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*CORRESPONDENCE Denghui Xu, ⋈ a504095919@163.com

SPECIALTY SECTION This article was submitted to Environmental Informatics and Remote Sensing, a section of the journal Frontiers in Environmental Science

RECEIVED 19 October 2022

ACCEPTED 28 December 2022 PUBLISHED 12 January 2023

CITATION

Lan G, Jiang X, Xu D, Guo X, Wu Y, Liu Y and Yang Y (2023), Ecological vulnerability assessment based on remote sensing ecological index (RSEI): A case of Zhongxian County, Chongqing. *Front. Environ. Sci.* 10:1074376. doi: 10.3389/fenvs.2022.1074376

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Ecological vulnerability assessment based on remote sensing ecological index (RSEI): A case of Zhongxian County, Chongqing

Guoxin Lan^{1,2}, Xiaolan Jiang^{1,2}, Denghui Xu^{3,4}*, Xianhua Guo^{1,2}, Yan Wu², Yixuan Liu^{1,2} and Yuzheng Yang^{1,2}

¹Research Institute of Three Gorges, Chongqing Three Gorges University, Chongqing, China, ²Key Laboratory of Water Environment Evolution and Pollution Control in Three Gorges Reservoir, Chongqing Three Gorges University, Chongqing, China, ³College of Ecology and Environment, Xinjiang University, Xinjiang, China, ⁴Key Laboratory of Oasis Ecology, Ministry of Education, Xinjiang University, Xinjiang, China

The ecological vulnerability evaluation index was established through Normalized Difference Vegetation Index (NDVI), Wetness (WET), Normalized Difference Build-up and Soil Index (NDBSI) and Land Surface Temperature (LST) indicators, comprehensively evaluate the ecological vulnerability of Zhongxian County of Chongqing in 2002, 2009, and 2016 by Principal Components Analysis (PCA), and analyze its spatio-temporal evolution. The vulnerability areas of five levels were calculated respectively, and the overall index of ecological vulnerability was also calculated. The index of remote sensing ecological index (RSEI) and Normalized Difference Vegetation Index decreased first and then increased; the Wetness index showed an upward trend; the Normalized Difference Build-up and Soil Index index increased first and then decreased; and the Land Surface Temperature index decreased. The ecological vulnerability body index (EVBI) shows a downward trend, and the incremental changes are mainly concentrated in the negligible vulnerability areas and light vulnerability area, while the medium vulnerability, strong vulnerability and extreme vulnerability area generally show a downward trend. Furthermore, the new increment of ecological vulnerability grade area concentrates on negligible vulnerability area and light vulnerability area from 2002 to 2016. In general, the ecological vulnerability gradually shifts to low vulnerability, and the ecological environment tends to develop healthily.

KEYWORDS

ecological vulnerability, RSEI, PCA, spatiotemporal evolution, ecological environment

1 Introduction

The social economy is developing rapidly, with intensifying contradiction between human and ecological environment. The irrational utilization of resources leads to the destruction of the surrounding ecological balance to a certain extent (Yan and Zhao, 2009), and affects the sustainable development of the ecosystem. The ecological fragility problem is more serious, which is the focus of sustainable development research and has attracted the attention of many scholars worldwide (Jackson et al., 2004; Ma et al., 2015; Gao and Zhang, 2018; Tian et al., 2021; Wang et al., 2021). The deepening scientific research diversifies ecological vulnerability assessment methods. For example, Zhang et al. (2021a) used fuzzy comprehensive method and analytic hierarchy process to study the ecological fragility of Yongding River. Teng et al. (2022) constructed an exposure-sensitivity-adaptive vulnerability assessment framework, established an ecological and social index system, determined the index weight by entropy weight method, and evaluated the change rules of ecological vulnerability (EV) and social vulnerability (SV). Zhang et al. (2021b) calculated the vulnerability of landscape types to determine the ecological vulnerability of coastal zone. Based on remote sensing (RS) and geographic information system (ArcGIS) technology, Wang and Su (2018) constructed the "Pressure-State-Response" framework and used PCA to evaluate the ecological vulnerability. Besides, Liu et al. (2020) built an ecological sensitivity-ecological resilienceecological pressure model to calculate the weight using the PCA method, and systematically evaluate the ecological vulnerability. The ecological vulnerability assessment helps us to understand the current the status quo of regional ecological vulnerability, which has a positive effect on the implementation of ecological environment governance plan. The data sources of evaluation indicators mainly include remote sensing, meteorological and other data. In addition, some studies combine RS and ArcGIS technology for ecological vulnerability evaluation. However, there are few studies that make full use of remote sensing indicators and remote sensing models for indepth analysis of ecological vulnerability evaluation. Wu (2005) constructed the ecological environment vulnerability equation and evaluation system based on RS technology, and used ASTER and TM data fusion technology to conduct quantitative remote sensing research on ecological environment vulnerability vegetation; Bai et al. (2009) extracted eight ecological factors including vegetation index, soil brightness and soil moisture index, elevation and slope, temperature and precipitation, and land use through RS and ArcGIS technology as evaluation indicators, and used the analytical hierarchy process (AHP) to evaluate the vulnerability of ecological environment; Zhu (2020) created 10 small indicators and 4 large indicators through the analysis of long time series multi-source remote sensing data (NDVI data, reflectance data, land use data, DEM data, lighting data, soil moisture data, precipitation data) and non-remote sensing data (protected areas), forming a set of assessment system to analyze the ecological vulnerability of the study area. Since the index system is subject to subjective influence, all the selected indicators are included in the evaluation model and the independence of the indicators is ignored, resulting in increased calculation and inaccurate results (Yao et al., 2016). Based on previous research results, multi index comprehensive evaluation model built by the evaluation method of the combination of ArcGIS and RS technology can effectively solve the problem of large-scale ecological vulnerability evaluation. It can not only reflect the current situation and distribution characteristics of ecological vulnerability, but also have objectivity and high reliability.

Zhongxian County is in the middle of Chongqing and in the hinterland of the sensitive and vulnerable area of ecological environment-the Three Gorges Reservoir area. Ecological vulnerability assessment is of great significance to master its ecological vulnerability characteristics and identify ecological and environmental problems (Wang et al., 2010). Therefore, this study employed remote sensing and geographic information system technology, and established an index system with NDVI, WET, NDBSI and LST based on RSEI (Xu, 2013) to comprehensively evaluate the ecological vulnerability of Zhongxian County from 2002 to 2016 using PCA, and reveal the spatio-temporal evolution of ecological vulnerability. This study aims to provide theoretical support and scientific basis for government decision-making for the ecological vulnerability protection of Zhongxian County.

2 Materials and methods

2.1 Study area

Zhongxian County (107° 3'E-108° 14'E, 30° 03'N-30° 35'N) is adjacent to Wanzhou District in the northeast, Dianjiang County in the west, Shizhu Tujia Autonomous County in the southeast, Fengdu County in the southwest and Liangping District in the north, with an area of about 2,178 km² (Figure 1). The territory of Zhongxian County is characterized by rolling hills, crisscross streams and rivers, and mainly hilly landform. It has the subtropical southeast monsoon mountain climate with the characteristics of warm and cold, sufficient sunshine and so on, which is significantly affected by the hilly terrain. Zhongxian County is a subtropical evergreen broadleaved forest belt with various vegetation types, which is suitable for the growth of many plants.

2.2 Data source and processing

Zhongxian County of Chongqing was chosen as the research area, and the remote sensing data set is provided by Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences (http://www.gscloud.cn) Landsat 5 TM image in 2002 and 2009, and Landsat 8 OLI image in 2016. Landsat 5 TM is a thematic mapper improved on the basis of MSS. It consists of seven bands, with a spatial resolution of 30 m for bands 1-5 and 7, and 120 m for band 6 (thermal infrared band). Landsat 8 carries an OLI land imager and a TIRS thermal infrared sensor. The OLI land imager consists of 9 bands with a spatial resolution of 30 m, including a 15 m panchromatic band. The TIRS thermal infrared sensor consists of 2 separate thermal infrared bands with a resolution of 100 m.The remote sensing images in 2002, 2009, and 2016 were radiometric calibrated by the environment for visualizing images (ENVI5.3) software, and the pixel value of the original image was converted into the reflectivity of the sensor. FLAASH (Fast line-of-sight atmospheric analysis of spectral hypercubes) absolute atmospheric correction images were adopted to reduce the differences in atmosphere and terrain of remote sensing images in different periods, and the impact on RSEI comparison between different images. The images of the study area were cropped, and the images of different phases were registered according to the quadratic polynomial and the nearest pixel method. The root mean square error of registration is less than .5 pixels. The data must be preprocessed, which is especially important for RSEI comparison between different categories and different temporal phases (Landsat 5 TM and Landsat 8 OLI_TIRS). When calculating the humidity index of the tasseled cap transformation, the correct formula should be selected, and the humidity of OLI cannot be calculated by the formula of TM, and the data based on reflectance cannot be calculated by the formula based on DN value. The DEM image of Zhongxian County is derived from the SRTMDEM 90M resolution raw elevation data provided by Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences (http://www. gscloud.cn). The world map is derived from the Natural Earth website (http://naturalearthdata.com), the administrative division



map of China is derived from the website (https://github.com/ GaryBikini/ChinaAdminDivisonSHP), and the administrative division map of Chongqing City and Zhongxian County is derived from 91 Weitu Assistant.

2.3 Research methods

2.3.1 Construction of evaluation index

Normalized Difference Vegetation Index (NDVI). Normalized Difference Vegetation Index (NDVI) is closely related to plant biomass, leaf area index and vegetation coverage (Goward et al., 2002), which was chosen in this paper to replace the greenness index, and the formula is as follows:

$$NDVI = (p_{NIR} - p_R) / (p_{NIR} + p_R)$$
(1)

where p_{NIR} and p_R is the reflectance of near infrared band and red band of Landsat 5 TM and Landsat 8 OLI_TIRS, respectively.

Wetness (WET): The brightness, greenness and humidity components of tassel hat transformation are related to surface physical parameters (Huang et al., 2002; Wang and Dong, 2013). Here, the Wetness index (WET) is expressed by humidity component. The expressions of reflectance image data of Landsat 5 TM and Landsat 8 OLI_TIRS are as follows (Crist, 1985; Baig et al., 2014):
$$\begin{split} Wet_{TM} &= 0.0315 p_B + 0.2021 p_G + 0.3102 p_R + 0.1594 p_{NIR} - 0.6806 p_{SWIR1} - 0.6109 p_{SWIR2} \eqno(2) \end{split}$$

where p_B , p_G , p_R , p_{NIR} , p_{SWIR1} , and p_{SWIR2} represent the reflectance of the blue, green, red, near infrared, shortwave infrared 1 and shortwave infrared 2 bands of Landsat 5 TM and Landsat 8 OLI_TIRS, respectively.

Normalized Difference Build-up and Soil Index (NDBSI). Urban land leads to the "drying" of the surface. In this paper, index-based built-up index (IBI) is used to replace the building index in the NDBSI. At the same time, the exposed land on the surface will also cause surface drying. NDBSI (Xu, 2013) can be calculated by the combination of index-based built-up index (IBI) and soil index (SI) (NASA, 2012):

NDBSI = (IBI + SI)/2

among,

$$IBI = \frac{\{2p_{SWIR1}/(p_{SWIR1} + p_{NIR}) - [p_{NIR}/(p_{NIR} + p_{R}) + p_{G}/(p_{G} + p_{SWIR1})]\}}{\{2p_{SWIR1}/(p_{SWIR1} + p_{NIR}) + [p_{NIR}/(p_{NIR} + p_{R}) + p_{G}/(p_{G} + p_{SWIR1})]\}}$$
(5)
$$SI = [(p_{SWIR1} + p_{R}) - (p_{R} + p_{NIR})/(p_{SWIR1} + p_{R}) + (p_{R} + p_{NIR})]$$
(6)

where p_G , p_B , p_R , p_{NIR} , and p_{SWIR1} are the reflectance of green, blue, red, near infrared and short wave infrared 1 bands of Landsat 5 TM and Landsat 8 OLI_TIRS remote sensing images, respectively.

(4)

	Principal component coefficient							
	Principal component	NDVI	WET	NDBSI	LST	characteristic value(λ)	Contribution rate (%)	Cumulative contribution rate (%)
2002	PC1	.30823	.69286	53954	36582	.01602	58.1833	58.1833
	PC2	.86611	46149	16475	.09870	.00878	31.8663	90.0496
	PC3	.02784	.32123	19904	.92543	.00247	8.9739	99.0235
	PC4	.39252	.45142	.80133	.00385	.00027	.9765	100.0000
2009	PC1	.37592	.57527	59417	41799	.01602	69.1266	69.1266
	PC2	.83399	35970	10546	.40492	.00878	16.2134	85.3400
	PC3	22024	.47777	24884	.81321	.00247	13.5068	98.8468
	PC4	.33859	.55805	.75757	00434	.00027	1.1532	100.0000
2016	PC1	.53986	.39012	67250	32265	.01894	77.3425	77.3425
	PC2	.39995	07374	15377	.90053	.00346	14.1453	91.4878
	PC3	.65342	63227	.29747	29118	.00193	7.8938	99.3816
	PC4	.34875	.66529	.66001	.01228	.00015	.6184	100.0000

TABLE 1 Principal component analysis of each index.

Land Surface Temperature (LST): The LST index is represented by land surface temperature (Xu, 2013), and the temperature value T at the sensor was calculated by using the model (NASA, 2018) in Landsat user manual. The real land surface temperature can be obtained only through specific emissivity correction:

$$L = gain \times DN + bias$$
(7)

$$T = K_2 / \ln (K_1 / L + 1)$$
(8)

$$LST = T/[1 + (\lambda T/p) \ln \varepsilon]$$
(9)

where L is the radiance value of Landsat 5 TM thermal infrared 6 band and Landsat 8 OLI_TIRS thermal infrared 10 band, and DN is the pixel value of the band. Gain and bias are the gain value and offset value of thermal infrared band respectively. T is the temperature value at the sensor, and K₁ and K₂ is the calibration parameter. Landsat 5 TM image, K₁ = 607.76 W/(m²·sr·µm), K₂ = 1,260.56 K, in Landsat 8 OLI_TIRS image K₁ = 774.89 W/(m²·sr·µm), K₂ = 1,321.08 K, λ is the wavelength of thermal infrared band, p = 1.438 × 10⁻² m K, and ε is the surface specific emissivity.

2.3.2 Index standardization

Different dimensions will cause the weight of each indicator to be unbalanced. Therefore, it is necessary to standardize the indicators and unify their dimensions between [0, 1] before PCA calculation (Xu, 2013). The normalization formula of each indicator is as follows:

$$SI_n = \frac{I_n - I_{\min}}{I_{\max} - I_{\min}}$$
(10)

where SI_n is the standardized value of the *n*th index, and its value is between [0, 1]. I_n , I_{max} and I_{min} represent the value, maximum value and minimum values of the *n*th index in pixel n, respectively.

2.3.3 Evaluation method

The ecological vulnerability index (EVI) can be calculated to understand the status and characteristics of ecological

vulnerability. The construction of the eco-index should accommodate both the appearance of a single indicator and the combination of information from the above four indicators. Therefore, how to represent multiple variables above with a single variable, that is key to this study. A frequently used method is to simply add up the individual indicators (Kearney et al., 1995), or to group the indicators to find the mean value and then add them up (Wang et al., 2007), or to multiply them by their respective weights and then add them up (Williams et al., 2009). However, both the correlation between indicators and the artificial determination of weights and other relevant factors can affect the results. Multidimensional statistical method of principal component analysis is a multidimensional data compression technique that selects a few important variables by linear transformation of multiple variables, and it takes the method of sequentially rotating the coordinate axes vertically to concentrate the multidimensional information into a few characteristic components, which often represent certain characteristic information (Xu, 2013). Therefore, this study was conducted by using the principal component transformation to construct the remote sensing ecological index, and the main information was concentrated on the first 1-2 principal components by removing the correlation among the indicators through the rotation of the spatial axes of the feature spectra. One of the other advantages of using principal component analysis is that the weights of each indicator are not artificially determined, but are determined automatically and objectively based on the contribution of each indicator to each principal component quantity. What this leads to is that bias in the results caused by weight settings that vary from individual to individual and from method to method can be avoided in the calculation. However, there is correlation among the evaluation indicators, and the information of each indicator will overlap during calculation, so the principal component analysis method is used. Principal component analysis can transform multiple indicators into a few uncorrelated

TABLE 2 Classification standard of ecological vulnerability in Zhongxian County, Chongqing (Fan et al., 2009; Ifeanyi et al., 2010; Ma et al., 2015; He et al., 2018).

Vulnerability	Grade	Standardized value of ecological vulnerability index	Ecological characteristics
Negligible vulnerability	Ι	<2.0	The structure and functions of the ecosystem are reasonably improved, and the ecosystem is stable with low pressure, strong ability to resist external disturbance and self-recovery, no ecological abnormality and low ecological vulnerability
Light vulnerability	Π	2.0-4.0	The structure and function of the ecosystem are relatively complete, and the ecosystem bears less pressure. The ecosystem is relatively stable, and has strong ability to resist external disturbance and self-recovery. There are potential ecological anomalies and low ecological vulnerability
Medium vulnerability	111	4.0-6.0	The structure and function of the ecosystem can still be maintained, and the pressure is large. The system is relatively unstable, and the external interference is more sensitive, the self-recovery ability is weak, and there is a small number of ecological abnormalities, and the ecological fragility is higher
Strong vulnerability	IV	6.0-8.0	Defects in the ecosystem structure and function, high pressure, unstable ecosystem, strong sensitivity to external interference, great difficulty in recovery after damage, many ecological abnormalities and high ecological vulnerability
Extreme vulnerability	V	≥8.0	The structure and function of the ecosystem are severely degraded and under great pressure. The ecosystem is extremely unstable and sensitive to external disturbance. It is extremely difficult or even irreversible to recover after damage, even irreversible, ecological abnormalities appear in a large area, and the ecological vulnerability is very high

TABLE 3 Four indicators and RSEI statistics in 2002 and 2016.

		2002		2009	2016	
Index	Mean value	Standard deviation	Mean value	Standard deviation	Mean value	Standard deviation
NDVI	.6716	.1233	.3834	.3741	.4931	.3817
WET	.6675	.1983	.7232	.1948	.7644	.0686
NDBSI	.6248	.2549	.7572	.2446	.5668	.2656
LST	.5721	.1042	.2234	.2310	.2731	.2635
RSEI	.5405	.0720	.5122	.0967	.7098	.0755

comprehensive indicators, and reflect the information expressed by more variables using fewer comprehensive indicators. Based on GIS 10.7 system calculation, this paper made principal component analysis on standardized indexes of NDVI, WET, NDBSI and LST. When the cumulative contribution rate of principal component reaches more than 85%, it can represent the information reflected by most variables (Table 1), and further calculate EVI (Yao et al., 2016; Wang and Su, 2018):

$$EVI = r_1 \gamma_1 + r_2 \gamma_2 + \dots + r_n \gamma_n \tag{11}$$

where EVI is the ecological vulnerability index. r_n and γ_n represent the contribution rate of the *n*th principal component and the *n*th principal component respectively.

Table 1 shows that the cumulative contribution rates of the PC1, PC2 and PC3 among the four indicators in Zhongxian County in 2002, 2009, and 2016 were 99.0235%, 98.8468%, and 99.3816% respectively, all greater than 85%, suggesting that they have concentrated the main information of the four indicators. In PC1, both NDVI and WET are positive, suggesting that both are good for the environment development, and both NDBSI and LST are negative.

Based on the PCA, the inversion model of ecological vulnerability assessment was calculated through Eq. 11 and Table 1 as follows:

- $EVI_{2009} = 0.6913 \times PC1 + 0.1621 \times PC2 + 0.1351 \times PC3$ (13)
- $EVI_{2016} = 0.7734 \times PC1 + 0.1415 \times PC2 + 0.0789 \times PC3$ (14)

where EVI_{2002} , EVI_{2009} , and EVI_{2016} represent the ecological vulnerability index in 2002, 2009 and 2016 respectively, and PC1-PC3 is the first three principal component factors of principal component analysis. Their cumulative contribution rate in the 3 years reached 99%, but most of the information of the PC4 is noise. So, the PC4 is ignored.

2.3.4 Classification of ecological vulnerability and overall index of ecological vulnerability

In order to better measure the ecological vulnerability, vulnerability index need to be standardized, and the formula is as follows:

$$SI_{EVI} = \frac{EVI_n - EVI_{min}}{EVI_{max} - EVI_{min}} \times 10$$
(15)



where SI_{EVI} represents the standardized value, and it is between 0 and 10. EVI_n , EVI_{min} , and EVI_{max} represent the actual value, minimum value and maximum value of ecological vulnerability index, respectively. The standardized EVI was divided into five vulnerability levels (Fan et al., 2009; Ifeanyi et al., 2010; Ma et al., 2015; He et al., 2018) according to the

relevant ecological vulnerability classification standards (Table 2), which are negligible vulnerability, light vulnerability, medium vulnerability, strong vulnerability and extreme vulnerability.

The ecological vulnerability body index (EVBI) calculated by multiplier model can analyze the overall difference of ecological

	2002		200)9	2016	
Grade	Area (km ²)	EVBI	Area (km ²)	EVBI	Area (km ²)	EVBI
I	27.0414	.012365	64.7010	.030532	653.9742	.299028
II	348.4044	.318614	.318614 556.4673		1,254.4140	1.14755
III	1,360.5140	1.866274	1,324.6460	1.875266	181.7620	.249331
IV	390.5784	.714364	169.4421	.319833	30.5271	.055834
V	7.4772	.017095	3.8763	.009146	2.3895	.005463
Total	2,134.0152	2.928711	2,119.1328	2.759961	2,123.0667	1.75681

TABLE 4 Area and EVBI distribution of ecological vulnerability in different years in Zhongxian County, Chongqing.

vulnerability in Zhongxian County, and the algorithm is as follows (Yao et al., 2016):

$$EVBI = \sum_{i=1}^{n} P_i \times A_i / S$$
(16)

where EVBI indicates the overall index of ecological vulnerability. P_i Indicates the class i vulnerability level value. A_i indicates the area of class i vulnerability. S represents the total area of the area. n Indicates the total number of vulnerability levels.

2.3.5 Extracting the spatio-temporal evolution pattern of ecological fragility

Based on ArcGIS 10.7 system, this paper spatially superimposed the ecological vulnerability level map in 2002–2009, 2009–2016 and 2002–2016 to extract the dynamic map of ecological vulnerability change. The algorithm is as follows (Deng et al., 2016; Guo et al., 2019):

$$Code_{Classification_{2002}_{2009}} = 10 \times Code_{Classification_{2002}} + Code_{Classification_{2009}}$$
(17)

$$Code_{Classification_{2009}_{2016}} = 10 \times Code_{Classification_{2009}} + Code_{Classification_{2016}}$$
(18)

$$Code_{Classification_{2022}_{2016}} = 100 \times Code_{Classification_{2022}} + 10 \times Code_{Classification_{2029}} + Code_{Classification_{2016}}$$
(19)

where Code_{Classification_2002}, Code_{Classification_2009} and Code_{Classification_2016} represent five vulnerability level type codes, respectively. I-V represent negligible, light, medium, strong and extreme vulnerability respectively. Code_{Classification2002_2009} is the change type code of ecological vulnerability level, which represents the transformation from ecological vulnerability level type in 2002 to ecological vulnerability level type in 2009. For example, I-V indicates the transformation from negligible vulnerability in 2002 to extreme vulnerability in 2009.

3 Results

3.1 Change characteristics of ecological vulnerability index

Table 3 demonstrates the statistical values of four indicators and the RSEI in 2002, 2009, and 2016. Due to the great diurnal temperature variation, the Land surface temperature index (LST) can only be compared through normalization (Carlson and Arthur, 2000; Xu et al., 2009). Therefore, the four indexes were normalized and the null value was removed to obtain the statistical values of each index. Table 3 shows the analysis results, the mean value of NDVI index beneficial to the ecological environment decreased from .6716 in 2002 to .3834 in 2009, with a decreased of 42.91%, and then increased to .4931 in 2016, indicating that the decrease of vegetation coverage in Zhongxian County gradually increased after a significant decline. In the other hand, the mean value of WET index increased from .6675 in 2002 to .7644 in 2016, an increase of 14.52%, suggesting that the water conservation capacity of Zhongxian County has improved. The mean values of NDBSI and LST indicators that having adverse effects on the ecological environment have decreased. The mean values of NDBSI increased from .6248 in 2002 to .7572 in 2009, and decreased to .5668 in 2016, and LST decreased significantly from .5721 in 2002 to .2234 in 2009 and increased to .2731 in 2016, indicating that the surface exposure of Zhongxian County has been reduced, the difference between hydrothermal balance has been reduced, and the adverse impact on the future ecological environment has been weakened. Based on the changes of the above four indicators, it roughly shows that the ecological environment of Zhongxian County is on the rise as a whole, and the environmental change is gradually developing in a good direction. The mean value of the RSEI decreased from .5405 in 2002 to .5122 in 2009 and increased to .7098 in 2016, indicating that the ecological environment quality in the study area fluctuated from 2002 to 2016, but the overall development trend showed a benign development trend, which was basically consistent with the comprehensive results of the indicators. The RSEI of Zhongxian County in 2002, 2009, and 2016 were shown in Figure 2. In order to further highlight the representativeness of the RSEI, the ecological index was divided into five grades, representing five grades including poor (I: .0-.2), poor (II: .2-.4), medium (III: .4-.6), good (IV: .6-.8) and excellent (V: .8-1.0). In 2002, the RSEI was dominated by medium (III) grade, accounting for 69.83%, and the percentages of good (IV) and excellent (V) grades were 22.47% and 1.39%, respectively, which were mainly distributed in areas with high terrain and little impact of human activities, while poor (I) and poor (II) areas accounted for .09% and 6.22%, which were mainly distributed in areas with frequent human activities. In 2009, the RSEI was dominated by medium (III) grade, accounting for 59.11%, poor (I) and poor (II) grades accounted for 1.06% and 17.17% respectively, and good (IV) and excellent (V) grades accounted for 19.94% and 2.72%



respectively. In 2016, the RSEI was dominated by good (IV) grade, accounting for 72.17%, and medium (III) and excellent (V) grades accounted for 11.21% and 14.89% respectively and the area of poor (I) and poor (II) areas was the least, accounting for .12% and 1.62%.

Among them, the areas with poor ecological environment quality were mainly concentrated in urban areas. On the whole, the quality of the ecological environment of Zhongxian County from 2002 to 2016 has improved.



TABLE 5 Area transfer matrix of different ecological vulnerability levels in Zhongxian County from 2002 to 2009 (km²).

Vulnerability level		2009						Reduction of
		Negligible vulnerability	Light vulnerability	Medium vulnerability	Strong vulnerability	Extreme vulnerability		
2000	Negligible vulnerability	18.8271	5.3928	.9135	.1035	.0054	25.2423	6.4152
	Light vulnerability	44.2962	211.7187	79.0515	8.8353	.2988	344.2005	132.4818
	Medium vulnerability	1.3545	326.7990	927.8190	93.8583	2.1222	1,351.9530	424.1340
	Strong vulnerability	.1602	11.6982	313.0740	62.7012	1.2276	388.8612	326.1600
	Extreme vulnerability	.0000	.0486	3.3075	3.8475	.2196	7.4232	7.2036
	Total of 2009	64.6380	555.6573	1,324.1655	169.3458	3.8736	2,117.6802	_
	Increment of 2009	45.8109	343.9386	396.3465	106.6446	3.6540	_	896.3946

Vulnerability level		2016						Reduction of
		Negligible vulnerability	Light vulnerability	Medium vulnerability	Strong vulnerability	Extreme vulnerability	2003	2007
2009	Negligible vulnerability	55.7811	7.4718	.8676	.3627	.0918	64.5750	8.7939
	Light vulnerability	274.3758	263.1519	15.4710	2.1735	.1647	555.3369	292.1850
	Medium vulnerability	288.3375	885.0816	132.8013	16.7679	.9918	1,323.9801	1,191.1788
	Strong vulnerability	34.2963	97.3287	27.9585	8.8038	.9036	169.2909	160.4871
	Extreme vulnerability	1.1709	1.0755	.5949	.7884	.2340	3.8637	3.6297
	Total of 2016	653.9616	1,254.1095	177.6933	28.8963	2.3859	2,117.0466	_
	Increment of 2016	598.1805	990.9576	44.8920	20.0925	2.1519	_	1,656.2745

TABLE 6 Area transfer matrix of different ecological vulnerability levels in Zhongxian County from 2009 to 2016 (km²).



FIGURE 5

Temporal and spatial evolution pattern of ecological vulnerability in Zhongxian County from 2002 to 2016 (water mask treatment, the picture at the lower left corner shows the location of Zhongxian administrative center).

Vulnerability	Vulnerability level	Unchanged area	Reduction area	Increment area
Negligible vulnerability	Ι	16.2585	8.3835	637.6878
Light vulnerability	II	85.8339	258.2001	1,168.0578
Medium vulnerability	III	80.9667	1,270.6686	96.4980
Strong vulnerability	IV	3.5865	385.2261	25.2738
Extreme vulnerability	V	.0207	7.4025	2.3634

TABLE 7 Dynamic change of area of different ecological vulnerability levels from 2002 to 2016 (km²).

3.2 Overall characteristics of ecological vulnerability

By calculating the ecological vulnerability body index (EVBI) of the four indicators, the ecological vulnerability grade area and EVBI distribution in 2002, 2009, and 2016 were inversed (Table 4), and the overall distribution pattern of ecological vulnerability in Zhongxian County was analyzed. The total ecological vulnerability area of the five grades of Zhongxian County decreased from 2,134.0152/km² in 2002–2,119.1328/km² in 2009, and increased to 2,123.0626/km² in 2016. The total value of ecological vulnerability body index (EVBI) decreased from 2.9986 in 2002 to 2.759961 in 2009, and fell to 1.75681 in 2016, with a large decline. According to the classification standard of ecological fragility in Zhongxian County, the ecological vulnerability was mainly medium vulnerability and strong vulnerability in 2002, the medium vulnerability grade accounted for 62.21% of the total area, while the strong vulnerability grade was 17.86%. In 2009, it was mainly medium vulnerability and light vulnerability, accounting for 62.51% and 26.26% of the total area respectively. In 2016, it was mainly light vulnerability and negligible vulnerability, accounting for 57.36% and 29.90% of the total area respectively. The areas of medium vulnerability, strong vulnerability and extreme vulnerability areas in 2009 decreased by 35.8680/km², 221.1363/km² and 3.6009/km² respectively compared with 2002, and the areas of strong vulnerability areas decreased significantly. In 2016, the area of medium vulnerability, strong vulnerability and extreme vulnerability areas decreased by 1,142.8840/km², 138.915/km² and 1.4868/km² respectively compared with 2009, and the area of medium vulnerability areas decreased significantly. From 2002 to 2016, the area of negligible vulnerability and light vulnerability areas continued to grow, with an increase of 626.9328/km² and 906.0096/km² respectively, indicating significant changes in vulnerability.

As shown in Figure 3, the ecological vulnerability grade of Zhongxian County was dominated by medium vulnerability and strong vulnerability in 2002, which were distributed in bands and flakes, and the negligible, light and extreme vulnerability areas were roughly distributed in dots and blocks. Among them, the spatial distribution of medium vulnerability and strong vulnerability areas in the southwest was dense, which was mainly due to the densely populated distribution and the great impact of human activities. In 2009, Zhongxian County was mainly distributed in light and medium vulnerability areas, and negligible vulnerability areas, strong vulnerability areas and extreme vulnerability areas were generally distributed in bands and dots. The areas with high vulnerability were significantly affected by human activities, while areas with low vulnerability were mainly affected by terrain, with less human activities, less pressure, and strong ability to resist external interference and self-recovery. In 2016, Zhongxian County was mainly distributed in negligible vulnerability areas and light vulnerability areas, and the medium vulnerability, strong vulnerability and extreme vulnerability areas were roughly scattered in dots. The areas with high vulnerability were mostly areas with high economic level, large urbanization construction land, small green space and frequent human economic activities. The areas with low vulnerability were mainly limited by their geographical conditions, small population density and low impact of human economic activities. The good surface vegetation coverage can promote the reduction of its ecological vulnerability. Through the analysis of the overall situation of ecological vulnerability, the overall ecological vulnerability of Zhongxian County in Chongqing was found to be mainly increased to the negligible vulnerability and light vulnerability area from 2002 to 2016, and the medium vulnerability, strong vulnerability and extreme vulnerability areas showed a downward trend. The overall index of ecological vulnerability decreased. The ecological vulnerability weakened with the implementation of ecological restoration and protection measures, and the ecosystem was restored and improved.

3.3 Spatio-temporal evolution characteristics of ecological vulnerability

The spatial variation of ecological vulnerability level in Zhongxian County during the past 15 years was further analyzed, the study was divided into two periods (2002-2009 and 2009-2016) for longitudinal comparative analysis. The spatial-temporal evolution characteristics of ecological vulnerability was calculated by Eqs 17, 18 (Figure 4), and the area transfer matrix of different levels of ecological vulnerability was calculated during 2002-2009 and 2009-2016 (Tables 5, 6). From 2002 to 2009, the area transfers of various ecological vulnerability levels totaled 896.3946/km² (Table 5). From 2002 to 2009, the level of ecological vulnerability mainly transferred from medium vulnerability and strong vulnerability to light vulnerability and medium vulnerability. In 2002, the transfer amount of medium vulnerability and strong vulnerability was 424.1340/km² and 326.1600/km² respectively, accounting for 47.31% and 36.39% of the total amount of ecological vulnerability; the transfer amount of negligible, light and extreme vulnerability was 6.4152/km², 132.4818/ km² and 7.2036/km², respectively, accounting for .72%, 14.78% and .80% of the total transfer volume. In 2009, the new increment of light vulnerability and medium vulnerability was 343.9386/km² and 396.3465/km² respectively, accounting for 38.37% and 44.22% of the total new increment; the new increment of negligible vulnerability, strong vulnerability and extreme vulnerability was 45.8109/km², 106.6446/km²

and 3.6540/km², accounting for 5.11%, 11.90% and .41% of the total increment. From 2009 to 2016, the area transfers of various ecological vulnerability levels totaled 1,656.2745/km2 (Table 6). From 2002 to 2009, the level of ecological vulnerability mainly transferred from light vulnerability and medium vulnerability to negligible vulnerability and light vulnerability. In 2009, the transfer amount of light vulnerability and medium vulnerability was 292.1850/km² and 1,191.1788/km² respectively, accounting for 17.64% and 71.92% of the total amount of ecological vulnerability; the transfer volume of negligible, strong and extreme vulnerability was 8.7939/km², 160.4871/km², and 3.6297/km², accounting for .53%, 9.69% and .22% of the total transfer volume. In 2016, the new increment of negligible vulnerability and light vulnerability was 598.1805/km² and 990.9576/km² respectively, accounting for 36.12% and 59.83% of the total new increment; the new increment of medium vulnerability, strong vulnerability and extreme vulnerability was 44.892/ km², 20.0925/km², and 2.1519/km² respectively, accounting for 2.71%, 1.21%, and .13% of the total increment.

With the support of ArcGIS 10.7 software, the spatial variation of ecological vulnerability levels during 2002-2016 was calculated by Eq. 19 (Figure 5), and the area dynamic change of different ecological vulnerability levels in Zhongxian County during 2002-2016 was obtained (Table 7). Overall, the new increase in the area of ecological vulnerability level from 2002 to 2016 is mainly in the area of negligible vulnerability areas, light vulnerability areas and medium vulnerability areas, while the transfer amount is mainly light vulnerability areas, medium vulnerability areas and strong vulnerability areas. Affected by natural and geographical conditions, areas with large topographic fluctuations and less human activities have low ecological vulnerability, flat terrain and areas along the river basin have high ecological vulnerability (Figure 5). On the whole, the distribution pattern of ecological vulnerability is higher in the eastern and southwestern regions, and lower in the central and southeastern regions. With the promulgation of national policies and the implementation of ecological and environmental protection measures, ecological vulnerability has been gradually shifted to low vulnerability. Although the accelerated urbanization process has led to the growth of strong vulnerability areas and extreme vulnerability areas, the growth rate is still small, and shows a downward trend. Generally speaking, the ecological environment of Zhongxian County is gradually developing in a good direction.

4 Discussion

The purpose of this study is to make a comprehensive quantitative assessment of ecological vulnerability in Zhongxian County, and to analyze the spatio-temporal evolution characteristics of ecological vulnerability. In order to evaluate the ecological vulnerability in more detail, the RSEI in 2002, 2009 and 2016 was calculated, and the ecological vulnerability assessment index system was constructed by using the indicators of NDVI, WET, NDBSI, and LST, and the ecological vulnerability of Zhongxian County was analyzed by the principal component analysis method. From 2002 to 2016, the RSEI showed a trend of first decreasing and then increasing, in which the WET index showed an increasing trend, the LST index showed a decreasing trend, the NDVI index showed a decreasing trend and then increasing trend, and the NDBSI index showed a rising trend and then decreasing trend. In general, the ecological environment quality was developing towards a good trend. The degree of ecological vulnerability is related to vegetation index, wetness, bare land surface, urban land and land surface temperature, which is consistent with the results of other studies (Tang et al., 2022; Zhang et al., 2022). In addition to investigating the change characteristics of ecological vulnerability indicators, another aspect of this study is to analyze the spatial and temporal evolution pattern of ecological vulnerability. From 2002 to 2016, the overall index of ecological vulnerability showed a downward trend. By 2016, the level of ecological vulnerability was mainly negligible vulnerability and light vulnerability, and most areas shifted to negligible vulnerability and light vulnerability, and the ecological vulnerability gradually changed to low vulnerability. In terms of spatial distribution, the distribution of ecological vulnerability from high to low basically showed a trend of gradual transition from plain to mountainous region, which was consistent with other reports (Li, 2010; Jin and Xu, 2022; Singh et al., 2022).

Due to the characteristics of multi-band and strong correlation of multispectral images, the internal information of multispectral images is highly redundant (Sun et al., 2016). The index calculated based on remote sensing image may have information redundancy. In order to avoid the influence of human factors and subjective conditions when constructing the ecological vulnerability assessment index system, the index system of RSEI was selected (Xu, 2013). There was no obvious correlation between the index systems. In addition, it can reflect the vegetation cover, soil moisture, surface exposure and land surface temperature (Wang et al., 2016), while the spatial principal component analysis can remove certain correlations among indicators and reduce data redundancy (Xu, 2013; Pan and Xiao, 2015). To sum up, this paper selects the indicators of NDVI, WET, NDBSI, and LST to construct an ecological vulnerability assessment index system, and principal component analysis is a desirable evaluation method. In this study, the ecological vulnerability of Zhongxian County was objectively evaluated through remote sensing and evaluation model to reveal the evolution drivers of its ecological vulnerability. In view of the obvious spatial differentiation characteristics of each index impact factor in different geographical units, the local government should coordinate the effective balance between economic development and ecological vulnerability management. Appropriate measures should be taken to prevent ecological fragility from becoming more fragile.

5 Results

Combined with remote sensing and ArcGIS technology, this paper calculates the RSEI through remote sensing model and constructs the ecological vulnerability evaluation index system, comprehensively and quantitatively evaluates the ecological vulnerability of Zhongxian County in 2002, 2009, and 2016 by PCA method, and analyzes the spatio-temporal evolution characteristics of ecological vulnerability. The key points of my conclusion are as follows.

(1) Based on the distribution characteristics, the RSEI showed a trend of first decreasing and then increasing, from .5405 in 2002 to .5122 in 2009, and then rising to .7098 in 2016. Among them, the average value of NDVI that are conducive to the ecological environment quality has a trend of first decreasing and then increasing, the WET has an upward trend, while the average value of NDBSI that are not conducive to the ecological environment quality has a trend of first increasing and then decreasing, and the LST has a downward trend, indicating that the vegetation coverage in Zhongxian County has decreased and then increased, the degree of surface exposure has decreased, and the difference between water and heat balance has decreased. On the whole, the impact on future ecological vulnerability is weakened.

- (2) The EVBI of Zhongxian County shows a downward trend. From 2002 to 2016, the EVBI changed from medium vulnerability and strong vulnerability to negligible vulnerability and light vulnerability, and the medium vulnerability, strong vulnerability and extreme vulnerability showed a general downward trend. The ecological vulnerability gradually weakens with the implementation of ecological restoration and protection measures, that is, the improvement of ecological environment is gradual.
- (3) The increment of ecological vulnerability level in 2002–2009 is mainly the increase in the area of light and medium vulnerability area, while the transfer amount is mainly the transfer of medium vulnerability and strong vulnerability. The increment of ecological vulnerability level in 2009–2016 is mainly the increase in the area of negligible vulnerability and light vulnerability area, while the transfer amount is mainly the transfer of light vulnerability and medium vulnerability. In general, the ecological vulnerability gradually changes to low vulnerability, and the ecological environment of Zhongxian County tends to benign development.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

GL: conceptualization; development or design of methodology; validation; formal analysis; writing-original draft preparation;

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visualization; data curation. XJ: supervision; writing-review and editing. DX: supervision; funding acquisition; writing-review and editing. XG: supervision; project administration; funding acquisition; writing-review and editing. YW: writing-review; data curation. YL: data curation. YY: data curation. All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by XG, grant number (National Social Science Fund I: 21BMZ141, Supported by the Open Fund of the Research Center for Sustainable Development of the Three Gorges Reservoir Area: 2021sxxyjd01, Humanities and Social Sciences Research Planning Project of Chongqing Municipal Education Commission: 21SKGH432) and GL, grant number (Chongqing Wanzhou District Science and Technology Committee Project: 201503050, Open Fund for Chongqing Key Laboratory of Water Environment Evolution and Pollution Control in the Three Gorges Reservoir Area: WEPKL2012MS-03).

Conflict of interest

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

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