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Dynamic vulnerability of ecological systems to climate changes across the Qinghai-Tibet Plateau, China

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ABSTRACT

At present, climate change has brought huge challenges to vegetation and ecosystems. As the Qinghai-Tibet Plateau (QTP) is a sensitive area of global climate change, the dynamic assessment of its ecological vulnerability is very important. In order to better quantify the relative size of the ecological vulnerability of the QTP, this study starts from the background characteristics and dynamic change process of the ecosystem, by fitting the vegetation index net primary productivity (NPP) and the temperature, precipitation and meteorological elements. The coefficients of autocorrelation multiple linear regression are used to construct an ecological vulnerability model from the three dimensions of "exposure-sensitivity-elasticity" to conduct a dynamic assessment of ecological vulnerability. Based on the evaluation results, from 2000 to 2015, the ecologically fragile areas were mainly distributed in the eastern and central areas of the QTP. The ecological fragility of the western region showed obvious discontinuities, with high and low vulnerabilities staggered. The three ecosystems of forest, grassland, and bare land have significant differences in their ecological vulnerability to climate change, showing a clear positive correlation in the three dimensions of exposure, sensitivity, and resilience, but in terms of the contribution rates of the three dimensions. The performance is relatively similar, and the relative relationship between the three dimensions is relatively balanced. The longitude and precipitation of the sample points have a greater impact on ecological vulnerability and its three dimensions, and the impact of precipitation on ecological vulnerability is more significant than that of temperature. This research provides theoretical support for plateau ecological conservation and ecological security under the influence of global climate.

1. Introduction

The concept of vulnerability was stemmed from the realm of natural disasters and has been applied to disaster management, ecology, public health, climate change, sustainability, etc. (Zhang et al., 2017). Moreover, due to the importance of vulnerability, vulnerability was even considered as part of basic science, becoming the theoretical basis and an important tool for studying climate change and ecosystems. (Downing 2000; Zhang et al., 2017). The changing patterns of projected climate changes in the 21st century potentially have profound impacts on the functioning of Earth's ecological systems (ecosystems) (Garcia et al., 2014; Wu et al., 2015; Seddon et al., 2016; Zhang et al., 2018). It is greatly emphasized to identify ecologically sensitive areas for ecosystem service provision and poverty alleviation (Seddon et al., 2016). Besides, there still stands a critical knowledge gap that how to identify and then prioritize those regions which are most sensitive to climatic variability (Seddon et al., 2016).

Meanwhile, vegetation, as an important component of the Earth system, modulates regional and global climate change by biogeochemical and biophysical feedbacks (Field et al., 2007; Peñuelas et al., 2009;

Abbreviations: QTP, Qinghai-Tibet Plateau.

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Tan et al., 2015; Zhang et al., 2018). In the backdrop of global warming, significant warming processes were observed over the Qinghai-Tibet Plateau (QTP) (Liu and Chen, 2000) with a temperature rise of about 0.4 °C per decade (Dong et al., 2012; Shen et al., 2014). This warming rate is believed to be higher than that in the northern and southern hemispheres as well as over the globe as a whole (Liu and Chen, 2000; Trenberth et al., 2007; Zhang et al., 2018). The QTP has a specific vegetation composition and climate features along with a low degree of human interference (e.g. Piao et al., 2011). In the QTP, intense solar radiation, longer sunshine duration, lower air temperature and pressure, less cloud cover, and discernable seasonal and spatial uneven distribution of precipitation render the QTP one of the major regional driver and amplifier of global climate changes (Liu and Chen, 2000; Dong et al., 2012; Che et al., 2014; Zhang et al., 2018). Therefore, more and more evidences show that vegetation across QTP is of high sensitivity to climate change (Shen et al., 2011; Dong et al., 2012; Che et al., 2014; Zhang et al., 2018). In this sense, it is of great scientific and practical merits in understanding of the dynamic vulnerability of ecological system over the QTP to climate changes and can also provide theoretical references for the evaluation of the ecological vulnerability of other regions over the globe to global changes and hence ecological conservation as well in the backdrop of warming climate.

However, there stand few reports addressing ecological vulnerability to climate changes across the QTP so far. Most previous studies concerned static ecological vulnerability evaluation (Liu et al., 2017; Yao et al., 2018). In addition, although the contents of some studies are dynamic evaluated, they only show slices of ecological vulnerability at different times (Hou et al., 2018). While, Leichenko and O'Brien (2002) argued that the environmental and socioeconomic contexts that influence vulnerability are in a state of continual change (Belliveau et al., 2006). Therefore, vulnerability should be dynamic but not a static state or snapshot in time (Kelly and Adger, 2000; Turner et al., 2003; O'Brien et al., 2004; Belliveau et al., 2006). In other words, ecological vulnerability should be variable and is changing as a process given changing natural environment and human interferences. Dynamic evaluation of ecological vulnerability is critical to understand eco-environment changes and can provide theoretical support for prediction of risks of ecological vulnerability. More than half of the previous related studies addressed future ecological risks and ecological vulnerability. While, <1/3 of the relevant studies are concerning dynamic evaluations of ecological vulnerability (e.g. Jurgilevich et al., 2017). However, recent years witnessed more and more researches addressing dynamic ecological vulnerability evaluation. Therefore, on one hand, studies related to dynamic ecological vulnerability evaluation are in rapid progress; on the other hand, there stand critical scientific issues to be addressed. In this sense, this study takes the dynamic ecological vulnerability in the QTP as a case study, shedding novel light on dynamic ecological vulnerability across frigid highlands.

Vegetation is the major target in dynamic ecological vulnerability evaluation (Xia et al., 2021). Every vegetation indicator has its own strength and limitation. Different choices of vegetation indicators can have direct impacts on ecological vulnerability evaluation. Actually, there stand numerous vegetation indicators such as Normalized Difference Vegetation Index (NDVI) (Zhang et al., 2018; Hou et al., 2020), Enhanced Vegetation Index (EVI) (Seddon et al., 2016; Shammi and Meng, 2021), Leaf Area Index (LAI) (Chang et al., 2018), Net Primary Productivity (NPP) (Klemm et al., 2020), and Gross Primary Productivity (GPP) (Padfield et al., 2017). Wherein, NPP is a key component of the terrestrial carbon cycle and is believed to be the initial step of the carbon cycle in which atmospheric CO_2 is fixed by plants (Schimel et al., 2001; Wang et al., 2016). The responses of NPP to climate change and CO_2 are key processes having the potential to significantly modify the climate-carbon feedback and future atmospheric CO_2 levels (Wang et al., 2016). In this study, we use NPP as the indicator to analyze ecological vulnerability to climate changes across the QTP.

There stand a range of methods used for ecological vulnerability evaluation. Bourgoin et al. (2020) developed a framework to assess ecological vulnerability. Besides, the fuzzy analytic hierarchy process (Guo et al., 2020b; Hou et al., 2020), the principal component analysis (Jin et al., 2021), the integrated system dynamic model (Zhang et al., 2017), and complex network approach (Wang et al., 2020) were also used in dynamic ecological vulnerability evaluation practice. However, the above research methods are mostly analyzed from the perspective of the integrity of the study area and rarely discussed from the perspective of the differences within the ecosystem. Actually, the resilience dynamics and response thresholds of different ecosystem types show different characteristics (Folke et al., 2004). If there are inherent differences in the ecological vulnerability of different ecosystems, the comparison between different ecosystems will ignore the ecological response within the ecosystem. Ecosystem types and dominant species can be identified by land use, and most studies indicate that land use/land cover change is one of the main drivers of terrestrial ecosystem productivity (Li et al., 2021; Zhang et al., 2014).

In this study, we attempt to propose a novel analysis framework to evaluate ecological vulnerability across the QTP. This analysis framework involves a range of techniques and models such as the piecewise linear regression method (Cao et al., 2018) and the multivariable linear regression model (Li et al., 2018), realizing the dynamic evaluation of ecological vulnerability over the QTP. Meanwhile, we also used the regular grid sample (RGS) method (Peng et al., 2014) to identify different ecological subsystems based on land use and land cover types and to evaluate ecological vulnerability for different ecological subsystems. We also investigate different mechanisms behind the responses of ecosystems to climate changes and other external factors and future tendencies.

The objectives of this study: (1) we propose a novel framework to quantify and perform a dynamic evaluation of ecological vulnerability over the QTP; (2) we attempt to describe aspects of the ecological vulnerability for different ecosystems over the QTP in the backdrop of warming climate. In this case, we define different ecosystems based on different land use and land cover types and use the RGS method for dynamic evaluation of ecological vulnerability for different ecosystems due to changing climate. Besides, we also attempt to predict and elucidate the ecological vulnerability of the QTP due to future climate changes. Based on the analysis of this study, we also tentatively provide suggestions for ecological conservation of the QTP in a changing environment with an aim to mitigate ecological degradation and alleviate ecological vulnerability.

2. Data

The NPP datasets are sourced from the National Earth System Science Data Center, China, at http://www.geodata.cn. The NPP datasets are based on the data products of the GLASS (Global Land Surface Satellite) with a spatial resolution of 5 km, the LAI (leaf area index) and the FPAR (Fraction of Absorbed Photosynthetically Active Radiation), and also the ERA-Interim meteorological data (Cui et al., 2016; Yu et al., 2018; Wang et al., 2020). The spatial resolution is also 5 km and the time scale is 8 days. Monthly temperature and monthly precipitation data are also sourced from the National Earth System Science Data Center, China, at http://www.geodata.cn, and the spatial resolution is 1 km. The Digital Elevation Model data (DEM) and land use data are sourced from the ASTER GDEM v3 and the GLOBELLAND30 of the NASA&METI at http://www.globallandcover.com/home.html?type = data (Chen et al., 2014) and the spatial resolution is 30 m (Fig. 1). The study time interval we focus on in this study is during 2000–2015. This article assumes that the land use type at each sampling point does not change.

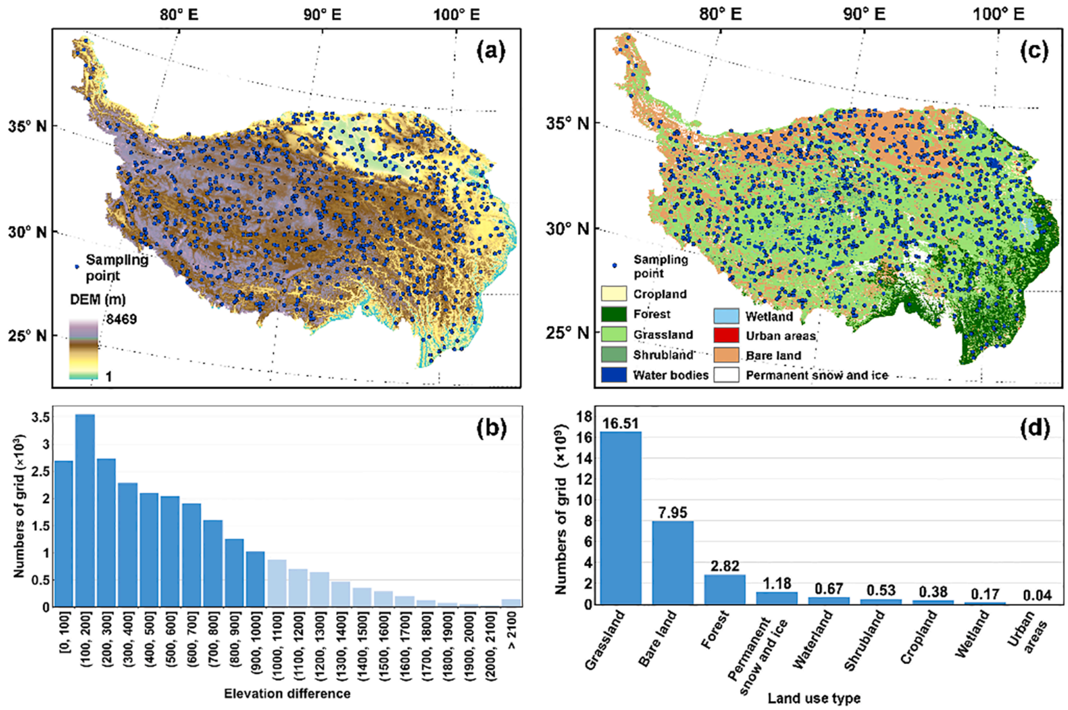

Fig. 1. DEM of the sampling points (a); Histogram of altitude difference based on sampling grid cells with size of 3 km × 3 km (b); Land use types of the sampling point (c); Histogram of land use types over the study region, the QTP (d).

3. Methods

3.1. Regular grid sample (RGS) method

In this study, we use the RGC method in the identification of ecological system types and in the development of the model for ecological vulnerability evaluation (Fig. 2). The sampling method used in this study is similar to the sequential sampling procedure in Statistics (Wald, 1945). The number of the samples is not specified in advance in the sampling procedure, the sampling points that meet the conditions are selected until the sample size is reached (Peng et al., 2014). In order to ensure the uniformity and stationarity of the samples within the study region and minimize the impacts of terrain and topography on sampling results, we limit the altitude difference during sampling. By sampling in 3 km × 3 km sampling grid cells every 0.1°in the study area (Fig. 1b), we counted the altitude difference in each sampling grid cell. As a result, it is appropriate to set the altitude difference to be less than or equal to 1000 m, because if the threshold set here is higher than 1000 m, the screening conditions may be meaningless. On the contrary, a small threshold value will cause most of the sampling points to be concentrated in the central and western part of the QTP, which directly affects the uniformity of the sampling points distribution.

The specific steps of the RGS method are introduced here. Firstly, random points are generated within the study area and these random sample points are used as the center of the sampling region with grids within 3 km × 3 km zone. The screening condition is based on the threshold value of 1000 m. If the conditions are met and the relevant points are accepted sampling points, and one sample will be added to the total number of samples; otherwise, the candidate random point will be discarded and keep the total number of samples unchanged until the total number of samples reaches 1000. The spatial distribution of the final sampling points and their correspondence with DEM and land use types are shown in Fig. 1a and c. It can be seen that the selected sampling points distribute at all altitudes and land use types in the study area. In this case, the representativeness of the sampling points can be well confirmed.

3.2. Screening out the major ecosystem types

Based on the percentage of land use types of the study region (Fig. 1d), we can see that the main land use types in the QTP region are grassland, bare land, and forest. Therefore, here we focus on three types of ecosystems, i.e. grassland, bare land, and forest. The identified ecosystem in this study is defined as the land use types such as grassland, bare land, and forest types with area percentage of greater than 80% to the total area within 3 km of each sample point. For the sample points that do not meet the above conditions, they are also classified as "others" (Fig. 2).

3.3. Multiple linear regression technique

Vegetation changes are of long-term memory feature, i.e. the current state of the vegetation is the combined result of the current climate condition and the properties of the past vegetation condition (De Keersmaecker et al., 2015). Meanwhile, the landscape ecology itself is also of persistence and resistance. Therefore, considering the lagging response to climate changes and the importance of ecosystem persistence in ecological vulnerability, here we apply AR(1) multiple linear regression to fit each sample point and regard NPP as the combined result of temperature anomalies, precipitation anomalies, and past NPP changes. The responses of each ecosystem to climate changes can be defined as:

$$NPP_t = \alpha \times Temp_t + \beta \times Pre_t + \gamma \times NPP_{t-1} + \varepsilon \quad (1)$$

Where NPP_t and $NPP_{t\text{-}1}$ are the standardized NPP anomalies at time *t* and *t*-1, respectively. $Temp_t$ is the standardized temperature anomaly at time *t*. Pre_t is the standardized precipitation anomaly at time *t*. α, β, and γ are the coefficients of the AR(1) multiple linear regression model. In order to avoid the influence of the correlations between meteorological variables, we perform principal components regression (PCR) with the z-values calculated from the monthly mean and standard deviation to determine the relative importance of each element. Based on the significance test, the coefficients of the three variables are obtained (De

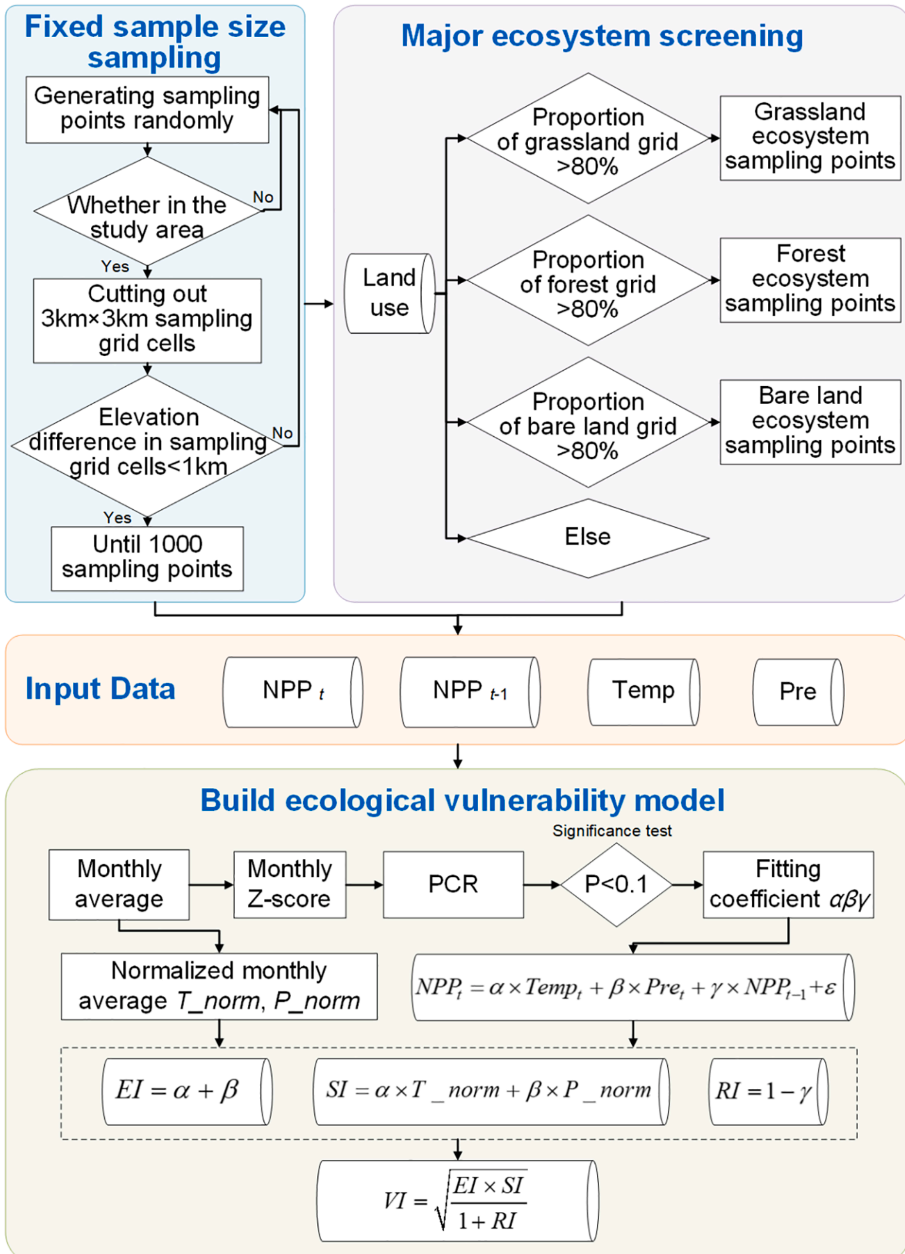

Fig. 2. Working procedure of this current study. (NPP: Net primary productivity anomalies; Temp: Temperature anomalies; Pre: Precipitation anomalies; PCR: Principal Components Regression; T_norm: normalized monthly average temperature anomaly time series; P_norm: normalized monthly average precipitation anomaly time series; EI: Exposure Index; SI: Sensitivity Index; RI: Resilience Index; VI: Vulnerability Index).

Keersmaecker et al., 2015; Seddon et al., 2016). In order to ensure comparability of the model coefficients, α, β, and γ are normalized to be between 0 and 1.

3.4. Ecological vulnerability evaluation model

We attempt to develop an ecological vulnerability index system from the three dimensions of "exposure-sensitivity-resilience" (De Lange et al., 2010). In this study, "exposure" refers to the degree to which the vegetation or ecosystem is influenced by climate change (Loarie et al., 2009), which can be expressed by the rate of climate change. Sensitivity refers to the extent to which the ecosystem may be affected under a certain disturbance or pressure (Weißhuhn et al., 2018). Resilience refers to the ability that one system is back to the baseline state after being disturbed or influenced by external factors (Turner et al., 2003). Exposure, sensitivity, and resilience will all bring about the spatial heterogeneity of ecological vulnerability (Kling et al., 2020).

The coefficients of the multiple linear regression models are all related to the three dimensions of ecological vulnerability. α and β indicate the response or resistance matric to abnormal temperature and precipitation, and the higher absolute α and β values indicate lower resistance to climate changes and vice versa. Positive or negative α and β values indicate the positive and negative responses of vegetation to climate changes (De Keersmaecker et al., 2015). γ quantifies the similarity of vegetation status between two vegetation conditions, which is the memory effect of the ecosystem itself. The larger γ means that the ecosystem needs longer time to restore to balance, that is, it is in negative correlation with the resilience dimension. Therefore, in this study, the coefficients corresponding to temperature and precipitation anomalies are used to characterize exposure and sensitivity (Seddon et al., 2016), and resilience can be characterized by autoregressive fitting coefficients related to vegetation restoration time and persistence (Simoniello et al., 2008; Dakos et al., 2012), being calculated from the fitting coefficients at the previous time (Carpenter et al., 2011). In addition, with reference to the definition and correlation of exposure, sensitivity, resilience and ecological vulnerability, the model for ecological vulnerability is as follows (Li et al., 2018):

$$EI = \alpha + \beta \tag{2}$$

$$SI = \alpha \times T\_norm + \beta \times P\_norm \tag{3}$$

$$RI = 1 - \gamma \tag{4}$$

$$VI = \sqrt{\frac{EI \times SI}{1 + RI}} \tag{5}$$

Wherein, *EI* is the Exposure Index; α and β are the fitting coefficients of temperature and precipitation anomalies, respectively; *SI* is the Sensitivity Index obtained by the weighted summation of the standardized meteorological anomalies and related fitting coefficients (Seddon et al., 2016). $T_{\_norm}$ and $P_{\_norm}$ represent the mean values of the normalized temperature and precipitation anomaly series, respectively; *RI* represents the Resilience Index, and γ is the approximate value of $NPP_{t\text{-}1}$ in Eq.(1). *VI* is the Vulnerability Index, and *EI*, *SI*, and *RI* correspond to the exposure, sensitivity, and resilience indexes in Eqs. (2), 3, and 4, respectively. For the sake of the comparative analysis between exposure, sensitivity, and resilience, we standardize *EI*, *SI*, *RI*, and *VI*.

3.5. Analysis of influencing factors

In order to identify the influencing factors of ecological vulnerability, we take the longitude, latitude, and altitude related to the location of the sample points, as well as the annual average values of the air temperature and precipitation at the sample points, as the variables in the analysis of the relations between EI, SI, RI, VI and above-mentioned influencing factors. In addition, the ecosystem may have discontinuous ecological responses to external influencing factors. Given a certain critical threshold, the ecological responses to external influencing factors will be subject to a shift to another response state (Groffman, et al., 2006). We quantified relations between the above-mentioned five influencing factors and EI, SI, RI, and VI by the piecewise linear regression model.

4. Results

4.1. Spatial patterns of the ecological vulnerability across the QTP

Before calculating ecological vulnerability, it is necessary to have a basic understanding of the temporal-spatial distribution characteristics of the input data: we obtained the annual average NPP, air temperature, and precipitation and analyzed related temporal-spatial patterns as shown in Fig. 3. We observed higher air temperature and larger precipitation in southeastern QTP and air temperature and precipitation are decreasing from southeastern QTP to northwestern QTP (Fig. 3). NNP follows a similar spatial pattern when compared to those of air temperature and precipitation with the largest annual average NPP of 357 $gC/m^2\cdot d$. Meanwhile, NPP and air temperature are increasing from 2000 to 2015 with similar changing patterns (Guo et al., 2020a). Moreover, fluctuations of NPP and air temperature are similar, showing remarkable impacts of air temperature changes on NPP variations.

Based on Fig. 2, we map the spatial pattern of EI, SI, RI, and VI across the QTP (Fig. 4). It can be seen from Fig. 4 that the EI is the highest in the northeastern part of the QTP, and is followed by the southeastern part of QTP. Vegetation in the northeastern part of the QTP is mainly dominated by desert and temperate meadows (Zhang et al., 2018), and this kind of vegetation is highly sensitive to climate changes. Vegetation in the southeastern part of the QTP is dominated by the evergreen broadleaf forest and tropical rainforest. Besides, the terrain here is of remarkable difference in elevation. Temperature changes have profound impacts on vegetation changes and hence higher EI (Zhang et al., 2018). We observe higher SI in the eastern part of the QTP when compared to SI in the western part of the QTP, while higher SI in the southeastern part

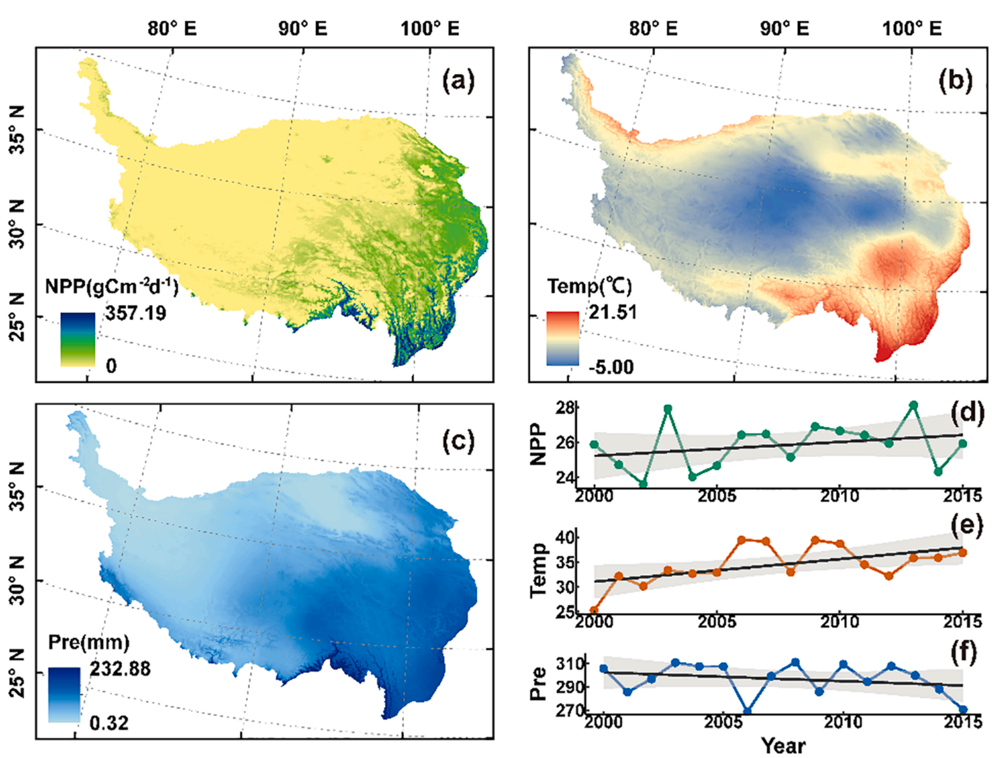

Fig. 3. Spatial pattern of annual average NPP (a, d), air temperature (b, e) and precipitation (c, f) over the study region, the QTP, during 2000–2015.

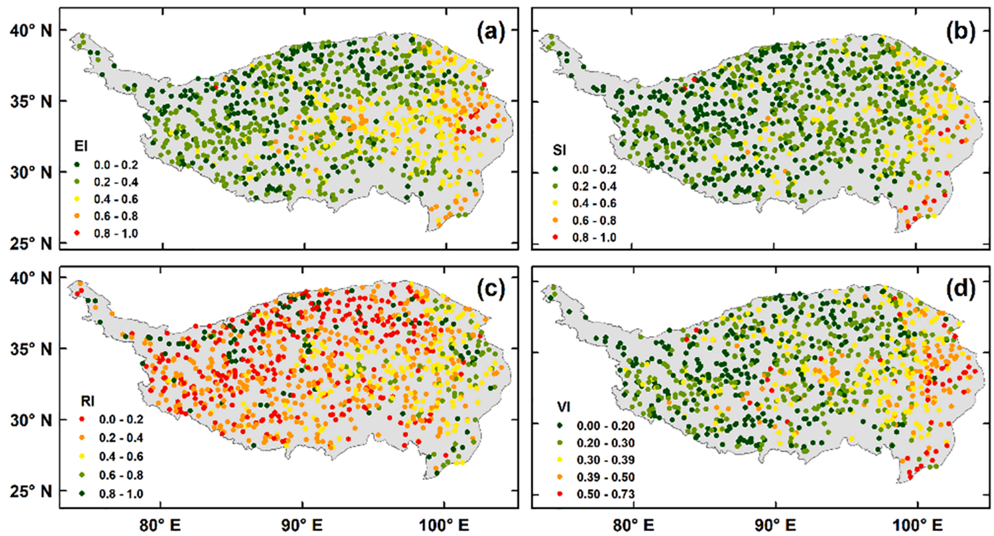

Fig. 4. Spatial pattern of exposure index (EI, a); sensitivity index (SI, b); resilience index (RI, c) and ecological vulnerability index (VI, d) of the sampling points over the QT.

of the QTP than the northeastern part of QTP. Eastern QTP is dominated by Alpine shrub meadows and western QTP is dominated by Alpine steppe (Zhang et al., 2018). Higher intensity of human activities can be found in eastern QTP than western QTP (Guo et al., 2020a) and hence higher SI in eastern QTP than western QTP. RI shows obvious spatial heterogeneity in the northwestern QTP with most of the sample points with RI<0.4 and greater than 0.8, while the overall stronger flexibility and resilience of the ecological system in eastern QTP. Vegetation in eastern QTP is mainly meadow, shrub, and forests, and vegetation in western QTP is mainly the Alpine steppe (Zhang et al., 2018). Besides, higher soil moisture can be found in eastern QTP than in western and northwestern QTP (Fan et al., 2019). Moreover, desert is dominant in the northwestern QTP. All these factors combined to trigger higher RI in eastern QTP than in northwestern QTP. Meanwhile, VI is similar to EI in spatial patterns. Higher VI can be found in central and eastern QTP than in western QTP. The ecological vulnerability of the eastern and central areas of the QTP to climate change is higher than that of the western QTP. Although vegetation in the western QTP is less resilient and adaptable, lower exposure and lower sensitivity combined to drive lower ecological vulnerability in the western QTP.

4.2. *Comparison of ecological vulnerability*

The major ecosystem types were screened based on all convergent sample points, including 509 grassland ecosystem sample points, 152 bare land ecosystem sample points, and 16 forest ecosystem sample points (and 240 other ecosystems). The three dimensions of ecological vulnerability, i.e. exposure, sensitivity, and resilience, among the major ecosystems are shown in Fig. 5. It can be seen from Fig. 5 that there stand profound differences among the three major ecosystems ($p < 0.0001$),

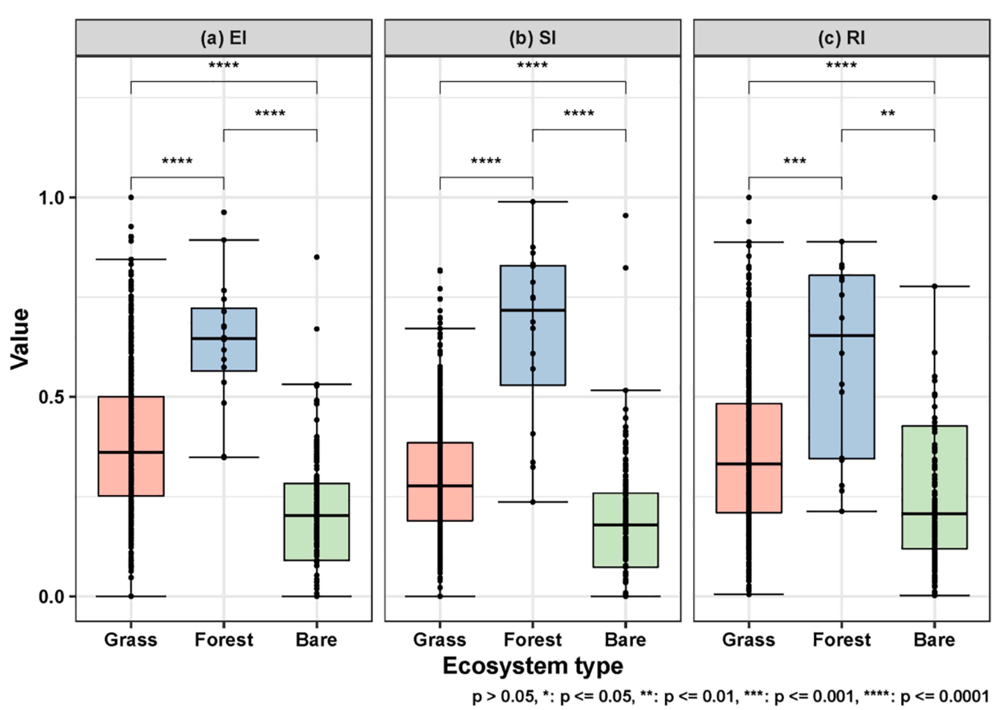

Fig. 5. Boxplots for EI (a), SI (b) and RI (c) of the grassland, forest and bare land over the QTP.

except for the RI of forest and grassland, forest and bare land.

The three dimensions of exposure, sensitivity, and resilience of each ecosystem are in obvious positive correlations, indicating that given the weak adaptability and resilience of the ecosystem, the exposure and sensitivity of the ecosystems to the increased air temperature and increased precipitation are also relatively low, and vice versa. As a result, the ecological environment in each region of the QTP could maintain a stable state. The EI, SI, and RI of the forest ecosystem are the highest among the three ecosystems and most of them are higher than 0.5 with a smaller inter-quartile range of EI, indicating little changes in the exposure of the forest ecosystem. The RI of the forest ecosystem has poor stability, because "ecological memory" plays an important role in its response process to external influencing factors. The scale, frequency, and degree of past or recent disturbances, the interactions of multiple disturbances, and the response of different species to climate changes will affect the resilience of the forest ecosystem (e.g. Johnstone et al., 2016). The EI, SI, and RI of the bare land ecosystem are the lowest among the three ecosystems. The inter-quartile ranges of the RI are relatively large, which means the coexistence of the high and low values of the RI of the bare land ecosystem on the QTP. This finding implies enhancement of the resilience of arid ecosystems due to warming climate over the QTP (Yu et al., 2021). Or two alternate stable states occur, enhancing the resilience of bare land ecosystems (D'Odorico et al., 2005; Borgogno et al., 2007). The EI, SI, and RI of the grassland ecosystem are between the other two ecosystems analyzed in this current study. The RI may be closely related to the species diversity of the ecosystem (Pfisterer and Schmid, 2002; Geng et al., 2019), and overgrazing does not reduce the stability of the grassland ecosystem (Ganjurjav et al., 2019).

4.3. Relations amongst exposure, sensitivity and resilience

Fig. 6 shows balanced relationships amongst all convergent sample points and the exposure, sensitivity, and resilience of the three ecosystems considered in this study. In other words, these three ecosystems considered in this study have small differences in the relative contribution rates of the three dimensions. The scatters in the ternary diagrams are roughly distributed around the center point. At the center of the kernel density, EI accounts for about 30% to 40%, SI accounts for about 20% to 40%, and RI accounts for about 20% to 40%. To a certain extent, this confirms the rationality that the coefficients of the three independent variables in the ecological vulnerability function (Eq. (5)) are all 1.

In the ternary diagrams of grassland and bare land ecosystems, the wide distribution of scatters indicates that the structure of these ecosystems is more diverse and there are many unstable states. The distribution of scatters presents an ellipse, and the major axis of the ellipse is almost perpendicular to the RI axis. This shows that RI fluctuates greatly, and the main dimension affecting the ecological vulnerability of grassland and bare land can possibly be explained by resilience.

Forests are quite different from the other two ecosystems. When compared to the kernel center of the ternary diagram of the grassland and bare land ecosystems, the core density center of the forest ecosystem shifts slightly to the sensitivity index. At the center of its kernel density, EI accounts for about 25% to 45%, SI accounts for about 30% to 40%, and RI bout 20%~40%, which is closer to the center of the triangle. This may be due to differences in the response patterns of different vegetation types to climate change, in which the internal sensitivity of forest ecosystems is higher and is more susceptible to climate change (Anjos et al., 2018). Accordingly, if ecological degradation occurs or land use types change, it may lead to a "flow" in the proportion of three dimensions: RI moves to both sides, EI gradually increases, and SI slightly decreases.

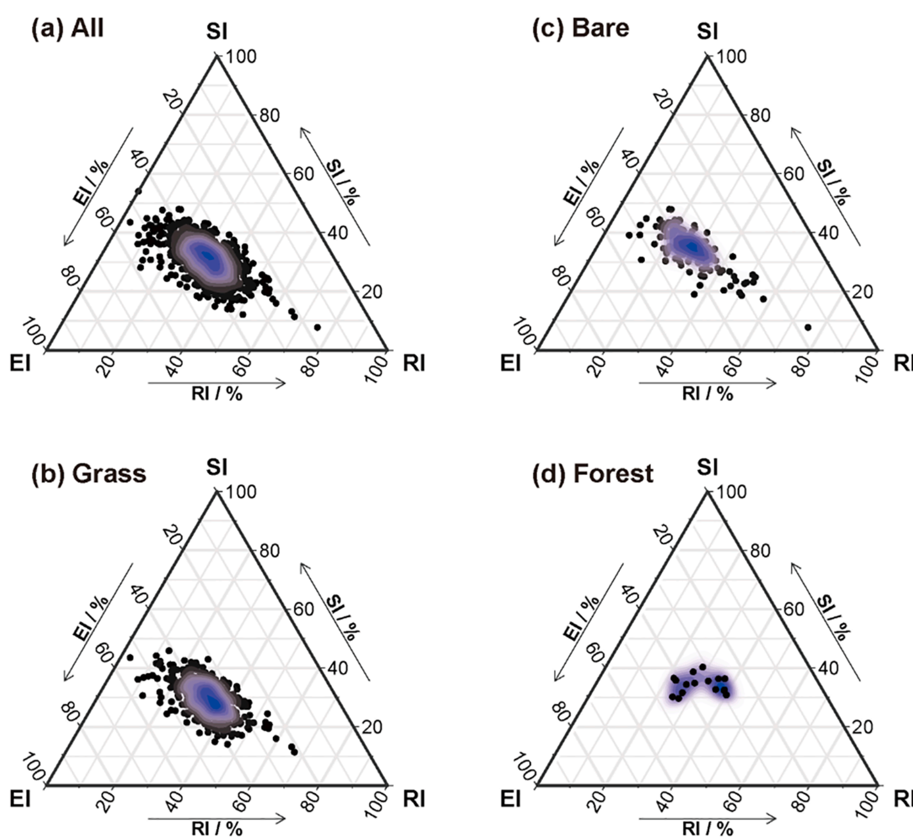

Fig. 6. Relationships between EI, SI and RI and all sample points (a), grassland ecosystem sample points (b), bare land ecosystem sample points (c), and forest ecosystem sample points (d).

4.4. Influencing factors behind ecological vulnerability

The piecewise linear regression model results of nonlinear fitting show obvious piecewise characteristics (Fig. 7). We find that the breakpoints are respectively at latitude 28.6°N and 33°N, longitude 97°E, altitude 3744 m, the average annual air temperature is 26-40℃/a, and the annual average precipitation is 515–650 mm/a (Table 1). Besides, there stands a positive correlation between longitude, average precipitation and EI, SI, RI, VI ($p < 2.2e^{-16}$), and a negative correlation between latitude and EI, SI, RI, VI, which further clarifies the area range with high ecological vulnerability in the southern region of QTP.

As the altitude increases, EI, SI, RI, VI first increase and then decrease. Although the slope and intercept of the nonlinear regression model for the grassland and bare land ecosystems are different, the breakpoints are basically the same, i.e. about 3500 m in altitude (Fig. 8). It shows that the response processes of these two ecosystems, such as exposure, sensitivity, and resilience, will change at the same time after reaching the threshold. Due to few sample sites, the forest ecosystem will not be analyzed. The existence of the threshold means that changes in vertical zoning or non-climatic factors such as bacteria may lead to changes in the structure of the ecosystem (Geng et al., 2019; Hu et al., 2020), which indirectly affects the response process of the ecosystem. It also helps to arouse human concerns for the area of the QTP with an altitude of 3400 ~ 3800 m. In addition, the average precipitation has a more significant correlation with the ecological vulnerability than the annual average temperature, indicating that the increase in ecological vulnerability caused by precipitation may be more sensitive than by temperature (Liu et al., 2013).

4.5. Sampling technique and models

The main advantage of the sampling technique used in this research is to minimize the interference and impact by abnormal data and to reduce the uncertainty through the selection of sample sampling points, the selection of main ecosystems, and the further eliminate abundant sampling data based on the fitting coefficients of the models. However, we do have certain subjectivity in the selection threshold of sample points, such as selecting an altitude difference of 1000 m, sampling range of 3 km × 3 km, and the main ecosystem satisfying land use types accounting for more than 80%, etc. These may affect the portability between different regions, and specific analyses and adjustments need to be made according to the characteristics of the ecological environment of the region itself.

The ecological vulnerability in this study focuses on highlighting the dynamic change process of the ecosystem, analyzing relative ecological vulnerability rather than absolute ecological vulnerability, so its temporal and spatial distribution characteristics may be different from existing studies (e.g. Xia et al., 2021). Taking the bare land ecosystem as an example, the climate is arid and the soil quality is poor, and it is basically in the final stage of ecological degradation. The absolute vulnerability of bare land ecosystems calculated by using methods such as index weights is generally higher than that of forest and grassland ecosystems. However, from a practical point of view, even under conditions of a harsher ecological environment, the ecological pattern and

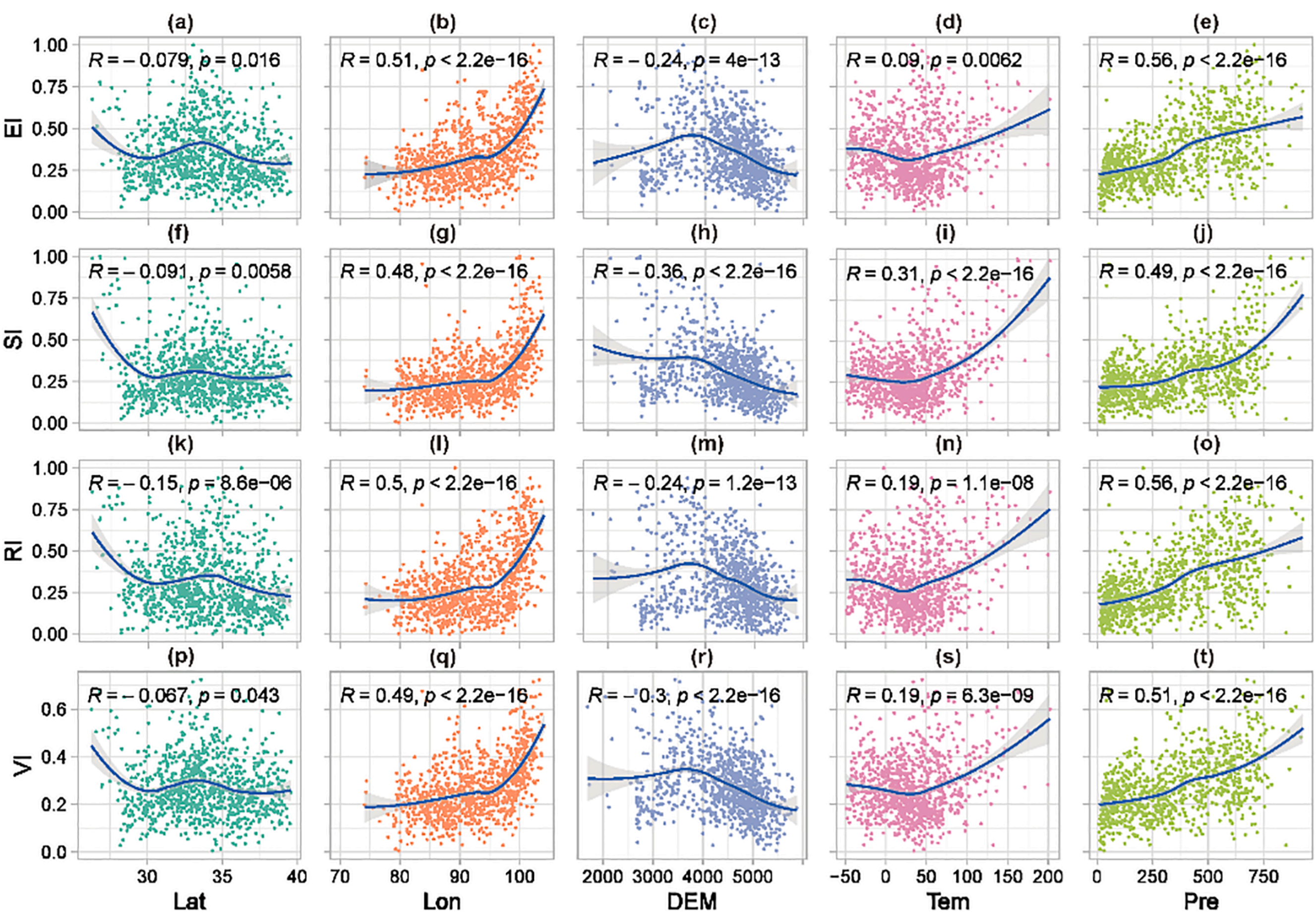

Fig. 7. Changes of exposure index (EI), sensitivity index (SI), resilience index (RI), and ecological vulnerability index (VI) with latitude, longitude, altitude, average temperature, and average precipitation. (Lat.: the latitude of the sample point (unit: °); Lon.: the longitude of the sample point (unit: °): DEM: DEM data corresponds to the altitude at the sample point (unit: m); Tem.: the annual mean value of the temperature time series (unit: ℃/a); Pre.: the annual mean value of the precipitation time series at the sample point (unit: mm/a)).

Table 1
Threshold values of stepwise linear regression models for sampling points.

	Lat.		Lon.	DEM	Tem.	Pre.
EI	28.639***	33.603***	97.853***	3744.193***	28.235***	-
SI	28.644***	32.853***	97.249***	3743.801	40.9*	648.423***
RI	28.693***	34.481***	97.278***	3743.965***	26.752***	515.059***
VI	28.643***	33.033***	97.494***	3745.479**	37.811**	647.042***

***: $p < 0.001$; **: $p < 0.01$; *: $p<=0.05$. Lat.: latitude; Lon.: longitude; DEM: digital elevation model; Tem.: temperature; Pre.: precipitation.

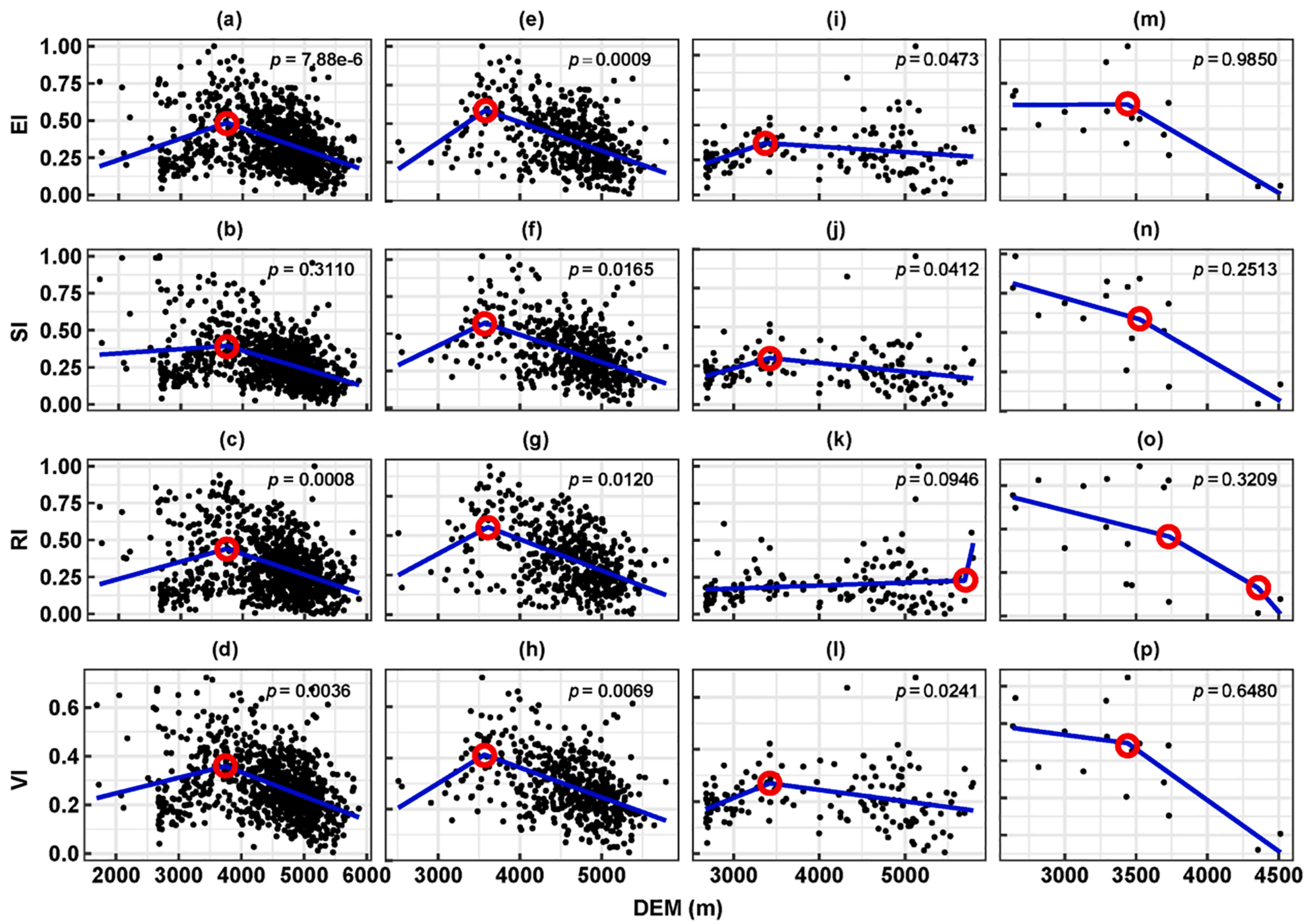

Fig. 8. The elevation breakpoints of different ecosystems by piecewise linear regression. Fig. 8a, d show the piecewise linear fitting result of all sampling points; Fig. 8e, h show the piecewise linear fitting result of the grassland ecosystem sampling points; Fig. 8i, l show the piecewise linear fitting result of the bare land ecosystem sampling points; Fig. 8m, p show Piecewise linear fitting results for the sampling points of the forest ecosystem.

ecological process of bare land may not have a significant impact. Therefore, overemphasizing the absolute vulnerability of bare land ecosystems actually lacks reference significance for improving the ecological status and proposing prevention and control measures.

From the perspective of ecological vulnerability models, considering that the QTP ecosystem is still dominated by natural evolution and the degree of human activity disturbance is low (Zheng et al., 2000; Zhou et al., 2011), this study did not fully consider the impact of human activities on ecological vulnerability. With the further development and implementation of urbanization and ecological protection measures in the QTP (Bao, 2006), ongoing research can be combined with other land use types within the sampling range of the main ecosystem, or explore the ecological vulnerability changes caused by human activities such as construction land and grazing. What's more, appropriately add human factors to the ecological vulnerability model to improve it, such as the construction of ecological protection areas, returning grazing to grassland, urbanization, and patterns.

4.6. Adaptive strategy

Studies have shown that once the balance of the ecosystem is broken, it may lead to sudden ecological changes (Li et al., 2017). Therefore, it is vital and urgent to take adaptive countermeasures against the ecological vulnerability of the QTP in time.

In summary, in order to maintain the ecological balance of the QTP, we put forward some suggestions and countermeasures for the QTP as follows:

1. For bare land ecosystems, we focus on enhancing its resilience in response to possible changes in the ecological pattern such as the transition from permafrost to bare land. It is necessary to treat large areas of bare land and desert, and strictly control the expansion of desertification to prevent the connection of discontinuous bare land.
2. Due to the poor stability of the RI of forest ecosystems, we can increase the species diversity of the forest ecosystem and connect flaky forests by planting artificial forests to change the current

situation of simple ecological structure and forest fragmentation. In addition, due to the high exposure and sensitivity, it is necessary to improve the real-time monitoring level of meteorological elements such as temperature and precipitation in the QTP.

In the case of exceeding the specified threshold, extreme weather events, fires, or meteorological and hydrological disasters, ecological warnings are issued in a timely manner to help local government personnel to be vigilant and avoid the imbalance of the forest ecosystem.

3. For large areas of grassland ecosystems, the exposure, sensitivity, and resilience are maintained at a stable and balanced level. Only natural factors may not cause serious ecological and environmental problems. It is recommended that governments could focus on areas with an altitude of 3400 ~ 3800 m to reduce the negative impact of human activities and avoid large-scale grassland degradation caused by the imbalance of the ecosystem.

5. Conclusions

We developed an ecological vulnerability model based on three dimensions of "Exposure-Sensitivity-Resilience" by fitting the coefficients of the autocorrelation multiple linear regression of NPP, temperature, and precipitation. We attempt to evaluate ecological vulnerability from a dynamic viewpoint and we obtain some interesting and important findings as follows:

(1) We successfully map the ecological vulnerability over the QTP. During the period from 2000 to 2015, regions with ecological vulnerable are found mainly in the eastern and central areas of the QTP. The ecological vulnerability of the western regions of the QTP is subject to obvious discontinuities in spatial sense and regions with high and low ecological vulnerabilities are spatially interchangeable.

(2) Responses of the ecological vulnerability of forest, grassland, and bare land ecosystems to climate change are in significant differences. Each ecosystem has significant positive correlations in the three dimensions of exposure, sensitivity, and resilience. Besides, the values of EI, SI, RI show that forest ecosystem > grassland ecosystem > bare land ecosystem, and the resilience of forest and bare land ecosystem is unstable. However, the contribution of EI, SI, and RI to ecological vulnerability is similar.

(3) The five influencing factors considered in this current study such as longitude, latitude, altitude, average temperature, and precipitation are in a piecewise linear correlation with EI, SI, RI, and VI. The breakpoints of the same influencing factors are basically the same, and precipitation has a more significant correlation with ecological vulnerability than temperature.

(4) We also propose the countermeasures about how to enhance mitigation of ecosystems to changing climate. Bare land ecosystems can improve their ecological resistance through measures such as desertification control to constrain the expansion of desertification. Forest ecosystem can increase its resilience by increasing species diversity and improving forest fragmentation, strictly control ecological thresholds, and timely issue of ecological warnings to deal with high exposure and high sensitivity. The natural factors of the grassland ecosystem may not cause serious ecological and environmental problems, and the negative impact of human activities at the altitude of 3400 ~ 3800 m can be mainly prevented.

CRediT authorship contribution statement

Qiang Zhang: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources. **Ruyue Yuan:** Conceptualization, Data curation, Formal analysis. **Vijay P. Singh:** Writing – review & editing. **Chong-Yu Xu:** Writing – review & editing. **Keke Fan:** Writing – review & editing. **Zexi Shen:** Writing – review & editing. **Gang Wang:** Writing – review & editing. **Jiaqi Zhao:** Writing – review & editing.

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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