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Spatio-temporal changes of ecological vulnerability across the Qinghai-Tibetan Plateau

Mu Xia[a,b], Kun Jia[a,b,*], Wenwu Zhao[c,d], Shiliang Liu[e], Xiangqin Wei[f], Bing Wang[a,b]

[a] State Key Laboratory of Remote Sensing Science, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China
[b] Beijing Engineering Research Center for Global Land Remote Sensing Products, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China
[c] State Key Laboratory of Earth Surface Processes and Resource Ecology, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, PR China
[d] Institute of Land Surface System and Sustainable Development, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, PR China
[e] State Key Laboratory of Water Environment Simulation, School of Environment, Beijing Normal University, Beijing, China
[f] Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100101, China

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ABSTRACT

The Qinghai-Tibetan Plateau (QTP) has the most fragile ecosystems in the world. Over the past decades, QTP is suffering from increasing external pressures of climate change, human activities, and natural hazards, thus ecological vulnerability assessment is crucial for its sustainable development. This study proposes an objective and automatic framework to assess the ecological vulnerability in the QTP under the threats of mountain hazards, ecosystem degradation and human economic activities and then analyze its spatio-temporal patterns from 2000 to 2015. An ecological vulnerability index (EVI) is established by integrating natural and anthropic factors based on sub-systems of land resources, hydro-meteorology, topography, and social economics. Seventeen indicators are selected to reflect ecological conditions and their weights are determined by principle component analysis and entropy weighting methods. Then, the EVI values are automatically categorized into five vulnerability levels of potential, light, moderate, heavy, and very heavy to illustrate their spatio-temporal patterns across the QTP. Results indicated that spatial distributions of EVI across the QTP exhibited similar patterns during the study period at an overall heavy level. Among all the indicators, vegetation was the dominant driver for ecological vulnerability. Based on trend analyses during the study period, approximately 10.43% of the QTP, mainly distributed in Tibet Autonomous Region, experienced significant increase in ecological vulnerability, while 7.38%, mainly distributed in Qinghai Province, experienced significant ecological vulnerability declination. However, more detailed analyses showed that after the implementation of several ecological protection programs, the increasing trend of ecological vulnerability was eased and more regions experienced significantly decreasing vulnerability. This indicated the ecological restoration projects conducted by the government were efficient in reducing ecological vulnerability.

1. Introduction

Global and regional ecosystems are experiencing huge pressures resulted from climate change (Debortoli et al., 2019; Jiang et al., 2018; Li et al., 2018; Ofori et al., 2017; Pandey and Bardsley, 2015; Yu et al., 2010), human activities (Gang et al., 2018; Nguyen and Liou, 2019; Santer et al., 2018) and natural hazards (Nguyen et al., 2019; Papathoma-Köhle et al., 2019). Thus, assessing the vulnerability of ecosystems is of great significance for environmental management and sustainable development. The Qinghai-Tibetan Plateau (QTP), known as the third pole, is drawing increasing attention on its unprecedented ecological condition changes. The QTP possesses ecosystems with huge diversity due to the great variation of topography and climate (Liu et al., 2018). In addition, the QTP is going through a greater temperature rise compared with other regions in the world during recent decades (Dong et al., 2012). According to meteorological station measurements, reanalysis and remote sensing data, the existing warming trend may continue in the future (Kang et al., 2010). Warming of the QTP can lead to glacier retreat, inconsistent snow cover change, permafrost melting, which influences far beyond the QTP itself by changing the water supply of billions of people downstream and altering the Earth's atmospheric circulation (Qiu, 2008). Therefore, with the most fragile and sensitive

* Corresponding author at: State Key Laboratory of Remote Sensing Science, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China.
E-mail address: jiakun@bnu.edu.cn (K. Jia).

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ecosystems on the Earth, ecological vulnerability (EV) assessment over the QTP becomes crucial for sustainable development at both regional and global scales.

Although multiple definitions of ecological vulnerability have been raised (Thywissen, 2006), the definition proposed by Turner et al. (2003) is considered the most consistent with current researches, which refers to vulnerability as "the degree to which a system, sub-system, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or a stress/stressor" (Beroya-Eitner, 2016). Hinkel (2011) pointed out that there was also a "bewildering array of terms" expressing either similar (e.g., risk, sensitivity and fragility) or inversely similar ideas (e.g., resilience, adaptive capacity and stability). Moreover, ecosystem vulnerability, environment vulnerability and eco-environment vulnerability are always used interchangeably with ecological vulnerability (Beroya-Eitner, 2016). Therefore, the above-mentioned combinations of terms typically represent the same concept in literatures. In this study, the most commonly used term "ecological vulnerability" is adopted to express this concept. EV, as the intrinsic property of an ecosystem, only reveals under external disturbances (De Lange et al., 2010).

As one of the most vulnerable regions in the world, the QTP is suffering from multiple threats over the past decades. Due to its unique topography, mountain hazards including landslide, debris flow, flash flood and collapse have happened frequently (Ma et al., 2004). In addition, severe ecosystem degradation including desertification, deforestation and grassland degradation has been induced by climate change and land management (Cui and Graf, 2009). Ecosystem degradation can be modelled as the interactive dynamics of a stepwise process with feedbacks. When ecosystem components are changed under external disturbances, the changes will continue to feedback on one another to cause a spiraling declination in ecosystem structure and function. Moreover, the increasing human economic activities, such as road constructions and inappropriate land use, have also casted threats on the regional ecosystem. Therefore, this study evaluates the EV under the above-mentioned threats over the QTP based on four sub-systems, including land resources, hydro-meteorology, topography and social economics. Comprehensive and spatially explicit restoration strategies can be made based on EV assessments in terms of reducing the impacts from external pressures (Li et al., 2018). Therefore, EV assessment is instrumental for decision-makers in identifying the key areas for environmental protection, and enacting appropriate ecological restoration strategies in constructing the ecological security barrier.

A number of researches have performed EV assessments within the coupled natural conditions and human activities over different regions. Both Zhao et al. (2018) and He et al. (2018) assessed EV for mainland China and pointed out western China was suffering from the most severe ecological pressures, among which Tibet Autonomous Region and Qinghai province had the highest degree of EV. However, these national EV assessments are performed based on administrative units. More typically, EV assessments are performed at regional scales since EV-related indicators are strongly localized and case-specific (Beroya-Eitner, 2016). Studies performed over medium scale regions, like Tibetan Autonomous Region, always adopt spatial data with 500 m or 1 km spatial resolution. Wang et al. (2008) assessed EV for Tibet Autonomous Region in 2004 and provided corresponding management suggestions at 1 km scale, and the eco-security of Tibet at 500 m spatial resolution in 2007 was evaluated by Wang et al. (2010) using a geographic information system-based decision support system. In addition, EV assessments can also be performed over smaller regions, including small river basins (Li et al., 2006, 2009; Manfré et al., 2012; Xue et al., 2019), national reserves (Nandy et al., 2015; Zou and Yoshino, 2017), and administrative units like cities (Choudhary et al., 2018; Liou et al., 2017; Nguyen et al., 2016; Sahoo et al., 2016). The abovementioned studies are primarily performed using 30 m spatial resolution Landsat data. Moreover, a group of studies have been conducted over small regions on the QTP, including Sanjiangyuan region (Liu et al., 2017), northeastern margin (Zhou et al., 2010), and northwestern alpine grassland (Li et al., 2020a). However, EV assessments and its annual change patterns over the entire QTP is still rare. Therefore, this study is intended to propose a framework for EV assessment over the entire QTP at 500 m resolution and explore the annual spatial–temporal change patterns over 16 years.

Weighting is also an important part in establishing an EV assessment framework. As the majority of studies aggregate indicators using the weighted sum, the EV assessment results are sensitive to the weights applied (Wang et al., 2008). Current weighting approaches can be categorized into two groups: subjective and objective methods. Subjective methods require opinions from various experts (e.g., researchers, citizens, politicians) to score indicators (Nardo et al., 2008). Analytic hierarchy process (AHP) (Saaty, 1977; Saaty and Vargas, 1991) is the most widely used subjective weighting approach in ecological researches (Song et al., 2010; Wang et al., 2010). Other methods include fuzzy methods (Enea and Salemi, 2001), grey methods (Sahoo et al., 2016; Yonghong, 2002), artificial neural network methods (Park et al., 2004) and so on. Some studies also aggregated indicators using outranking procedures, which performed pairwise comparisons of indicators and built the credibility matrix by votes (El-Zein and Tonmoy, 2015). However, weights from these methods are directly affected by the subjective judgements of the experts. The objective weighting methods estimate indicator weights based on the intrinsic structure of the data. Principle component analysis (PCA) (Wold et al., 1987) is capable of projecting multivariate indicators into independent directions, which has been adopted in multiple EV assessments and proved to be a robust technique in reducing the dimensions and extracting relationship among selected indicators (Li et al., 2006; Nandy et al., 2015; Zou and Yoshino, 2017). However, PCA is only suitable for highly correlated indicators and is inappropriate for estimating weights of poorly correlated indicators (Nardo et al., 2008). Furthermore, discussions about the plausibility of performing PCA weighting approach for multivariate indicators are always neglected in existing researches. If input indicators are not adequate for PCA, the results may be problematic with increased uncertainties. Dziuban and Shirkey (1974) suggested that the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity were effective methods to test sample adequacy for PCA. Therefore, these two tests are introduced in priority to the weighting procedure in this study. For indicators failed these two tests, entropy method will be adopted to estimate the weights. Entropy weighting is also one of the most used objective weighting methods for ecological assessment studies (Zhao et al., 2018; Zhou et al., 2017), which determines indicator weights based on the information entropy of each indicator (Shannon, 1948). However, entropy method is more likely influenced by outliers. Therefore, entropy method is adopted as the backup plan for indicators inappropriate for PCA. To summarize, this study introduces sample adequacy tests to determine the proper weighting approach, which can further improve the credibility of the results.

Therefore, the main purpose of this study is to propose an objective and automatic framework for ecological vulnerability assessment in the QTP. First, the ecological vulnerability index (EVI) regarding to the threats of mountain hazards, ecosystem degradation and human economic activities is obtained from the model consisted of four sub-systems, including land resources, hydro-meteorology, topography, and social economic. The four sub-systems synthetically consider factors from natural and anthropic sub-systems. Second, an assessment framework is established to integrate the processes of objective indicator weighting, EVI calculating and categorizing. Sample adequacy tests are introduced in selecting the proper weighting approach to increase the credibility of assessment results. The framework is also applicable for EV evaluation over other regions. Third, the spatio-temporal EV patterns over the QTP from 2000 to 2015 is analyzed and regions with significant changes are identified, which is seldomly performed over the QTP by existing researches.

2. Methodology

2.1. Study area

The Qinghai-Tibetan Plateau (QTP) (Fig. 1), located in western China, is well known as the "Roof of the World" (Liu et al., 2018). It lies between 26°N to 39°N and 73°E to 104°E, covering the entire Tibet Autonomous Region and parts of Qinghai, Sichuan, Gansu, Yunnan provinces and Xinjiang Uygur Autonomous Region of China with a total area of approximately 2.5 million square kilometers and an average altitude over 4000 m. The QTP and its surroundings contain the largest number of glaciers in the world except the polar regions. These glaciers, as headstreams of many prominent Asian rivers, including the Yangtze river, the Nu River, the Indus River and so on (Yao et al., 2012), are providing food, fresh water and many other ecosystem services to billions of people downstream. From the northeastern to the southwestern QTP, forest, shrub, alpine grassland, alpine meadow and alpine desert ecosystems are distributed successively, with wetland ecosystems located among them. Severe desertification, deforestation and grassland degradation was induced by human activities (Cui and Graf, 2009). However, on the whole, vegetation across the QTP experienced an increasing trend during the past decades with the northeastern regions showing a consistent greening trend while the southwestern regions being browning in 2000s and starting greening since 2010 (Li et al., 2020b). The population over the QTP is much smaller than its surrounding regions. The entire region shares similar cultural background and the policies are more tilted toward environmental protection rather than economic development. Therefore, with its unique environmental and anthropic conditions, the QTP is an appropriate geographic unit for EV assessment.

2.2. Framework for EVI assessment

An automatic and objective framework integrating indicators from land resources, hydro-meteorology, topography, and social economic sub-systems was proposed to perform EVI assessment over the QTP from year 2000 to 2015 (Fig. 2). Indicator weights were estimated using objective weighting approaches based on the intrinsic characteristics of data rather than subjective opinions from experts. In addition, KMO test and Bartlett's test of sphericity were used to test sample adequacy and determine the proper weighting approach, which will be further explained in Section 2.2.2. Finally, EVI was classified into a certain number of categorizes to provide a generalized understanding about the degree of the EV across the QTP.

2.2.1. Indicator selection

To evaluate the vulnerability regarding to the threats induced by mountain hazards, ecosystem degradation, and human economic activities, indicators were selected based on four sub-systems of land resources, hydro-meteorology, topography, and social economics (Table 1). Even though the assessment was performed based on a sub-system framework, the selected indicators well covered the exposure, sensitivity, and adaptive capacity aspects of EV. Geospatial data were selected to represent the four sub-systems considering the nature of the threats, spatial resolution and accuracy comprehensively. The EVI values, quantitative expression of EV, were firstly calculated for each sub-system, and then integrated into the final EVI across the study area.

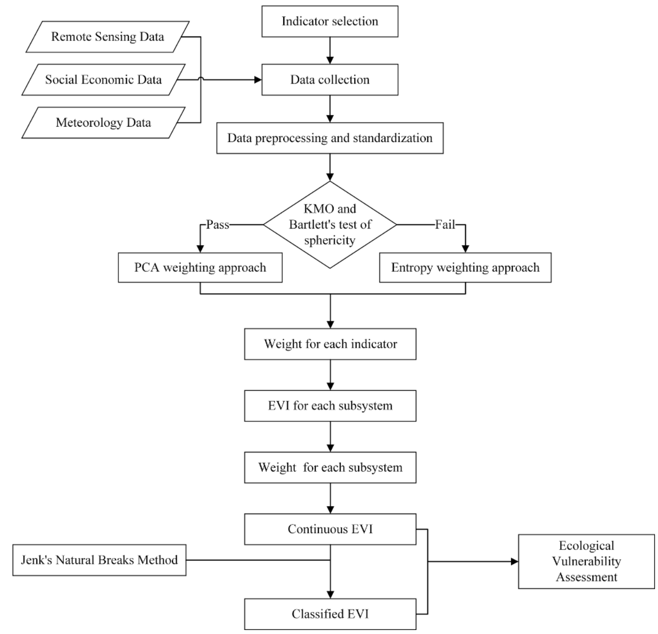

Fig. 2. Flowchart of the EVI framework.

Land resources sub-system directly reflects the land cover changes. Most importantly, it is capable of revealing the vegetation dynamics over the study period. The selected indicators included vegetation parameters and Land Use and Land Cover (LULC) data. Vegetation parameters estimated by remote sensing techniques have long been served as a significant role in environmental and ecological studies. Commonly used vegetation parameters include Leaf Area Index (LAI) (Chen et al., 2019), Fractional Vegetation Cover (FVC) (Jia et al., 2016), Gross Primary Productivity (GPP) (Frazier et al., 2013), Normalized Difference Vegetation Index (NDVI) (Yu et al., 2010), and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) (Wang et al., 2015). These vegetation parameters directly reflect vegetation growth and density. These parameters vary in their intrinsic physical meanings. For instance, LAI denotes to the vertical density of vegetation, while FVC denotes to

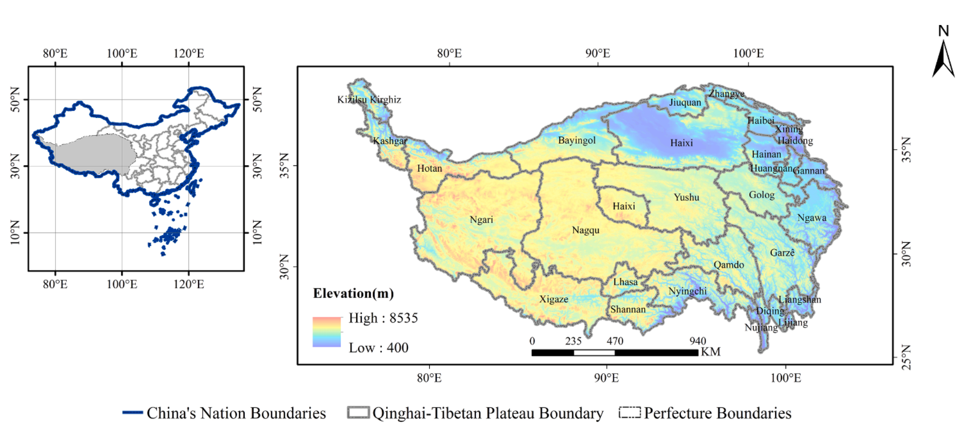

Fig. 1. Location of the study area.

Table 1
Key indicators of EVI, effect directions, and spatial and temporal resolutions of the selected data.

Sub-systems	Indicators	Effect direction	Resolutions	Data sources
Land resources	Leaf Area Index	–	1 km/8 day	Xiao et al. (2016)
	Fractional Vegetation Cover	–	500 m/8 day	Jia et al. (2015)
	Gross Primary Productivity	–	500 m/8 day	Cai et al. (2014)
	Normalized Difference Vegetation Index	–	500 m/8day	Xiao et al. (2017)
	Fraction of Absorbed Photosynthetically Active Radiation	–	1 km/8 day	Xiao et al. (2015)
	Land Use and Land Cover	+	500 m/annual	Friedl et al. (2010)
Hydro-meteorology	Evapotranspiration	–	1 km/8 day	Yao et al. (2014)
	Albedo	+	1 km/8 day	Liu et al. (2013)
	Precipitation	–	1 km/annual	http://www.resdc.cn/
	Temperature	–	1 km/annual	
	Distance to waterways	+	500 m	https://www.openstreetmap.org/
Topography	Elevation	+	90 m	http://www.gscloud.cn/
	Slope	+		
	Aspect	+		
Social economics	Distance to roads	–	500 m	https://www.openstreetmap.org/
	Population	+	1 km/5 years	http://www.resdc.cn/
	Gross Domestic Product	+	1 km/5 years	

the vegetation density in horizontal direction. All the above-mentioned parameters were selected to fully explore and utilize the information contained by vegetation. Due to better performances in spatial–temporal coverage and validation accuracies compared with other similar satellite products (Cai et al., 2014; Jia et al., 2015; Liang et al., 2013; Xiao et al., 2015, 2017, 2016), Global LAnd Surface Satellite (GLASS) products were selected as the data sources for these vegetation parameters. In addition, LULC, as the result of interactions between natural factors and human activities, is also an important factor in EV assessment (Jin et al., 2019). Moderate resolution image spectroradiometer (MODIS) annual product MCD12Q1 (Friedl et al., 2010), released by the United States National Aeronautics and Space Administration (NASA), was adopted in this study. The International Geosphere-Biosphere Programme (IGBP) class scheme was aggregated and reclassified into six new categories, which were scored to 0.2, 0.4, 0.6, 0.8 and 1 (Table 2). Land cover types of water and snow and ice were excluded in this study.

Hydro-meteorology indicators were selected to show the climate changes and hydrological conditions. Due to the severe impacts of climate change on ecological environment (Li et al., 2018; Pandey and Bardsley, 2015), meteorology indicators, especially temperature and precipitation, are crucial components for EV assessment. Annual precipitation and temperature at 1 km resolution, were provided by the Data Center for Resource and Environment Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn/). Both precipitation and temperature datasets were established using interpolation method (Hutchinson, 1998) based on daily observations from over 2400 meteorology stations in China. Apart from climate indicators, evapotranspiration (ET) and albedo are also important indicators for EV assessment in that they are pivotal drivers for the formation of the QTP's monsoon climate type (Wu et al., 2012). GLASS ET and albedo products were selected for further evaluation due to their better performances in accuracy and spatial continuity compared with similar products (Liu et al., 2013; Yao et al., 2014). Moreover, distance to waterways is also a significant factor based on its ability to describe the hydrological conditions of water availability across the study area. This indicator was calculated based on vectors of waterway networks derived from Open Street Map (OSM), an open source website providing geographic data contributed by volunteers worldwide with high accuracy (Wang et al., 2013). Rivers, canals and streams among the waterways were chosen for further analyses.

Table 2
Reclassified information about land use and land cover.

Original Classes	Reclassified	Score
Evergreen needle leaf evergreen broad leaf/ deciduous needle leaf/deciduous broad leaf/mixed forest	Forest	0.2
Closed/open shrubland	Shrubland	0.4
Savannas, grasslands, wetlands, croplands	Savannas, grasslands, wetlands, croplands	0.6
Urban and built-up	Urban and built-up	0.8
Barren and sparsely vegetated	Barren and Sparsely Vegetated	1.0
Water, snow and ice	Water, snow and ice	No Data

For topography sub-system, elevation, slope angle, and slope aspect, generated from Shuttle Radar topography Mission (SRTM) Digital Elevation Model datasets, were obtained from Geospatial Data Cloud (http://www.gscloud.cn/) in the spatial resolution of 90 m. Regions at higher altitudes are more likely to suffer from climate extremes, while steep topography can lead to considerable runoffs, bringing in soil erosion and landslides. Slope aspects facing the north receive less solar illumination than that facing the south, which is also an influence factor for vegetation growth. Therefore, topography should be considered as an essential aspect in evaluating regional EV.

Social economic indicators were selected to quantify anthropic pressures across the study area. The selected indicators include population, gross domestic production (GDP), and distance to roads. High values of population and GDP directly reflect the human pressure and intensity of economic activities. Population and gross domestic production (GDP) data in 2000, 2005, 2010 and 2015 at 1 km resolution were obtained from RESDC. In this study, population and GDP data for each year were also employed in the EVI calculation over the latter four years (e.g. population and GDP in 2000 was adopted for assessments in 2000, 2001, 2002, 2003 and 2004). Moreover, distance to roads is selected to reflect the degree of human involvement. To avoid overestimating the impacts of roads, distances were only computed based on primary and secondary roads provided by OSM.

2.2.2. Data preprocessing and standardization

EVI assessment was performed at 500 m spatial resolution and annual temporal resolution. Indicators at other spatial resolution were resampled to 500 m using nearest neighbor method. Vectors of waterways and roads were transformed into raster data at 500 m spatial resolution and the distances from each pixel to the nearest waterway and road were calculated, as the indicators of distances to waterways and roads. In addition, for indicators with 8-day temporal resolution, annual datasets were generated using a maximum value composite (MVC) method. After data preprocessing, the effect directions of each indicator were determined. The effect directions express whether each indicator has a positive or negative relationship with ecological vulnerability (Table 1).

Next, data standardization was performed for all indicators. Indicators are distributed at various scales with different units, making them unable to be compared or integrated. Therefore, z-score method (Eq. (1)) was applied to standardized the indicators to a uniform scale with the mean values of 0 and the standard variations of 1.

$$Z = \begin{cases} \frac{x-\mu}{\sigma}, x \text{ is a positive indicator} \\ \frac{\mu - x}{\sigma}, x \text{ is a negative indicator} \end{cases} \quad (1)$$

where Z is the standardized indicator, x is the input original indicator, μ is the arithmetic mean of x and σ is the standard deviation of x.

2.2.3. Weighting approach

Estimating the weights for all the indicators and sub-systems is another key step in EVI assessment. An objective approach incorporating PCA and entropy weighting approaches was developed to estimate weights for each indicator. Even though PCA method is effective in selecting representative features from highly correlated multivariate datasets by projecting the original data into independent directions, it is not suitable for all datasets. According to Dziuban and Shirkey (1974), datasets with low correlation are inappropriet for factor and component analysis, and they pointed out KMO test (Kaiser, 1970) and Bartlett's test of sphericity (Bartlett, 1950) were effective methods to test the sampling adequecy for factor and component analysis. Sampling adequacy measured by KMO varies from 0 to 1 and are often categorized as in the 0.90 s, 0.80 s, 0.70 s, 0.60 s, 0.50 s, and below 0.50, referring to marvelous, meritorious, middling, mediocre, miserable, and unacceptable adequacy to perform factor or component analysis (Kaiser and Rice, 1974), respectively. Bartlett's test of sphericity checks if redundancy exists in variables that can be summarized with some factors. Therefore, when the indicators failed to past KMO test the Bartlett's test of sphericity, the entropy method steps in to estimate weights based on information entropy, which is also a widely applied objective weighting approach for ecological studies and always produces reasonable results (Yu et al., 2015; Zou et al., 2006). In this study, datasets with the KMO index greater than 0.60 and the p-value for the Bartlett's test of sphericity less than 0.01 are defined suitable for PCA.

Weight estimation process based on PCA is described as follows. Suppose X is the input standardized $n \times p$ matrix with n observations and p variables. S is the $n \times p$ matrix with columns representing the principle components (PCs) extracted from X. C is the $p \times p$ principle component coefficients for X. The columns in S and C is arranged in descending order in terms of eigenvalues, eig. The explanatory ability of the i-th PC e_i is calculated using:

$$e_i = \frac{eig_i}{\sum_{i=1}^{p} eig_i} \quad (2)$$

where eig_i is the i-th eigenvalue and the sum of e_i is 1. The top m number of PCs should be selected to satisfy the criterion $\sum_i^m e_i \geq \beta$, where β is determined based on research requirements ($\beta = 0.85$ in this study). Thus, the importance of each variable could be acquired by the top m columns in C and e as:

$$im_i = \frac{\sum_i^p \sum_j^m C_{i,j} e_j}{\sum_j^m e_j} \quad (3)$$

where $C_{i,j}$ is the element in matrix C in position (i,j). The final weight for the i-th variable w_i is calculated using:

$$w_i = \frac{im_i}{\sum_i^p im_i} \quad (4)$$

with the sum of w_i equals to 1.

Entropy weighing method estimates indicator weights based on the disorder degree of an indicator, also referred to as information entropy. An indicator with higher information entropy is equivalent to its higher variation and greater contribution to the whole system, leading to a larger weight. Entropy information is the quantitative index denoting to this concept. The entropy information e_j of the j-th indicator is computed using:

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln(p_{ij}) \quad (5)$$

where m is the total number of observations, and $k = 1/\ln(m)$. p_{ij} is the proportion of the i-th observation on the j-th indicator and is obtained by:

$$p_{ij} = \frac{Z_{ij}}{\sum_{i=1}^{m} Z_{ij}} \quad (6)$$

Therefore, the weight for the i-th indicator w_i can be acquired by:

$$w_i = \frac{1 - e_i}{k - \sum e_i} \quad (7)$$

All the indicator weights were calculated from year 2000 to 2015, and the final weights of each indicator is obtained from the arithmetic means over the study period.

2.2.4. EVI computation and classification

The final ecological vulnerability index for each year during the study period is calculated as:

$$EVI = \sum_i^n wg_i \times EVI\_sys_i \quad (8)$$

where wg_i and EVI_sys_i are the global weight and ecological vulnerability of the i-th system, and n is the total number of systems. EVI_sys_i is acquired using:

$$EVI\_sys_i = \sum_j^m wl_i \times Z_i \quad (9)$$

where wl_i and Z_i are the local weight and standardized data for the j-th indicator, respectively, and m is the total number of indicators in the i-th system.

In order to achieve a basic generalization for the EV over the study area and provide more intuitive knowledge for decision making, EVI values are often graded into several categories showing the degree of the EV. In this study, Jenks natural breaks (Jenks, 1963) method is applied to classify continuous EVI values into five levels: potential ($EVI \leq -0.83$), light ($-0.83 < EVI \leq -0.38$), moderate ($-0.38 < EVI \leq 0.02$), heavy ($0.02 < EVI \leq 0.36$), and very heavy ($EVI > 0.36$).

3. Results

3.1. Final weight to each indicator

Table 3 shows the final global and local weights for each indicator and sub-system. The weights can reflect the significances of indicators or sub-systems in the whole EVI assessment framework. Based on the global weights of four sub-systems, the land resources sub-system plays the most important role with the highest weight. All five vegetation parameters establish similar significances and the total weight of vegetation parameters sums up to 0.2966, which indicates that vegetation is the dominant driver in EV across the QTP. More flourishing green vegetation is efficient in water and soil conservation and climate adjustment, leading to a higher ecological stability. The social economic sub-system, reflecting anthropic pressures on the environment, shows the least significance in the assessment framework. This is probably because the QTP is less explored by human beings and it is one of the least urbanized regions in the world.

Table 3
Final weights for each variable.

Systems	Global Weight (wg_i)	Indicators	Local Weight (wl_i)	Overall Weights
Land Resources	0.3391	LAI	0.1719	0.0583
		FVC	0.1758	0.0596
		GPP	0.1752	0.0594
		NDVI	0.1760	0.0597
		FAPAR	0.1756	0.0596
		LULC	0.1255	0.0426
Hydro Meteorology	0.2697	ET	0.1418	0.0382
		Albedo	0.2128	0.0574
		Precipitation	0.1164	0.0314
		Temperature	0.2653	0.0716
		distance to water	0.2637	0.0711
Topography	0.2583	Elevation	0.4231	0.1093
		Slope	0.3241	0.0837
		Aspect	0.2529	0.0653
Social Economics	0.1329	distance to roads	0.0880	0.0117
		Population	0.4652	0.0618
		GDP	0.4468	0.0594

3.2. Spatial patterns of EVI

The distributions of continuous EVI and EVI levels are presented in Figs. 3 and 4, respectively. Throughout the study period, EVI values varied from −2 to 1.5, with higher values indicating more vulnerable ecosystems. Generally, EVI increased from the eastern to the western

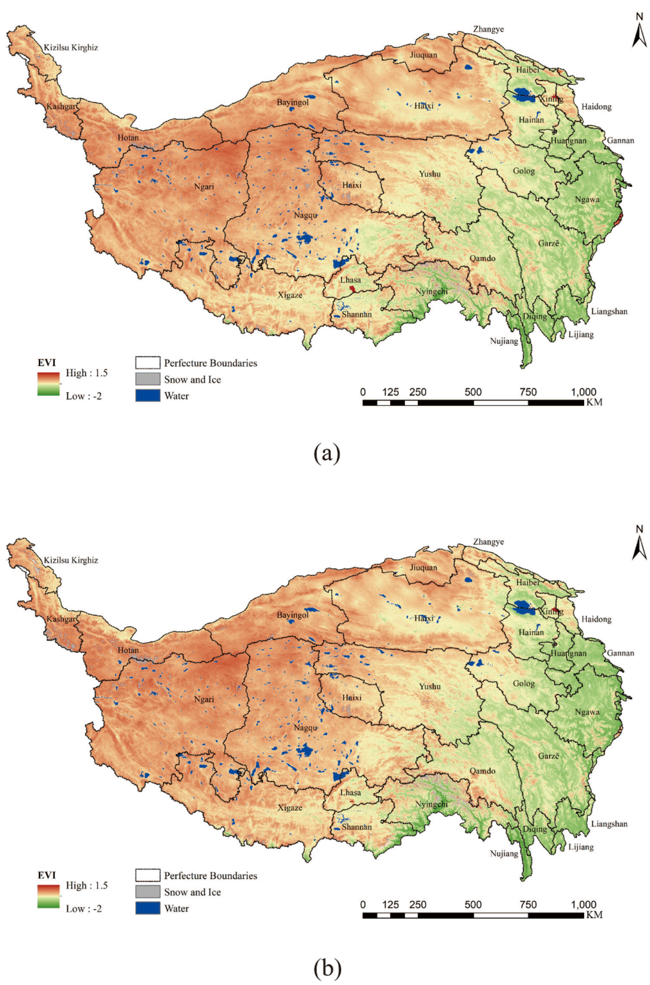

Fig. 3. Continuous EVI distributions in (a) 2000 and (b) 2015.

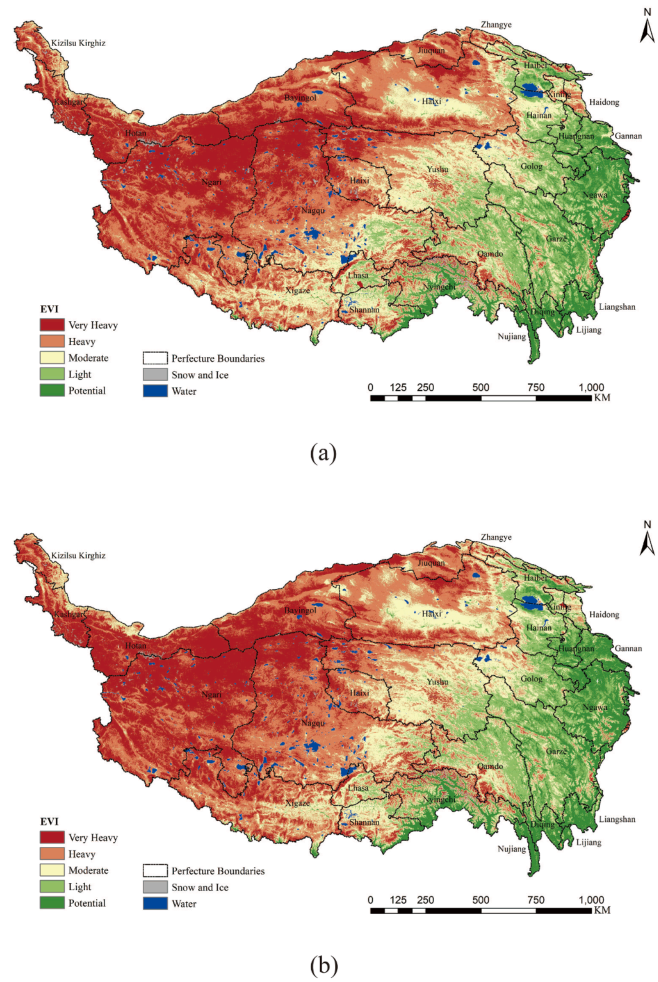

Fig. 4. EVI level distributions in (a) 2000 and (b) 2015.

QTP, with the highest values in northern Ngari prefecture, which may be resulted from low vegetation coverage, high altitudes, and severe climate conditions. Moreover, high EVI values also appeared around large cities including Lhasa and Xining. This may be caused by the unbalanced economic development across the QTP, which was reflected in huge population and GDP in big cities and extremely low values over remote regions. Similar patterns of EVI distribution were spotted in Figs. 3 and 4. However, the southwestern regions of the QTP experienced obvious EVI increase. Among all five levels, the moderate level experienced the greatest variations, while other categories shifted slightly within a small range.

Fig. 5 shows the proportions of each EVI category from 2000 to 2015. The proportions of the EVI levels showed stable annual variations. Over the study period, regions with “heavy” vulnerability accounted for the largest proportion over 30%, while regions with “potential” vulnerability accounted for the least proportion less than 10%. Both “potential” and “very heavy” categories experienced a growing trend. Due to regions with “moderate”, “heavy”, and “very heavy” vulnerabilities accounted for almost 80% of the entire study area, the EVI level across the QTP can be defined as “heavy”. Therefore, actions should be taken immediately in construction of ecological security barriers of the QTP environment.

3.3. Temporal patterns of EVI

Mann-Kendall (MK) trend test (Forthofer and Lehnen, 1981; Mann, 1945; Williamson et al., 2015; Yang et al., 2018; Yuan et al., 2007) was performed on continuous EVI values from year 2000 to 2015 to identify

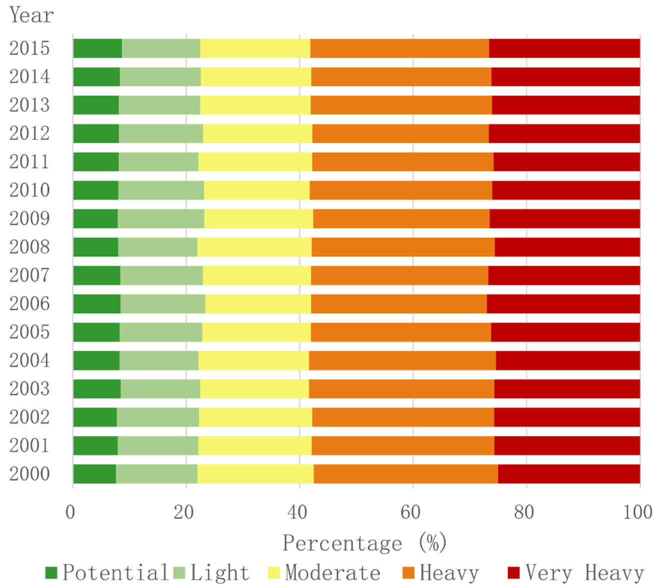

Fig. 5. Proportions of each EVI category from 2000 to 2015.

regions where significant EVI happened (Fig. 6). The significance level of 0.05 was adopted, which indicated the null hypothesis of no trend should be rejected when the standard normal test statistic $|Z| > 1.96$. Regions with significant increasing vulnerability mainly distributed in the western parts of the QTP, accounted for 10.43% of the total study area. Regions with significant decreasing vulnerability occupied 7.38% of the total area, mostly distributed in Qinghai province, northeastern of the study area. Tibet was suffering from serious deteriorate in EV, meanwhile, EV in Qinghai was significantly reduced. This is in accordance with the vulnerability assessment in mainland China performed by Zhao et al. 2018, which indicates Tibet is the most vulnerable province in mainland China, and Qinghai is the second with slightly lower vulnerability than Tibet. Generally, Tibet has higher altitude, lower temperature and precipitation compared to that of Qinghai, which makes environment in Tibet more fragile.

In the early 21st century, the State Council and other departments of Chinese government implemented a series of ecological environmental protection programs to construct the ecological security barriers of the QTP. The major programs and their corresponding times of approval are listed in Table 4. A number of eco-environmental protection and

Table 4
Major programs for constructing ecological security barriers of the QTP.

Times of approval	Major Programs
2005	General Plan for Ecological Conservation and Construction of Sanjiangyuan Nature Reserve, Qinghai Province
2007	Ecological Environment Protection and Comprehensive Controlling Plan of Qinghai Lake Basin
2009	Protection and Construction of Ecological Security Barrier Plan in Tibet (2008–2030)
2011	Regional Ecological Construction and Environmental Protection Plan of Qinghai-Tibetan Plateau (2011–2030)

restoration projects were carried out under these programs. Considering the lag between approval, conduction, and effects showing of such programs, the year 2007 was selected as a break point to divide the study period into two periods representing before and after the implementation of eco-environmental projects. Therefore, MK trend analysis was performed respectively from 2000 to 2007 and from 2008 to 2015 to discover the temporal change patterns of EVI (Fig. 7). During these two periods, area with significantly increased EVI accounted for 6.22% and 3.14% of the total area, and regions with significantly decreased EVI accounted for 3.52% and 3.98%, respectively. The results may be inferred that the environment vulnerability of the QTP has been reduced generally. Specifically, a greater area experienced increasing ecological vulnerability during the first period, while more regions went through

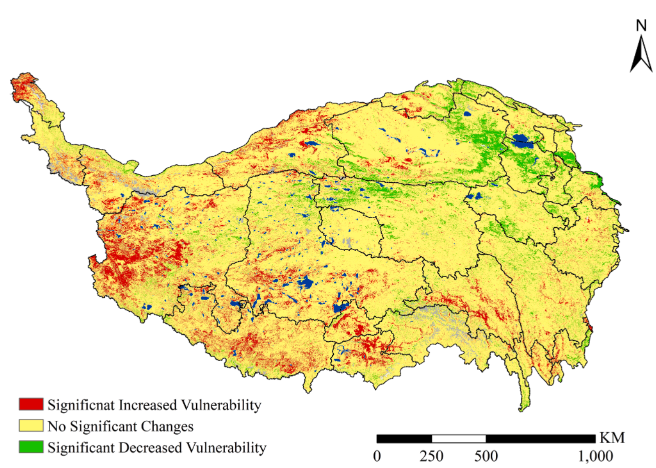

Fig. 6. Regions with no significant EVI changes (in yellow), significant increasing EVI (in red) and significant decreasing EVI (in green) from 2000 to 2015. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

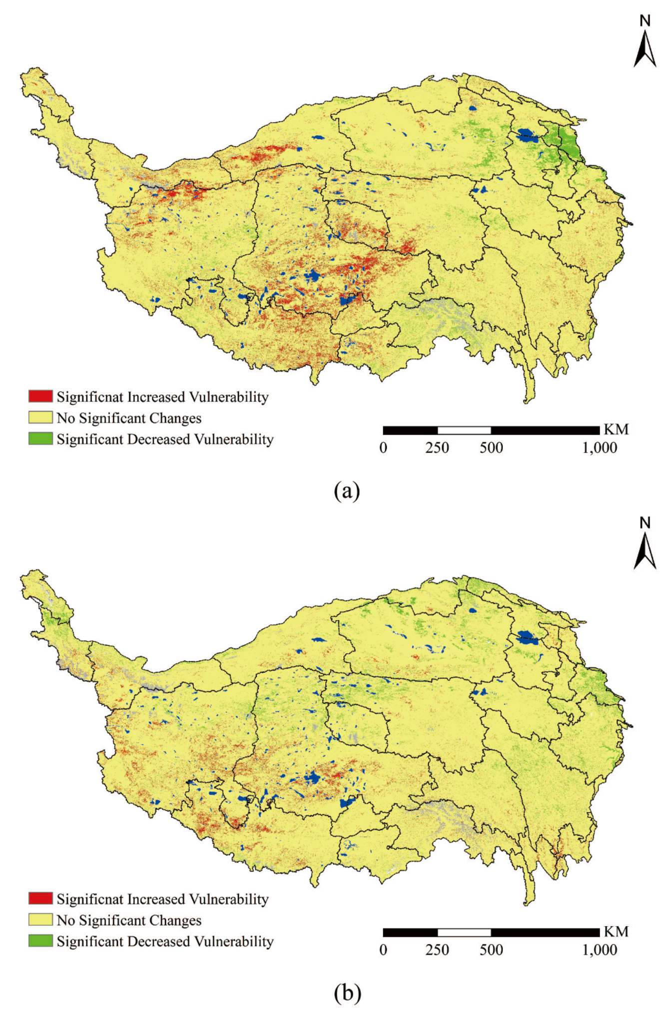

Fig. 7. MK trend analyses during the period from (a) 2000 to 2007; (b) 2008 to 2015.

decreasing vulnerability during the second period after the eco-environmental projects were carried out. The changing trend on central and eastern regions of the QTP was transformed from significant increasing to decreasing, indicating the increasing ecological vulnerability trend during the first period have been successfully terminated and turned to a decreasing trend after the conduction of eco-environmental projects. There were also small proportions of areas, mainly located on the southeastern of QTP, suffering from the opposite trends which were changed from significantly decreasing to increasing ecological vulnerability. The reasons should be further studied using high-resolution remote sensing data.

Fig. 8 shows the percentages of areas with different EVI changing trends per administrative prefecture. Generally, a certain prefecture underwent either significant EVI growth or declination. More than 20% area of Kizilsu Kirghiz, Lhasa, and Ngari experienced EVI growth, Shannan and Xigaze were following next, with almost 20% of the area suffering from significantly increasing ecological vulnerabilities. These prefectures are mainly distributed in Tibet except for Kizilsu Kirghiz, partly located on the far end tail of the QTP, belongs to Xinjiang. In Haidong, Hainan and Zhangye, around 30% area went through significant declination in vulnerability, with barely no significant EVI growth. Prefectures and cities located on the southwestern of the QTP were under considerable increasing vulnerabilities in ecological environment, while the vulnerabilities over the northeastern QTP were greatly reduced, indicating increasing ecological capacity and stability.

4. Discussion

4.1. The spatio-temporal patterns of EVI in the QTP

The overall ecological vulnerability level of the QTP can be evaluated as "heavy", since it occupies the largest area proportions over 30% and the area proportion of "moderate", "heavy", and "very heavy" levels account for almost 80% over the study period (Fig. 5). Spatial distributions of EVI in the QTP establish a remarkable pattern with increasing vulnerability from eastern to western regions, in accordance with the distribution of forest, shrub, alpine grassland, alpine meadow and alpine desert ecosystems. The southeastern QTP has the slightest ecological vulnerability, even though this region has steep slopes which increase the risks for mountain hazards. The warm and humid air from Pacific is transported up the river valleys, bringing in the warm climate and relatively high precipitations of 300 mm to 600 mm. Moreover, this climate condition boosts vegetation growth and production, leading to a less vulnerable ecological environment. Ngari Prefecture, located on the southwestern boundary of mainland China, is suffering from the highest ecological vulnerability in the QTP. The annual precipitation in Ngari, ranging from 140 mm to 320 mm, is relatively low. In addition, the high altitudes, accompanied by low temperatures, can lead to its bare and sparsely vegetated land cover, which is highly vulnerable to natural and anthropic pressures.

With regard to the temporal patterns established by the trend analyses, the ecological vulnerability in Qinghai province experienced more evident reduction compared with that of the Tibet, indicating Qinghai province has higher resilience to natural and anthropic pressures compared with Tibet. Based on EVI trend analyses before and after the implementation of eco-environmental projects, it can also be inferred that the conduction of such projects helps to ease the increasing trends and enhances the decreasing trends of EV. This indicates that eco-environmental protection projects were indeed effectively in ecological restoration of the QTP. Moreover, since eco-environmental conservation and construction plans for Qinghai are adopted earlier, and the ecological environment of Qinghai are more helpful for vegetation growth with lower elevation and better hydrology conditions, eco-environmental projects are more likely to achieve good results in Qinghai than Tibet.

4.2. Driving forces of EVI in the QTP

According to the weights presented in Table 3, the land resources is serving as the most important sub-system for EVI in the QTP, while

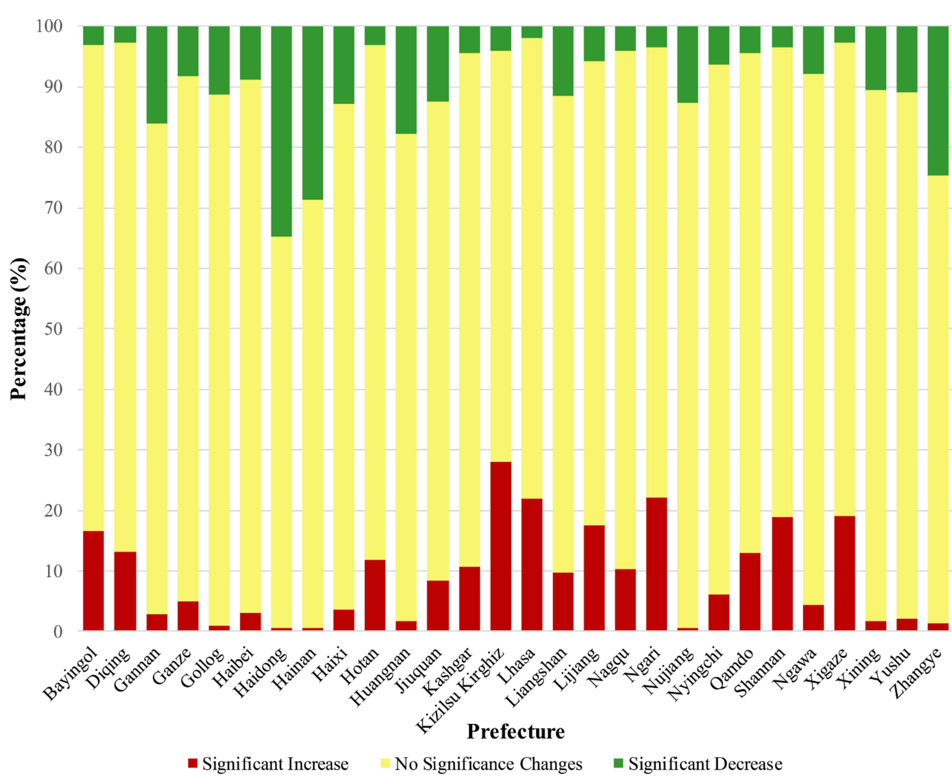

Fig. 8. Percentages of EV changing trends in 28 prefectures.

social economics sub-system accounts for the least significance. The prosperity of green vegetation is the dominant driving force among all selected indicators due to its ecosystem functions in water and soil conservation, biodiversity and climate adjustment. Climate factors, including temperature, precipitation, albedo are basic environmental factors influencing vegetation dynamics (Zhu et al., 2016). Temperature and albedo are more important in determining the ecological vulnerability. In addition, distance to waterway is also an important indicator since water availability is crucial for ecological stability. Moreover, topology factors are the characterizations of the Earth's internal forces. Elevation and slope are evaluated as the most influential factors in this sub-system in that temperature drops with the increasing of altitude, and steep slopes are more likely to bring in mountain hazards. For social economics, population is the most significant driver, since it directly reflects the involvement of human beings. However, under the severe natural condition for human lives, the QTP is less populated compared to other regions in the world. Local governments have also taken controls in urbanization, land exploitation, and tourism development in protecting the QTP from anthropic pressures. Therefore, the social economic indicators weight less in the EVI framework. In general, green vegetation, elevation, slope, and temperature are the most dominant drivers causing the ecological vulnerability in the QTP.

Therefore, the eco-environmental projects conducted by the Chinese government to increase the green vegetation coverage in the QTP is beneficial for ecological stability. Many projects to restore green vegetation by planting trees were carried out during recent years. However, based on ground survey, trees planted in Qinghai have an overall greater survival rates than that of Tibet. On the Tibet Plateau, some trees were dead a year or two after their plantation due to the severe hydrological and meteorological conditions. Under this situation, Tibet government is cultivating trees and other species of vegetation suitable for local environment with great effort in order to raise survival rates of vegetations and enhance the stabilities of the ecological environment. Spatio-temporal analyses of EVI patterns serves as an effective tool in environmental management and decision making, and the details of eco-environment projects can be continuously investigated and revised by local government.

4.3. Advantages and limitations of the proposed method

This study provides an objective and automatic framework for EV assessment and analyses spatial and temporal distribution characteristics over the QTP. The framework is effective in integrating indicators representing natural and anthropic impacts for EV assessment. One advantage of this study is that it introduced sampling adequacy tests to determine the more appropriate weighting approach in generating results with higher credibility. Previous studies evaluating EV across the QTP mostly utilizes subjective weighting methods based on expert opinions (Wang et al., 2008, 2010). However, Moldan and Bilharz (1997) points out it is best to control the maximum number of indicators to 10–12 in that more indicators introduce cognitive stress in the experts. The improved weighting approach also accelerates the weighting process without the expert consulting. Therefore, the improved objective weighting approach is better for this study in dealing with multiple indicators and effectively estimating indicator weights based on the intrinsic features of the indicators compared with subjective methods. In addition, this study analyzed the spatio-temporal EV patterns from 2000 to 2015 and identified the most vulnerable regions, which was seldom provided by previous researches.

However, there are also some limitations of this study. First, aggregating the indicators using an additive method has some drawbacks. Theoretically, to use the additive or multiplicative approach, indicators should be independent of one another and the system should be completely understood, which might never be satisfied in the real situation (El-Zein and Tonmoy, 2015). Therefore, the merit of the results drawn from these methods might be limited. More appropriate approaches should be taken into consideration in future studies. Second, the objective method determines the indicator weights based on the structure of data, which may not necessarily in accordance with the actual importance of a given indicator towards measuring EV (Hinkel, 2011; Tonmoy et al., 2014). Therefore, subject weighting method can be applied when the ecosystem is well understood. Third, the QTP is a relatively large region for EV assessment in that the ecosystem processes are hard to be fully identified. Future studies will be conducted over local regions with significantly increasing vulnerabilities to further explore the causations of the vulnerable ecosystems. Lastly, due to the limitations of data availability, this study did not involve more aspects in livestock migrations and human activities like grazing, which will be taken into consideration for future studies.

5. Conclusion

This study developed an objective and automatic framework for evaluating ecological vulnerability over the Qinghai-Tibetan Plateau under the pressure of mountain hazards, ecosystem degradation, and human economic activities, and analyzed the spatial distribution and temporal variation patterns of EVI from 2000 to 2015. The proposed EV assessment framework synthetically reflected natural conditions and anthropic activities across the QTP and provided an objective and automatic method incorporating indicator weighting, EVI calculation and categorizing procedures. The framework introduced sampling adequacy tests in determining appropriate weighting approach to produce valid results. Spatio-temporal patterns established by this study indicated that the QTP was suffering from heavy ecological vulnerability. Spatial distribution of EVI established similar patterns over the study period, with ecological vulnerabilities increasing from eastern to western regions. EVI over the QTP was highly influenced by vegetation conditions, elevation and temperature. Temporal changes were not huge, with 10.43% and 7.38% of the total area experienced significant increased and decreased ecological vulnerability, respectively. Furthermore, after the conduction of eco-environmental projects, the increasing trend of ecological vulnerabilities was greatly reduced and more regions went through significant decreasing vulnerabilities. For future study, areas with significant increasing EVIs should be investigated with higher spatial resolution data.

CRediT authorship contribution statement

Mu Xia: Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Kun Jia:** Conceptualization, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Wenwu Zhao:** Writing - review & editing, Supervision, Funding acquisition. **Shiliang Liu:** Writing - review & editing, Supervision. **Xiangqin Wei:** Writing - review & editing. **Bing Wang:** 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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Appendix A. Supplementary data

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