The Study of Quantitative Assessment of Regional Eco-environmental Vulnerability Based on Multi-source Remote Sensing

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Abstract. How to estimate vulnerability of eco-environment quickly and accurately is an important research to predict the trend of environmental change in the future. Based on the analysis of the previous methods of eco-environment assessment, we tried to build a quantitative assessment model of eco-environment vulnerability by multi-source remote sensing data. The model focuses on extracting the change information of vegetation and land cover types from remote sensing (RS) data, and reveals the law of eco-environment vulnerability change. In the process of building the model, the correlation between normalized difference vegetation index (NDVI) and topographic data was analysed. The nonlinear regression method was used to estimating vegetation coverage taken as one of the main parameters of the model. And then, the model was applied to a specific study area. The quantitative assessment used Multi temporal data obtained to calculate the vulnerability values. It described the spatial distribution and variation characteristics of eco-environmental vulnerability in this region. We also estimate the accuracy and stability of the model. The calculation results show that we can quickly evaluate regional eco-environmental vulnerability and improve the efficiency of ecological environment monitoring through our proposed model.

1. Introduction

Eco-environment is material basis for human survival and development. The study of the change of eco-environment vulnerability is an important prerequisite for the formulation of regional sustainable development strategy. Eco-environment vulnerability refers to the sensitivity and self-repair ability of eco-environment when it receives external stimuli or disturbances. It is the result of the interaction of nature, man-made and the evolution of ecosystem. It can quantitatively reflect the change of regional environment. The assessment of eco-environmental vulnerability is an important part of regional ecological comprehensive evaluation. In recent years, it has been widely applied to geography, ecology and environmental science research.

At present, more and more scholars have adopted RS and GIS to support the study of eco-environmental vulnerability. Eco-environment vulnerability quantitative assessment methods describe the effects of environmental vulnerability, stability, sensitivity, and environmental stresses quantitatively on the system. [1] used mathematical language of ecology to propose a basis method for judging the eco-environment vulnerability zones. [2] used the statistical model to calculate eco-environmental vulnerability density distribution. [3] studied the vulnerability assessment by means of vegetation change of multi-source remote sensing data. The study of eco-environment vulnerability involves many fields, such as geology and ecology which is very comprehensive and complex. Therefore, the methods, evaluation index system and classification standards used in the traditional evaluation methods are diversified. The methods usually focus on how to determine the vulnerability evaluation index, the weight setting, and the criteria to specify the stability of each index. They need a long time to deal with the original data, and the research process is time-consuming. So they can't fully, quickly evaluate the status and trends of eco-environmental vulnerability. It is worthy of further study in how to use remote sensing data with the new mathematical method for rapid quantitative assessment.

In this study, we developed a new model for quantitative assessment based on the quantitative evaluation equation built by predecessors, verified the accuracy and stability of the model. First, we extracted the vegetation index, land cover classification, topographic data from the remote sensing image of multi-source. Second, we analysed the relationship between vegetation index and topographic data in the study area, used multiple nonlinear regression method to derive the evaluation factors needed for quantitative assessment model. Through model calculation results, a rapid evaluation results was obtained, as the hierarchy of vulnerability assessment is formed. Meanwhile, we analysed the regularity for vulnerability quantity change and its drivingmechanism in the study area from 2008 to 2010. At last, we discussed the existing problems in our research work, and prospected the future work.

2. Methods

2.1.Main idea

This paper referred to the empirical formula provided by [4], it used correlation analysis of ecological environment vulnerability to build a quantitative assessment model. As shown in (1).

$$\mathbf{F} = \frac{\boldsymbol{U}}{\boldsymbol{f}} \tag{1}$$

Where F is the assessment value of eco-environmental vulnerability, U is the gradient of types of land cover, and *f* is the vegetation coverage of change area.

$$\mathbf{U} = \frac{\Delta \boldsymbol{S_i}}{\boldsymbol{S_i}} \tag{2}$$

Where $\Delta \boldsymbol{S_i}$ is variation of land cover from previous year to the following year, $\boldsymbol{S_i}$ is total area of the land type in the following year, and $\mathbf{i}$ is the land cover type.

$$\boldsymbol{f} = \frac{(\boldsymbol{NDVI}-\boldsymbol{NDVI_{min}})}{(\boldsymbol{NDVI_{max}}-\boldsymbol{NDVI_{min}})} \tag{3}$$

As shown in (3), where f is the value of estimated vegetation cover, NDVI is normalized difference vegetation index, and $\mathbf{NDVI}_{max}$ and $\mathbf{NDVI}_{min}$ are maximum and minimum values in the study area of same year. We calculated the land change area, the total area of land, $\mathbf{NDVI}_{max}$ and $\mathbf{NDVI}_{min}$ annually by writing the IDL program, calculated the evaluation value by substituting the formula (1) according to the estimated vegetation cover. In the IDL environment, we made a comprehensive analysis of elevation, slope and aspect of digital terrain in the study area. We selected the mainly factors related to vegetation into the equation, got results of vulnerability evaluation. Finally the regional eco-environment vulnerability comprehensive evaluation grade is obtained. The experimental procedure is shown in Figure 1.

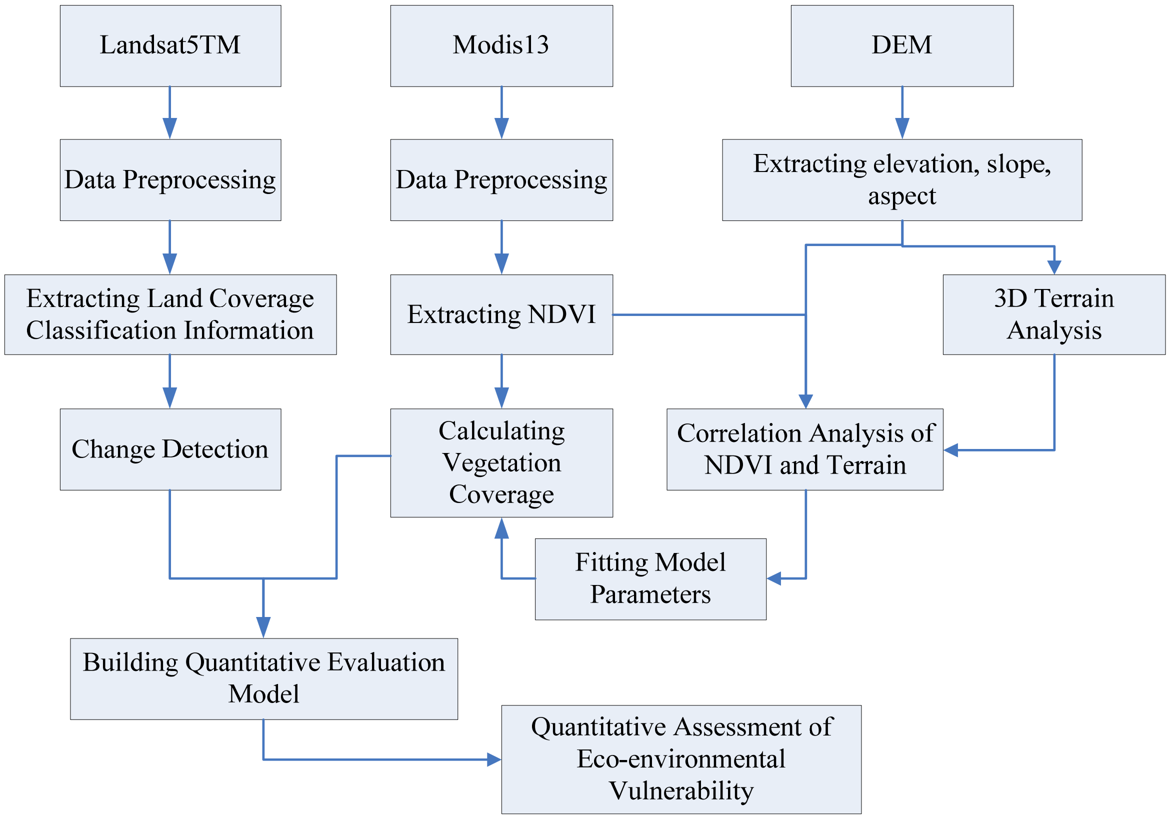


Figure 1. Experimental process.

2.2.Data source

The study area is located in Zoige County of Sichuan Province, China. It is at the junction of Sichuan, Gansu and Qinghai, and on eastern edge of Qinghai and Tibet Plateau, elevation of 3400~3900m. The largest distance between East and North is about 150 km, and the total area is about km^2. It is an important source of water conservation in the upper reaches of Yangtze River and Yellow River. It is also the largest remaining highland peat wetland in China. The whole study area forms a relatively complete geographical and natural system, which is a representative of eco-environment vulnerability (Figure 2.).

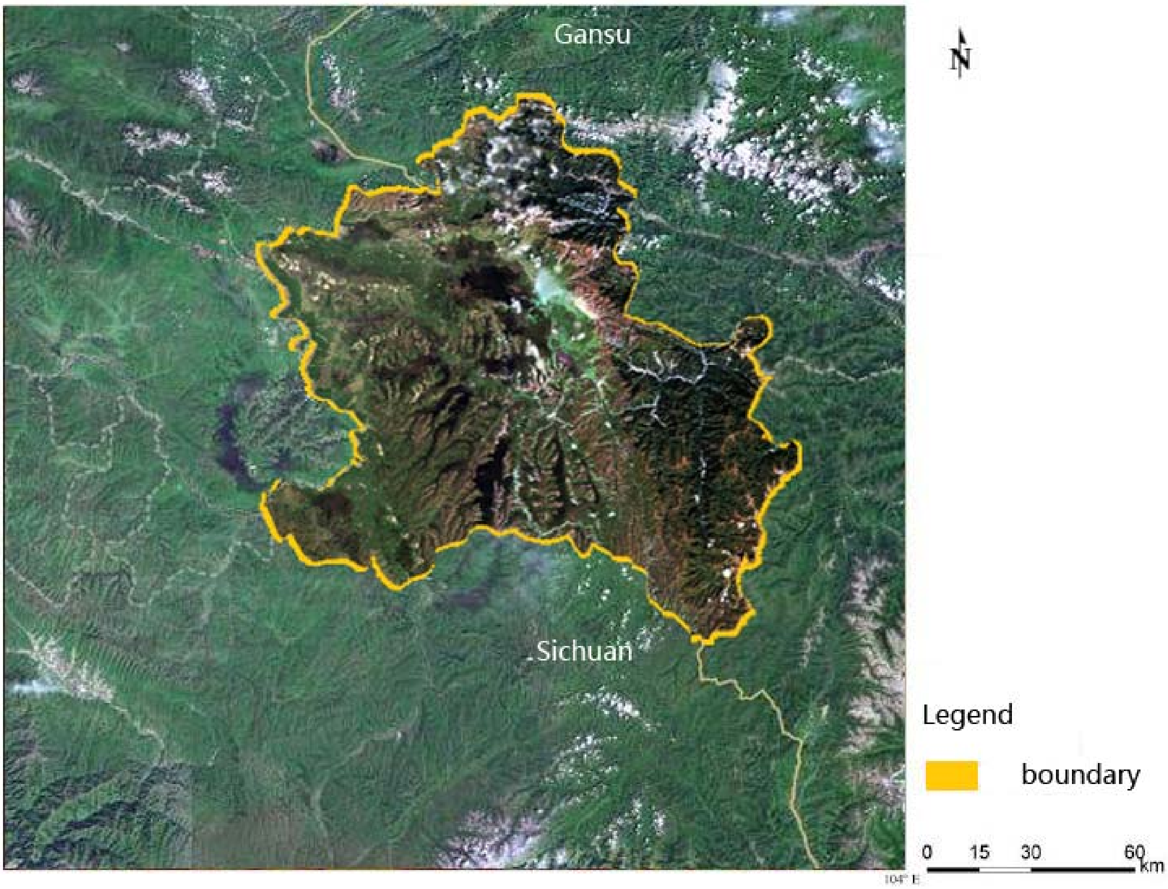


Figure 2. Research area overview

2.2.1.Data of Land Coverage

In this paper, Landsat5 TM data were used to the land cover classification extracting, after that the land cover type change rate is obtained. Remote sensing data were collected in study area from 2008 to 2010. We selected every scene with an average cloud cover of less than 10% of the images, and the imaging time was between July and September. We matched and stitched the images by each scene, then extracted the region of interest according to vector map of study area.

The land cover types in study area include rivers, lakes, peat bogs, swamp meadows, wet meadows, shrubs, shrubs, forests, sandy land, bare land, bare rocks and building land. Among them, rivers, lakes, peat bogs, swamp meadows and wet meadows are main types [5]. This paper referenced to the "National Remote Sensing Monitoring of Land Use/Land Cover Classification System"(P.R.China). Considering the simplicity of model, land coverage types are divided into: grassland, forest land, bare land (bare soil, sandy land, bare rock, snow), water zone (rivers, lakes, swamps, artificial land),swamp and artificial land(residents land, cultivated land, road). In the ENVI environment, land cover classification and post classification processing were completed (Figure 3.).

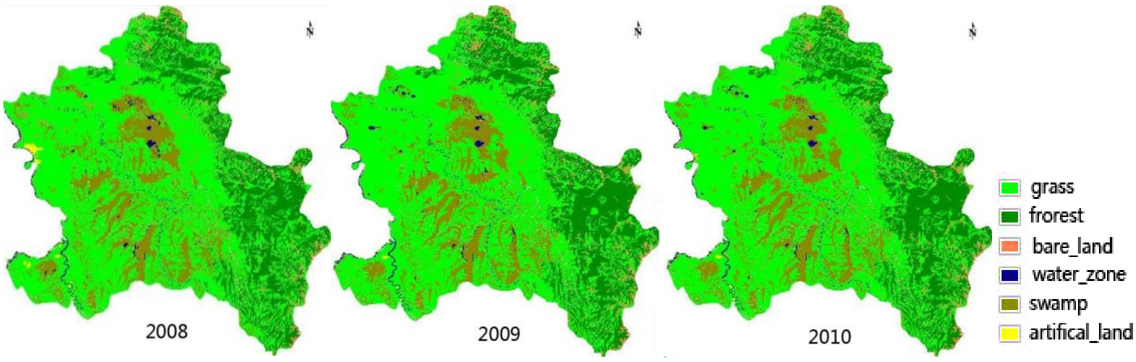


Figure 3. Land cover types from 2008 to 2010.

2.2.2.Data of Vegetation Index

In this paper, MOD13A1 data products from 2008 to 2010 were collected to obtain NDVI dataset. In ENVI environment, we used HANTS (Harmonic Analysis of Time Series) to process annual data [6], and generated spatiotemporal series data sets, then calculated the annual value of NDVI by band computing tools. The results were used to analyzing the correlation between change of NDVI and topographic data. And then we estimated vegetation coverage in the estudy area (Figure 4.).

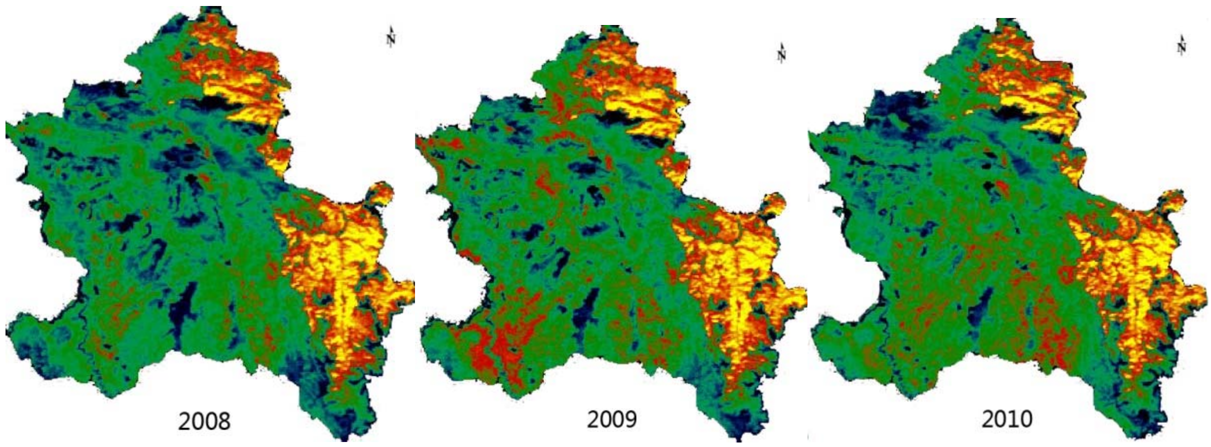
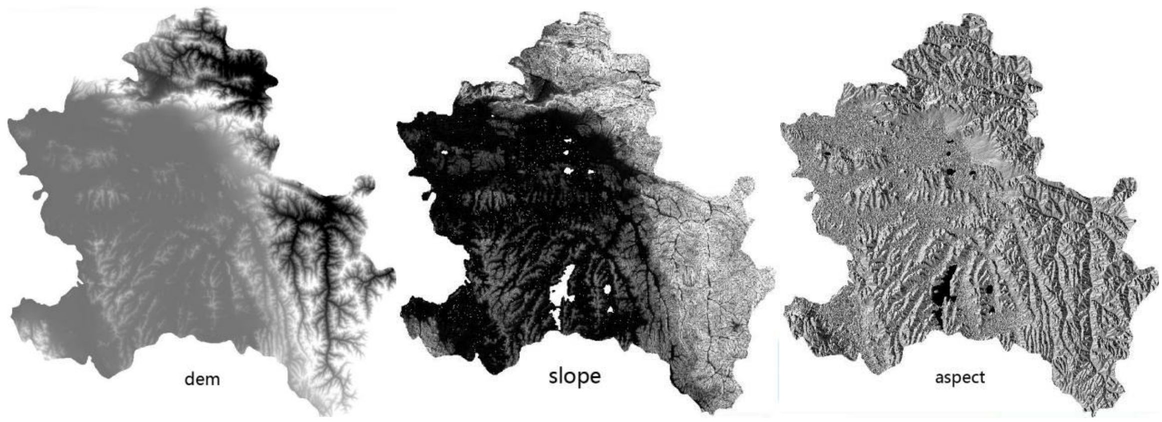


Figure 4. NDVI in 2008~2010.

2.2.3.Data of Digital Terrain

In this study, SRTMDEMUTM data products was selected to extract elevation values (Figure 5.(a)). SRTMSLOPE data products was selected to extract slope values (Figure 5.(b)). The SRTMASPECT data products were selected to extract aspect values (Figure 5.(c)). These data were used to analyzing their correlation with NDVI, estimate vegetation cover and provide parameters for quantitative evaluation model.



(a) (b) (c)

Figure 5. Topographic data.

2.3.Model building

2.3.1.Land cover change rate

In this paper, a statistical tools of ENVI were used to calculating land cover change rate of all types of adjacent years. According to results in this study, change type, area, pixels number were obtained, and percentage change rate of land cover type is obtained (Table 1.).

Table 1. Gradient of land cover type change in 2008~2010.

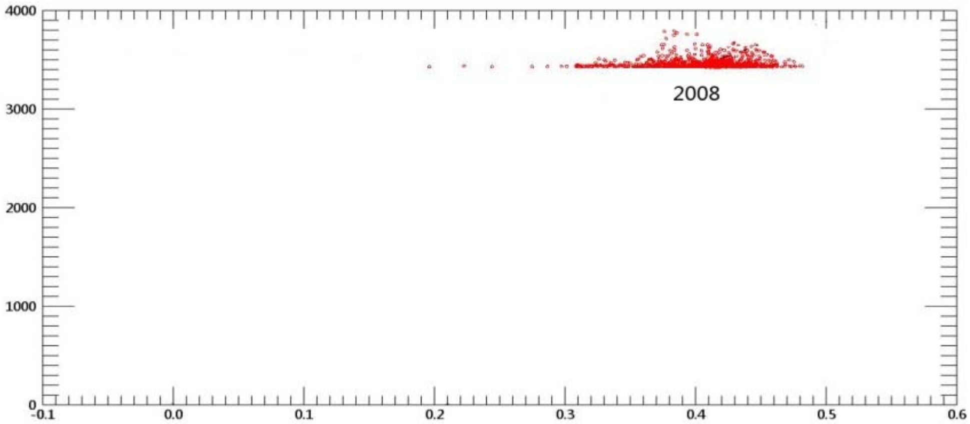
	Grass (%)	Forest(%)	Bare (%)	Water(%)	Swamp(%)	tifici Artificial (%)	Total(%)
2008~ 2009	0.25732	0.09383	0.24308	0.03161	0.27164	0.00041	0.89788
2009~ 2010	0.13459	0.24870	0.15962	0.02148	0.06835	0.14751	0.78025

2.3.2.Vegetation coverage

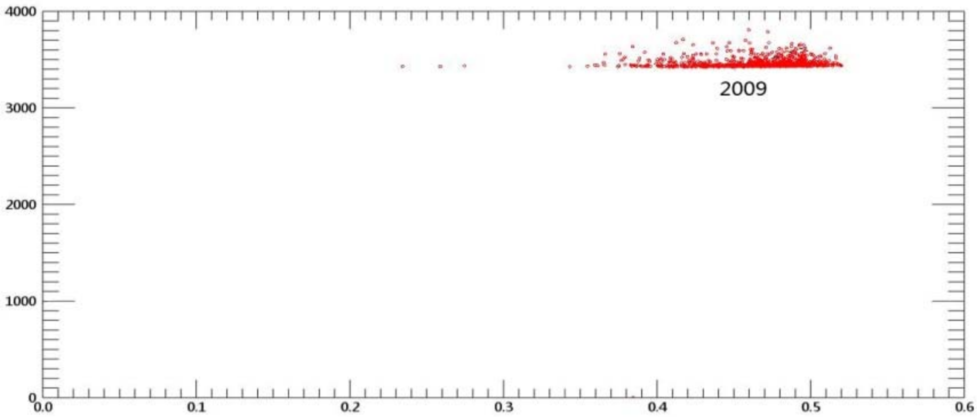
The assessment model constructed in our study mainly depended on gradient of vegetation coverage and land cover types. Because of the change of vegetation with change of topographic condition, NDVI also varies with terrain [7]. Therefore, topographic factors are one of the important indexes to evaluate the vulnerability of eco-environment. The study of vegetation index, terrain height, slope and aspect is beneficial to accuracy of quantitative assessment of regional eco-environmental vulnerability [8]. In this paper, the correlation between NDVI and terrain data has been analysed.

First, NDVI was superimposed with data of elevation, slope and aspect. And then, IDL programs were written to generate random sampling points within the rectangle window specified in study area, and obtained NDVI values, elevation, slope and aspect values corresponding to the same coordinate in each year. Finally, data files were generated NDVI- elevation, NDVI-slope, NDVI-aspect by programs.

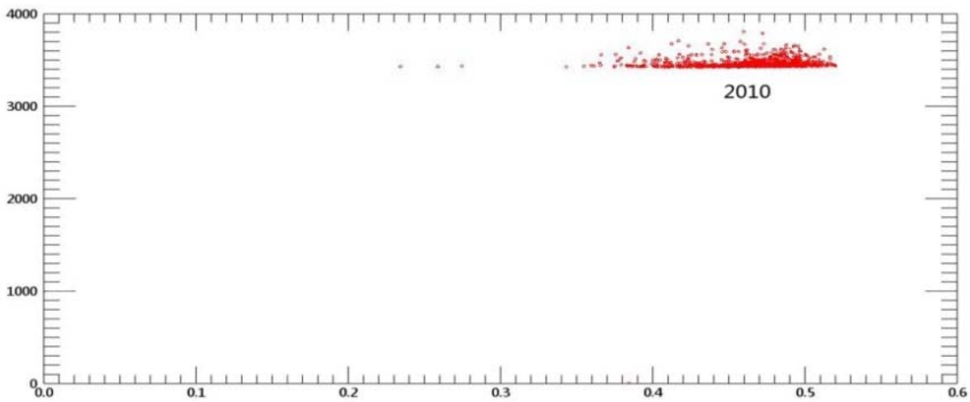
The scatter plots of NDVI with topographic elevation are observed by IDL programs, and more than 2000 sampling points are analysed statistically. As can be seen in Figure 6, the NDVI increases at first and then decreases with the increase of elevation. The change law is consistent with the vertical zone of vegetation distribution. As can be shown in Figure 6, it has a meaning of some function fitting.



(a)



(b)



(c)

Figure 6. Relationship between NDVI and elevation.

The distribution of NDVI with slope and aspect is similar, and there is no obvious regularity change. The data is low correlation with all kinds of fitting functions. The correlation coefficients between NDVI and slope and aspect are mostly less than 0.2, so the regression analysis and function fitting are used only for NDVI and elevation (Table 2.). As the scatter plot shows that there is an obvious regular change between NDVI and elevation. However there is no obvious linear or nonlinear relationship. We speculated that some converted values of NDVI had nonlinear relationship with the elevation values.

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Table 2. Analysis of correlation between NDVI and topography.

Year	NDVI-Elevation	NDVI-Slope	NDVI-Aspect
2008	0.71743188	0.13728386	0.14996434
2009	0.68646128	0.12319367	0.19483329
2010	0.81255774	0.13585131	0.15946412

In this paper, we tried to take natural logarithm of absolute value of mean difference between NDVI and mean value of NDVI. We found that relationship between converted value and elevation. It is supposed that $Y = \ln|NDVI_{mean} - NDVI|$, where Y is conversion value of NDVI. The scatter of elevation value by IDL program is generated. We analysed the shapes of fitting function according to the distribution of scatter plot (Figure 7.).

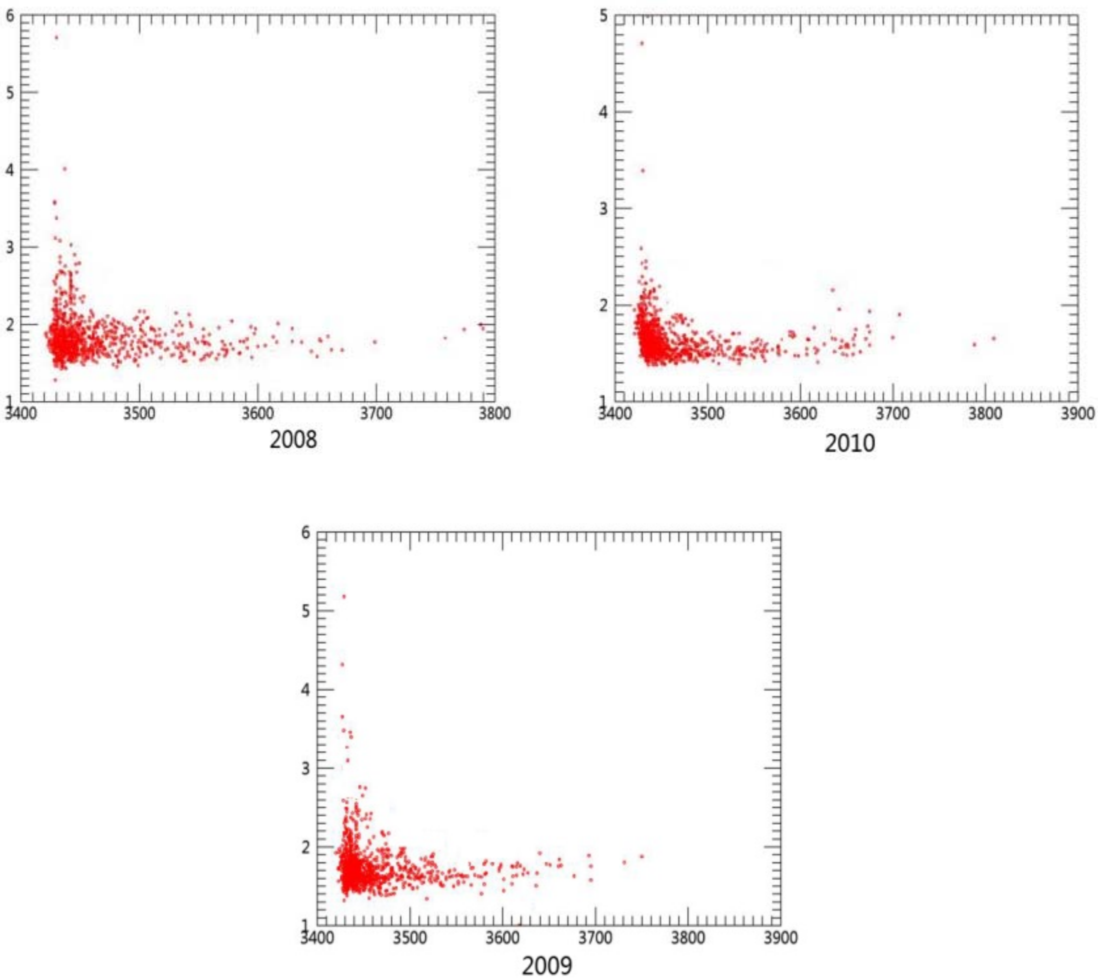

Figure 7. Nonlinear relationship between NDVI and elevation.

2.3.3.Assessment model

We found that distribution characteristics of scatter plots were very close to power function of ‘e’. Therefore, a multivariate nonlinear regression equation is designed to fit the data points. The regression parameters are calculated by IDL programming. The formula proposed can be shown in (4).

$$Y = C * e^{ax+b} \tag{4}$$

Where Y is absolute value of the mean of NDVI and NDVI difference, and x is value of elevation. a, b and C are undetermined parameters in the formula. Through in (4), NDVI of any unknown area can be estimated. So the vegetation coverage in study area is also able to be estimated. Figure 8 shows the relationship between calculated the fitting function and Y.

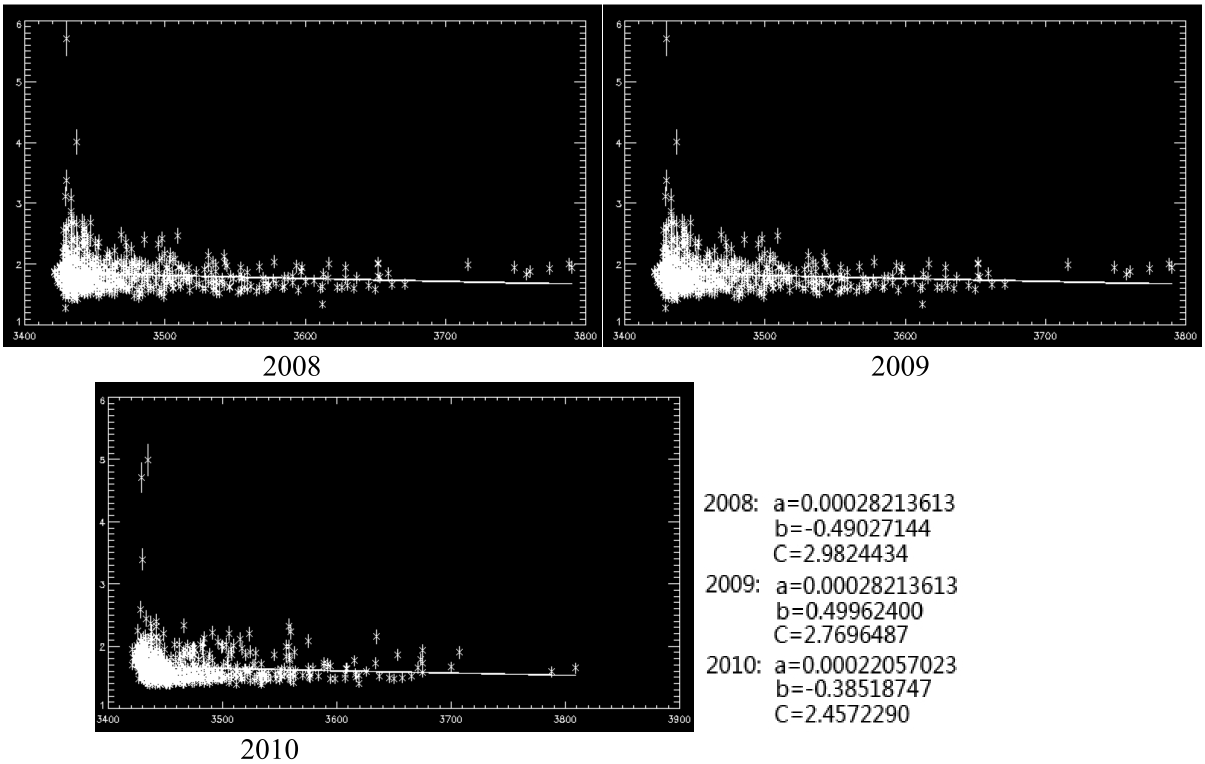

Figure 8. Nonlinear fitting function of NDVI.

The obtained parameters a, b and C were substituted into the nonlinear regression equation. In this study, NDVI values were fitted by multiple nonlinear regression method as parameter of the evaluation model. The annual vegetation coverage was obtained. After calculation, the evaluation value was normalized. And the value range was limited between 0 and 1 as well.

3. Results and analysis

The accuracy of NDVI estimation of fitted function is checked by statistical method (Table 3.). By repeatedly obtaining lots of random sampling points, deviation between true values and estimated values were calculated. Results suggested that average deviation was less than 2%. We considered the fitting results could be used in practice.

Table 3. Sample of NDVI Estimation Accuracy Test.

Number	Longitude	Latitude	Real value	Estimated value	Deviation
1	102.75681	33.853596	0.332574	0.309816	0.022758
2	102.71236	33.803324	0.430787	0.420941	0.009846
3	102.76891	33.533067	0.470265	0.483198	0.012933
4	102.80880	33.726011	0.430283	0.410982	0.019301
5	102.88259	33.512340	0.438404	0.410371	0.028033
6	102.75681	33.853596	0.332574	0.330297	0.002277
… …					

In this study, NDVI was fitted by multiple nonlinear regression method as parameter of the assessment model. Based on that, the annual estimated value of vegetation coverage was obtained. Because of assessment unit difference, results will be different. So the unit selection is closely related. This paper took raster data as the information carrier, used grid unit as the smallest one of assessment, based on model calculation determined the extent of eco-environment according to small classification level. We classified vulnerability indicators into 5 levels: no vulnerability (I), slight vulnerability (II), common vulnerability (III), moderate vulnerability (IV) and severe vulnerability (V). This method was used to grading the assessment results from 2009 to 2010. The threshold was used as the evaluation to be classification level. Finally, the quantitative assessment images were generated based on experimental results (Figure 9.).

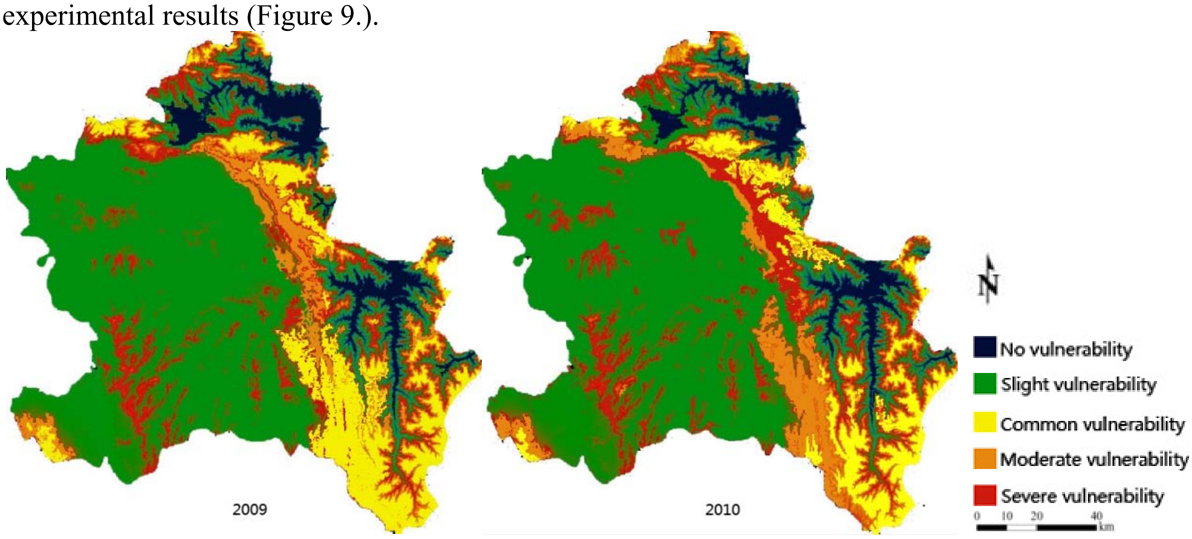

Figure 9. Eco-environment vulnerability quantitative evaluation.

According to the results of vulnerability mainly formed in 0.2~0.8, the regional eco-environment vulnerability serious mainly concentrated in the northeast and southwest parts. Here is the edge of swamp, bare land surface and building land, frequent human activities area. The edge of the swamp transition zone water and grass, internal system of extreme instability, prone to succession of eco-environment, and bare land surface is quite fragile, cultivated land of frequent human activities will inevitably lead to reverse the development of eco-environment. A region with sight vulnerability must be mainly covered by dense vegetation along the river, such as distribution of high grass coverage area and eastern forest coverage area. Based on time scale analysis, from 2008 to 2010, increase of IV level is very obvious, while other levels have shown different degrees of dynamic change.

4. Conclusions

In summary, we studied how to build a rapid quantitative assessment model of regional eco-environmental vulnerability from the point of view of vegetation and land cover types based on multi-source remote sensing data. In this paper, a scheme of model building was realized according to the idea of study route. At last, assessment results show that proposed model can quickly assess the vulnerability of eco-environment and improve the efficiency of environmental monitoring. However, there are many factors causing vulnerability in different area. It's very hard to have a model that sums up all important factors that lead to vulnerability. For future work, we will furthermore research how to select effective parameters corresponding to different region and improve model more effective.

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