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Developing a system for comprehensive regional Eco-environmental quality assessment in mountainous areas—A case study of Western Sichuan, China

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Eco-environmental quality assessment is an important process for ensuring sustainable regional development because it encourages the construction of an ecological civilization. This assessment also lays a foundation for informing digital management and decision-making for the ecological environment in the near future. Due to the particularity of mountainous areas, its Eco-environmental quality assessment needs to be deeply specific and may require re-working. Here, the AHP-Entropy model was developed and constructed to scientifically analyze and evaluate the Eco-environmental quality in mountainous Western Sichuan in 2009 and 2019 at the township (street) unit. It is based on indicators representing Biological richness, Vegetation cover, Water network density, Land stress, and Social-economic stress. This newly developed model offers a more complete assessment, is based on more easily acquired data and has a higher accuracy than past models. The Eco-environmental quality index (EQI) representing eco-environmental quality (EEQ) has five levels of rating: Better, Good, Moderate, Bad and Worse. After applying this model to the region, the results show that: 1) The ecological environmental quality in the Western Sichuan mountains has improved over the past 10 years. 2) The eco-environment in the study area is generally Good, with small areas receiving a rating of Moderate. 3) The areas considered Better are mainly distributed on Longmen Mountain, Daliang mountain and Qionglai mountain, while the Moderate areas are mainly distributed in the western Chengdu Plain, the Panzhihua urban area, and Shaluli mountain. 4) The areas rated Better earn their rating due to high vegetation coverage, high habitat quality, and low degree of land degradation, such as land desertification and soil erosion. The areas with moderate eco-environmental quality were mainly affected by frequent human activity or serious land

degradation. This comprehensive regional Eco-environmental quality assessment can also be used in other areas with mountains.

1 Introduction

The Eco-environment increasingly bears the lasting effects of human activity. A good ecological environment is not only an important prerequisite for continued human development, but is also the basic condition that allows for human survival and social stability (Zhao et al., 2016). Adhering to a standard of sustainable development requires the ongoing assessment of Eco-environmental quality. However, regional Eco-environmental quality assessments are difficult because they survey a broad area. This extremely complex comprehensive assessment requires in-depth research on the local resources and the geographic area (Fu et al., 2001). The essence of a regional Eco-environmental quality (EEQ) assessment is to identify the state and direction of evolution of a regional eco-environment by exploring the main Eco-environmental problems and contradictions in the region, as well as the achievements of eco-environmental management. Taken together, the results inform digital decision-making for regional Eco-environmental management.

The Eco-environmental quality is directly affected by local factors representing natural conditions as well as by anthropogenetic activities (Boori et al., 2021). These factors can be quantitatively described by climate, terrain, land cover and vegetation data derived from remote sensing (Hu and Xu, 2019; Huang et al., 2021). The parameters and indicators that will represent the characteristics of a regional ecological environment must be scientifically and reasonably selected as part of the quantitative Eco-environmental quality (EEQ) assessment. The selected indicators here come from the remote sensing ecological index (RSEI), Ecological index (EI) and an indicator system based on the PSR (Boori et al., 2021) or DPSIR framework (Wang et al., 2018). The remote sensing ecological index (RSEI) is commonly used in EEQ assessment by many scholars in China (Xu et al., 2019; Jing et al., 2020; Liao and Jiang, 2020; Zhu et al., 2020; Huang et al., 2021), and these indicators were also used by Karbalaei Saleh (Karbalaei Saleh et al., 2021) to evaluate the Ecological quality of Isfahan in Iran. RSEI uses four environmental components (Greenness, Wetness, Dryness and Heat) to represent climate and terrestrial biophysical variables. The weight of each index is calculated using principal component analysis (PCA). Although it is objective and easy to calculate, RSEI does not fully reflect the EEQ because it fails to account for ecological stress caused by Social-economic factors. The Ecological index (EI) was revised to be the Technical Criterion for Ecosystem Status Evaluation (Ministry of Ecology and Environment the People's Republic of China, 2015). The multifactor indicators of EI include Biological abundance index (B_1), Vegetation coverage

index (B_2), Water network density index (B_3), Land stress index (B_4) and Pollution load index (B_5). These five indicators reflect the richness of organisms in the assessment area, the height of vegetation cover, the amount of water, the stress intensity, and the pressure from pollutants, respectively. The weight of each index is calculated using the analytic hierarchy process (AHP) method. EI is commonly used in EEQ assessments by many scholars (Shan et al., 2019; Jing et al., 2020; Chen et al., 2021; Li L. et al., 2021; Sun et al., 2021; Ouyang et al., 2022; Wang et al., 2022), and is based on 15 indicators. It was used to evaluate the ecological quality of the Samara region in Russia, using the base PSR framework (Boori et al., 2021). The index system of the EI method reflects the comprehensive eco-environmental quality (EEQ) of the study area relatively well. Past assessment methods include AHP, the entropy method, the ecological footprint method (Miao et al., 2016), grey correlation degree (Guo and Farouk, 2021) and the fuzzy comprehensive assessment method. However, there is no single assessment model that can effectively assess the ecological environment quality of a mountainous area due to the complexity in its surface and terrain. Therefore, general technical guidelines cannot be copied and a new method must be devised.

The AHP-entropy method is applicable to the assessment of geological disaster susceptibility (Qi and Wang, 2021) and urban human settlement quality (Li et al., 2014) in mountainous areas, and it is also applicable to the eco-environmental quality assessment. AHP has been combined with remote sensing and GIS by many scholars to assess the eco-environmental quality (EEQ) (Li et al., 2007; Xiong et al., 2007; Zhang et al., 2021). This study attempts to develop an eco-environmental quality assessment system (AHP-Entropy Methods) in mountainous areas and takes the mountains in Western Sichuan as an example. The weight of both expert experience and objective evaluation factors is considered for this hybrid model. The multifactor indicators of the EI method are adopted and improved upon. For one, Landsat's surface coverage and MODIS images are a better data source from which to extract evaluation factors. Considering that the pollution load index calculation in the original specification was obtained from statistical data based on the township unit, the accuracy was rather low. Instead, the model proposed here uses the Social-economic stress index (SESI), which has higher accuracy and is easier to be obtained. The assessment units are composed of a series of many factors that affect the Eco-environmental quality (EEQ). When a grid is used as the assessment unit, it is difficult to obtain such specific statistical data. On the other hand, the county as the assessment unit is too

FIGURE 1
Location of the study area.
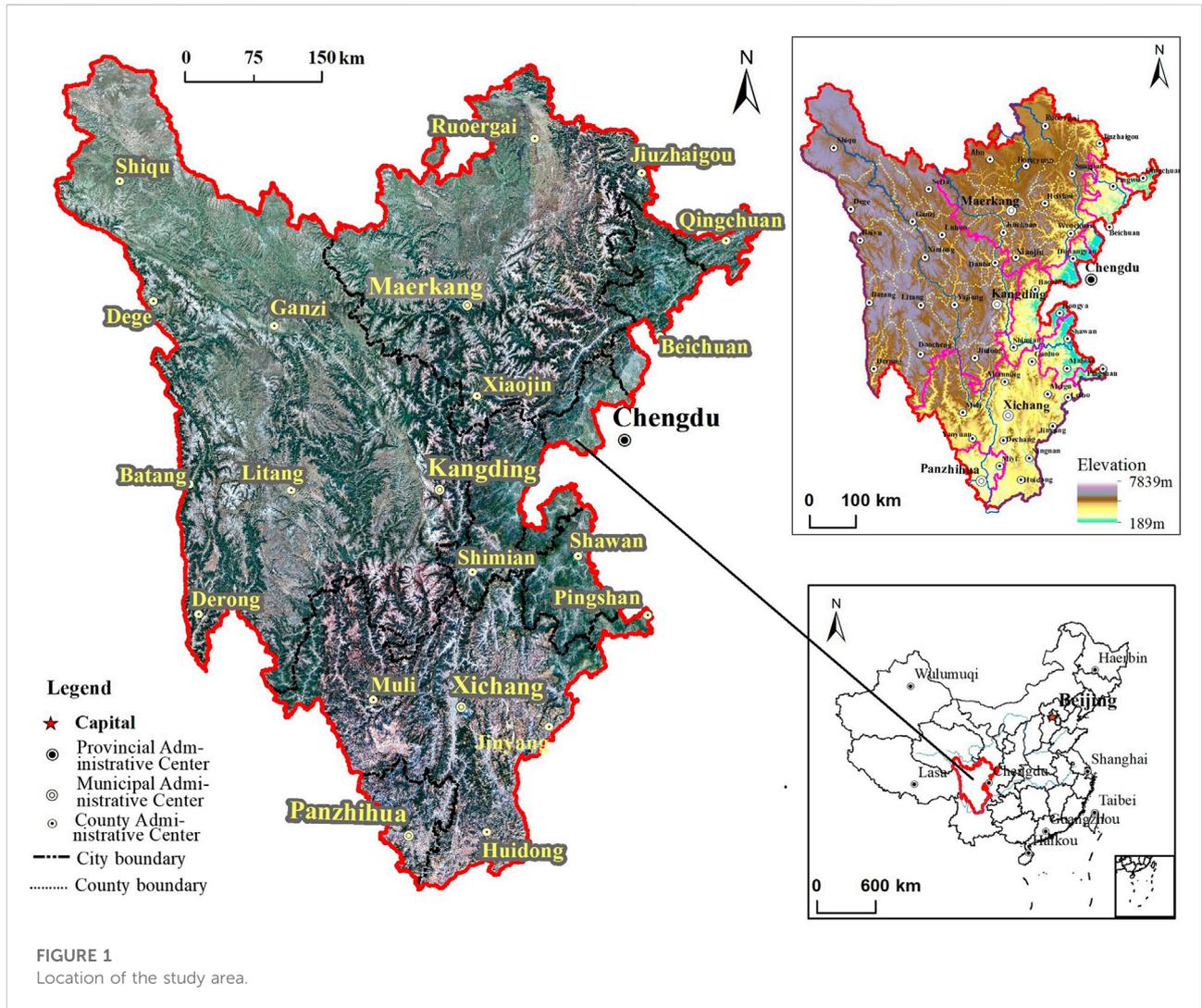
large and the accuracy is much lower. For China, township statistical data, which is at an intermediate scale, is available. Here, we were able to use township as the unit of Eco-environmental quality (EEQ) assessment.

The mountainous area in Western Sichuan, China, is an important part of the Sichuan-Yunnan Forest and the biodiversity of the Zoigê Steppe Marsh is a national key ecological function area in China (Li et al., 2015). It is an important water source in the upper reaches of the Yangtze River and the Yellow River and is an important barrier for China's ecological security. At the same time, it also provides important ecosystem services to the world and is rightly an ecosystem protection priority area (Brooks et al., 2006; Naidoo et al., 2008). However, this area faces some ecological problems, such as wetland degradation, grassland desertification (Wen et al., 2013), serious rodent damage, serious soil erosion (Liu et al., 2005) and weakening of biodiversity service function (Yang

et al., 2022). Through investigating and documenting the current state of the economy, society, ecological environment, natural geography and meteorology, the assessment of the regional ecological environment is the basis for informing the ecological protection and restoration of land space and the management and control of the use of natural ecological space.

2 Overview of the study area and methods

2.1 Overview of the study area

Western Sichuan (Figure 1) (26.02°N to 34.32°N and 97.3°E to 106.2°E) is characterized by plateau and mountains ranging from 189 to 7839 m, covering 78 counties and 1,341 townships. This area is at the southeast edge of the Qinghai-Tibet Plateau and
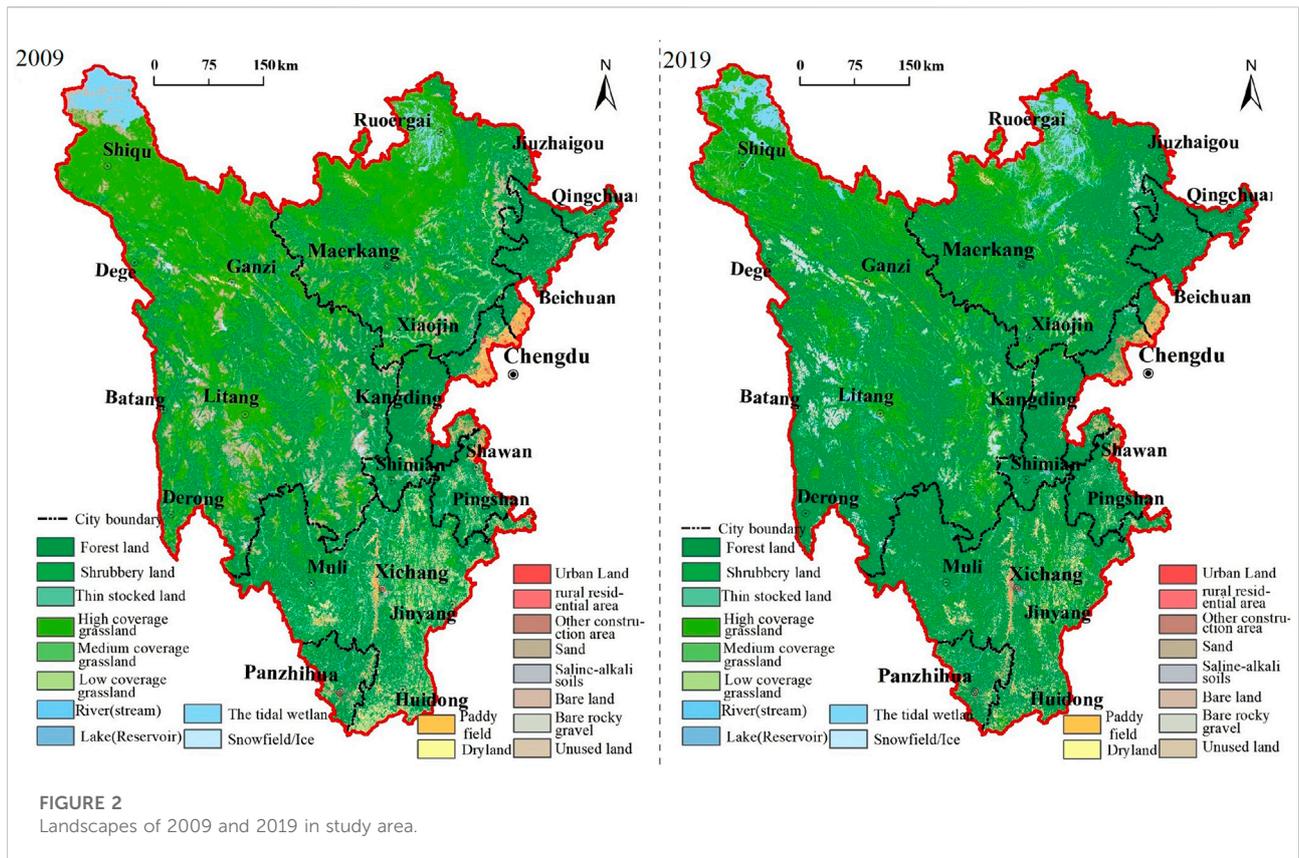
FIGURE 2
Landscapes of 2009 and 2019 in study area.

crosses the first and second steps of China's terrain. The soil types in this study area are mainly meadow, dark brown, yellow brown, and brown.

Because it is affected by the Indian Ocean and Pacific monsoon circulation, the region is dry and cold in winter, and wet and rainy in summer. Altitude plays an important role in regional climate variation. There are five climatic regions: cold temperate zone, temperate zone, warm temperate zone, central subtropical zone, and south subtropical zone. Ecosystem types in the study area are diverse, with meadows, broad-leaved shrubs, coniferous forests and broad-leaved forests as the main ones, followed by the less frequent mixed coniferous and broad-leaved forests and unvegetated deserts. As a green ecological barrier and an important water source in the upper reaches of the Yangtze River and the Yellow River, the region plays a very important strategic role in maintaining national ecological security. There are various types of vertical natural belts in mountainous areas of Western Sichuan. According to the structural characteristics of the basic zone, the vertical natural zone can be divided into subtropical humid type, middle subtropical humid type, south subtropical alternating type, warm temperate semi humid type, cold temperate semi humid type and sub cold zone semi-arid type (Zheng and Gao, 1984; Zheng and Yang, 1985). The landscapes of 2009 and 2019 in

study area can be seen in Figure 2. The landscapes in the study area are mainly woodland and grassland.

2.2 Data sources and methods

Constructing an assessment system suitable for the study area was the core of this revised ecological environment quality (EEQ) assessment, and it proved to be a complex process. Based on the data availability and regional characteristics of the Western Sichuan mountains, this paper develops a eco-environmental quality assessment system designed for mountainous regions (AHP-Entropy Method).

The methodology for evaluating EEQ used in this study consists of four steps: first, a system of indicators is established. Second, the AHP-entropy method is applied to determine the weight of each indicator. Third, the EQI values are calculated by the compound model. Fourth, the EQI performance is evaluated according to a defined classification. The full process is shown in Figure 3.

2.2.1 Data and pre-processing

The data used in this study mainly includes DEM, surface cover, soil, vegetation cover, remote sensing images,

TABLE 1 Basic information of data sources.

Data	Resolution	Time period	Source
DEM	30 m	—	http://www.gscloud.cn/
Land cover	30 m	2010, 2020	http://data.casearth.cn/sdo/detail/5fbc7904819aec1ea2dd7061
Soil	1:1000000	2012	Harmonized World Soil Database (v1.2)
			http://www.tpdc.ac.cn/zh-hans/data/844010ba-d359-4020-bf76-2b58806f9205/
Meteorological data	—	1985–2020	China Meteorological data network
			http://data.cma.cn
Population and GDP	County	2009, 2019	The website of Sichuan Provincial Bureau of statistics
			http://tjj.sc.gov.cn/index.shtml
River and lake	90 m	2013, 2019	1. Global hydrological data (HydroSHEDS) https://hydrosheds.org/downloads
	1:250,000		2. National Catalogue service For Geographic lnformation
			https://www.webmap.cn/main.do?method=index
Stratum exposure and geological structure data	1:200,000	—	The basic geological data are mainly from China Geological Survey (shared data)
NDVI/MOD13Q1	250 m	2009, 2019	http://modis.gsfc.nasa.gov/
EVI/MOD17A2H	500 m		
Landsat7 ETM + Landsat8-OLI_TIRS	30 m	2009, 2019	USGS
			https://earthexplorer.usgs.gov/
desert (sand) distribution data set in China	1:100,000	2000	National Cryosphere Desert Data Center (China)
			https://doi.org/10.12072/ncdc.Westdc.db0027.2021

meteorology, hydrology, basic geology, socio-economic and demographic data (Table 1).

The data processing method is as follows:

1) The slope, topographic relief and slope length were extracted from DEM data, normalized (maximum and minimum normalization) and resampled to obtain the slope and slope length factor map.
2) The surface coverage data was mosaiced and clipped by the region of the study area.
3) The soil erodibility factor was calculated according to the content ratio of sand, silt, clay and organic carbon in the soil (Wang et al., 2001).
4) The IDW interpolation method was used for spatial interpolation of meteorological stations to obtain the temperature and precipitation map.
5) The vegetation coverage of study area was extracted from MODIS data.
6) Based on the resident population, county area and regional tertiary industry GDP, the population density and per capita tertiary industry GDP were calculated.
7) The river and lake data sets of multiple 1:250,000 maps involved in the study area were mosaiced and clipped to obtain the factor for calculating the water network density index factor.
8) Extraction of carbonate rock outcropping area from formation rock types in regional geological map.

9) We used MODIS data (MOD09A1, NDVI/MOD13Q1, EVI/MOD17A2H) to estimate and analyze spatial and temporal distribution of NPP of the study area in 2009 and 2019, based on the Carnegie-Ames-Stanford Approach (CASA) model (Yuan et al., 2006; Yu et al., 2009).

2.2.2 Construction of assessment indicators system and standardization

The system of indicators for this Eco-environmental quality assessment (Table 2) was constructed using a Biological abundance index (BAI), Vegetation coverage index (VCI), Water network density index (WNDI), Land stress index (LSI) and Social-economic stress index (SESI), which respectively reflect the abundance of organisms, the level of vegetation cover, the abundance of water resources, land stress caused by land degradation, and environmental pressure brought by social and economic development.

Non-dimensional quantitative model. With each indicator differing in its nature, the unit and dimensions were also inconsistent, and so standardization of indicators was necessary. We used Eq. 1,2 to standardize these data from various sources (Xie et al., 2012):For positive indicators:

$$x'_i = \frac{x_i - x_{i\ min}}{x_{i\ max} - x_{i\ min}} \times 100 \tag{1}$$

For reverse indicators:

TABLE 2 Evaluation index system.

Goal	Indicator	Attribute	Sub-indicator	Attribute
Eco-environmental quality (EEQ) A_1	Biological richness index (BRI) B_1	+	Habitat quality index (HQI) C_1	+
			Biodiversity index (BI) C_2	+
	Water network destiny index (WNDI) B_2	+	River length/Area of evaluation unit C_3	+
			Area of areal waters/Area of evaluation unit C_4	+
			Water resources/Area of evaluation unit C_5	+
	Vegetation coverage index (VCI) B_3	+	Vegetation coverage C_6	+
	Land stress index (LSI) B_4	-	Severe erosion area /Area of evaluation unit C_7	-
			Desertification area /Area of evaluation unit C_8	-
			Severe karst rocky desertification area /Area of evaluation unit C_9	-
			Construction land area /Area of evaluation unit C_{10}	-
	Social-economic stress index (SESI) B_5	-	Population density index C_{11}	-
			Per capita output value of primary industry C_{12}	-
			Per capita output value of secondary industry C_{13}	-
			Per capita output value of tertiary industry C_{14}	-

$$x_i^{'} = \left(1 - \frac{x_i - x_{i\ min}}{x_{i\ max} - x_{i\ min}}\right) \times 100 \qquad (2)$$

where i is the assessment unit, x_i represents the original value of i, x_{imax} and x_{imin} represent the maximum and the minimum value of i .For convenience, all transformed data was magnified 100 times.

2.2.3 Calculation of sub-indicator

Some sub-indicators can be obtained directly through data pre-processing, while others needed to be obtained through model calculations.

2.2.3.1 Habitat quality index

The InVEST model introduced the habitat quality as a proxy for biodiversity assessment (Berta Aneseyee et al., 2020; Zhang et al., 2020). Habitat quality index refers to the comprehensive index reflecting the Eco-environmental quality of the assessed area.

The habitat suitability of each LULC type and the relative sensitivity of each habitat type versus its threat were determined by the Landscape types of low habitat suitability in the study areas (Table 3). The parameters of each threat's relative impact weight, its maximum effective distance, and distance-decay function were determined according to the literature listed in Table 4.

2.2.3.2 Biodiversity index

Biodiversity and Net Primary Productivity (NPP) are intricately linked in complex ecosystems such that a change in the state of one of these variables can be expected to have an impact on the other (Costanza et al., 2007).

Biodiversity maintenance function is the key role an ecosystem plays in maintaining gene, species and ecosystem diversity. It is one of the most important functions provided

by an ecosystem. NPP data sets, meteorological data sets and elevation data sets were used to evaluate biodiversity. The formula can be Seen in Eq. 3.

$$S_{bio} = NPP_{mean} \times F_{pre} \times F_{tem} \times (1 - F_{alt}) \qquad (3)$$

S_{bio} represents the biodiversity maintenance capability index, NPP_{mean} represents the average value of net primary productivity of vegetation for many years, F_{pre} represents the annual average precipitation index, F_{tem} represents the annual average temperature index, F_{alt} represents the altitude index.

2.2.3.3 Land stress index

Land stress index was used to evaluate the degree of stress on land quality in the area, which was expressed by the stress types such as soil erosion, construction land, land desertification and land rocky desertification per unit area in the evaluation area (Xie et al., 2020).

The Universal Soil Loss Equation is the most widely used erosion equation (Okan and Nilgun, 2002; Alewell et al., 2019). The USLE equation is described as .

$$A = R \times K \times LS \times C \times P \qquad (4)$$

A = soil loss in tons ha^{-1}yr^{-1};R = rainfall runoff factor in tons-m ha^{-1};K = soil erodibility factor;LS = topographic factor;C = cover and management factor;P = support practice factor.

The amount of soil erosion was calculated according to the USLE Model, and any area with an erosion modulus greater than 5,000 was regarded as an area of strong erosion.

Karst rocky desertification is a progressive process of land degradation where soil is seriously or thoroughly eroded. The sensitivity assessment of rocky desertification was based on such factors as limestone exposure, topography and vegetation

TABLE 3 The sensitivity of different landscapes to threat factors.

Name	Habitat suitability	Paddy field	Dry land	Urban	Rural settlements	Other construction land	Barren lands
Paddy field	0.3	0.3	0.3	0.5	0.7	0.6	0.57
Dry land	0.3	0.3	0.3	0.5	0.7	0.6	0.57
Thick Woodland	1	0.8	0.8	0.5	0.85	0.8	0.25
Shrub wood	0.9	0.7	0.7	0.8	0.45	0.7	0.35
Sparse woodland	0.7	0.6	0.6	1	0.7	0.5	0.4
High coverage Grassland	0.8	0.5	0.5	0.6	0.5	0.4	0.4
Medium coverage Grassland	0.75	0.55	0.55	0.65	0.55	0.5	0.5
Low coverage Grassland	0.7	0.5	0.5	0.7	0.5	0.55	0.55
Rivers and canals	0.8	0.65	0.65	0.85	0.3	0.2	0.15
Lakes and reservoirs	0.7	0.7	0.7	0.9	0.3	0.1	0.2
Urban	0	0	0	0	0	0.2	0.6
Rural settlements	0	0	0	0	0	0.7	0.6
Other construction land	0	0	0	0.7	0.6	0	0.6
Barren lands\Sand\Saline-alkali soils\Unused land	0.7	0	0	0	0	0	0

TABLE 4 Weights for threat factors of the study area.

Threats	Max.D[a] (km)	Weight	Decay type
Paddy field	0.5	0.5	Exponential
Dry land	0.5	0.5	Exponential
Urban	10	1	Exponential
Rural settlements	2	0.7	Exponential
Other construction land	1	0.5	linear
Barren lands	10	0.3	Exponential

coverage (Huang and Cai, 2006; Bai et al., 2013; Chen et al., 2019). The formula can be seen in Eq. 5.

$$S_i = \sqrt[3]{D_i \times P_i \times C_i} \quad (5)$$

S_i represents rocky desertification sensitivity index of the region i, D_i, P_i and C_i were respectively the percentage of carbonate rock exposed area, topographic slope and vegetation coverage in i assessment unit. The percentage of carbonate rock exposed area (Di) was calculated using Regional geological data through an overlay analysis method. At the same time, the third monitoring results of rocky desertification in karst areas of Sichuan Province were referenced. The natural boundary method and expert knowledge were used to determine the grading and assignment standard for each index. The sensitivity grade values corresponded to different evaluation indexes. A soil rocky desertification sensitivity greater than 5 was regarded as an extremely sensitive area of soil rocky desertification.

The desertification results in 2009 and 2019 were interpreted and processed from ETM+ and landsat-8 images of a desert

(sand) distribution data set in China (National Cryosphere Desert Data Center (China)). The results of the fifth desertification monitoring in Sichuan Province are used for reference.

2.2.4 AHP-entropy methods

The combination of the analytic hierarchy process and the entropy weight method not only makes full use of the judgment of expert knowledge, but it also leaves room for reasoning and evaluation of objective data. It has comparative advantages, and it is still scientific.

2.2.4.1 AHP method

Goal (A) was broken down into Indicator (B), and Sub-indicator (C) to establish the pair-wise comparison matrix. The matrix was expressed with $A = (a_{ij})_{n \times n}$.

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \quad (6)$$

A represents a positive reciprocal matrix, which satisfies $a_{ij} > 0$, $a_{ji} = \frac{1}{a_{ij}}$

Relative importance of B1, B2, B3, B4 and B5 were analyzed by Expert Judgment System. In this research, we analyzed the relationship between various factors in the system and established the hierarchical structure of the system (Table 5).

To determine the consistency of a matrix, the eigenvectors of matrix A, W and λ_{max} need to be solved. W can be calculated by assigning each element a relative importance, and W can be translated into a normalized weight vector $W = (\omega_1, \omega_2, ..., \omega_n)$ by the following steps:

TABLE 5 A−B judgment matrix and Normalization of the AHP model.

A–B judgment matrix

A_1	B_1	B_2	B_3	B_4	B_5
B_1	1	2	2	3	4
B_2	1/2	1	2	2/3	2
B_3	1/2	1/2	1	1.5	2
B_4	1/3	2/3	2/3	1	4/3
B_5	1/4	1/2	1/2	3/4	1

Normalization (sum product method)

A_1	B_1	B_2	B_3	B_4	B_5
B_1	0.387	0.429	0.324	0.387	0.387
B_2	0.194	0.214	0.324	0.194	0.194
B_3	0.194	0.107	0.162	0.194	0.194
B_4	0.129	0.143	0.108	0.129	0.129
B_5	0.097	0.107	0.081	0.097	0.097

TABLE 6 AHP-entropy composite weight.

Indicator	Sub-indicator	AHP weight	Entropy weight	Comprehensive evaluation value
Biological richness index (BRI) B_1	Habitat quality index (HQI) C_1	0.1914	0.154	0.176
	Biodiversity index (BI) C_2	0.1914	0.211	0.199
Water network destiny index (WNDI) B_2	River length/Area of evaluation unit C_3	0.111	0.09	0.103
	Area of areal waters/Area of evaluation unit C_4	0.037	0.025	0.032
	Water resources/Area of evaluation unit C_5	0.022	0.03	0.025
Vegetation coverage index (VCI) B_3	Vegetation coverage C_6	0.224	0.105	0.176
Land stress index (LSI) B_4	Severe-erosion area/Area of evaluation unit C_7	0.059	0.012	0.04
	Desertification area/Area of evaluation unit C_8	0.043	0.008	0.029
	Severe karst rocky desertification area/Area of evaluation unit C_9	0.019	0.016	0.018
	Construction land area/Area of evaluation unit C_{10}	0.007	0.023	0.013
Social-economic stress index (SESI) B_5	Population density index C_{11}	0.036	0.078	0.053
	Per capita output value of primary industry C_{12}	0.008	0.09	0.041
	Per capita output value of secondary industry C_{13}	0.036	0.064	0.047
	Per capita output value of tertiary industry C_{14}	0.016	0.094	0.047

1) The matrix obtained by uniting the column vectors of the judgment matrix was recorded as: $B = (b_{ij})$

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \qquad (7)$$

The matrix obtained by uniting the column vectors of the judgment matrix was shown in Table 5.

2) The weights of B_1, B_2, B_3, B_4, and B_5 could be obtained using the following formula:

$$\omega_j = \frac{\sum_{i=1}^{j} b_{ij}}{j} \qquad (8)$$

Using the above method, the weights of B_1, B_2, B_3, B_4 and B_5 were 0.383, 0.224, 0.17, 0.128 and 0.096, respectively. (3)

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^{n} \frac{(AW)i}{\omega_i} \qquad (9)$$

$$AW = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \times \begin{matrix} \omega_1 \\ \vdots \\ \omega_j \end{matrix} \qquad (10)$$

where W represents the corresponding eigenvector of λ_{max} and W_i (i = 1, 2, … ,n) is the weight value for ranking. In our research, λ_{max} = 5.0586.

4) Calculating the consistency index (CI):

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (11)$$

$\lambda_{max} = 5.0586$, n = 5, $CI = 0.015$.

5) Further, the consistency ratio (CR) can be calculated as follows:

$$CR = \frac{CI}{RI} \quad (12)$$

RI represents the average random consistency index. When *CR* represents less than 0.1, the matrix had a reasonable consistency. Otherwise, the matrix should be changed. The calculated results of weight would be accepted when the consistency ratio was satisfactory. In this research, *RI* = 1.12, *CR* = 0.013 < 0.10.

Then using the method above, the normalized feature vector, consistency check and λ_{max} etc of sub-indicator layers was calculated for corresponding indicator layers. After the above analytic process, the weights of all elements in a level of the hierarchy can be obtained relative to the whole level directly above, which was totally ranked.

2.2.4.2 Entropy weight method

The Entropy method employs an objective weighting method, which refers to determining the indicator weight according to the information provided by the observed values of each indicator.

1) A new judgment matrix $B = (b_{ij})_{m \times n}$ was formed through the normalized multi-objective decision matrix $X = (x_{ij})_{m \times n}$ in Eqs 1, 2.

2) The proportion of the *i* th evaluating object on the *j* th indicator was calculated, the calculation formula can be Seen in Eq. 13.

$$f_{ij} = \frac{1 + b_{ij}}{\sum_{i=1}^{m}(1 + b_{ij})} \quad (13)$$

3) If the entropy value of the *j* th evaluation indicator was defined as H_j, the calculation formula can be seen in Eq. 14.

$$H_j = -\frac{1}{\ln m}\left[\sum_{j=1}^{n}(f_{ij} \ln f_{ij})\right] \quad (14)$$

4) The weight of entropy of each evaluating indicator could be expressed as:

$$\beta_j = \frac{1 - H_j}{\sum_{j=1}^{n}(1 - H_j)} \quad (15)$$

2.2.4.3 Determination of the overall weights

According to the weight α_i, calculated using the analytic hierarchy process, and Weight β_i, calculated using the entropy method, the final weight ω_i of each index was calculated using the preference coefficient of 0.6. The final composite weight can be seen in Table 6.

$$\omega_i = \alpha_i * 0.6 + 0.4 * \beta_i \quad (16)$$

2.2.4.4 Calculation of indicator

The indicators were calculated from sub-indicators, the calculation formula can be Seen in .

$$(BAI, WNDI, VCI, LSI, SESI) = \sum_{k=1}^{n}\left(\frac{\omega_k \times x_i^{'}}{(\omega_1 + \omega_2 + \cdots \omega_n)}\right) \quad (17)$$

where BAI represents the Biological abundance index, VCI represents Vegetation coverage index, WNDI represents Water network density index, LSI represents Land stress index and SESI represents Social-economic stress index. $x_i^{'}$ represents the value of each index, ω represents the weight of each index, and *n* is the total number of indices, *i* = 1, 2, 3,..., n, such as n = 2 when WNDI is calculated.

2.2.4.5 Comprehensive index of Eco-environmental quality evaluation

The comprehensive index of Eco-environmental quality was obtained by the weighted sum of each index value, the formula can be seen in Eq. 18.

$$EQI = \sum_{k=1}^{m}(\omega_k \times x_i^{'}) \quad (18)$$

where EQI represents the synthetic index of eco-environment quality, $x_i^{'}$ represents the value of each index, ω represents the weight of each index, and *m* is the total number of indices, *i* = 1, 2, 3,..., m,., ω_k represents a normalized weight such that $\sum \omega_k = 1$.

2.2.4.6 Classification of ecological environment

Following the Technical Criterion for Ecosystem Status Evaluation (HJ192-2015) (Ministry of Ecology and Environment the People's Republic of China, 2015) issued in 2015 by the Ministry of Ecology and Environment of the People's Republic of China, the Eco-environmental quality index (EQI) has been used by many scholars (Zhu et al., 2020; Li L. et al., 2021; Sun et al., 2021; Ouyang et al., 2022) to express the Eco-environmental quality (EEQ). With EQI, Eco-environmental quality is classified as one of five levels: Better (EQI≥75) Good (55 < EQI<75), Moderate (35 < EQI≤55), Bad (20 < EQI≤35) and Worse (EQI≤ 20). This standard of five levels was also adopted in this study. The change trend of EEQ (ΔEQI) was classified into one of five levels: Significantly improving (ΔEQI≥6), Slightly improving (2<ΔEQI<6), Unchanged (-2<ΔEQI≤2), Slightly declining (-6<ΔEQI ≤ -2) and Significantly declining (ΔEQI≤3).

3 Results

The basic data required for each Sub-indicator is shown in Figure 4 (2009) and Figure 5 (2019).

FIGURE 3
Technical processes of estimating EQI based on multisource data.
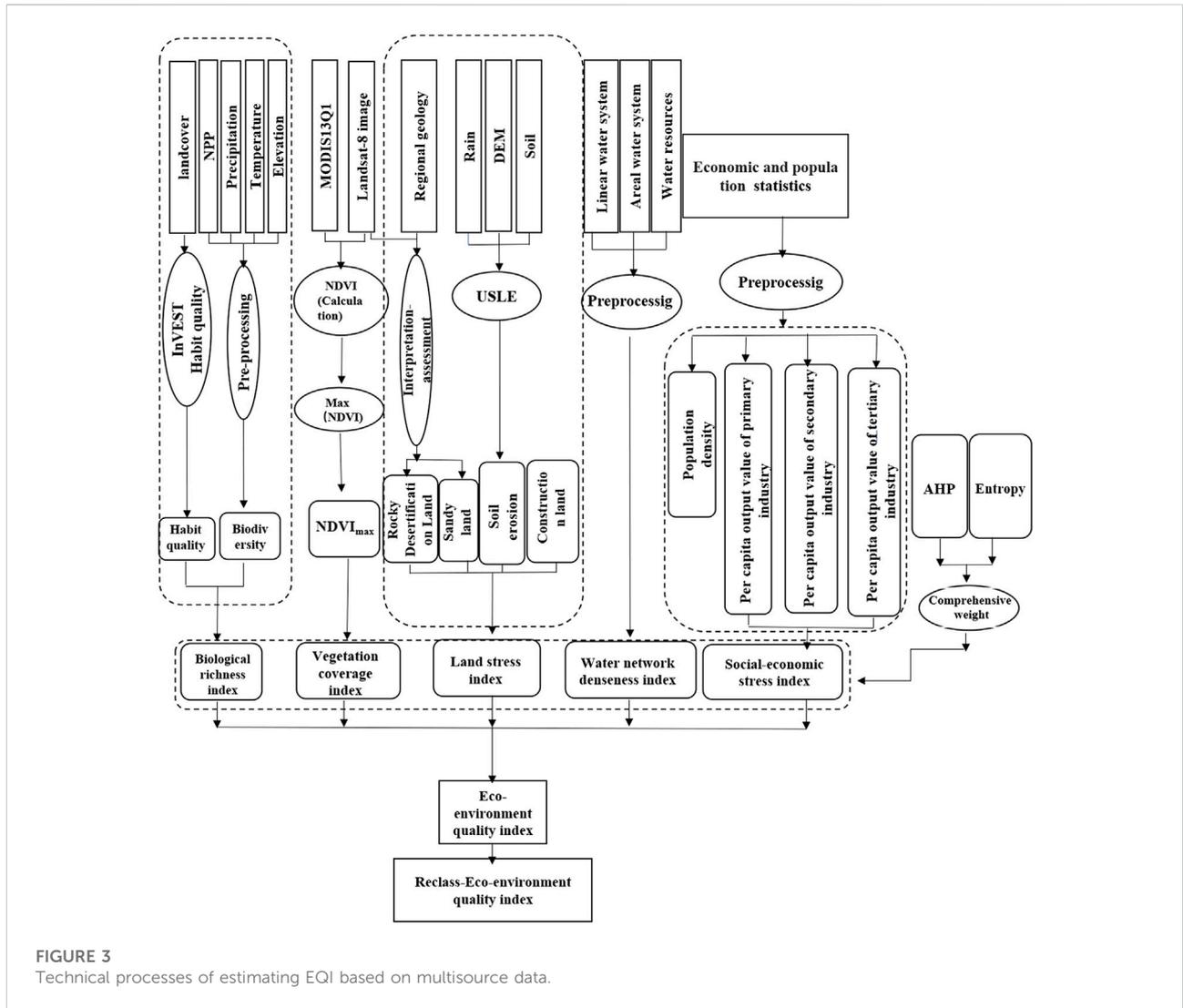
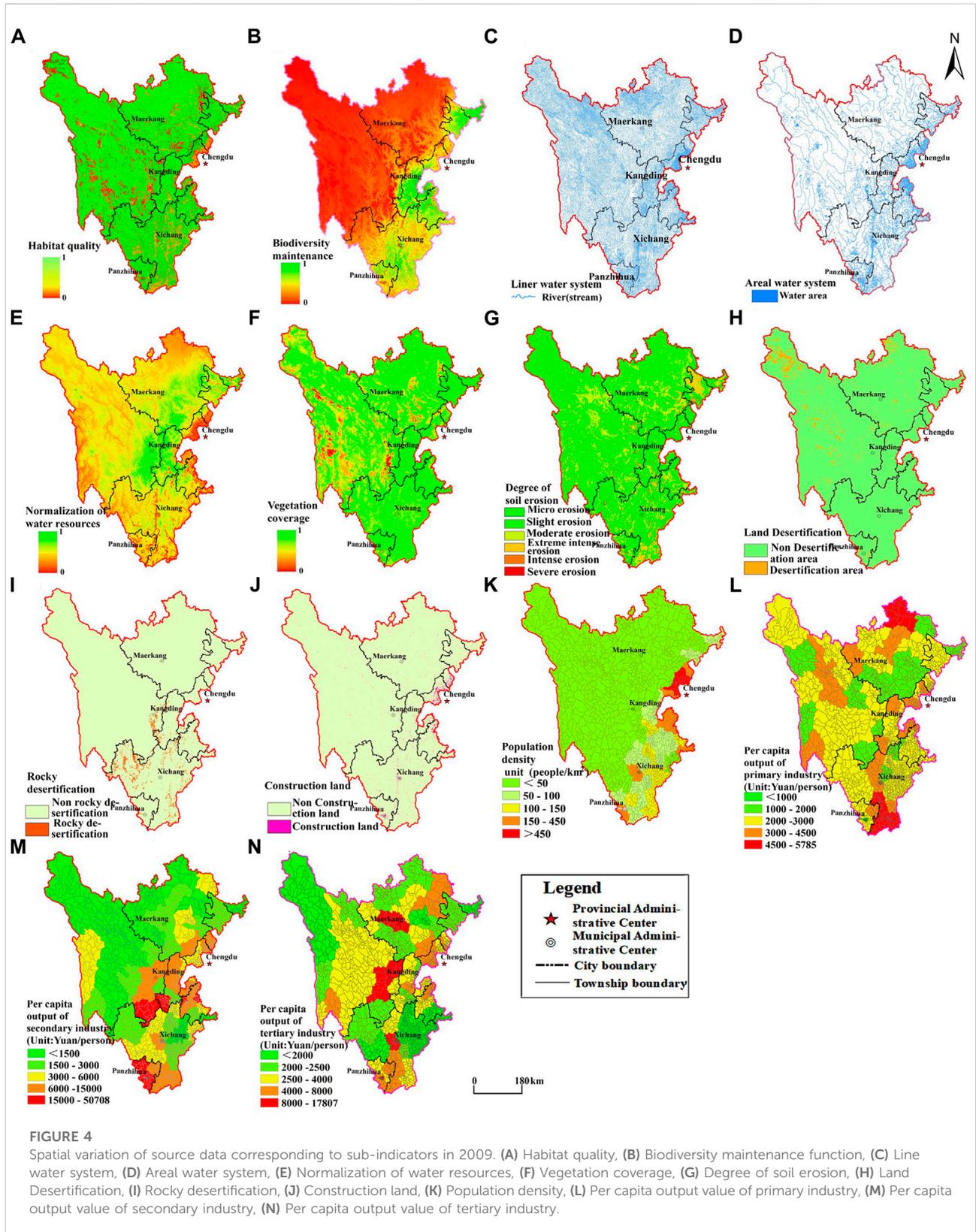## 3.1 Biological richness index

In the analysis, the areas with high habitat quality were mainly distributed in Longmen Mountain, Minshan Mountain, the southern section of Shaluli mountain and Daliang Mountain, while the areas with low habitat quality were mainly distributed in the towns on the edge of the Chengdu Plain and the Panzhihua urban area.
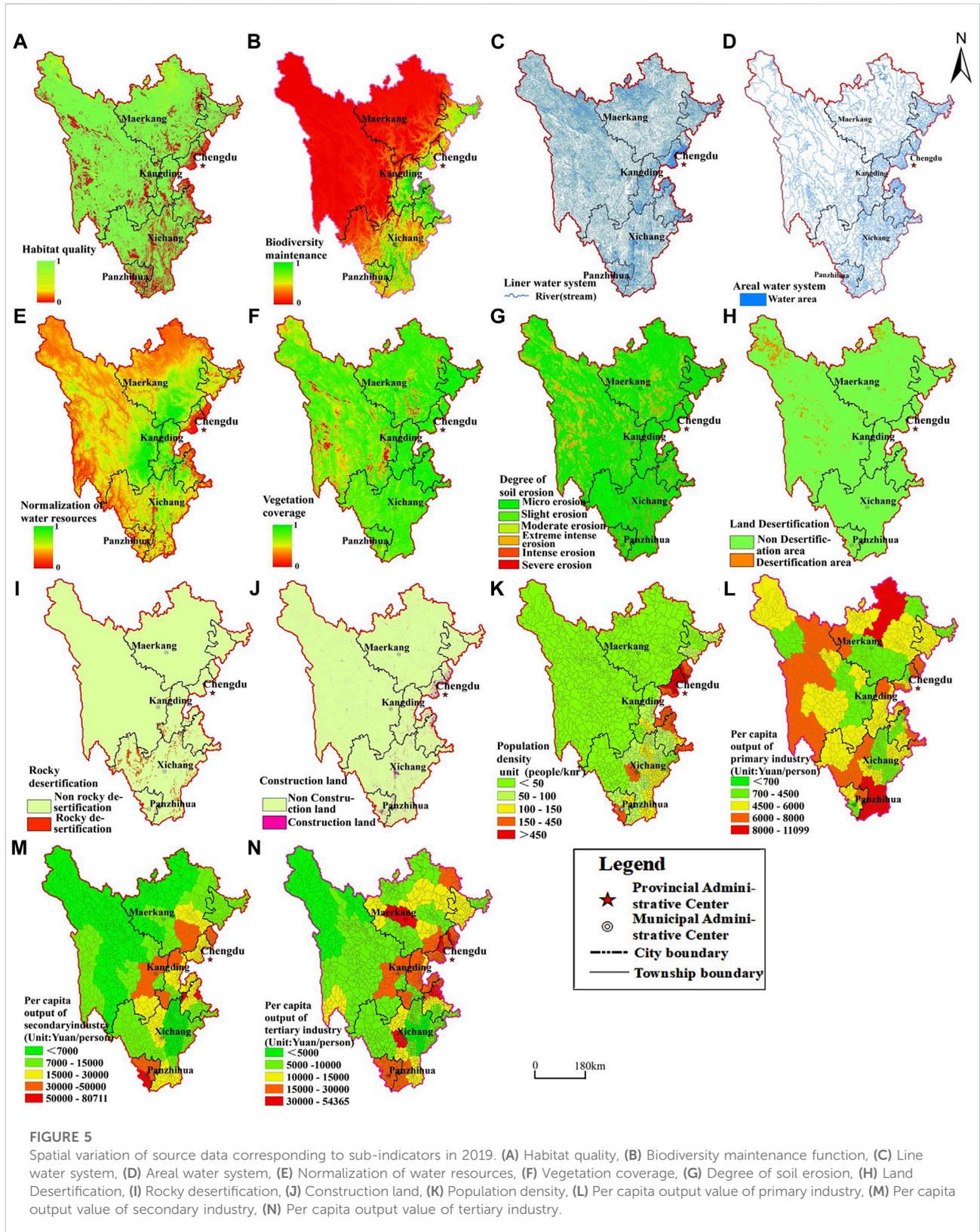
The biodiversity index was obtained using NPP, temperature, rainfall, and elevation factors. The biodiversity index was high in the south, low in the north, high in the east and low in the west. The regions with high biodiversity were mainly distributed in the eastern and southern mountain areas such as Longmen Mountain, Qionglai mountain system, Daliang Mountain and Jinping Mountain; The biodiversity index of Western Sichuan Plateau was low due to high altitude and low temperature. Similarly, the biodiversity index, derived from the biodiversity conservation function importance index, also mirrored this spatial distribution.

The areas with high biological richness were mainly distributed in the middle and high mountains around the basin of Sichuan Basin. The areas with low biological richness were mainly distributed in the extremely high mountain areas of Shaluli mountain and Shiqu country (Figures 6A, Figures 7A).

3.2 Vegetation coverage index

First, the landsat-8 image was radiometrically calibrated, then the near-infrared band and red band were calculated to extract the NDVI value. Then the mean value of NDVI in each town was counted by using the zoning statistical tool. The areas with high vegetation coverage were mainly distributed in the Middle-Low mountains, around the basin of Sichuan Basin, and the areas with low vegetation coverage were mainly distributed in the extremely high mountain areas of Shaluli mountain, Daxue

FIGURE 4
Spatial variation of source data corresponding to sub-indicators in 2009. **(A)** Habitat quality, **(B)** Biodiversity maintenance function, **(C)** Line water system, **(D)** Areal water system, **(E)** Normalization of water resources, **(F)** Vegetation coverage, **(G)** Degree of soil erosion, **(H)** Land Desertification, **(I)** Rocky desertification, **(J)** Construction land, **(K)** Population density, **(L)** Per capita output value of primary industry, **(M)** Per capita output value of secondary industry, **(N)** Per capita output value of tertiary industry.

FIGURE 5
Spatial variation of source data corresponding to sub-indicators in 2019. **(A)** Habitat quality, **(B)** Biodiversity maintenance function, **(C)** Line water system, **(D)** Areal water system, **(E)** Normalization of water resources, **(F)** Vegetation coverage, **(G)** Degree of soil erosion, **(H)** Land Desertification, **(I)** Rocky desertification, **(J)** Construction land, **(K)** Population density, **(L)** Per capita output value of primary industry, **(M)** Per capita output value of secondary industry, **(N)** Per capita output value of tertiary industry.

FIGURE 6

Assessment indicator in year 2009. **(A)** Biological richness index, **(B)** Water network density index, **(C)** Vegetation coverage index, **(D)** Land stress index, **(E)** Social-economic stress index.
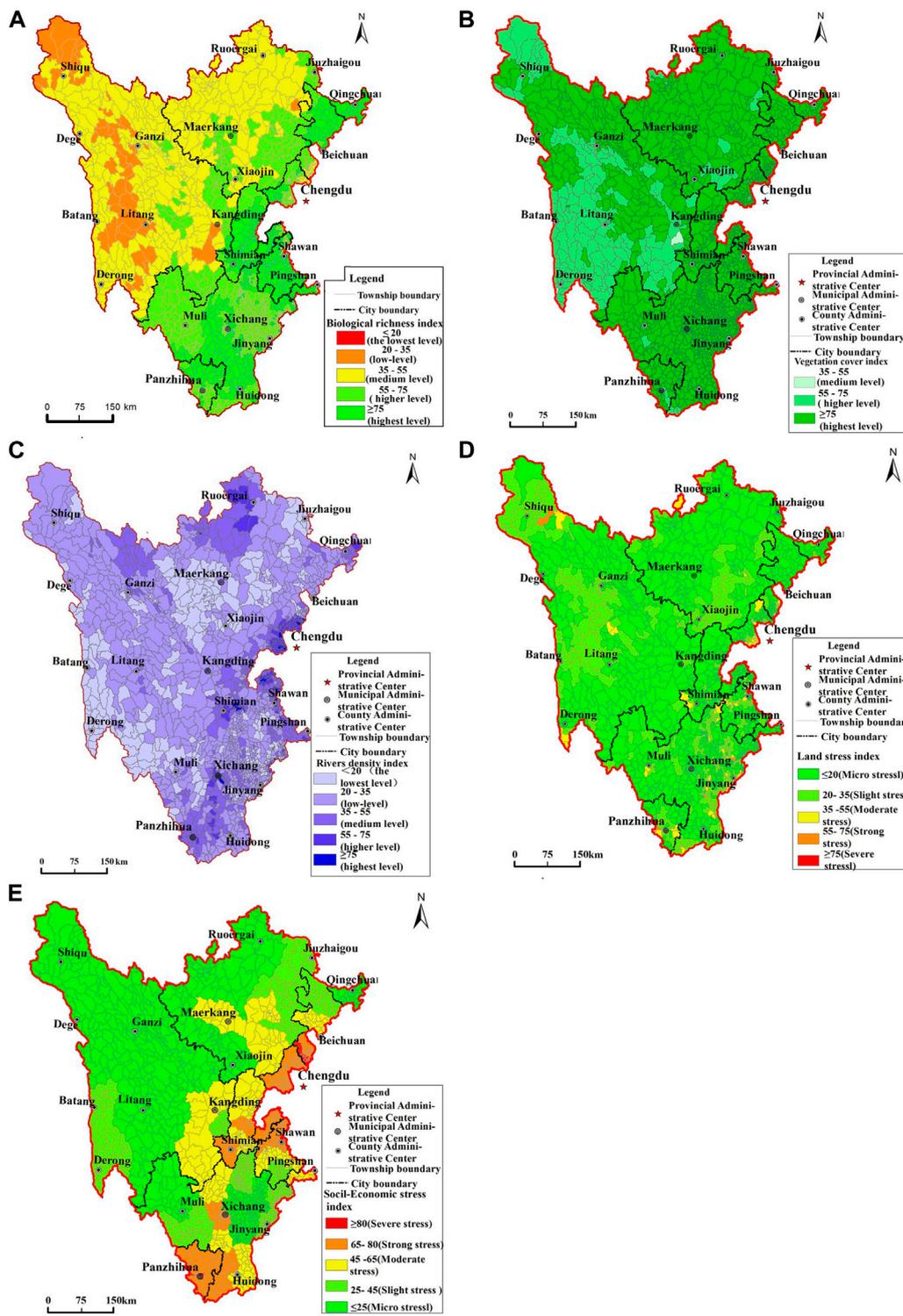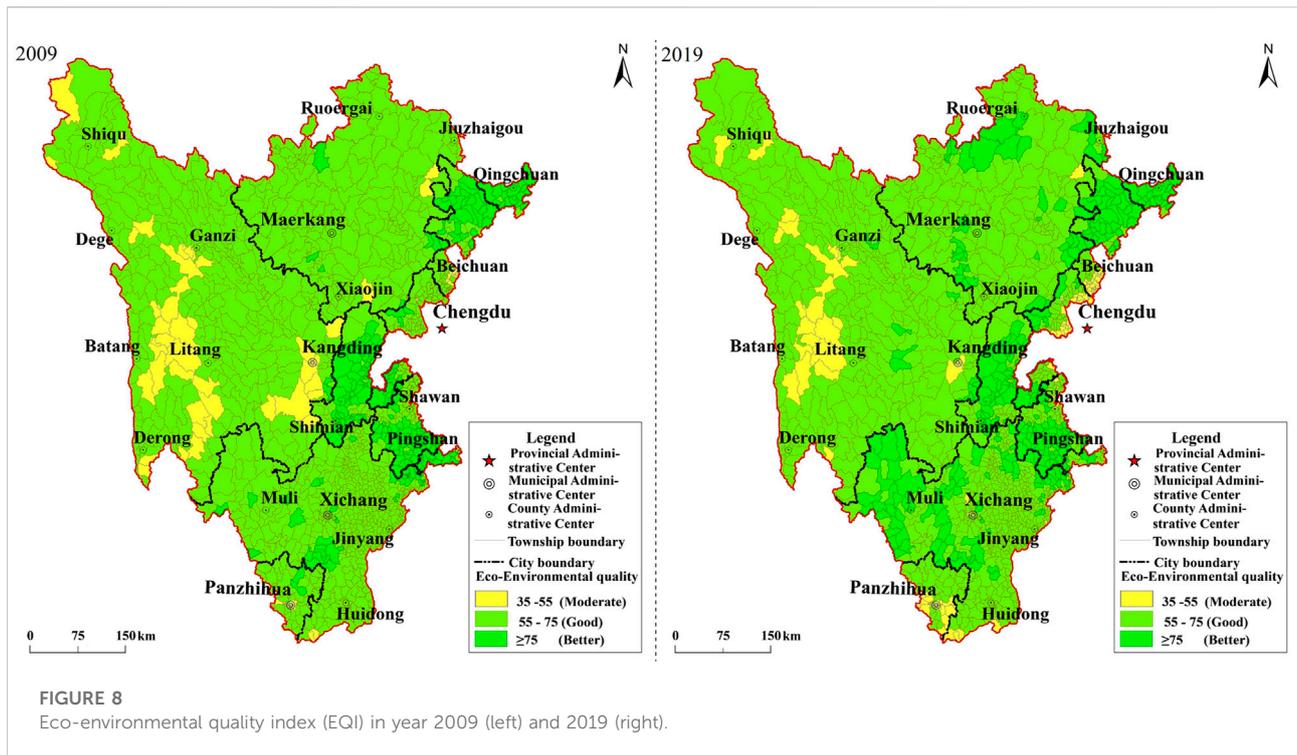
FIGURE 7
Assessment indicator in year 2019. **(A)** Biological richness index, **(B)** Water network density index, **(C)** Vegetation coverage index, **(D)** Land stress index, **(E)** Social-economic stress index.

FIGURE 8
Eco-environmental quality index (EQI) in year 2009 (left) and 2019 (right).

mountain and Qionglai mountain, the dry hot and dry river valley and the Grassland degradation area of Changsha-Gongma Nature Reserve Figures 6B, Figures 7B).

3.3 Water network density index

The water network in the study area was dense, and the main water systems included Jinsha River, Yalong River, Minjiang River and Dadu River in the Yangtze River Basin, Bai River and Heihe River in the Yellow River Basin, among which Jinsha River, Yalong River, Minjiang River, Dadu River and Yellow River Basin account for a high proportion of this area.

The water network density index was calculated according to the extracted water network line elements, area elements and water resources. According to the results of the analysis (Figures 6C, Figures 7C), the areas with high water network density index were mainly distributed in the Middle-Low mountains area at the edge of Sichuan Basin, Anning River Valley and Zoigê wetland.

3.4 Land stress index

The Universal Soil Loss Equation (USLE), which includes local rainfall, soil erodibility, slope gradient and slope length factors in its formula, was used to analyze the degree of soil erosion in the study area. The degree of soil erosion in the study area was mainly micro

and mild. The areas with a high degree of soil erosion were mainly distributed in extremely high mountains and dry hot arid river valleys, and the high plains around the basin and plateau areas have a low degree of soil erosion. The degree of soil freeze-thaw erosion was high in extremely high mountain areas, and the dry hot arid valley areas were seriously affected by rainstorms in the summer.

According to the image analysis and surface coverage data, the desertification in the study area occurred across the Shiqu grassland wetland, Shaluli mountain, Panzhihua and Zoigê grassland wetland; The desertification in the west and north was mainly caused by the degradation of grassland and wetland, and the desertification in Danba and Xiaojin in the middle was mainly due to beach desertification (this region was distributed in a belt along the river).

The degree of rocky desertification in the study area was calculated using the carbonate exposure percentage, topographic slope, and vegetation coverage. The rocky desertification area accounted for 1.48% of the total area, and was mainly distributed in Muli, Yanyuan and on the Daliang mountain.

The degree of land stress in the study area was analyzed in combination with the results of soil erosion, land desertification, land rocky desertification and construction land analyses. The degree of land stress in the study area (Figure 6D, Figure 7D) mainly ranged from micro to mild. The area with a high degree of land stress was mainly distributed in the desertification area of Shiqu; the area with a high degree of freeze-thaw erosion was on Shaluli mountain, the dry valley area of Minjiang river and in Derong; and the area with strong soil erosion was in the middle reaches of the Jinsha river.
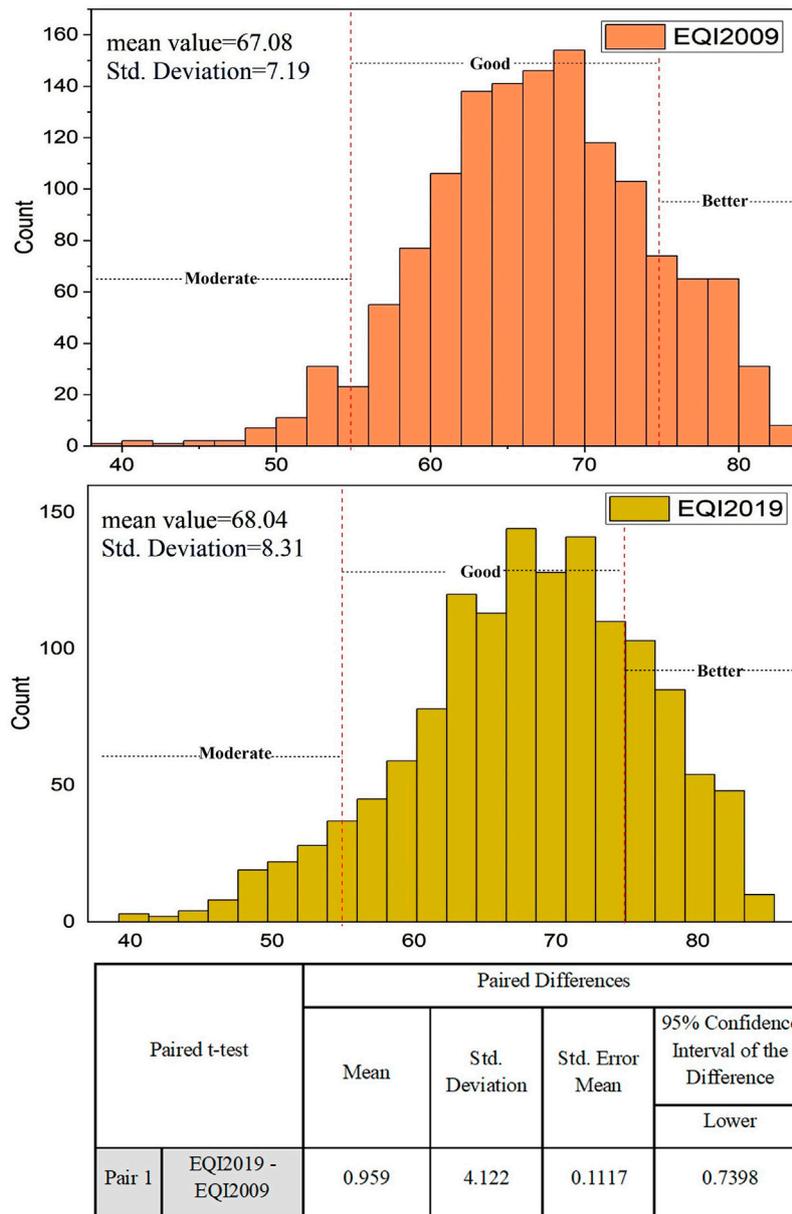
FIGURE 9
EQI value distribution in year 2009 and 2019 (Including paired *t*-test).

3.5 Social-economic stress index

Through analyzing population density and the value of per capita output of primary, secondary and tertiary industries, we found that the Social-economic stress index reflects the spatial distribution characteristics (Figures 6E, Figure 7E), with high levels in the east, low levels in the west, high levels in the south and low levels in the north. The areas with high stress were mainly distributed in the main urban areas of Panzhihua and Shifang, followed by Xichang, the subordinate counties of Chengdu, Deyang,

Panzhihua, Leshan, and Meishan. The Social-economic stress index in Northwest Sichuan was low overall.

3.6 Eco-environmental quality

The Eco-environmental quality was calculated based on the various assessment factors and the Eco-environmental quality Index formula. The Eco-environmental quality of the study area was rated Moderate, Good, and Better (Figure 8), throughout.

FIGURE 10
The changes of Eco-environmental quality Index between year 2009 and 2019 (ΔEQI).
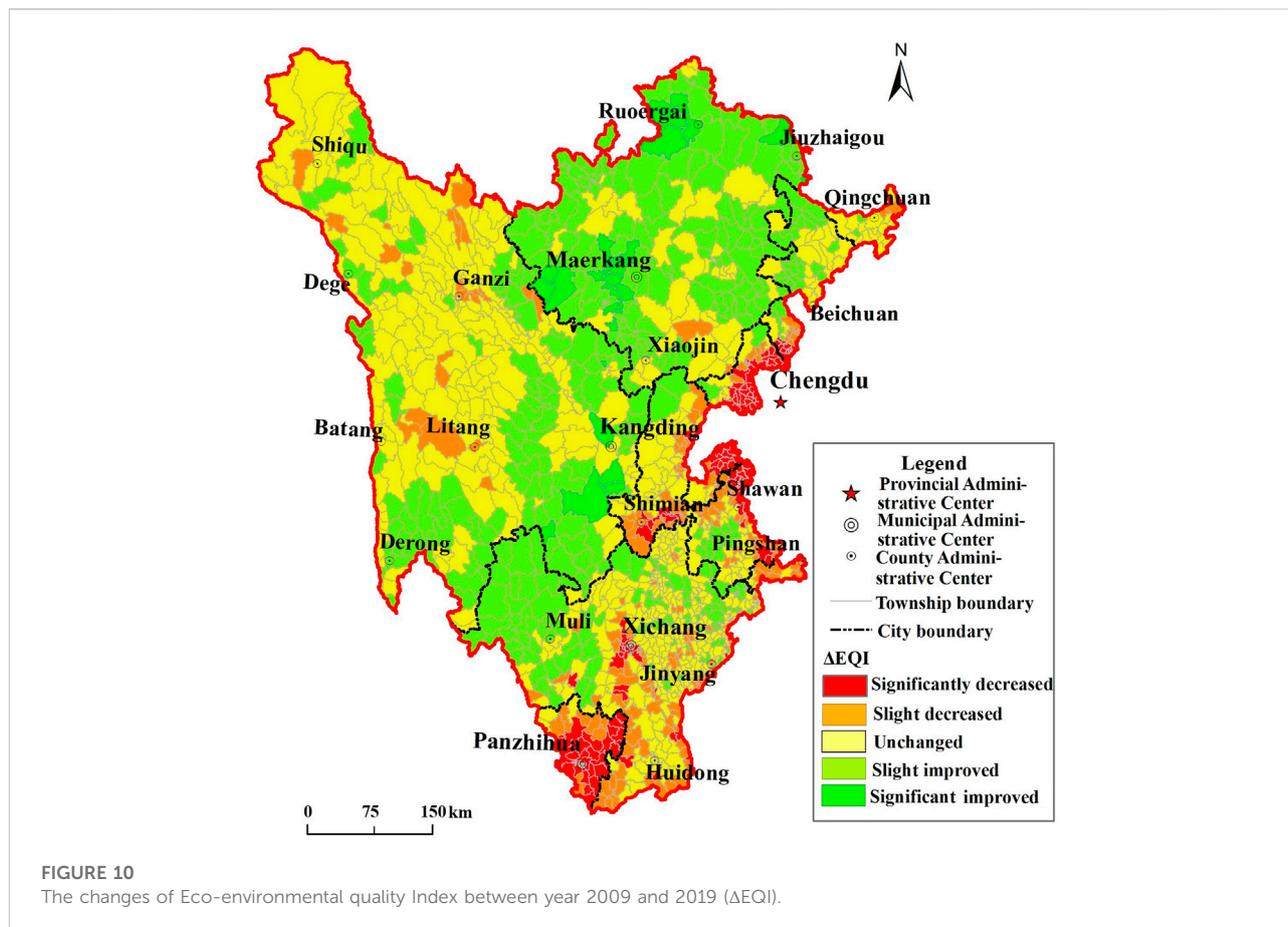
The Eco-environmental quality of the study area was mainly Good, with a small proportion of the area considered Moderate (Figure 9).

The areas with Better Eco-environmental quality were mainly distributed in the mountain area around the Sichuan basin, including the north section of the Longmen Mountain, the south section of the Longmen Mountain, the eastern part of Qionglai Mountain, Daliang Mountain, and in Muli County. The vegetation coverage in these areas was high. The land coverage was mainly forest, and the land stress and social-economic stress were both low.

The areas with Moderate Eco-environmental quality were mainly distributed in the transition zone from the Chengdu plain to the Western Sichuan mountains, the Panzhihua urban area and Shaluli mountain area. These areas had low vegetation coverage, poor habitat quality and great social-economic pressure.

In the 10-year period from 2009 to 2019, the change of Eco-environmental quality Index (ΔEQI) was in the range of 4.5≥ΔEQI>−7.6, (Figure 10). The areas with positive changes in Eco-environment are mainly distributed in Aba Prefecture, Daxue mountain and the south section of Shaluli mountain. In contrast, the Eco-environmental quality had deteriorated significantly on the edge of Sichuan Basin and in the towns of Panzhihua city.

According to the paired *t*-test of EQI values in 2009 and 2019 (Figure 9), the ecological environment experienced little change, and overall it tended to improve.

4 Discussion

4.1 Advantages and disadvantages to the proposed method

The assessment of regional ecological environment is required for ecological environment protection and restoration planning. Previous assessment methods have been based on the analytic hierarchy process (AHP) (Li et al., 2007; Xiong et al., 2007; Zhang et al., 2021) and Entropy method (Zhang et al., 2014; Zhao et al., 2018; Zhang et al., 2022). Analytic hierarchy process (AHP) alone cannot satisfy the relatively perfect rational assignment of index weights due to the scale of the region. On the other hand, the entropy method makes full use of the information provided by the original index to eliminate the subjectivity of the weight value of each factor. However, the entropy method also has some shortcomings. For one, the same evaluation factor will have different weight values under different

FIGURE 11
Moderate Eco-environmental quality and obvious degradation area.
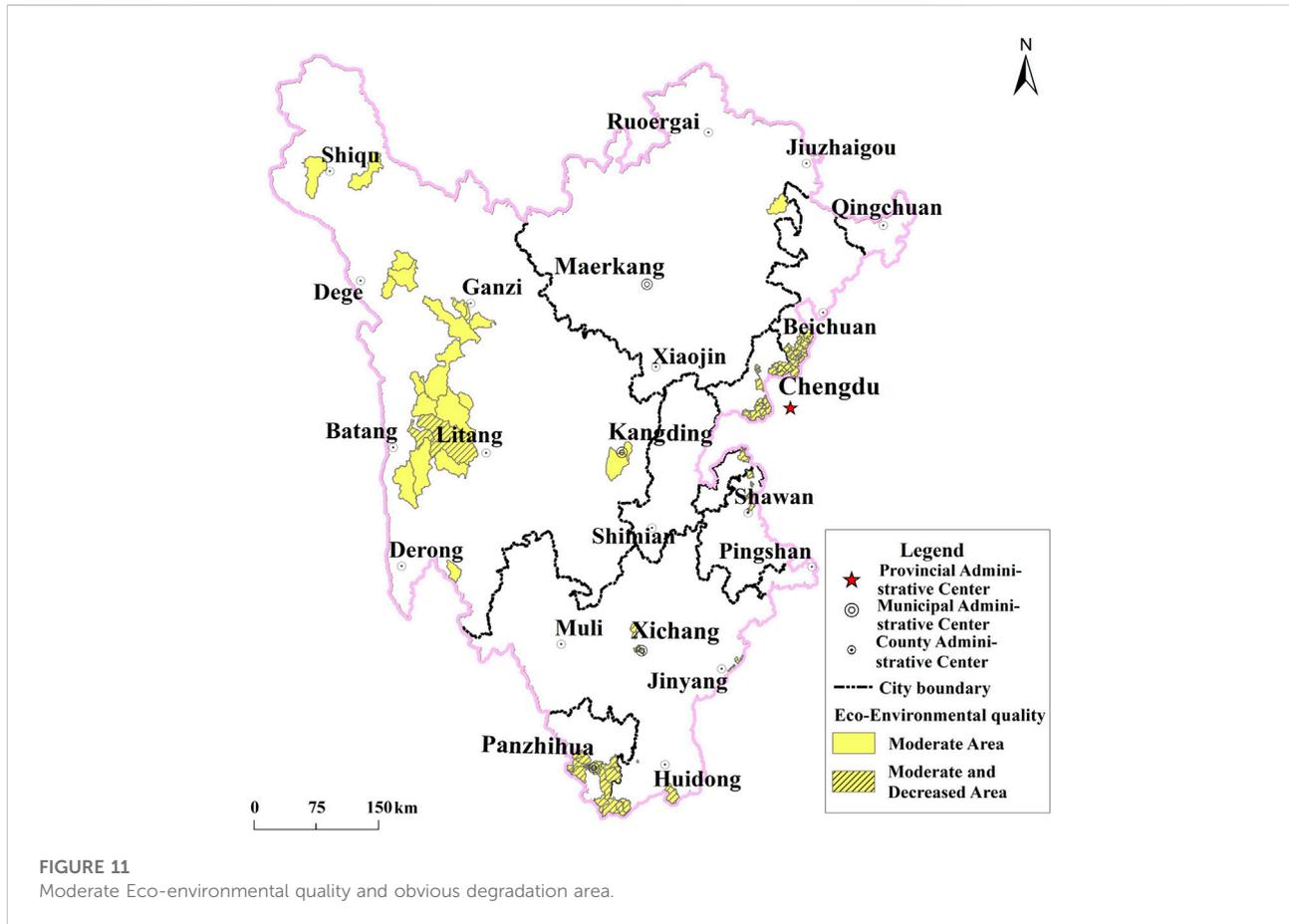
evaluation schemes, ignoring the judgment of experienced decision makers.

The ecological environment assessment is built on the remote sensing ecological index (RSEI) and the EI index. Indicators required by RSEI method are greenness, humidity, dryness, and heat, which can only be extracted from remote sensing images. Although it is more objective, the indicators for Eco-environmental quality assessment are imperfect. The EI index method was first established by the Ministry of ecological environment in 2006 and was revised in 2015. The indicators are Biological richness index, Vegetation coverage index, Water network density index, Land stress index, Pollution load index and Restricted index, which altogether completely reflect the Eco-environment. However, the pollution stress index is mainly based off the statistical data obtained from sparse monitoring stations, so its accuracy is poor at a large-scale range.

This study adopted and improved the EI index system. AHP-Entropy Methods, which consider expert experience and data objectivity, were used to determine the indicator weight. Previous models for biodiversity assessment are based on the spatial distribution of rare animals and plants, but this data is difficult to simulate in space. This paper proposes using the NPP model to quantify the status of biodiversity (Barral and

Oscar, 2012; Zhang et al., 2016). The pollutant emission was based on the quantitative monitoring at a single station, so the interpolation accuracy is low. The degradation of the ecological environmental is directly related with the growth of economic development of the region (He et al., 2014; Li Y. R. et al., 2021). A society and economics subsystem (residential density, GDP of per capita, population density) was used to evaluate regional eco-environmental quality (Li et al., 2007; Sun et al., 2013). The Social-economic stress index (SESI) reflects the degree of pollution in the ecological environment caused by the discharge of three wastes due to production and living activities.

However, the indicators listed here are still not perfect. In future research, we intend to rebuild the basic framework of Eco-environment assessments according to ecological pattern, ecological function, biodiversity and ecological stress.

4.2 Driving factors of EEQ change

The areas with Moderate Eco-environmental quality and obvious degradation are mainly distributed in the Marginal Towns of the Sichuan Basin in Chengdu, Deyang and Leshan, and in some towns in Panzhihua and the Anning River Valley

(Figure 11). Through this analysis, we found that economic development is a major social and economic stress in these areas. For instance, the area of construction land is increasing due to ongoing urbanization in these areas, and conversely the area of ecological land, such as forest and grassland, is decreasing sharply.

The areas where the eco-environment is improving are widely distributed and account for a large proportion of the Aba Prefecture (Figure 10). The 2008 Wenchuan earthquake caused great damage to the ecological environment and serious damage to vegetation in this area. By 2019, the ecological environment had improved, with vegetation coverage having increased and soil erosion gradually fading.

4.3 Suggestions on the implementation of ecological restoration

By using a township as the assessment unit, this analysis can assist local governments in making decisions, such as the determination of key areas of ecological restoration and the fund allocation of ecological restoration projects.

Because the areas with Moderate Eco-environmental quality and obvious degradation are mainly located in urban areas, relevant measures should be taken to improve the quality of the urban ecological environment. These measures may include: Building an urban internal ecological corridor, a suburban ecological protection green space, a forest belt around the city and a Country Park; Implementing sewage treatment, treatment of black and odorous water bodies and comprehensive treatment of water environment; Protecting and repairing urban green spaces, expanding storage space, and building an ecological infrastructure system; Improving the park system and greenway network.

Grassland desertification and degradation are serious issues in hilly plateau areas (Shiqu County and Shaluli mountains), and so measures such as minimizing grazing and planting artificial grass should be taken. The soil erosion along the Jinsha River in Panzhihua is also a serious concern, and so the control of water needs to be addressed to avoid soil loss.

5 Conclusion

To understand the ecological environment of the mountainous area, this study developed a comprehensive regional Eco-environmental quality assessment system specific to mountainous areas. 14 indicators from five aspects (biological richness, vegetation cover, water network density, land stress, and social-economic stress) were selected. The combination of chromatographic analysis and the entropy method helped objectively determine the factor weights, and finally, the ecological environment of Western Sichuan was comprehensively evaluated and analyzed through a spatial perspective. Township-level regions are an important part of China's national economic and social structure

and have relevant geographical, spatial, and administrative independence, which was conducive to the formulation and implementation of targeted policies. Therefore, this study takes the township administrative region as the research object, with the help of remote sensing data and GIS technology. A comprehensive assessment of Eco-environmental quality (EEQ) is key to regional environmental protection and sustainable development. This method combines traditional ecological principles with remote sensing, GIS technology, landscape ecology and ecosystem service assessment, and will potentially impact sustainable development strategies.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Author contributions

XC and SC performed field investigation. XC and DX organized the data and performed the analysis. XC wrote the original draft of the manuscript. ZH and WP reviewed and edited the manuscript. KF and GF performed the visualization. All authors contributed to the article and approved the submitted version.

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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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