Ecological sensitivity and its driving factors in the area along the Sichuan–Tibet Railway

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Abstract

Understanding spatial and temporal characteristics and driving factors of ecological sensitivity are an essential prerequisite for effectively managing environmental changes and steering the rational use of land resources. This study employed the Analytic Hierarchy Process and Coefficient of Variation methods to calculate the weights of ten indicators from 2000 to 2018. Then, spatiotemporal change patterns of ecological sensitivity along the Sichuan–Tibet Railway were analyzed. At the same time, four individual parameters, including soil erosion, land use status, topographic factors, and climate conditions, were evaluated to create a multi-perspective understanding of the entire ecological sensitivity. The key factors affecting ecological sensitivity were explored through a geographic detector model. The results indicate that the ecological sensitivity along the Sichuan–Tibet Railway is predominantly high or moderate, with higher sensitivity observed in the western regions and lower sensitivity in the eastern regions. From 2000 to 2018, the ecological environment showed a trend of deterioration, and the spatial and temporal distribution patterns of the four parameters are closely related to the extensive ecological sensitivity. Based on the GeoDetector results, the spatial distribution of ecological sensitivity is mainly related to digital elevation model, precipitation, and air temperature. The interaction between different factors can enhance the effect on ecological sensitivity. The interaction between precipitation and Vegetation Coverage (FVC) has the largest effect.

1 Introduction

In the context of the composite system encompassing resources, environment, and development, the ecosystem plays a crucial role in supporting human existence and societal development (Duan et al., 2020; Viikari, 2004). Ecological sensitivity refers to the extent to which an ecosystem is susceptible to or responsive social or environmental changes (Shi et al., 2018; Tsou et al. 2017a). It is an effective and comprehensive measure of an ecosystem's self-regulation (Zhang et al., 2012). Regions with higher levels

of ecological sensitivity are typically more vulnerable to disturbances and exhibit lower resilience, whereas regions with lower ecological sensitivity tend to be more resistant to such changes (Duan & Wu, 2005). Achieving sustainable use of ecosystems requires striking a balance between exploitation and protection (Gao et al., 2010; Ouyang et al., 2000). Therefore, it is necessary to investigate ecological sensitivity that can provide an important basis to avoid further deterioration of an ecological environment (Fan et al., 2019; Miles et al., 2001; J. Wang et al., 2018).

Over time, ecological sensitivity research has undergone significant development, with an increasing focus on theoretical deepening and enriching content. The spatial scales incline to be diversified, such as parks, mountains, industrial parks, watersheds, and plains (Chi et al., 2019a; Su et al., 2021; Tsou et al. 2017b). Ecological sensitivity evaluation is also closely related to land carrying capacity (Wu & Hu, 2020), ecological land analysis (Beroya-Eitner, 2016), and nature reserve planning (Briceño-Elizondo et al., 2006). Research scale mainly involves national, provincial, and municipal areas and tends to be microscopic (Wang et al. 2016; Xiong et al. 2018). Previous research on a national scale mainly focused on eco-environmental issues from a comprehensive assessment perspective (Jagtap et al., 2003; Liu & Zhang, 2011). Those at the provincial scale of associated research are also gradually deepening (Peng & Deng, 2021). However, studies conducted at the municipal and county level are still in the developing stage (Dong et al., 2022; Tong & Shi, 2020). Research methodology of ecological sensitivity has evolved from the early traditional, isolated, and one-sided evaluation method to the multifactor comprehensive research (Chi et al., 2019b; Modica et al., 2021; Williams et al., 2022). Through a comprehensive review and analysis of relevant literature, we identified a limited number of quantitative studies investigating the interaction of driving factors on ecological sensitivity, particularly regarding the plateau ecosystem along the Sichuan–Tibet Railway, which has not received sufficient attention.

As the "Third Pole" of the world, the Qinghai–Tibet Plateau has faced multiple threats over the past decades. In addition, climate changes, land use and management, and excessive logging have caused desertification and grassland degradation in the regional ecological environment (Li & Song, 2021). The Sichuan–Tibet Railway Project implemented in the Tibet Plateau is one of the most well-known projects in China. Once the railway is in operation, anthropological driving factors coupling with natural elements might exert profound impact on the local ecosystem in the surrounding areas radiating from the railway lines. For ecosystems in those radiating areas in the Tibet Plateau, the spatiotemporal characteristics of ecological sensitivity and its driving mechanisms remain unknown. To meet the demands of ecological restoration and sustainable development associated with railway construction, it is necessary to evaluate ecological sensitivity and driving forces in the ecosystems along the Sichuan–Tibet Railway. Such studies will provide crucial insights for balancing economic development and environmental preservation in this region.

The primary objective of this study is to explore the spatiotemporal characteristics of ecological sensitivity and the impacts of eight selected factors: land use (LU), salinization index (SRSI), air temperature (TEM), precipitation (PRE), population density (PD), digital elevation model (DEM), relief amplitude (RA), and vegetation coverage (FVC). Three questions will be investigated: (1) What is the overall ecological sensitivity in the various counties along the Sichuan–Tibet Railway?(2) What is the spatiotemporal distribution pattern? and (3) What are the key drivers influencing changes in ecological sensitivity?

2 Materials and methods

2.1 Study area

The Sichuan–Tibet Railway is one of the key transportation construction projects in China's 13th Five-Year Plan. It is divided into three sections: Chengdu-Kangding Railway, Kangding- Nyingchi Railway, and Nyingchi-Lhasa Railway. Our study area includes 21 counties along the railway from Ya 'an (Sichuan Province) to Nyingchi (Tibet) at a length of 1011 km (Fig. 1). Climate zones along the railway range from the subtropical humid climate zone of the Sichuan basin to the sub-temperate humid and sub-arid zone of the Qinghai-Tibet plateau. Annual rainfall is between 400 and 1900 mm, with the maximum air temperature in summer and minimum air temperature in winter of 40 °C and −20 °C, respectively (Li et al. 2017). High mountains and deep valleys are widely distributed along the railway, and the spatial difference in natural environment is obvious, with an elevation difference of more than 4000 m. The main landscape types in the area along the Sichuan–Tibet Railway include grassland, shrub, forest, and wetland. Yucheng District, located in the Ya'an city of Sichuan Province, is the only "eco-climate city" in China with a forest coverage rate of 74.96% (Peng et al., 2010). The Chinese government strives to protect the ecological environment along the railway. An ecological sensitivity study is of great significance for regional sustainable development.

2.2 Data sources

2.2.1 Remote sensing data

For the land use (LU) classification, we utilized Landsat 5 TM images of 2000 and 2010, as well as Landsat 8 OLI images of 2018 obtained from the United States Geological Survey. Before performing the classification, the remote sensing data underwent preprocessing steps, including radiometric and geometric corrections, atmospheric correction, and orthorectification. The supervised classification technique of maximum likelihood classifier algorithm is used to generate LU maps. This method is widely used for land cover classification due to its ability to distinguish between different land cover types. Prior
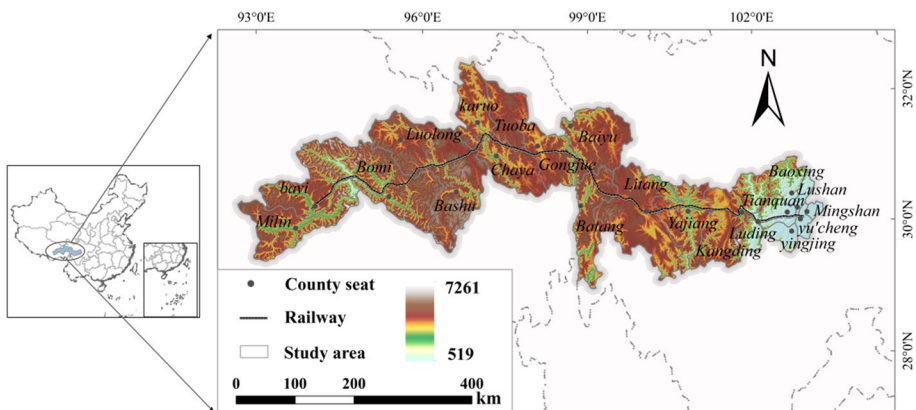

Fig. 1 Location of the study area

physiographical knowledge of the study area, along with supportive ancillary data and national classification standards, guided the identification of six LU classes, namely cultivated land, woodland, grassland, water, residential land, and unused land. We employed the maximum likelihood classifier algorithm for land use classification, considering prior knowledge of the study area, ancillary data, and national classification standards. Specific band combinations were selected based on their spectral characteristics and ability to differentiate the land covers of interest.

1. *Cultivated land*: To identify cultivated land, Landsat 5 TM utilizes a combination of Band 4 (Red), Band 3 (Green), and Band 2 (Blue), while Landsat 8 OLI utilizes Band 6 (SWIR 1), Band 5 (Near-Infrared), and Band 2 (Blue). The red and green bands capture higher reflectance in cultivated areas, while the blue band aids in distinguishing different land cover types. The inclusion of SWIR1 in Landsat 8 OLI enhances the differentiation of cultivated areas.
2. *Woodland*: Both Landsat 5 TM (Band 4, Band 5, Band 3) and Landsat 8 OLI (Band 5, Band 4, Band 3) employ a combination of red, near-infrared, and green bands to identify woodland areas. Woodlands display higher reflectance in the near-infrared spectrum and relatively lower reflectance in the red and green bands due to vegetation absorption and reflection patterns.
3. *Grassland*: By combining different bands, such as red, green, and blue (TM: Band 4, Band 3, Band 1; OLI: Band 5, Band 4, Band 2), grassland can be distinguished from other land cover types. This combination captures the relatively higher reflectance in the red and green bands and lower reflectance in the blue band, which are characteristic of grasslands.
4. *Water*: The identification of water is accomplished through the combination of red, green, and blue bands in both Landsat 5 TM (Band 4, Band 3, Band 2) and Landsat 8 OLI (Band 5, Band 6, Band 4). Water exhibits lower reflectance in the red band and higher reflectance in the near-infrared and shortwave infrared bands, making this combination effective in identifying water bodies.
5. *Residential land*: To identify residential land, both Landsat 5 TM (Band 7, Band 4, Band 3) and Landsat 8 OLI (Band 7, Band 6, Band 4) utilize a combination of shortwave infrared, red, and green bands. The unique reflectance properties of built-up areas, including rooftops and paved surfaces, are captured by the shortwave infrared band, while the red and green bands provide additional information for distinguishing residential areas.
6. *Unused land*: By utilizing a combination of red, near-infrared, and shortwave infrared bands (TM/OLI: Band 4, Band 5, Band 7), unused or unutilized land areas can be identified. This combination takes advantage of the relatively uniform reflectance characteristics exhibited by unused land compared to other land cover types.

By selecting these specific bands, we maximized the discriminative power of the classification algorithm, allowing for accurate identification and mapping of the land covers of interest. To verify the accuracy of the LU classification, we compared the results with high-resolution images from Google Earth for the corresponding years. Furthermore, an accuracy assessment was conducted using ERDAS IMAGINE software, which involved comparing the classified map with ground truth data obtained from field surveys or existing land cover datasets.

Normalized difference vegetation index (NDVI) and surface reflectance products provided by the National Aeronautics and Space Administration Data Center were used to

compute ecological sensitivity indicators. MODIS NDVI product (MOD13A1) was generated every 16 days with a spatial resolution of 250 m. We extracted vegetation coverage index of vegetation (FVC) growth season (June to August) using the pixel binary model (Ge et al., 2018). The MOD09A1 (8 Day) product with a spatial resolution of 500 m was used to compute land salinization index (SRSI). Prior to the computation, the surface reflectance data underwent radiometric and atmospheric corrections to ensure accurate and consistent results. Radiometric correction adjusted the pixel values to account for sensor-specific characteristics and atmospheric interference, while atmospheric correction removed atmospheric effects that could affect the accuracy of the salinization index calculation.

2.2.2 Meteorological data

Numeric-formatted meteorological datasets (daily air temperature (TEM) and precipitation (PRE)) from 2000 to 2018 were obtained from the China Meteorological Science Data Center (http://data.cma.cn). Selected meteorological stations are distributed throughout the study area and surrounding regions. Spatial distribution maps of air temperature and precipitation for 2000, 2010, and 2018 were obtained by inverse distance weight interpolation using ArcGIS software. The average annual rainfall erosivity (R) was calculated following Zhang and Fu (2003).

2.2.3 Other data sources

The Digital Elevation Model (DEM) derived from Shuttle Radar Topography Mission (SRTM) data, which provides elevation information at a resolution of 90 m. The SRTM data are collected by radar sensors onboard the space shuttle, enabling the generation of digital elevation models for large areas. After undergoing data fusion, correction, outlier removal, and cropping preprocessing, the SRTM data yield terrain data that are more precise and dependable. Subsequently, various terrain-related parameters, including slope, aspect, and relief amplitude (RA), are calculated to offer supplementary insights into the topography and its distinctive features.

Soil type data were extracted from Harmonized World Soil Database v1.2, which is a raster database with a spatial resolution of 30 arc-seconds (1 km). Soil properties include soil organic carbon content, sand, silt, and clay content. The specialized population density (PD) datasets from 2000 to 2018 were provided by WorldPop (https://www.worldpop.org/) at a resolution of 30 arc-seconds.

There are variations in the data sources and spatial accuracy of the datasets employed. To ensure consistency and comparability, all the aforementioned datasets were standardized to the WGS_1984_UTM projection and resampled to a resolution of 500 m.

2.3 Research methods

2.3.1 Establishment of an indicator system for ecosystem sensitivity assessment

Ecological conditions are distinct in different regions. Due to the various definitions used in different disciplines, there is currently no international standard or rule to evaluate ecological sensitivity. Considering data acquisition, environmental characteristics, spatial resolution, etc., ten indices from soil erosion (rainfall erosivity, soil texture), land status (land

use and vegetation coverage), topographic factors (elevation, slope, and aspect), and climate conditions (Annual mean air temperature and precipitation) were employed to establish an evaluation index system (Table 1). All indicators were divided into five levels from insensitive to extremely sensitive, with scores assigned as 1, 3, 5, 7, and 9, respectively.

2.3.2 Determination of weights of the indices

Analytic hierarchy process (AHP) can evaluate the longitudinal control of an index layer, but has difficulty in reflecting internal and horizontal structure control of each single factor. Quantification of the weight of each factor is subjective. The coefficient of variation (CV) method can reveal the relationship between the internal and horizontal structure and each factor, eliminating effectively inherent subjectivity of an analytic hierarchy process. In particular, indicators of greater differences can better reflect the gap between the evaluated units. Therefore, the weight (Table 1) exhibits notable objectivity by combining AHP and CV. The expression is as follows:

Average and standard deviation of each indicator layer are:

$$\overline{A_j} = \frac{1}{n} \sum_{i=1}^{n} A_{ij} \quad (i = 1, 2, 3, \cdots, 10; j = 1, 2, 3, \cdots, n) \tag{1}$$

$$\sigma_j = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(A_{ij} - \overline{A_i}\right)^2} \tag{2}$$

Coefficient of variation of each indicator layer is:

$$V_i = \frac{\sigma_j}{\overline{A_j}} \tag{3}$$

Weight of each evaluation factor is:

$$F_i = \frac{V_i P_i}{\sum_{i=1}^{n} V_i P_i} \tag{4}$$

where i is the evaluation index, and j is the evaluation index factor. n is the number of indicators. A_i and$_i$ are the average value and standard deviation of each index layer, respectively. V_i is the coefficient of variation, P_i is the weight of each factor, and F_i is the comprehensive weight of ecological sensitivity.

2.3.3 Assessment of ecological sensitivity

With geographic information system (GIS) technology, we can map the comprehensive ecological sensitivity index by combining all assessment indices as shown in Eq. 5:

$$X = \sum_{i=1}^{n} ui \cdot wi, \, i = 1, 2, 3, \ldots \ldots, n \tag{5}$$

where X is the comprehensive ecological sensitivity, n is the number of indexes, W_i is the weight of index i, and u_i is the ecological sensitivity of index i. The larger the X is, the

Table 1 Ecological sensitivity factor classification system

Classification	Index system	Assessment criteria					Weight	
		Extremely sensitivity (9)	Highly sensitivity (7)	Moderately sensitivity (5)	Lightly sensitivity (3)	Insensitivity (1)	Local weight	Overall weight
Soil erosion	Rainfall Erosivity (MJ·mm/(hm²·h))	>5000	4000~5000	3000~4000	2000~3000	≤2000	0.304	0.041
	Soil texture	Silt sand, silt	Loam, clay powder, clay soil	Very fine sand, loam	Coarse sand, fine sand, clay	Gravel, sand	0.541	0.073
	Relief Amplitude(m)	400~500	300~400	200~300 500~600	100~200 600~1000	0~100 >1000	0.156	0.021
Land use status	Land use type	Water, glacier, Permanent snow	Woodland, grass-land, Wetland, shrub	Cultivated land	unused land	residential land	0.146	0.037
	Vegetation coverage	≤10	10~30	30~60	60~80	>80	0.854	0.217
Topographic factor	Slope(°)	>40	30~40	20~30	10~20	≤10	0.794	0.197
	Aspect	North	Northeast, Northwest	East, West	Southeast, Southwest	Flat, South	0.065	0.016
	Elevation	>4500	4000~4500	3500~4000	2000~3500	≤2000	0.141	0.035
Climatic condition	Air temperature	>8	3~8	0~3	-5~0	≤-5	0.154	0.056
	Rainfall	≤700	700~900	900~1000	1000~1100	>1100	0.846	0.307

higher the level of ecological sensitivity will be, and vice versa. Based on the provisional regulations on ecological function regionalization—Technical Guide for Delineating Ecological Function Red Line, and other relevant norms and standards, the evaluation results were divided into five levels: ecologically insensitive area, mildly sensitive area, moderately sensitive area, highly sensitive area, and extremely sensitive area (Table 2).

2.3.4 Driving force analysis of ecological sensitivity

A geographic detector model can quantitatively explore driving mechanisms of geographical phenomena without any restrictions or hypothesis in terms of variables (Li et al., 2013; Onozuka & Hagihara, 2017; Ren et al., 2014). This model includes factor detector, ecological detector, risk detector, and interaction detector. In this study, factor detector and interaction detector were applied to analyze the driving factors of ecological sensitivity. Factor detector can quantitatively identify the explanatory capability of independent variable X for dependent variable Y with the q-value. And the interaction detector can detect the interactive effects of two explanatory variables $X1$ and $X2$ on Y. We opted for eight indices, DEM, RA, LU, TEM, PRE, FVC, SRSI, and PD as the independent variables (influence factors) and the comprehensive ecological sensitivity index as the dependent variable for the geographic detector model.

3 Results and analysis

3.1 Spatiotemporal variation characteristics in ecological sensitivity

In general, the ecological sensitivity of the Sichuan–Tibet Railway has an obvious geographical spatial variation (Fig. 2a–c). The region with highly sensitive and extremely sensitive levels were macroscopically scattered and locally concentrated. The extremely sensitive areas are distributed in the western regions (e.g., Bomi and Basu counties) along the Sichuan–Tibet Railway. In these areas, the surface structure is simple, soil erosion is serious, resulting in poor ecological environment quality. The highly and moderately sensitive areas were distributed widely, covering more than 50% of the study area. Regions with a moderately sensitivity level were clustered around lightly and insensitive areas. Highly and moderately sensitive areas are mainly located in the central regions and western regions

Table 2 Classification of ecologically sensitive areas

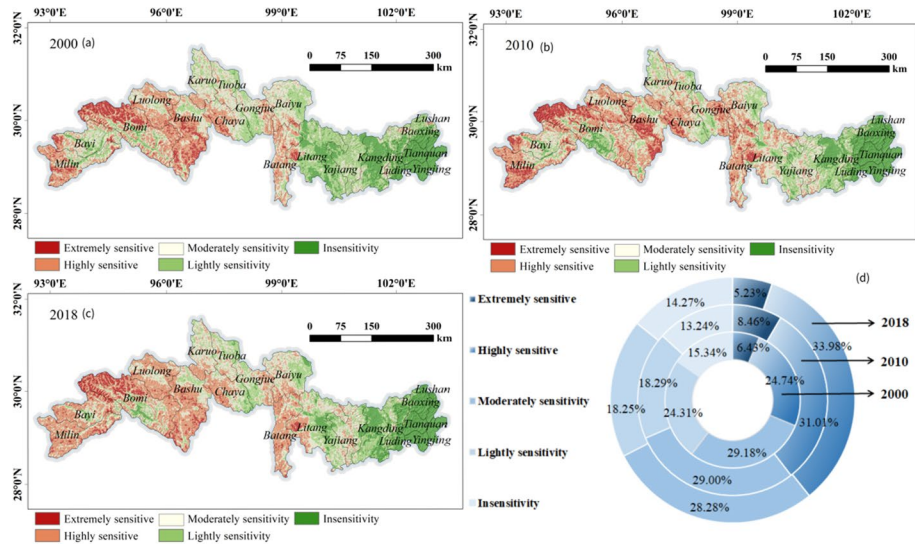| Category	Extremely sensitive	Highly sensitivity	Moderate sensitivity	Lightly sensitivity	Insensitivity
Soil erosion	≥4.7	3.8~4.7	3.2~3.8	2.5~3.2	≤2.5
Land use Status	≥6.3	5.3~6.3	3.5~5.3	2.4~3.5	≤2.4
Topographic factor	≥7.0	5.8~7.0	5.2~5.8	4.1~5.2	≤4.1
Climatic condition	≥8.3	6.8~8.3	4.7~6.8	3.0~4.7	≤3.0
Comprehensive assessment	≥6.4	5.8~6.4	5.3~5.8	4.7~5.3	≤4.7
Hierarchical value	9	7	5	3	1

Fig. 2 Spatially distributed ecological sensitivity and areal proportion of different levels in 2000, 2010 and 2018

(e.g., Milin, Luolong, and Baiyu counties). The areas with light and intensive sensitivity are located in the eastern regions (e.g., Litang, Yajiang, Kangding, and Yingjing counties).

From 2000 to 2018, the study site was dominated by areas of moderately sensitive, highly sensitive, and extremely sensitive. Taking year 2018 as an example, areas of these three levels accounted for 28.28%, 33.97%, and 5.23% of the total, respectively (Fig. 2d). After assignment, average ecological sensitivity level was 5.17, 5.43, 5.37 in 2000, 2010, and 2018, respectively, indicating that the ecological environment of the study area might have deteriorated from 2000 to 2010. However, there was a slight decline from 2010 to 2018. This phenomenon may be due to the resilience of the ecological environment (Wohlfart et al., 2016). Over the study period, extremely sensitive areas increased first and then decreased with an overall changing rate of 1.18%, while insensitive areas decreased first and then, increased. Mildly sensitive and moderately sensitive areas showed a continuous downward trend. The average proportion of moderately sensitive areas was 28.82%. During 2000–2010 and 2010–2018, the main dynamic type was converted from the moderately sensitive level to the highly sensitive level, concentrated in the western part of the study area.

3.2 The variation characteristics of parameters

Evaluating the effects of each parameter will be helpful for ecological conservation and management since it will give us insight into which parameters are the most important. At the same time, decision-makers can better understand the relationship between soil erosion, land status, topography, climatic conditions, and ecological sensitivity.

With regard to change in soil erosion, as shown in Fig. 3a–c, the central area is highly sensitive to soil erosion due to its large terrain fluctuation. In eastern areas such as Tianquan County and Baoxing County, soil erosion sensitivity is low. From 2000 to 2018, soil
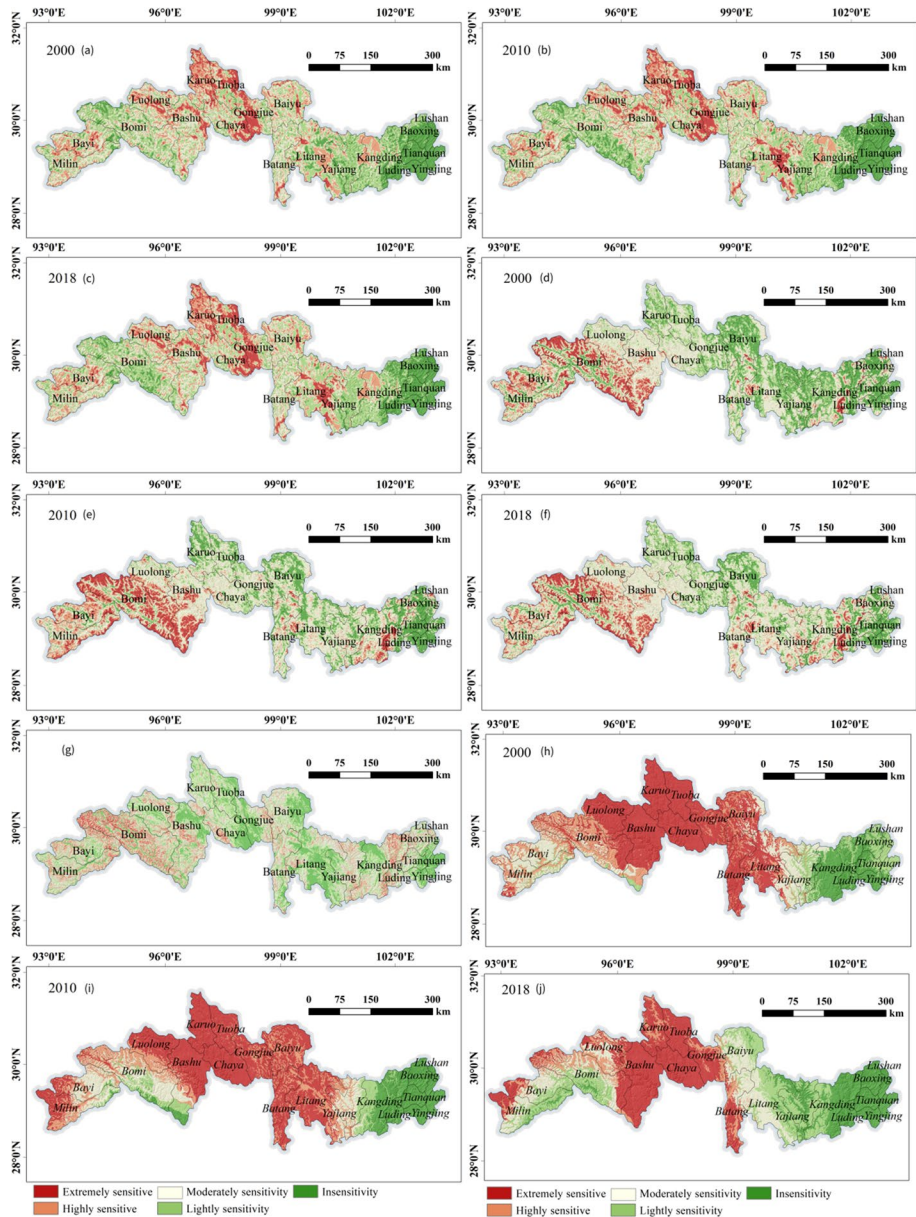
Fig. 3 Spatial distribution of ecological sensitivity due to a single factor. **a–c** show soil erosion in 2000, 2010, and 2018; **d–f** show land status in 2000, 2010, and 2018; **g** shows topographic factors; and **h–j** show climatic conditions in 2000, 2010, and 2018

erosion tended to deteriorate in the surrounding area of the metropolis region. Conversely, there was an obvious improvement in remote mountain areas. Specifically, the situation in the west has improved, such as in Bomi County. Soil erosion worsened in the eastern, especially in Litang and Yajiang counties.

As can be seen from Fig. 3d–f, the land use status in the western region was generally worse than that in the eastern region. This might relate to poor vegetation coverage due to land desertification (Karamesouti et al., 2018; Xu et al., 2019). From the west to the east, the sensitivity level decreased, implying that the land condition gradually improved. From 2000 to 2018, the moderately sensitive areas showed a trend of increasing eastward, while the low sensitive (lightly sensitive and insensitive) areas in the east showed a trend of decreasing.

The map of topographical factors (Fig. 3g) displays the interactive distribution of regions with high and low sensitivities. The overall distribution pattern is high in the west (e.g., Bomi, Basu, and Milin counties) and low in the east (e.g., Litang, Yajing, and Tianquan counties). Different slope directions have deferent solar radiation intensities and illumination times, which resulted in significant differences in regional ecological effects. Among them, higher and steeper terrains will lead to higher ecological sensitivities.

Figure 3h–j indicates that areas of high sensitivity to climate change were concentrated in the western and central regions. From 2000 to 2010, the high-sensitive areas such as Milin, Bayi, Bomi and Litang counties showed an increasing trend. From 2010 to 2018, the high-sensitive area decreased obviously, and the low sensitive area expanded significantly (e.g., Milin, Baiyu, Litang, and Batang counties). These results emphasize the importance of climate changes in the growth of vegetation at the local level (Gratani, 2014; J.-F. Wang et al. 2016). For instance, as an important factor for large-scale change of land surface, air temperature and rainfall can directly influence crop production, vegetation growth, and water content in soil (e.g., Yucheng and Baoxing counties).

3.3 Determinants and interactions of ecological sensitivity

3.3.1 Significance analysis of driving factors

The geographical detector model was applied to identifying the impacts of driving factors on ecological sensitivity. Independent variables were composed of both anthropogenic and natural factors, and the values of ecological sensitivity in 2000, 2010 and 2018 were selected as the dependent variable. From Fig. 4, the average power of determining ecological sensitivity for the driving factors in descending order is: DEM (0.444) > PRE (0.358) > TEM (0.342) > FVC (0.257) > SRSI (0.169) > LU (0.163) > PD (0.161) > RA (0.072). This means that DEM, PRE, TEM were the key factors for the ecological sensitivity. Although the explanatory power of other factors was less than 30%, they also exerted an influence on the spatial differentiation to some extent. From 2000 to 2018, the explanation intensity of PRE and TEM tended to increase. Especially, the PRE experienced a continual increase from 0.190 in 2000 to 0.514 in 2018. Comparatively, except for the DEM, LU, and PD, which slightly changed with time, the other three indices all decreased to some extent.

3.3.2 Interaction of influencing factors of ecological sensitivity

From Table 3, it can be inferred that the interaction of any driving factor with another factor has a more significant impact on the ecological sensitivity than a driving factor itself. The results from the interaction are mostly bi-enhanced $(q(\times 1 \cap \times 2) > \text{Max}(q(\times 1), \ q(\times 2)))$, with a few being nonlinearly enhanced $(q(\times 1 \cap \times 2) > q(\times 1))$. The nonlinearly enhanced effect means the synergetic effect of
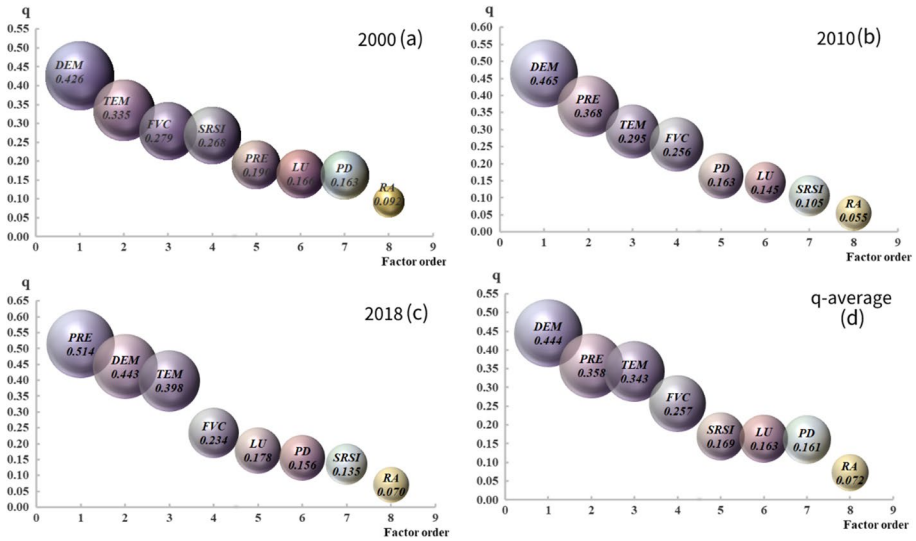
Fig. 4 Importance of driving factors influencing ecological sensitivity. Land use, Salinization Index, Temperature, Precipitation, Population density, Digital Elevation Model, Relief Amplitude, and Vegetation Coverage are represented by LU, SRSI, TEM, PRE, PD, DEM, RA, FVC, respectively

Table 3 Results of interactive detector

	LU	SRSI	TEM	PRE	PD	DEM	RA	FVC
LU	0.145							
SRSI	0.204**	0.105						
TEM	0.345**	0.345**	0.295					
PRE	0.527*	0.594*	0.620**	0.368				
PD	0.235**	0.207**	0.364**	0.560*	0.163			
DEM	0.484**	0.491**	0.487**	0.637**	0.478**	0.465		
RA	0.185**	0.152**	0.358*	0.466*	0.223*	0.525*	0.055	
FVC	0.324**	0.277**	0.437**	0.656*	0.342**	0.549**	0.295**	0.256

Land use, Salinization Index, Air temperature, Precipitation, Population density, Digital Elevation Model, Relief Amplitude, and Vegetation Coverage are represented by LU, SRSI, TEM, PRE, PD, DEM, RA, FVC, respectively

**Bi-enhanced $(q(\times 1 \cap \times 2) > Max(q(\times 1), q(\times 2)))$

*Nonlinearly enhanced $(q(\times 1 \cap \times 2) > q(\times 1) + q(\times 2))$

$X1$ and $X2$ exceeds the sum of their separate effects, e.g., SRSI and PRE (59.4%), LU and PRE (52.7%), and DEM and RA (52.5%). Meanwhile, the bi-enhanced effect means that the synergetic effect of $X1$ and $X2$ is stronger than each individual effect, e.g., FVC and TEM (43.7%), LU and DEM (48.4%), and SRSI and PD (20.7%). Unlike the results of single-factor detection, the impact of LU, PD, and RA on ecological sensitivity was highlighted after interacting with several other factors, and approximately 47% of the q values of the pairwise interaction exceeded 0.4. Notably, interaction between PRE and

FVC yielded the largest effects that further confirmed the importance of PRE and FVC in ecological sensitivity.

4 Discussion

4.1 Spatial and temporal characteristics of ecological sensitivity

The spatiotemporal analysis of ecological sensitivity is commonly applied to quantify the interaction between ecosystems and human activities as well as environmental changes. It serves as a crucial foundation for ecological and environmental protection, providing a scientific basis for the sustainable development of the ecological environment (Jiang et al., 2021). The Sichuan–Tibet Railway, being an important transportation route in China, traverses diverse ecological landscapes, making it imperative to assess its ecological sensitivity. However, previous studies in this area have been limited. Understanding the ecological sensitivity of this region is vital for the implementation of appropriate conservation measures and the promotion of sustainable development (Andriantiatsaholiniaina et al., 2004). Our findings revealed a high temporal variability and spatial correlation of ecological sensitivity along the Sichuan–Tibet Railway. Notably, the western and central regions exhibited significant spatial clustering of highly sensitive areas, which can be attributed to the unique natural environmental characteristics and human activity density in these areas. Importantly, we observed an eastward expansion of high-sensitivity areas from 2000 to 2018, indicating a gradual deterioration of the ecological environment in the eastern regions. This trend may be influenced by changes in land use, climate, and the cumulative impact of human activities in the eastern regions.

In this study, the sensitivity of four parameters was analyzed individually. With remote sensing and GIS, the spatial distribution of soil erosion, land use status, topographic factors, and climate conditions could be visualized more intuitively and quantitatively (Fig. 4a–j). Overall, the dramatic spatiotemporal changes of various parameters had a complicated influence on the ecological sensitivity along the Sichuan–Tibet railway. Our results highlight the importance of factors such as soil erosion and land use conditions in shaping ecological sensitivity patterns. Previous studies (Borrelli et al., 2020; Wang et al., 2017, 2021) have emphasized that higher rainfall erosivity and looser soil texture can lead to soil erosion, while vegetation cover plays a crucial role in reducing soil erosion. The robust ecosystem structure, high resistance capacity, suitable climatic conditions, and fast-growing natural vegetation observed in the eastern regions have been found to contribute to their lower susceptibility to rainfall-induced soil erosion. This finding supports the conclusions drawn in previous studies (Cardinale et al., 2011; J. (Jingle) Wu 2006) that have emphasized the importance of ecosystem characteristics in enhancing the ability of ecosystems to withstand environmental pressures. Furthermore, the relief amplitude, which refers to the variation in elevation within a given area, has emerged as a significant driver of soil erosion. Studies by Shi et al. (2012) have shown that relief amplitude not only influence the amount and velocity of surface runoff but also affect the distribution and concentration of water flow. Areas with irregular terrain and pronounced relief amplitudes tend to experience concentrated flow in certain channels or depressions, which can lead to localized erosion and the formation of gullies (Wang et al., 2016a, 2016b; Tang et al., 2019). Moreover, the convergence of runoff in these areas can result in increased erosion rates, as the erosive force is concentrated in specific locations (Xu et al., 2022a, 2022b; Tang et al., 2022).

Topographic and climatic conditions exert a significant influence on the ecological sensitivity of the study area. The characteristics of the terrain, including altitude, slope, and aspect, play a crucial role in shaping the distribution and composition of ecosystems (Wu et al., 2022; Zhao et al., 2021). These topographic factors directly impact the availability of resources such as sunlight, moisture, and nutrients, thereby influencing vegetation coverage and biodiversity patterns (Cui et al., 2022; Hou et al., 2021a, 2021b). Research has shown that climate change and variability have already impacted the region's ecological systems, particularly the vegetation cover and water resources (Scheiter et al., 2020; Li et al., 2013; Zhang et al., 2018). For instance, a study by Xu et al., (2022a, 2022b) found that the warming and drying trends in the region have led to significant reductions in the vegetation cover, which has increased the soil erosion and reduced the ecosystem services. Similarly, Krishnaswamy et al., (2014) and Dai et al. (2011) observed that the increase in precipitation intensity has exacerbated the soil erosion and landslides in the study area, posing a significant threat to the railway's stability and safety.

4.2 Ecological sensitivity attribution

The application of the geographic detection model has provided quantitative evidence supporting the significance of DEM, PRE, and TEM as influential factors in determining ecological sensitivity along the Sichuan–Tibet Railway. This model allows for a comprehensive analysis of these factors and their relationships with ecological conditions. The positive relationship between DEM and ecological sensitivity highlights the role of terrain characteristics in determining the sensitivity of the ecosystem. This aligns with the understanding that topographic factors influence the distribution of resources such as sunlight, moisture, and nutrients, thereby shaping vegetation coverage and biodiversity patterns (Cao et al., 2018; Sun et al., 2014). Additionally, the model reveals the importance of climatic factors, specifically PRE and TEM, in influencing ecological sensitivity. Precipitation and temperature are fundamental components of the climatic regime, and their variations can significantly impact ecosystems (Peñuelas & Filella, 2001; Walther et al., 2002). Adequate precipitation levels are crucial for maintaining soil moisture and supporting vegetation growth (W.-Y. Shi et al. 20; B. Wang et al., 2014), while temperature affects the metabolic processes of organisms and regulates ecosystem functions (YVON-DURO-CHER et al., 2011).

Moreover, the interaction detector analysis offers valuable insights into the combined effects of driving factors on ecological sensitivity. By considering the interactions between variables, such as the interaction between PRE and SRSI, the model enhances its explanatory power and provides a more comprehensive understanding of the factors influencing ecological sensitivity. This finding implies that the availability of precipitation and the characteristics of the terrain can interact to influence ecological conditions in the study area. These results are consistent with the research conducted by Ke et al. (2022) and Sun et al. (2022), who emphasize the importance of considering the interactions between driving factors in ecological assessments.

The integrated analysis of the geographic detection model and the interaction detector provides policymakers with invaluable knowledge for decision-making regarding conservation and sustainable development along the Sichuan–Tibet Railway. This knowledge allows for the prioritization of conservation efforts, the implementation of targeted measures, the restoration of degraded ecosystems, and the promotion of sustainable land use practices (Kang et al., 2021). By incorporating these findings into policy and planning processes,

policymakers can ensure the long-term ecological health and resilience of the region while facilitating sustainable development.

While our study provides valuable insights, we acknowledge several limitations. Firstly, the assessment cells were set to a resolution of 500 m x 500 m, which may limit the ability to capture local sensitivity characteristics at smaller scales. Consequently, some small-scale sensitivities may not have been fully accounted for in the ecological sensitivity management. To address this limitation, further research could consider conducting a comparative analysis at multiple scales to assess the necessity for downscaling and to capture finer-grained variations in ecological sensitivity. Secondly, while this study comprehensively evaluated the impact of soil erosion, land use status, topographic factors, and climate conditions on ecological sensitivity, there may be other indicators that could potentially impact ecological sensitivity, albeit to a lesser degree due to their relative stability over time but with spatial differences. It would be valuable for future long-term evaluations to incorporate a more comprehensive theoretical framework that considers additional indicators, providing a more holistic understanding of ecological sensitivity dynamics. By acknowledging these limitations, future studies can build upon the current research and address these gaps to further enhance the accuracy and applicability of ecological sensitivity assessments. The incorporation of multiple scales and additional indicators would contribute to a more nuanced understanding of ecological sensitivity patterns and aid in the development of a comprehensive theoretical framework for long-term evaluations.

5 Conclusions

In this study, our objective was to assess the ecological sensitivity along the Sichuan–Tibet Railway by considering multiple factors, including soil erosion, land status, topographic factors, and climate conditions. We employed the Analytic Hierarchy Process (AHP), coefficient of variation (CV), and a geographical detector model to quantitatively evaluate ecological sensitivity and analyze its spatial and temporal evolution patterns, as well as identify the key driving factors over an 18-year period. The findings of our study indicate that the ecological sensitivity levels were predominantly characterized by areas of high and moderate sensitivity, which accounted for more than 50% of the study area. Specifically, the western regions, such as Bomi, Basu, and Milin counties, exhibited high ecological sensitivity due to their simple surface structure and severe soil erosion. Conversely, the eastern regions, characterized by more favorable natural conditions, demonstrated lower ecological sensitivity. Furthermore, the analysis of ecological sensitivity levels in 2000, 2010, and 2018 revealed a progressive deterioration of the ecological environment over time. This highlights the urgency and importance of implementing effective ecological restoration and management measures to mitigate further degradation along the Sichuan–Tibet Railway. Regarding the influence of different factors on ecological sensitivity, our study identified a complex relationship among soil erosion, land status, topographic factors, and climate conditions. The digital elevation model (DEM) emerged as the most significant influencing factor, followed by precipitation (PRE), air temperature (TEM), vegetation coverage (FVC), salinization index (SRSI), land use (LU), population density (PD), and relief amplitude (RA). Moreover, the interaction between these driving factors played a crucial role in enhancing ecological sensitivity, with the largest enhanced effects observed between precipitation (PRE) and vegetation coverage (FVC).

Overall, our study provides important insights into the ecological sensitivity along the Sichuan–Tibet Railway. The findings highlight the dominant areas of ecological sensitivity, the temporal deterioration of the ecological environment, and the complex influence of various factors on ecological sensitivity. These findings contribute to a better understanding of the region's ecological dynamics and provide a basis for decision-making processes related to ecological restoration, sustainable development, and environmental protection. Moving forward, it is crucial to consider multiple scales, incorporate additional indicators, and develop a comprehensive theoretical framework to further enhance the accuracy and applicability of ecological sensitivity assessments in the region.

Data availability The datasets generated during and/or analyzed during the current study are not publicly available due to restrictions and data privacy concerns. However, the corresponding author (zhangtb@cdut.edu.cn) can be contacted for reasonable requests regarding the data used in this study, subject to any applicable restrictions and permissions. The remote sensing data, including Landsat 5 TM images of 2000 and 2010, and Landsat 8 OLI images of 2018, were obtained from the United States Geological Survey (USGS). These datasets can be accessed and obtained directly from the USGS EarthExplorer website (https://earth explorer.usgs.gov/). The meteorological data, including daily air temperature (TEM) and precipitation (PRE) from 2000 to 2018, were obtained from the China Meteorological Science Data Center. Access to these datasets can be requested from the China Meteorological Science Data Center (http://data.cma.cn). The Digital Elevation Model (DEM) derived from Shuttle Radar Topography Mission (SRTM) data can be obtained from the SRTM data archive (https://www2.jpl.nasa.gov/srtm/). Soil type data from the Harmonized World Soil Database v1.2 can be accessed and downloaded from the database's official website (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/). The specialized population density (PD) datasets used in this study were provided by WorldPop and can be accessed through their website (https://www.worldpop.org/). All other data, including the land use classification maps and calculated ecological sensitivity indicators, are included in this published article and its supplementary information files.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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