration and accelerates the flow of population, capital, and information. These dynamics alter the supply and demand of land resources, and ultimately induce spatial spillover effects in LER. To mitigate LER associated with major land use types, targeted policy measures are necessary to safeguard urban ecological security.

As a typical city with a UR above the threshold (62.10%), Shanghai is located in China's eastern Yangtze River Delta alluvial plain, which experienced fluctuating UR from 2011 to 2019 and showed an initial increase followed by a decrease and a subsequent rebound. During this period, LER first rose, then declined, while consistently maintaining medium-risk levels, with spatial variations showing lower risk in central urban zones as compared to suburban and exurban areas. The city's land use composition primarily consists of cropland, built-up areas, and water bodies as illustrated in Fig. 8. To address rapid population growth, authorities should implement strict population control measures while optimizing distribution patterns. The notable reduction in cropland and increased fragmentation calls for the establishment of urban green agriculture demonstration zones. For built-up areas characterized by low green coverage and high separation, developing suburban centers and green networks is highly recommended. Meanwhile, the decline in water bodies necessitates the creation of ecological corridors and a multitiered river management system to alleviate ecological pressures.

For cities with a UR below the threshold (62.10%), the UR has generally continued to rise during recent years, contributing effectively to the reduction of ecological risks. The land use patterns in such cities are typically dominated by cropland, forest, water, and built-up land. To counteract the shrinkage of arable land and increased landscape separation, it is recommended to promote farmland renovation projects and improve cropland management. In areas with relatively low vegetation coverage, accelerating the implementation of forest land protection and restoration projects is advised. To address the reduction in water area and agricultural nonpoint source pollution, comprehensive and integrated water management in metropolitan areas should be enhanced, along with establishing ecological compensation mechanisms for water conservation. Regarding the noticeable expansion of built-up land and fragmentation of rural settlements, raising the UR and promoting sustainable urban–rural integration are proposed.

LERs are intensifying as a result of expanding urban human activities. The United Nations has designated 2021 to 2030 as the UN Decade on Ecosystem Restoration to address ecosystem degradation, climate change, and biodiversity loss. Similarly, China has promoted ecological restoration projects, urban resilience initiatives, and green space enhancement. However, critical ecosystems, including water bodies, wetlands, and cropland, continue to decline, threatening ecological and food security while exacerbating landscape fragmentation. Notably, LER increased in eastern coastal and northern regions of China during the study period, which underscores the need for targeted mitigation policies. To address these challenges, cities should adopt differentiated strategies based on urbanization levels. For cities with UR below 62.1%, priorities include expanding vegetation coverage, constructing ecological barriers, and improving

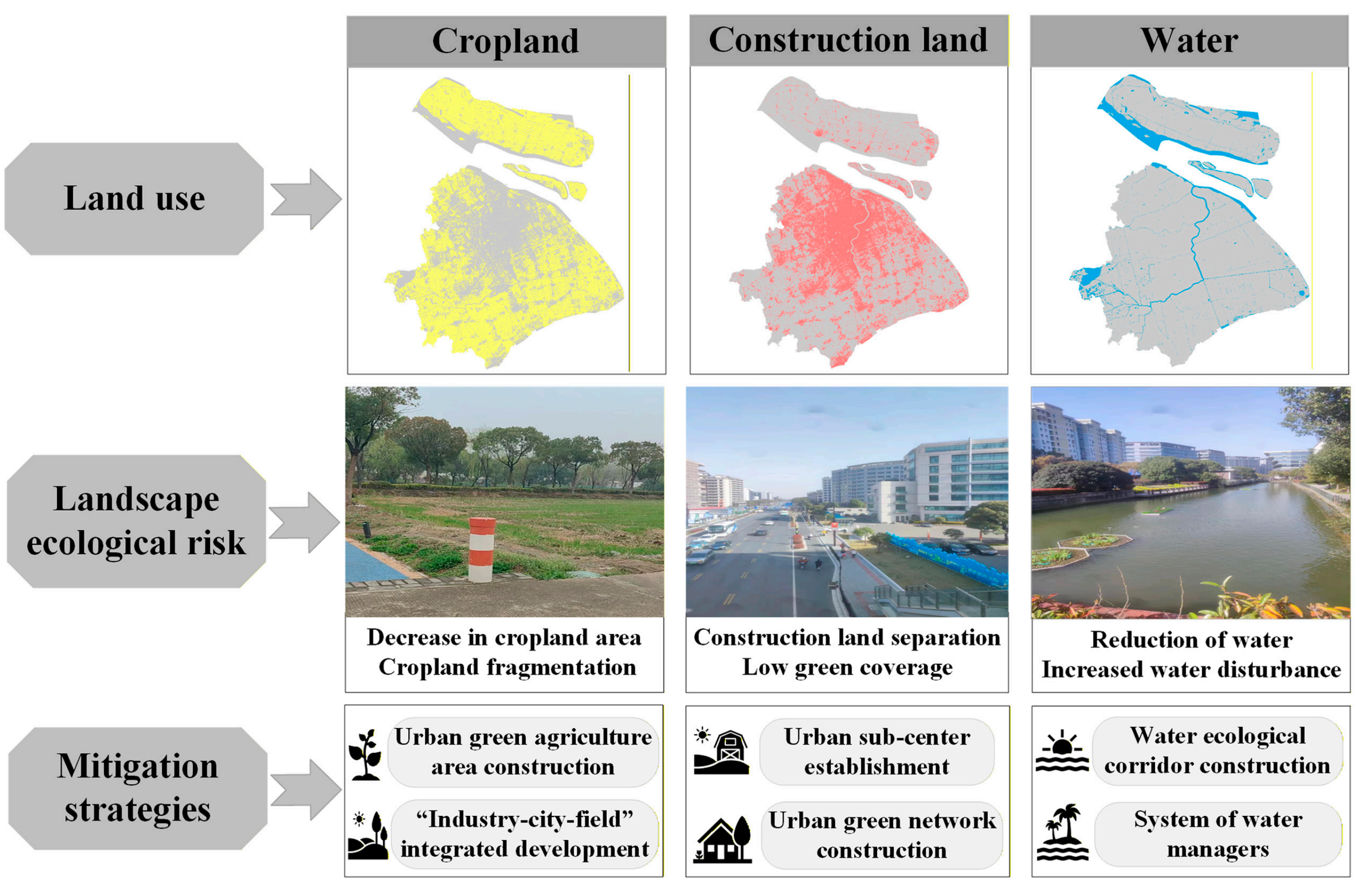

Fig. 8. Landscape ecological risk and mitigation strategies in Shanghai.

land use efficiency through urban renewal and industrial optimization approaches. Road networks should also be rationally planned to increase the per-capita road area. For cities with UR above 62.1%, measures should focus on optimizing blue-green spaces, establishing ecological safety networks, and promoting industrial upgrading. Reducing PD may also help in alleviating ecological pressure. Interventions such as stringent environmental regulations, afforestation, and ecosystem restoration can mitigate landscape disturbance, enhance ecological resilience, and stabilize vulnerable ecosystems.

This study also identified and quantified the spatial spillover effects of LER in Chinese cities. Ecological protection and restoration strategies should be formulated according to landscape characteristics to alleviate these existing spillover effects. Strengthening communication and cooperation between upstream and downstream regions through coordinated management, along with joint implementation of ecological protection and restoration projects, can help prevent the spread of ecological risks such as soil erosion, land degradation, and biodiversity loss. These efforts facilitate rational resource allocation and improve ecological environmental quality. Compensation mechanisms for forest and grassland conservation should also be refined to enhance economic benefits in ecological protection areas. The ecological protection red line imposes stricter regulatory requirements to ensure ecological functionality, environmental quality, and sustainable use of natural resources. At this stage, emphasis should be placed on improving the quality of ecological spaces while maintaining their scale. The government should also enhance natural resource asset accounting and fiscal transfer systems to ensure adequate ecological compensation. These steps will likely increase the quantity and quality of green spaces and promote landscape patch consolidation in urbanized areas and, as a result, contribute to sustainable urban development in the long term.

Nonetheless, we also note several limitations. First, changes in LER can also be influenced by suddenly implemented national and local policies; thus, policy factors should be further quantified in the future. Further, the current study only evaluated urban LER based on administrative units; however, the nonlinear influence of UR on LER based on grid scale due to the continuity of natural ecological elements should also be considered, so that the administrative constraints can be taken into account, and feasible references for cross-regional ecological restoration strategies that ultimately minimize LER can also be provided. In addition, the measurement on LER can also be improved with high accuracy through the incorporation of on-site experiments and better availability of relevant reliable datasets.

Conclusion

This study analyzed changes in LER in Chinese cities, examined the threshold effects of UR on LER in different analytical schemes, and investigated the spatial spillover effects of LER. The main conclusions are as follows:

LER in Chinese cities initially increased before stabilizing and exhibited distinct spatial patterns. Most cities maintained moderate-to-low risk levels, with higher-risk areas concentrated predominantly in northern China. Approximately 65% of cities experienced increased LER between 2011 and 2019, particularly in eastern and northern regions. Low-LER cities typically had URs below 60%, while high-risk clusters occurred at UR < 50% or > 80%. The following drivers exhibited nonlinear effects on LER at different urbanization levels: PD only reduced LER when UR exceeded 80.49%, and the positive impact of PGDP on LER further enhanced for cities that exceeded the UR threshold of 62.10%. Spatial analysis revealed stronger LER–UR autocorrelation and clustering in high-UR cities (>62.10%), whereas low-UR cities demonstrated greater spillover effects. These results showed that a differentiated ecological environmental governance system should be constructed, and relevant integrated protection and restoration projects could help to realize ecological civilization goals.

The findings offer scientific evidence for achieving coordinated development between urbanization and ecological conservation. Based on city-specific conditions, the following policy recommendations are proposed: For cities with a UR below 62.10% and low LER, it is advisable to incorporate dynamic monitoring mechanisms and incentives for eco-friendly industries to balance regulatory control and urban development. These measures can be implemented in conjunction with existing policy frameworks, such as the “Opinions on Strengthening Ecological Environment Zoning Control” [43]. For cities with a UR under 62.10% but high LER, it is essential to enhance ecological restoration funding and strengthen the construction of forest reserves to mitigate anthropogenic degradation [44]. In highly urbanized areas (UR > 62.10%) facing high LER—such as Shanghai—the implementation of initiatives like the “Beautiful China Construction Pilot Demonstration Area” [45] is recommended. This could involve establishing ecological restoration demonstration zones, incorporating binding targets (e.g., minimum proportions of ecological space in urban plans), and developing cross-regional restoration mechanisms. In cities where UR exceeded 62.10% but with low LER, efforts may focus on promoting market-based mechanisms for realizing ecological values, with the goal of attracting external investments into projects such as sponge city construction.

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Data Availability

The datasets used and analyzed in this article are freely available from the corresponding authors on reasonable request.

Supplementary Materials

Fig. S1

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