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Spatiotemporal analysis of ecological vulnerability in the Tibet Autonomous Region based on a pressure-state-response-management framework

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ABSTRACT

The Qinghai-Tibet Plateau is facing a crisis of ecological degradation against a background of global warming and the intensification of human activities. With the aim of evaluating the spatial and temporal distribution of ecological vulnerability, this study established a new comprehensive pressure-state-response-management (PSRM) model based on the differences in the relative importance of indicators in a vulnerability evaluation system in different regions. The factors influencing ecological vulnerability were determined by calculating the correlation coefficient between the ecological vulnerability index (EVI) and the potential impact factors. The results showed that the spatial distribution of EVI in the Tibet Autonomous Region varied significantly, gradually decreasing from southeast to northwest. The regional ecological environment gradually improved from 2000 to 2015 and the EVI score increased. Following the establishment of national nature reserves in 2005, the areas that were extremely vulnerable in 2000 (accounting for 53% of the total area) were transformed into severely vulnerable or moderately vulnerable areas. The proportion of non-vulnerable areas also increased from 3% in 2010 to 6% in 2015 as cities expanded. The correlation analysis among vectors showed that GDP, population density, the proportion of tertiary industry, education level and policy support were strongly correlated with the EVI. Human activity had a greater impact on the EVI in urban areas. Our study provides suggestions for more sustainable development pathways to reduce environmental pressure and protect the fragile ecological environment. The approach used here can provide technical support and references for the ecological assessment and restoration of other high-altitude zones in China or elsewhere in the world.

1. Introduction

Many ecological and environmental problems have emerged in association with global climate change and human activities; these have a substantial impact on the ecosystems on which humans depend for survival and development (Jiang et al., 2018; Khan et al., 2017). The vulnerability of natural resources and ecological conditions increases when the external pressures exceed the ecological tolerance. Humans modify the environment through various activities (Li et al., 2020a). When humans consume resources to meet their living needs, they exert pressure on the natural environment through production and consumption activities, which change the resource stocks and environmental quality. Changes in resources and the environment then impact the human system, and humans take corresponding measures after receiving feedback from factors such as resource depletion and environmental degradation.

Vulnerability reflects the degree to which a natural or social system is adversely affected by climate change. It is a function of the characteristics, speed and intensity of climate change within the system, as well as its sensitivity and adaptability. The ecological vulnerability index

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(EVI) can quantify the range of ecosystem vulnerabilities in a region based on the environmental responses of a set of species assemblages as observed in a selection of reference sites; it has become an important method for the diagnosis and identification of ecological problems (Lv et al., 2019). Although the concept of ecological vulnerability was first proposed in 1989, a unified definition has not yet been formed (Beroya-Eitner, 2016). The concept of ecological vulnerability is constantly expanding as human understanding of the irreplaceable function of ecosystems deepens. The definition of ecological vulnerability was extended to include the self-healing capacity and response sensitivity when exposed to external pressure (Peng et al., 2016). In recent years, green development has gradually become the consensus of the international community. Understanding how to promote economic development without destroying regional ecosystems has also become a research focus. Driven by this demand, many studies have been carried out on regional ecological vulnerability (Ma et al., 2020).

Many comprehensive evaluation models such as the pressure-state-response (PSR) model, driver-pressure-state-impact-response (DPSIR) model, and the system-dynamic (SD) model have been used in the ecological vulnerability assessment. Tang et al. (2020) combined a water resources balance sheet with a PSR model to analyze the pressure exerted on the environment through production and consumption activities. The PSR model can assess the changes in resources and environment from human activities, and changes after feedback such as resource depletion and environmental degradation have been acted upon. The driver factor was added to the DPSIR model and SD model to characterize the threat indicators according to importance, severity, and probability of occurrence (Malekmohammadi and Jahanishakib, 2017; Zhang et al., 2017). With the increasing impact of government activities on the ecological environment, more scholars have acknowledged the importance of considering management decisions in the comprehensive assessment of EVI (Gu et al., 2020; Hopkins et al., 2020; Yang et al., 2020).

The management decisions of government include policies and financial support for the protection of the ecological environment (Hopkins et al., 2020). They reflect the importance of the government and the public for local ecological environment protection, which is significant for ecological environment construction. Incorporating government policies and public behavior into the PSR model, to construct a new comprehensive model, can reflect ecological vulnerability at long time scales under the influence of multiple index changes.

Ecosystems at high altitudes, particularly those with an average elevation of more than 4000 m, are extremely fragile. They are highly sensitive to climate change and anthropogenic activities (Jiang et al., 2020). The main problems for the fragile ecological environment include freezing and thawing erosion, hydraulic erosion, land desertification, salinization, and water scarcity. The fragile ecosystems on the Qinghai–Tibet Plateau are undergoing profound changes because of greater economic development and population growth (Liu et al., 2017). Increasing human activities such as engineering construction, production and living activities have damaged the local ecological system. The difficulty of restoration coupled with the plateau's natural ecosystem increases its sensitivity. In the past 20 years, the population of the Tibet Autonomous Region has increased by 50%, and the gross domestic product (GDP) and the proportion of the tertiary industry have increased 10 fold (statistical year books). The impact of human activities on the ecological environment is growing, and problems such as grassland degradation and soil erosion are becoming more prominent. Therefore, conducting a vulnerability assessment of the ecological environment on the plateau and proposing targeted opinions based on the assessment are significant for future sustainable development.

In this study, a pressure-state-response-management (PSRM) model was established to evaluate the ecological vulnerability of the Tibet Autonomous Region under the pressure of the natural environmental conditions and anthropogenic interference. The spatiotemporal variation in the EVI indicator and its criterion layers were identified. The causal analysis of ecological vulnerability was calculated using the correlation coefficient of the attribute matrix. The results of the studies propose steps for ecological protection and sustainable development in the high-altitude Tibet Autonomous Region.

2. Materials and methods

2.1. Study area

The Tibet Autonomous Region lies at the heart of the Qinghai-Tibet Plateau with the highest average elevation in the world. It is located between 26°50′–36°53′ N and 78°25′–99°06′ E (Fig. 1). The Tibet Autonomous Region covers an area of more than 1.2 million km^2, accounting for more than half of the total area of the Qinghai-Tibet Plateau. Approximately 92% of the area is higher than 4,000 m above sea level. It is the second-largest province in China and contains seven administrative regions including Lhasa, Shannan, Qamdo, Nyingchi, Nachu, Shigatse and Ali. The Tibet Autonomous Region has a unique alpine ecosystem bacause of its high average altitude (above 4000 m), low annual average temperature (around −2.4 °C) and complex topography. Global warming and human activities have increased the ecological and environmental problems in Tibet, exceeding the ecological carrying capacity and exacerbating ecological vulnerability; this is mainly manifested in soil degradation, land desertification and soil erosion (Wang et al., 2021). The open-pit extraction of mineral resources, which is mainly located in Lhasa, Shannan, Shigatse and Ali, has caused regional surface and groundwater pollution (Ding et al., 2021). A series of measures setting an ecological red line, strengthening the environmental protection system, restoring degraded ecology, and improving government supervision has been implemented to maintain regional ecosystem services (Gao et al., 2020).

2.2. Data sources and indicators

This study collected data on the natural environment, human activities and management behaviors from 2000 to 2015 to assess ecological vulnerability (Table 1). Data on temperature, precipitation, lake area and land use were collected from the Qinghai–Tibet Plateau Scientific Data Center (Du and Yi, 2019; Liu, 2019; Zhang et al., 2014). Data on GDP, Normalized Difference Vegetation Index (NDVI) and a Digital Elevation Model (DEM) were collected from the Resources and Environment Data Center of the Chinese Academy of Sciences (Xu, 2018). Data on population density, quantity of livestock at the end of the year, the proportion of tertiary industry, policy support, education level and green area for each administrative unit were collected from the statistical yearbooks. The human disturbance index was calculated based on the proportion of built and cultivated area (see *Eq. (1)* below). The ecological data such as the average annual rainfall, the average annual temperature, slope, DEM, NDVI and the rate of change in grassland are at the resolution level of 1 km × 1 km. In order to assess the ecological vulnerability of the area, the statistical data were converted into 1 km × 1 km raster grids based on the principle of equal distribution within the region. There are total of 1,200,880 grid cells were abtained in this study (Cheng et al., 2015; Zhang et al., 2017).

2.3. Conceptual framework for ecological vulnerability

2.3.1. The PSRM evaluation model

The PSRM model consisted of 15 indicators in four layers. The four layers of interaction formed the logical relationship of "what happened, why it happened, how to deal with it, and on what basis". The unsustainable impact of human activities in the region on the ecological environment constitutes the pressure layer. The state of the ecological environment will change under the impact of human economic development. For example, engineering activities will change the slope and affect the stability of rock strata. The response is a series of measures and

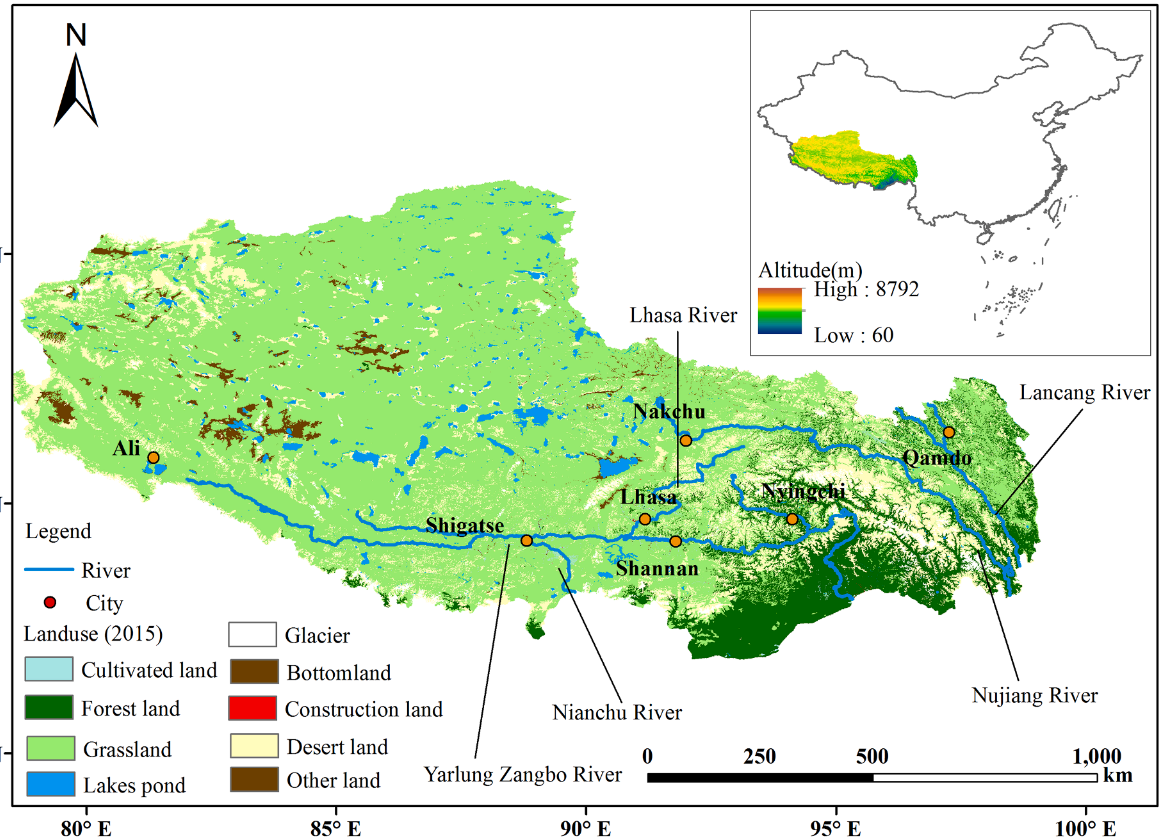

Fig. 1. Geographical location and topography of the study area.

Table 1
The evaluation indicators and their sources.

Criterion layer	Indicator	Resolution ratio	Data sources	Direction
Pressure	GDP	1 km*1km	http://www.resdc.cn/DOI/doi.aspx?DOIid=49	+
	The proportion of tertiary industry	city level	Statistical yearbook of the Tibet autonomous region	+
	Density of population	county level	Statistical yearbook of the Tibet autonomous region	−
	Livestock inventory at the end of the year	city level	Statistical yearbook of the Tibet autonomous region	−
	Human disturbance index	city level	https://data.tpdc.ac.cn/zh-hans/	−
State	Average annual rainfall	1 km*1km	https://data.tpdc.ac.cn/zh-hans/	+
	Average annual temperature	1 km*1km	https://data.tpdc.ac.cn/zh-hans/	+
	Slope	1 km*1km	http://www.resdc.cn/DOI/DOI.aspx?DOIid=50	−
	Dem	1 km*1km	http://www.resdc.cn/DOI/DOI.aspx?DOIid=50	−
Response	NDVI	1 km*1km	http://www.resdc.cn/DOI/doi.aspx?DOIid=49	+
	Rate of change in grassland cover	1 km*1km	https://data.tpdc.ac.cn/zh-hans/	+
	Rate of change in the lake area	city level	https://data.tpdc.ac.cn/zh-hans/	−
Management	Policy support	city level	Statistical yearbook of the Tibet autonomous region	+
	Residents' education level	city level	Statistical yearbook of the Tibet autonomous region	+
	Afforestation area	city level	Statistical yearbook of the Tibet autonomous region	+

countermeasures to prevent and reduce the negative impact of human activities and restore the ecological environment to achieve sustainable development. The change in the state of the ecological environment and its response feeds back to human activities, and corresponding management measures are taken to protect the ecological environment. The relationship between each indicator layer is shown in Fig. 2.

The pressure subsystem mainly refers to the effect of human activities (Hua et al., 2011). In the last 20 years, Tibet has experienced increasing pressure from rapid economic and social development. The high altitude, mountainous conditions and cold temperatures of the region make the natural environment more vulnerable ecological damage. The changes in human activities and natural conditions have a great impact on local ecology. Therefore, the per capita GDP (P1), the proportion of tertiary industry (P2), the population density (P3), the livestock inventory at the end of the year (P4) (Niu et al., 2021) and the human disturbance index (P5) were selected for this subsystem. The formula for calculating the human interference index is as follows:

$$\mathrm{HDI} = \frac{P + D + R + U + S + O}{A} \tag{1}$$

where, P is paddy field area, D is dry land area, R is canal area, U is urban land area, S is a rural residential area, O is other construction land area, and A is total area.

The status subsystem refers to the status of the ecosystem and natural environment (Hua et al., 2011). The Qinghai–Tibet Plateau is sensitive to climate change (Chen et al., 2014), and therefore the average annual precipitation (S1), average annual temperature (S2), relief amplitude (S3) and elevation (DEM) (S4) were selected in this study.

The response subsystem refers to the region's ability to bear external pressure, which is reflected in the strain capacity of the regional

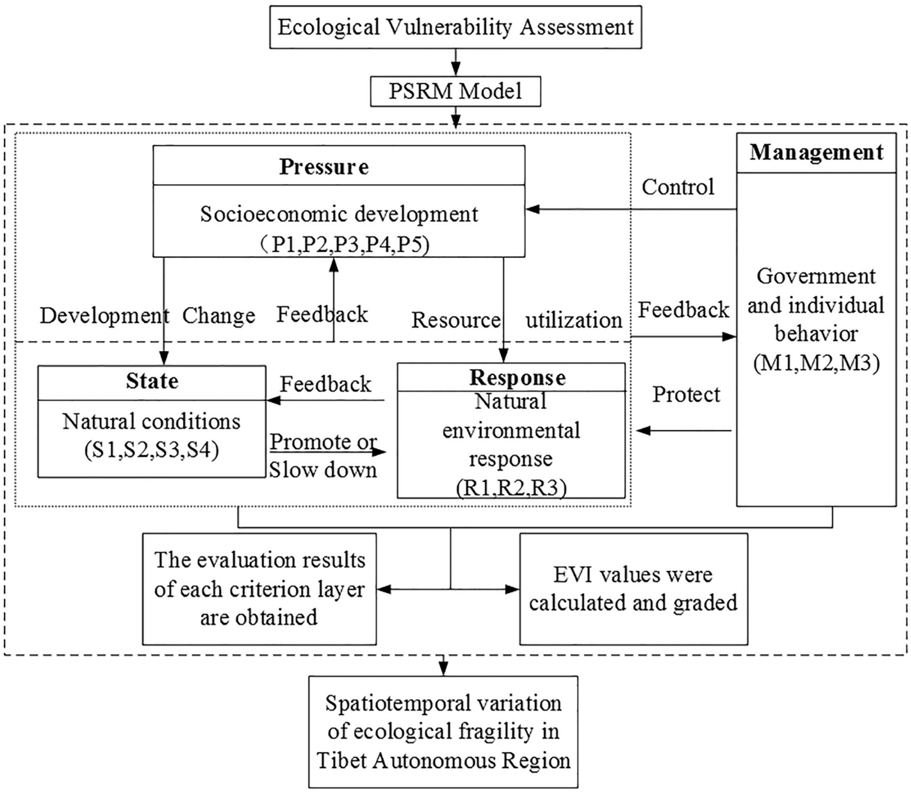

Fig. 2. The evaluation indicator framework of ecological vulnerability based on PSRM. Note. P: Pressure; P1: GDP; P2: The proportion of tertiary industry; P3: Density of the population; P4: Livestock inventory at the end of the year; P5: Human disturbance index; S: State; S1: Average annual rainfall; S2: Average annual temperature; S3: Slope; S4: Dem; R: Response; R1: NDVI index; R2: Rate of change grassland cover; R3: Rate of change in lake area; M: Management; M1: Policy support; M2: Residents' education level; M3: Afforestation area.

ecosystems under environmental pressure (Lv et al., 2019). The normalized difference vegetation index (NDVI) (R1), grass cover area (R2) and rate of change in lake area (R3) were included in the system to represent the tolerance of vegetation and lakes to environmental change. The formula for calculating NDVI is as follows:

$$\mathrm{NDVI} = (\mathrm{NIR\text{-}R})/(\mathrm{NIR} + \mathrm{R}) \tag{2}$$

where, *NIR* is the near-infrared reflectance value of MODIS, and *R* is the reflectance value of the infrared wave band.

The management subsystem mainly refers to the measures taken by society and individuals to reduce and prevent the adverse effects of human activities on the environment (Hopkins et al., 2020). It includes the actions of reducing and preventing the negative impacts of governments and individuals, and restoring the ecological environment as a remedy for changes in the ecological environment that are unfavorable to human survival and development. This study selected policy support (M1), residents' education level (M2) and the area of national parks and natural reserves (M3) as the indicators of the management subsystem. These indicators reflect the changes in people's awareness and behavior towards ecological protection.

2.3.2. The weight of indicators

A comparison matrix of the importance of the indicators was constructed by expert judgment based on the scale shown in *Table s6*. A total of 13 experts from different fields were invited to judge the relative importance of selected indicators. Their professional position, years of ecological service, and educational level were the main factors considered when identifying experts. The expert information is shown in the Appendix (*Table s7*).

To obtain reliable comparison matrix results, the consistency of the matrix was checked through the tested coefficient (CR). If CR < 0.1, the deviation was acceptable and the judgment matrix was considered to have passed the consistency test; otherwise, it was not satisfactory. The calculation formula for CR is as follows:

$$CI = \frac{\lambda - \mathrm{n}}{\mathrm{n} - 1} \tag{3}$$

$$CR = \frac{CI}{RI} \tag{4}$$

where, *CR* is the consistency ratio, λ is the largest characteristic root, *n* is the matrix order, *CI* is the consistency index, and *RI* is the random consistency index which is determined by expert judgment. Finally, the weighted average from each expert was taken as the final score of each indicator.

The indicators were divided into positive and negative according to the correlation with ecological fragility. For the positive indicators, as the positive index value increased, the habitat conditions improved (*Eq. (5)*). For the negative indicators, as the negative index value increased, the habitat conditions worsened (*Eq. (6)*).

$$X_i = \frac{x_i - min(x_i)}{max(x_i) - min(x_i)} \mathrm{X_i} = \frac{\mathrm{x_i} - \min(\mathrm{x_i})}{\max(\mathrm{x_i}) - \min(\mathrm{x_i})} \tag{5}$$

$$X_i = \frac{max(x_i) - x_i}{max(x_i) - min(x_i)} \tag{6}$$

where, X_i is the standardized value of the vulnerability assessment indicator *i*, x_i is the original data of the vulnerability assessment indicator *i*, $max(x_i)$ is the maximum value of indicator *i*, and $min(x_i)$ is the minimum value of indicator *i*.

The weight of each indicator was determined by the analytic hierarchy process (AHP). The attribute hierarchy of the AHP method had three levels: the overall goal for ecological vulnerability was on the top level, the multiple criteria of pressure, state, response and management that define alternatives were on the middle level, and the 15 indicators as competing alternatives were on the bottom level. The relative importance of each indicator in the middle and bottom level was judged by experts according to the comparison matrix (*Tables s1 ~ s6*) in the Appendix. The weights for each indicator and layer are shown in Fig. 3.

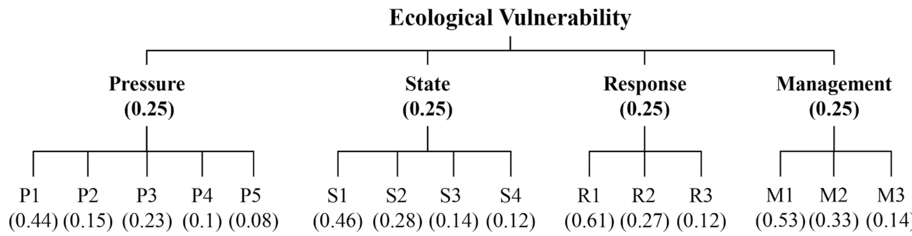

Fig. 3. The weights of 15 indicators and 4 layer.

2.3.3. *Ecological vulnerability evaluation*

The ecological vulnerability index (EVI) was used to indicate the degree of ecological vulnerability. A lower EVI means that the ecological environment is more fragile and more vulnerable to destruction. The calculation of the EVI is as follows:

$$\mathrm{EVI} = \sum_{j=1}^{n} W_j L_j \mathrm{EVI} = \sum_{j=1}^{n} W_j L_j \tag{7}$$

$$L_i = \sum\nolimits_{i=1}^{n} W_i C_i \tag{8}$$

where, *EVI* is the ecological vulnerability index, W_j is the weight of each level of pressure, state, response and management, $L_j$is the evaluation score for pressure, status, response and management, n = 4. W_i is the weight of each indicator, C_i is the normalized value of each indicator, and *n* is the total number of indicators.

3. Results

3.1. *Spatiotemporal distribution of different criterion layers and EVI*

The scores of the different layers from 2000 to 2015 were calculated based on the PSRM model (Fig. 3). The scores for all districts and counties included in the study area and the changes in four periods are displayed in Figs. 4, 5. Generally, the spatial distribution of these layers has not changed substantially in the past 15 years, but the average score has changed substantially over time.

For the pressure layer, as the score decreased, the pressure for the region increased. In the last 15 years, the center of the lowest score moved from the northwest to the southeast. The lowest scores in 2000 and 2005 were 0.52 and 0.73 in Nakchu and Shigatse, respectively, while the lowest score in 2010 was 0.48 in Qamdo. By 2015, the lowest scores dropped to 0.21 in Lhasa. The score for the pressure layer in the Nagqu region showed a trend of increasing fluctuation, which indicated that the pressure on the ecological environment in this region was decreasing gradually. However, the pressure scores for Lhasa and Qamdo showed a gradual downward trend, indicating that the ecological environment in these regions was under increasing pressure from social and economic development. From 2000 to 2015, Tibet experienced rapid population growth, especially in Nyingchi and Lhasa, which saw population growth of 36% and 35%, respectively. In contrast to the southeast region, the northwest region had less ecological pressure and a higher ecological score. This was mainly because of the establishment of nature reserves in northwest China (Qiangtang Nature Reserve) and the gradual improvement of animal husbandry management, which controlled the number of livestock using fences and grazing contracts. The annual number of livestock in Nagqu and Ali showed an upward trend from 2000 to 2005, but a significant downward trend from 2005 to 2015. The statistical data showed that the annual number of livestock of 2015 decreased by 12% compared with that in 2000 in Nagqu. In future, more than 130,000 people will be relocated to the southeast with the implementation of a relocation plan for the extremely high-altitude areas in Tibet (Zhou et al., 2020). This will lead to a growing regional difference in the pressure layer.

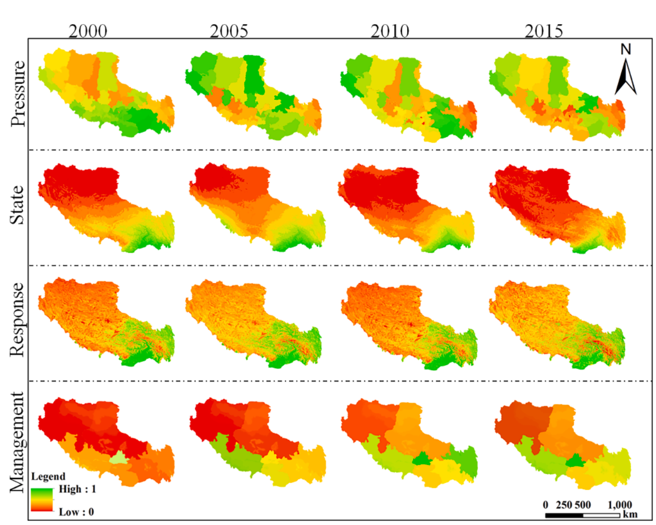

Fig. 4. The spatial distribution of different criterion layers and EVI in four periods.

For the state layer, as the score increased, the ecological environment improved. In terms of spatial distribution, the score of the state decreased from southeast to northwest with the highest score was 0.75 in Nyingchi whereas the lowest was 0.12 in Ali. In terms of temporal variations, there were slight fluctuations over time from 2000 to 2015 in the scores for the state layer. From 2000 to 2005, the average score for the status layer increased slightly from 0.28 to 0.29, because of the improvement in hydrothermal conditions. From 2005 to 2015, the score decreased substantially because of changes in the average annual temperature and average annual rainfall, which dropped from − 0.13℃ to − 0.38℃, and decreased from 572 mm to 267 mm, respectively.

For the response layer, as the score for the region increased, the ecological environment improved. Generally speaking, the score decreased gradually from southeast to northwest from 0.8 to 0.1, respectively. It was consistent with the changes in NDVI (decreasing from 0.92 in the southeast to 0 in the northwest) and was mainly influenced by the hydrothermal combination and human social activities. Although the hydrothermal combination in 2015 was not as high as that in 2000, the growth of vegetation was affected by the long-term hydrothermal conditions in the region. Furthermore, the ecological and environmental protection policies implemented by the local government resulted in afforestation of 35,862 ha in 2015, a fivefold increase over 2000. For example, most regions with high NDVI scores were located in Nyingchi and Qamdo, with an average score of more than 0.6, while those with low NDVI scores were mainly located in relatively higher altitude areas such as Nagqu and Ali, with an average score of <0.2. In particular, the urban management area of Lhasa was dominated by urban construction, which resulted in a lower score in the status layer, but does not mean that it is unfit for human habitation.

For the management layer, as the regional score increased, the management level increased. It included three indicators: policy support, education level, and the afforestation and nature reserve area. The major differences in administrative policies between different

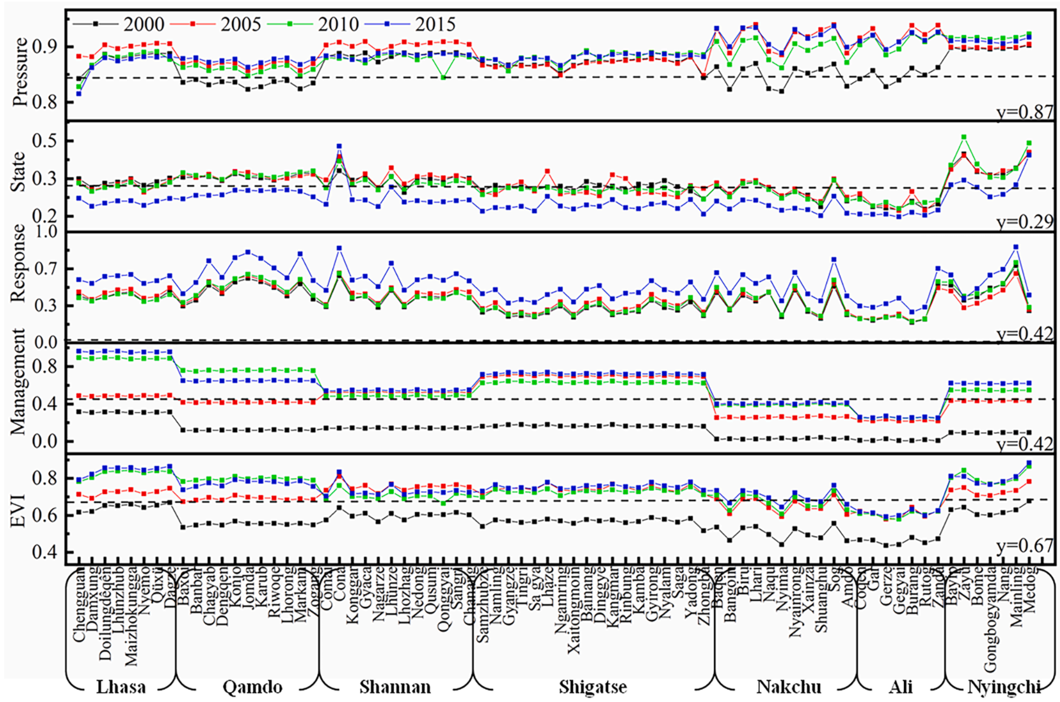

Fig. 5. The ecological vulnerability index values of 74 counties in four periods, where y represents the average value of different criterion layers in the four periods.

administrative regions resulted in great spatial and temporal differences in the three indicators. In 2000, there was still a lack of policies on ecological and environmental protection in Tibet. The highest score for the management layer was only 0.3 in Lhasa, followed by 0.2 in Qamdo; the scores in the other five regions were below 0.1. After 2005, a series of ecological protection projects such as afforestation, grassland contract responsibility system, construction of nature reserves and ecological relocation were carried out, and the management score significantly increased. In 2015, the management scores for Lhasa and Nyingchi also further improved, mainly because of the continuous improvement of residents' education level and enhanced awareness of ecological protection. From 2010 to 2015, the number of secondary school graduates in Lhasa increased by 2,383 and that in Nyingchi increased by 823. In Shigatse, the number of secondary school graduates fell by 1,430, resulting in a slight drop in management scores in 2015.

The spatiotemporal distribution of EVI and the proportion of different vulnerability levels are shown in Fig. 6. In general, the EVI represents the sensitivity of the natural environment to various influencing factors. To quantify the changes in ecologically fragile areas, the EVI score was divided into five grades. The breakdown was as follows: class I was an extremely vulnerable area ($0 < EVI < 0.2$), class II was a severely vulnerable area ($0.2 < EVI < 0.4$), class III was a moderately vulnerable area ($0.4 < EVI < 0.6$), class IV was a slightly vulnerable area ($0.6 < EVI < 0.8$) and class V was a non-vulnerable area ($0.8 < EVI < 1$).

In 2000, approximately 53% of the area was extremely vulnerable, mainly in the northwest, which has high altitudes and poor hydrothermal conditions (Fig. 6). With the establishment of the national nature reserves in 2005, the extremely vulnerable areas tended to be transformed into severely vulnerable and moderately vulnerable classes. Meanwhile, the proportion of moderately vulnerable and slightly vulnerable areas increased because of the improvement of government management ability and awareness of the need for social-ecological

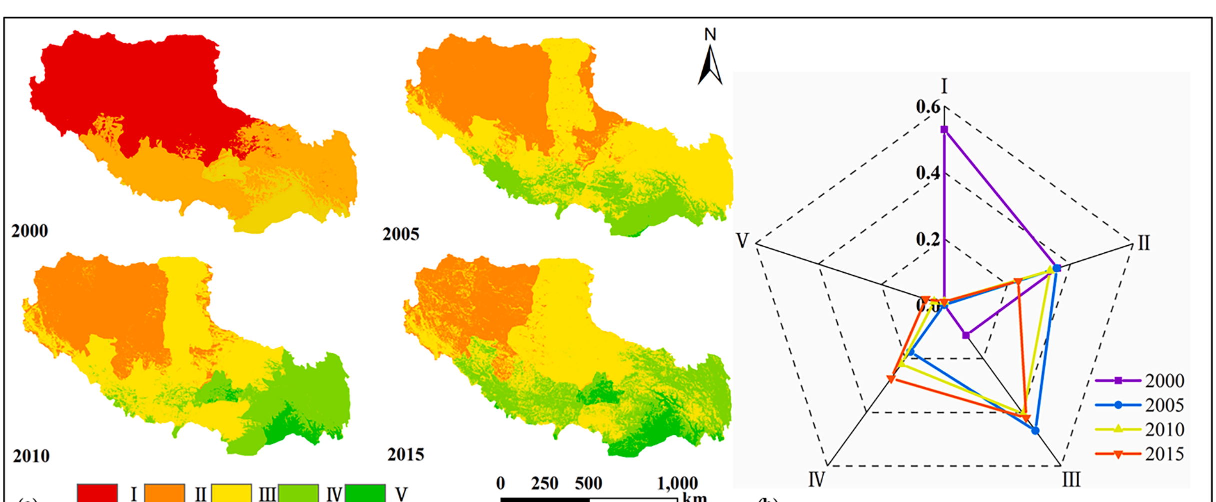

Fig. 6. Spatiotemporal distribution of EVI (a), and proportion of different vulnerability levels (b).

protection. Furthermore, the urban areas in Lhasa, Nyingchi and Qamdo were classed as non-vulnerable areas because of the progress of urbanization; the proportion increased from 3% in 2010 to 6% in 2015.

3.2. Causal analysis of ecological vulnerability

The results of the ecological vulnerability analysis above showed that the regions with higher vulnerability usually had lower scores in the response layer and state layer. A higher score for the pressure layer also had an impact on the ecological vulnerability of local areas. Therefore, to identify the drivers of the ecological vulnerability in different regions, the correlation coefficient between the 15 evaluation indicators and EVI indicators were calculated. For each indicator in the same region, the average value at the four time points was formed into a 1-dimensional quaternion vector.

$$X_i = (x_{i,2000}, \quad x_{i,2005}, x_{i,2010}, x_{i,2015}) \tag{9}$$

where, $X_i$is the vector value of the given evaluation indicator at i region, $x_{i,2000}$,$x_{i,2005}$, $x_{i,2010}$ and $x_{i,2015}$ are the standard value of the given evaluation indicators in the i region in 2000, 2005, 2010 and 2015, respectively. In this study, the value of 2000 was set as 1, and the value of other years was divided by the value of the year 2000 as the standard value.

The correlation between different indicators was analyzed by calculating the correlation coefficient between vectors (Chen et al., 2011). The formula is as follows:

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{10}$$

where, $\overline{X}$ is the average value of the indicator vectors in the seven regions, Y_i is the vector value of the EVI at i region, $\overline{Y}$ is the average value of the EVI in the seven regions.

In general, the indicators of population density, the proportion of tertiary industry, policy support and residents' education level had a higher correlation coefficient (>0.8) with the EVI index (Fig. 7). This meant that ecologically vulnerable areas had a close relationship with human activities (Yang et al., 2021), ecological protection and restoration measures. In the study area, the correlation coefficient between policy support and EVI in all regions was above 0.9, except for Shigatse, which was 0.7. The correlation coefficient between EVI and the human disturbance index was lower than 0.6 except in Lhasa and Shigatse. This showed that the ecological protection and restoration measures will reduce the influence of socioeconomic development on the ecological environment and increase the impact of natural conditions (Li et al., 2020b). The afforestation area increased from 1,611 to 11,348 ha and the number of middle school graduates increased from 3,300 to more than 10,800 from 2000 to 2015. The government and the public are increasingly aware of ecological protection. Lhasa has the highest population density in the Tibet Autonomous Region, with a population density of approximately 250 people /km^2 in the urban area of Lhasa. The intensity of human development activities had a great impact on the ecological environment.

The correlation coefficient between policy support and EVI was relatively high for Nagqu and Qamdo, which indicated that the formulation of ecological and environmental protection policies promoted the improvement of the regional ecological environment. To some extent, the establishment of the policy limited the increase in livestock at the end of the year and the human disturbance index. Between 2000 and 2015 the annual number of livestock in Nagqu and Qamdo fell from 6.09 million to 5.25 million and from 3.45 million to 2.73 million, respectively. The human disturbance index increased slightly, by 0.8% and 0.3%, respectively, in Nagqu and Qamdo. The NDVI in Qamdo increased from 0.51 in 2000 to 0.56 in 2015, an increase of 10%. The increase rate had a high correlation coefficient with the increase in the EVI. These

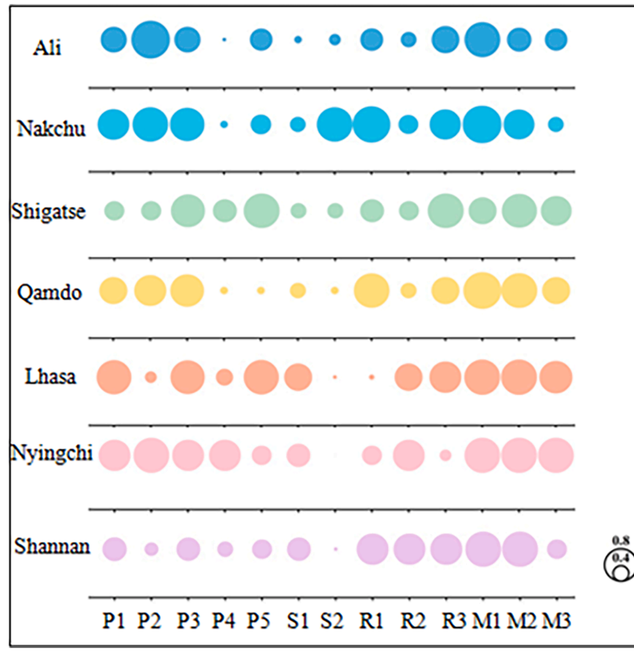

Fig. 7. Correlation coefficient distribution diagram of EVI and single factor indicators in seven cities. P1: GDP; P2: The proportion of tertiary industry; P3: Density of the population; P4: Livestock inventory at the end of the year; P5: Human disturbance index; S: State; S1: Average annual rainfall; S2: Average annual temperature; S3: Slope; S4: Dem; R: Response; R1: NDVI index; R2: Rate of change grassland cover; R3: Rate of change in lake area; M: Management; M1: Policy support; M2: Residents' education level; M3: Afforestation area.

increases were mainly because of the implementation of ecological relocation and ecological forest construction projects. To protect the fragile ecological environment of Nagqu, the Qiangtang National Nature Reserve was established in 2005 (Xu and Zou, 2020), which increased the EVI significantly. In Shannan, the indicators with a high correlation coefficient for EVI were NDVI, policy support and education level. Among these, the average value of NDVI in the whole region was as high as 0.55, making a substantial contribution to the improvement of the local ecological environment. Similar to Shannan, there was also relatively high NDVI in Nyingchi because the hydrothermal conditions were suitable for vegetation growth (Su et al., 2019). Nyingchi is located in the southernmost part of the study area, with an average altitude of 3,100 m, average annual precipitation of 650 mm, and an average annual temperature of 8.7℃. Good hydrothermal conditions were also the most suitable for human habitation in the seven regions, along with the relatively flat terrain and low altitude. The population density was relatively high at 1.85 people/km^2, and there was also a high proportion of tertiary industry (0.55) in Nyingchi. Most of the Ali region comprised nature reserves owing to its sparse population. Therefore, the indicator with the highest EVI correlation coefficient was policy support.

4. Discussion

4.1. Trends of ecological vulnerability in the Tibet Autonomous region

The industrial and resource development activities were controlled with the implementation of a series of ecological security policies (Adedoyin et al., 2021). However, the continuing social and economic development is still putting pressure on the fragile and sensitive local ecosystems. The development of the regional economy may bring challenges for the ecological environment (Qin and Zheng, 2010), and the increases in population, primary and tertiary industries further exacerbate the conflict between humans and land (Zhang and Liu, 2004). Furthermore, as the global climate continues to warm, uncertainties such as rising snowlines, vegetation degradation and increased soil erosion are increasingly affecting regional ecosystems (Ishida et al., 2019; Wang et al., 2020).

The GDP of Tibet has grown from 424 million dollars in 1990 to 22.6 billion dollars in 2018 (Fig. 8). Tertiary industry made the biggest contribution: from 1990 to 2018, tertiary industry in the Tibet Autonomous Region accounted for 36%–49% of GDP. Tourism was the main pillar, and its proportion of tertiary industry grew from 1% to 68%. The development of environmentally-friendly tertiary industry can reduce the degree of damage to the ecological environment caused by human development activities and is conducive to the restoration and protection of the ecological environment. Socioeconomic growth has led to an increase in the population living in cities and towns. From 1995 to 2018, the proportion of the rural population in the total population decreased from 83% to 69%, and the proportion of the urban population increased from 17% to 31%. The concentration of the population is conducive to the unified implementation of ecological planning and construction, and also to improving ecological protection education. As more people move from rural areas to urban areas, livestock farming is affected. The annual number of large livestock first increased and then decreased over the study period, which alleviated the pressure on grassland to some extent and protected the fragile grassland ecosystem.

To better protect the fragile ecosystems of the Qinghai–Tibet Plateau, a remote sensing monitoring center for the ecological environment in Tibet was established in 2017. A total of 180 million dollars was allocated to promote the construction of ecological security barriers. By the end of 2020, the rate of forest coverage in the study area reached 12.14%, and approximately 45% of the region's land area was included in the red line for ecological protection. Approximately 47 nature reserves, which cover a total area of 412,200 km^2, were established. A comprehensive ecological development plan is gradually being established to realize the harmonious coexistence between man and nature and explore an innovative model of sustainable development on the plateau.

4.2. Suggestions for sustainable development of the ecological environment in the Tibet Autonomous region

Sustainable development is a long-term strategy to reduce environmental pressure and protect the fragile ecological environment. The ecosystems of the Qinghai–Tibet Plateau are ecologically fragile, with severe erosion from wind, water, and freezing. Therefore, the protection of the local ecological environment should focus on maintaining the integrity of the existing natural ecosystems, strengthening the protection of the border ecotones, and reducing social and economic activities in this area. Measures such as returning farmland to forest and grassland and restoring natural vegetation are effective means of ecological vulnerability protection. Environment-friendly industries such as tourism services, solar energy, wind, and hydropower energy can promote the coordinated development of ecology and the economy in fragile areas. In severely ecologically fragile areas, ecological monitoring and early warning services should be strengthened to strictly control human economic activities and curb ecological degradation.

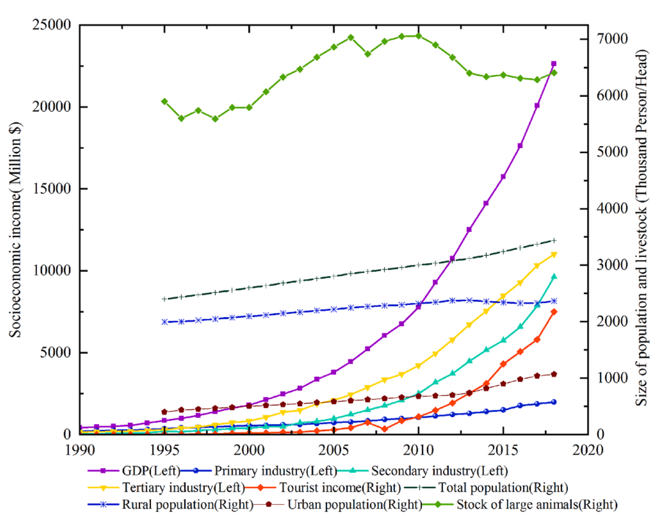

Fig. 8. Trend chart of major social and economic indicators in Tibet Autonomous Region in the past 30 years.

4.3. Limitations of this study

Given that uncertainty exists in any assessment of vulnerability, the quantitative assessment framework of this study has some limitations that are driven by a variety of sources for both the ecological and socioeconomic processes of the evaluation. Development and change in regional ecological vulnerability are affected by the regional background conditions, natural environment conditions, social and economic development conditions, and the behavior of the government and the public. In this study, data over a long time span (from 2000 to 2015) were used. Problems such as missing data, insufficient resolution, or a lack of uniform standards for obtaining raw data can lead to uncertainty. For example, some raw data were collected at the resolution of the administrative region level. To carry out unified raster calculation in GIS, these data were converted into a high resolution 1 km × 1 km grid, which increased the uncertainty of the data source.

The weight assignment of each index can also bring uncertainty to the evaluation results. Methods such as principal component analysis, expert scoring and entropy weighting are commonly used in index weight assignment. In this study, the expert scoring method was used to determine the index weight. The resulting weights may fluctuate depending on the subjective judgment of the experts given the similar natural environments, population distribution, and human production activities. However, the uncertainty caused by the weights was within an acceptable error range.

The selection of the evaluation index itself is subjective because the evaluation process needed to determine multiple evaluation indexes (Chen et al., 2010). The ecological vulnerability assessment system is a comprehensive system that is affected by many factors in a natural environment and social environment. Although the constructed index system is relatively comprehensive and reasonable, because of the influence of subjective factors in the construction of the index, the selection of different evaluation indexes and weights will have an impact on the whole evaluation result.

Finally, in this paper, the future development direction of ecological vulnerability in the region was projected based on the socio-economic data from the past 30 years. However, this prejection was insufficient, and the future development direction was uncertain owing to the lack of dynamic tracking data. In the next step of the study, more accurate and more comprehensive data should be pursued so as to further reduce the uncertainty of ecological vulnerability evaluation results. It should be focused on predicting the regional future trend of ecological vulnerability, in line with the long-term goal of sustainable development requirements, complementing the study of regional ecological vulnerability assessment.

5. Conclusions

This study comprehensively evaluated EVI in Tibet between 2000 and 2015. A PSRM model was established to assess the spatiotemporal variation of the EVI. The average value of all indicators at four past time points was formed into a one-dimensional quaternion vector, and the correlation coefficient between 15 evaluation indicators and the EVI indicators was calculated through vector correlation analysis. Finally, proposals for ecological protection and sustainable development were outlined to support the protection of the fragile ecological environment on the Qinghai-Tibet Plateau.

As revealed from the results of this study, the spatial difference in the EVI in the study area was significant. It gradually decreased from southeast to northwest, and the lowest value area appeared in Lhasa. However, the EVI improved over time: the proportion of moderately and relatively vulnerable areas was relatively high, although the proportion of non-vulnerable areas was small. The evaluation system established in this research was based on a comprehensive consideration of the field conditions in the research area. Different plateau areas have different social backgrounds and natural conditions. In the future, climate change models can be incorporated into assessment systems, ecological vulnerability assessment research should be carried out according to local conditions, and an assessment system suitable for the research area should be established. The assessment system in this paper can provide a reference for analyzing the ecological vulnerability of the Qinghai–Tibet Plateau.

CRediT authorship contribution statement

Yongjian Jiang written original draft, Bin Shi given the conceptualization and written review & editing, Guijin Su contributed to funding acquisition, Ying Lu contributed to supervision, Qianqian Li contributed to validation, Jing Meng contributed to formal analysis, Yanpeng Ding contributed to investigation, Shuai Song contributed to visualization, Lingwen Dai contributed to Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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