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RESEARCH ARTICLE

Early warning level identification and evolutionary trend prediction of ecological risk in the upper Chang Jiang (Yangtze R.), China

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Abstract Ecological risk is a dynamic reflection of ecosystem stability and harmonious social development. The role played by risk identification and evolutionary trend prediction as mediators between ecological risk management and prevention is complex. However, current studies have difficulty identifying where, when, and how ecological risk evolves. Here, we constructed a double evaluation index system of ecological risk source hazard and ecological risk receptor loss degree to quantitatively evaluate and simulate ecological risk in the upper Chang Jiang (Yangtze R.) (UYR). Then, we adopted the normal cloud model to identify the ecological risk level at different scales in the UYR. Finally, we leveraged set pair analysis to reveal the future evolution trend of ecological risk in the UYR. The following conclusions were drawn. 1) From 2015 to 2018, the ecological risk in the UYR exhibited significant spatial aggregation characteristics, with a spatial distribution pattern of "high in the west, low in the east". The risk value increased from [0, 0.28] to [0, 0.32], an increase of 12.49%. 2) The ecological risk level of the UYR in 2015 and 2018 was in a high-alert state, but the risk value showed a downward annual trend. The comprehensive ecological risk value decreased from 0.5295 to 0.5135. 3) The ecological risk of 67% of the cities in the UYR will decrease in the future, and will increase in 33% of the cities. 4) The probability of geological disasters was the most significant ecological risk source in the UYR. Ecosystem service value significantly impacted ecological risk receptors loss degree in the UYR.

Keywords watershed ecological risk, the upper Chang Jiang (Yangtze R.), early warning

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1 Introduction

Ecological risk is the likelihood of an ecosystem or landscape function being damaged due to anthropogenic interference (Ni et al., 2019; Cao and Song, 2022; Liang and Song, 2022). Ecological risk assessment is used to study the degree of damage caused by various risk pressure sources to an ecosystem's components, structures, and functions (Gibbs, 2011; Probert et al., 2020; Liao et al., 2022). The deterioration of ecological risk depends on the pressure from risks posed on ecosystems under different scales and risk sources. Understanding the probability of ecological risk, ecological risk warning level, and future evolution trends is crucial for managing ecological risk.

In the past, attempts enacted "zero risk" management objectives to ensure that an ecosystem was stable within an absolutely safe boundary. However, ecological risk depends on long-term socioecological and natural ecosystems that do not disappear. The rejection of the "zero risk" management goal prompted quantifying ecological risk under the model of balancing risk levels and reducing risk costs. Major related studies cover four areas. 1) Driving factor analysis. Emphasis has shifted from single factors to multiple risk sources—the simultaneous influence of multiple risk receptors on ecosystem processes (Jin et al., 2020; Li et al., 2020; Karimian et al., 2022; Wang et al., 2022; Zhang et al., 2022a). Driving factors are determined by considering natural and artificial factors (Gong et al., 2021). Among them, natural driving factors mainly comprise elevation (Guo et al., 2022), slope (Xue et al., 2019), climate (Fu et al., 2020), precipitation (Liu and Chen, 2020; Duan et al., 2022), and Normalized Difference Vegetation Index (NDVI) (Ran et al., 2022). The driving factors of human influence usually consider the influencing factors of frequent human activities, such as land use structure (Wang et al., 2021b; Liu et al., 2022), social economy (Shi et al., 2021), population density (Ai et al., 2022), and urbanization level (Xie et al., 2021). For example, using a geographical detector, (Karimian et al. 2022) explored the impact of driving factors (e.g., human disturbance index, NDVI) on ecological risk. 2) Ecological risk assessment methods. Ecological risk assessment systems have experienced major shifts as environmental chemical contaminants span across ecological events (bioengineering or biological invasion) and composite risk sources (natural ecological risk, human activity ecological risk) increase. The methods used for ecological risk assessment have also changed from the sample sampling method to the index calculation method and model simulation method. The sample sampling method mainly assesses environmental chemical contaminants. In environmental science, heavy metals such as Pb, Zn, Cu, Cd, and As have been sampled to explore the risks caused by heavy metal pollution to the environment (Chen et al., 2019; Yao et al., 2019; Proshad et al., 2022). Index calculation methods are widely used in larger-scale areas, including correlation analysis (Liu et al., 2020b), relative risk assessment (Vezi et al., 2020), DPSIRM model (Du et al., 2023), and fuzzy composite index method (Jiao et al., 2021). Model simulation method includes Monte Carlo model (Liu et al., 2020a), geographically weighted regression (Li et al., 2022), spatial autocorrelation (Ji et al., 2021), coupled coordination models (Shi et al., 2022), geographic detectors (Yang et al., 2022), and Bayesian network models (Guo et al., 2020). Zhang et al. (2020) simulated the risk relationship between urban agglomerations and air pollution and water pollution using a Bayesian network model. Liu and Chen (2020) used a probabilistic risk characterization method to explore ecological risk evolution. 3) Ecological risk simulation. Previous studies were based mainly on retrospective ecological risk assessment, that is, evaluating the hazard of specific risk caused by known pressure after the risk source is known or predicted to have entered the environment. At present, the prediction of ecological risk evolution trends is based mainly on dynamic spatial evolution analysis and static temporal evolution analysis using historical data (Wu et al., 2021a). The transfer matrix method (Wang et al., 2020) and future simulation data (Wang et al., 2021a) are commonly used in the analysis of ecological risk evolution trends based on dynamic spatial evolution. The risk change rate, or variable coefficient, is often used to characterize the evolution trend of ecological risk under static temporal evolution. Qiao et al. (2021) combined a transfer matrix and landscape pattern index to explore the spatiotemporal evolution pattern of landscape ecological risk. Wang et al. (2021a) explored the future ecological risk evolution trend of the Qinghai-Tibet Plateau using simulation data. Ran et al. (2022) used the coefficient of variation to explore the change rate of landscape ecological risk in the Chang Jiang (Yangtze R.) Economic Belt.

Ecological risk assessment follows the basic structural framework of “problem formation-risk analysis-risk characterization”. At present, a research paradigm of “risk classification-risk identification-evolution simulation” has formed. The classification of the early warning level determines the identification of risk areas, determining the simulation of the evolution trend. The interaction of multisource impact factors aggravates the probability of ecological risk. In addition, the uncertainty of the impact factor easily causes uncertainty and ambiguity in determining the early warning level. With the leap from historical evolution trend simulation to future evolution trend prediction, revealing the relationship between various uncertainty factors and quantitatively predicting the future risk evolution trend has become a major problem. The normal cloud model and set pair analysis provide a rich foundation for identifying risk warning levels and predicting evolutionary trends. The normal cloud model considers both the ambiguity of the data and the uncertainty of the evaluation level and can objectively analyze the ecological risk membership level. Set pair analysis combines the advantages of uncertain systems and can simulate the future evolution trend of complex systems. Both are increasingly used in decision-making for environmental protection, risk assessment, and disaster prediction. For example, Ge et al. (2020) coupled set pair analysis and a cloud model to explore the impact of comprehensive environmental risks caused by dam breaks in Henan Province. Wan et al. (2021) used set pair analysis to predict future river health levels in semiarid basins. He and Ruan (2022) used the normal cloud model to classify the ecological security of Anhui Province, which improved the scientificity and accuracy of the regional ecological security evaluation results.

Despite these advances, some gaps still remain. 1) Ecological receptors pay more attention to landscape entities and ignore the value loss relationship between ecosystems and human well-being. Ecosystem services are a bridge connecting human well-being and ecosystem processes (Faber and van Wensem, 2012). Previous studies usually included ecosystem service functions (soil conservation serviceability, water conservation serviceability, and habitat protection serviceability) in ecological risk assessment (Wang et al., 2023). However, the relationship between risk receptor loss and ecosystem service value is often not explained in practice. 2) The dynamic and uncertainty of the ecological risk process are ignored, and many research methods do not constrain the ambiguity of the data. 3) Insufficient prediction of future ecological risk. Most previous studies stop at the evaluation stage and then analyze the influencing factors. Or these studies are based only on the predicted land use structure to infer the future landscape ecological risk evolution trend. These previous studies ignored how the ecological risk evolution trend driven by multiple influencing factors will evolve in the future.

This paper focuses on the following issues. 1) How can an ecological risk assessment model be constructed by integrating ecosystem service value and the uncertainty of ecological risk? 2) What is the speed, depth, and complexity of future ecological risk evolution in the upper reaches of the UYR at different scales? To achieve these research purposes, we first adopted probability loss and comprehensive index models to quantitatively measure the ecological risk value in the UYR based on the ecological risk assessment framework, introducing indices such as ecosystem service value and function. Second, we used a normal cloud model to quantitatively deduce the ecological risk level of the UYR at different scales. Finally, we used the set pair analysis method to predict future ecological risk change trends in the UYR dynamically. The findings provide a reference for the monitoring and management of ecological risk.

2 Materials and methods

2.1 Research area

The UYR involves 9 provinces and cities, 51 prefecture-level cities, and 389 district counties and county-level cities (Fig. 1). It is approximately 4500 km long, accounting for about 70% of the total length of the Chang Jiang (Yangtze R.). The UYR is a key area for ecological protection and social development, facing ecological risk issues caused by frequent natural disasters, population growth, and wasted water resources (Zhang et al., 2022b). In 2015, the UYR had an annual resident population of about 159 million, an urbanization rate of about 46.28%, a GDP of about 51790 billion yuan, a natural growth rate of 5.98‰, and a disposable income of 22781.7 yuan for urban residents. Until 2018, the UYR had an annual resident population of about 164 million, an urbanization rate of about 50.15%, a GDP of about 8696.5 billion yuan, a natural growth rate of 5.97‰, and a disposable income of 28907 yuan for urban residents. The increase in population and urbanization rate increased the population pressure in the UYR year by year, which threatened the ecological security barrier function in the UYR to a certain extent. The early warning of ecological risk in the UYR straightly affects the effectiveness of regional ecological security construction, which is not only related to its own regional ecological security but also affects the ecological security of the country and even Asia. Thus, there was an urgent need to assess and provide early warning of ecological risk in the UYR.

2.2 Data sources and research methodology

This study selected 2015–2018 as the research period, and the main data sets required included vector data, raster data, and statistical data, as summarized in Table 1.

3 Methodology

3.1 Methodology framework

This study was initiated by examining ecological risk sources and ecological risk receptors to establish the ecological risk assessment index system. Then, we calculated current and future ecological risk in the UYR based on the ecological risk index system (Fig. 2).

3.2 Construction of the ecological risk assessment index system

Ecological risk has the characteristics of multiple risk sources and multiple risk receptors (Shen et al., 2023).

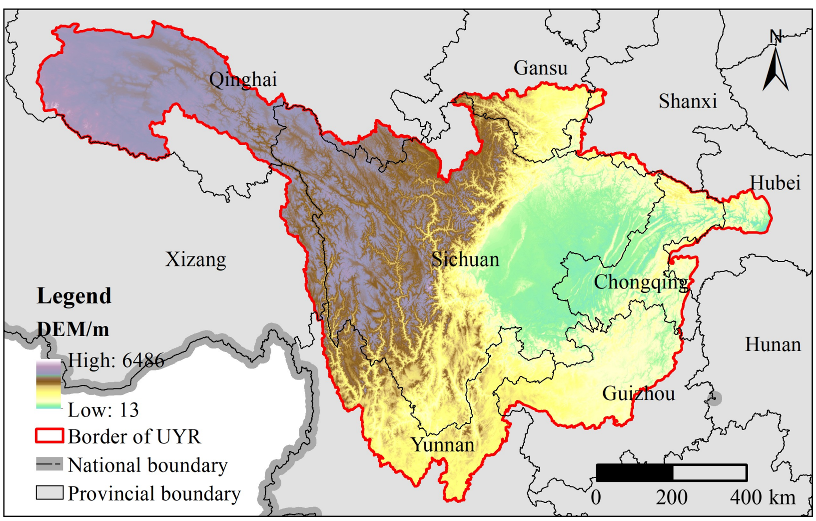

Fig. 1 The location of the research area.

Table 1 List of data types and data sources

Type	Data	Resolution	Year	Data sources
Vector data	China's administrative division	/	/	Resource and Environmental Science and Data Center
	China's major river systems	/	/	Resource and Environmental Science and Data Center
	China's nine major river basin areas	/	/	Resource and Environmental Science and Data Center
	China's geological disaster spatial distribution points	/	2015	Resource and Environmental Science and Data Center
Raster data	Land Use/Cover Change data	1000 m	2015–2018	Resource and Environmental Science and Data Center
	Net primary productivity (NPP)	1000 m	2015–2018	MOD17A3
	Soil data	1000 m	2015–2018	Harmonized World SoilDatabase (HWSD)
	Degree of soil erosion	30 m	2015–2018	Spatial Distribution Data ofSoil Erosion in China
Statistical data	Socioeconomic data	/	2015–2018	National Bureau of Statistics
	Pollution source data	/	2015–2018	National Bureau of Statistics

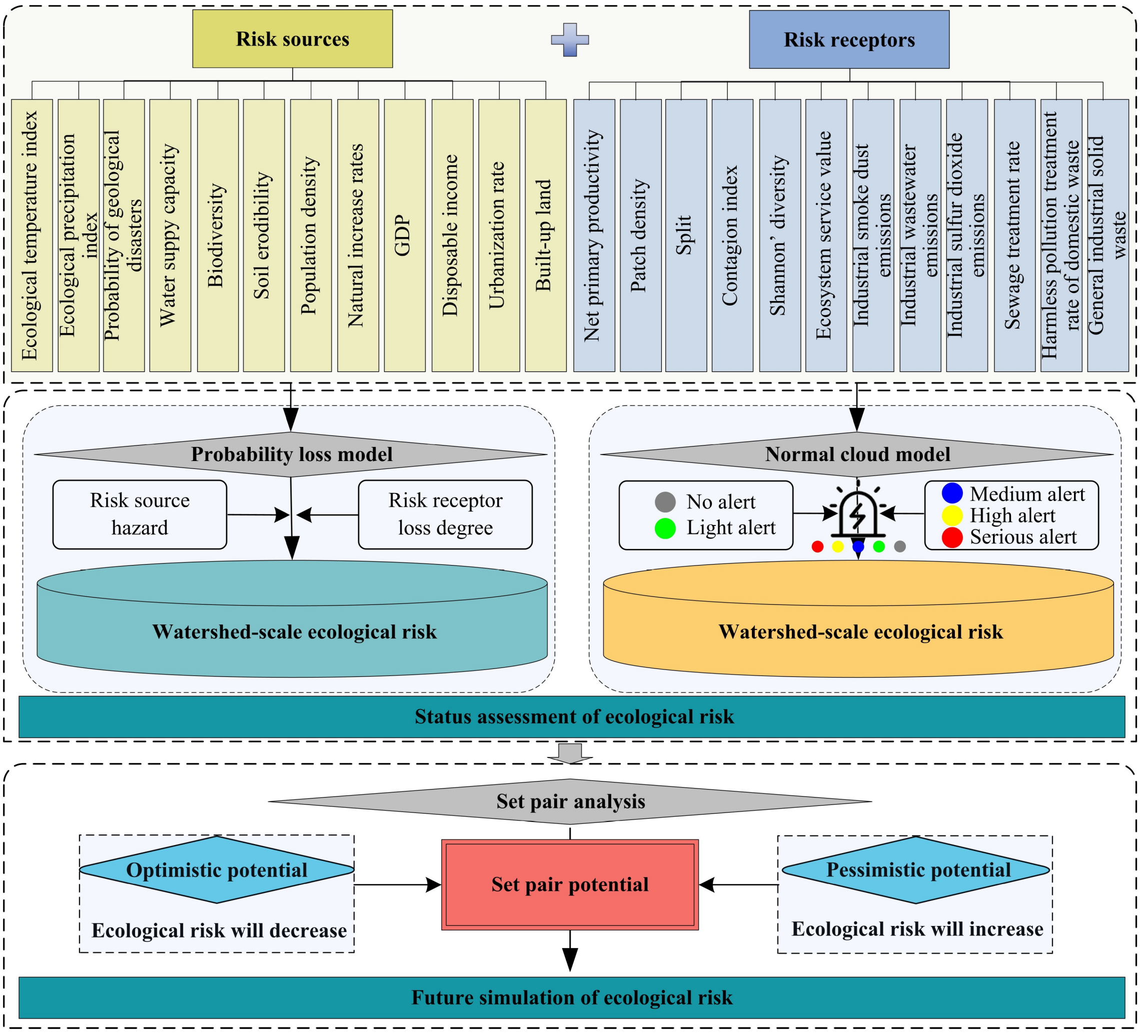

Fig. 2 Methodology framework.

Comprehensive ecological risk assessment must establish a scientific and complete index system. The hazard of the risk source reflects the risk pressure placed on a region (Fang and Xu, 2023). Risk sources such as geological disasters and meteorological disasters are easily generated in the UYR (Wu et al., 2023). Thus, we selected the ecological temperature index, ecological rainfall index, probability of geological disasters, water supply capacity, biodiversity, and soil erosion degree to characterize natural disasters (Kebede et al., 2021; Wang et al., 2024; Xu and Matsushima, 2024). Meanwhile, the social economy and human activities in the UYR were more active, and we selected the human impact (e.g., population, construction land, economic development) to characterize human activity disasters (Feng et al., 2021; Wu et al., 2021b). Specific indexes are described in Table 2.

The receptor loss degree is measured by the ecological stability index and ecological loss value (Xu et al., 2004). The risk receptor loss degree reflects the damage that a receptor may experience under the threat of exposure to risk factors. The role of risk sources could lead to changes in land use structure and human well-being. Thus, we chose the landscape pattern index, which can reflect ecological stability, and the artificial pollution index, which can reflect the value of ecosystem loss, as the evaluation index (Zhao et al., 2022; Zhang et al., 2023; Zhang et al., 2024). Specific indexes are described in Table 3.

3.3 Ecological risk assessment model

First, we used the comprehensive index method to construct a quantitative evaluation model of the hazard of ecological risk sources in the UYR. The formula is

$$P = \sum w_i x_i, \quad (1)$$

where P is the probability of the ecological risk source, x_i is the ith evaluation index used to measure the probability of the risk source, w_i is the weight of the ith evaluation index, and the index weight is obtained through the analytical hierarchy process.

Second, based on the evaluation index system of ecological risk receptor loss in the UYR, we combined the risk index method and probabilistic loss model to construct a quantitative evaluation model of ecological risk receptor loss degree in the UYR (Xu et al., 2004; Munns et al., 2009; Wang and Nan, 2013):

$$D = \sum (NPP \times \sum w_i v_i) + \sum (es \times \sum w_i p_i), \quad (2)$$

where D is the loss degree of the ecological risk receptor in the UYR; v_i is the ith index to measure the landscape

Table 2 The index system of hazard assessment of ecological risk sources

Risk sources	Index	Index description
Natural risk sources	Ecological temperature index	Characterize the probability of extreme temperature such as high temperature, freezing, and other natural disasters
	Ecological precipitation index	Characterize the probability of extreme precipitation such as floods, droughts, and other natural disasters
	Probability of geological disasters	Characterize the probability of geological disasters
	Water supply capacity	Characterize the stability of the ecosystem
	Biodiversity	Characterize the stability of the ecosystem
	Soil erodibility	Characterize the resistance of the ecosystem
Human risk sources	Population density	Characterize the stress of population on the natural environment
	Natural increase rates	Characterize the stress of population growth on the natural environment
	GDP	Characterize the stability of social economic system
	Disposable income	Characterize the stability of social economic system
	Urbanization rate	Characterize the impact of human disturbance on ecological risk
	Built-up land	Characterize the impact of human disturbance on ecological risk

Table 3 The index system of loss degree assessment of ecological risk receptors

Risk receptor loss degree	Index	Index description
Ecological stability	NPP	Measure the maximum damage degree of the ecosystem stability in theory
	Patch density	Characterize the degree of landscape fragmentation
	Split	Characterize the degree of landscape fragmentation
	Contagion index	Characterize the degree of agglomeration or extension trend of different patch types
	Shannon' diversity	Characterizing landscape heterogeneity
Ecological loss value	Ecosystem service value	Measure the maximum damage degree of ecosystem value loss in theory
	Industrial smoke dust emissions	Characterize the degree of air pollution loss
	Industrial wastewater emissions	Characterize the degree of water pollution loss
	Industrial sulfur dioxide emissions	Characterize the degree of air pollution loss
	Sewage treatment rate	Characterize the degree of water pollution loss
	Harmless pollution treatment rate of domestic waste	Characterize pollution treatment capacity
	General industrial solid waste	Characterize pollution treatment capacity

vulnerability index; and w_i is the weight of the ith index. The landscape vulnerability indices, including Patch density, Split, Contagion index, and Shannon's diversity were obtained by Fragstats4.

Finally, we constructed a quantitative evaluation model of comprehensive ecological risk in the UYR based on the probabilistic loss model:

$$R = P \times D, \quad (3)$$

where R is the ecological risk in the UYR, P is the harmfulness of ecological risk sources, and D is the loss degree of ecological risk receptors.

3.4 Ecological risk early warning level identification model

Ecological risk is a complexity including multiple factors like nature, socio-economics, and governmental decision-making, and its evolution trend, risk degree, and influence mechanism are uncertain. Thus, the evaluation of ecological risk must have the ability to deal with uncertain factors and overcome subjective bias. The normal cloud model considers the ambiguity of data and uncertainty of the evaluation level and can objectively analyze the membership level of each index factor (Bai et al., 2023). The definition of the normal cloud model is composed of expectation (Ex), entropy (En), and hyper entropy (He), and is defined as follows:

$$\mu_1 = \mathrm{e}^{-\frac{(x-Ex)}{2En'^2}}. \quad (4)$$

Assume that U is a quantitative domain of numerical representation and that X belongs to a subset of U. T is a qualitative notion of U. If element x in domain A corresponds to membership μx in T satisfying $\mu x \sim N$ (Ex, En^2), then the distribution of T from U to the membership interval in the belonging space is defined as the cloud model. When En' satisfies $En' \sim N$ (En, He^2), the cloud model is a normal cloud model. The algorithm steps can be presented as follows.

1) Establish a set of ecological risk early warning indices:

$$A = \{ep, ed, er\}. \quad (5)$$

We selected the three indices of risk source probability (ep), risk damage degree (ed), and comprehensive ecological risk (er) in the UYR. To complete the ecological risk early warning of the evaluation index at the prefecture-level city scale, the partition statistical tool was used in ArcMap10.4 to determine the mean value of each index to the prefecture-level city.

2) Establish the membership relationship between ecological risk early warning indices and early warning levels.

The upper and lower limits of ecological risk warnings were set. As a result of the uncertainty of the index in the division of membership grade, the following was used:

$$Ex_{ij} = \left(x_{ij}^{f} + x_{ij}^{l}\right)/2, \quad (6)$$

where i is the different early warning indexes, j is the ecological risk level in which index i is located, and Ex_{ij} is the expectation of the risk level of index i. X_{ij}^{f} and X_{ij}^{l} are the upper and lower boundary values of each early warning index, respectively. Since the critical value of index i belongs to two ecological risk levels, the following were used:

$$\exp\left[-\frac{\left(x_{ij}^{f} - x_{ij}^{l}\right)}{8\left(En_{ij}\right)^2}\right] = 0.5, \quad (7)$$

$$En_{ij} = \left|x_{ij}^{f} - x_{ij}^{l}\right| / 2.355. \quad (8)$$

By consulting relevant literature and data characteristics, we found that previous research mostly used the Jenks method to divide ecological risk into five levels (Gong et al., 2021; Fang and Xu, 2023; Yi et al., 2023). Thus, we used the Jenks Optimizations method to determine the evaluation criteria (Table 4). The Jenks method is a data classification method designed to determine the best arrangement of values into different classes (Bai et al., 2022). The method addresses the problem of how to split a range of numbers into contiguous classes to minimize the squared deviation within each class.

Hyper entropy (He) is the dispersion degree of the cloud droplets converging into the cloud layer, which is presented as the thickness of the cloud on the visual cloud map. Super entropy is based on the dispersion degree of the visual cloud image, and we defined He = 0.01. According to the level of each early warning index in Table 4, the expectation (Ex) and entropy (En) of each index were determined by Eqs. (6) and (8). The results are shown in Table 5.

Table 4 The classification standard of the ecological risk warning level

Warning level	No alert	Light alert	Medium alert	High alert	Serious alert
Indicating light					
Comprehensive ecological risk	[0–0.01]	(0.01–0.03]	(0.03–0.06]	(0.06–0.09]	(0.09–0.32]
Ecological risk sources	[0–0.10]	(0.1–0.28]	(0.28–0.35]	(0.35–0.43]	(0.43–0.74]
Ecological risk receptor loss degree	[0–0.01]	(0.01–0.18]	(0.18–0.36]	(0.36–0.56]	(0.56–1.60]

Table 5 Expectation and entropy of the ecological risk early warning index (Ex, En)

Scale	Risk warning level				
	No alert	Light alert	Medium alert	High alert	Serious alert
Comprehensive ecological risk	(0.005, 0.004)	(0.02, 0.0084)	(0.045, 0.013)	(0.075, 0.013)	(0.205, 0.098)
Ecological risk sources	(0.050, 0.042)	(0.190, 0.076)	(0.315. 0.030)	(0.390, 0.034)	(0.585, 0.132)
Ecological risk receptors	(0.005, 0.004)	(0.095, 0.072)	(0.270, 0.076)	(0.460, 0.085)	(1.080, 0.442)

According to each evaluation index's expectation (Ex) and entropy (En), we set $N = 10000$ times, and MATLAB can draw the normal cloud model of different indices.

According to the cloud model drawn by MATLAB, the normal distribution of 10,000 cloud droplets in different warning level intervals can be clearly seen.

3) Calculate the membership degree of each index

The expectation (Ex), entropy (En), and hyper entropy (He) in Table 4 were substituted into the forward cloud generator written by Python 2.7 to obtain the membership degree of the corresponding warning level of each index of ecological risk. To improve the accuracy of the membership degree results, we set the cycle parameter n to 10,000 times, and the average value obtained was the final membership degree under different alarm conditions corresponding to each index:

$$y_{ij} = \sum_{j=1}^{5}\left(\sum \mathrm{e}^{-\frac{(x_i - Ex)^2}{2(En')^2}} / n\right), \tag{9}$$

where y_{ij} is the degree of affiliation of the ith early warning index corresponding to the jth level; x_i is the value of the ith early warning index; En' is a random number satisfying $En' \sim N\,(En, He^2)$; and n is the number of times the membership degree is calculated.

4) Determine the level of ecological risk early warning

Through the principle of maximum affiliation, the warning level corresponding to the maximum affiliation was used as the ecological risk warning level for each prefecture-level city in the UYR.

3.5 Ecological risk evolution trend model

The interaction of ecological risk factors increases the complexity and uncertainty of ecological risk early warning. From the perspective of dialectical thinking, set pair analysis (SPA) quantifies the relationship and transformation between various uncertain factors and scientifically describes the risk evolution trend under a specific ecological risk background (Zeng et al., 2021). First, set pair analysis was used to construct set pairs for sets with uncertainty. Second, we analyzed the identity, discrepancy, and contradiction of specific attributes in the set pair. Finally, the connection degree was used to characterize the relationship between the identity, discrepancy, and contradiction of this set pair. The formula is as follows:

$$\mu_2 = a + b \cdot i + c \cdot j, \tag{10}$$

where μ_2 is the connection degree, $\mu_2 \in [-1,1]$; a is the degree of the same attribute, that is, identity degree; b is the discrepancy degree; c is the contrary degree; a, b, and c are all positive numbers and satisfy $a + b + c = 1$; i is the uncertainty coefficient of discrepancy, and $i \in [-1,1]$; and j is the contradictory coefficient, which is selected according to the specific situation. The definite evaluation process is as follows:

1) Determination of evaluation level

According to the connection degree of ecological risk, we used the principle of equal division to divide it into five grades: no alert: [1, 0.6); light alert: [0.6, 0.2); medium alert: [0.2, −0.2); high alert: [−0.2, −0.6); and serious alert: [−0.6, −1].

2) Calculation of index connection degree

Based on the classification of evaluation grades, we refined the connection function to explore the future evolution trend of ecological risk in the UYR. Eq. (10) was extended to $\mu_2 = a + b_1 \cdot i_1 + b_2 \cdot i_2 + b_3 \cdot i_3 + c \cdot j$, and the connection degree of a single index factor was determined. For the negative index, the calculation formula of the quaternary connection degree is as follows:

$$\mu_2 = \begin{cases} 1,\ X_i \leqslant S_{i1} \\ (S_{i2} - X_i)/(S_{i2} - S_{i1}) + (X_i - S_{i1})/(S_{i2} - S_{i1})\,i_1,\ S_{i1} < X_i \leqslant S_{i2} \\ (S_{i3} - X_i)/(S_{i3} - S_{i2})\,i_1 + (X_i - S_{i2})/(S_{i3} - S_{i2})\,i_2,\ S_{i2} < X_i \leqslant S_{i3} \\ (S_{i4} - X_i)/(S_{i4} - S_{i1})\,i_2 + (X_i - S_{i3})/(S_{i4} - S_{i3})\,j,\ S_{i3} < X_i \leqslant S_{i4} \\ 1j,\ X_i > S_{i4} \end{cases}. \tag{11}$$

For the positive index, the calculation formula of the quaternary connection degree is as follows:

$$\mu_2 = \begin{Bmatrix} 1,\ X_i \leqslant S_{i1} \\ (X_i - S_{i2})/(S_1 - S_{i2}) + (S_{i2} - X_i)/(S_{i1} - S_{i2})i_1,\ S_{i2} \leqslant X_i < S_{i1} \\ (X_i - S_{i3})/(S_{i2} - S_{i3})i_1 + (S_{i3} - X_i)/(S_{i2} - S_{i3})i_2,\ S_{i3} \leqslant X_i < S_{i2} \\ (X_i - S_{i4})/(S_{i3} - S_{i4})i_2 + (S_{i4} - X_i)/(S_{i3} - S_{i4})j,\ S_{i4} \leqslant X_i < S_{i3} \\ 1j,\ X_i < S_{i4} \end{Bmatrix}, \tag{12}$$

where b_1, b_2, and b_3 are the discrepancy degrees, a is the possibility of belonging to a level, that is, a, b_1, b_2, b_3, and c are the possibility of each district and county belonging to no alert, light alert, medium alert, high alert, and serious alert. X_i is each of the different indices, and S_{i1}, S_{i2}, S_{i3}, S_{i4}, and S_{i5} are the early warning level standards under this index.

After adding the weight of the index, the connection degree of identity, opposition, and difference becomes:

$$\mu_2 = \sum_{K=1}^{S} W_K + \sum_{K=S+1}^{S+F} W_K i + \sum_{K=S+F_1}^{N} W_K j, \tag{13}$$

where W_K is the weight of index i.

3) Set pair potential calculation analysis

The set pair potential reflects the degree of identity-discrepancy-contrary connection between two sets. The ratio of the contact degree between no alert and serious alert is the set pair potential of ecological risk in the UYR. The formula is as follows:

$$P_H = a/c. \tag{14}$$

Pessimistic trend analysis was used to analyze the future trend of ecological risk in the UYR from a pessimistic perspective. First, all the differences, namely, high alert, medium alert, and light alert, were transformed into serious alert. Second, the ratio of the converted no alert to all the converted serious alerts was used to study the ecological risk situation in the UYR. Finally, an analysis was carried out from the most negative perspective. The formula is as follows:

$$P_B = a/(b+c). \tag{15}$$

Set pair optimism refers to the analysis of the future trend of ecological direction in the UYR from an optimistic perspective, which is contrary to the pessimistic trend. First, all high alert, medium alert, and light alert were transformed into no alert. Second, the converted ratio of no alert to serious alert was used to study the ecological risk situation in the UYR. Finally, an analysis was carried out from the most positive perspective. The formula is as follows:

$$P_o = (a+b)/c. \tag{16}$$

4 Results

4.1 Temporal and spatial patterns of ecological risk in the UYR

4.1.1 Temporal and spatial patterns of ecological risk sources in the UYR

During 2015–2018, the hazard of ecological risk sources possessed significant spatial differences, with a decentralized and combined distribution pattern (Fig. 3). The high-value areas were distributed primarily along the Three Gorges Reservoir area, along the Qinling-Minshan-Qionglai Mountains and the Chang Jiang (Yangtze R.) source. The low-value areas were mainly located in the central region of the UYR. The probability range of ecological risk sources expanded from [0.12, 0.67] to [0.11, 0.73] in 2018, showing a ‘high-value increase-low value decrease’ state. Specifically, the hazard of ecological risk sources was increasing, among which low-risk values, primarily in the western and southern regions, were replaced by high-risk values.

From the perspective of prefecture-level cities (Fig. 3), in 2015, the ecological risk of Haixi was the highest, reaching 0.3956, while Qiandongnan’s was the lowest, at only 0.2167. In 2018, the ecological risk of Chongqing was the highest, reaching 0.4037, while Qiandongnan’s was the lowest, at only 0.2591. From the perspective of risk fluctuations, the hazard of risk sources in 14 cities, including Leshan, Meishan, and Ya’an, decreased from 2015 to 2018. The hazard of risk sources in 37 cities, including Yichang, Longnan, and Chuxiong, increased.

4.1.2 Temporal and spatial patterns of ecological risk receptor loss degree in the UYR

The difference between the actual receptor loss degree in 2015 and 2018 was small, demonstrating a pattern of “west low east high, south low north high” (Fig. 4). The low-value areas showed a plane shape and were distributed in the Sichuan Basin and Hengduan Mountains. The high-risk areas were mainly located in the Yungui Plateau and showed a gradient-increasing

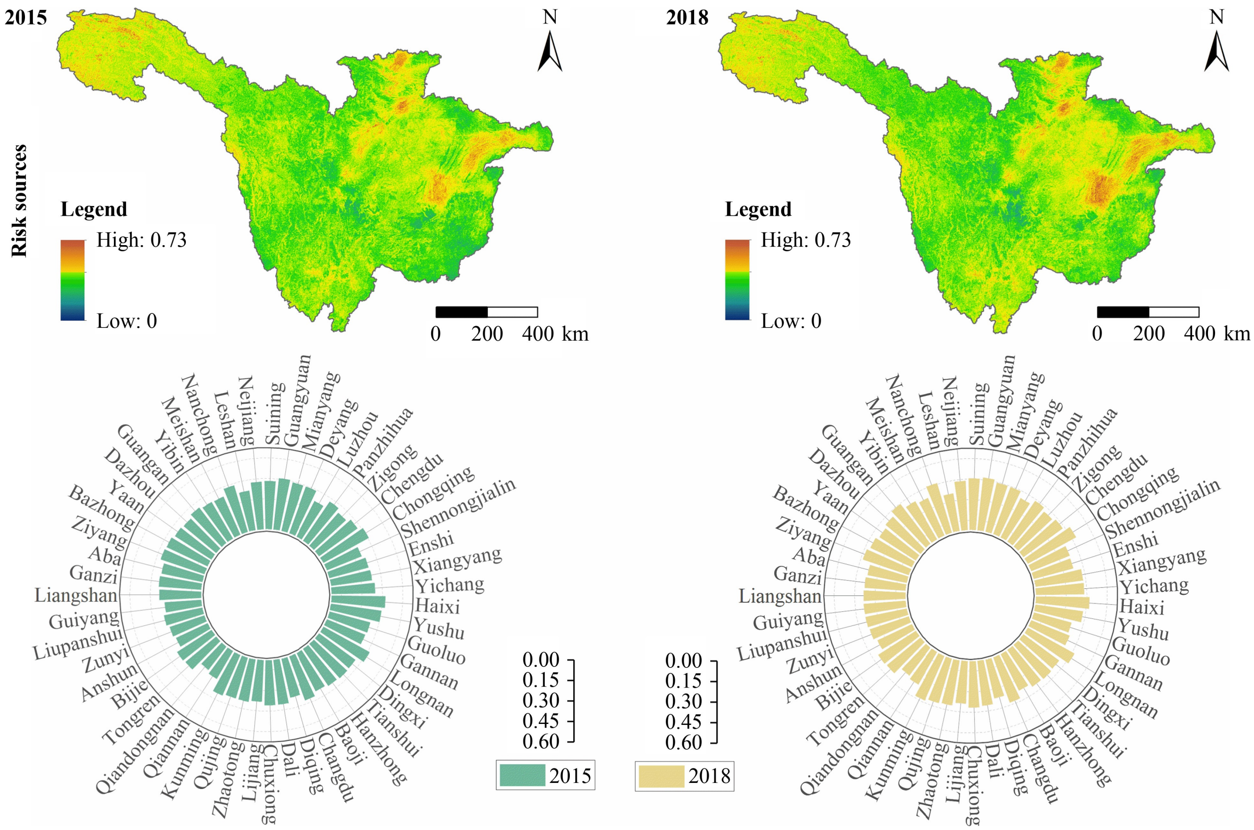

Fig. 3 Temporal and spatial evolution patterns of ecological risk sources in the UYR from 2015 to 2018.

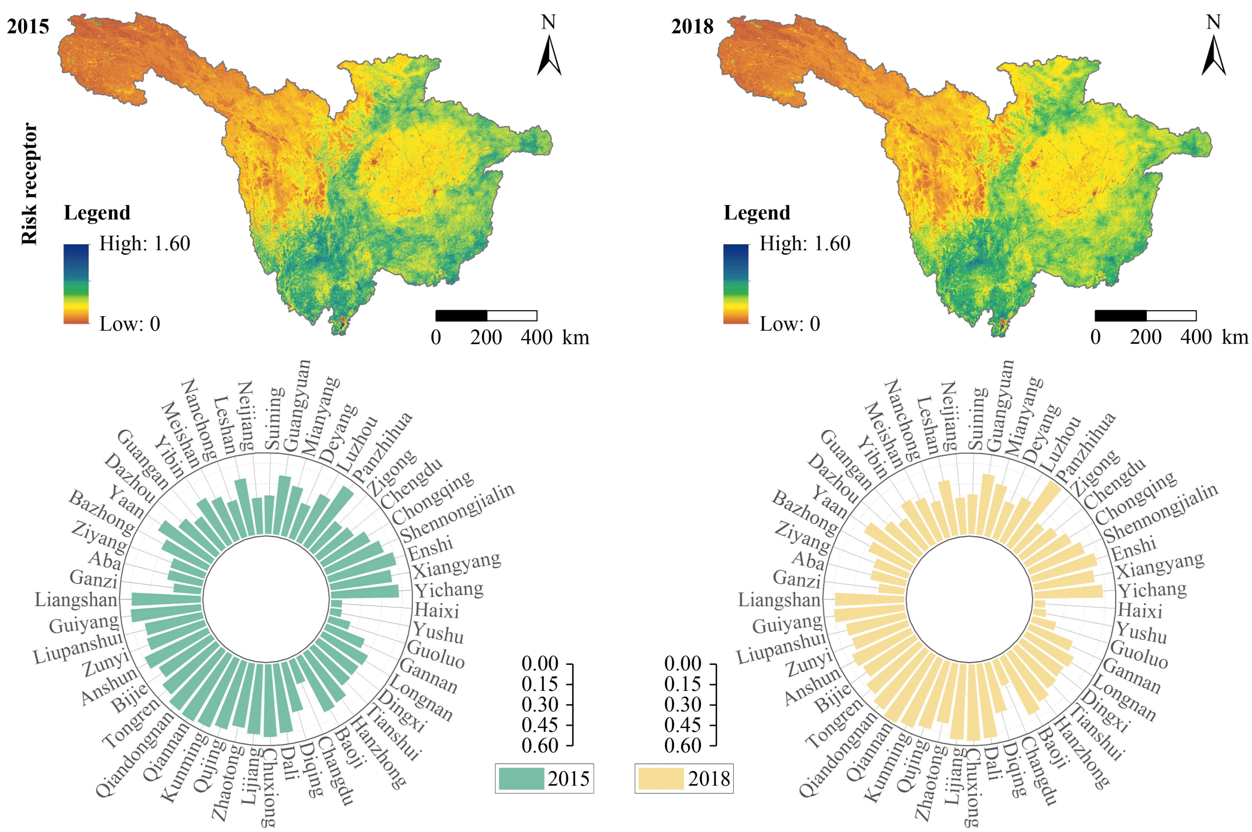

Fig. 4 Temporal and spatial evolution patterns of ecological risk receptors in the UYR from 2015 to 2018.

trend from north to south. The range of receptor loss did not alter from 2015 to 2018, and the overall was generally consistent, all of which were [0, 1.60]. However, there were small fluctuations in some areas. The degree of receptor loss in the Chongqing section of the Three Gorges Reservoir area decreased, while that near the Hengduan Mountains increased yearly.

From the perspective of prefecture-level cities (Fig. 4), in 2015, the degree of receptor loss was highest in Qiannan, reaching 0.5677, while that in Haixi was the lowest, at only 0.0812. In 2018, the degree of receptor loss was highest in Panzhihua, reaching 0.5806, while that of Haixi was the lowest, at only 0.0804. From the perspective of the changing trend, the degree of receptor loss in 14 cities, including Xiangyang, Enshi, and Shennongjia, exhibited a decreasing pattern from 2015 to 2018. The ecological risk of 37 cities, including Lijiang, Yichang, and Yushu, increased.

4.1.3 Temporal and spatial patterns of comprehensive ecological risk in the UYR

The comprehensive ecological risk presented a north–south radial expansion-type aggregation trend (Fig. 5). The high ecological risk areas were mostly in the Three Gorges Reservoir area, the Qinling-Minshan-Qionglai Mountain area, and a major part of southwest China. The low-risk areas were primarily distributed throughout the Sichuan Basin and the Hengduan Mountains. The Chang Jiang (Yangtze R.) source has the lowest ecological risk. The hazard range of ecological risk sources expanded from [0, 0.28] in 2015 to [0, 0.32] in 2018. The highest value of comprehensive ecological risk increased among which the low risk mainly in the western region was replaced by high-risk sources.

From the perspective of prefecture-level cities (Fig. 5), in 2015, the comprehensive ecological risk of Panzhihua was the highest, reaching 0.0912, while Yushu's was the lowest, at only 0.0159. In 2018, Chuxiong's comprehensive ecological risk was the highest, reaching 0.0948, while Haixi's was the lowest, at only 0.0152. From a risk change trend perspective, there was a discernible decline in the ecological risk of 13 cities, namely Enshi, Haixi, and Chongqing, from 2015 to 2018. The ecological risk of 38 cities, including Yichang, Qiandongnan, and Kunming, increased.

4.2 Differential distribution of ecological risk early warning levels in the UYR

4.2.1 Differential distribution of early warning level of ecological risk source hazard

The early warning results of ecological risk sources in the UYR are shown in Fig. 6. In 2015 and 2018, there were no no-alert areas in the UYR. In 2015, the high-alert areas

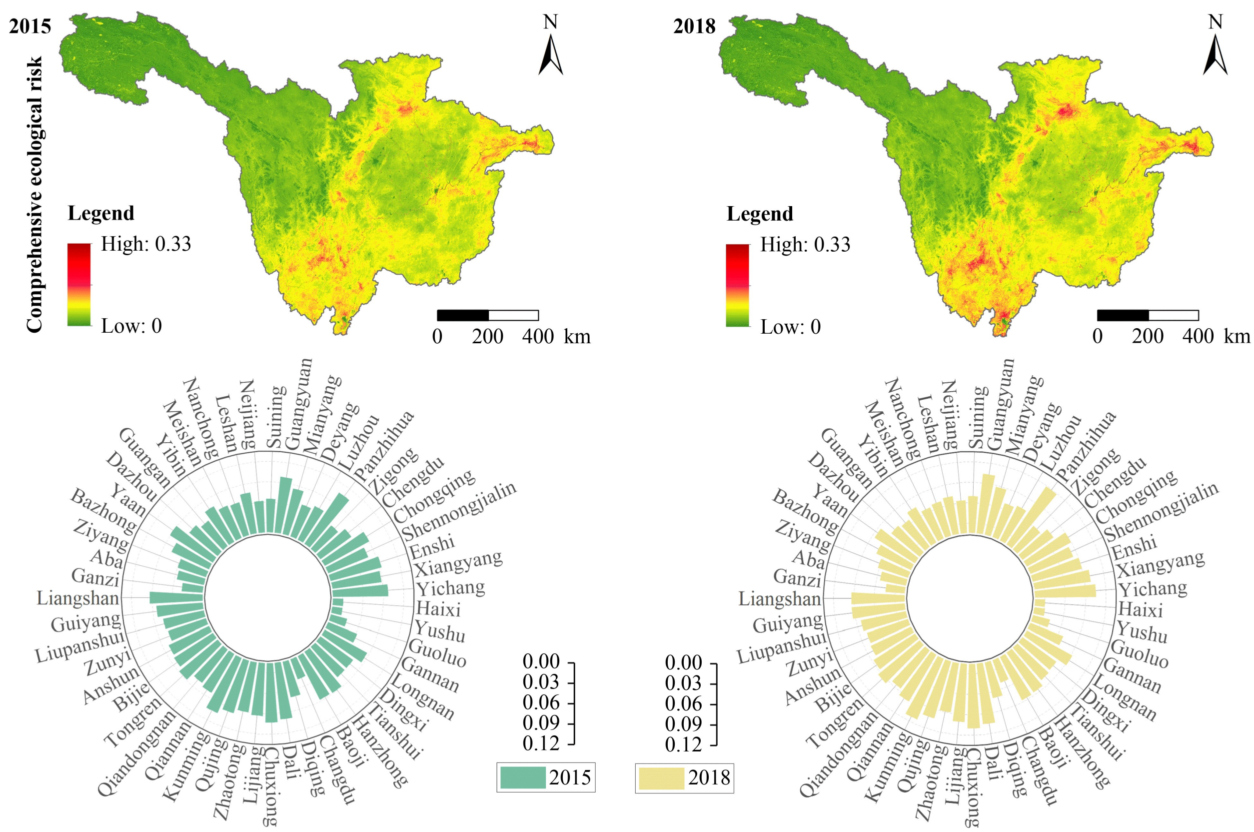

Fig. 5 Temporal and spatial evolution patterns of comprehensive ecological risk in the UYR from 2015 to 2018.

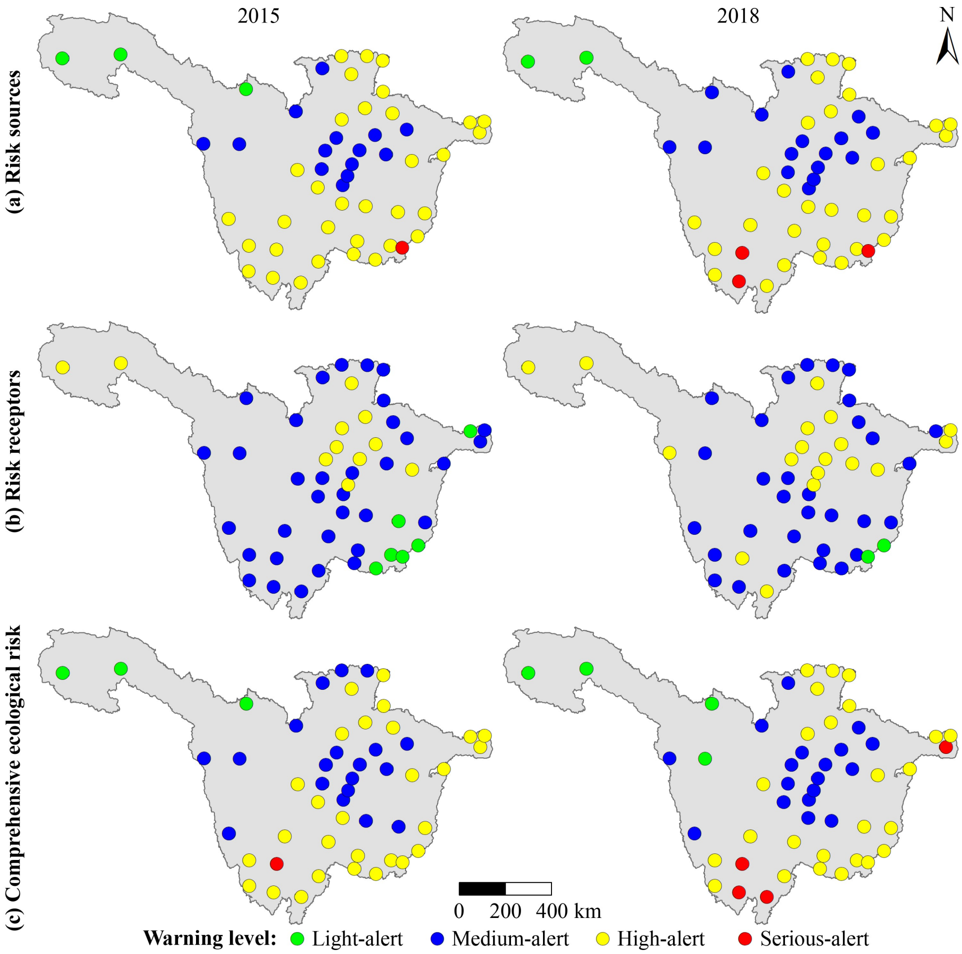

Fig. 6 Temporal and spatial distributions of ecological risk early warning in the UYR from 2015 to 2018.

included 11 cities, such as Chongqing, Chengdu, and Deyang, accounting for 21.57%. The medium-alert area had 34 prefecture-level cities, such as Yichang, Xiangyang, and Lijiang, accounting for 66.67%. The light-alert area included 6 prefecture-level cities, such as Guiyang, Zunyi, and Anshun, accounting for 11.76%. In 2018, the high-alert area had 18 cities, such as Chongqing, Yichang, and Xiangyang, accounting for 35.29%. The medium-alert area included 31 cities, such as Zigong and Luzhou, accounting for 60.78%. The light-alert area had only two cities, Qiandongnan Prefecture and Qiannan Prefecture. Compared with 2015, the probability of ecological risk sources in the UYR increased in 2018. Specifically, the number of cities in the high-alert area increased from 11 to 18, and the number of medium-alert areas decreased from 34 to 31. Furthermore, the number of light-alert areas was reduced from 6 to 2.

4.2.2 Differential distribution of the early warning level of the ecological risk receptor loss degree

The early warning results of the ecological risk receptor loss degree in the UYR showed that the serious-alert area in 2015 included only Qiannan Buyi and Miao Autonomous Prefecture. The high-alert area had 33 cities, such as Chongqing, Zunyi, and Baoji, accounting for 64.71%. The medium-alert area included 14 cities, such as Chengdu and Changdu, accounting for 27.45%. The light-alert area included three prefectures: Guoluo, Haixi, and Yushu. There were no no-alert areas here. In 2018, the serious-alert area had the three cities of Qiannan, Panzhihua, and Chuxiong. The high-alert areas included 30 cities, such as Anshun, Baoji, and Chongqing, accounting for 58.82%. The medium-alert areas included 16 cities, such as Chengdu, Bazhong, and Changdu, accounting for 31.37%. Only two cities, Haixi and Yushu, were light-alert areas. Compared with 2015, the number of cities in the high-alert areas increased from 1 to 3, while that of light-alert areas decreased from 3 to 2.

4.2.3 Differential distribution of early warning level of comprehensive ecological risk

The comprehensive ecological risk early warning results in the UYR showed that only Panzhihua was a serious-alert area in 2015. The high-alert areas included 28 cities, such as Chongqing, Chengdu, and Ya'an, accounting for 54.90%. The medium-alert areas included 19 cities, such as Chengdu, Zunyi, and Changdu, accounting for 37.25%.

The light-alert areas included three prefectures, Guoluo, Haixi, and Yushu, and there were no no-alert areas. In 2018, the serious-alert area had four cities: Panzhihua, Kunming, Yichang, and Chuxiong. The high-alert areas included 25 cities, such as Baoji, Zunyi, and Chongqing, accounting for 49.02%. The medium-alert areas included 18 cities, such as Chengdu, Bazhong, and Changdu, accounting for 35.29%. The light-alert areas included the four cities of Yushu, Guoluo, Haixi, and Ganzi. Compared with 2015, the number of cities in serious-alert areas increased from 1 to 4, and the number of light-alert areas increased from 3 to 4. The above comparative analysis showed that the ecological risk from 2015 to 2018 showed an increasing trend.

4.3 Simulation of future ecological risk evolution trends in the UYR

To predict and analyze the future spatial and temporal distributions and evolution trends of ecological risk in the UYR, we calculated the region's set pair potential, optimistic potential, and pessimistic potential (Fig. 7). Set pair potential. The cities with increased ecological risk level in the UYR accounted for 33% and were distributed primarily in the southern and eastern regions. The counties with decreased ecological risk accounted for 67% and were distributed mainly in the north-west and northern areas. Thirty-four cities, including Luzhou and Zunyi, had the same trend. By strengthening ecological risk control and environmental protection measures, ecological risk developed in a good direction. Seven cities, including Chongqing and Chengdu, showed the opposite trend; that is, the ecological risk level of these cities will increase in the future.

Distance range of the set pair potential (Fig. 8). The set pair potential of 43 cities in the UYR was closer to the pessimistic potential, namely, the smaller deterioration space. This means that the ecological risk has high stability in long-term development in the future. Meanwhile, their set pair potential was far from the optimistic potential, indicating that they have a large room for improvement. Although cities such as Xiangyang, Chongqing, and Chengdu have a worsening trend of ecological risk in the future, their set pair potential was closer to pessimism. Despite the deterioration, the space for deterioration was still small. The set pair potential of 8 cities was relatively close to the optimistic potential, indicating that the trend of system opposition was heavy. Although there was room for improvement, the positive range was limited in the short term. Additionally, the distance to pessimism was far away, and the space for deterioration was large. Once the status was not well maintained, the ecological risk in the region may be greatly reduced. Although cities such as Leshan, Meishan, Guang'an, and Tianshui had a good development trend in the future, their set pair potential was far from optimistic. If they are blindly optimistic, this will easily lead to a sharp decline in ecological risk. Fluctuation range of the set pair potential. The fluctuation range of the set pair potential on Haixi was the smallest, at [0.84, 2.72], while that of Dazhou was the largest, at [0, +∞].

5 Discussion

5.1 Influence factor analysis of the spatial and temporal pattern changes in ecological risk in the UYR

The probability of geological disasters and water supply capacity were the main driving forces affecting the spatial

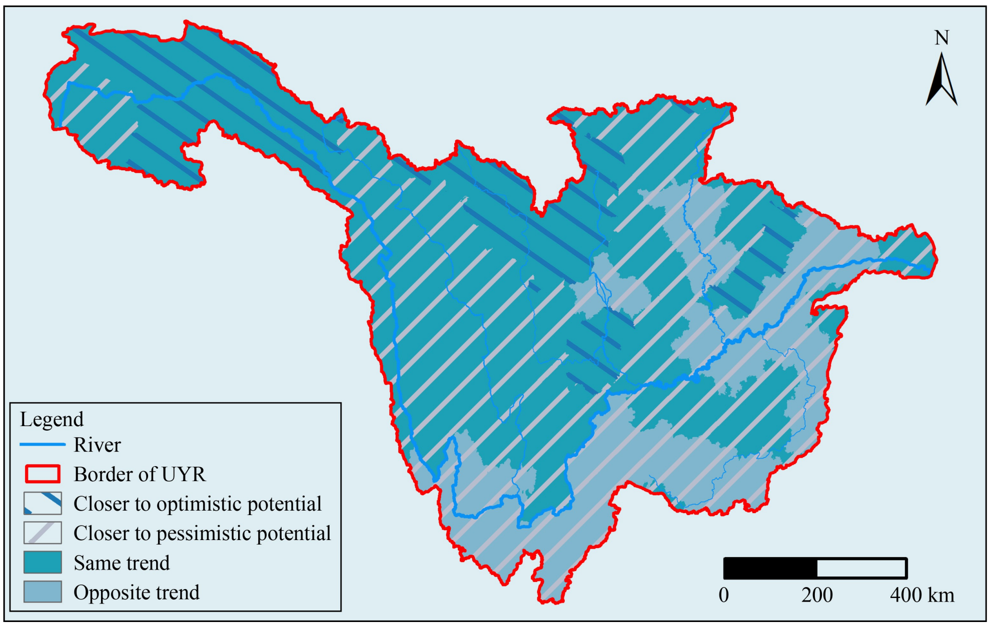

Fig. 7 Distribution pattern of future ecological risk evolution trends in the UYR.

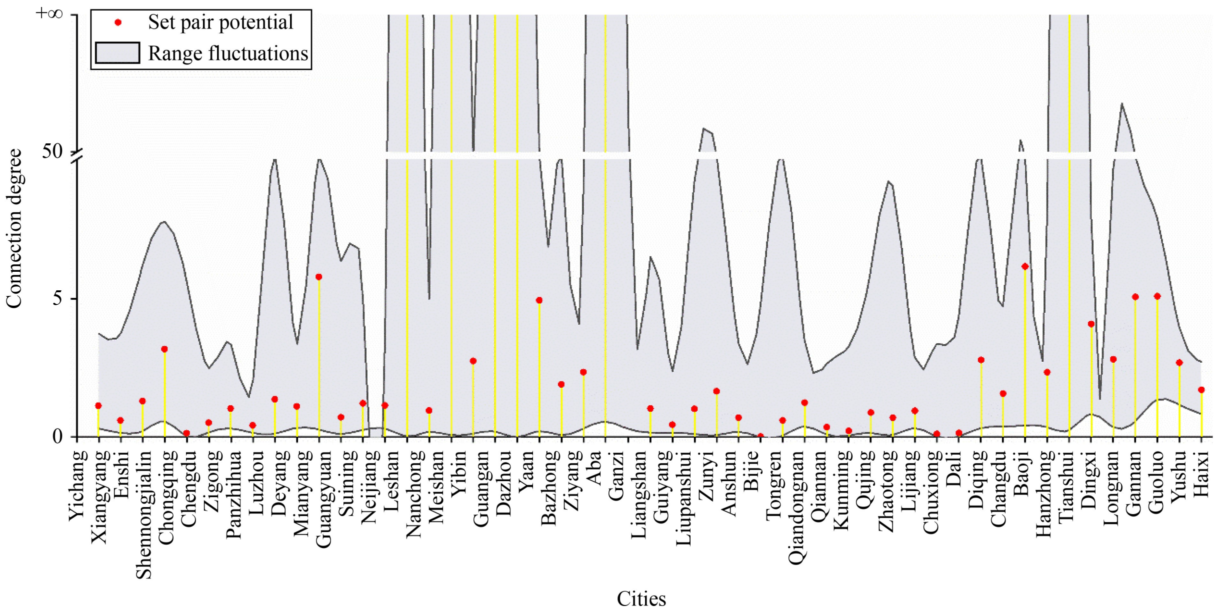

Fig. 8 Distribution pattern of future ecological risk evolution trends of prefecture-level cities in the UYR.

and temporal pattern evolution of natural ecological risk sources. As shown in Fig. A1 in the annex, the high incidence area of geological disasters was mainly in the Sichuan Basin. The water supply capacity of each region changed significantly from 2015 to 2018. From 2015 to 2018, the unit water supply capacity of Guizhou Province decreased by 87.1463 mm, and that of Qinghai Province decreased by 145.7014 mm. Due to these factors, the UYR's high-risk areas were centered in the Chongqing section of the southwestern mountainous area, the northern region (Guangyuan and Longnan sections), and the Chang Jiang (Yangtze R.) source.

GDP and urbanization rate were the main driving forces affecting human ecological risk sources' spatial and temporal pattern evolution. Human activity disturbance was usually the main limiting factor for ecological risk changes (Liu et al., 2023). As shown in Fig. A2 in the annex, from 2015 to 2018, affected by the economic radiation and attraction of the Chengdu-Chongqing urban agglomeration, the population density, GDP, per capita disposable income, and urbanization rate of the region were based on Chengdu and Chongqing, showing a 'two-core' type of rapid growth (Figs. A1 and A2). The population density increased from [0, 141905] in 2015 to [0, 154160] in 2018, and GDP surged from [0, 988550] to [0, 1099991] million yuan. Disposable income increased from [17899.9, 34728.1] to [22193.5, 43970.7] yuan. The urbanization rate increased from [19.57, 84.06] to [19.46, 87.62]. These factors caused the spatial and temporal distribution pattern of ecological risk in UYR (The high-risk areas gradually gathered in the Chengdu-Chongqing urban agglomeration.).

The spatial and temporal distribution of ecosystem service value and receptor loss degree were highly similar, indicating that ecosystem service value was the main driving force affecting receptor loss degree (Fig. A3 and Fig. A4). Human activity pollution changed the spatial and temporal distribution of ecosystem service value, affecting ecological receptor loss's spatial and temporal pattern. Industrial smoke dust emissions, industrial wastewater emissions, and industrial sulfur dioxide emissions all showed a high distribution pattern in the south and low in the north, with high-value areas distributed in the Yungui Plateau. The emissions of the climate pollution index in the Yungui Plateau were high, but the disposal rate of domestic waste was low, which resulted in the distribution trend of receptor loss in the south and north from 2015 to 2018.

5.2 Analysis of ecological risk impact processes in different watersheds

The watershed is a complex ecological unit that spans multiple regions and scales. Risk sources and risk receptors are changing with changes in the ecological environment. Specifically, changes in the research environment, research perspective, and research scale will cause changes in risk sources and risk receptors. Therefore, the characterization of the impact of different watersheds on ecological risk is different (see Table 6). For example, the risk sources of the Wei River Basin selected heavy metal pollution—the risk receptors selected physical habitat quality and water environment quality (Yang et al., 2020). In contrast, the Luojiang Xiaoxi basin's risk sources selected natural environmental and human social factors, and the risk receptors considered landscape patterns (Na et al., 2023). For watershed ecological risk, the existing research was still mainly based on traditional ecological risk analysis, less on ecosystem services as a receptor, and linking it

Table 6 Comparison of ecological risk assessment in different watersheds

Study area	Risk source	Risk receptor	Methods
Huaihe River Basin (Zhu and Cai, 2023)	Natural disaster risk; human activity risk	Landscape pattern	Principal component analysis
Wei River Basin (Yang et al., 2020)	Heavy metal pollution	Physical habitat and water environment quality	Improved TOPSIS model
Dongjiang River (Karimian et al., 2022)	Heavy metals	Human health and ecosystems	Bayesian Networks
Brunette River watershed (Zandbergen, 1998)	Natural conditions; human activities; physical stressors; biological stressors	Physical exposure; chemical exposure	GIS
Chang Jiang (Yangtze R.) in Jiangsu (Lu et al., 2023)	Natural disasters and human activities	Natural-social-ecological systems	PSR model; Moran's I; the cold and hot spot analysis method
Shenzhen River-Bay Wastershed (Yang et al., 2011)	Nature disaster\Human pressure	Aquatic ecosystems	PSR model
Luojiang Xiaoxi basin (Li et al., 2023)	Ecological and natural environmental factors, human social factors	Natural environment-human society-landscape pattern	Spatial principal component analysis

with public value. Munns et al. (2016) indicated that taking ecosystem services as the end point of evaluation can better coordinate the relationship between ecological risks and human well-being and improve the value of risk assessment for environmental decision-making. Wang et al. (2024) further suggested that incorporating ecosystem services in regional ERA improves its efficiency and practicability. Some scholars have also pointed out that ecosystem service value is a suitable assessment endpoint because it is closely related to ecological processes, risk sources, and human well-being (Faber et al., 2019; Pan et al., 2021). In this research, we introduced water supply capacity and ecosystem services value that can reflect ecosystem service functions to enable the integration of human well-being and ecological risk assessment. The research results can better inform the derivation of environmental quality standards.

Ecological risk sources are complex and diverse natural disasters and human disturbance factors. Ecological risk receptors are complex natural-social-economic systems. A microecological risk assessment method for a single pollutant and a single risk receptor is not feasible. The expert scoring method has a lower workload and a higher efficiency, but it is subjective and lacks objective quantitative expression. The comprehensive ecological risk assessment method based on the PSR model, or its extended model is relatively mature. It can objectively and quantitatively express regional ecological risk. However, the interpretation of the connotation of ecological processes is insufficient. Risk factors are deterministic in the impact mechanism on the ecological environment, but their classification, development trend, and mutual influence have uncertainty characteristics such as ambiguity, variability, and randomness. Li et al. (2023) pointed out that incorporating uncertainty into risk assessment is an important step toward an effective ecological risk. Therefore, methods of ecological risk assessment must have the ability to deal with deterministic information and uncertain information at the same time. The normal cloud model and set pair analysis address the relationship and transformation between the system's deterministic and uncertain factors. Therefore, this method can more accurately evaluate the ecological risk of complex systems. Munns et al. (2009) pointed out that linking assessment endpoints to public values can help identify economic methods appropriate for monetary damage determinations. We used the probabilistic loss model to link ecological values to human well-being. This research's conclusions align with the natural, social, and economic status of the UYR. The areas with higher risk warning levels were distributed in areas with frequent geological disasters, ecologically fragile or economically developed areas.

6 Conclusions

The double evaluation index system of ecological risk source hazard and ecological risk receptor loss can effectively characterize the ecological risk measurement value. The hazard of risk sources in the UYR increased from [0.12, 0.67] to [0.11, 0.73] in 2018, and the high-value areas were distributed mainly in the Three Gorges Reservoir area of Chongqing. The risk receptor loss degree range did not change, all between [0, 0.16], and the high-value areas were distributed in the Yungui Plateau. The comprehensive ecological risk value also increased yearly, from [0, 0.28] in 2015 to [0, 0.32] in 2018, the highest in the Yungui Plateau, the Three Gorges Reservoir Area, and the Minshan-Qionglai Mountains.

The proportion of high-risk levels in the UYR, about 57%, was much higher than that of low-risk levels, about 8%. From 2015 to 2018, the proportion of serious-alert increased from 2% to 8%, mainly distributed in the Yungui Plateau. The high-alert rate decreased from 55% to 49%, primarily distributed in the Yungui Plateau and the Three Gorges Reservoir area. The rate of medium alert dropped from 37% to 35%, mainly distributed in the Sichuan Basin. Light alert increased from 6% to 8%, mainly distributed in the UYR source.

In the future, the number of cities with good development trends will be twice that of cities with deterioration trends, and the deterioration space of all cities will be smaller. The ecological risk of 34 cities, including Luzhou and Zunyi, will develop in a good direction. The ecological risk level of 17 cities, including Chongqing and Chengdu, had an upward trend. Among them, approximately 84% of the cities had less deterioration space and higher stability in future development. Approximately 16% of the cities had a heavy opposition trend and a limited range of benefits in the short term.

The risk receptor loss degree is an important driving force for forming spatial and temporal patterns of comprehensive ecological risk. The spatial and temporal distributions of the receptor loss degree and the comprehensive ecological risk were highly similar, showing a distribution pattern of low from east to west and high from north to south. Among them, ecosystem service value had the most significant impact on the loss of receptors. The probability of disaster occurrence had the most significant impact on the hazard of risk sources.

Data availability The data sets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

CRediT authorship contribution statement Dongjie GUAN: Conceptualization, Writing-Original draft preparation. Jiameng CAO: Methodology, Software, Data curation. Danan HUANG: Conceptualization, Supervision. Lilei ZHOU: Visualization, Validation, Formal analysis.

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Competing interests The authors declare that they have no competing interests.

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Appendix

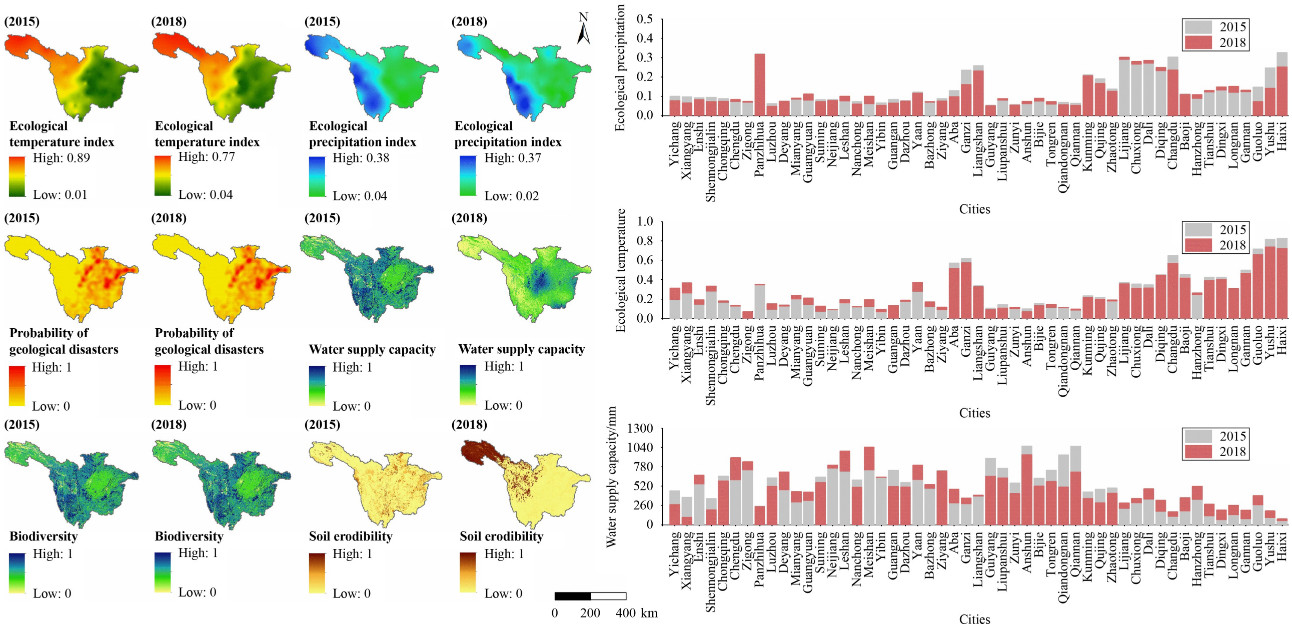

Fig. A1 Trends of natural ecological risk sources in the UYR from 2015 to 2018.

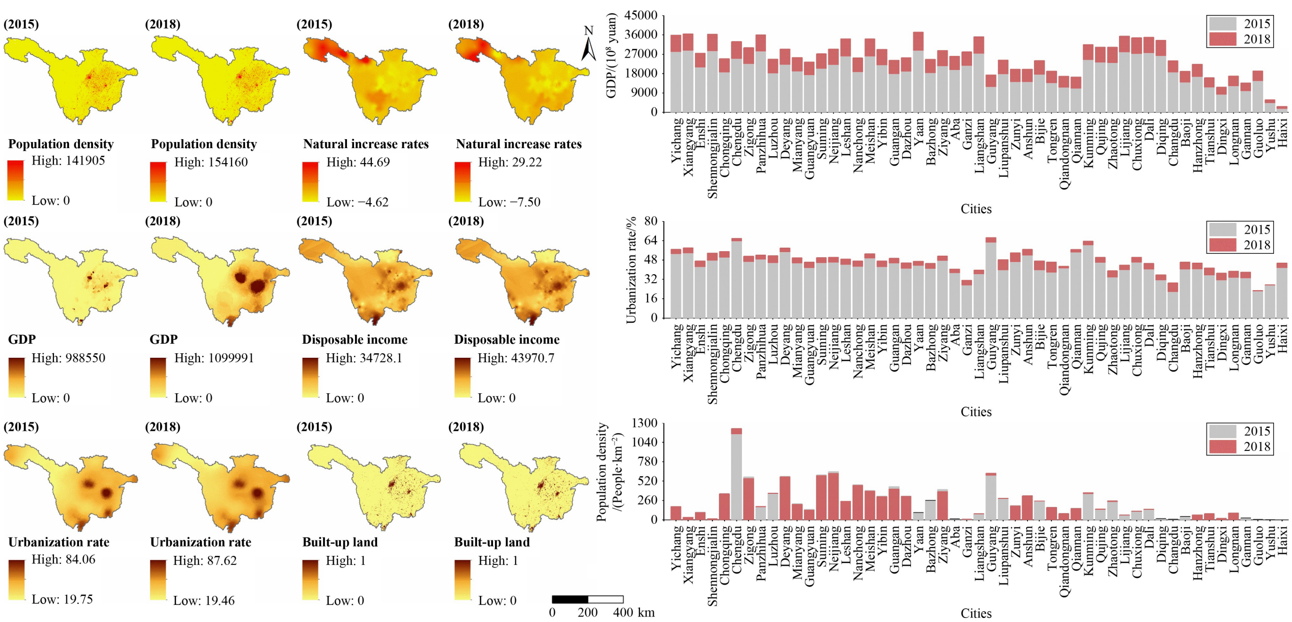

Fig. A2 Trends of human ecological risk sources in the UYR from 2015 to 2018.

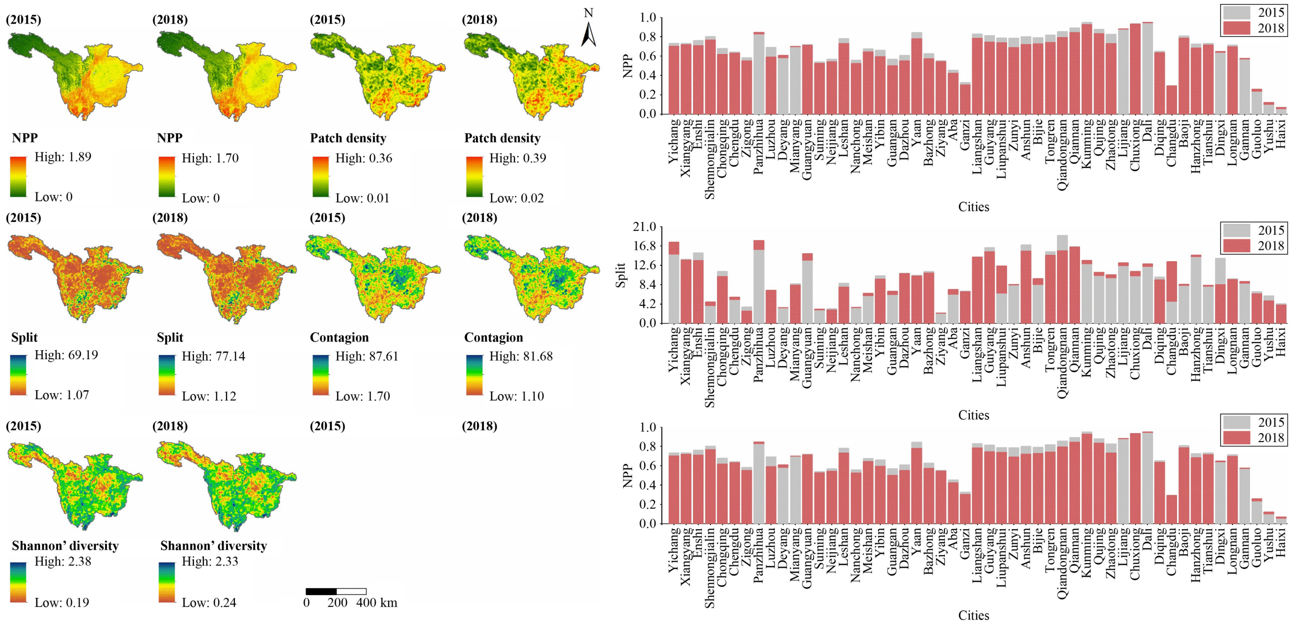

Fig. A3 Trend of ecological stability loss degree in the UYR from 2015 to 2018.

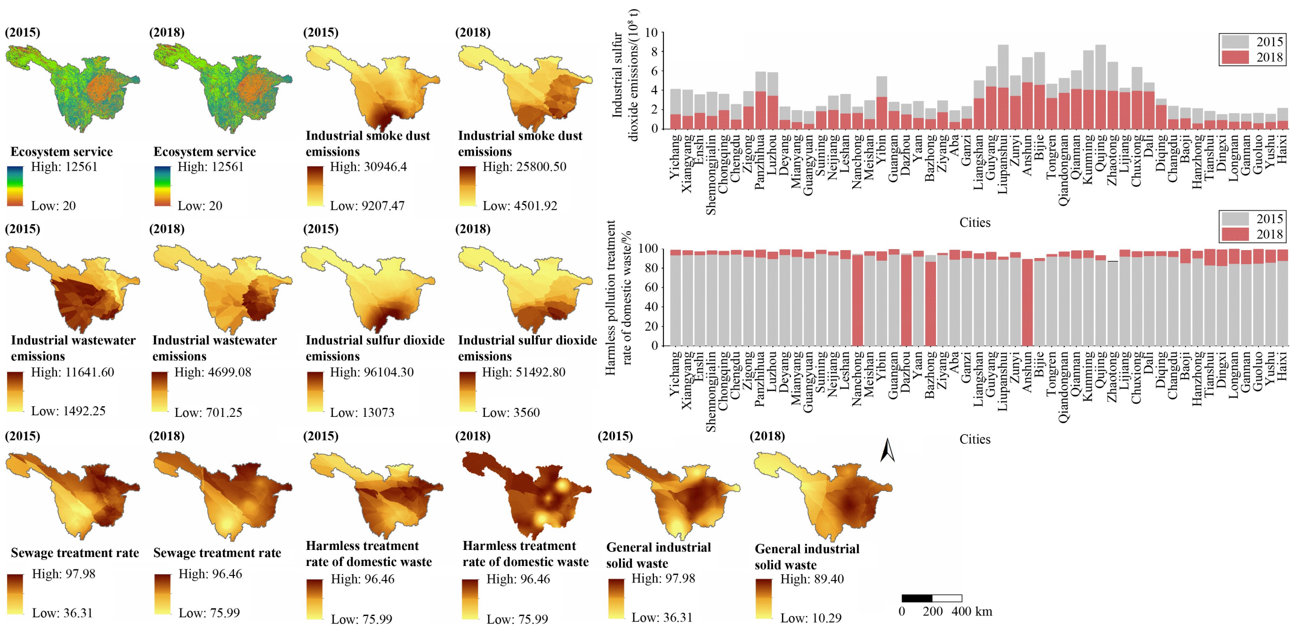

Fig. A4 Trend of ecological value loss degree in the UYR from 2015 to 2018.