Ecological Indicators 137 (2022) 108744

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Original Articles

Exploring changes in landscape ecological risk in the Yangtze River Economic Belt from a spatiotemporal perspective

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ARTICLE INFO

Keywords:
Ecological risk assessment
Land use change
Landscape pattern
Spatiotemporal pattern
Yangtze River Economic Belt

ABSTRACT

Landscape ecological risk reflects the extent to which ecosystems are threatened by human activities and environmental changes and is increasingly seen as the basis for decision-making in regional ecosystem management. Although the Yangtze River Economic Belt (YREB) has experienced drastic land use changes affected by human activities, the spatiotemporal heterogeneity of ecological risk in the region has not been thoroughly investigated. This study develops and applies an ecological risk assessment framework that integrates landscape pattern characteristics and landscape vulnerability dynamics to analyze spatiotemporal variations in landscape ecological risk in the YREB from 2000 to 2018. The results show moderate risk levels across most of the YREB during the study period, but risk was notably higher in the western and northern regions. Due to the gradual improvement in regional policies and the implementation of ecosystem restoration projects, there is a clear trend of risk reduction, and the area previously designated as high or medium–high risk was reduced by more than 150,000 km^2 over the study period. Approximately 45% of the study area, where the risks are more difficult to mitigate or maintain at lower levels, was identified as a key area for future risk management. Significant spatiotemporal differences in ecological risks underscore the necessity of implementing spatially differentiated risk management strategies and long-term dynamic monitoring. This study provides a reference for future land use optimization and sustainable landscape management in the YREB.

1. Introduction

Maintaining the stability of ecosystem structure and functions is at the core of sustainable development (Luo et al., 2018; Paukert et al., 2011; Wade et al., 2011). However, intense human activities cause profound changes in landscape patterns and ecological processes, generating certain ecological risks that seriously threaten human well-being (Bryan et al., 2018; Frazier et al., 2019; Wang et al., 2020). There is a growing interest in using ecological risk assessment (ERA) to manage risk and support ecosystem conservation. ERA is the process of evaluating the likelihood that adverse ecological effects may occur or are occurring as a result of exposure to one or more stressors (Forbes and Galic, 2016; USEPA, 1998). It links human activities to environmental conditions and provides a way to identify problems that pose a hazard to ecosystems, thereby playing an active role in the decision-making of environmental managers (Mann et al. 2021; Piet et al. 2017; Shea and Thorsen 2012).

Early ERAs focused on particular site-specific hazards in small geographic areas, such as monitoring the impact of toxic chemicals on local human health (Landis, 2003; Loibl and Smidt, 1996; Suter, 1990). In recent decades, the growing scope of climate change and human activities has triggered numerous regional and global environmental crises and challenges (Hope, 2006; Lal et al., 2021; Landis et al., 2013). There has been a clear trend of broadening the scope of ERAs to accommodate larger-scale impacts and management responses. However, as scale increases, it becomes increasingly difficult to deal with compounding risks and their complex spatial heterogeneity (Serveiss, 2002; Wang et al., 2020). Within this context, landscape ecological risk has been proposed and defined as the possible adverse consequences of the interaction of landscape patterns and ecological processes under the influence of natural or human factors (Ayre and Landis, 2012; Hunsaker et al., 1990; Peng et al., 2015a). In this framework, "landscape" refers to a spatially heterogeneous area consisting of a combination of local ecosystems or land use types (Forman, 1995; Gaines et al., 2004). It is widely

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https://doi.org/10.1016/j.ecolind.2022.108744
Received 10 December 2021; Received in revised form 27 February 2022; Accepted 28 February 2022
Available online 3 March 2022

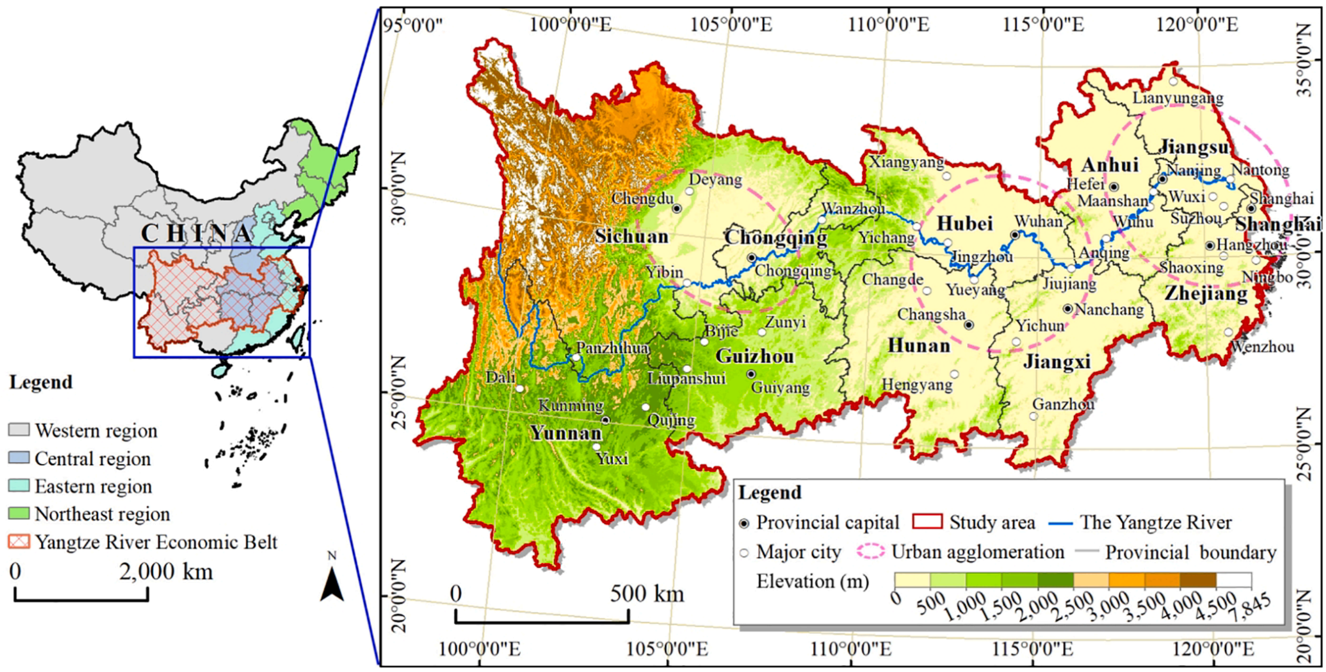

Fig. 1. The location of the YREB. Note: The 11 provinces/municipalities are labeled in bold font; from west to east, pink dotted circles mark the Cheng-Yu, middle reaches of the Yangtze River, and Yangtze River Delta urban agglomerations.

considered an ideal scale for studying human activities and their environmental effects (Wu, 2019). The framework treats the deviation of a heterogeneous landscape mosaic from the optimal landscape pattern as an indicator of risk and emphasizes risk expression in terms of specific spatial patterns for ecological functions and processes (Cao et al., 2019; Xu et al., 2021). Moreover, the evaluation object of a landscape ERA is the integral landscape in the region rather than a single ecosystem, which highlights the goal of protecting the overall structure and functions of the entire landscape. To some extent, it enables the characterization of integrated ecological risks from multiple stressors through landscape features and provides a pathway for ecological risk mitigation based on landscape pattern optimization (Goussen et al., 2016; Zhang et al., 2020). As a result, landscape ERA has become an important tool in macroecosystem management (Mo et al., 2017; Van den Brink et al., 2016).

As theories have developed rapidly, a method for quantifying landscape ecological risk based on pattern-process feedback mechanisms has recently been proposed (Li et al., 2020; Peng et al., 2015a; Wang et al., 2021). Specifically, the method relies on two main indicators: landscape disturbance and landscape vulnerability. The product of these two indicators is used to estimate potential ecological losses, which is then combined with risk probabilities to calculate the specific risk value of the region (Cao et al., 2019). To date, this method has been adopted in many regional studies on river basins (Wang et al., 2020), coastal areas (Zhang et al., 2020), ecologically fragile areas (Gong et al., 2021; Jin et al., 2019; Wang et al., 2021), mining areas (Peng et al., 2015b), and megacities (Li et al., 2020; Mo et al., 2017), among others. These studies have demonstrated the advantages of the method, i.e., the integrated characterization and spatial visualization of ecological risks with limited *in situ* observations, and some have noted possible limitations (Wang et al., 2021). Reliable quantification is a prerequisite for the analysis and management of ecological risks. The oversimplification of key steps in the existing method (i.e., quantifying landscape vulnerability as a constant based on expert opinion) is a major concern (Cao et al., 2019; Mo et al., 2017; Wang et al., 2021). In reality, ecosystems represent a dynamic continuum of functioning and can be characterized by varying degrees of vulnerability according to changes in external stressors as well as internal properties (Hunsaker et al., 1990; Landis et al., 2013; Solovjova, 2019). Approaches that consider only the static differences between landscape types do not sufficiently reflect the spatial and temporal heterogeneity of risk, especially in larger areas or across time (Goussen et al., 2016; Paukert et al., 2011). Therefore, this method still needs targeted improvements for practical application.

The Yangtze River Economic Belt (YREB) is an important geographic region in China with a large population, an active economy, and rich ecological resources (Zhang et al., 2021). After years of high-intensity development and unsustainable land use, a series of eco-environmental problems have occurred, such as vegetation degradation, rapid contraction of lakes and wetlands, and substantial water and air pollution (Hu et al., 2017; Li et al., 2014). To support environmental management in the YREB, recent research has paid considerable attention to various forms of ERAs of effects such as natural disasters (Zhang et al., 2017), environmental pollution (Wu et al., 2019), climate change (Meng et al., 2016), and deteriorating human health (Hu et al., 2017). However, few studies have investigated the consequences of the cumulative effects of human activities and environmental changes on natural ecosystems across the YREB, and this knowledge gap has prevented progress in regional environmental management.

The objective of this paper is to develop and apply an ERA framework that integrates landscape pattern characteristics and landscape vulnerability dynamics to analyze spatiotemporal variations in landscape ecological risk in the YREB from 2000 to 2018. We hypothesize that there is significant spatiotemporal heterogeneity in landscape ecological risk in the YREB due to human activities and associated environmental changes. To test this hypothesis, we first improve the current, landscape pattern-based method to develop a landscape ERA model that is more appropriate for dynamic studies. We then calculate the landscape ecological risk index (LERI) to analyze the changes in risk in the YREB from a spatiotemporal perspective. Based on the findings, we propose key areas and targeted advice for future risk management. In the context of increasingly strict ecological protection and accelerated socioeconomic development, this study supports land use optimization and sustainable landscape management in the YREB.

Table 1
Dataset details and sources.

Data	Details	Resolution	Sources
Land use data	2000, 2005, 2010, 2015, and 2018	30 m	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn)
Basic geographic data	Vector data of administrative boundaries, cities, and rivers	Line/point data	
Digital elevation model (DEM)	For extracting the slope and elevation	30 m	
Socioeconomic raster data	Population density rasters for 2000, 2005, 2010, 2015, and 2018	1 km	WorldPop data platform (https://www.worldpop.org)
	GDP density raster data* for 2000, 2005, 2010, and 2015	1 km	National Earth System Science Data Center (http://www.geodata.cn)
Meteorological data	Precipitation and temperature for 2000, 2005, 2010, 2015, and 2018	Point data	China Meteorological Data Service Centre (http://data.cma.cn)
Net primary productivity (NPP)	2000, 2005, 2010, 2015, and 2018	1 km	US National Aeronautics and Space Administration (http://modis.gsfc.nasa.gov)
Normalized difference vegetation index (NDVI)	2000, 2005, 2010, 2015, and 2018	1 km	US Geological Survey (USGS) (https://www.usgs.gov)

Note: Missing GDP density data for 2018 are calculated based on available GDP data combined with the real growth rate over the past 15 years and expected growth.

2. Materials and methods

2.1. Study area

The YREB consists of 11 provinces/municipalities along the Yangtze River and spans three major regions in China (Fig. 1). It covers approximately 2.05 million km^2, accounting for 21.27% of the total land area of China. After years of rapid development, the YREB occupies a leading position in China's overall economic development. In 2018, the total GDP and resident population of the YREB were approximately 4230.26 billion yuan and 598.71 million, respectively, both accounting for more than 40% of the national totals. Three major urban agglomerations (i.e., Cheng-Yu, the middle Yangtze River, and the Yangtze River Delta) have formed, showing the great vitality of regional economic development.

At the same time, the YREB is seen as a demonstration zone of the ecological civilization concept in China, playing an irreplaceable role in maintaining national ecological security. Over 40% of the YREB is forested, and the area of surface water bodies comprises approximately 20% of the total in China (Zhang et al., 2021). However, the ecological environment has been extensively degraded by human activities, posing a serious threat to ecological security and sustainable development. Recognizing the need to protect the ecological environment, the Chinese government proposed an ambitious goal of green development in the YREB in 2016 (Liu et al., 2018). Within this context, quantifying the spatiotemporal patterns of landscape ecological risk will contribute to establishing risk alert mechanisms and is important for coordinated development between economic prosperity and ecological security.

2.2. Materials

The data needed to measure ecological risk are shown in Table 1. The land use database is currently one of the most accurate remote sensing-based monitoring products in China, and its comprehensive evaluation accuracy is above 93% (Ning et al., 2018; Zhang et al., 2020). Land use is

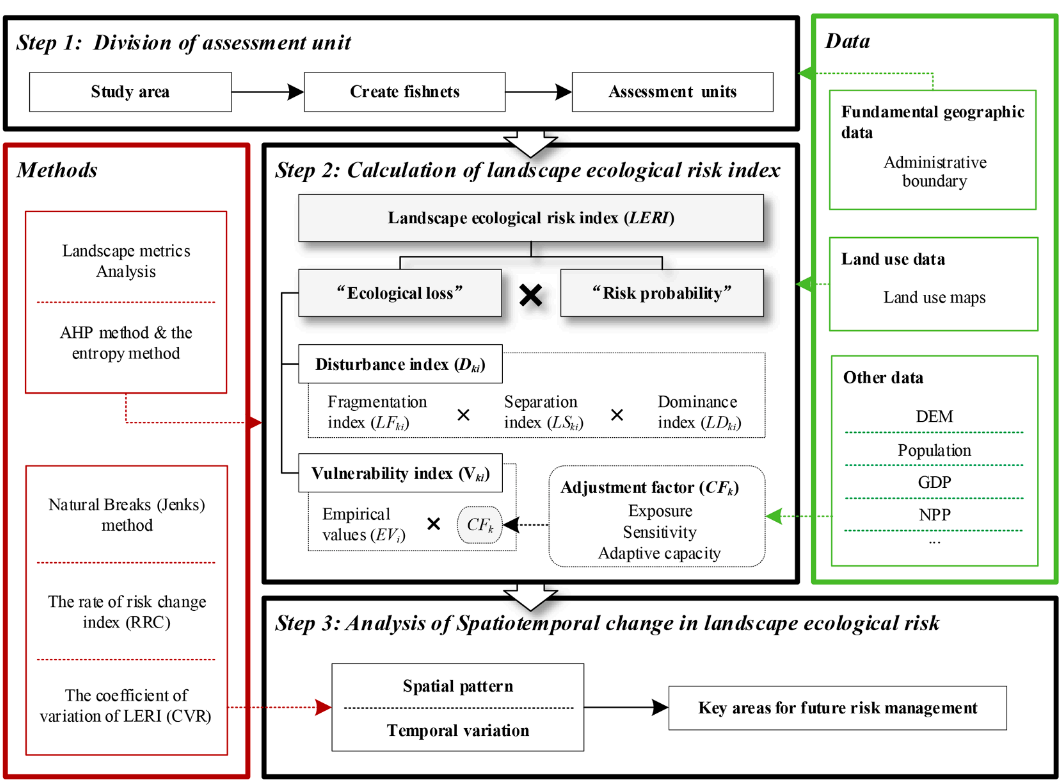

Fig. 2. The three-step framework for analyzing landscape ecological risk and spatiotemporal change.

classified into six categories: cropland, woodland, grassland, water, urban land, and unused land. Both precipitation and temperature datasets (at 1 km spatial resolution) were generated using kriging interpolation based on point observations from meteorology stations in the YREB. Note that the LERI calculation is performed at the original resolution of each dataset to avoid data loss from resampling.

2.3. Methods

The framework developed here to analyze landscape ecological risk comprises three steps (Fig. 2). In Step 1, a grid with 2324 assessment units (30 km × 30 km) covering the entire continental area of the YREB is created, following prior studies (Chen et al., 2020; Zhang et al., 2020). In Step 2, an improved landscape ERA method is developed to estimate the LERI for each grid unit in 2000, 2005, 2010, 2015, and 2018 (see section 2.3.1). In Step 3, the patterns and dynamics of ecological risk in the YREB during the period 2000–2018 are analyzed, and key areas for risk management are discussed.

2.3.1. Calculation of the LERI

A landscape pattern-based approach is used here to calculate the LERI. This method represents ecological risk as the product of "ecological loss" and "risk probability" (Cao et al., 2019). "Ecological loss" is composed of two components: the landscape disturbance index (D_i) and landscape vulnerability index (V_i) (Mo et al., 2017; Zhang et al., 2020). D_i captures the magnitude of landscape disturbance caused by human activities and natural changes, and V_i captures the ability of landscape components to maintain a stable ecological structure and functions (Li et al., 2020). "Risk probability" is estimated based on the area of each land use type, which reflects the contribution of each land use type to the overall landscape risk (Xu et al., 2021). The LERI is calculated as follows:

$$LERI_k = \sum_{i=1}^{n} \sqrt{D_{ki} \times V_{ki}} \times \frac{A_{ki}}{A_k} \tag{1}$$

where k is the assessment unit, i is the land use type, $LERI_k$ is the landscape ecological risk index of unit k, D_{ki} is the landscape disturbance index of land use type i in unit k, V_{ki} is the landscape vulnerability index of land use type i in unit k, A_{ki} is the area of land use type i in unit k, and A_k is the area of unit k.

Drawing on recent studies, we chose three landscape metrics—fragmentation, separation, and dominance—to calculate D_i. Landscape fragmentation (LF_i) describes the fragmentation degree of each land use type, which reflects human modification; higher values indicate greater landscape disturbance (Mann et al., 2021; Wang et al., 2020). Landscape separation (LS_i) reflects the degree of separation or isolation between land use patches. Land use types with a higher degree of separation are characterized as more dispersed and complex in their geographical distribution, which is generally considered negative for landscape connectivity (Zhang et al., 2020). Landscape dominance (LD_i) indicates the degree of influence of a given land use type on the landscape (Dalloz et al., 2017; Gong et al., 2021). Fragstats software was used to compute these landscape metrics (McGarigal et al., 2012). The formulae are as follows:

$$D_{ki} = aLF_{ki} \times bLS_{ki} \times cLD_{ki} \tag{2}$$

$$LF_{ki} = n_{ki}/A_{ki} \tag{3}$$

$$LS_{ki} = \frac{A_k}{2A_{ki}} \sqrt{\frac{n_{ki}}{A_k}} \tag{4}$$

$$LD_{ki} = \frac{Q_i + M_{ki}}{4} + \frac{L_{ki}}{2} \tag{5}$$

where LF_{ki}, LS_{ki}, and LD_{ki} are the landscape fragmentation index, landscape separation index, and landscape dominance index of land use type i in unit k, respectively; variables a, b and c represent the weights of LF_{ki}, LS_{ki} and LD_{ki} and take the values of 0.5, 0.3 and 0.2, respectively (Li et al., 2020; Wang et al., 2021); and n_{ki} is the number of patches of land use type i in unit k, Q_i is the ratio of units of land use type i to the total units, M_{ki} is the ratio of the number of patches of land use type i to the total number of patches in unit k, L_{ki} is the ratio of the area of land use type i to the total area of unit k, and A_{ki} and A_k have the same definitions as those given in Eq. (1).

Vulnerability is conceptualized as susceptibility to exposure to perturbations or external stresses, sensitivity to perturbation, and a lack of adaptive capacity (De Lange et al., 2010; Gallopín, 2006). In prior research, the vulnerability of different land use types was ranked by experts, with 6 being the most vulnerable and 1 the least vulnerable: unused land = 6, water = 5, cropland = 4, grassland = 3, woodland = 2, and urban land = 1 (Chen et al., 2020; Li et al., 2020; Wang et al., 2020). These rankings are used as an empirical value (EV_i) in this study and then combined with a composite adjustment factor (CF_k) to obtain a modified vulnerability index (V_{ki}) that reflects the spatial and temporal heterogeneity of landscape vulnerability. These indicators are computed as follows:

$$V_{ki} = EV_i \times CF_k \tag{6}$$

$$CF_k = EF_k / \overline{EF_k} \tag{7}$$

$$EF_k = \sum_{j=1}^{8} w_j \times m_{jk} \tag{8}$$

where V_{ki} is the modified landscape vulnerability index of land use type i in unit k, EV_i is the empirical value of landscape vulnerability of land use type i, CF_k is an adjustment factor for unit k, EF_k is the weighted sum of indicators in unit k, w_j is the weight of indicator j, and m_{jk} is the standardized index value.

The adjustment factor (CF_k) that we introduce here is calculated using multiple indicators related to the three dimensions of vulnerability: exposure, sensitivity, and adaptive capacity. As an intrinsic property of an ecosystem, vulnerability is revealed only under external disturbances (Dai et al., 2021). Therefore, in most formulations, exposure is considered one element constituting vulnerability that reflects how the ecosystem comes into contact with stressors (De Lange et al., 2010; Khan et al., 2021). Sensitivity is an intrinsic property of the ecosystem and is defined as the degree to which the system is affected by those perturbations (Qiu et al., 2015). Vulnerability increases with sensitivity, making the structure and functions of the landscape more susceptible to change by external disturbances. Adaptive capacity is the system's ability to cope with hazards and their consequences, in contrast to vulnerability (Gallopín, 2006). Ecosystems with stronger adaptive capacity can reduce ecological risks by moderating or offsetting the potential for damage (Huang et al., 2012). In sum, we selected eight indicators to account for these three dimensions based on previous studies that have confirmed the reliability of these indicators for quantifying landscape vulnerability (Appendix A and B).

2.3.2. Analysis of spatiotemporal change in landscape ecological risk

The analysis of spatiotemporal changes in the LERI is conducted in three steps (Fig. 2). First, ecological risk levels are classified using natural breaks. Natural breaks are ideal for visualizing naturally occurring tendencies in the data, as they reduce within-class variance and maximize between-class variance (Liu et al., 2019; Picado-Aguilar and Aguero-Valverde, 2020). The LERIs for all units from 2000, 2005, 2010, 2015, and 2018 were combined and classified into ten intervals. Every two adjacent intervals were combined, resulting in five risk levels.

Second, the rate of risk change index (RRC) is constructed to compare the difference in the rate of the LERI increase between units in different periods, thus identifying the spatial and temporal heterogeneity of risk changes (Zhong et al., 2020). The RRC index is the average

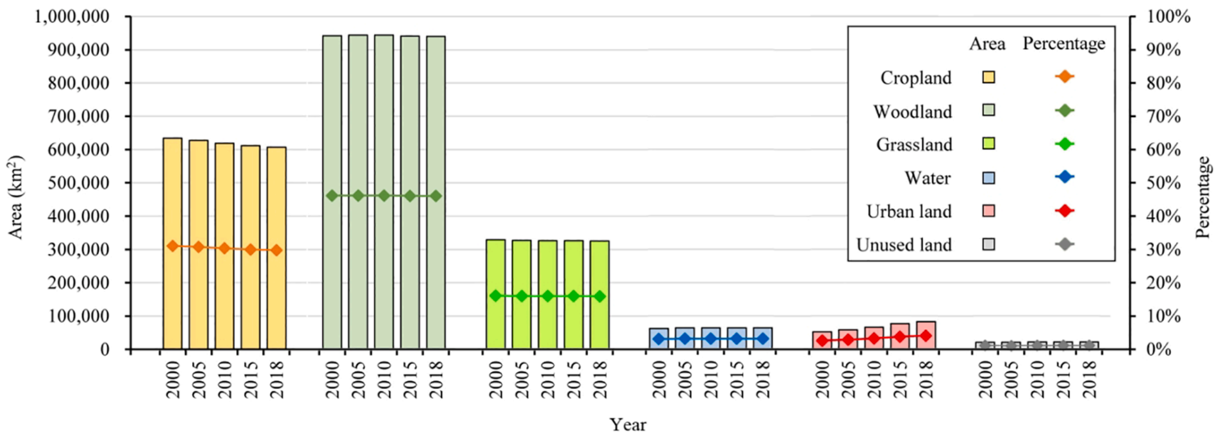

Fig. 3. Change in area and percentage of the six land cover types from 2000 to 2018.

Table 2
Transfer matrix for the different land cover types from 2000 to 2018 (unit: km^2).

Land use types		Land use types in 2018						Total area of land lost
		Cropland	Woodland	Grassland	Water	Urban land	Unused land	
Land use types in 2000	Cropland	570,986	23,283	6,736	5,295	27,692	106	63,112
	Woodland	22,258	902,144	11,412	1,539	4,783	210	40,202
	Grassland	6,482	13,440	305,714	1,168	1,150	1,002	23,241
	Water	3,183	825	673	54,666	1,702	768	7,151
	Urban land	4,329	505	187	342	46,772	15	5,378
	Unused land	56	144	864	672	29	19,165	1,766
Total area of land added		36,308	38,197	19,872	9,016	35,355	2,102	140,850

annual increase in the LERI of a unit as a percentage of the initial LERI value. Large, positive index values indicate faster rates of risk growth, smaller values indicate slower risk growth, and negative values indicate decreased risk. RRC is computed as follows:

$$RRC_k = (LERI_k^{t2} - LERI_k^{t1})/LERI_k^{t1} \times \frac{1}{\Delta t} \times 100\% \tag{9}$$

where RRC_k is the rate of risk change of unit k; $LERI_k^{t2}$ and $LERI_k^{t1}$ are the landscape ecological risk index of unit k at time $t1$ and $t2$, respectively; and Δt is the time span from $t1$ to $t2$.

Third, the stability of the ecological risk of each unit is observed by calculating the coefficient of variation in the LERI (CVR) (Döring and Reckling, 2018). In general, the larger the CVR is, the weaker the risk stability. The CVR is calculated as follows:

$$CVR_k = SD_k/MN_k \tag{10}$$

where CVR_k is the coefficient of variation in the LERI in unit k, SD_k is the standard deviation of the LERI in unit k, and MN_k is the mean of the LERI in unit k.

3. Results

3.1. Land use change from 2000 to 2018

There were considerable differences in the area and change trajectories of each land use type across the study period (Fig. 3). In general, the YREB is dominated by woodland, cropland, and grassland. Despite a

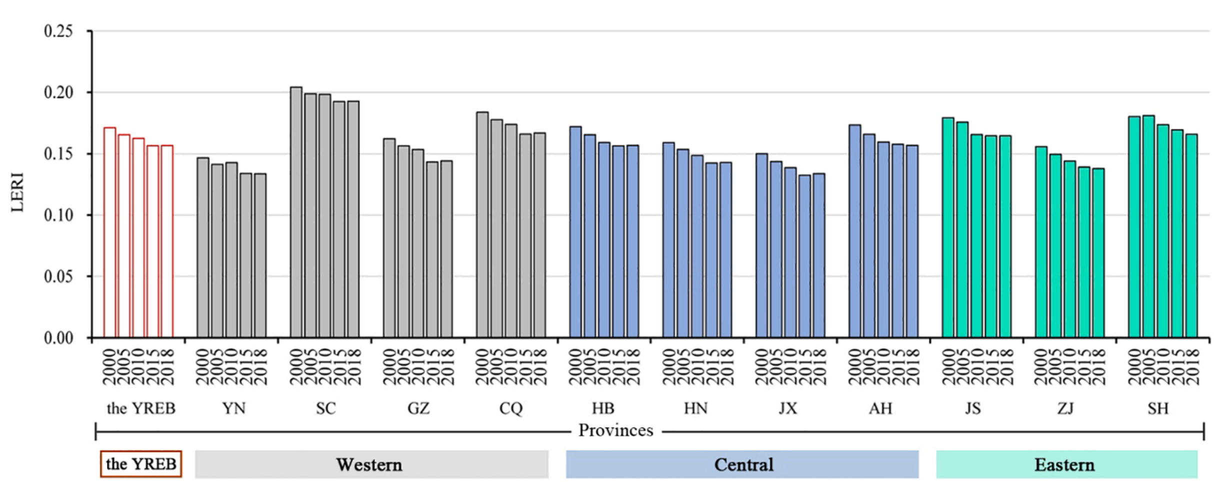

Fig. 4. Average LERI values for the YREB and provinces from 2000 to 2018. Notes: YN: Yunnan, SC: Sichuan, GZ: Guizhou, CQ: Chongqing, HB: Hubei, HN: Hunan; JX: Jiangxi; AH: Anhui, JS: Jiangsu, ZJ: Zhejiang, SH: Shanghai.

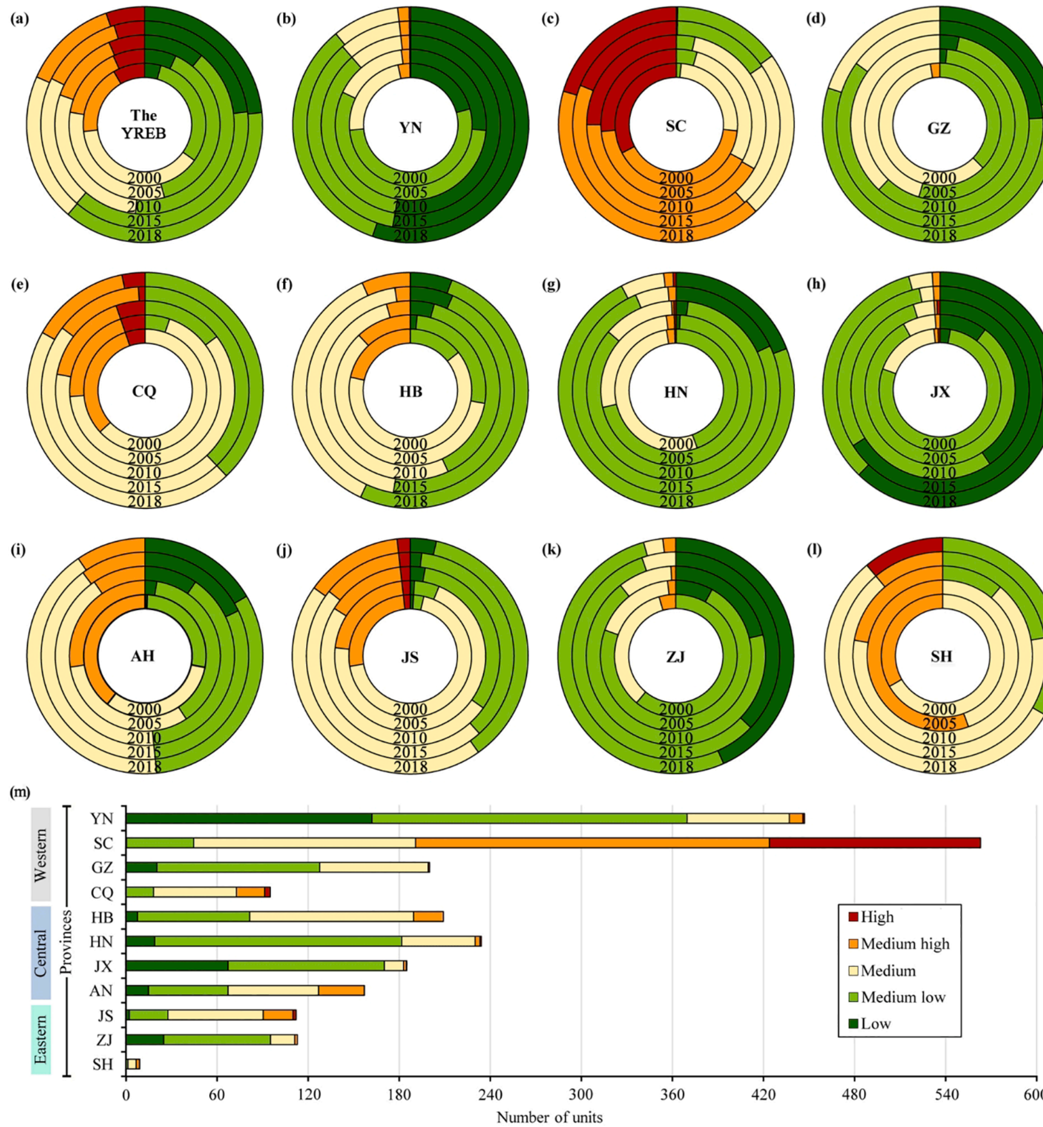

Fig. 5. Risk structure for the five time periods. (a–l): The percentage of risk levels from 2000 to 2018. (m): The average number of units at different risk levels from 2000 to 2018. Notes: YN: Yunnan, SC: Sichuan, GZ: Guizhou, CQ: Chongqing, HB: Hubei, HN: Hunan; JX: Jiangxi; AH: Anhui, JS: Jiangsu, ZJ: Zhejiang, SH: Shanghai.

slight decrease in area of 2109 km^2 over the study period, woodland remained the most extensive land use type throughout the region, covering 940,300 km^2 in 2018 and accounting for 46.09% of the YREB. In contrast, cropland and grassland decreased at rates of 1491 km^2 and 190 km^2 per year, respectively, over the 18-year study period. The cumulative reduction in cropland area was 26,843 km^2, and this figure would have reached 63,112 km^2 if the supplementation of cropland by other land types had not been taken into account. With the accelerated rate if urbanization, urban land was the only land use type for which a continual increase was observed over the study period. While the area of urban land in 2018 represented only 4.03% of the study area, urban areas grew 1.57 times compared to 2000, with a net increase of 29,975 km^2. As a result, in addition to the loss of cropland (approximately 27,692 km^2), approximately 4783 km^2 of woodland, 1702 km^2 of water, and 1150 km^2 of grassland were lost to urban development (Table 2).

3.2. Spatiotemporal dynamics of landscape ecological risk

3.2.1. Spatial patterns of landscape ecological risk

The LERI was calculated for all assessment units and averaged across the 11 provinces and the entire YREB. The average LERI values of the YREB in 2000, 2005, 2010, 2015 and 2018 were 0.1712, 0.1655, 0.1625, 0.1565 and 0.1566, respectively. These findings demonstrate that ecological risk in the YREB decreased steadily from 2000 to 2015 and then stabilized at a relatively low level. The provincial-scale value showed a similar trend. The overall ecological situation in most provinces improved significantly from 2000 to 2015, as evidenced by decreasing risk, and then stabilized after 2015. Some provinces, including Sichuan, Chongqing, Jiangsu, and Shanghai, had relatively higher risk throughout the study period, while Yunnan, Guizhou, Hunan, and Jiangxi had relatively lower risk (Fig. 4).

The natural breaks classification resulted in five categories: high ($0.2176 \leq$ LERI ≤ 0.2935), medium–high ($0.1838 \leq$ LERI < 0.2176), medium ($0.1570 \leq$ LERI < 0.1838), medium–low ($0.1339 \leq$ LERI < 0.1570), and low ($0.0802 \leq$ LERI < 0.1339). These results show that the risk structure of the YREB changed from predominantly medium to high in 2000 and then to predominantly medium–low to low by 2018. This change is evidenced by the growth in the dark-green and light-green rings in 2018 (Fig. 5a). The number of low-risk units increased by 443 (19.07%) from 2000 to 2018. The trends for the provinces were similar to those for the entire YREB, with the majority seeing growth in the low- and medium–low-risk categories and decreases in the high- and

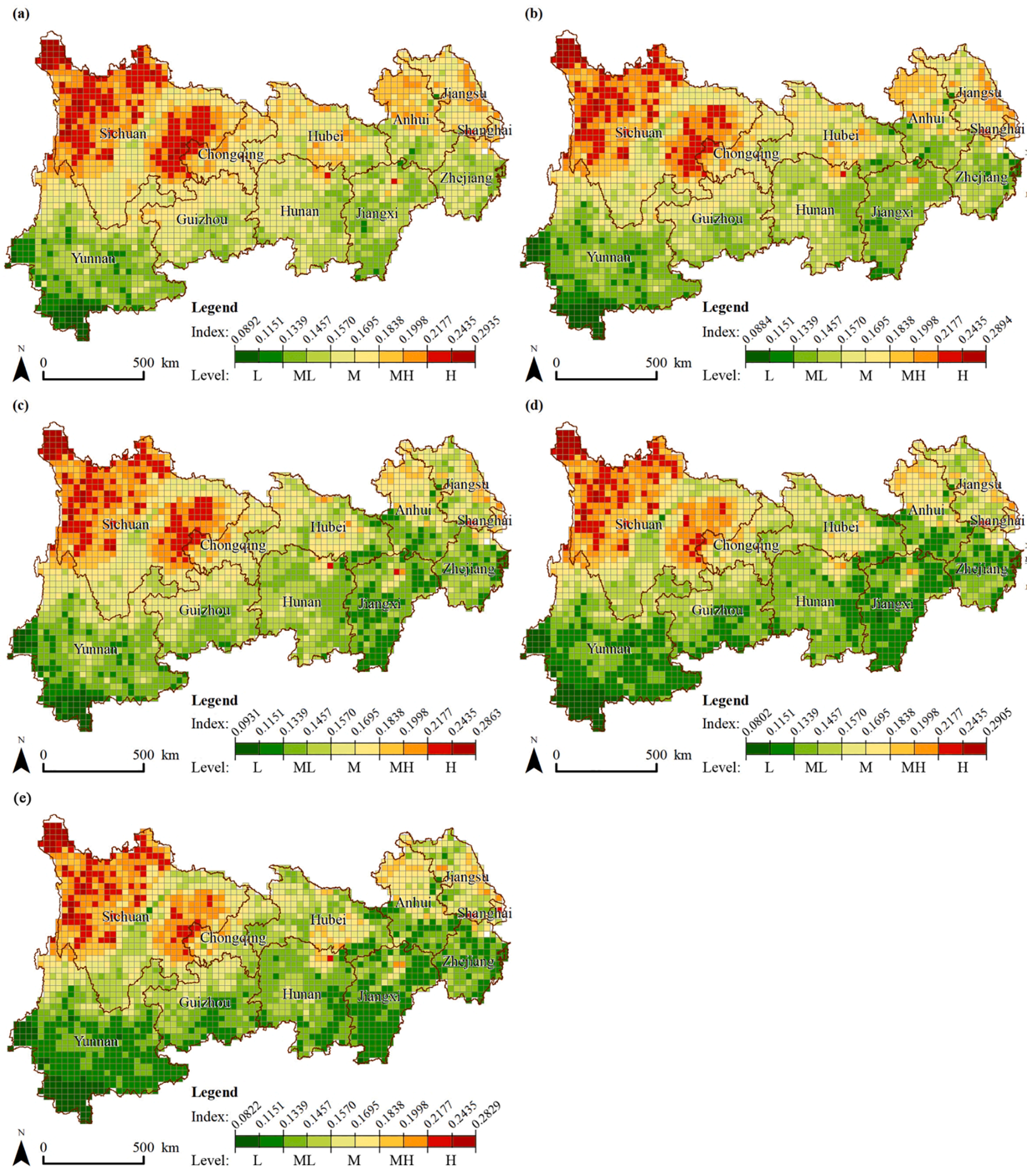

Fig. 6. Maps of landscape ecological risk levels in 2000 (a), 2005 (b), 2010 (c), 2015 (d), and 2018 (e). Notes: L (low), ML (medium–low), M (medium), MH (medium–high), H (high).

medium–high-risk categories (Fig. 5b–l). High- and medium–high-risk units were concentrated mainly within Sichuan Province, and the low- and medium–low-risk units were concentrated mainly in Yunnan, Hunan, and Jiangxi Provinces (Fig. 5m). Shanghai was dominated by medium- to high-risk units throughout the study period but had a weaker impact on the risk structure changes in the entire YREB due to the small size of the province.

At the grid scale, the spatial patterns of the LERI show higher risk in the north Yangtze River area, including the eastern Tibetan Plateau, Sichuan Basin, and Yangtze River Delta. Areas of lower risk are located in the south, mainly the Yunnan-Guizhou Plateau and the Jiangnan Hills (Fig. 6a–e). Over the study period, many units transitioned to an adjacent risk level. For example, many high-risk units shifted to medium–high risk, particularly in Sichuan, Anhui, and Jiangsu Provinces. Low- and medium–low-risk areas expanded, especially moving from south to north, and together, these two categories covered over 60% of the study area by 2018. Additionally, areas of higher risk emerged in certain urban agglomeration areas, such as eastern Sichuan and mideastern Hubei,

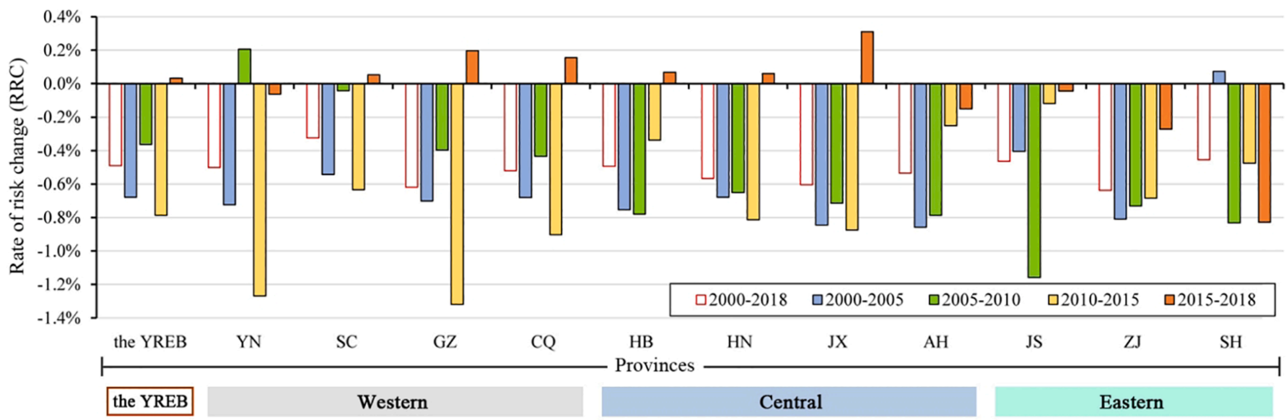

Fig. 7. The rate of risk change for the YREB and provinces in different periods. Notes: YN: Yunnan, SC: Sichuan, GZ: Guizhou, CQ: Chongqing, HB: Hubei, HN: Hunan; JX: Jiangxi; AH: Anhui, JS: Jiangsu, ZJ: Zhejiang, SH: Shanghai.

after 2015.

3.2.2. Spatiotemporal differences in risk changes

The average RRC value of the YREB was −0.49% during 2000–2018. RRC values were lower than the overall YREB value for all provinces except Sichuan, Jiangsu, and Shanghai, indicating that the risk for most provinces declined faster than the risk for the whole study area. When the RRC for the YREB is compared in the different periods, the overall risk declined more rapidly in periods I (2000–2005) and III (2010–2015) and slightly more slowly in period II (2005–2010), with RRC values of −0.68%, −0.79%, and −0.39%, respectively. However, risk in period IV (2015–2018) increased at a rate of 0.39% per year. The same trend occurred in most of the provinces. In addition, the provinces with the most significant changes in each period were Anhui, Jiangxi, and Zhejiang in period I; Jiangxi, Shanghai, and Anhui in period II; Guizhou, Yunnan, and Chongqing in period III; and Shanghai, Jiangxi and Zhejiang in period IV (Fig. 7).

Changes in ecological risk were unevenly distributed. From 2000 to 2018, approximately 99.1% of the units showed risk reduction at a rate of 0% to −1.59% per year. The remaining units that exhibited slightly increased risk were concentrated mainly in eastern Jiangsu and Shanghai Provinces (Fig. 8a). In period I, the units with declining risk were distributed mostly in the central and western regions (Fig. 8b). In period II, there was a clear eastward trend in the areas with declining risk. Large contiguous areas of increasing risk emerged in the southwestern provinces, such as Yunnan and Sichuan (Fig. 8c). In period III, the pattern of units with predominantly declining risk resurfaced, but with a generally faster decline in the north and slower decline in the south (Fig. 8d). In the last period, the units displaying growth in risk increased, covering more than 60% of the study area (Fig. 8e). However, the rate of change was generally lower in the units showing risk growth than in those with declining risk, so the overall risk in the study area did not increase considerably.

3.3. Key areas for ecological risk management

Given the limited resources for management, it is necessary to understand where the most important areas are in order to orient policymaking efforts accordingly (Grantham et al., 2020; Lu et al., 2020). This study sought to identify key areas for future risk management in terms of the dynamic characteristics of ecological risk, including risk status, risk mitigation effectiveness, and risk stability. Accordingly, the three types of key areas are i) stable high-risk areas, ii) risk reduction-lagged areas, and iii) risk-unstable areas. Stable high-risk areas are places where the risk level remained high during the entire study period; these areas thus pose serious and ongoing threats to regional ecological security, which is usually of great concern to risk managers. Risk reduction-lagged areas are areas where the rate of risk reduction was slower, signaling that deficiencies may exist in environmental protection measures that managers have implemented. Risk-unstable areas are areas that did not maintain a stable level of risk under the influence of changing environmental conditions and therefore have a higher probability of increased risk in the future.

To identify key areas, 20% was determined as a threshold for the LERI, RRC, and CVR based on input from experts and local managers. Note that the threshold is flexible and can be adjusted in different regions. We extracted all units falling above the LERI threshold for stable high-risk areas, the RRC threshold for risk reduction-lagged areas, and the CVR threshold for risk-unstable areas. Stable high-risk areas comprise 413 units, with most distributed in the northwestern portion of the YREB and forming two clusters: the West Sichuan Plateau and Sichuan Basin (Fig. 9a). Risk reduction-lagged areas comprise 465 units, of which 62% overlap with stable high-risk areas (Fig. 9b). The remaining units in this category are located mainly in the border area of Hubei and Hunan Provinces and the Yangtze River Delta. Risk-unstable areas comprise 465 units that have little overlap with the previous two types and are scattered in the mountainous and hilly areas of the provinces (Fig. 9c). When the three types are combined, there are a total of 1046 key units for risk management, accounting for 45% of the study area (Fig. 9d). Sichuan Province had the most key areas, followed by Yunnan and Jiangxi Provinces.

4. Discussion

As an integrated and cumulative consequence of multiple stressors, the landscape ecological risk in the YREB is associated with spatiotemporal changes in environmental, socioeconomic, and political factors. Temporally, the overall ecological risk throughout the YREB decreased over the study period with the reduction in medium- to high-risk areas; this finding is consistent with the ecological construction efforts made by the Chinese government. Since 1998, the Chinese government has invested approximately $351.6 billion (in 2015 USD) to implement nationwide ecological programs such as the Natural Forest Conservation Program and the Grain to Green Program (Bryan et al., 2018). In the YREB, over 5.73 million hectares of cultivated land concentrated in mountainous and hilly areas were converted to woodlands, which increased regional forest cover to 41.3% (MEE, 2017). The area of soil erosion was reduced by 3.9 million hectares from 2011 to 2018, and the frequency of natural disasters such as desertification, landslides, and flooding was also considerably reduced (SASS, 2021). In addition, 165 national nature reserves aimed at preserving important ecosystems and habitats for rare species were established in the YREB (Xu et al., 2020). In sum, these measures have contributed to environmental improvements in the YREB.

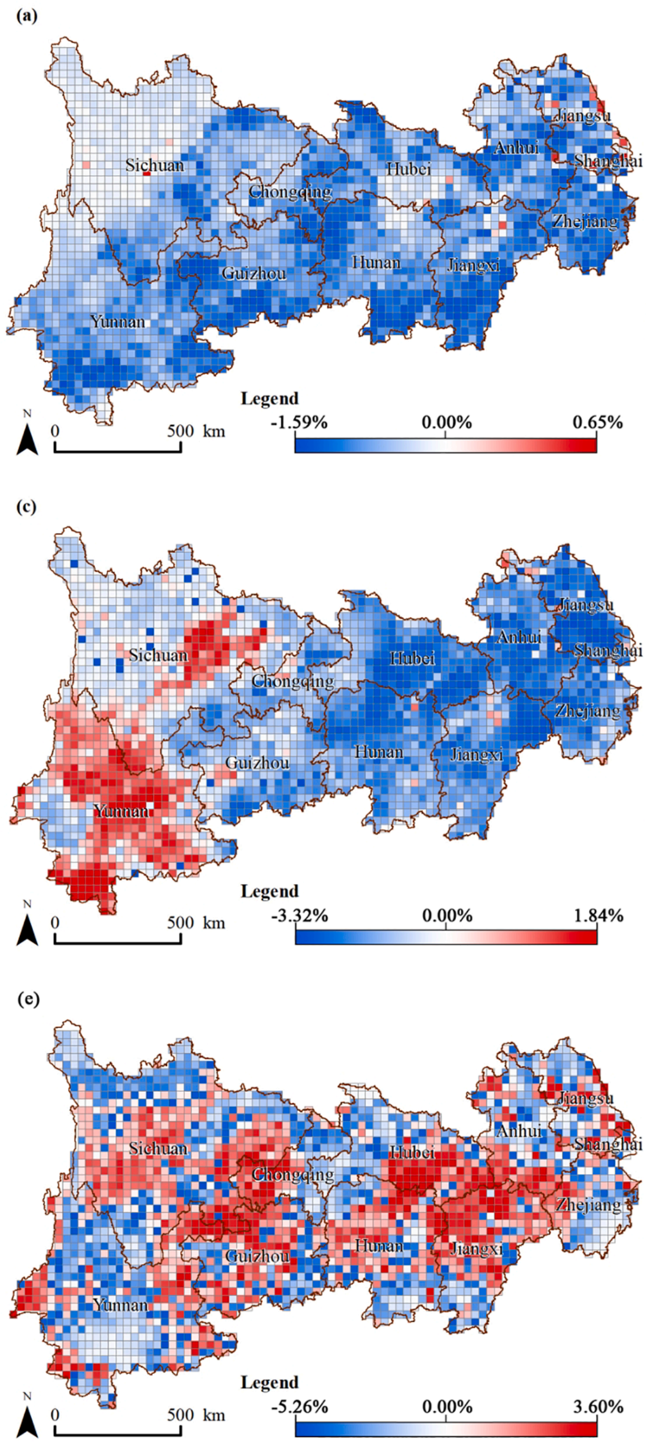

Fig. 8. Maps of the rate of risk change during 2000–2018 (a), 2000–2005 (b), 2005–2010 (c), 2010–2015 (d), and 2015–2018 (e).

However, differentiation policy interventions have also increased the unevenness of risk reduction in the YREB. For instance, the Chinese government gradually increased its land use control and urban planning efforts after the disorderly urban development of the late 20th century (Qu et al., 2020; Zhang et al., 2020). The *National General Land Use Planning in China*, implemented in 1996, strictly limits the amount of land that can be developed in different areas of an administrative district, allowing for more sustainable land use for urban development. *The Regulations of Basic Farmland Protection*, announced in 1999, designated large areas of high-quality arable land around cities as basic farmland that cannot be occupied at will. Rural residential land consolidation extended the reach of land use optimization from urban to rural areas, thus significantly optimizing the rural landscape structure. Facilitated by these measures, ecological conditions around cities in the middle and lower reaches of the Yangtze River changed from destructive to restorative. In contrast, the upper reaches have been treated cautiously and protected from large-scale restoration projects due to the fragile ecological conditions, which has caused a lag in ecological risk mitigation in the region (Fig. 8a).

Spatially, landscape ecological risk in the YREB shows significant

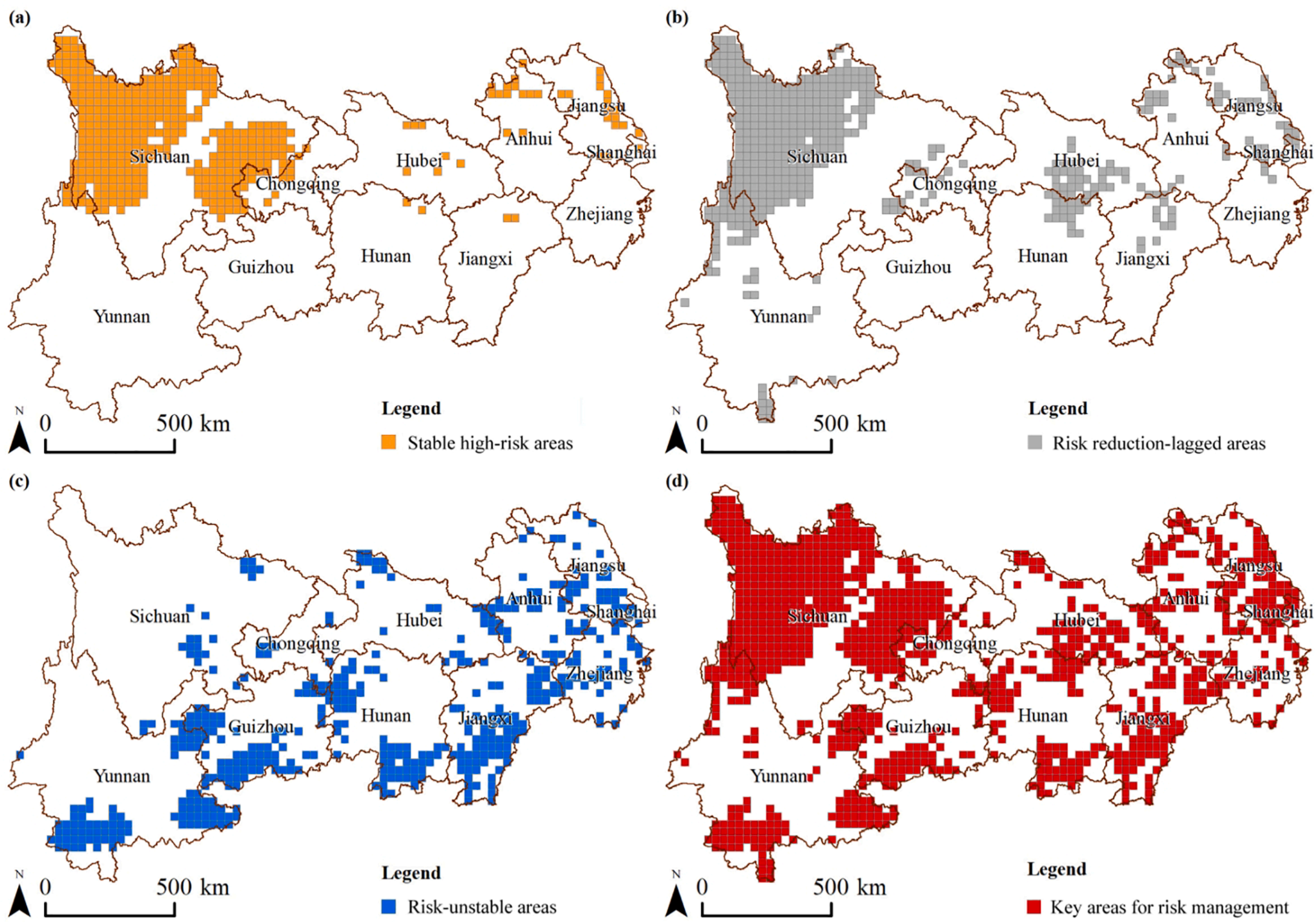

Fig. 9. Spatial distribution of stable high-risk areas (a), risk reduction-lagged areas (b), risk-unstable areas (c), and key areas for risk management (d).

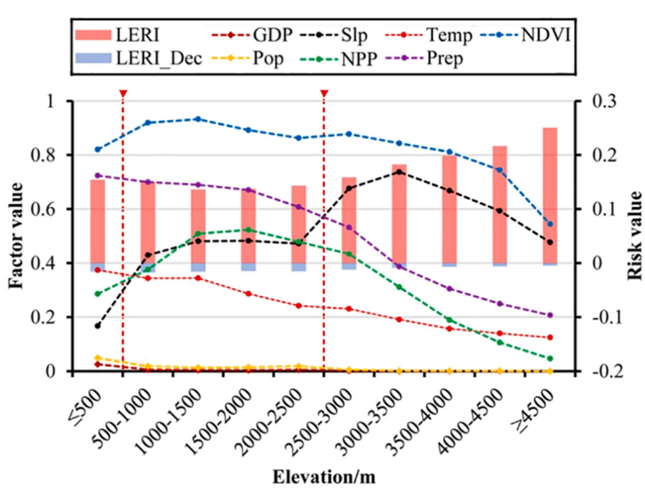

Fig. 10. Relationship between the landscape ecological risk index (LERI), elevation, and other factors, including GDP, population density (Pop), slope (Slp), temperature (Temp), precipitation (Prep), net primary productivity (NPP), and normalized difference vegetation index (NDVI). LERI_Dec is the difference between the LERI in 2018 and the LERI in 2000. The factor value is the mean of the normalized values of all units within the elevation interval in 2018.

heterogeneity under the influence of multiple factors. Zonal statistics based on elevation intervals show that ecological risk first decreases and then increases in response to the changing factors (Fig. 10). More specifically, the area below 500 m in elevation consists of plains and hills and is mainly in the middle and lower reaches of the Yangtze River, where ecological risk is generally low (Fig. 1). There is abundant precipitation and moderate temperatures, which are more suitable for wildlife survival and vegetation growth (Li et al., 2014). However, it is also an area of concentrated population and economic development, with numerous large cities. High-intensity industrial and agricultural activities put tremendous pressure on regional ecosystems, increasing local ecological risks (Hu et al., 2017). In contrast, the area between 500 and 2500 m in elevation has less urban and agricultural land use and thus significantly less human disturbance of the environment. Additionally, the vegetation density is high, fostered by adequate temperatures and precipitation (Lu et al., 2020). These factors are beneficial for maintaining natural landscapes and ecological vitality, and the ecological risk in the region is generally low. As elevation increases above 2500 m, the topography of the region becomes extremely complex, while the temperatures, precipitation, and productivity level of vegetation also drop to a low level. This leads to increased landscape vulnerability, exacerbating the occurrence of natural hazards such as desertification, landslides, and debris flows and making the adverse ecological consequences of human interference much more severe than at lower elevations (Wang et al., 2020). As a result, the West Sichuan Plateau exhibited the highest risk during 2000–2018 (Fig. 6a–e).

Based on our analysis, the following measures are considered to be important points of departure for future risk management in the YREB. First, we recommend strengthening the leading and supervisory role of the government in risk management. A risk management system that prioritizes key areas through adequate policy guidance and financial support should be established as soon as possible. It will be crucial to formulate policies and regulations to clarify the responsibilities of all entities, including the government, enterprises, and individuals. To balance the interests of stakeholders and stimulate environmental contributions, ecological compensation must be further improved (Lu et al., 2020; Xu et al., 2020). In addition, regional coordination mechanisms should be established for key conservation areas across administrative regions, such as the Chengdu-Chongqing Economic Circle, to jointly address major issues of economic development and ecological protection through cooperation (Xu et al., 2021). Second, we recommend integrating risk management into development planning. In the next round of territorial spatial planning in the YREB, ecological "red zones" should be delineated to compulsorily protect valued and fragile ecological spaces. Plans should also be made for development intensity, industrial land use layout, and the retirement of farming and grazing to regulate regional development and construction (Lu et al., 2020). Additionally, there is a complementary need to develop detailed conservation plans with the goal of creating sustainable landscapes for each city, especially the construction of green ecological corridors (Luo et al., 2020). Third, we recommend developing and applying more new technologies. Nature-based solutions should be widely applied to the restoration of ecologically fragile areas because of their great potential for improving ecological resilience (Virah-Sawmy et al., 2016). In addition, ecological monitoring technologies for natural disasters, vegetation dynamics, and biodiversity are necessary to prevent possible future threats to ecological security.

There are some limitations in this study. First, the evaluation cells were set to a resolution of 30 km $\times$ 30 km to reasonably control the complexity of the calculation (Mo et al., 2017; Wang et al., 2021). Some local risk characteristics cannot be captured at that scale, which means that the results are not a panacea that informs all levels of risk management. Comparative analysis of multiple scales is an important direction for further research (Li et al., 2020). Second, the accuracy of the assessment results is constrained by the underlying data. For example, although the land use map used in the study is one of the most accurate remote sensing monitoring data products in China (Zhang et al., 2020), there are still deviations between the classification results and the actual situation. Timely updating of data is necessary for future risk assessment and management. Finally, although the suitability of ERA methods based on landscape pattern indices has been proven in many studies, these methods do not yet provide a desirable assessment endpoint (Gong et al., 2021). Incorporating ecosystem services into landscape ERA has become a powerful trend due to the great potential to enhance the directionality of risk management (Forbes and Galic, 2016; Munns et al., 2016). In the future, we will make efforts in these directions to advance the growth of knowledge and experience.

5. Conclusions

Drastic land use changes have significantly altered landscape patterns and ecological processes, posing a potential threat to regional sustainable development. This study develops an ERA framework that integrates landscape patterns and landscape vulnerability dynamics to assess landscape ecological risk in the YREB from 2000 to 2018. The study is the first attempt of its kind. The results confirm that natural conditions and human activities together dominated the spatiotemporal patterns of ecological risks in the YREB for the eighteen years of the study. The fragile and sensitive environment has made the upper Yangtze River the highest-risk area in the YREB. At the same time, higher-risk clusters are found in urban areas such as the Cheng-Yu urban agglomeration and the Yangtze River Delta urban agglomeration, illustrating the negative impact of human disturbance on ecosystems. Temporally, ecological risk in the YREB presents a decreasing trend, and the areas designated as high or medium–high risk decreased by 150,000 km^2. These findings are a positive sign that actions taken by the Chinese government, such as reasonable land use control and continuous ecological restoration, can reduce ecological risks. Overall, approximately 45% of the study area is currently in a relative emergency situation for risk management. For the YREB to become a sustainable region, it is necessary to strengthen the adaptive management of ecological risks through policy innovation, planning guidance, and technology innovation for ecosystem restoration. As valuable empirical evidence, the findings of this study can be used to directly support the decision-making process. In a wider context, this work will benefit those seeking to apply similar assessments, especially when performing landscape ERA in rapidly changing environmental conditions, as it reduces assessment uncertainty with improvements to the methodology.

CRediT authorship contribution statement

Penglai Ran: Conceptualization, Methodology, Writing – original draft. **Shougeng Hu:** Supervision, Conceptualization, Writing – review & editing. **Amy E. Frazier:** Methodology, Writing – review & editing. **Shijin Qu:** Data curation, Formal analysis. **De Yu:** Investigation. **Luyi Tong:** Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the Key Project from the National Social Science Foundation of China (Grant No. 18ZDA053). A.E.F. is partially supported by the U.S. National Science Foundation (Grant No. 1934759).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2022.108744.

References

Ayre, K.K., Landis, G.W., 2012. A Bayesian approach to landscape ecological risk assessment applied to the upper Grande ronde watershed, Oregon. Hum. Ecol. Risk Assess. 18, 946–970. http://www.tandfonline.com/loi/bher20.

Bryan, B.A., Gao, L., Ye, Y., Sun, X., Connor, J.D., Crossman, N.D., Stafford-Smith, M., Wu, J., He, C., Yu, D., Liu, Z., Li, A., Huang, Q., Ren, H., Deng, X., Zheng, H., Niu, J., Han, G., Hou, X., 2018. China's response to a national land-system sustainability emergency. Nature. 559 (7713), 193–204. https://doi.org/10.1038/s41586-018-0280-2.

Cao, Q., Zhang, X., Lei, D., Guo, L., Sun, X., Kong, F., Wu, J., 2019. Multi-scenario simulation of landscape ecological risk probability to facilitate different decision-making preferences. J. Clean Prod. 227, 325–335. https://doi.org/10.1016/j.jclepro.2019.03.125.

Chen, J., Dong, B., Li, H., Zhang, S., Peng, L., Fang, L., Zhang, C., Li, S., 2020. Study on landscape ecological risk assessment of hooded crane breeding and overwintering habitat. Environ. Res. 187, 109649. https://doi.org/10.1016/j.envres.2020.109649.

Dai, X., Gao, Y.u., He, X., Liu, T., Jiang, B., Shao, H., Yao, Y., 2021. Spatial-temporal pattern evolution and driving force analysis of ecological environment vulnerability in Panzhihua City. Environ. Sci. Pollut. Res. 28 (6), 7151–7166. https://doi.org/10.1007/s11356-020-11013-6.

Dalloz, M.F., Crouzeilles, R., Almeida-Gomes, M., Papi, B., Prevedello, J.A., 2017. Incorporating landscape ecology metrics into environmental impact assessment in the Brazilian Atlantic forest. Perspect. Ecol. Conserv. 15 (3), 216–220. https://doi.org/10.1016/j.pecon.2017.07.002.

De Lange, H.J., Sala, S., Vighi, M., Faber, J.H., 2010. Ecological vulnerability in risk assessment—a review and perspectives. Sci. Total Environ. 408 (18), 3871–3879. https://doi.org/10.1016/j.scitotenv.2009.11.009.

Döring, T.F., Reckling, M., 2018. Detecting global trends of cereal yield stability by adjusting the coefficient of variation. Eur. J. Agron. 99, 30–36. https://doi.org/10.1016/j.eja.2018.06.007.

Forbes, V.E., Galic, N., 2016. Next-generation ecological risk assessment: predicting risk from molecular initiation to ecosystem service delivery. Environ. Int. 91, 215–219. https://doi.org/10.1016/j.envint.2016.03.002.

Forman, R.T.T., 1995. Some general principles of landscape and regional ecology. Landsc. Ecol. 10 (3), 133–142. https://doi.org/10.1007/BF00133027.

Frazier, A.E., Bryan, B.A., Buyantuev, A., Chen, L., Echeverria, C., Jia, P., Liu, L., Li, Q., Ouyang, Z., Wu, J., Xiang, W.-N., Yang, J., Yang, L., Zhao, S., 2019. Ecological civilization: perspectives from landscape ecology and landscape sustainability science. Landsc. Ecol. 34 (1), 1–8. https://doi.org/10.1007/s10980-019-00772-4.

Gaines, K.F., Porter, D.E., Dyer, S.A., Wein, G.R., Pinder, J.E., Lehr Brisbin, I., 2004. Using wildlife as receptor species: a landscape approach to ecological risk assessment. Environ. Manage. 34 (4), 528–545. https://doi.org/10.1007/s00267-004-0261-0.

Gallopín, G.C., 2006. Linkages between vulnerability, resilience, and adaptive capacity. Glob. Environ. Change-Human Policy Dimens. 16 (3), 293–303. https://doi.org/10.1016/j.gloenvcha.2006.02.004.

Gong, J., Cao, E., Xie, Y., Xu, C., Li, H., Yan, L., 2021. Integrating ecosystem services and landscape ecological risk into adaptive management: insights from a western mountain-basin area, China. J. Environ. Manage. 281, 111817. https://doi.org/10.1016/j.jenvman.2020.111817.

Goussen, B., Price, O.R., Rendal, C., Ashauer, R., 2016. Integrated presentation of ecological risk from multiple stressors. Sci. Rep. 6, 36004. https://doi.org/10.1038/srep36004.

Grantham, H.S., Shapiro, A., Bonfils, D., Gond, V., Goldman, E., Maisels, F., Plumptre, A. J., Rayden, T., Robinson, J.G., Strindberg, S., Stokes, E., Tulloch, A.I.T.T., Watson, J. E.M., Williams, L., Rickenbach, O., 2020. Spatial priorities for conserving the most intact biodiverse forests within Central Africa. Environ. Res. Lett. 15, 0940b5. https://doi.org/10.1088/1748-9326/ab9fae.

Hope, B.K., 2006. An examination of ecological risk assessment and management practices. Environ. Int. 32 (8), 983–995. https://doi.org/10.1016/j.envint.2006.06.005.

Hu, B., Jia, X., Hu, J., Xu, D., Xia, F., Li, Y., 2017. Assessment of heavy metal pollution and health risks in the soil-plant-human system in the Yangtze River Delta, China. Int. J. Environ. Res. Public Health. 14, 1042. https://doi.org/10.3390/ijerph14091042.

Huang, Y., Li, F., Bai, X., Cui, S., 2012. Comparing vulnerability of coastal communities to land use change: analytical framework and a case study in China. Environ. Sci. Policy. 23, 133–143. https://doi.org/10.1016/j.envsci.2012.06.017.

Hunsaker, C.T., Graham, R.L., Suter, G.W., O'Neill, R.V., Barnthouse, L.W., Gardner, R. H., 1990. Assessing ecological risk on a regional scale. Environ. Manage. 14 (3), 325–332. https://doi.org/10.1007/BF02394200.

Jin, X., Jin, Y., Mao, X., 2019. Ecological risk assessment of cities on the Tibetan Plateau based on land use/land cover changes – case study of Delingha city. Ecol. Indic. 101, 185–191. https://doi.org/10.1016/j.ecolind.2018.12.050.

Khan, N.A., Gao, Q., Abid, M., Shah, A.A., 2021. Mapping farmers' vulnerability to climate change and its induced hazards: evidence from the rice-growing zones of Punjab, Pakistan. Environ. Sci. Pollut. Res. 28 (4), 4229–4244. https://doi.org/10.1007/s11356-020-10758-4.

Lal, P., Shekhar, A., Kumar, A., 2021. Quantifying temperature and precipitation change caused by land cover change: a case study of India Using the WRF Model. Front. Environ. Sci. 9, 766328. https://doi.org/10.3389/fenvs.2021.766328.

Landis, W.G., 2003. Twenty years before and hence; ecological risk assessment at multiple scales with multiple stressors and multiple endpoints. Hum. Ecol. Risk Assess. 9 (5), 1317–1326. https://doi.org/10.1080/10807030390248500.

Landis, W.G., Durda, J.L., Brooks, M.L., Chapman, P.M., Menzie, C.A., Stahl, R.G., Stauber, J.L., 2013. Ecological risk assessment in the context of global climate change. Environ. Toxicol. Chem. 32 (1), 79–92. https://doi.org/10.1002/etc.2047.

Li, W., Wang, Y., Xie, S., Sun, R., Cheng, X., 2020. Impacts of landscape multifunctionality change on landscape ecological risk in a megacity, China: a case study of Beijing. Ecol. Indic. 117, 106681. https://doi.org/10.1016/j.ecolind.2020.106681.

Li, X., Yu, X., Jiang, L., Li, W., Liu, Y., Hou, X., 2014. How important are the wetlands in the middle-lower Yangtze River region: an ecosystem service valuation approach. Ecosyst. Serv. 10, 54–60. https://doi.org/10.1016/j.ecoser.2014.09.004.

Liu, Y., Zhang, X., Kong, X., Wang, R., Chen, L., 2018. Identifying the relationship between urban land expansion and human activities in the Yangtze River Economic Belt, China. Appl. Geogr. 94, 163–177. https://doi.org/10.1016/j.apgeog.2018.03.016.

Liu, Y., Li, T., Zhao, W., Wang, S., Fu, B., 2019. Landscape functional zoning at a county level based on ecosystem services bundle: methods comparison and management indication. J. Environ. Manage. 249, 109315. https://doi.org/10.1016/j.jenvman.2019.109315.

Loibl, W., Smidt, S., 1996. Ozone exposure Areas of potential ozone risk for selected tree species in Austria. Environ. Sci. Pollut. Res. 3 (4), 213–217. https://doi.org/10.1007/BF02986962.

Lu, S., Tang, X.u., Guan, X., Qin, F., Liu, X.u., Zhang, D., 2020. The assessment of forest ecological security and its determining indicators: a case study of the Yangtze River Economic Belt in China. J. Environ. Manage. 258, 110048. https://doi.org/10.1016/j.jenvman.2019.110048.

Luo, F., Liu, Y., Peng, J., Wu, J., 2018. Assessing urban landscape ecological risk through an adaptive cycle framework. Landsc. Urban Plan. 180, 125–134. https://doi.org/10.1016/j.landurbplan.2018.08.014.

Luo, Q., Zhou, J., Li, Z., Yu, B., 2020. Spatial differences of ecosystem services and their driving factors: a comparation analysis among three urban agglomerations in China's Yangtze River Economic Belt. Sci. Total Environ. 725, 138452. https://doi.org/10.1016/j.scitotenv.2020.138452.

Mann, D., Anees, M.M., Rankavat, S., Joshi, P.K., 2021. Spatio-temporal variations in landscape ecological risk related to road network in the Central Himalaya. Hum. Ecol. Risk Assess. 27 (2), 289–306. https://doi.org/10.1080/10807039.2019.1710693.

McGarigal, K., Cushman, S.A., Ene, E., 2012. FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical and Continuous Maps. Computer software program produced by the authors at the University of Massachusetts, Amherst, Available at the following web site: http://www.umass.edu/landeco/research/fragstats/ fragstats.html.

MEE PRC., 2017. The ecological and environmental protection planning for Yangtze River Economic Belt. http://www.mee.gov.cn/gkml/hbb/bwj/201707/t20170718_418053.htm. Accessed 17 July 2017.

Meng, L., Wang, C., Zhang, J., 2016. Heat injury risk assessment for single-cropping rice in the middle and lower reaches of the Yangtze River under climate change. J. Meteorol. Res. 30 (3), 426–443. https://doi.org/10.1007/s13351-016-5186-z.

Mo, W., Wang, Y., Zhang, Y., Zhuang, D., 2017. Impacts of road network expansion on landscape ecological risk in a megacity, China: a case study of Beijing. Sci. Total Environ. 574, 1000–1011. https://doi.org/10.1016/j.scitotenv.2016.09.048.

Munns, W.R., Rea, A.W., Suter, G.W., Martin, L., Blake-Hedges, L., Crk, T., Davis, C., Ferreira, G., Jordan, S., Mahoney, M., Barron, M.G., 2016. Ecosystem services as assessment endpoints for ecological risk assessment. Integr. Environ. Assess. Manag. 12 (3), 522–528. https://doi.org/10.1002/ieam.1707.

Ning, J., Liu, J., Kuang, W., Xu, X., Zhang, S., Yan, C., Li, R., Wu, S., Hu, Y., Du, G., Chi, W., Pan, T., Ning, J., 2018. Spatiotemporal patterns and characteristics of land-use change in China during 2010–2015. J. Geogr. Sci. 28 (5), 547–562. https://doi.org/10.1007/s11442-018-1490-0.

Paukert, C.P., Pitts, K.L., Whittier, J.B., Olden, J.D., 2011. Development and assessment of a landscape-scale ecological threat index for the lower Colorado River Basin. Ecol. Indic. 11 (2), 304–310. https://doi.org/10.1016/j.ecolind.2010.05.008.

Peng, J., Dang, W., Liu, Y., Zong, M., Hu, X., 2015a. Review on landscape ecological risk assessment. Acta. Geogr. Sin. 04, 664–677. https://doi.org/10.11821/dlxb201504013. In Chinese.

Peng, J., Zong, M., Hu, Y., Liu, Y., Wu, J., 2015b. Assessing landscape ecological risk in a mining city: a case study in Liaoyuan City, China. Sustainability. 7, 8312–8334. https://doi.org/10.3390/su7078312.

Picado-Aguilar, G., Aguero-Valverde, J., 2020. Emergency response times and crash risk: an analysis framework for Costa Rica. J. Transp. Health 16, 100818. https://doi.org/10.1016/j.jth.2019.100818.

Piet, G.J., Knights, A.M., Jongbloed, R.H., Tamis, J.E., de Vries, P., Robinson, L.A., 2017. Ecological risk assessments to guide decision-making: methodology matters. Environ. Sci. Policy. 68, 1–9. https://doi.org/10.1016/j.envsci.2016.11.009.

Qiu, B., Li, H., Zhou, M., Zhang, L., 2015. Vulnerability of ecosystem services provisioning to urbanization: a case of China. Ecol. Indic. 57, 505–513. https://doi.org/10.1016/j.ecolind.2015.04.025.

Qu, S., Hu, S., Li, W., Wang, H., Zhang, C., Li, Q., 2020. Interaction between urban land expansion and Land Use Policy: an analysis using the DPSIR framework. Land Use Pol. 99, 104856. https://doi.org/10.1016/j.landusepol.2020.104856.

SASS., 2021 Annual report on the ecological development of Yangtze River Economic Belt (2019–2020). http://cyrdebr.sass.org.cn/2020/1223/c5775a100923/page.htm. Accessed 23 December 2020.

Serveiss, V.B., 2002. Applying ecological risk principles to watershed assessment and management. Environ. Manage. 29 (2), 145–154.

Shea, D., Thorsen, W., 2012. Chapter twelve—ecological risk assessment. Prog. Molec. Biol. Transl. Sci. 112, 323–348. https://doi.org/10.1016/B978-0-12-415813-9.00012-X.

Solovjova, N.V., 2019. Ecological risk modelling in developing resources of ecosystems characterized by varying vulnerability levels. Ecol. Model. 406, 60–72. https://doi.org/10.1016/j.ecolmodel.2019.05.015.

Suter II, G.W., 1990. Endpoints for regional ecological risk assessments. Environ. Manage. 14, 9–23. https://doi.org/10.1007/BF02394015.

USEPA., 1998. Guidelines for ecological risk assessment. https://www.epa.gov/risk/guidelines-ecological-risk-assessment. Accessed 28 November 2021.

Van den Brink, P.J., Choung, C.B., Landis, W., Mayer-Pinto, M., Pettigrove, V., Scanes, P., Smith, R., Stauber, J., 2016. New approaches to the ecological risk assessment of multiple stressors. Mar. Freshw. Res. 67, 429–439. https://doi.org/10.1071/MF15111.

Virah-Sawmy, M., Gillson, L., Gardner, C.J., Anderson, A., Clark, G., Haberle, S., 2016. A landscape vulnerability framework for identifying integrated conservation and adaptation pathways to climate change: the case of Madagascar's spiny forest. Landsc. Ecol. 31 (3), 637–654. https://doi.org/10.1007/s10980-015-0269-2.

Wade, A.A., Theobald, D.M., Laituri, M.J., 2011. A multi-scale assessment of local and contextual threats to existing and potential U.S. protected areas. Landsc. Urban Plan. 101 (3), 215–227. https://doi.org/10.1016/j.landurbplan.2011.02.027.

Wang, B., Ding, M., Li, S., Liu, L., Ai, J., 2020. Assessment of landscape ecological risk for a cross-border basin: a case study of the Koshi River Basin, central Himalayas. Ecol. Indic. 117, 106621. https://doi.org/10.1016/j.ecolind.2020.106621.

Wang, H., Liu, X., Zhao, C., Chang, Y., Liu, Y., Zang, F., 2021. Spatial-temporal pattern analysis of landscape ecological risk assessment based on land use/land cover change in Baishuijiang national nature reserve in Gansu Province, China. Ecol. Indic. 124, 107454. https://doi.org/10.1016/j.ecolind.2021.107454.

Wu, J., 2019. Linking landscape, land system and design approaches to achieve sustainability. J. Land Use Sci. 14 (2), 173–189. https://doi.org/10.1080/1747423X.2019.1602677.

Wu, S., Zhou, S., Bao, H., Chen, D., Wang, C., Li, B., Tong, G., Yuan, Y., Xu, B., 2019. Improving risk management by using the spatial interaction relationship of heavy metals and PAHs in urban soil. J. Hazard. Mater. 345, 108–116. https://doi.org/10.1016/j.jhazmat.2018.09.094.

Xu, X., Jiang, B.o., Chen, M., Bai, Y., Yang, G., 2020. Strengthening the effectiveness of nature reserves in representing ecosystem services: the Yangtze River Economic Belt in China. Land Use Pol. 96, 104717. https://doi.org/10.1016/j.landusepol.2020.104717.

Xu, W., Wang, J., Zhang, M., Li, S., 2021. Construction of landscape ecological network based on landscape ecological risk assessment in a large-scale opencast coal mine area. J. Clean Prod. 286, 125523. https://doi.org/10.1016/j.jclepro.2020.125523.

Zhang, W., Chang, W.J., Zhu, Z.C., Hui, Z., 2020. Landscape ecological risk assessment of Chinese coastal cities based on land use change. Appl. Geogr. 117, 102174. https://doi.org/10.1016/j.apgeog.2020.102174.

Zhang, Y., Fan, G., He, Y., Cao, L., 2017. Risk assessment of typhoon disaster for the Yangtze River Delta of China. Geomat. Nat. Hazards Risk. 8 (2), 1580–1591. https://doi.org/10.1080/19475705.2017.1362040.

Zhang, Y., Sun, M., Yang, R., Li, X., Zhang, L.e., Li, M., 2021. Decoupling water environment pressures from economic growth in the Yangtze River Economic Belt, China. Ecol. Indic. 122, 107314. https://doi.org/10.1016/j.ecolind.2020.107314.

Zhong, Y., Lin, A., He, L., Zhou, Z., Yuan, M., 2020. Spatiotemporal dynamics and driving forces of urban land-use expansion: a case study of the Yangtze River Economic Belt, China. Remote Sens. 12, 287. https://doi.org/10.3390/rs12020287.