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Spatiotemporal Evolution and Influencing Factors of Landscape Ecological Vulnerability in the Three-River-Source National Park Region

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Abstract: The increasing impact of global warming and human activities has exacerbated the ecological environment in the Three-River-Source National Park Region (TNPR). Understanding the temporal and spatial evolution of landscape ecological vulnerability (LEV) and its influencing factors are crucial to the implementation of environmental management. Here, we aimed to: 1) construct a LEV assessment model integrating landscape structure and function; 2) analyze the temporal and spatial evolution of TNPR's LEV from 1995 to 2015; 3) use geographic detectors to reveal the regional influence factors of TNPR's LEV. The main findings were: 1) grasslands, water, and bare land are important landscapes of TNPR, accounting for 98.37% of the total area. During the study period, there were significant differences in the area of different landscapes; except for desert, shrub, and urban land, the other landscape areas showed a decreasing trend. 2) During the study period, the LEV of TNPR showed a downward trend; except for grasslands, the ecological vulnerability of the other landscapes decreased steadily. Furthermore, a pattern of conversion from high to low vulnerability grade was observed in the study area. In terms of spatial distribution, the LEV level shows a trend of high at both ends (east and west) and low in the middle. 3) Overall, the impact of natural factors on the ecological vulnerability of the TNPR was significantly higher than that of human factors. In conclusion, our study provides a scientific basis for landscape structure optimization and the management of regional ecological vulnerability.

Keywords: landscape structure; landscape function; landscape ecological vulnerability; geographical detectors; influencing factors; Three-River-Source National Park

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1 Introduction

Since the mid-20th century, global warming and human activities have changed and affected the ecosystems more intensely than in any other period in history (Millennium Ecosystem Assessment, 2005). Thus, the Earth has entered what has come to be known as the Anthropocene, a period driven by human activity (Sun et al., 2020). The increase in the intensity and scope of human activities has led to a series of ecological issues, such as ecosystem degradation, soil erosion, and loss of biodiversity. Human activities continue to affect the evolution of ecosystems on the earth's surface (Duan and Luo, 2021). With the intensification of the impact of global ecosystem changes, research on the relationship between human and land is also deepening (Tian and

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Chang, 2012; Qu and Wu, 2021). As an important form of measuring the stability of regional ecosystems (Hong et al., 2016; Huang et al., 2020), ecological vulnerability has triggered research and discussion on a global scale. The superiority of ecological vulnerability assessments in quantitative or semi-quantitative analysis and identification of the degree of ecosystem vulnerability makes it widely used in climate change, geology, economics, and many other fields (Zhang et al., 2018). Although there are many existing ecosystem vulnerability assessment studies in the world, a unified assessment model has not yet been formed. Therefore, various evaluation methods are used by scholars to evaluate ecological vulnerability. Analytic Hierarchy Process (AHP), Fuzzy sets, Pressure-state-response' model (PSR), and Principal components analysis (PCA) are the most popular evaluation methods at present (Liu et al., 2014; Zhao, 2016; Xue et al., 2019; Xu et al., 2020).

With the deepening of ecological vulnerability assessment research, scholars have found that landscape pattern is the embodiment of landscape spatial heterogeneity (Ren et al., 2018), and its index is closely related to the vulnerability degree of regional ecological environment. Therefore, exploring ecological vulnerability from the perspective of landscape pattern has received increasing amounts of attention by many international organizations and institutions (Polsky et al., 2007). Landscape ecological vulnerability (LEV) research mainly focuses on two aspects: exploring the responsiveness and correlation of LEV to the disturbance of human activities (Sati, 2015; Tian et al., 2019); and constructing the LEV model. Lu et al. (2011) used the landscape pattern index, combined with the soil erosion sensitivity and rocky desertification sensitivity index to construct a LEV model, and Zhang et al. (2019) proposed a LEV model that combines the weighting of the landscape vulnerability index and the population pressure index. The existing LEV assessment research revealed models are mostly built from the landscape pattern level. While external disturbances cause changes in landscape patterns, they also cause changes in landscape functions. Thus, building an LEV model that integrates both landscape functions and patterns is of great importance for enriching the content of the LEV assessment system (Zhang et al., 2020) and promoting the application of comprehensive integrated landscape ecological vulnerability assessment methods (Qu and Wu, 2021).

Against the backdrop of constructing an ecological civilization on the Qinghai-Tibet Plateau and officially establishing the Three-River-Source National Park (TNP), carrying out a dynamic assessment of landscape ecological vulnerability in the TNPR is the scientific basis for the precise implementation of environmental management and standardization of various construction and protection behaviors (Wang et al., 2019; Zhou et al., 2021). This study, therefore, focuses on TNPR, constructs a LEV evaluation system from dual aspects of landscape pattern and landscape function, and dynamically analyzes the LEV of the landscape and the regional differences of LEV with the help of GeoDetector model to provide scientific reference and theoretical support for the restoration, protection, and utilization of the TNPR ecological environment.

2 Materials and Methods

2.1 Study area

The TNPR is located in the southern part of Qinghai Province, China. Its geographic location is 31°39′N–36°12′N and 89°45′E–102°23′E (Fig. 1). It is the birthplace of the Yangtze, Yellow, and Lancang rivers, which have 25%, 49%, and 15% of their total water volume coming from this area, respectively, and contains up to 200 billion m^3 of glacial resources. The TNPR is a sensitive and trigger area for climate change in Asia, the Northern Hemisphere, and even at a global scale (Wang et al., 2009); therefore, it is an extremely important part of China's security barrier that has an irreplaceable strategic ecological position. The 'TNP (Pilot) International Assessment Report' highlighted that the Qinghai region and the Qinghai-Tibet Plateau are already experiencing the impact of climate change. In April 2016, a pilot system was established for the TNP which integrated the functional resources of various departments and regions to restore the overall ecological system. In 2021, the TNP was officially established and became the first national park in China. This shift in protection from a nature reserve to a national park as well as a change in the utilization model will affect the landscape ecological evolution of this region.

2.2 Data

The data used in this study came from the National Qinghai-Tibet Plateau Data Center (https://data.tpdc.ac.

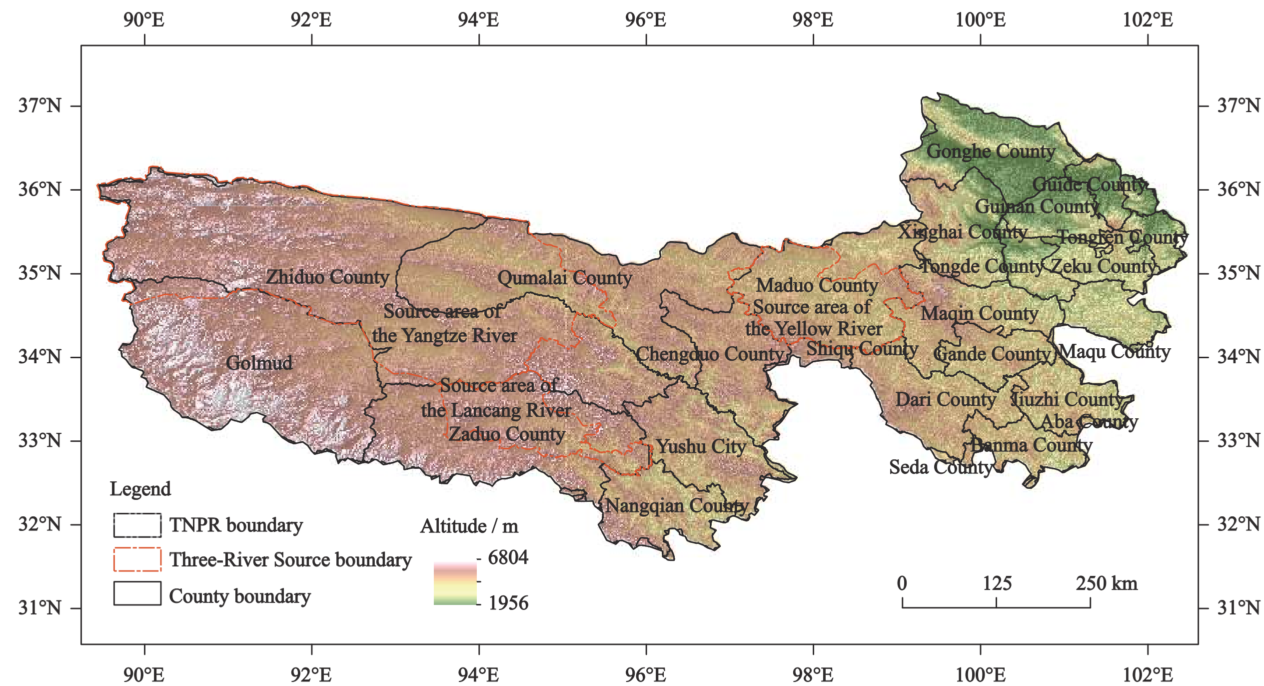

Fig. 1 Overview of the Three-River-Source National Park Region (TNPR)

cn/zh-hans/), where land cover data were selected from 1995, 2005 and 2015, with a resolution of 300 m × 300 m (Xu, 2019). The national land use classification standard (GB/T 21010−2017) was used to divide land cover into eight categories: woodland, grassland, shrubland, water, urban land, desert, bare land, and glacier. The basic map data included vector data, such as the boundary and administrative scope of the TNPR, which comes from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/data.aspx?DATAID=213).

Accurately identifying the factors influencing ecological vulnerability in the TNPR is crucial for its ecological protection and management. The dynamic evolution of LEV is the result of changes in the degree of human activity disturbances and the coping ability of the system. This article adheres to the principle of combining nature and humanities when discussing the factors that influence the evolution of LEV. The selected natural factors included elevation and slope (Zhang et al., 2020), annual average temperature (AAT) (Zeng et al., 2021), average annual precipitation (AAP) (Zhang et al., 2015), normalized vegetation index (NDVI) (National Oceanic and Atmospheric Administration, 2018), and the stable distribution of frozen soil (SDFS) (Ran, 2019). Human factors included population density (POP), gross domestic product (GDP), road network density (RND), and residential area distribution (RAB) (Wei, 2019; Peng et al., 2020) (Tab.1).

2.3 Research method

2.3.1 Landscape ecological vulnerability (LEV) index

The LEV depends on the degree of impact of external environmental disturbance on the landscape system and the coping ability of the system itself (Sun et al., 2014). At present, there is no international consensus on the definition of LEV (Zhang et al., 2019). To summarize the existing research, this study defines LEV as, landscape patterns and ecological processes that interact under external disturbances such as natural conditions or human activities, to change the organization, function, and characteristics of landscape systems (Metzger et al., 2005; Tian et al., 2019; Zhang et al., 2019; Huang et al., 2020).

Under the dual influence of natural conditions and human activities, the size, arrangement, and form of landscape patterns have showed considerable differences (Ren et al., 2018) that are not only a reflection of the heterogeneity of land cover, but also a result of the disturbance of ecological processes at different scales. The destruction and degradation of landscape patterns have a significant impact on regional ecosystems (Sun et al., 2014). The functions of hydrological regulation,

Table 1 The factors influencing landscape ecological vulnerability in the Three-River-Source National Park Region

Type of factor	Factor name	Explanation
Natural factors	Elevation	Measures the altitude of the area
	Slope	Calculated from elevation data to measure the steepness
	Annual average temperature (AAT)	Arithmetic mean of daily average temperature for each day of the year
	Average annual precipitation (AAP)	Reflects the basic situation of precipitation in the area
	NDVI	Assesses vegetation growth status, coverage changes, *etc*.
	Stable distribution of frozen soil (SDFS)	Reflects the distribution of annual frozen soil stability
Human factors	GDP	Measures the level of regional economic development
	Population density (POP)	Measures the intensity of regional human activities
	Road network density (RND)	Measures the degree of development of the regional transportation network
	Residential area distribution (RAB)	Reflects the distribution of human communities

climate regulation, soil conservation, and other functions of the landscape serve the landscape system. When the landscape system changes under external disturbance, the regional landscape function also changes. The landscape ecosystem comprises the landscape structure and landscape function, while the landscape function reflects the landscape structure. Both landscape structure and function jointly affect the LEV (Fig. 2).

(1) Landscape structural vulnerability (LSV)

Landscape structural vulnerability (LSV) is generally constructed using the landscape sensitivity index (LSI) and landscape adaptive index (LAI) (Han et al., 2010). LSI reflects the degree of external disturbance of the landscape itself. It is composed of the landscape interference index (U_i) and landscape vulnerability index (V_i). The change of LSI is affected by the intensity of external disturbance and the characteristics of landscape change (Zhang et al., 2021a).

The U_i is mainly composed of fragmentation, separation and dominance. The specific formula is as follows:

$$U_i = aC_i + bN_i + cD_i \tag{1}$$

where U_i is the landscape interference index, i is a certain landscape type, C_i is the fragmentation, N_i is the separation, D_i is the dominance, a, b, c are the weight assignments for the fragmentation, separation and dominance, respectively, and their values are 0.5, 0.3, 0.2 (Peng et al., 2005).

The V_i is mostly based on the expert scoring method, to assign a value to the ability of landscape types to resist external interference. According to existing research, each landscape type is divided into five levels according to the degree of external disturbance: lower (0–0.2), low (0.2–0.4), general (0.4–0.6), high (0.6–0.8), higher (0.8–1.0). Experts from the Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Anhui Normal University, East China Normal University, Sun Yat-sen University and other units were selected to assign values. 108 A total of 15 questionnaires were returned in this study, and the expert scores were averaged. The vulnerability index after treatment was: farmland 0.136, forest 0.013, grassland 0.246, shrub 0.008, water body 0.294, urban land

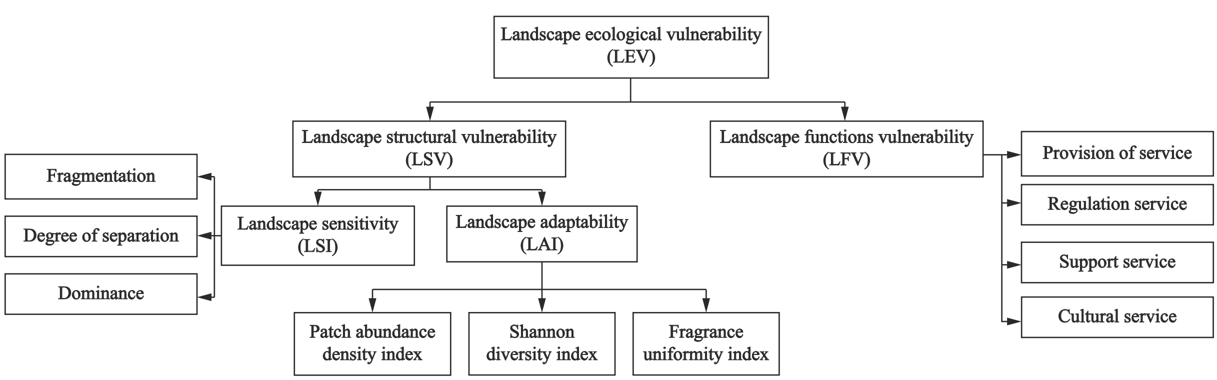

Fig. 2 Theoretical analysis framework of landscape ecological vulnerability

0.127, desert 0.035, bare land 0.211, and glacier 0.029.

The specific formula of *LSI* is as follows:

$$LSI = \sum_{i=1}^{n} \frac{A_{ki}}{A_k} U_i \times V_i \tag{2}$$

where n is the number of landscape types; i is a certain landscape type; A_{ki} is the area occupied by the i-th landscape type in the k-th small area in the grid; A_k is the area of the k-th small area.

Referring to related studies, LAI is mainly composed of the Patch Rich Density Index (PRD), Shannon Diversity Index (SHDI) and Shannon Evenness Index (SHEI) to reflect the ability of landscapes to adapt and recover under external disturbances. These indices are mainly based on land use data and calculated using Fragstats4.2 (Han et al., 2010; Zhang et al., 2016). The specific formula is as follows:

$$LAI = PRD \times SHDI \times SHEI \tag{3}$$

The specific formula of *LSV* is as follows:

$$LSV = LSI \times (1 - LAI) \tag{4}$$

(2) Landscape functional vulnerability (LFV)

There is a complex relationship between landscape function and its surrounding environment, energy, and information. This relationship changes under the influence of external disturbances, which in turn causes changes within the landscape. This change is most prominently manifested through shifts in a series of functions, such as water regulation, climate regulation, and soil and water conservation in each landscape type (Peng et al., 2005). Since this study aimed to explore the relative ecological vulnerability of various landscape types, the ecosystem service value equivalent factor algorithm was used to quantify the functional vulnerability of landscapes, and the functional difference between landscape types was expressed by reference to the ecosystem service value equivalent (Zhang et al., 2020). The specific formula is as follows:

$$LFV = 1 - \sum_{i}^{m} \frac{A_i}{A} \times ESV_i \tag{5}$$

where A_i represents the area occupied by the i-th landscape type in the grid, m represents the number of landscape types, A represents the grid area, and ESV_i represents the i-th landscape type ecosystem service.

(3) Regional LEV

Overall, landscape structure endows the landscape with functional attributes, and the differentiation of landscape function is also an important manifestation of structural differences. Jiang et al. (2015) pointed out that the landscape structure and function are not only the key to the evaluation of the river ecosystem, but also have a profound impact on the landscape ecological security. Zhang et al. (2020) constructed a LEV model based on *LSV* and *LFV* and tested the feasibility and significance of the model empirically. Based on this, we calculated LEV as the geometric mean of *LSV* and *LFV* (Li et al., 2016b). The equation is as follows:

$$LEV = \sqrt{LSV \times LFV} \tag{6}$$

2.3.2 GeoDetector model

GeoDetector is a new statistical method that can detect spatial stratified heterogeneity and reveal the driving factors behind it (Zhang et al., 2021b). It is also an analytical method based on spatial superposition and set theory (Wang and Xu, 2017). Here, we used geographical detectors to examine the factors affecting the ecological vulnerability of the TNPR and the regional differences in the impact of each factor. The equation is as follows:

$$P_{D,H} = 1 - \frac{1}{n\sigma H^2} \sum_{e=1}^{m} n_{De} \sigma^2 H_{D,e} \tag{7}$$

where D is the impact factor, H is the area index, $P_{D,H}$ is the explanatory power of D to H, n and σ^2 are the overall sample number and variance of *LEV* in the TNPR, m is a certain factor number of categories, and n_{De} is the number of samples of index D in category e. The value range of $P_{D,H}$ is [0, 1]. The larger the value, the greater the impact of this factor on the ecological vulnerability of the landscape.

3 Results

3.1 Changes in landscape types

In the past 20 yr, the landscape structure of TNPR has been relatively stable. Grass, water, and bare land are the most important landscape types of TNPR. In 2015, grassland, water bodies, and bare land accounted for 98.37% of the total landscape area of TNPR (Tab. 2). Among them, grassland occupied the dominant position, accounting for 91.08%, followed by water and bare land, which accounted for 5.28% and 2.22%, respectively.

Table 2 Changes in the landscapes of the Three-River-Source National Park Region from 1995 to 2015

Landscape type	Landscape area ratio / %			1995–2015	1995–2015
	1995	2005	2015	Change rate / %	Single landscape dynamic degree / %
Farmland	0.5176	0.5352	0.5151	−0.0134	0.7431
Forest	0.2767	0.2772	0.2754	−0.0002	0.0007
Grassland	91.0751	91.0779	90.6570	−0.0011	−0.0118
Shrub	0.0249	0.0249	0.0249	0	−0.1103
Water	5.2819	5.2190	5.2575	−0.0049	0.1849
Urban land	0.0342	0.0372	0.0341	0.0003	4.1795
Desert	0.3408	0.3366	0.7986	135.4139	−0.2492
Bare land	2.2235	2.2667	2.2133	−0.0035	−0.2106
Glacier	0.2253	0.2254	0.2242	−0.0035	0.2917

From 1995 to 2015, the landscape structure of TNPR maintaining stable. The landscape area of desert, bare land, shrub, and grassland showed a decreasing trend, among which the reduction in the desert landscape was relatively obvious. Among them, the area of farmland was the largest with a changing rate of –0.0134%. The reduction of the water landscape was second only to that of farmland, with a growth rate of –0.0049%. Among the landscape types with increased area, the area of desert increased the most, with a growth rate of 135.4139%. The proportion of shrub land remained relatively stable, accounting for 0.0249% of the total area from 1995 to 2015, indicating that the increase or decrease of this landscape type was relatively small.

According to the area change trend of TNPR landscape types from 1995 to 2015, it can be divided into two phases: a period of slight fluctuations (1995–2005) and a period of intensified changes (2005–2015). During the slight fluctuation stage, the fluctuation range of various landscape areas is relatively small. Except for shrub, water, and desert, the rest of the landscape types mainly increased. In the intensified stage of change, the range of changes in the area of each landscape was relatively large, among which the area of grassland and bare land tended to decrease, and the area of water bodies relatively increased. In addition, the change in trend of the landscapes in the second phase (2005–2015) was more consistent with the overall landscape change in the trend of TNPR from 1995 to 2015. This explains to a certain extent that the restoration of the ecological environment and protection plan implemented by TNPR from 2005 to 2015 played an important role in the management and maintenance of the regional ecological environment.

3.2 Evaluation of landscape ecological vulnerability (LEV)

3.2.1 Analysis of landscape structural vulnerability (LSV)

From 1995 to 2015, the LSV index in the TNPR continued to decline, and its downward trend experienced a slow-to-fast downward trend. The changes in its downward trend also reflect the phased characteristics of the LSV index under different periods of natural factors such as climate change and human disturbance. From 1995 to 2015, the LSV index structure of each landscape in the study area was relatively stable. Grassland, water, and bare land had higher LSVs. Grassland had the largest LSV range (0.0049–0.0055), followed by water and bare land, with indices ranging from 0.0035 to 0.0038 and 0.0014 to 0.0017. From the perspective of a change in situation, the LSV of the grassland showed an inverted V-shaped trend (increased at first and then decreased), while the water body and bare land showed a ‘step-like’ decrease.

According to the results, LSV was divided into five grades (highest, high, middle, low, and lowest) with the help of the natural discontinuity point classification method (Fig. 3). The LSV distribution of TNPR showed a pattern of ‘large agglomeration and small dispersion’. Highest vulnerability areas and high vulnerability areas were mainly distributed in Golmud City, north of Zhiduo County in the source area of the Yangtze River, and north of Gonghe County in the northeast of the study area. Some of the highest vulnerability areas were scattered in Maduo County, the source region of the

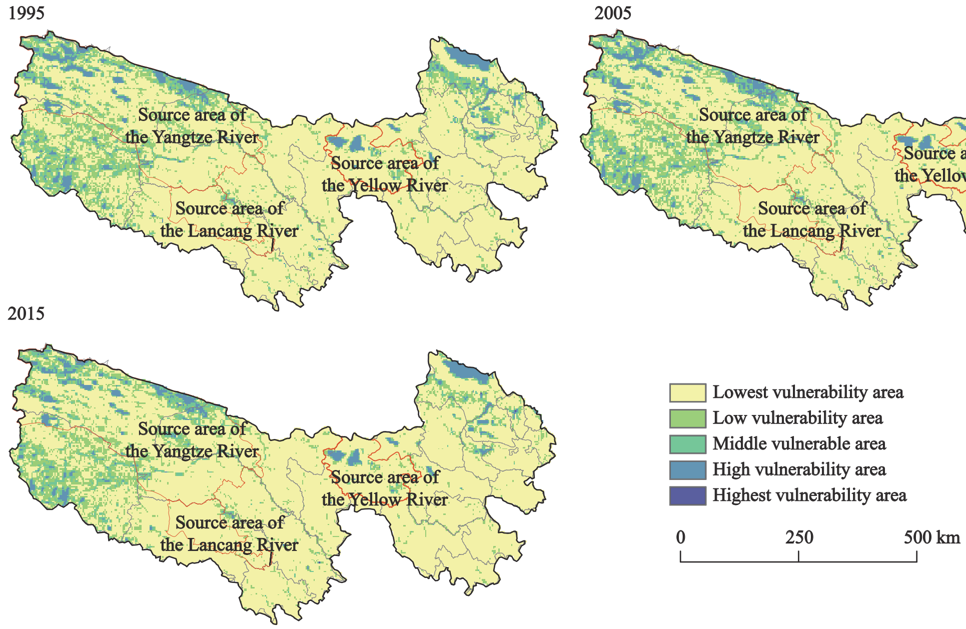

Fig. 3 Spatiotemporal evolution of landscape structural vulnerability in the Three-River-Source National Park Region from 1995 to 2015

Yellow River, and lowest vulnerability areas were mainly distributed around highest vulnerability areas and high vulnerability areas. The lowest vulnerability areas were distributed on a large scale, mainly in Zaduo County, Cheng Duo County, Yushu City, Shiqu County in the central area of TNPR, and Gande County and Jiuzhi County in the southeast. From 1995 to 2015, the area of fragile landscape patterns in TNPR decreased significantly. The main reduction area was mainly distributed in the northern part of the source area of the Yangtze River.

3.2.2 Analysis of landscape functional vulnerability (LFV)

From 1995 to 2015, the LFV in the TNPR changed slightly, and only a small increase of 0.5397 occurred in 2005. The study area can mainly be classified as the lowest vulnerability area, and the area in this category is increasing yearly. In 1995, 2005, and 2015, the lowest vulnerability areas accounted for 78.65%, 79.23%, and 80.09% of the total area, respectively. The increase in the lowest vulnerability area was mainly due to the conversion from the highest and high vulnerability areas.

Except for lowest vulnerability areas, the distribution of vulnerability areas of all levels was relatively scattered (Fig. 4). Highest vulnerability areas and middle vulnerability areas were scattered on a large scale in Golmud City in the west of the study area and Zhiduo County in the source area of the Yangtze River. The reason is that the fragmentation of the landscape in this area is relatively high, and the scale of water distribution is large, which makes the landscape ecosystem in this area more sensitive and weaker in resisting risks. Therefore, the degree of LFV is generally high. In the eastern part of the study area, cultivated land, urban land, and grassland are distributed on a larger scale. The disorderly use of urban land and cultivated land has caused strong disturbance to the regional ecosystem, resulting in high LEV in the region.

3.2.3 LEV in the TNPR

(1) Temporal evolution of LEV

From 1995 to 2015, the overall LEV of TNPR showed a downward trend. Except for grassland landscapes, the ecological fragility of other landscapes declined steadily. Over the past 20 years, the LEV of the water landscape and farmland have decreased by 0.024, and 0.001, respectively. The LEV of grassland showed a fluctuating downward trend. From 1995 to 2005, its LEV increased from 0.2166 to 0.2170. From 2005 to 2015, the implementation and effectiveness of a series of targeted ecological protection and management measures restrained the growth of LEV in grassland. By 2015, the LEV of grassland had dropped to 0.2051 (Fig. 5).

From 1995 to 2015, the vulnerability levels of different areas were transformed, yet the direction and pro-

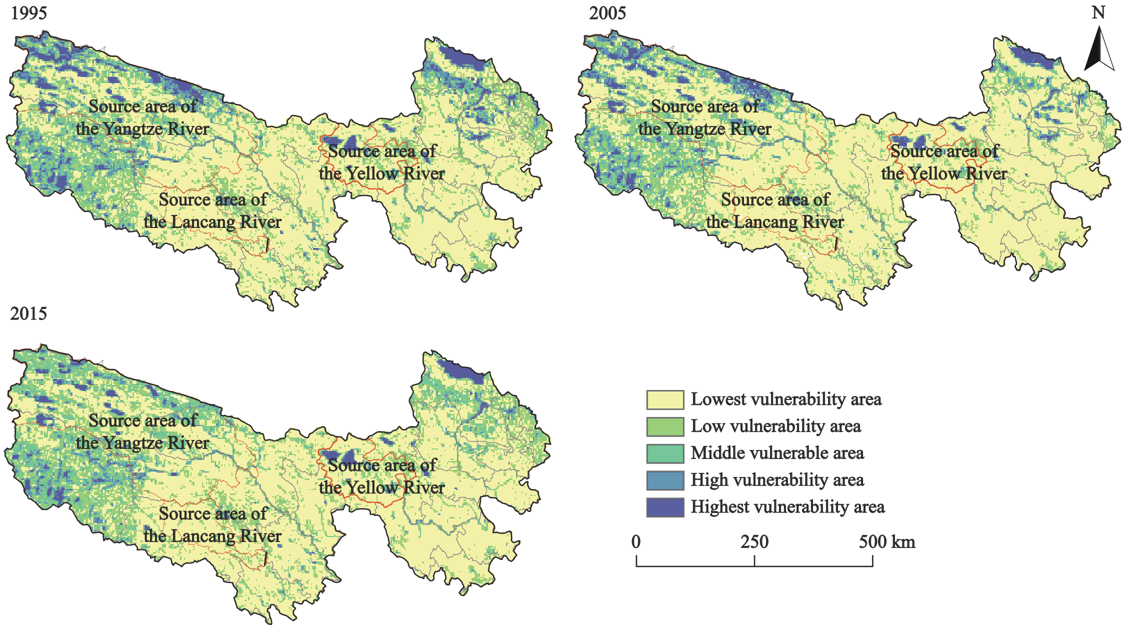

Fig. 4 Spatiotemporal evolution of the landscape functional vulnerability in the Three-River-Source National Park Region from 1995 to 2015

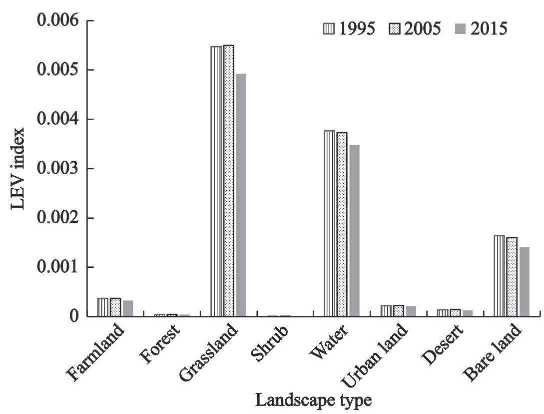

Fig. 5 Changes in landscape ecological vulnerability (LEV) among the different landscape types in the Three-River-Source National Park Region

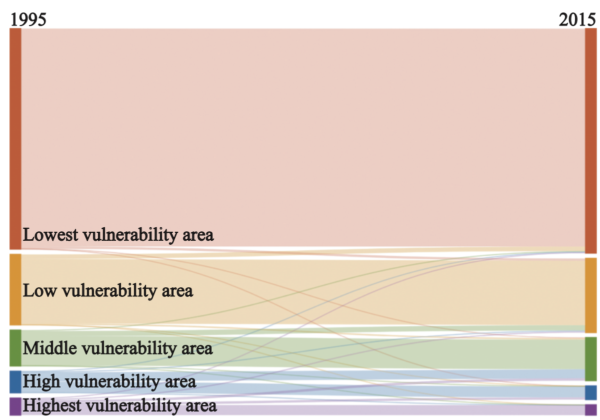

Fig. 6 The area transfer matrix of landscape ecological vulnerable in the Three-River-Source National Park Region from 1995 to 2015

portion of transformation differed (Fig. 6). The high vulnerable areas had the most loss, accounting for 33% of the total, followed by the highest and middle vulnerability levels, accounting for 21% and 20% of loss, respectively. Both the highest and high vulnerable areas were mainly transferred to middle vulnerable areas, with 9181.05 km^2 and 2505.07 km^2 transformed, respectively, while the lowest vulnerable are was mainly transferred to the middle vulnerable area, with a total of 81% being transferred. Areas with high levels of vulnerability were transferred by a larger extent than the other categories to medium, low, and lowest vulnerability areas. The areas of land transformed were as high as 13 566.01 km^2, 9746.58 km^2, and 6701.52 km^2, respectively. The incoming and outgoing directions show that the main vulnerability level of the study area has changed from high to low.

(2) Spatial distribution of LEV

LEV in the TNPR presented a distribution pattern of high at both ends (east and west) and low in the middle, and the LEV level gradually decreased from both ends to the central area (Fig. 7). Highest vulnerable areas and high vulnerable areas were often laid out together in the southwestern part of the study area of Golmud City, the

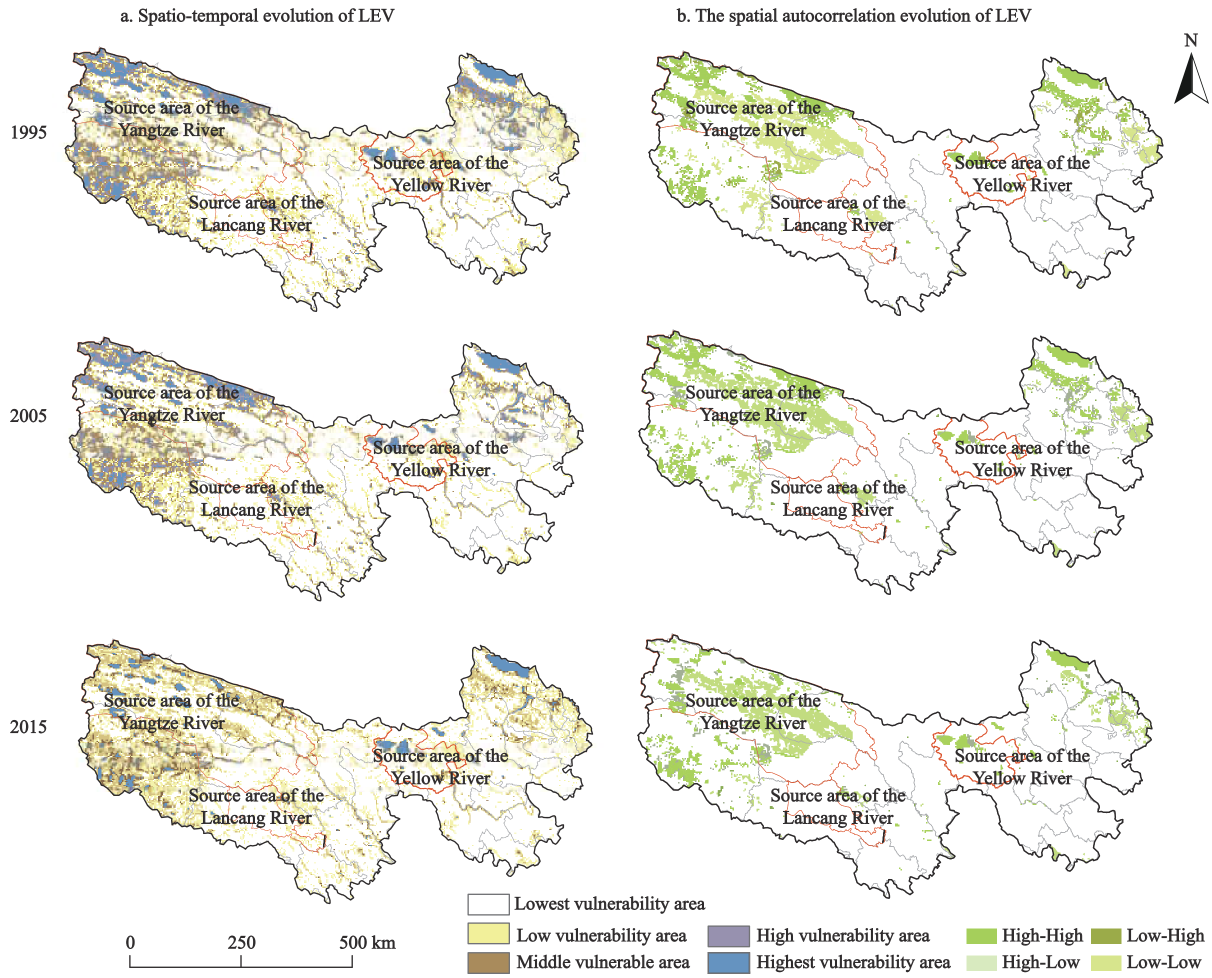

Fig. 7 The distribution of landscape ecological vulnerability and spatial autocorrelation in the Three-Rivers-Source National Park Region from 1995 to 2015

western part of the Republican County, and Zhiduo County in the Yangtze River source area, and only a small area in the northern part of Mado County, in which highest vulnerable areas were scattered. The reason for the relatively high ecological vulnerability of the landscape at the east and west ends of the study area is that they contain seven purely pastoral counties and one pastoral township where human grazing activities are more frequent, which in turn causes greater damage to regional stability. Thus, the stability of landscape ecosystems has been greatly damaged. The middle vulnerable areas were mainly distributed around the highest and highly vulnerable areas, and only some of them were sporadically interspersed with lowest vulnerable areas in the central area.

The LEV distribution of TNPR has spatial correlation characteristics and strong agglomeration. In 1995, 2005 and 2015, the Moran's *I* index for the distribution of the ecological vulnerability of the landscape in the study area was 0.7433, 0.7133, and 0.7040, respectively. High-High clusters are mainly distributed in the north of Zhiduo County at the source area of the Yangtze River, in the south of Golmud City, and the north of Republican County in the east, as well as in a small area in Maduo County in the source area of the Yellow River. Low-Low agglomerations occurred mainly in the northwestern part of the central part of Zhiduo County, and their zone-like distribution became more stable.

3.3 Factors influencing LEV in the TNPR

3.3.1 Key factors affecting LEV

There were differences in the strength of the explanation of regional LEV based on different dimensional factors. Natural factors have a higher impact on the LEV of the overall landscape of TNPR than human factors. Stable distribution of frozen soil (SDFS), Slope, and Elevation are the key factors affecting LEV (Fig. 8). Among the natural factors, SDFS has the most significant impact on the LEV of the landscape in the study area (0.1297). Degradation of permafrost has inhibited vegetation growth, resulting in a significant decline in vegetation coverage, decreased species diversity, and increased soil permeation and water storage (Li et al., 2016a). Furthermore, SDFS has become an important environmental factor affecting vegetation stability in the TNPR. Residential area distribution (RAD) was the human factor with the greatest influence on the LEV, with an explanatory power of 0.0280. Settlements are the core layout of various intensive human activities, such as agricultural production, construction of transportation corridors, and grazing. A series of unreasonable development activities caused by the increase in population pressure has aggravated the negative impact of human activities on vegetation ecology (Zhang et al., 2017). Therefore, the density of settlements has a negative feedback effect on LEV.

3.3.2 Difference of influencing factors of LEV among the different source areas

The impacts on the ecological fragility of the landscape in the TNPR have regional differences. Although natural factors played a more prominent role than anthropogenic factors within each area, there were differences in the explanatory power structure of the factors.

In the source area of the Yellow River, natural factors had a slightly higher impact on regional LEV than human factors, but the difference in the influence of the two dimensions was small. The influence of slope was 0.0474, which represents a key natural factor in the source area of the Yellow River. The area with a gentle slope was favorable for the growth of vegetation, while the area with relatively gentle slope in the source area of the Yellow River had more frequent human activities, which seriously inhibited the growth and recovery of vegetation, so that even if the water and heat conditions in the gentle slope area of the source area were good, the LEV was relatively low. The influence of GDP was 0.0431, and was second only to Slope in the ranking of explanatory power of regional factors. GDP influence was also relatively high in all areas, indicating that the degree of human activity in the source area of the Yellow River was higher than that in the other two source areas.

The main influencing factor in the source area of the Yangtze River was Average annual temperature (AAT). Under the background of global warming, the trend of temperature increase in the source area of the Three Rivers is significant. The variability of the annual average temperature, average maximum temperature, and average minimum temperature in the TNPR from 1961 to 2012 were 0.33°C/10yr, and 0.28°C/10yr, and

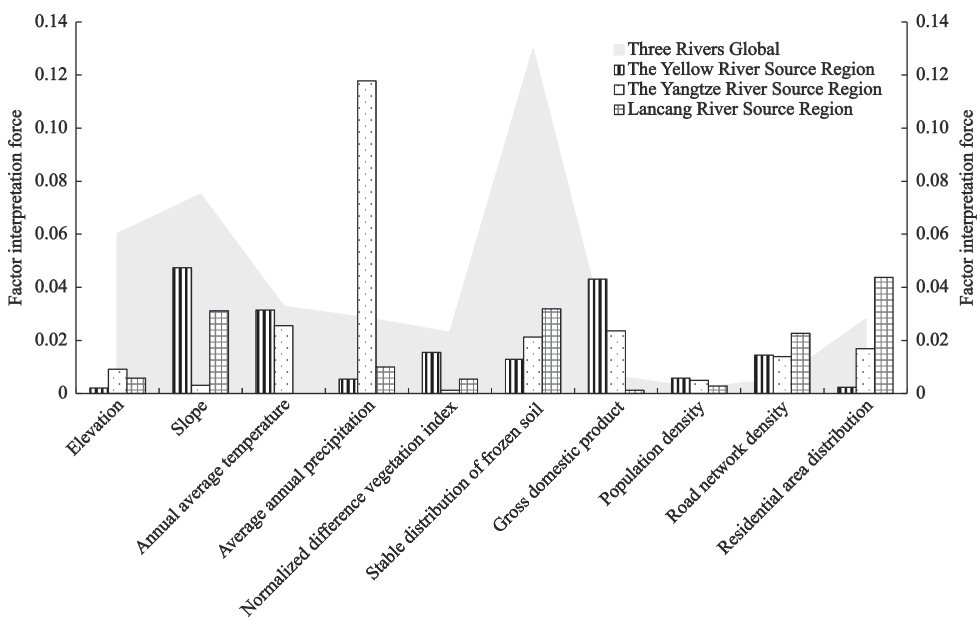

Fig. 8 The explanatory power of the different influencing factors in the three river source areas and the Three-River-Source National Park Region from 1995 to 2015

0.4°C/10yr, respectively (Yang and Fan, 2019), which are significantly higher than the average temperature rise rate in the Qinghai-Tibet Plateau (0.28°C/10yr, 0.25°C/10yr and 0.36°C/10yr)(Xu et al., 2019). The rate of the increase in temperature is the most prominent in the source area of the Yangtze River, ranging from 0.6 to 1.2°C/10yr (Meng et al., 2020). The continuous increase in temperature leads to the degradation of permafrost. The reduction of the area of permafrost will accelerate water and soil erosion, resulting in vegetation degradation, and even for desertification, and the heating rate of the source areas of the Lancang River and the Yellow River is equivalent, ranging from 0.3°C/10yr–0.6°C/10yr. In addition, GDP was also key to high LEV in this area, with an influence of 0.0236. GDP represents the intensity of human disturbances. The source area of the Yangtze River is located in the northwest of the TNPR and contains a number of towns and counties mainly focused on animal husbandry. The higher the GDP, the greater the frequency of grazing activities in this area, and the greater the impact on the regional LEV.

The main influencing factor in the source area of the Lancang River was, as in the source area of the Yangtze River, AAT (Fig. 8). However, the intensity of its influence was greater in this area (0.0759 vs. 0.074). Moreover, SDFS and AAT jointly affected LEV in the source area of the Lancang River, with an influence of 0.0319. The source area of the Lancang River is located in the core area of the TNPR, where snow accumulates year-round and glaciers are widespread at high altitudes. Glacial meltwater is the main recharge of surface runoff in the area. However, the rise in temperature is changing the amount of snow and ice meltwater in the area. Consequently, the permafrost area is gradually shrinking, which in turn has a series of effects on regional vegetation and soil ecosystems.

4 Discussion

4.1 LEV in the TNPR

Numerous studies have shown that in the past 20 yr, the ecological environment of TNPR has experienced a change process from a slight to significant deterioration to a slight improvement (Tong et al., 2014; Shao et al., 2016). The results of this study show that from 1995 to 2015, the LEV of TNPR showed a stepwise downward trend, and the overall ecological environment fragility was alleviated. The main reasons for these contradicting results are: 1) grassland degradation and ecological environment deterioration in the TNPR mainly occurred in the 1970s (Wang and Cheng, 2001; Sun et al., 2016), while the starting year of this study was 1995, and the pattern of grassland degradation in the TNPR has been stable since the 1990s (Liu et al., 2008). 2) Since 2000, national and local governments have strengthened their ecological protection policies and measures. In 2000, Qinghai Province established a provincial nature reserve in TNPR, and in 2005, the State Council launched an ecological environment protection and construction project in TNPR (Li et al., 2011). 3) Since 2004, TNPR has entered a warm-wet cycle, and the optimization of the climatic conditions has promoted the recovery of the ecosystem to some extent (Tong et al., 2014). In addition, the analysis of the area conversion flow of each LEV level shows that, from 1995 to 2015, each LEV level area in the TNPR was converted to a lower level. In general, the LEV of the TNPR showed a significant decreasing trend. This study shows that the effects of the ecological projects implemented by the state, with large-scale human, material, and financial resources invested in the ecological restoration of the TNPR, are already visible, and that grassland degradation has been controlled.

4.2 Impact of SDFS on LEV in the TNPR

By comparing previous studies on the factors influencing LEV, we found that the studies mostly considered the two dimensions of nature and humanity. In this study, the results of Zhang et al. (2020) and Huang et al. (2020) were used as references for the selection of two-dimensional factors and general indicators such as slope, NDVI, elevation, climate, and Population density (POP). Rao et al. (2021) and Peng et al. (2020) discussed the factors affecting vegetation cover changes in TNPR. They emphasized that different stable types of permafrost have crucial differences in regional vegetation cover changes, and that increases in the stability of the permafrost results in smaller vegetation cover changes. Based on this, we included SDFS as a special index among the factors impacting LEV in the TNPR. Comparing these factors revealed that the impact of human activities on LEV was significantly lower than that of natural factors. Among the natural factors, SDFS had the most significant impact on the LEV of the TNPR, with an explanatory power of 0.1297. The stability of the permafrost is related to temperature, and the rise in temperature causes the melting of the permafrost, especially for the types of permafrost with weak stability. The melting of the permafrost not only increases soil moisture but also intensifies the migration of soil moisture (Shang et al., 2018). The negative or positive effects of permafrost melting on regional ecosystems are closely related to factors such as Elevation and Slope. In areas with low a slope and elevation, the melting of permafrost mostly presents positive effects such as increased soil moisture and improved vegetation growth conditions, whereas in areas with a high slope and elevation, it can increase soil moisture loss and exacerbate vegetation root water deficit (Zhu et al., 2018; Rao et al., 2021). Therefore, SDFS plays a significant role in natural factors, such as temperature, slope, and elevation.

4.3 Optimization of the LEV assessment model

Under the dual pressure of global environmental changes and human activities, the landscape presents significant hierarchies, and landscape structure and function change dramatically (Sun and Liu, 2011), leading to land desertification, glacier melting, and ecosystem problems. These are obvious in the process of landscape structural and functional decline that is taking place in the TNPR (Jiang et al., 2015). Current studies have focused on the assessment of LEV at the level of landscape structure (Ortega et al., 2012; Sun et al., 2014; Zhang et al., 2016; Huang et al., 2021), ignoring the changes in ecosystem function caused by landscape alienation and the binary characteristics of landscape function and structure (Ren and Wang, 2007; Fu et al., 2009). Based on the two-dimensional logic principle of the dialectical unity of structure and function, this study integrates LFV assessment into the existing LSV assessment method to construct a LEV assessment model integrating both structural and functional dimensions, in which the quantification of LFV is mainly based on the value of ecosystem services (Zhao et al., 2015). The construction of this assessment model not only considers the ecological significance of surface-level landscape structural changes, but also considers the ecological impact of changes in landscape function, which is deeply related to human well-being. In addition, due to the differences in the functional attributes of different landscapes and their performance values for human services, subtle changes in landscape area have a great impact on the presentation of regional landscape functions. Thus, the construction of this evaluation model can significantly improve the micro-differences in landscape structures through the assessment of LFV. By integrating landscape structure and function, a comprehensive LEV assessment model was constructed to analyze how LEV has evolved in the TNPR, providing a scientific basis for the optimization of landscape structure in the region and the management and control of regional ecological vulnerability.

5 Conclusions

(1) From 1995 to 2015, the landscape structure of the TNPR was relatively stable. Grassland, water, and bare land were the main components of the landscape in the TNPR, accounting for 98.13% of the total area. Furthermore, the range of changes in the area of the different landscapes differed. Except for desert, shrub, and urban land, the other landscape areas showed a decreasing trend. Compared with other landscape types, the area of shrub changed slightly.

(2) From 1995 to 2015, the LEV of the TNPR showed a downward trend. Except for grassland landscape, the ecological vulnerability of the other landscape types decreased steadily. Although grassland showed a downward trend, its volatility was strong. From 1995 to 2015, a pattern of conversion from the highest to lowest vulnerability grade was observed in the study area. The area corresponding to areas of high vulnerability showed the largest decrease, and the decrease was accompanied by an increase in the area of middle vulnerable areas. The main contributor to this increase was the highly vulnerable area. In terms of spatial distribution, LEV was high at both ends (east and west) and low in the middle, and the level gradually weakened from both ends to the central region.

(3) The impact of the different factors on the ecological vulnerability of regional landscapes differed. Specifically, the impact of natural factors was higher than that of human factors. SDFS was a key natural factor affecting the ecological vulnerability of the study area, while RAD was the human factor with the greatest impact on the ecological vulnerability of the study area.

Regional differences in the factors affecting the ecological vulnerability of landscapes were observed. The main drivers in the Yellow River source area were Slope and GDP, those in the Yangtze River source area were AAT and GDP, and those in the Lancang River source area were AAT and SDFS.

(4) In this study, researchers need to differentiate treatment between landscape interference index, landscape vulnerability index and assign values on the basis of detailed understanding of the economic development model and land use of the study area. This kind of differentiated treatment and assignment of values is highly subjective. In future research, how to reasonably differentiated treatment and assign values to the interference and vulnerability of landscape types from an objective perspective still needs to be further explored. In addition, due to the limited time for data acquisition, this study only analyzed the spatiotemporal evolution of the ecological vulnerability of the TNPR from 1995 to 2015. In the future, we will continue to focus on updating data and integrating multi-source data to overcome this limitation and prepare for subsequent studies on the LEV of the TNPR. The evaluation model described in this study provides a scientific basis for landscape structure optimization in the region and the management and control of regional ecological vulnerability.

References

Duan Quntao, Luo Lihui, 2021. Summary and prospect of spatialization method of human activity intensity: taking the Qinghai-Tibet Plateau as an example. *Journal of Glaciology and Geocryology*, 43(5): 1582–1593. (in Chinese)

Fu Bojie, Zhou Guoyi, Bai Yongfei et al., 2009. The main terrestrial ecosystem services and ecological security in China. *Advances in Earth Science*, 24(6): 571–576. (in Chinese)

Han Zhenhua, Li Jiandong, Yin Hong et al., 2010. Analysis of ecological security of wetland in Liaohe River delta based on the landscape pattern. *Ecology and Environmental Sciences*, 19(3): 701–705. (in Chinese)

Hong W Y, Jiang R R, Yang C Y et al., 2016. Establishing an ecological vulnerability assessment indicator system for spatial recognition and management of ecologically vulnerable areas in highly urbanized regions: a case study of Shenzhen, China. *Ecological Indicators*, 69: 540–547. doi: 10.1016/j.ecolind.2016.05.028

Huang Muyi, Zhong Yong, Feng Shaoru et al., 2020. Spatial-temporal characteristic and driving analysis of landscape ecological vulnerability in water environment protection area of Chaohu Basin since 1970s. *Journal of Lake Sciences*, 32(4): 977–988. (in Chinese). doi: 10.18307/2020.0407

Huang Yue, Cheng Jing, Wang Peng, 2021. Spatiotemporal evolution pattern and driving factors of ecological vulnerability in agro-pastoral region in northern China: a case of Yanchi County in Ningxia. *Arid Land Geography*, 44(4): 1175–1185. (in Chinese)

Jiang X, Xu S G, Liu Y Y et al., 2015. River ecosystem assessment and application in ecological restorations: a mathematical approach based on evaluating its structure and function. *Ecological Engineering*, 76: 151–157. doi: 10.1016/j.ecoleng.2014.04.027

Li Huixia, Liu Guohua, Fu Bojie, 2011. Response of vegetation to climate change and human activity based on NDVI in the Three-River Headwaters region. *Acta Ecologica Sinica*, 31(19): 5495–5504. (in Chinese)

Li Jing, Sheng Yu, Wu Jichun et al., 2016a. Mapping frozen soil distribution and modeling permafrost stability in the source area of the Yellow River. *Scientia Geographica Sinica*, 36(4): 588–596. (in Chinese)

Li Shuai, Ma Wenchao, Gu Yanwen et al., 2016b. Analysis of spatial-temporal changes in landscape fragmentation in the Ningxia Yellow River Valley. *Acta Ecologica Sinica*, 36(11): 3312–3320. (in Chinese)

Liu Honghong, Wang Ni, Xie Jiancang et al., 2014. Assessment of ecological vulnerability based on fuzzy comprehensive evaluation in Weihe River Basin. *Journal of Shenyang Agricultural University*, 45(1): 73–77. (in Chinese)

Liu Jiyuan, Xu Xinliang, Shao Quanqin, 2008. The spatial and temporal characteristics of grassland degradation in the Three-River Headwaters region in Qinghai province. *Acta Geographica Sinica*, 63(4): 364–376. (in Chinese)

Lu Yuan, Su Wenjing, Hua Cui, 2011. Analysis of ecological vulnerability in Zuojiang River Basin based on landscape pattern and ecosystem sensitivity. *Research of Soil and Water Conservation*, 18(3): 78–82,87. (in Chinese)

Meng Xianhong, Chen Hao, Li Zhaoguo et al., 2020. Review of climate change and its environmental influence on the Three-River Regions. *Plateau Meteorology*, 39(6): 1133–1143. (in Chinese)

Metzger M J, Leemans R, Schröter D, 2005. A multidisciplinary multi-scale framework for assessing vulnerabilities to global change. *International Journal of Applied Earth Observation & Geoinformation*, 7(4): 253–267. doi: 10.1016/j.jag.2005.06.011

Millennium Ecosystem Assessment, 2005. *Ecosystems and Human Well Being: Synthesis*. Washington, DC, USA: Island Press.

National Oceanic and Atmospheric Administration, 2018. GIMMS NDVI3g dataset for Sanjiangyuan (1982–2015). National Tibetan Plateau Data Center.

Ortega M, Saura S, González-Avila S et al., 2012. Landscape vulnerability to wildfires at the forest-agriculture interface: half-century patterns in Spain assessed through the SISPARES monitoring framework. *Agroforestry Systems*, 85(3): 331–349.

doi: 10.1007/s10457-011-9423-2

Peng Jian, Wang Yanglin, Jing Juan et al., 2005. Research on integrated regional planning of urban landscape functions: a case study in Shenzhen city. *Acta Ecologica Sinica*, 25(7): 1714–1719. (in Chinese)

Peng Kaifeng, Jiang Weiguo, Hou Peng et al., 2020. Spatiotemporal variation of vegetation coverage and its affecting factors in the Three-River-Source National Park. *Chinese Journal of Ecology*, 39(10): 3388–3396. (in Chinese)

Polsky C, Neff R, Yarnal B, 2007. Building comparable global change vulnerability assessments: the vulnerability scoping diagram. *Global Environmental Change*, 17(3-4): 472–485. doi: 10.1016/j.gloenvcha.2007.01.005

Qu Bowei, Wu Lezhi, 2021. Landscape ecological vulnerability assessment based on structural and functional vulnerability. *Journal of Central China Normal University (Natural Sciences)*, 1 –22[2021-01-08]. http://kns.cnki.net/kcms/detail/42.1178.N.20211209.0642.002.html. (in Chinese)

Ran Youhua, 2019. Permafrost stability type map for Sanjiangyuan in 2010s. National Tibetan Plateau Data Center. (in Chinese)

Rao Pinzeng, Wang Yicheng, Wang Fang, 2021. Analysis on the NDVI change and influence factors of vegetation cover in the Three-River Headwaters Region. *Acta Agrestia Sinica*, 29(3): 572–582. (in Chinese)

Ren Jintong, Yang Keming, Chen Qunli et al., 2018. Spatio-temporal variation of vulnerability of landscape ecology of Caohai wetland. *Journal of Ecology and Rural Environment*, 34(3): 232–239. (in Chinese)

Ren Zhiyuan, Wang Lixia, 2007. Spatio-temporal differentiation of landscape ecological niche in western ecological frangible region. *Journal of Geographical Sciences*, 17(4): 479–486. doi: 10.1007/s11442-007-0479-x

Sati V P, 2015. Landscape vulnerability and rehabilitation issues: a study of hydropower projects in Garhwal region, Himalaya. *Natural Hazards*, 75(3): 2265–2278. doi: 10.1007/s11069-014-1430-y

Shang Zhanhuan, Dong Quanmin, Shi Jianjun et al., 2018. Research progress in recent ten years of ecological restoration for ‘Black Soil Land’ degraded grassland on Tibetan Plateau——Concurrently discuss of ecological restoration in Sangjiangyuan region. *Acta Agrestia Sinica*, 26(1): 1–21. (in Chinese)

Shao Quanqin, Zhao Zhiping, Liu Jiyuan et al., 2016. The characteristics of land cover and macroscopical ecology changes in the source region of Three Rivers on Qinghai-Tibet Plateau during last 30 years. *Geographical Research*, 29(8): 1439–1451. (in Chinese)

Sun Caizhi, Yan Xiaolu, Zhong Jingqiu, 2014. Evaluation of the landscape patterns vulnerability and analysis of spatial correlation patterns in the lower reaches of Liaohe River Plain. *Acta Ecologica Sinica*, 34(2): 247–257. (in Chinese)

Sun Jing, Liu Jianguo, Yang Xinjun et al., 2020. Sustainability in the Anthropocene: telecoupling framework and its applicationss. *Acta Geographica Sinica*, 75(11): 2408–2416. (in Chinese)

Sun Qingling, Li Baolin, Xu Lili et al., 2016. Analysis of NDVI change trend and its impact factors in the Three-River Headwater Region from 2000 to 2013. *Journal of Geo-Information Science*, 18(12): 1707–1716. (in Chinese)

Sun Xianbin, Liu Hongyu, 2011. The effect of land use on landscape ecological risk in Yancheng coastal area, Jiangsu province. *Remote Sensing for Land & Resources*, 23(3): 140–145. (in Chinese)

Tian Peng, Li Jialin, Jiang Yimei et al., 2019. Ecological vulnerability of the bay landscape and its response to human activities: a case study of the East China Sea. *Acta Ecologica Sinica*, 39(4): 1463–1474. (in Chinese)

Tian Yaping, Chang Hao, 2012. Bibliometric analysis of research progress on ecological vulnerability in China. *Acta Geographica Sinica*, 67(11): 1515–1525. (in Chinese)

Tong L G, Xu X L, Fu Y et al., 2014. Wetland changes and their responses to climate change in the ‘Three-River Headwaters’ Region of China since the 1990s. *Energies*, 7(4): 2515–2534. doi: 10.3390/en7042515

Wang Genxu, Cheng Guodong, 2001. Characteristics of grassland and ecological changes of vegetations in the source regions of Yangtze and Yellow Rivers. *Journal of Desert Research*, 21(2): 101–107. (in Chinese)

Wang Jinbang, Liu Jiyuan, Shao Quanqin et al., 2009. Spatial-temporal patterns of net primary productivity for 1988-2004 based on glopem-cevsa model in the ‘Three-River Headwaters’ region of Qinghai province, China. *Chinese Journal of Plant Ecology*, 33(2): 254–269. (in Chinese)

Wang Jinfeng, Xu Chengdong, 2017. Geodetector: principle and prospective. *Acta Geographica Sinica*, 72(1): 116–134. (in Chinese)

Wang S X, Du J K, Li S et al., 2019. Impact of tourism activities on glacial changes based on the tourism heat footprint (THF) method. *Journal of Cleaner Production*, 215: 845–853. doi: 10.1016/j.jclepro.2019.01.120

Wei Da, 2019. Geographical distribution of major ecological projects on the Tibetan Plateau. National Tibetan Plateau Data Center. (in Chinese)

Xu Chaoxuan, Lu Chunxia, Huang Shaolin, 2020. Study on ecological vulnerability and its influencing factors in Zhangjiakou area. *Journal of Natural Resources*, 35(6): 1288–1300. (in Chinese). doi: 10.31497/zrzyxb.20200603

Xu Erqi, 2019. Land use of the Tibet Plateau in 2015 (Version 1.0). National Tibetan Plateau Data Center. (in Chinese)

Xu Lijiao, Hu Zeyong, Zhao Ya’nan et al., 2019. Climate change characteristics in Qinghai-Tibetan Plateau during 1961–2010. *Plateau Meteorology*, 38(5): 911–919. (in Chinese)

Xue Lianqing, Wang Jing, Wei Guanghui, 2019. Dynamic evaluation of the ecological vulnerability based on PSR modeling for the Tarim River Basin in Xinjiang. *Journal of Hohai University (Natural Sciences)*, 47(1): 13–19. (in Chinese)

Yang Jiaxing, Fan Yuxin, 2019. Analysis of climate change and its environmental effects in the Three River source areas from

1961 to 2012. *Journal of Qinghai Environment*, 29(4): 169–175. (in Chinese)

Zeng Yuxi, Zhong Linsheng, Yu Hu, 2021. Spatial and temporal evolution of recreational function in the Sanjiangyuan region of Qinghai province under climate change. *Acta Ecologica Sinica*, 41(3): 886–900. (in Chinese)

Zhang Hang, Chen Hai, Shi Qinqin et al., 2020. Spatiotemporal evolution and driving factors of landscape ecological vulnerability in Shaanxi province. *Arid Zone Research*, 37(2): 496–505. (in Chinese)

Zhang Renhe, Su Fengge, Jiang Zhihong et al., 2015. An overview of projected climate and environmental changes across the Tibetan Plateau in the 21st century. *Chinese Science Bulletin*, 60(32): 3036–3047. (in Chinese). doi: 10.1360/N972014-01296

Zhang Xiao, Lu Lin, Zhang Xiaoyao et al., 2021a. Impact of Chernobyl nuclear accident on regional landscape pattern and habitat quality. *Acta Ecologica Sinica*, 41(4): 1303–1313. (in Chinese)

Zhang Xiao, Zhang Xiaoyao, Lu Lin et al., 2021b. Evolution characteristics and driving factors of basin multi-scale landscape pattern under the tourism disturbances: a case study of the Xin 'an River Basin. *Acta Ecologica Sinica*, 41(9): 3415–3428. (in Chinese)

Zhang Xueling, Yu Wenbo, Cai Haisheng et al., 2018. Review of the evaluation methods of regional eco-environmental vulnerability. *Acta Ecologica Sinica*, 38(16): 5970–5981. (in Chinese)

Zhang Xuemei, Wang Kelin, Yue Yuemin et al., 2017. Factors impacting on vegetation dynamics and spatial non-stationary relationships in karst regions of southwest China. *Acta Ecologica Sinica*, 37(12): 4008–4018. (in Chinese)

Zhang Yue, Zhang Fei, Wang J et al., 2016. Evaluation of the landscape patterns vulnerability and analysis of spatial temporal patterns in the typical region of the Ebinur Lake.. *Journal of Catastrophology*, 31(3): 222–229.

Zhang Yujuan, Qu Jianguang, Liang Xin et al., 2019. New method of constructing landscape ecological vulnerability index and rationality verification. *Science of Surveying and Mapping*, 44(11): 129–136. (in Chinese)

Zhao Jing, 2016. *Based on RS and GIS the Erguna Wetlands Ecological Vulnerability Assessment*. Chengdu: Southwest Jiaotong University. (in Chinese)

Zhao Xiaoqing, Wang Xingyou, Xie Pengfei et al., 2015. Spatiotemporal changes of landscape eco-security based on structure and function safety: a case study of a large artificial forest planted area in Ximeng county, China. *Geographical Research*, 34(8): 1581–1591. (in Chinese)

Zhou Kan, Liu Hanchu, Fan Jie et al., 2021. Environmental stress intensity of human activities and its spatial effects in the Qinghai-Tibet Plateau national park cluster: a case study in Sanjiangyuan region. *Acta Ecologica Sinica*, 41(1): 268–279. (in Chinese)

Zhu Yurong, Xu Kaiyu, Fu Yongchao, 2018. Characteristics and impacts of permafrost changes during 1961–2017 in the Three-River Headwaters Region. *Qinghai Science and Technology*, 25(6): 73–76. (in Chinese). doi: 10.3969/j.issn.1005-9393.2018.06.015