Environmental Science and Pollution Research (2021) 28:7151–7166
https://doi.org/10.1007/s11356-020-11013-6

RESEARCH ARTICLE

# Spatial-temporal pattern evolution and driving force analysis of ecological environment vulnerability in Panzhihua City

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Received: 1 June 2020 / Accepted: 25 September 2020 / Published online: 7 October 2020


## Abstract
Panzhihua City, a typical eco-fragile region for agro-sylvo-pastoral industry in China, is located in the dry-hot valley of the Jinsha River, characterized by its big landform undulation, great elevation difference, uneven hydrothermal conditions, and complex geological structure. As a crucial ecological barrier in upper reaches of the Yangtze River, this area is abundant in water resources and mineral resources, such as vanadium and titanium. However, due to its over-development for nonnatural urban economy in the mining industry, agriculture, and animal husbandry, ecological problems are getting worse. Such problems as soil erosion and groundwater pollution have led obvious ecological degeneration in Panzhihua city. Therefore, for protecting the eco-environment and planning construction, it is significant to scientifically recognize that how eco-environment changes based on spatial-temporal, and how the driving mechanism affects Panzhihua city. Nowadays, there are some theories and methods that study eco-environmental protection and city construction in Panzhihua, but they are not comprehensive enough to study its spatial-temporal evolution and driving-force system. This study takes Panzhihua City as the research area of which evaluation factors, for example, topography, soil, vegetation, and meteorological factors, are chosen to construct an evaluation system suitable for the ecological environment vulnerability of Panzhihua City. These factors are selected in three aspects, which are ecological sensitivity, ecological recovery, and ecological pressure from 2005 to 2015 in this area. Then, spatial principal component analysis method, CA-Markov model, and dynamic degree model are applied to analyze the spatial-temporal evolution for ecological vulnerability based on three periods from 2005 to 2015 in Panzhihua City. Besides, GeoDetector is used to quantitatively analyze how spatial-temporal disparities change and what drives them to change. The results show that (1) during these 10 years, the overall ecological fragility of Panzhihua City is steadily increasing from northwest to southeast. The overall ecological quality is moderate, and regional differences are obvious. Places of moderate vulnerability or above are distributed in central and eastern regions of frequent human activities; places of mild vulnerability or below are distributed in the regions of Yanbian County and Miyi County. (2) The comparison of the changing rates based on vulnerability levels is severe > potential > moderate > mild > slight. The overall vulnerability changes within a small trend, showing a balanced two-way transition state between adjacent vulnerability levels. The comprehensive index for overall ecological vulnerability decreases period by period. (3) The interactions between each two factors toward spatial differentiation and explanatory power by ecological vulnerability show a two-factor-enhanced relation, indicating that multiple factors form the ecological vulnerability of Panzhihua City.

**Keywords** Panzhihua City · Ecological vulnerability · Spatial-temporal evolution · GeoDetector

## Introduction

Favorable ecological environment guarantees the continuous development of human civilization. But due to large-scale development in west China and social-economical development in demand for natural resources, human activities in western China pushed much pressure on ecological environment, causing an aggravating regional eco-environmental problem in this area, which breached the rule of green

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economy and sustainable development. Therefore, it is of vital importance for achieving regional sustainable development to analyze the cause and effect of eco-environmental vulnerability and to evaluate its vulnerability levels. This analysis and evaluation not only benefit for protecting ecological environment but also can show important factors for measuring the economical development in this region (Yang et al. 2019). In the early twentieth century, Clement firstly introduced ecotone into ecological study and the concept of ecological vulnerability presented in researches at home and abroad (Nelson et al. 2010). Later on, Timmerman (1981) introduced ecological vulnerability into geoscience, and the researchers like Verhuff and Foster developed this concept with other meanings (Doerfliger et al. 1999). With the booming development of eco-environmental vulnerability research, different people from different fields, such as Niu (1989), Zhu (1991), and Mörtberg et al. (2007), had diverse understanding about eco-environmental vulnerability. But generally speaking, the vulnerability of different ideals all showed an irreversible volatility in structure and function, when it was interfered by its own factors, external environment, and human activities in a certain spatial scale.

Recently, researchers from all over the world conducted different studies and achieved fruitful results about eco-environmental vulnerability. From the aspect of study model, researchers established different evaluation systems based on different research perspectives, for example, pressure, status and respond system, sensitive, resilience and pressure system, cause and effect system, and driving force, pressure, statue, influence, response, and management system. They also established a relatively comprehensive evaluation system based on different research areas. However, the research aiming at the southwestern mountainous areas in China is rare, where natural hazards influence the place, a place that belongs to resources economy region. The evaluation methods mainly are principal component analysis (Abson et al. 2012), Bayesian network (Ayre and Landis 2012), support vector machine (Xian et al. 2014), and projection pursuit (Shao et al. 2016). For example, Wu et al. (2012) evaluated the eco-environmental vulnerability for resources-based cities in China based on PSR method and entropy weight method; Turvey (2007) evaluated the vulnerability for developing countries in aspects of coastal index, suburban index, urbanization index, and the fragility of natural disasters by synthetical index method; Muradyan and Asmaryan (2015) evaluated it for mountainous landscape areas in Armenia by computing landscape ecological index with four basic integration and by weighted summation based on GIS; Li and Fan (2014) evaluated it for Xijiang economic belt and hilly and gully region of loess plateau in China. However, all these methods contain two problems: One is the subjectivity of evaluation factor weighting. For instance, analytic hierarchy process (AHP) has a great influence on the evaluation results under the artificial influence. Another is the regional adaptability of models. Because of the different geographical location, geographical conditions and the external and internal pressure of the ecosystem are not the same, constructing an evaluation system that reflects the ecosystem environment of the region in order to lead the follow-up evaluation results be more empirical and convincing. From the perspective of research content, it mainly analyzes the vulnerability of ecological environment in a single year in a specific research area from the aspects of quantitative characteristics, spatial distribution, spatial differentiation, and zoning in different time and space scales, while the analysis on the changes and driving forces of the vulnerability of ecological environment in different years is relatively insufficient. Moreover, there are few reports about results of spatial clustering analysis on the vulnerability of ecological environment (Lin et al. 2018). In view of this, three levels of “Pressure - Sensitivity - Recovery” were established to select effective indicators to establish an ecological environment vulnerability assessment system, and the method of spatial principal component analysis and GeoDetector statistics are utilized to quantitatively analyze the spatial-temporal pattern of Panzhihua’s ecological environment vulnerability in three periods of 2005–2015 and its driving factors in order to provide scientific support for the overall and better planning for constructing of green civilization in Panzhihua City, responding to the sustainable development path of China’s ecological civilization construction.

## Data and processing

### Study area

Panzhihua City, covering an area of 7440 km$^2$, is bordered by Liangshan Prefecture to the southwest of Sichuan Province, Yongren, and Huaping County to the northeast of Yunnan Province, lying from 26° 05′ to 27° 21′ north latitude and 101° 08′ to 102° 15′ east longitude. To its geographical conditions, this city is located in the Panxi Rift Valley, a valley that is high in the northeast and low in the southwest. From east to west, its topography gradually decreases, which causes sharp elevation differences and diverse landform. In this area, mountains, valleys, and basin interconnect with each other, shaping a unique mountainous and hilly area. But mountains are the major landform, while the basin only covers 0.16% of the total. To its economic and political conditions, this city is an important transportation hub which connects southwest Sichuan and northwest Yunnan by Chengdu-Kunming Railway. It is as well a regional central city and a distribution center for trading. The location of the study area is shown in Fig. 1.

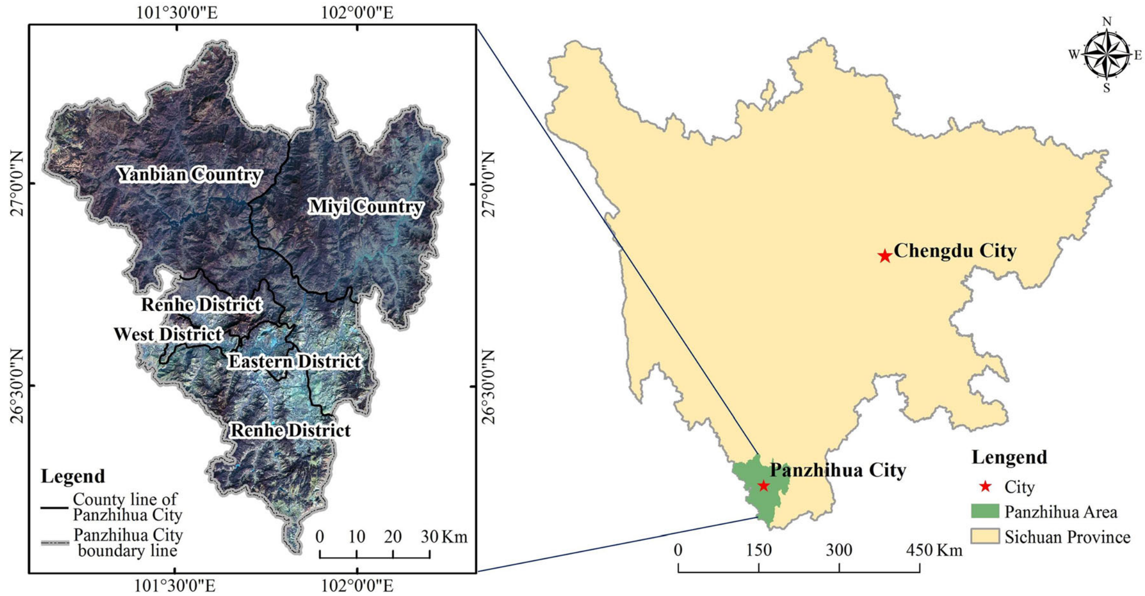



**Fig. 1** Location of the study area

## Data source and preprocessing

### Data collection

**Remote sensing data** The image data in the study are from Geospatial Data Cloud, a remote sensing data sharing site in China. Some high-resolution images in 1990–2015 are mainly from the Google Earth, Remote Sensing Monitoring Projects for Environmental Development of Mineral Resources in China, and Comprehensive Remote Sensing Survey for Natural Resources in Southwest China (Sichuan-Guizhou). The information about remote sensing data is shown in Table 1 and Table 2.

**Non-remote sensing data** This paper mainly chooses seven kinds of non-remote sensing data, which are vegetation data, land-use data, topography and geomorphology data, soil data, meteorological data, mining area data, and socioeconomic data. Their detailed information is in Table 3.

### Data processing

**Unification** This research unifies all thematic data and research results data into TIF Grid format, with 30 × 30 m the size of evaluation unit, Xi'an 1980 the geographic coordinate system, and 102° the central longitude of Gauss Kruger projection system. This process ensures the uniformity of spatial units in all data and the accuracy of mathematical logic operation in the following research processes.

**Radiometric correction** This research corrects the radiometric values of TM, ETM, and OLI images based on 2005, 2010, and 2015 in study area, respectively. Since some Landsat TM images have no-value stripes, they are processed by destripe method. After all those processes for each image, such as radiometric calibration, atmospheric correction, geometric correction, image mosaic, and image clipping, study area's preprocessed images are acquired.

**Extraction** This research then establishes remote sensing information interpretation keys based on the Classification Standard of Land Use Status in China (GBT 21010-2007). Combined with support vector machine model and visual interpretation classification method, research extracts land-use information. It shows that the classification accuracy of land use types in Panzhihua City is over 85%.

**Standardization** This research sorts out the data from different meteorological stations and the data from statistical yearbooks into standard format. Then, these attribute data are transformed into spatial data by multiple regression calculation,

**Table 1** Information of remote sensing image data

| Data type | Spatial resolution (m) | Design area ($km^2$) | Actual acquired area ($km^2$) | Acquisition percentage (%) |
|---|---|---|---|---|
| Pleiades | 0.5 | 642 | 642 | 100 |
| GF-1 | 2 | 1280 | 1280 | 100 |

**Table 2** Sources and descriptions of remote sensing data

| Remote sensing data types (Landsat) | Data sources | Resolution (m) | Orbit serial number | Collection time |
|---|---|---|---|---|
| TM | Geospatial Data Cloud (http://www.gscloud.cn/) | 30 | 130041 | 2005–2015 |
| ETM | | 30 | 130042 | 2005–2015 |
| OLI | | 30 | 131041 | 2005–2015 |

residual calculation, and inverse distance weight interpolation. Finally, based on the image interpretation of each period, research obtains land-use data. These could calculate the biological abundance index, landscape diversity index, and the proportion of cultivated land.

## Framework

### Research technique route

This research gathered the information about the resources, topography, population, and economy of Panzhihua City and collected relevant literature to analyze its spatial and temporal evolution of the ecological environment vulnerability. For the first step, we established an evaluation system that is based on ecological pressure, ecological sensitivity, and ecological recovery from various index data. For the second step, we adopted such methods as supervised classification, multiple regression and residual interpolation, nuclear density estimation, vegetation inversion, soil erosion calculation, and so on to establish the spatial data base of evaluation index. For the third step, we determined the weight, computed the vulnerability values of Panzhihua City, classified values into different levels, calculated the area of each level, and analyzed the characteristics of spatial heterogeneity for ecological environment vulnerability in the study area. For the fourth part, by using CA-Markov model, dynamic degree, trend index, and comprehensive index of ecological vulnerability, we analyzed the change trend and change rate of the overall vulnerability in the study area, accomplishing the analysis of temporal pattern evolution rule for ecological environment vulnerability. For the last step, we found humanistic driving factors that affected the region by using GeoDetector, which supported the ecological civilization construction with scientific theory. The specific technical route is shown in Fig. 2.

### Establishment of evaluation model

In a certain region and period, the ecosystem has an unstable internal framework that is sensitive to external interference. But at the same time, it shows its resilience to evolve in a direction that is not conducive to its own development because of lacking coping capacity. Ecological sensitivity, ecological recovery, and ecological pressure model (SRP model), which contains many important indexes from ecological vulnerability, is applied to comprehensively assess ecological vulnerability in a particular area. Its main processes are as follows: picking indexes that are closely related to ecological vulnerability; setting weight value and exponent for each index; multiplying each weight value and exponent; and accumulating the results. The eco-vulnerability index (EVI) is finally acquired. The formula is as follows.

$$E_{EVI} = \sum_{i=1}^{n} F_i \times W_i \tag{1}$$

where EEVI is eco-vulnerability index value, $F_i$ is the $i$th research index's exponent, and $W_i$ is the corresponding weight

**Table 3** Sources and descriptions of non-remote sensing data

| Non-remote sensing data types | Data sources | Collection time |
|---|---|---|
| Vegetation data | Landsat TM/ETM/OLI series image inversion | 2005–2015 |
| Land use data | Landsat series image data | 2005–2015 |
| Topographical and geomorphic data | Digital Elevation Data of 30 m Resolution (GDEMDEM) in Geospatial Data Cloud (http://www.gscloud.cn/) | |
| Soil data | Resource and Environment Science Data Center of Chinese Academy of Sciences (http://www.resdc.cn/); soil type data of 1:1 million in China Soil Database | |
| Meteorological data | China Meteorological Science Data Network (http://data.cma.cn/) | 2005–2015 |
| Mining area data | The application form for mineral resources exploration (database), the latest regional mineral resources planning, the distribution of mineral resources, and other related written information, data forms, etc. | |
| Socio-economic data | Panzhihua City Statistical Yearbook | 2005–2015 |

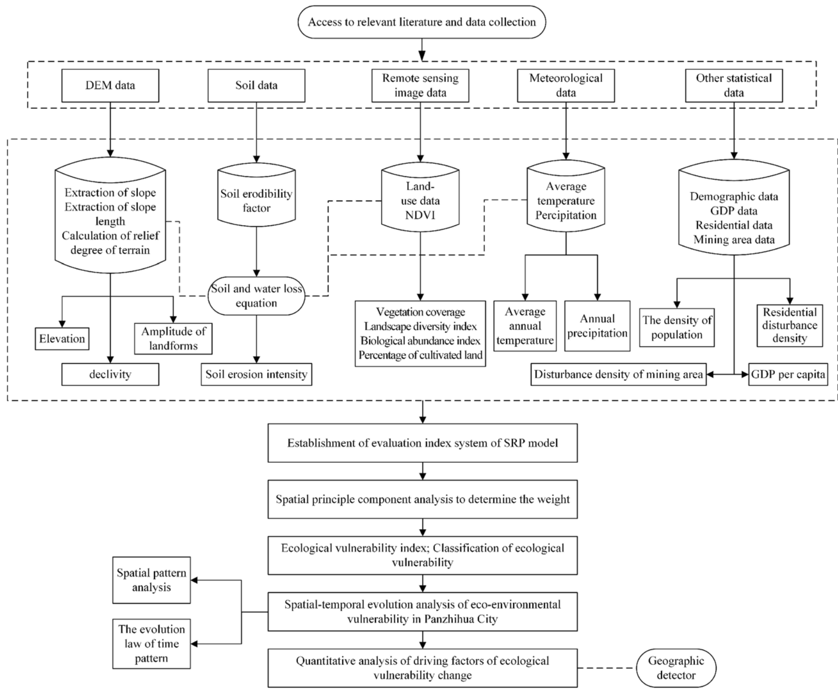



**Fig. 2** Technical route of assessing spatial and temporal evolution of the ecological environment vulnerability in Panzhihua City

value of the $i$th research index ($1 \le i \le n$).

## Extraction of evaluation indexes

This research considered the ecosystem stability to establish the vulnerability evaluation model of Panzhihua City, with multi-level evaluation index, and comprehensive evaluation index system effectively and systematically evaluated the ecological environment of a region. From this aspect, we established SRP conceptual model, which considered ecological sensitivity, ecological recovery, and ecological pressure that are based on the eco-environmental vulnerability of Panzhihua City.

Ecological sensitivity refers to a series of ecosystem reactions against the internal and external interference (Yin et al. 2006), including topographic factors, surface factors, meteorological factors, and soil factors. Ecological recovery refers to the ability of self-regulation and self-repair for the interference, which is related to the internal structure of the ecosystem (Wang et al. 2010; Yang et al. 2012), including landscape structure, ecological vitality, and ecological functions. Ecological pressure refers to the physiological effects caused by interference factors mainly from human activities (Li et al. 2015), including human social and economic activities.

Since different factors have different effects on the vulnerability, this research selects 14 eco-environmental constraint factors based on SRP model including terrain factors, soil factors, landscape structure, and intensity of human activities. These factors construct the eco-environmental vulnerability assessment system of Panzhihua City. The system is shown in Fig. 3.

## GeoDetector

Generally speaking, different factors forced the spatial distribution of a geographic phenomenon, so similar spatial distribution law will exist in the spatial distribution of its influencing factors. GeoDetector is a new statistical method to detect spatial heterogeneity and explain the potential driving factors which affected their geographical phenomena. Its basic geographical idea is that if the variance of sub-regions in the whole geographical study area is less than the total variance of the area, spatial heterogeneity will exist. GeoDetector was firstly used to analyze the correlation between disease incidence and geographical environment (Wang and Xu 2017). Yet in recent years, it is gradually applied to the driving analysis between habitat suitability of pandas and environmental factors, between spatial distribution of mountain torrents and human nature factors (Liao et al. 2016; Xiong et al. 2018). It is also used to identify the influencing factors of spatial differentiation and study the explanatory force mechanism (Wang et al. 2018; Zhao et al. 2018).

GeoDetector is composed of risk detector, factor detector, ecological detector, and interaction detector. This research analyzed the quantitative correlation between the eco-environmental vulnerability and its human driving factors from 2005 to 2015 by factor detector and interaction detector, and then analyzed the relative importance among driving factors which affect the fragility of regional eco-environment and how important the interaction is to the environment of Panzhihua City. The detailed information about detectors is as follows.

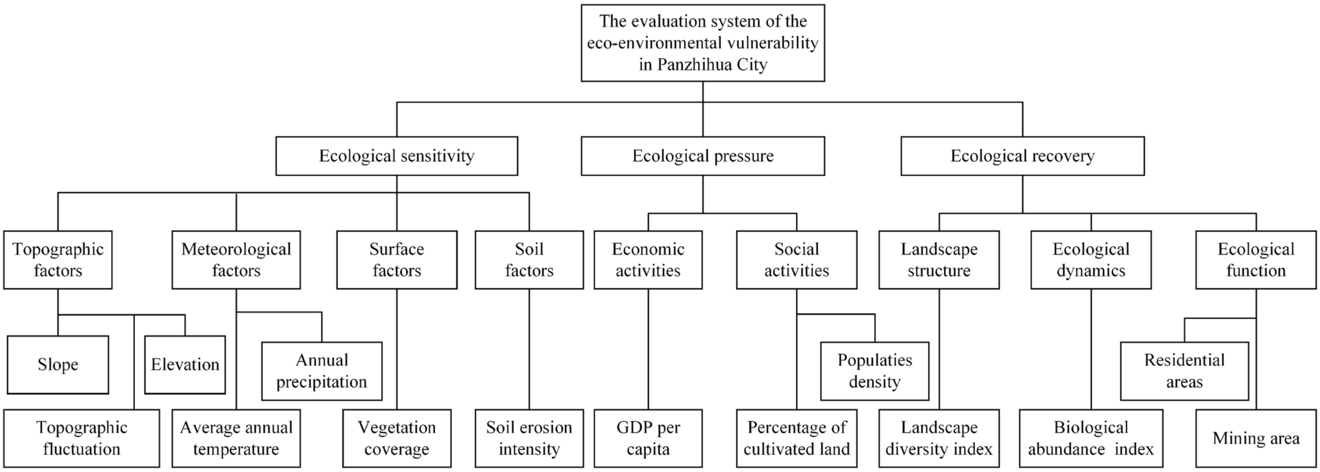



**Fig. 3** The eco-environmental vulnerability assessment system of Panzhihua City

Factor detector: it is to detect how much an evaluation index *X* expressed dependent variable *Y*. Factor explanatory power QD,H will measure the value. A higher value shows a greater contribution to the ecological environment vulnerability, and vice versa. The formula is as follows.

$$\mathrm{Q_{D,H}} = 1\text{-}\frac{1}{\mathrm{n}\sigma^2}\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{n_h}\sigma_{\mathrm{h}}^2 \qquad (2)$$

where D is evaluation index. H is vulnerability index of the ecological environment. $\mathrm{Q_{D,H}}$ ranging from 0 to 1 is the explanatory power of the evaluation index factors to the ecological environment vulnerability. *n* and L is the number of samples and the number of index classifications. $\mathrm{n_h}$ is the sample size of *h* level. $\sigma^2{}_\mathrm{h}$ is the variance of eco-environmental vulnerability index of h level.

Interaction detector: it is to detect whether the interaction between the detection index factors *x1* and *x2* enhances or weakens the dependent variable *Y*, or the interaction influences it independently. The classification of related interaction types is shown in Table 4.

In Table 4, $Q_{D,H}(x1 \cap x2)$ is the interaction between $Q_{D,H}(x1)$ and $Q_{D,H}(x2)$. Min ($Q_{D,H}(x1)$, $Q_{D,H}(x2)$) and max ($Q_{D,H}(x1)$, $Q_{D,H}(x2)$) are the extraction of the maximum and minimum values between $Q_{D,H}(x1)$ and $Q_{D,H}(x2)$.

All in all, as a useful statistical method, GeoDetector is able to detect spatial heterogeneity and reveal its driving forces. It can also detect the contribution rate of each factor to the model and extract useful spatial correlation rules from huge spatial database. Therefore, it is widely applied to analyze how geographical element patterns evolve and what its regional spatial heterogeneity is.

## Driving force analysis index

Following the principles of data science, systematization, purpose, and operability, here, we take into account three factors: natural, economic, and social, according to the actual situation of the study area ecosystem (Jia et al. 2020; Li and Fan 2014; Ma et al. 2015; Ma et al. 2019). The ecological vulnerability of the study area was analyzed by selecting 14 representative indicators as drivers from three aspects: ecological sensitivity, ecological resilience, and ecological stress level. Among them, ecological sensitivity refers to the likelihood of the ecosystem generating environmental problems under external influences (Qi et al. 2017), which includes three components: surface factors, meteorological factors, and topographic factors. Surface factors include soil erosion intensity and vegetation cover. Meteorological factors include annual precipitation and annual average temperature. Topographic factors include elevation, slope, and topographic undulation. Ecological resilience refers to the ability of ecosystems to self-regulate and recover from internal and external disturbances (Qi et al. 2017). This paper chose four factors which consist of landscape pattern index, degree of disturbance from mining and settlements, and biological abundance index. The resilience of ecosystems in the study area was reflected from landscape structure, functional layer, and vitality layer. Ecological stress degree is the degree of stress on the ecosystem caused by disturbance factors originating from human socio-economic activities (Li et al. 2015), so this paper uses population density, GDP per capita, and arable land occupancy ratio measure

**Table 4** Interaction type classification of interaction detector

| Basis | Interaction |
|---|---|
| $Q_{D,\ H}(x_1 \cap x_2) < \mathrm{Min}(Q_{D,\ H}(x_1), Q_{D,\ H}(x_2))$ | Nonlinear enhancement |
| $\mathrm{Min}(Q_{D,\ H}(x_1), Q_{D,\ H}(x_2)) < Q_{D,\ H}(x_1 \cap x_2) < \mathrm{Max}(Q_{D,\ H}(x_1), Q_{D,\ H}(x_2))$ | Single factor nonlinearity attenuation |
| $Q_{D,\ H}(x_1 \cap x_2) > \mathrm{Max}(Q_{D,\ H}(x_1), Q_{D,\ H}(x_2))$ | Two-factor enhancement |
| $Q_{D,\ H}(x_1 \cap x_2) = Q_{D,\ H}(x_1) + Q_{D,\ H}(x_2)$ | Independent |
| $Q_{D,\ H}(x_1 \cap x_2) > Q_{D,\ H}(x_1) + Q_{D,\ H}(x_2)$ | Nonlinear enhancement |

the ecological stress degree of the study area from anthropogenic activity stress and economic development level stress.

## Results

### Distribution characteristics of spatial pattern

This research reclassified the ecological environment vulnerability values from 2005 to 2015 in Panzhihua City, and then gained three periods of vulnerability classification results in this area, which is shown in Fig. 4. According to the classification results, the research also counted the coverage and area proportion of each classification, which is shown in Table 5.

The results showed that, from 2005 to 2015, the eco-environmental vulnerability index of Panzhihua City ranged from 0.30 to 1.31 with an annual average of 0.45, shown in Fig. 5. According to the analysis of statistics in Table 5, the comparison of the overall area ratio of ecological environment vulnerability levels in Panzhihua City from 2005 to 2015 was slight > mild > moderate > potential > severe ecological vulnerability area coverage, where the severe vulnerability state in the three periods only covered 1.39%, 1.22%, and 0.97% of the total area, a relatively small area. At the macro level, the overall fragility of the eco-environment in Panzhihua City decreased from southeast to northwest. The overall eco-environmental quality of the study area was in a slight state, and the overall vulnerability was between mild and moderate.

### Local distribution characteristics of fragile area

We obtained the statistical classification about coverage and its proportion through overlapping the three periods' ecological vulnerability classification results of Panzhihua City in 2005, 2010, and 2015 with the districts and counties of Panzhihua City. The detailed information is shown in Fig. 6 and Fig. 7.

According to the three periods of classification eco-environmental vulnerability results in Panzhihua City, it can be seen that the moderately fragile areas or above mainly distribute in the southern part of the West District, the eastern part of Miyi County, the northern part of Renhe District, and the eastern part of the East District. Urban population mainly concentrates in the East District and the West District of Panzhihua City, where the proportion of moderate vulnerability is larger than that in other districts and counties. These areas have more frequent human activities, such as city construction, mineral resources exploitation, lager land use, and urbanization, so it is sensitive to eco-environmental damage. Since the damage is not easy to restore and control in this area, its self-recovery ability of the ecosystem is relatively poor. Therefore, it is necessary to strengthen the protection of ecological construction in these areas and keep ecological environment from developing in a wrong direction.

### The changing rate of eco-environmental vulnerability

Based on the state transition of CA - Markov model, this research conducted the role-in and role-out area statistics for each vulnerability level in three periods, which are 2005 to 2010, 2010 to 2015, and 2005 to 2015, and then gained the horizontal transfer matrix results for each vulnerability level. The results are shown in Tables 6, 7, and 8. On this basis, this research quantitatively evaluated the vulnerability levels and overall eco-environmental vulnerability in Panzhihua City combined with single dynamic degree and comprehensive dynamic degree (Ma et al. 2013; Yao et al. 2017). Then, combined with the transfer matrix results of each period and the dynamic attitude model, this research calculated the single dynamic degree of each vulnerability level and the comprehensive, dynamic degree of the overall vulnerability level of

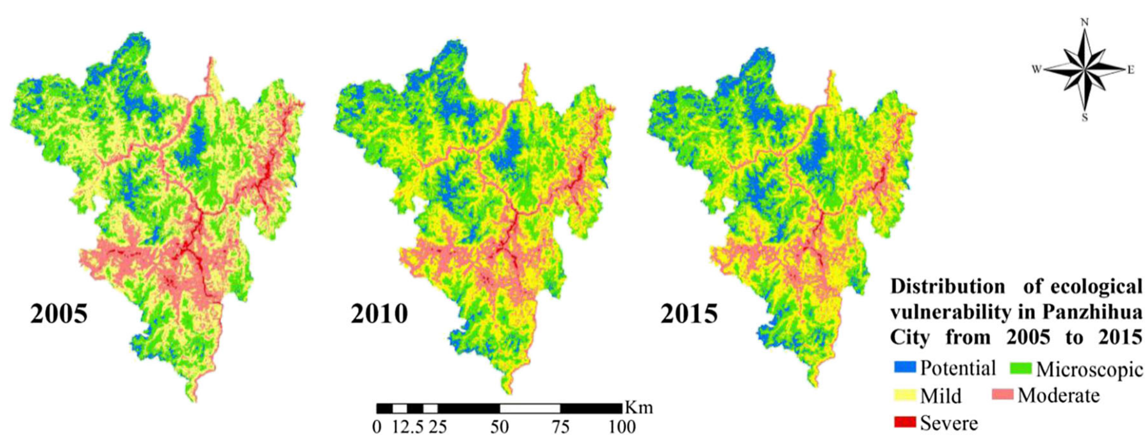



**Fig. 4** Classification result of eco-environment vulnerability assessment in Panzhihua City from 2005 to 2015

**Table 5** The coverage and area proportion of each classification based on eco-environmental vulnerability in Panzhihua City

| Vulnerability level | 2005 | | 2010 | | 2015 | |
|---|---|---|---|---|---|---|
| | Area/km$^2$ | Percentage/% | Area/km$^2$ | Percentage/% | Area/km$^2$ | Percentage/% |
| Potential | 612.15 | 8.25 | 660.71 | 8.91 | 750.60 | 10.12 |
| Slight | 2522.80 | 34.00 | 2568.54 | 34.62 | 2665.84 | 35.94 |
| Mild | 2828.27 | 38.12 | 2801.45 | 37.76 | 2759.17 | 37.20 |
| Moderate | 1353.34 | 18.24 | 1298.48 | 17.50 | 1168.97 | 15.76 |
| Severe | 102.81 | 1.39 | 90.17 | 1.22 | 71.92 | 0.97 |

Panzhihua City in three periods. The results are shown in Table 9.

From the aspect of single dynamic analysis, the comparison of dynamic degree for each eco-environmental vulnerability level from 2005 to 2010 is severe 2.59% > potential 1.54% > moderate 0.82% > slight 0.36% > mild 0.19%. Among them, the area of potential and slight vulnerability levels increased from 2005 to 2010, while severe and moderate vulnerability levels decreased during this period. Besides, the comparison of dynamic degree from 2010 to 2015 is severe 4.42% > potential 2.66% > moderate 2.08% > slight 0.75% > mild 0.30%. Among them, the area of moderate and severe vulnerability levels also decreased, and these two levels were transforming to mild and moderate level.

From the aspect of synthetic rate of change analysis, the range of the overall change in 2010–2015 was greater than that in 2005–2010. During the whole period from 2005 to 2015, the change rate of the overall eco-environmental vulnerability level in Panzhihua City was 0.38%, and the average annual change rate in these 10 years was 0.04%. During 2005–2015, the severe vulnerability decreased and potential vulnerability increased. Additionally, other vulnerabilities to a small extent tended to develop toward good ecological environment quality.

## Driving force analysis

Ecological vulnerability is usually related to economic development. According to the various ecological environment problems in Panzhihua City from 2005 to 2015. In the research, 5411 points were randomly generated in the study area by treating 500 m as the minimum unit through spatial analysis. Besides, the independent variables are the mean value of 14 driving factors extracted by masks, and dependent variables are the annual average of three-period ecological vulnerability value in Panzhihua City. According to the variable partition table (Table 10) and the two mathematical models of factor detection and interaction detection in geographic detectors, the detection statistical analysis is carried out.

GeoDetector revealed the explanatory power of each influence factor for eco-environmental vulnerability. The comparison about significant influence of these factors is vegetation coverage (0.611) > elevation (0.562) (0.529) > annual average temperature (0.529) > annual average precipitation (0.499) > landscape diversity index (0.471) > residential density (0.177) > biological abundance index (0.143) > cultivated land proportion (0.122).

The results show that the change of eco-environmental vulnerability in Panzhihua City is caused by synthetic effect of different natural conditions and human activities. Some natural conditions, such as high altitude, dense vegetation. and poor climate, make it difficult for human beings to live, but leave a good ecological environment. However, other places with low elevation, suitable temperature, abundant precipitation, and proper vegetation make it suitable for developing social economy but lead a relatively poor ecological environment. In recent 10 years, the main driving factors of the change in Panzhihua City are vegetation coverage, elevation, landscape diversity index, annual precipitation, and annual

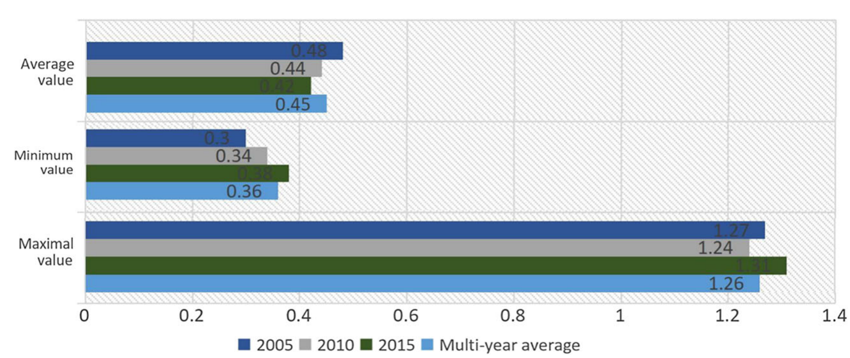



**Fig. 5** Histogram of minimum, maximum, and mean value based on eco-environmental vulnerability in Panzhihua City

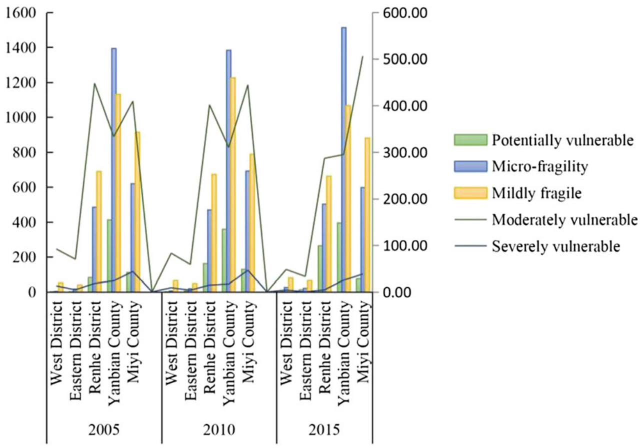
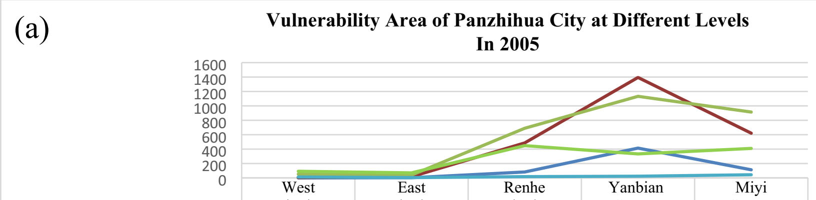



**Fig. 6** Scale map of vulnerability areas at different levels

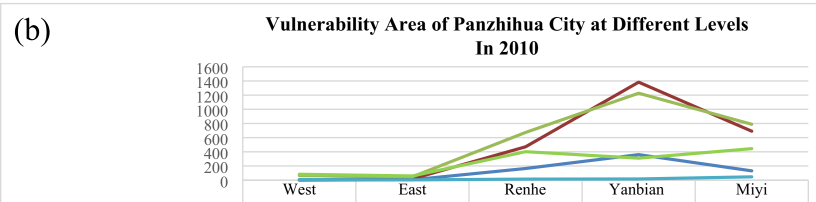
average temperature. The partition results of each one of the 14 factors and the classification result of eco-environmental vulnerability levels are shown in Figure 8.

To sum up, the natural factors and human activity-related factors mainly influenced the overall eco-environmental vulnerability of Panzhihua City from 2005 to 2015. Among these factors, regional natural factors are in the dominant position, and human-related factors take second place. Especially, such natural factors as the vegetation coverage, elevation, precipitation, temperature, landscape diversity index, and biological abundance have much influence. But some human-related factors, such as residential density and cultivated land ratio, also play a certain role in influencing the regional ecological environment in ecological resilience and ecological pressure.

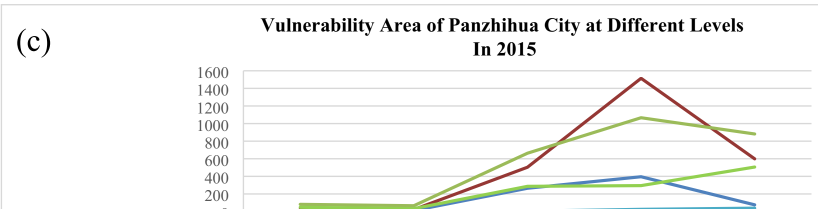
**Fig. 7** Eco-environmental vulnerability at different levels in three periods (**a**–**c**)




| | West District | East District | Renhe District | Yanbian County | Miyi County |
|---|---|---|---|---|---|
| Potential vulnerability | 0.12 | 2.81 | 82.58 | 413.82 | 112.83 |
| Slight vulnerability | 4.58 | 17.17 | 486.1 | 1394.26 | 620.69 |
| Mild vulnerability | 52.76 | 39.6 | 689.35 | 1132.43 | 914.13 |
| Moderate vulnerability | 92.16 | 70.26 | 448.07 | 333.23 | 409.61 |
| Severe vulnerability | 12.62 | 4.45 | 17.94 | 23.81 | 44 |




| | West District | East District | Renhe District | Yanbian County | Miyi County |
|---|---|---|---|---|---|
| Potential vulnerability | 0 | 5.32 | 164.15 | 360.39 | 130.85 |
| Slight vulnerability | 5.54 | 18.61 | 470.5 | 1383.03 | 690.86 |
| Mild vulnerability | 64.74 | 47.84 | 673.11 | 1227.35 | 788.41 |
| Moderate vulnerability | 83.13 | 58.95 | 401.73 | 310.04 | 444.62 |
| Severe vulnerability | 8.82 | 3.57 | 14.5 | 16.61 | 46.67 |




| | West District | East District | Renhe District | Yanbian County | Miyi County |
|---|---|---|---|---|---|
| Potential vulnerability | 1.89 | 11.93 | 264.75 | 395.7 | 76.34 |
| Slight vulnerability | 26.11 | 22.65 | 503.65 | 1514.56 | 598.87 |
| Mild vulnerability | 81.96 | 66.2 | 663.01 | 1066.35 | 881.65 |
| Moderate vulnerability | 48.17 | 33.36 | 286.72 | 294.8 | 505.92 |
| Severe vulnerability | 3.9 | 0.11 | 4.26 | 25.2 | 38.46 |

**Table 6** Transfer matrix of eco-environmental vulnerability level 2005–2010 ($km^2$)

| 2010 (below)/2005 (right) | Potential | Slight | Mild | Moderate | Severe | Transferred to total area |
|---|---|---|---|---|---|---|
| Potential | 435.17 | 228.21 | 6.63 | 0.02 | 0.00 | 234.87 |
| Slight | 174.48 | 1879.08 | 512.63 | 2.29 | 0.00 | 689.39 |
| Mild | 11.68 | 411.25 | 2047.26 | 330.92 | 0.29 | 754.15 |
| Moderate | 0.10 | 4.19 | 260.71 | 993.89 | 39.53 | 304.53 |
| Severe | 0.02 | 0.00 | 1.00 | 26.16 | 62.98 | 27.17 |
| Total turning out area | 186.27 | 643.65 | 780.96 | 359.39 | 39.83 | |

**Table 7** Transfer matrix of eco-environmental vulnerability level 2010–2015 ($km^2$)

| 2015 (below)/2010 (right) | Potential | Slight | Mild | Moderate | Severe | Transferred to total area |
|---|---|---|---|---|---|---|
| Potential | 501.91 | 243.44 | 17.21 | 0.23 | 0.01 | 260.90 |
| Slight | 166.21 | 1973.89 | 517.47 | 8.17 | 0.00 | 691.85 |
| Mild | 1.79 | 349.07 | 2024.04 | 383.84 | 0.38 | 735.08 |
| Moderate | 0.12 | 2.07 | 241.66 | 878.77 | 46.25 | 290.11 |
| Severe | 0.00 | 0.00 | 1.01 | 27.41 | 43.50 | 28.42 |
| Total turning out area | 168.12 | 594.58 | 777.36 | 419.65 | 46.65 | |

**Table 8** Transfer matrix of eco-environmental vulnerability level 2005–2015 ($km^2$)

| 2015 (below)/2005 (right) | Potential | Slight | Mild | Moderate | Severe | Transferred to total area |
|---|---|---|---|---|---|---|
| Potential | 432.30 | 307.95 | 22.24 | 0.33 | 0.01 | 330.52 |
| Slight | 186.46 | 1816.50 | 642.94 | 19.84 | 0.00 | 849.24 |
| Mild | 2.48 | 393.89 | 1874.72 | 486.40 | 1.62 | 884.40 |
| Moderate | 0.20 | 4.38 | 285.19 | 818.61 | 60.52 | 350.28 |
| Severe | 0.00 | 0.01 | 3.14 | 28.11 | 40.67 | 31.26 |
| Total turning out area | 189.14 | 706.23 | 953.50 | 534.68 | 62.14 | |

Other driving factors have little explanatory effect on the vulnerability, and they can not be used as the main driving factors for evaluating regional vulnerability. However, various unreasonable and excessive human activities affect vegetation coverage, landscape pattern change, soil and water conservation, precipitation, and temperature. Human beings are the main driving force of the eco-environmental vulnerability. The explanatory power of the factors is shown in Fig. 9.

**Table 9** Dynamic changes in ecological vulnerability in Panzhihua City from 2005 to 2015 (%)

| Single dynamic | 2005–2010 | Average annual | 2010–2015 | Average annual | 2005–2015 | Average annual |
|---|---|---|---|---|---|---|
| Potential | 1.54 | 0.31 | 2.66 | 0.53 | 2.10 | 0.21 |
| Slight | 0.36 | 0.07 | 0.75 | 0.15 | 0.55 | 0.06 |
| Mild | − 0.19 | − 0.04 | − 0.30 | − 0.06 | − 0.25 | − 0.02 |
| Moderate | − 0.82 | − 0.16 | − 2.08 | − 0.42 | − 1.45 | − 0.15 |
| Severe | − 2.59 | − 0.52 | − 4.42 | − 0.88 | − 3.51 | − 0.35 |
| Total turning out area | 0.25 | 0.05 | 0.51 | 0.10 | 0.38 | 0.04 |

**Table 10** Description of driving factor partition of geographic detector

| Drive factor | Segment description |
|---|---|
| Elevation (m) | 1:> 4000; 2:3500~4000; 3:3000~3500; 4:2500~3000; 5:2000~2500; 6:1500~2000; 7:1000~1500; 8:< 1200 |
| Slope (°) | 1:0~5; 2:5~10; 3:10~15; 4:15~20; 5:20~25; 6:25~30; 7:30~35; 8:35~40; 9:> 40 |
| Topographic fluctuation (m) | 1:< 150; 2:150~250; 3:250~350; 4:350~450; 5:450~550; 6:> 550 |
| Vegetation coverage | 1:> 0.8; 2:0.6~0.8; 3:0.4~0.6; 4:0.2~0.4; 5:< 0.2 |
| Annual precipitation (mm) | 1:> 1050; 2:950~1050; 3:850~950; 4:750~850; 5:< 750 |
| Average annual temperature (°) | 1:> 20; 2:15~20; 3:10~15; 4:5~10; 5:< 5 |
| Soil erosion intensity (t/km$^2$·a) | 1:< 500; 2:500~2500; 3:2500~5000; 4:5000~8000; 5:8000~15,000; 6:> 15,000 |
| Landscape diversity index | 1:< 0.2; 2:0.2~0.5; 3:0.5~0.7; 4:0.7~1.0; 5:> 1.0 |
| Biological abundance index | 1:> 80; 2:60~80; 3:40~60; 4:20~40; 5:< 20 |
| Disturbance density of mining area points | 1:< 0.3; 2:0.3~1.0; 3:1.0~2.0; 4:2.0~3.5; 5:> 3.5 |
| Disturbance density in residential areas | 1:< 0.2; 2:0.2~0.7; 3:0.7~1.4; 4:1.4~2.5; 5:> 2.5 |
| GDP per capita (yuan/people) | 1:> 100,000; 2:50,000~100,000; 3:30,000~50,000; 4:20,000~30,000; 5:< 20,000 |
| Population density (people/km$^2$) | 1:< 400; 2:400~800; 3:800~1200; 4:1200~1500; 5:> 1500 |
| Percentage of cultivated land | 1:< 0.2; 2:0.2–0.4; 3:0.4–0.6; 4:0.6–0.8; 5:> 0.8 |

## Discussion

This research took Panzhihua City as research area, and followed the general idea of analyzing the current situation by constructing the index model through regional ecological problems. Based on multi-temporal remote sensing data, several years of meteorological station data, and other statistical data, this research analyzed the causes and characteristics of the eco-environmental vulnerability. Due to the frequent human activities in the study area, the ecosystem of Panzhihua City got some pressure to develop. This research also scientifically analyzed the performance factors of the ecological environment vulnerability from 2005 to 2015 in the aspects of ecological pressure, ecological sensitivity, and ecological recovery, which screened out some of the practical and typical comprehensive factors. Then, we established the evaluation index system for the eco-environmental vulnerability in Panzhihua City. Besides, this research adopted the methods, such as supervised classification, vegetation inversion, regression analysis, landscape pattern index, biological abundance index, and spatial interpolation, to construct the spatial database for evaluation factors based on three periods from 2005 to 2015.

The spatial principal component analysis method is able to eliminate the influence among evaluation indexes, and has the advantage of reducing the workload of index selection and determining the weight objectively and reasonably. So, this research utilized the spatial principal component analysis method to evaluate the regional and overall eco-environmental vulnerability of Panzhihua City. Besides, this analyzed the area change, overall state change trend, and quality state of the vulnerability in three period from 2005 to 2015 in Panzhihua City with the help of CA-Markov model, land-use dynamic degree model, overall trend state index, and comprehensive eco-environmental vulnerability index.

Considering that the GeoDetector has the ability of detecting spatial heterogeneity, revealing its driving force, showing the contribution rate of each factor to the model, and extracting useful spatial correlation rules from the huge spatial database, this research used GeoDetector to analyze the relationship among these individual factors in the fragility of Panzhihua's eco-environment and in human driving factors for Panzhihua City during the whole period.

Based on the spatial distribution results of fourteen evaluation indicators and three periods of spatial analysis results for the regional eco-environmental vulnerability, quantitative statistics analysis was carried out to study the driving force and the eco-environmental vulnerability by factor detector and interaction detector in GeoDetector. The result showed that the spatial distribution of vegetation coverage has the greatest similarity to ecological vulnerability in Panzhihua City. The explanatory power of elevation, precipitation, temperature, and landscape diversity are relatively strong, and they are the main driving forces of the eco-environmental vulnerability of Panzhihua City. The explanatory power of per capita GDP is not that good. In addition, the main driving factors of ecological vulnerability in different regions also differentiate with each other, where vegetation status, landscape diversity, and elevation play a dominant role in different eco-environmental vulnerability levels in different districts and counties. But in the result of interaction detection, the research found that, compared with single-driving factor, the interaction between each two driving factors has more influence on the ecological environmental vulnerability of Panzhihua City. It proved that multiple driving factors comprehensively influenced the

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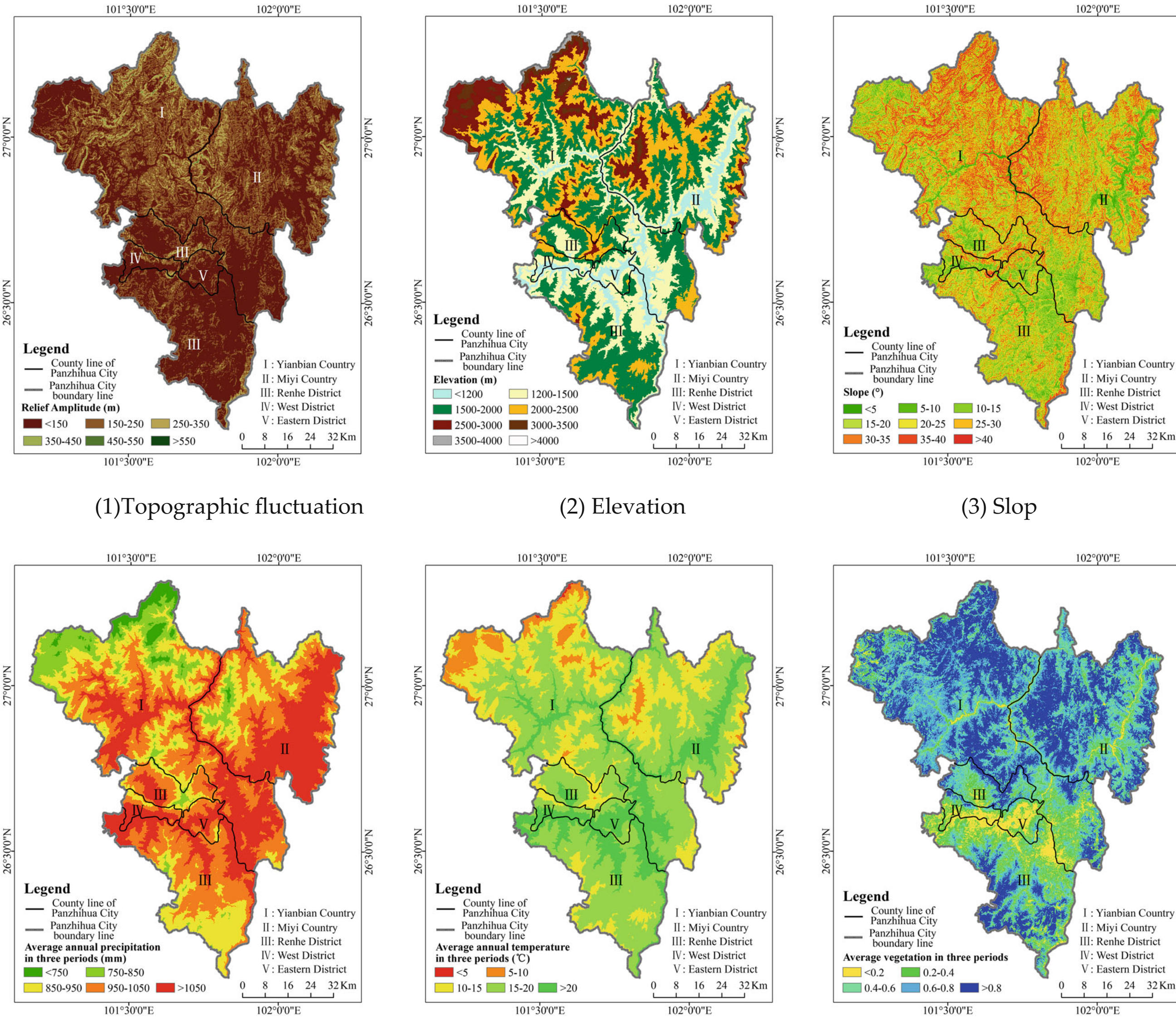



(1)Topographic fluctuation (2) Elevation (3) Slop

(4) Annual precipitation (5) Average annual temperature (6) Vegetation coverage

**Fig. 8** The partition results of each factors (1–14) and the classification result of eco-environmental vulnerability levels (15)

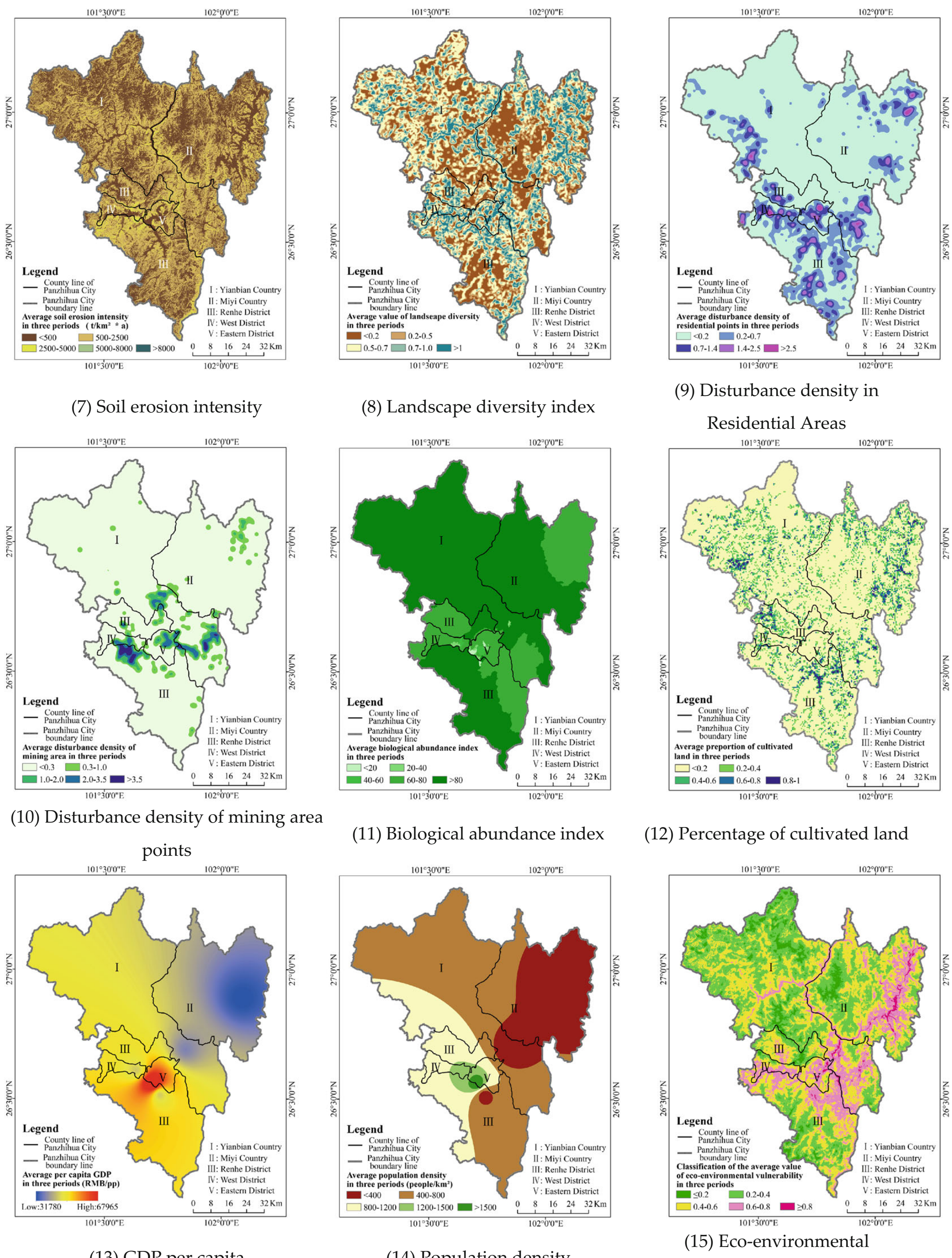
vulnerability of an area's ecological environment. It also showed that the SRP evaluation system constructed in this research can effectively evaluate the ecological environment vulnerability of the study area.

However, the evolution of the spatial and temporal pattern of eco-environment vulnerability in Panzhihua City from 2005 to 2015 was also affected by many other uncontrollable natural factors and multi-level human social and economic factors. What is more, this kind of research needs to involve a wide range of scientific fields. It should be a much more complicated analysis for the evolution of eco-environmental vulnerability in Panzhihua City. Therefore, more factors should be considered in the future research.

## Conclusion

Based on the special physical and geographical characteristics of Panzhihua City and the framework of SRP evaluation system, 14 relevant factors to the eco-environmental vulnerability in Panzhihua City were selected to establish the evaluation index system. Based on spatial principal composition analysis method, this research analyzed the spatial and temporal evolution characteristics and driving forces of the vulnerability in this area from 2005 to 2015. The conclusions are as follows:

(1) Spatial heterogeneity for ecological environment vulnerability: from 2005 to 2015, for different vulnerability




(7) Soil erosion intensity

(8) Landscape diversity index

(9) Disturbance density in Residential Areas

(10) Disturbance density of mining area points

(11) Biological abundance index

(12) Percentage of cultivated land

(13) GDP per capita

(14) Population density

(15) Eco-environmental vulnerability levels

**Fig. 8** (continued)

levels, slightly fragile area has the largest proportion, then mild fragile, moderate, potential, and severe. The severe fragile area has the smallest proportion. The overall level of ecological vulnerability increased from northwest to southeast. The overall ecological environment quality of Panzhihua City was at a slight status.

(2) Temporal variation characteristics of eco-environmental vulnerability: from 2005 to 2015, the comprehensive index of the three periods' eco-environmental vulnerability in Panzhihua City gradually decreased. In these 10 years, the area of slight and potential vulnerability level increased with an annual rate of 0.21 and 0.06,

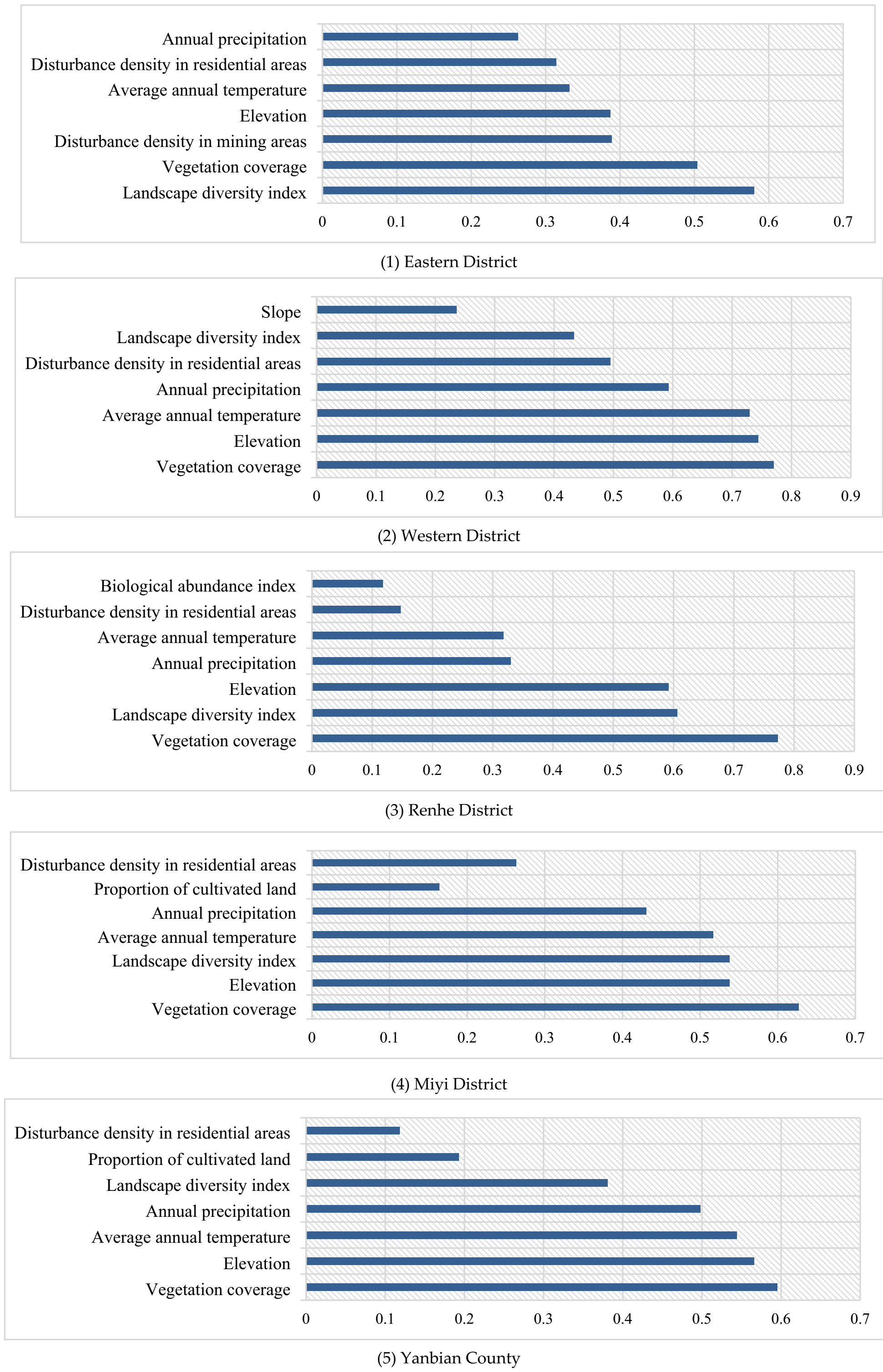



**Fig. 9** Histogram of the explanatory power of the main driving factors of different districts and counties in Panzhihua City (1–5)

respectively. The area of slight, moderate, and severe vulnerability level increased with an annual rate of 0.02, 0.15, and 0.35, respectively. It proves that the bi-directional transition of the vulnerability level in Panzhihua City has changed into balanced transition in these 10 years.

(3) Driving mechanism of ecological environment vulnerability: vegetation coverage has the greatest similarity to eco-environmental vulnerability, followed by elevation, precipitation, temperature, and landscape diversity. These factors have a relatively strong explanatory power. However, per capita GDP has the weakest explanatory

power. It shows that vegetation coverage, landscape diversity index, elevation, precipitation, and temperature are the main driving forces for the eco-environmental vulnerability in Panzhihua City. Besides, this research verified that multiple driving factors shaped the eco-environmental vulnerability of a region, showing that SPR model can well evaluate the ecological environment vulnerability of the study area.

**Authors' contributions** X. D. initiated and designed the research. Y. G., X. H., T. L., and B. J. conducted the experiment. X. D., Y. G., X. H., and T. L. contributed to the writing and development of the manuscript. H. S. and Y. Y aided in analyzing the results. All authors discussed the results and contributed to the final manuscript.

**Funding** This research was funded by the Key Project of Humanities and Social Sciences of Colleges and Universities of Sichuan Province (No.: ZHYJ17-ZD01), and the National mining environment recovery control status remote sensing geological survey and monitoring of the system (DD20190705). Research on Key Technologies of Vegetation Ecological Water (layer) Remote Sensing Monitoring and Resource Retrieval in the Western Sichuan Plateau (KJ-2020-5).

**Availability of data and materials** All the data and materials related to the manuscript are published with the paper, and available from the csorresponding author upon request (daixiaoai@163.com).

## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethical approval** Not applicable

**Consent to participate** All the co-authors agreed to participate in the research.

**Consent to publish** All the co-authors agreed to publish the manuscript.

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