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Provincial evaluation of vulnerability to geological disaster in China and its influencing factors: a three-stage DEA-based analysis

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Abstract China is a country with frequent natural disasters. In order to prevent the losses caused by disaster, this paper plans to make evaluation on vulnerability to geological disaster in 31 provinces in China based on overcoming the disadvantages of traditional data envelopment analysis evaluation methods. The research selected some relevant indexes in China from 2004 to 2010, including the frequency of geological disasters, GDP, population density, personal injury and property loss so as to analyze vulnerability to geological disaster in each province (municipality), and it found that geological vulnerability in China presented an overall pattern of East China < Central China < West China. In addition, it found from the analysis of the influencing factors of vulnerability that industrial development and scientific and technological advancement could reduce vulnerability to geological disasters significantly, while the growth in per-capita GDP and mean sea level could increase vulnerability to geological disasters to a certain extent. Meanwhile, the research indicated that the investment in the prevention and control of geological disasters in China did not have significant effects on the whole vulnerability to geological disasters.

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1 Introduction

China is a vast country with abundant resources, and it is also a country with frequent natural disasters. Taking geological disaster as an example, statistical data from China City Statistical Yearbook show that from 2004 to 2010, an average of 32,500 geological disasters struck China per year. The annual economic losses caused by the geological disasters reached up to RMB 3.638 billion Yuan, with the injuries and deaths of 1533 people. It can be seen that the geological disasters impose relatively a great threat upon people's lives and property. Therefore, many scholars are sparing no efforts to study and explore the issues concerning the prevention and control of geological disasters (e.g., Manchao 2009; Zhiqiang 2008), and they appeal to analyze and settle the issues at a deeper level so as to offer more accurate and effective theoretical and practical guide to the prevention and control of geological disasters in China (Yueping 2008; Runqiu 2007).

At the beginning, scholars mainly focused on impacts on the geological disasters from different landforms, environments or rock structures and put emphasis on the occurrence probability of disasters (e.g., Liu et al. 2005; Dominey-Howes 2002). Subsequently, some scholars pointed out that the study on geological disasters should not only focus on possibility of disasters, but also focus on the potential losses that may be caused by disasters in different regions, namely the vulnerability (Fedeski and Gwilliam 2007; Malheiro 2006). Vulnerability to geological disaster refers to the extent of loss or injury that a certain region may suffer when exposed to geological disasters (Berkes 2007). The greater the vulnerability to geological disaster in a certain region is, the greater the potential losses from geological disaster in the region will suffer. Generally, these losses include personal injury and death or property loss (Wei et al. 2004).

In recent years, concerning disaster vulnerability, different scholars have adopted various methods to evaluate that of different kinds of disasters (e.g., Tapsell et al. 2002; Fedeski and Gwilliam 2007; Zou and Wei 2009). For example, Oliver-Smith (1999) used a historical recording method to assess Peru's vulnerability. Cutter et al. (2006) adopted some proxy dataset to establish an index for vulnerability assessment. Aceves-Quesada et al. (2007) applied a multi-criteria-GIS method on vulnerability assessment in a volcanic risk evaluation in Central Mexico. Huang et al. (2013) applied a DEA (data envelopment analysis) model in the assessment of vulnerability to natural hazards in China. In addition, other methods such as structural equation model (Zou 2012) and gray correlation model evaluation (Conglan and Qingchun 2007) have also been used by some scholars for assessing vulnerability. Among these, evaluation methods based on GIS and DEA have been proved to be more accurate and practical and hence been widely accepted and adopted by scholars.

Unfortunately, despite certain advantages in evaluation, GIS- and DEA-based vulnerability evaluation methods have some disadvantages as well. Firstly, GIS-based evaluation method needs to collect a large quantity of complicated data and reports, including landform, topography, housing and population characteristics and so on (Fedeski and Gwilliam 2007). Since some detailed data about many regions are not available, this evaluation method is constantly restricted by the objective data. Secondly, DEA-based evaluation method refers to the thinking of "input–output" in organization, using factors causing disaster losses as input indexes and the final results (loss of life and property loss) as output indexes to calculate the "input–output" efficiency for vulnerability assessment (Jun et al. 2012; Yuan et al. 2013). Given that, the higher the "input–output" efficiency of the system is, the higher the vulnerability of this region will be. This method simplifies the

evaluation process of vulnerability to geological disaster to a large extent. However, in recent years, some scholars pointed out that this method failed to exclude interference of "fortune" factors from external environments (such as climate change) to the "input–output" system (Lee 2008). In addition, it is difficult for this method to order the regions whose system efficiency value reaches up to the highest (Nahra et al. 2009).

With regard to the deficiency of DEA-based evaluation method, some scholars have proposed super-efficiency DEA evaluation method and three-stage DEA evaluation method (Fried et al. 2002; Zhu 2001), among which the super-efficiency DEA evaluation method can overcome the difficult problem of non-ordering in case that the system effective value reaches the highest value "1," while the three-stage DEA evaluation method can get rid of the interference from some external "fortune" factors and revise the "input–output" system effective value, so this method is more accurate in the evaluation of the system efficiency compared with the traditional method (Ebrahimnejad et al. 2014) and is theoretically more advantageous in the evaluation of vulnerability to geological disaster. However, to our knowledge,it is surprising that the three-stage DEA-based evaluation method has not been applied to the evaluation of vulnerability to geological disaster since it was proposed. Thus, in consideration of the special circumstance of frequent geological disasters in China, this paper plans to evaluate vulnerability to geological disaster in different provinces and regions in China based on three-stage DEA evaluation method. Our purpose is to make a more comparative analysis and to find out some key influencing factors of vulnerability to geological disasters, with the expectation of providing more accurate and objective reference and guide for the prevention and control of geological disaster in China.

2 Research procedure and methodology

2.1 Research procedure

This paper proceeded with the evaluation of vulnerability to geological disaster from analyzing the "input–output" process, focusing on the main factors which may bring loss during the geological disasters. And based on this analysis, we selected the representative indexes and used the introduced DEA-based model to evaluate the "input–output" efficiency for preliminary vulnerability assessment. Further, we proposed and checked some potential environmental factors that may influence the system vulnerability. Finally, under the control of all environmental influencing factors, we conducted a more comprehensive
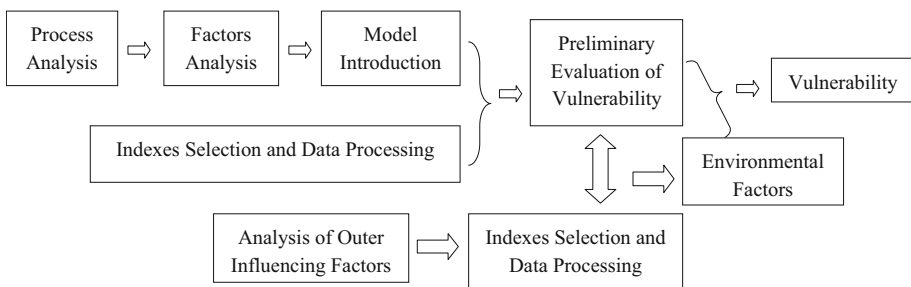

Fig. 1 Research procedures

evaluation on vulnerability to geological disasters in each region of China. The detail is shown as follows (Fig. 1).

2.2 Research methodology

Data envelopment analysis (DEA) was firstly proposed by operations research experts Charnes et al. (1978). After over 30 years of development, later researchers proposed super-efficiency DEA model and three-stage DEA model based on it, and later on, multi-stage DEA model. The three-stage DEA-based model included two kinds: One was proposed by John Ruggiero (1998) and was used for the performance evaluation of the police departments in 49 states in USA by Gormana and Ruggiero (2008); the other one was proposed by Fried et al. (2002). Two kinds emphasized particularly on different aspects: The former focused on finding and integrating other relevant interference factors; and the latter focused on getting rid of the influences from the external factors and the random factors. Since this paper emphasizes particularly on evaluating the vulnerability to geological disaster and seeking for the potential related influencing factors, we followed Gormana and Ruggiero's (2008) way to assess vulnerability to the geological disaster. It is worth to note that Gormana and Ruggiero (2008) used traditional DEA model on the first evaluation stage, and as we mentioned above, it failed to rank the decision-making units whose efficiency value reaches the highest "1." So, we meant to integrate the super-efficiency model and three-stage model to evaluate vulnerability to the geological disasters in China. The detailed procedures and steps are indicated as follows:

1. The first stage: super-efficiency DEA model

DEA (data envelopment analysis) is a kind of mathematical programming model, and it can estimate stochastic frontier of effective production based on a set of multi-input and multi-output values. Then, based on the efficient stochastic frontier, it can calculate the efficiency of each decision-making unit. However, the traditional DEA evaluation model has a great disadvantage, namely that it fails to distinguish the decision-making units with the efficiency value equals to the highest value "1." Therefore, later researchers proposed super-efficiency DEA model, which is shown as Formula (1) (Xue and Harker 2002), where θ is the efficiency evaluation value, X_j are the input index, Y_j are the output index, λ_j are the variable coefficient, ε are Archimedes infinitesimal, and s^-, s^+ are, respectively, the slack variables of input surplus and output deficiency. $\theta \in (0, 1]$, when $\theta \geq 1$, which indicated the input–output level of the decision-making unit reaches the optimal efficiency; otherwise, it fails to reach the optimal efficiency level.

$$\begin{cases} \min \theta \\ s.t. \sum_{\substack{j=1 \\ j \neq j_0}}^{n} X_j \lambda_j + s^- \leq \theta X_0 \\ \sum_{\substack{j=1 \\ j \neq j_0}}^{n} Y_j \lambda_j - s^+ \geq Y_0 \\ \lambda_j \geq 0, s^+ \geq 0, s^- \geq 0, \quad j = 1, 2, 3, n \end{cases} \tag{1}$$

If the occurrence process of geological disaster in each region is seen as an "input–output" system, then we can analyze it based on the generation mechanism and factors which produce disaster loss so as to determine the input and output variables, and based on that make a preliminary assessment on vulnerability to geological disasters. When a certain

region produces a relatively more output with a relatively less input, the vulnerability can be considered high. Previous researches show that losses from geological disasters are mainly determined by two factors: (1) the disaster itself, frequency and grade of the geological disaster. The more frequent and higher grade the geological disaster is, the higher the threat from the disaster is in this region. This factor is mainly determined by geological environments in different regions. (2) The potential affected factors in disaster stricken areas, chiefly including demographic factor and economic factor (Jun et al. 2012; Huang et al. 2012).

In different potential affected environments, the geological disaster at the same grade will result in different losses. For example, when a disaster occurs in a population density area, it will threat more lives and cause more potential economic losses. Generally, the main potential affected factors are lives and property. Based on the input and output variables, we can make a preliminary calculation on geological disaster vulnerability in certain region. It can be known from the concept of vulnerability that under the same disaster-causing environment and potential damage environment, the greater the disaster losses are in this region, the higher the vulnerability to geological disaster will be in this region. In other words, the higher the "input–output" efficiency value is, the higher the vulnerability of the region will be. Detail information for the "input–output" evaluation process of vulnerability to geological disaster is shown below (Fig. 2):

2. The second stage: Tobit regression analysis

Since evaluation values obtained in the first stage are based on the ideal circumstance without the interference from external environment. However, interference from external factors might lead to a certain deviation from the true results. Therefore, it is necessary to find out the external interference factors so as to control these interference factors in the further evaluation. Previous studies indicated that disaster vulnerability were mainly affected by natural factors, including climatic and geographical conditions; economic factors, referring to the economic development level; and man-made prevention factors, which is reflected in the interferences of man on the disaster, such as their conscious disaster prevention behaviors. (Yamin et al. 2005; Donner and Rodríguez 2008; Zou 2012). With the potential influencing factors as the independent variables, and the efficiency value obtained in the first stage as the dependent variables, significance test of Tobit regression analysis was conducted by us to further review which external factors affect and interfere
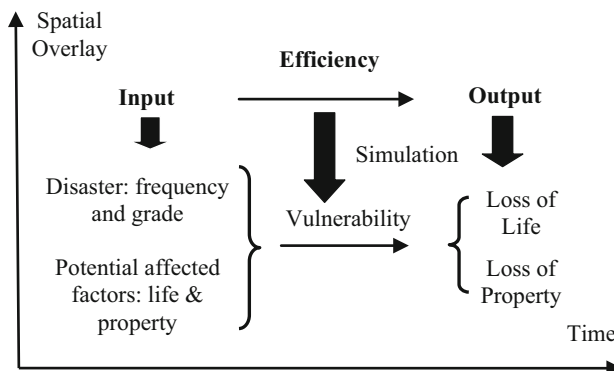

Fig. 2 Evaluation process of vulnerability

the vulnerability to geological disasters. The regression model can be expressed with the following formula (2):

$$y = \alpha + \sum_{J=1}^{R} \beta_l z_{lj} + \varepsilon_j \qquad (2)$$

3. The third stage: super-efficiency DEA analysis after input adjustment

We adjust the input variables with the component of environmental factor z_j^* obtained from the Tobit regression analysis in the second stage. The environmental factor can be denoted with Formula $z_j^* = \sum_{l=1}^{R} \widehat{\beta_l z_{lj}}$. We added these environmental factors as an input variable so as to control the interferences caused by them. In this way, by considering of the impacts from other environmental factors, a relatively more accurate efficiency value of each decision-making unit can be obtained.

3 Preliminary evaluation of vulnerability to geological disaster in each province

3.1 Selection and processing of indexes

As above mentioned, as losses from geological disasters are determined by disaster itself and potential affected factors, we selected indexes to denote these two factors as input. And since the loss caused by disaster mainly includes injuries and death of people and economic losses, we adopted these two indexes as output variables. Through the efficiency evaluation of the "input–output" system, vulnerability to geological disaster in a certain region can be evaluated. As geological disasters are frequent in different provinces (municipalities) in China, it is difficult to evaluate and determine the grade of so many geological disasters, and thus we were unable to obtain their grade data. So this paper only selected "the frequency of the disaster" as disaster factors for evaluation. In addition, population density and GDP of each province (municipality) were, respectively, selected as the potential affected factors. The detailed data sources and processing methods of the variables are shown in Table 1.

Table 1 Selection and processing of the indexes of the vulnerability evaluation

Factors	Measure and data source
Disaster	Mean of disaster frequency in each province over the years "China Environmental Statistical Yearbook 2005–2011"
Potential affected factors	Mean of population density in each province over the years "China City Statistical Yearbook 2005–2011"
	Mean of GDP sum in each province over the years "China City Statistical Yearbook 2005–2011"
Outcome	Mean of injuries and death of people and economic loss in each province over the years "China Environmental Statistical Yearbook 2005–2011"

Table 2 Preliminary results of the vulnerability evaluation

BE.JI	TI. JI	HE.BE	SH.XI	MMG	HE.NA	HU.BE	HU.NA	LI.NI	JI.LI	HLJ	SH.HA	JA.SU	HA.NA	CO.QI	SI.CU
3.35 %	206.82 %	12.8 %	338.43 %	102.73 %	25.04 %	55.94 %	17.99 %	122.66 %	122.48 %	16.96 %	0.00 %	74.08 %	14.26 %	44.80 %	34.87 %
ZH.JI	AN.HU	FU.JI	JA.XI	SH.DO	XI.ZA	SH.XI	GA.SU	GU.XI	YU.NA	NI.XA	XI.JI	GU.DO	GU.ZH	QI.HA	
39.71 %	18.37 %	24.25 %	10.56 %	9.71 %	762.68 %	101.21 %	301.78 %	48.50 %	155.83 %	5.00 %	36.12 %	28.08 %	67.67 %	72.75 %	

3.2 Preliminary evaluation

Based on the method prescribed in Table 1, we collected the data and used super-efficiency DEA model for calculation with EMS software. Through simulation, preliminary evaluation values of geological disaster vulnerability in each province (municipality) of China were obtained as follow.

Table 2 presents all the vulnerability assessment results. As shown in the table, Shanghai and Beijing present the lowest vulnerability, being 0 and 3.35 %, respectively, while Tibet and Shanxi present the highest, being 762.68 and 338.43 %, respectively. There are nine provinces with the value of θ not less than 1, including Tianjin, Shanxi, Inner Mongolia, Liaoning, Jilin, Yunnan, Tibet, Shaanxi and Gansu. These provinces, except Tianjin, are behindhand in economic development. While provinces such as Beijing and Shanghai present the lowest vulnerability are of advanced economy, with θ vulnerability values of 0 and 3.92 %. These results indicate that vulnerability to geological disaster may be related to the economic development to a certain extent. Besides, most of the provinces are located in the west region of China, where topographic and climatic conditions are worse than those in Central and East China, implying that natural factors such as geographical and climatic factors may also have impact on disaster vulnerability. The approximate trend in the above table suggests that the value of θ presents the pattern of East China < Central China < West China, which is similar to the overall pattern of Chinese economy and technical level. Since economy and technical level may determine the prevention investment demand in disaster and prevention quality and skill, they indicate that geological disaster vulnerability may also have connection to man-made prevention factors such as investment in prevention and technical development. Further, this paper proceeds with these potential influencing factors and explores their impacts on vulnerability to geological disaster.

4 Analysis of influencing factor of vulnerability to the geological disaster

4.1 Selection and processing of indexes for potential influencing factors

Previous researches and the above analysis show that vulnerability to geological disaster is mainly influenced by natural factors, economic factors and man-made prevention factors. In order to identify these factors and control them in the further evaluation, we selected some related indexes. Among them, as to natural factors, one geographical index (altitude

Table 3 Selection and processing of potential influencing factors

Factors	Variable	Data and process
Natural factors	Annual precipitation and average altitude	China statistical Yearbook 2005–2011 Calculate the mean of all the historical data of each variable
Economic factors	Industrial growth ratio and per-capita GDP	China statistical Yearbook 2005–2011 Calculate industrial growth ratio and the mean of each variable
Man-made prevention factors	Trading in technology market; and total investment in the disaster	China statistical Yearbook 2005–2011 Calculate the mean of all the historical data of each variable

Table 4 Correlations

Variable	1	2	3	4	5	6
θ value	1					
Annual precipitation	−0.34	1				
Average altitude	−0.17	−0.05	1			
Trading in technology market	−0.18	0.05	0.65	1		
Per-capita GDP	−0.38	−0.21	−0.17	0.29	1	
Industrial growth ratio	−0.07	0.36	−0.92	−0.19	0.02	1
Total investment in disaster prevention	0.74	−0.44	−0.23	−0.39	−0.39	−0.09

Table 5 Regression results

Variable	Coefficient	P value
Intercept	2.943*	0.033
Annual precipitation	−0.001	0.070
Average altitude	0.001**	0.002
Trading in technology market	−0.040*	0.023
Per-capita GDP	0.051*	0.021
Industrial growth ratio	−7.252*	0.013
Total investment in disaster prevention	−0.00001	0.225
R^2	0.659	

$N = 31$;* $P < 0.05$, ** $P < 0.01$ (two-tailed test)

above sea level) and one climatic index (the annual average precipitation) were selected. As to economic development factors, the indexes of per-capita GDP and the proportion of industrial growth were selected. Per-capita GDP is concerning economic volume and proportion of industrial growth concerning the economic structure. About the man-made prevention factors, the prevention quantity and prevention quality were all considered. As for quantity, we selected total prevention investment index; and for quality, trading in technology market index was selected. The detailed data sources and processing methods are shown in Table 3.

4.2 Analysis of influencing factors: Tobit regression

We collected data according to the methods prescribed in Table 3. With results obtained from Table 2 as dependent variables and data indexes collected in Table 3 as independent variables, we calculated the correlation between indexes and conducted Tobit regression with software Eviews5.0. All of the results are presented below (Tables 4, 5).

As shown in Table 5, the indexes passing the significance test at the level of 5 % include the mean altitude, volume of trading in technology market, per-capita GDP and industrial growth ratio. The regression result indicated that: Firstly, the industrial growth ratio is the most significant factor affecting the vulnerability to regional geological disaster ($r = -7.252$, $P < 0.05$). The reason behind that may be that industrial growth can accelerate the upgrade of infrastructure and modernized buildings, which in turn enhances the ability of disasters prevention and reduces losses from geological disasters effectively. Secondly, scientific and technical improvement is also a key variable to reduce vulnerability to regional geological disasters significantly ($r = -0.04$, $P < 0.05$), as more

scientific methods or higher technical tools could be adopted to prevent the losses from geological disasters. Thirdly, among natural factors, annual precipitation is not significantly related to vulnerability ($r = -0.001$, ns). However, the altitude plays a role in accelerating the vulnerability to geological disaster to a certain extent ($r = 0.001$, $P < 0.01$), which might because the geographical environment of mountainous regions is normally with relatively high altitude. In addition, the total investment in prevention and control of disasters did not pass the significance test, implying that present disasters control and prevention investment in China is unable to impose a significant influence on geological disasters.

Finally, what worth noting is that previous studies indicate that there exists a reverse "U"-shape relationship between economic development and geological disaster vulnerability, implying that economic development is a double-edged sword (Schumacher and Strobl 2011). On the one hand, rich people tend to suffer more potential property losses from disasters. On the other hand, economic development accelerates the increasing demand for the prevention and control of geological disasters, and thus more advanced equipment may be adopted in prevention so as to reduce the losses. In other words, when economic development brings more positive aspects than negative ones, losses can be reduced effectively; otherwise, losses tend to increase significantly. However, the data in our research did not prove the reverse "U"-shape relationship ($r = 0.002$, ns). The result indicated that Chinese economic development was positively related to vulnerability to geological disaster ($r = 0.051$, $P < 0.05$). So, it seemed that China is just at the first half of the reverse "U"-shape relationship generally. That is to say, the level of geological disaster prevention and control failed to keep pace with the economic development in China.

5 Evaluation of adjustment of vulnerability to geological disaster

Following the three-stage DEA method step, we adjusted the input variables with the component of environmental factors which were calculated from the Tobit regression analysis results above. We added these environmental factors as control variables to conduct super-DEA analysis again, and the results are shown in the following table.

Table 6 presents the final evaluation results of vulnerability to geological disaster in different regions of China. As shown in the table, province with the highest vulnerability to geological disaster is Tibet ($\theta' = 762.23$ %), a region with the highest altitude on Tibet Plateau. The θ' value in Yunnan, Gansu and Shanxi is above 300 % also, indicating an extremely high vulnerability. The economic development, industrial development, and scientific, technical and education level of these place are all far below the average level in China. Provinces with the lowest vulnerability to geological disaster are Shanghai and Beijing. The former is the financial center of China, and the other is the political center of China. The economic development, industrial development, and scientific, technical and education level in these two regions are far above the average level, so it is reasonable to believe the result. Comparing the results in Table 4 with those in Table 6, the vulnerability evaluation value of these provinces including Hunan, Guangxi, Sichuan and Chongqing increased significantly, indicating that these provinces are affected by "fortune" factors greatly. In general, the vulnerability to the geological disaster in China presents the pattern of "East China < Central China < West China" approximately.

In order to rank the vulnerability to geological disaster in each province in China, we conducted a cluster analysis using the results obtained from the final Super-efficiency DEA

Table 6 Values (θ) of the vulnerability to geological disasters

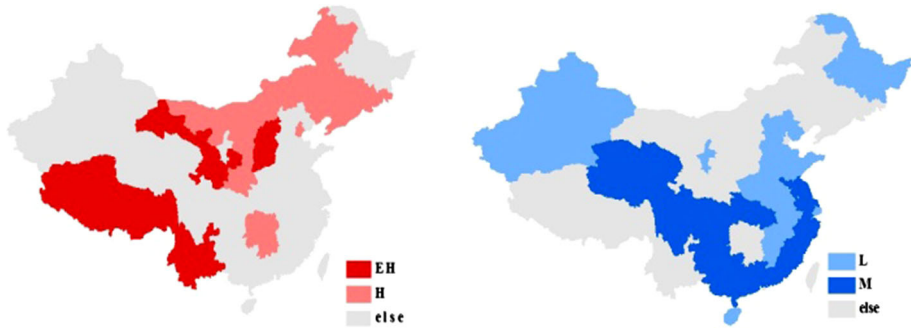| BE.JI	TI. JI	HE.BE	SH.XI	MMG	HE.NA	HU.BE	HU.NA	LI.NI	JI.LI	HLJ	SH.HA	JA.SU	HA.NA	CO.QI	SI.CU
4.57 %	206.82 %	12.81 %	338.43 %	102.73 %	28.73 %	64.86 %	141.68 %	122.66 %	122.48 %	16.96 %	0.00 %	74.08 %	16.27 %	77.86 %	92.18 %
ZH.JI	AN.HU	FU.JI	JA.XI	SH.DO	XI.ZA	SH.XI	GA.SU	GU.XI	YU.NA	NI.XA	XI.JI	GU.DO	GU.ZH	QI.HA	
50.10 %	49.40 %	75.21 %	39.11 %	9.71 %	762.23 %	104.66 %	411.08 %	82.69 %	327.22 %	5.00 %	35.12 %	54.32 %	67.67 %	72.75 %	

Fig. 3 Distribution diagram of vulnerability to geological disasters in China

analysis. Taking consideration of the setting meaning of θ' value (if $\theta \leq 1$, it implies that the efficiency is invalid; if $\theta \geq 1$, it implies that efficiency is valid) at the same time, we ranked the vulnerability of provinces into four types. By use of ARCGIS9.3 software, the pictorial diagram is presented in Fig. 3. As shown in the map, we can easily identify that the regions with extremely high or high vulnerability are distributed in the north and southwest of China. In contrast, those with the lowest vulnerability regions are mostly located in the East of China. More interestingly, the regions with similar rank of vulnerability demonstrate a spatial aggregation appearance.

6 Conclusions and suggestions

This paper, overcoming the deficiency of the traditional DEA analysis method, represents the first effort to adopt the three-stage DEA-based analysis method for vulnerability assessment in 31 provinces in China. The results indicated that the grade of vulnerability to geological disaster in China presents the pattern of "East China < Central China < West China" as a whole. The provinces with extremely high vulnerability to geological disaster are the undeveloped regions including Gansu, Tibet and Yunnan, while the ones with low vulnerability are the regions with advanced economic and education level, including Beijing and Shanghai. Meanwhile, it is indicated by the findings that industrial growth level, scientific and technical level, economic development and the altitude are several important factors affecting the vulnerability to the geological disaster in China, among which the industrial growth level and the scientific and technical level can significantly reduce the vulnerability to geological disaster, while the economic development and the altitude play a minor role in positive prediction of the vulnerability.

Although the previous researches have explored the issue of vulnerability to geological disaster in China to some extent, DEA-based researches are not frequently adopted. In addition, previous researches with other methods seldom selected provinces in China as research object, so it is difficult to make comparison with the conclusions in this paper. However, in the few researches on evaluation of vulnerability to natural disasters with the provinces in China as research subjects, their results also presented an "East China < Central China < West China" pattern (e.g., Huang et al. 2013), which offered a valid evidence for the conclusions in this paper to some extent. In addition, the evaluation of the vulnerability to geological disaster in our analysis was conducted after the

controlling some external influencing factors. So, there is no doubt that the result and conclusions are more objective and accurate.

In view of our results and conclusion analysis, the prevention and control of geological disasters should pay attention to following points: Firstly, the regions with complex topography, high altitude, mountains and poor technological development should be the focus points of disaster prevention and control. Secondly, more resources should be invested in education in order to improve the technological development and in turn improve defending skill and preventive tools. Besides, prevention funds should be allocated more to the regions where geological disaster happens frequently and economic behind development. At last, the region with extensive economic growth mode of high investment, high consumption and high pollution should be transformed into green, recycling and sustainable economic development mode.

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