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Original Article

Simulation of critical transitions and vulnerability assessment of Tibetan Plateau key ecosystems

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Abstract: Critical transitions in ecosystems may imply risks of unexpected collapse under climate changes, especially vegetation often responds sensitively to climate change. The type of vegetation ecosystem states could present alternative stable states, and its type could signal the critical transitions at tipping points because of changed climate or other drivers. This study analyzed the distribution of four key vegetation ecosystem types: desert, grassland, forest-steppe ecotone and forest, in Tibetan Plateau in China, using the latent class analysis method based on remote sensing data and climate data. This study analyzed the impacts of three key climate factors, precipitation, temperature, and sunshine duration, on the vegetation states, and calculated the critical transition tipping point of potential changes in vegetation type in Tibetan Plateau with the logistic regression model. The studied results showed that climatic factors greatly affect the vegetation states and vulnerability of the Tibetan Plateau. In comparison with temperature and sunshine duration, precipitation shows more obvious impact on differentiations of the vegetations status probability. The precipitation tipping point for desert and grassland transition is averagely 48.0 mm/month, 70.7 mm/month for grassland and forest-steppe ecotone, and 115.0 mm/month for forest-steppe ecotone and forest. Both temperature and sunshine duration only show different probability change between vegetation and non-vegetation type, but produce opposite impacts. In Tibetan Plateau, the transition tipping points of vegetation and non-vegetation are about 12.1°C/month and 173.6 h/month for the temperature and sunshine duration, respectively. Further, vulnerability maps calculated with the logistic regression results presented the distribution of vulnerability of Tibetan Plateau key ecosystems. The vulnerability of the typical ecosystems in the Tibetan Plateau is low in the southeast and is high in the northwest. The meteorological factors affect tree cover as well as the transition probability that occurs in different vegetation states. This study can provide reference for local government agencies to formulate regional development strategies and environmental protection laws and regulations.

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1 Introduction

It has been widely recognized that the health of key ecosystems has great importance to human welfare (Bryan 1992; Jonston et al. 2018, 2021; Yin et al. 2020, 2021; Burra et al. 2021). The critical transition in complex ecosystems can indicate the radical changes when thresholds are passed at tipping points (Scheffer 2012). The vulnerability assessment plays an important role in regional planning, sustainable development evaluation, global environmental status and development trends assessment (Sasaki et al. 2015). The research of vulnerability originates from the study of natural disasters and extended to the ecosystem, social sciences, geosciences, sustainable sciences, etc., and it is being paid more attention to the theory of sustainable development (IPCC 2014; Berrouet et al. 2018).

It is becoming increasingly clear that many ecological systems have critical thresholds—so-called tipping points—at which the system shifts catastrophically from one state to another (Scheffer et al. 2009; Johnston et al. 2021), implying critical transitions at tipping points in response to altered climate or other drivers (Hirota et al. 2011). Ecological thresholds are usually defined as "points or zones of abrupt change in ecological relationships" (Huggett 2005; Groffman et al. 2006; Ficetola and Denoe¨l, 2009). Since the 21st century, climate change has affected the growth of vegetation and even the structure and function of the system. Many researchers have defined the concepts and types of ecological thresholds and have analyzed the critical transitions at tipping point under global changes (Uehara 2013; Yang et al. 2019).

The main research methods for ecological thresholds and critical transitions at tipping point include statistical analysis, frequency analysis, goal programming method, optimal segmentation theory and regression model analysis (Scheffer et al. 2012; Qian 2014; Gotts et al. 2018). The main indicator evaluation method is usually used for vulnerability assessment (Ferrara et al. 2012), which incorporated indicators and their weights for vulnerability assessment (Smith et al. 2014; Beccair 2016). The linear approach has been used to assess critical transition and vulnerability (Adger 2006); however, it brings up some challenges (Serna-Chavez et al. 2014) because it is still difficult to depict clearly when will the vegetation ecosystems transform under different types of threat. Most previous assessments do not address fully the meteorological factors and environmental change impact on ecosystems vulnerability or distinguish the effects of different meteorological factors on the transformation on ecosystems (Hirota et al. 2011; Staver et al. 2011; Berrouet et al. 2018).

It is necessary to understand the critical transitions of the ecosystems, especially investigating the key meteorological factors, in order to evaluate the vulnerability of the ecosystems (Qian 2014). Normally, the key ecosystems dominate or make important impact on a regional area, it may determine whether the regional area is likely to experience changes from the external threat. The key ecosystems in Tibetan Plateau area the forest, forest-steppe ecotone, grassland and desert, they are especially important and vulnerable (Guo et al. 2020), also, it is much necessary to know more about the critical transition and vulnerability of Tibetan Plateau key ecosystems. This study proposed a method to analyze the impact of meteorological factors on the critical transition and vulnerability of Tibetan Plateau key ecosystems. It aims to quantitatively study the thresholds and critical transitions at tipping points of the key elements of the ecological systems, and to reveal the internal processes of system evolution, mutation and transformation to research the evaluation of regional resource-environment system vulnerability.

2 Materials and Methods

2.1 Study area

The study area of Tibetan Plateau covers the Xizang, Qinghai, Gansu, Sichuan, Ningxia, Yunnan provinces and parts of Xinjiang province, and covers 3.63×10^6 km² between 73°-109°E and 21°-43°N (Jing et al. 2016). The overall climatic characteristics of the Tibetan Plateau are summarized as strong radiation, more sunshine, lower temperatures, and temperature decreases with height and latitude. The spatial distributions of 181 weather stations in the study area are present in Fig. 1. Eighty percent of the Tibetan Plateau area locates above 4000 m above sea level, and the temperature significantly reduced, the high altitude. In addition, the drought in alpine region is frequent because of the low precipitation, simple vegetation structure, and poor anti-interference ability. The vulnerability of ecosystems is manifested by vegetation destruction, forests and grasslands degradation, soil erosion, and soil desertification. The climate characteristics of the Tibetan Plateau cover from warm and humid in the southeast to cold and dry in the northwest.

2.2 Data sources

The MOD44B Vegetation Continuous Fields (VCF) product is a global representation of surface vegetation cover represented as gradations of three ground cover components: percent tree cover, non-tree cover and non-vegetated (bare). This data was downloaded from the NASA Land Processes Distributed Active Archive Center (LP DAAC). The VCF products provide a continuous, quantitative portrayal of land surface cover at 250-meter pixel resolution, with a sub-pixel depiction of percent cover in reference to the three ground cover components (Ishtiaque et al. 2016). Tree cover percentage was computed from the MOD44B at 500-meter resolution. Tree cover maps were computed based on Moderate Resolution Imaging Spectroradiometer (MODIS) inputs dating from 1 January 2015 to 31 December 2015.

The Tropical Measuring Mission (TRMM) is a joint endeavor between National Aeronautics and Space Administration (NASA) and Japan's National Space Development Agency (Kelley 2013). The TRMM 3B43 product provides monthly precipitation data at a spatial resolution of 0.25° × 0.25°, covering 50°N–50°S. We calculated the average monthly precipitation based on the data from January to December 2015.

Meteorological station data was obtained from China Ground Climate Data Monthly Dataset of National Meteorological Science Data Sharing Service Platform. This dataset is based on climatic observations from 756 basic, reference surface meteorological observation stations and automatic stations. We used ground measured data from 183 meteorological stations in the Tibetan Plateau, calculated average monthly precipitation, average monthly temperature, and average monthly sunshine duration from January 2015 to December 2015.

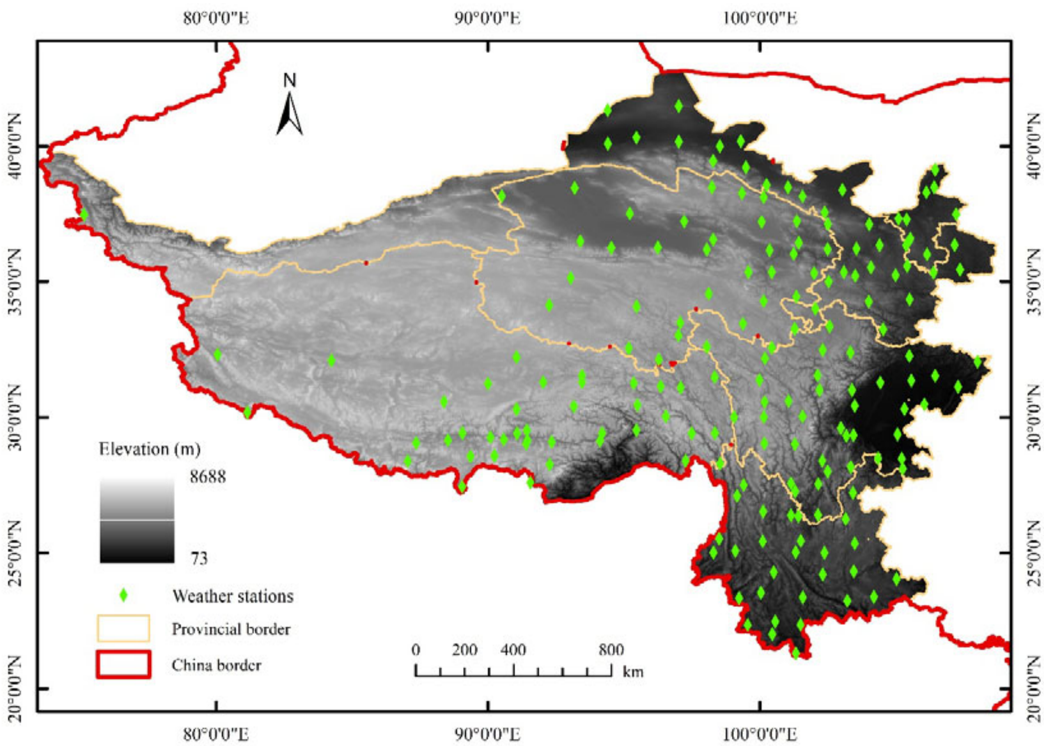


Fig. 1 Topography of the Tibetan Plateau key ecosystems and weather stations distributions.

The Digital Elevation Model (DEM) data with the spatial resolution of 90m was obtained from Shuttle Radar Topography Mission (SRTM). SRTM is mainly measured by the NASA and the National Mapping Agency of the Ministry of National Defense (NIMA) (Grohmann 2018). The acquired radar image data has been modeled as a digital terrain elevation model after processing.

2.3 Methods and flowchart

In the study, the meteorological and tree cover datasets were firstly processed. First, meteorological data were processed including data correction, interpolation and statistical analysis. Next, the tree cover percentage from the MOD44B product at 500-m resolution and computed the type of vegetation were exacted. Last, the critical factor thresholds and vulnerability were computed using logistic regressions between meteorological factors and vegetation cover. Considering the heterogeneous landscapes (e.g., forest-grassland-transitions), all the datasets were extracted at 1-km resolution and re-projected onto a UTM projection. All the geoprocessing steps and the data extraction were executed using ArcGIS 10.2 and Python 2.7. A flowchart is shown in Fig. 2.

2.3.1 Calibration of the TRMM data with Random forest algorithm

Due to the influence of terrain, altitude and atmosphere, the accuracy of TRMM data in the mountainous areas of northwest China is low. Therefore, Random Forest algorithm has been applied to Correct TRMM data. We used the Random Forest (RF) algorithm and meteorological stations to calculate the relationship between the distribution of TRMM precipitation data and the influencing factors (DEM, longitude, latitude). RF is a non-parameterized and ensemble-learning algorithm for regression and classification, has been increasingly applied because of its high accuracy (Eisavi et al. 2015). In regards to the regression in the categorical regression tree model, for each observed variable matrix X, there is a response vector Y to represent the response value of X (Gey and Nedelec 2005). The data of 183 meteorological stations are divided into two parts, 100 of which were used to train the Random Forest model and 83 of which were used for validation. The TRMM precipitation calibration with RF algorithm is processed as follows:

(1) The original precipitation dataset from the meteorological stations was converted into a point vector layer with attribute values of precipitation and latitude and longitude using ArcGIS software, and the point vector layer extracted the TRMM precipitation data and DEM of every station as attribute values.

(2) The difference was calculated between precipitation at the meteorological stations and the TRMM precipitation datasets ΔP_{trmm}:

$$\Delta P_{trmm} = P_{trmm} - P_{stations} \quad (1)$$

where P_{trmm} is the TRMM data of a station point, and $P_{stations}$ is the precipitation data of meteorological stations.

(3) The RF algorithm process was used to calculate the relationship between ΔP_{trmm} and DEM, longitude, latitude, and precipitation.

(4) The longitude, latitude, and altitude maps at a resolution of 0.25° were obtained by resampling, and the ΔP_{trmm} distribution map at 0.25° was calculated with the model from the last step.

(5) The calibrated TRMM precipitation was obtained by subtracting ΔP_{trmm} from the original

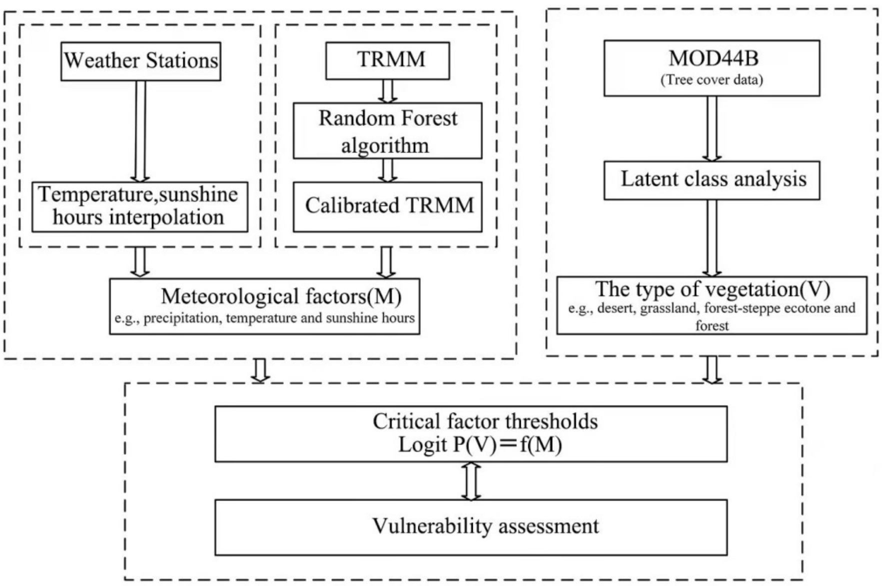


Fig. 2 Flowchart of critical transition calculation and vulnerability assessment of Tibetan Plateau key ecosystems.

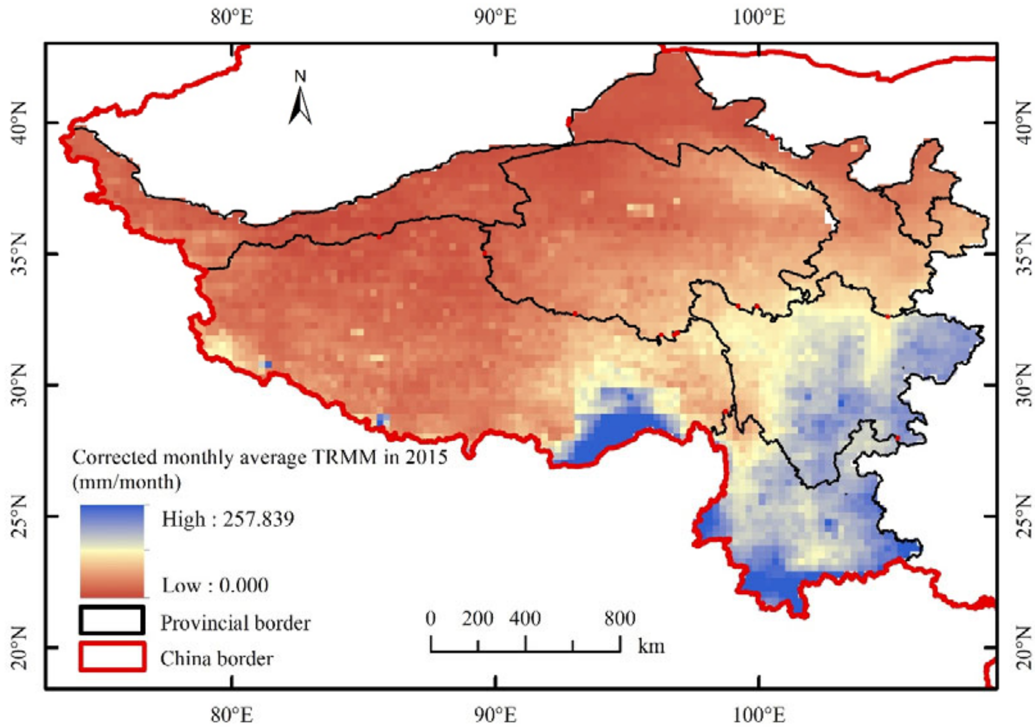


Fig. 3 Calibrated TRMM data over the Tibetan Plateau in 2015.

TRMM data.

Three evaluation indicators were computed to evaluate the calibrated TRMM data and the original TRMM data, they are the coefficient of determination (R^2), the bias, and the root mean square error (RMSE) (Duan and Bastiaanssen 2013; Katiraie-Boroujerdy et al. 2017), the formulas are as follows:

$$R^2 = \frac{\sum(p_c-\bar{p}_0)((p_0-\bar{p}_0)}{\sqrt{\sum(p_c-\bar{p}_0)^2}\sqrt{\sum(p_0-\bar{p}_0)^2}} \tag{2}$$

$$\mathrm{Bias} = \frac{\sum p_c}{\sum p_0} - 1 \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum(p_c-P_0)^2}{n}} \tag{4}$$

where P_c and P_0 are the TRMM data at the station point and precipitation of meteorological stations data, respectively.

R^2 is the square of the correlation coefficient, and the closer the value is to 1, the better the correlation, and the more reliable the TRMM precipitation data are. The bias reflects the degree to which the measured value is over- or under-estimated (Duan et al. 2012). The RMSE is a measure of differences between two variables and it is sensitive to the extreme values.

Fig. 3 shows the spatial distribution of TRMM data after correction. The evaluation results of the original and calibrated TRMM 3B43 data are shown in Fig. 4. It can be seen that the difference between the original and calibrated TRMM 3B43 in May, June, July and August is significant. The difference between the average monthly precipitation of meteorological stations and the calibrated TRMM 3B43 is small. The overall accuracy level has been significantly improved after calibration, with R^2 reaching a maximum of 0.99 and a minimum as low as 0.8. The calibrated TRMM

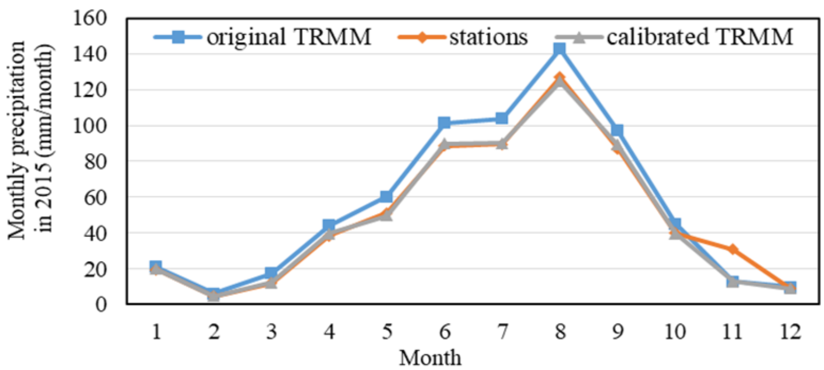


Fig. 4 Comparison of calibrated TRMM dataset with meteorological stations data and original TRMM.

data can be used for subsequent threshold and critical transition analysis.

2.3.2 Latent class analysis

In order to statistically test the number of modes of the tree cover frequency distributions and calculate vegetation types, latent class analysis method was applied. The statistical theory of latent class analysis is based on multivariate analysis of probabilities. Exploratory latent class analysis is that there are no predetermined assumptions for the number of potential categories and no specific limits on the parameters for potential category analysis. The latent variable model is determined purely from observed data, and the parameter estimation is performed in an unrestricted mode, so it is also called data-driven orientation (Weingessel 2012).

The main task of the exploratory latent class analysis is to determine that the variability of explicit variables can be best explained by several potential categories (Orea and Kumbhakar 2004). When the number of potential categories is T and it can explain the largest variation in explicit variables, the theoretical model will be the closest to the observed data. Thus, the T-cluster model is the best model. The process of exploratory latent class analysis is divided into the following five steps: first, estimate the initial model (1-cluster with T=1); second, gradually increase the number of categories, perform the parameter estimation for each model, and calculate the fitness; third, perform an adaptability test and a differential test to determine the best model; fourth, sort the categories and the parameter estimation results; and fifth, classify and determine the attribution category of each observation.

The parsimony criterion is a goodness-of-fit criterion that penalizes for each parameter of the model to determine the best number of fits for potential categories, which includes the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Chakrabarti and Ghosh 2011). Based on information theory and the maximum likelihood algorithm, AIC can be applied to the adaptation advantage comparison of different models:

$$L = (2\sum_{k=1}^{K} n_k \times log\frac{n_k}{\hat{n}_k})^{\frac{1}{2}} \quad (5)$$

$$\mathrm{AIC} = 2\mathrm{k} - 2\ln(L) \quad (6)$$

where L is the likelihood function, k is the number of model parameters, n is number of samples, $\widehat{n_k}$ is the average number of k parameters. The smallest AIC value indicates that the model is the best fit.

BIC is similar to AIC, it is also used to select the best model, but the penalty of BIC is greater than that of AIC. Meanwhile, BIC takes the number of samples into consideration to prevent excessively high model complexity due to high model accuracy when the size of samples is very large. BIC is a measure of the goodness of statistical model fit based on the likelihood function (Campos et al. 2018):

$$\mathrm{BIC} = k\ln(n) - 2\ln(L) \quad (7)$$

where, $k\ln(n)$ is the penalty term in the case that the dimension is too large and the training sample data is relatively small. In this way, the dimensional disaster phenomenon can be effectively avoided.

In the study, we normalized the tree cover data and took a random subsample of 1000 points. To analyze the numbers of the tree cover frequency distributions and determine the type of vegetations, latent class analysis and a maximum likelihood estimation algorithm have been applied to find the best fit for a certain number of normal distributions.

2.3.3 Logistic regressions

In order to analyze the impact of meteorological factors on typical ecosystem vegetation, logistic regressions method has been used to calculate the probability of vegetation. In the study, we need to consider the probability of vegetation under the influence of meteorological. However, we know that the relationship between probability and independent variables is difficult to describe using a linear model. Logistic regression differs from classical linear regression in that the modeled response is the probability of being in a category, rather than the observed quantity of a response variable (Stoklosa et al. 2016). Logistic regression allows building predictive models on a probabilistic basis (Motrenko et al. 2014). Similar to any other regression analysis, it predicts one or several predictor (independent) variables. Logistic regression applies to the original dependent variable, with a regression equation of the form:

$$Logit(p) = \ln\frac{p}{1-p} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (8)$$

where p is the probability, α is the intercept, $\beta = (\beta_1, \beta_2, \ldots, \beta_n)'$ denotes a vector of n coefficients, and $x = (x_1, x_2, \ldots, x_n)'$ is a set of values of the covariates. The coefficients β in the logistic regression model are commonly interpreted in terms of odds ratios, and reflects changes in odds ratios (Sun et al.

2018).

The unknown β needs to be estimated from observed data and is estimated using maximum likelihood assuming that the observations are independent, with a likelihood equation of the form:

$$\frac{\partial L(\beta)}{\partial \beta_r} = \sum_{i=1}^{n} x_r(y_i - q(\beta|x_i)) = 0 \qquad (9)$$

where r = 0, 1, ..., n, with respect to β, q is the probability function.

In the study, the polytomous logistic regression was used to calculate the probability, the categorical variable is a multi-class case and not a binary one. Polytomous logistic regression requires that the categorical variables are disordered and multi-categorical, unlike binary logistic regression, where a set a reference group is required (Gupta and Pardo 2007). For example, $y = (y_1, y_2, \ldots, y_n)'$ is a vector of categorical variables. We must specify a categorical variable as a base category and take y = 1 as the base category, with the logistic regression equation of the form:

$$Logit\ P_{i/1} = \ln\left[\frac{P(y=i|x)}{P(y=1|x)}\right] = \alpha + \beta_{i1}x_1 + \beta_{i2}x_2 + \cdots + \beta_{it}x_t = g_i(x)\ \ i = (2, 3, \ldots, n) \qquad (10)$$

where simultaneous equations consist of $(n-1)$ functions, the size of the parameter is $i \times (t + 1)$ and t is the number of independent variables. The logit function expresses the logit of class i and class 1, and the corresponding coefficient is represented by β_{it}, the ratio of class i to class t. As long as (n-1) functions are given, the results of the first class can be calculated:

$$P[y=1|x] + P[y=2|x] + P[y=3|x] + \ldots + P[y=n|x] = 1 \qquad (11)$$

$$P_1 + P_2 + P_3 + \ldots + P_n = 1 \qquad (12)$$

According to the functions above, the conditional probabilities of n categories are:

$$P1=P[y=1|x] = 1/(1+e^{g_2(x)}+\ldots+ e^{g_n(x)}) \qquad (13)$$

$$Pi=P[y=i|x] = e^{g_i(x)}/(1+e^{g_2(x)}+\ldots+ e^{g_n(x)}) \qquad (14)$$

$$g(z) = 1 / (1+e^{-z}) \qquad (15)$$

$$z = \beta_0 + \beta_1 x \qquad (16)$$

where x is the average monthly precipitation, average monthly temperature, or average monthly sunshine hours.

Logistic regression uses likelihood values to measure the goodness of fit of the model (we calculate -2 times the natural logarithm of the likelihood, which is abbreviated as -2LL). If one model is perfectly fitted, the value of the likelihood is 1, and -2LL is the smallest value. All the regressions were processed with Python 2.7.

Based on the Logistic regression equations, this study explores the relationship between ecosystem vegetation and climate factors, taking ecosystem vegetation (desert, grassland and forest) as dependent variable, taking the climatic elements (precipitation, temperature, sunshine hours) as the independent variable, to calculate the threshold value of climatic elements and predict the vulnerability of ecosystem in Tibetan Plateau.

3 Results and Discussion

3.1 Latent class analysis and the type of vegetation states

Fig. 5 showed obvious peaks and differences in the frequency distribution of tree cover. We compared the fit of the model of 1-6 classes based on latent class analysis and used a parsimony criterion to determine the classification results. Based on the BIC and AIC values, the class sizes of the optimal model are four class. We calculated the normal best-fit parameters and defined 0%-14% tree cover for desert, 15%-34% tree cover for grassland, 35%-59% tree cover for forest-steppe ecotone, and >59% tree cover for forest.

To discover the frequency distribution of tree cover, we performed normal distribution fitting curves for the four types of vegetation (Fig. 6).

3.2 Critical transitions of Tibetan Plateau key ecosystems at tipping points

The desert, grassland, forest-steppe ecotone and

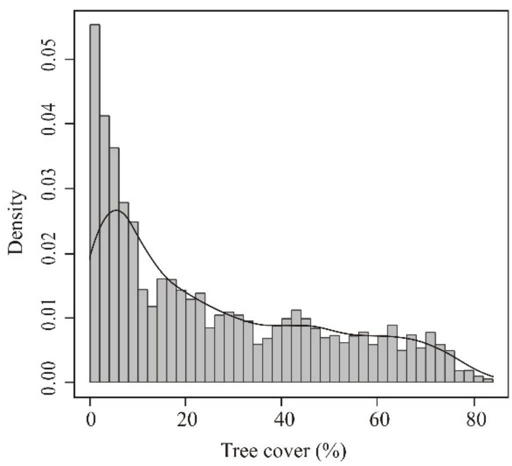


Fig. 5 Frequency distribution of tree cover in Tibetan Plateau in 2015.

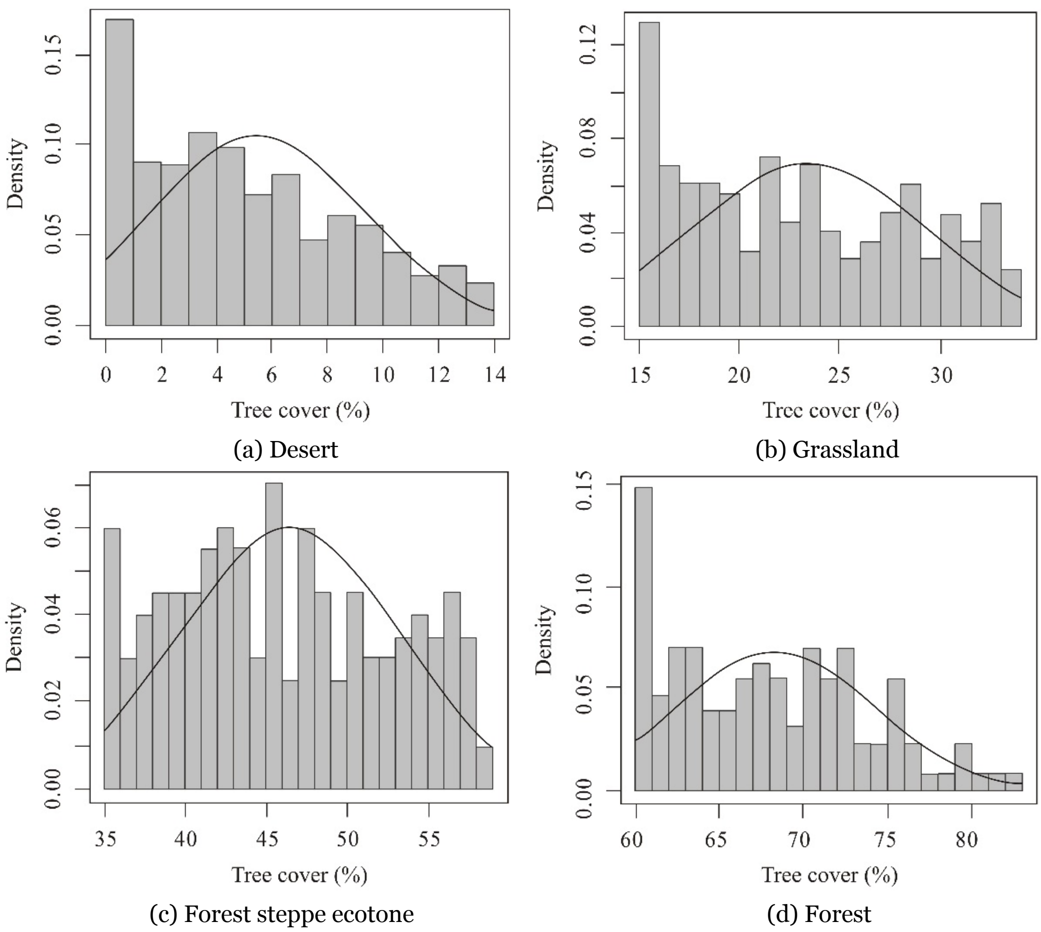


Fig. 6 Normal distribution fitting curves of four vegetation types in Tibetan Plateau in 2015.

forest states are defined on the basis of tree cover (T) as T<14%, 15 %< T<34%, 35 %< T<59%, and T>60%, respectively. We used the logistic regression equation to calculate the probability curve of the four-vegetation status depending on the precipitation, temperature and sunshine duration levels (Fig. 7).

The probability curves in Fig. 7 show how the vegetation status changes with precipitation, temperature and sunshine duration levels. It is clear that vegetation status, which changes with precipitation, temperature and sunshine duration levels, differs widely. Relatively, the precipitation shows much obvious impact on differentiations of the vegetation status probability. The data indicates that the greater the precipitation, the greater the tree cover and the greater the vegetation coverage (Fig. 7a). The four vegetation states at the end of their respective precipitation thresholds have lower probabilities and correspond to increases in the probabilities of neighboring states. According to the logistic regression equation, the tipping point of the precipitation is calculated (Table 1). The tipping point of the average precipitation of the desert and the grassland is average 48.0 mm/month, the precipitation tipping point of the grassland and forest-steppe ecotone is average 70.7 mm/month, the precipitation tipping point of the forest-steppe ecotone and forest is average 115.0 mm/month. Precipitation can is an important factor in controlling vegetation growth and can provide water for vegetation growth. It can be seen from the precipitation tipping point that the monthly average precipitation is greater than 48 mm, and the vegetation growth probability is larger. The spatial distribution of forest ecosystem and precipitation show similar spatial variation characteristics, that is, high precipitation corresponds to high vegetation cover. In short, in meteorological factors, precipitation affects the alternation of vegetation types to some extent.

However, changes in temperature and duration of sunshine are not as consistent with changes in

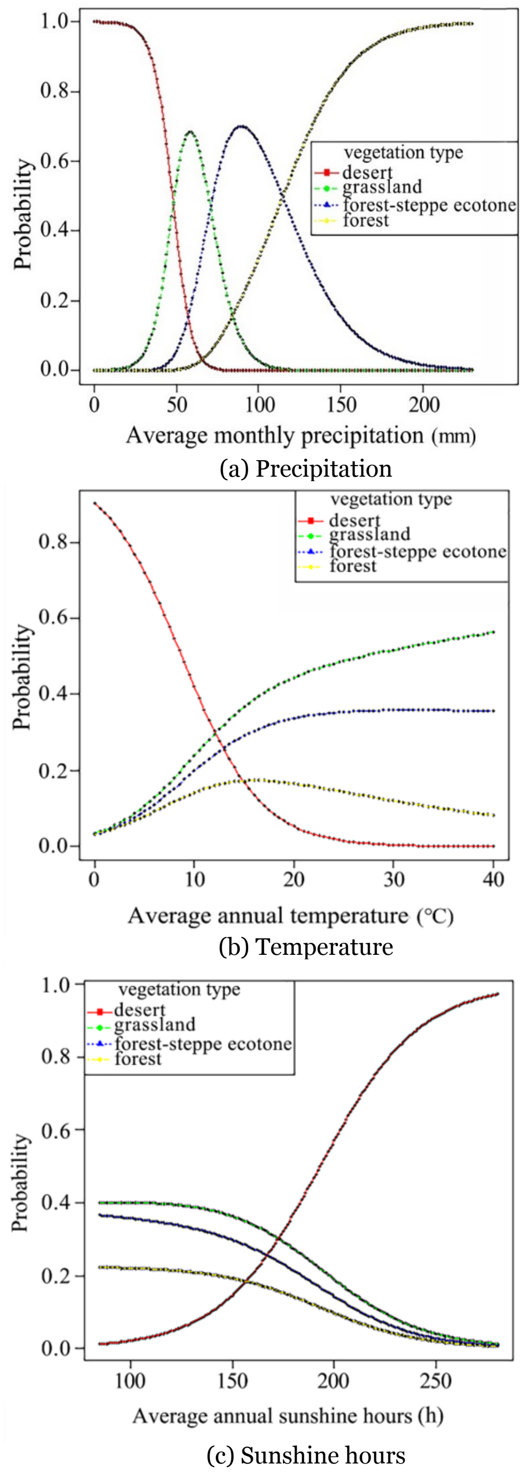


Fig. 7 Probability of being each vegetation type as functions of precipitation, temperature and sunshine hours.

vegetation status (Fig. 7b, 7c). Temperature shows the greatest impact on vegetation types (grassland, forest steppe ecotone and forest) and non-vegetation type (desert). However, temperature shows no significant effect and differentiation among vegetation types, and the tipping points of grassland, forest-steppe ecotone and forest do not exist in Tibetan Plateau. According to the logistic regression equation, the temperature tipping point is calculated (Table 1). When the temperature is lower than 12.1°C in Tibetan Plateau, the probability of desert is the highest. When the temperature exceeds 12.1°C, the probability of grassland, forest-steppe ecotone and forest increases, and the probability of grassland is the highest. The higher of the temperature, the larger the probability of grassland and forest-steppe ecotone (Fig. 7b). Meanwhile, Fig. 7b shows the probability of the existence of forest increases with increasing temperature and reaches a maximum at 15°C, and then the probability of the forest decreases with the increasing temperature. This shows clearly the high elevation of Tibetan Plateau impact on the forest ecosystem, because most of the forest in Tibetan Plateau is distributed in the southeast or south aspects of low elevation area.

The change of the probability curve under sunshine conditions is opposite to the probability curve under temperature conditions. And sunshine duration has no significant effect and differentiation among vegetation types either. In the Tibetan Plateau, the longer the sunshine duration, the more adversely the growth of vegetation is affected (Fig. 7c). Based on the logistic regression equation, the tipping point (Table 1) of sunshine hours is calculated. The desert ecosystem has the lowest probability of existence when the sunshine hours are lower than 173.6h. With the increase of sunshine hours, the probability of grassland, forest-steppe ecotone and forest ecosystems is reduced, and the growth probability of grassland and forest-steppe ecotone is higher than that of forest and desert when the sunshine hours are suitable.

There are large differences in the probability curves of vegetation types for temperature, precipitation and sunshine duration levels. First, lower temperature decreases the rate of photosynthesis and affects the growth of vegetation. With higher temperatures, there is an increase in surface evaporation which is not conducive to the preservation of soil moisture and thus has an adverse impact on the growth of vegetation. Second, the Tibetan Plateau area has a high altitude and large amounts of sunshine. When the sunshine duration is too long, it causes much surface evaporation, which

Table 1 The ecosystem transition tipping points (TPs) of different variables in Tibetan Plateau

Tipping points (TPs)	Desert and grassland	Grassland and forest-steppe ecotone	Forest-steppe ecotone and forest
TPs of precipitation (mm/month)	48.0	70.7	115.0
TPs of temperature (°C /month)	12.1	—	—
TPs of sunshine hours (h/month)	173.6	—	—

Note: "—" indicates data are unavailable or that there is no obvious transition tipping point.

leads to restricted vegetation growth due to the lack of soil water in Tibetan Plateau with insufficient precipitation. However, it can be enough for grassland and forest-steppe ecotone, and it is relative similar over the Tibetan Plateau. By comparison, precipitation in Tibetan Plateau shows much obvious difference, so as to the distinct spatial distribution of the four types vegetation of forest, forest-steppe ecotone, grassland, desert. The more sufficient precipitation, the higher tree cover.

The tipping points of climate elements are divided by key ecosystem changes, and the impact of climate change on vegetation systems is analyzed. The logistic regression model fits the relationship between meteorological elements and ecosystem vegetation types, which was used to analyze the tipping points of climate elements under ecosystem transformation and determines the trade-off relationship between climate change and ecosystem regulation functions (Polo-Akpisso et al. 2015).

3.3 Vulnerability assessment of Tibetan Plateau key ecosystems

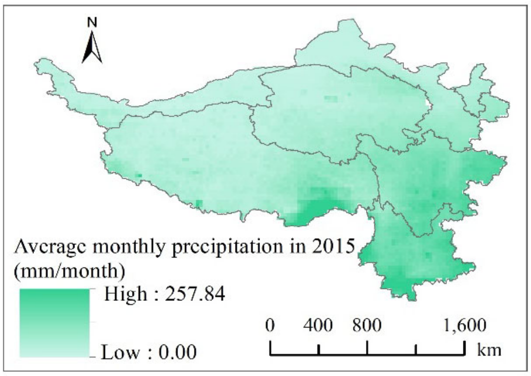
In the study, considering climatic factors and the types of vegetation in Tibetan Plateau key ecosystem, logistic regression method has been applied to quantitatively calculate regional vegetation conditions and vulnerability based on given meteorological factors, with the aim of analyzing the possibility of regional vulnerability by critical transition in meteorological elements.

The climate change can cause the reduction of the number of functional components, exacerbate the degradation of forests, grasslands and other ecosystems, increase the desertification area, reduce the productivity of ecosystems, destroy ecological structures and even degrade ecological functions. The ecosystem thus will show high vulnerability. Compared with the desert, grassland and forest-steppe ecotone, the internal structure of forest ecosystems is complex, with strong anti-interference ability and low ecosystem vulnerability. The vulnerability of desert, grassland, forest-steppe ecotone and forest of the Tibetan Plateau was computed under the influence of precipitation, temperature and sunshine duration using the logistic regression models. Therefore, the vulnerability of desert, grassland, forest-steppe ecotone and forest were expressed as the probability of finding a vegetation cover type at the local average monthly precipitation or averaged temperature or averaged sunshine duration.

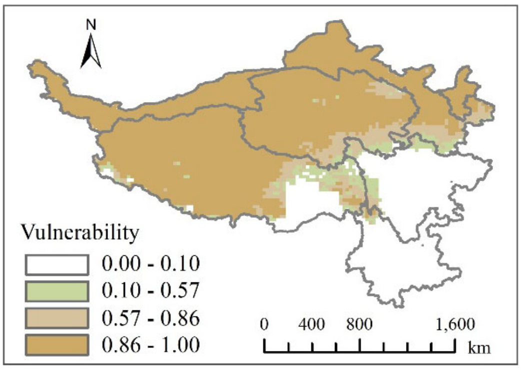
Fig. 8 shows the average monthly precipitation distribution and the simulated vulnerability from precipitation of desert, grassland, forest-steppe ecotone and forest. With the increase in precipitation, the probability of the area being forest-steppe ecotone and forest is larger, the vulnerability is weaker. Due to the influence of precipitation, desert has high probability and strong vulnerability in western and central Tibet, and parts of Qinghai, Gansu and Xinjiang. The grassland is mainly distributed in eastern Tibet, northwestern Sichuan, northern Yunnan, Qinghai and southern Gansu, and its vulnerability is lower than that of the desert ecosystem. Forest-steppe ecotone is mainly distributed in southeastern Tibet, central and eastern Sichuan, and central Yunnan. Forest ecosystems are mainly distributed in eastern and southern Sichuan, southern and eastern Yunnan, and have the lowest vulnerability.

The vulnerability of desert, grassland, forest-steppe ecotone, and forest significantly correlated to temperature and sunshine duration, which differs from the variation in precipitation, according to Fig.s 9-10. The vulnerabilities under the influence of temperature and the sunshine duration are obviously different in the desert (non-vegetated) state and in the state of vegetation, but they are not obvious of difference in vulnerability among the grassland, forest-steppe ecotone and forest.

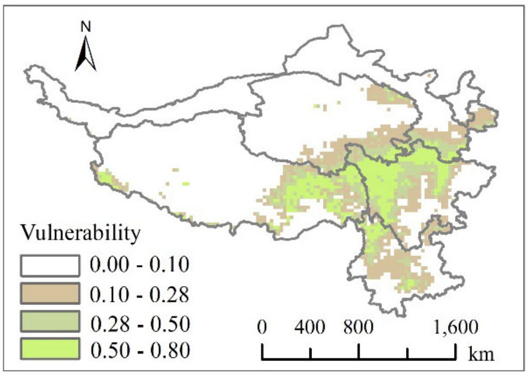
The temperature in internal area of Tibetan Plateau was low, and was high in lateral area inside the Tibetan Plateau (Fig. 9). The low temperature area shows high desert ecosystem vulnerability from the



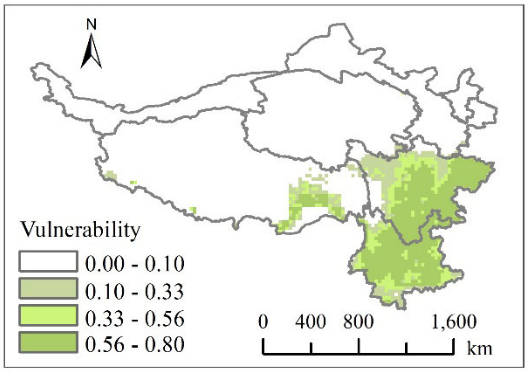
(a) Average monthly precipitation distribution Tibetan Plateau



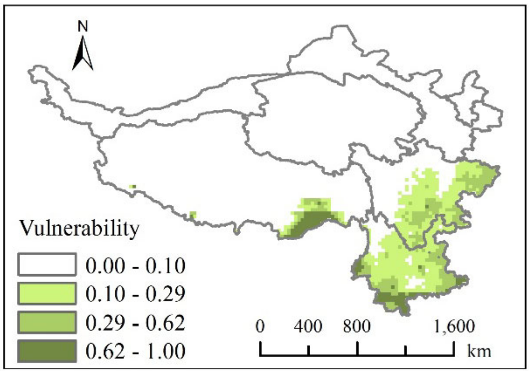
(b) Vulnerability of desert



(c) Vulnerability of grassland



(d) Vulnerability of forest-steppe ecotone



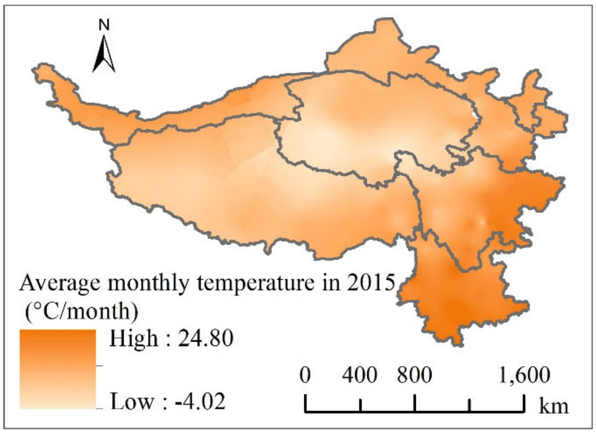
(e) Vulnerability of forest

Fig. 8 Vulnerability of desert, grassland, forest-steppe ecotone and forest on Tibetan Plateau under the influence of precipitation.

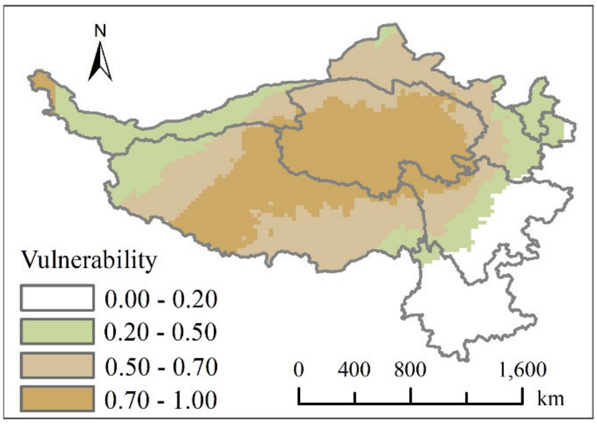
north area to the central and southwest Tibetan Plateau (Fig. 9b), where desert is mainly distributed. The grassland, forest and forest-steppe ecotone ecosystems show high and similar probability in high temperature in southeastern Tibetan Plateau, including parts of Sichuan, Yunnan, these areas are less vulnerable (Fig. 9c, 9d, 9e).

According to Fig. 10, the distribution of desert ecosystems was positively correlated with the sunshine duration distribution, and the grassland, forest-steppe ecotone and forest ecosystem fragility are negatively correlated. However, the vulnerability of grassland, forest-steppe ecotone and forest ecosystem show little differences affected by sunshine duration. Under the influence of sunshine, the desert distribution is similar to precipitation, mainly distributed in most area from central to southwest Tibetan Plateau, which area shows high vulnerability. The high probability of grassland, forest-steppe ecotone and forests are mainly distributed in eastern Yunnan and Sichuan provinces, these areas are less vulnerable.

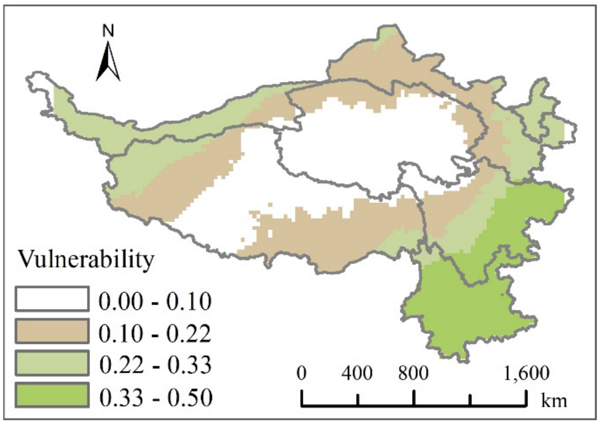
According to the influence of three meteorological factors, the most vulnerable areas in the study area are the central and western parts of Tibet, the central and western part of Qinghai, the western part of Xinjiang and Gansu, and the



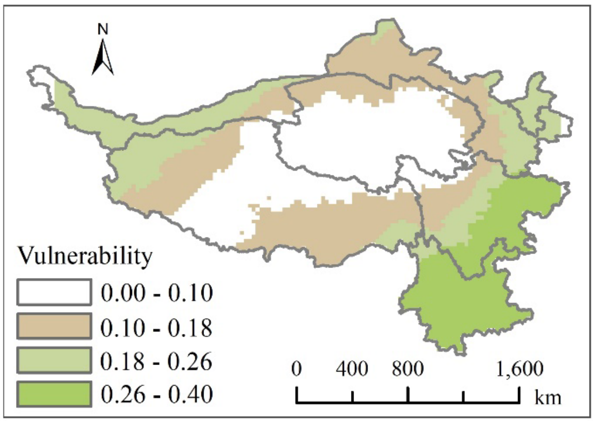
(a) Average monthly temperature distribution of Tibetan Plateau



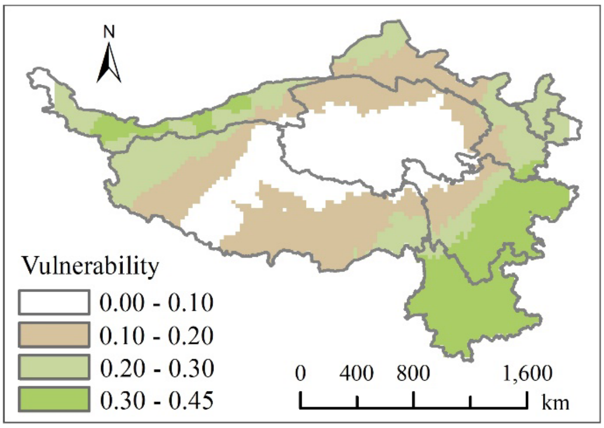
(b) Vulnerability of desert



(c) Vulnerability of grassland



(d) Vulnerability of forest-steppe ecotone



(e) Vulnerability of forest

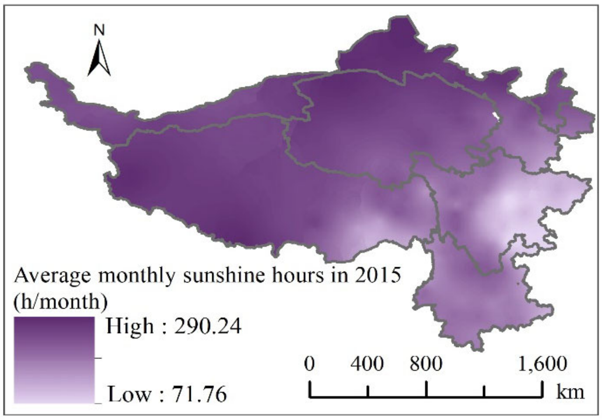
Fig. 9 Vulnerability of desert, grassland, forest-steppe ecotone and forest on Tibetan Plateau under the influence of temperature.

vulnerability of Yunnan and Sichuan provinces from northwest to southeast.

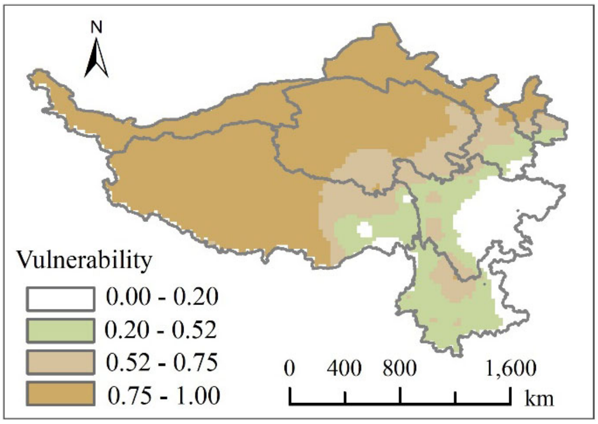
4 Discussion

4.1 Reviewing the proposed method

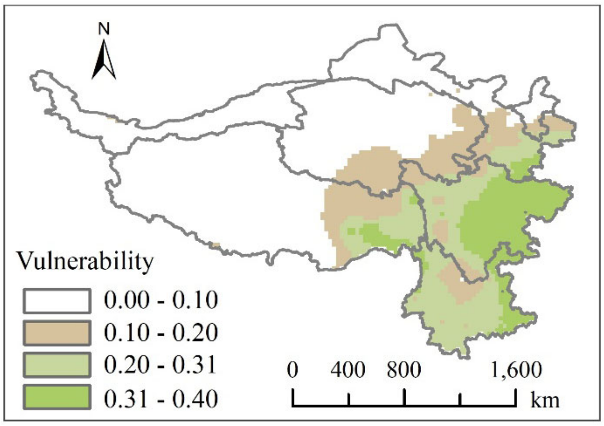
This study quantitatively studied critical transitions at tipping points of the key elements of the ecological system and discussed the vulnerability of the system under the influence of meteorological factors using latent class analysis and logistic regression analysis. The latent class analysis can test the number of modes of the tree cover frequency



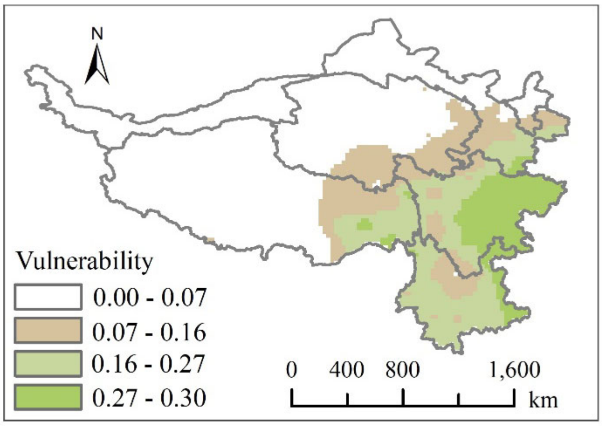
(a) Average monthly sunshine duration distribution of Tibetan Plateau



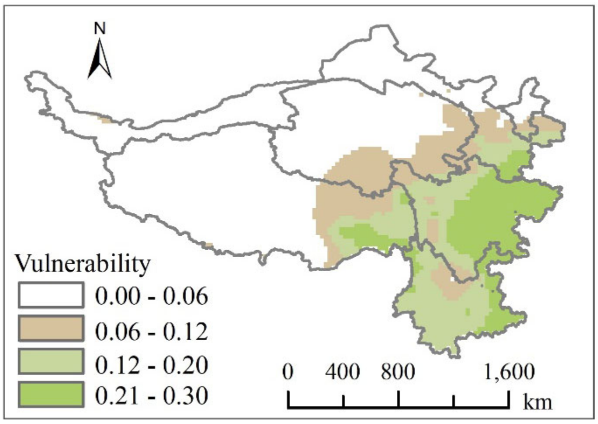
(b) Vulnerability of desert



(c) Vulnerability of grassland



(d) Vulnerability of forest-steppe ecotone



(e) Vulnerability of forest

Fig. 10 Vulnerability of desert, grassland, forest-steppe ecotone and forest on Tibetan Plateau under the influence of sunshine hours.

distributions and can determine the class of vegetation in the study area. The logistic regression analysis can calculate the relationship between the meteorological factors and the type of vegetation, and can provide effective regression tools to determine the influence of different meteorological factors on regional vegetation changes, and predict the distribution of vulnerability in regions. Logistic regression analysis indicates that, the vulnerability in the northwest of Tibetan Plateau key ecosystems is high and the southeast vulnerability is relatively low, according to the precipitation, temperature and sunshine duration levels.

Researchers often use AHP (analytic hierarchy process) method (Wang et al. 2008) to propose an environmental vulnerability index which incorporated

15 factors covering natural conditions, environmental issues, and human activities, these techniques integrated various spatial information, but the choice of indicators has a strong subjectivity, and it is difficult to understand what extent the factors play roles. Also some researchers (Metzager et al. 2006) integrated the potential impacts in a vulnerability assessment of ecosystem services, and proposed that the vulnerability maps of ecosystem services were combined by stratified potential impact and adaptive capacity indices. The results focused much on the land-use change scenarios, and climate change is used in the stratification of ecosystem service scenarios. The vulnerability under the influence of changes in meteorological factors is still needed furtherly study.

Generally, a relevant contribution of this study is that we used the logistic regression model to explore the spatial distribution of meteorological factors and vegetation systems, and then applied it to the spatial mapping of the vulnerability of Tibetan Plateau key ecosystems. The logistic regression curves show clearly how meteorological factors affect ecosystem vulnerability. Moreover, the results of the vulnerability maps give an intuitive over view to predict the vulnerability of different vegetation types for certain regions. This case study demonstrated that the proposed method is an effective approach for assessing the ecosystem transition and vulnerability.

4.2 Suggestion for ecosystem vulnerability management

This study connected the critical transition to different meteorological factors and found that the vulnerability of the state varies greatly with precipitation, that is, precipitation is a sensitive driving force for the transformation of forest, grassland, and forest-steppe ecotone in Tibetan Plateau. It is useful to estimate the vulnerability for the current ecological system. It can be inferred of a certain state given the climate situations in the future and can further be calculated the vulnerability to address disturbances such as drought or global warming.

The state of the ecosystem in the Tibetan Plateau poses enormous challenges for governments, scientists and local people. Current global changes, especially climate change, seriously affect the structural function of ecosystems. The quantitative vulnerability assessment can also provide effective environmental protection advice to government agencies and local people. The highly vulnerable area in the Tibetan Plateau should be paid more attention on protection and management, such as in the northwestern part of the Tibetan Plateau. It is necessary to customize appropriate economic development strategies and formulate laws and regulations for environmental protection according to local conditions. In addition, alpine trees or grass belts should be planted in desertification areas to reduce the speed of desertification. Meanwhile, the policymakers should make scientific regional development planning.

4.3 Future works

In the future works, it is also necessary to explore solutions for different climate scenarios and determine the ability of complex dynamic systems to adapt to critical transformations, which is critical to understanding dynamic systems and inferring the vulnerability of future global models. Also, it would be an assessable way of using the index evaluation method to calculate the regional overall vulnerability index, and use logistic regression to analyze the impact of single factors on regional vulnerability, and provide local governments with more scientific and targeted vulnerability governance and prevention recommendations.

5 Conclusion

This study focuses on the impact of meteorological factors of precipitation, temperature and sunshine duration in Tibetan Plateau on vegetation systems of forest, grassland, forest-steppe ecotone, and non-vegetation system of desert. The tipping point of meteorological factors between ecosystem transformation was calculated. And the ecosystems vulnerabilities were further assessed. In comparison with temperature and sunshine duration, the precipitation shows much obvious impact on differentiations of the vegetations status probability, and is the most sensitive meteorological factor for the four key ecosystems in Tibetan Plateau. The transition precipitation tipping point of desert and grassland is averaged 48.0 mm/month, and it is averaged 70.7 mm/month for grassland and forest-steppe ecotone, and averaged 115.0 mm/month for the forest-steppe ecotone and forest. The temperature and sunshine duration both only shows different probability change between vegetation and non-vegetation type, but appears the opposite impacts. In Tibetan Plateau, the transition tipping points of vegetation and non-vegetation are about 12.1°C/month and 173.6 h/month for the temperature and sunshine duration respectively. The influence simulations of the three meteorological factors all show high desert ecosystem vulnerability from the north area to the central and southwest Tibetan Plateau, where desert is mainly distributed, and the grassland, forest and forest-steppe ecotone ecosystems show high probability in southeastern Tibetan Plateau, where are less vulnerable. The studied results and methods can be a quantitative reference for the Tibetan Plateau ecosystem management and for diagnosing the ecosystems transformation, and can be reference for regional development and planning for decision makers.

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