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Assessing Vulnerability to Drought Based on Exposure, Sensitivity and Adaptive Capacity: A Case Study in Middle Inner Mongolia of China

LIU Xiaoqian[1], WANG Yanglin[1], PENG Jian[1], Ademola K BRAIMOH[2], YIN He[3]

(1. *Laboratory for Earth Surface Processes*, *Ministry of Education*, *College of Urban and Environmental Sciences*, *Peking University*, *Beijing* 100871, *China*; 2. *Global Land Project*, *Sapporo Nodal Office*, *Hokkaido University*, *Sapporo* 060-0809, *Japan*; 3. *Geomatics Laboratory*, *Geography Department*, *Humboldt-Universität zu Berlin*, *Berlin* 10099, *Germany*)

Abstract: In this paper, we proposed a framework for evaluating the performance of ecosystem strategies prepared for enhancing vulnerability reduction in the face of hazards due to climate change. The framework highlights the positive effects of human activities in the coupled human and natural system (CHANS) by introducing adaptive capacity as an evaluation criterion. A built-in regional vulnerability to a certain hazard was generated based upon interaction of three dimensions of vulnerability: exposure, sensitivity and adaptive capacity. We illustrated the application of this framework in the temperate farming-grazing transitional zone in the middle Inner Mongolia of the northern China, where drought hazard is the key threat to the CHANS. Specific indices were produced to translate such climate variance and social-economic differences into specific indicators. The results showed that the most exposed regions are the inner land areas, while counties located in the eastern part are potentially the most adaptive ones. Ordos City and Bayannur City are most frequently influenced by multiple climate variances, showing highest sensitivity. Analysis also indicated that differences in the ability to adapt to changes are the main causes of spatial differences. After depiction of the spatial differentiations and analysis of the reasons, climate zones were divided to depict the differences in facing to the drought threats. The climate zones were shown to be similar to vulnerability zones based on the quantitative structure of indexes drafted by a triangular map. Further analysis of the composition of the vulnerability index showed that the evaluation criteria were effective in validating the spatial differentiation but potentially ineffective because of their limited time scope. This research will be a demonstration of how to combine the three dimensions by quantitative methods and will thus provide a guide for government to vulnerability reduction management.

Keywords: vulnerability assessment; standardized precipitation index (SPI); exposure; sensitivity; adaptive capacity

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1 Introduction

Vulnerability refers to the frangible nature of a system faced with various types of potential disasters. As an effective description of the extent to which a system is susceptible to damages from climate changes, vulnerability assessment is indispensable in sustainability development (Kelly and Adger, 2000; IPCC, 2000). Vulnerability assessment is used not only in the development of climate change criteria but also in the characterization and identification of the response mechanisms of a coupled human and natural system (CHANS) in which there are highly organized interactions between the natural components and human activities (Turner *et al*., 2003a; Liu *et al*., 2007a).

The concept of vulnerability has largely distinct histories in the social and biophysical sciences. The most notable feature of a vulnerable system is the instability

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Corresponding author: WANG Yanglin. E-mail: ylwang@urban.pku.edu.cn

and sensitivity to outside threats, which are manifested in a developing direction against the interests of humanity and stability (Olga and Donald, 2002; Adger, 2006). Now, vulnerability has functioned as a health-related and social-economical measurement index (Yohe and Tol, 2002; Luers, 2003; Turner *et al*., 2003b; Eakin and Luers, 2006; Chang and Chao, 2011), and it also turns out to be the first step in the sustainable development encompassed in the analysis and identification of complexity (Smit and Wandel, 2006; Liu *et al*., 2007b). Human activity is an indispensable factor in this coupled system, not only because it is the main reason for ecosystem degradation but also because humans can play a positive role by adopting proper environmental management strategies to enhance the adaptive capacity of ecosystems. Many scholars have proposed additional concept of this positive ability in environmental management to the framework of vulnerability research. However, there has not yet been progress in achieving a standardized quantitative method to integrate it (O'Brien *et al*., 2004a; 2004b; Adger, 2006;).

Several scientists have proposed a theoretical framework that includes social-economic indicators (O'Brien *et al*., 2004b; Polsky *et al*., 2007), but there has been little advance in the quantifying method. Most studies on vulnerability have focused on the extent of exposure to a certain hazard, with little done to examine the comprehensive interactions or the adaptive capacity from a social-economic perspective (Adger, 2006; Hinkel, 2011). In addition, there have been limitations in the examined spatial scale. Former vulnerability assessments have mainly been focused on the macro-scale such as worldwide or multi-country (Birkmann, 2007), but variability among locations calls for a more practical approach, especially to adaptive capacity management.

Environmental problems in China are the most severe one of every major country, and the environment is fragile for different reasons in different regions (Liu and Diamond, 2005). In northwestern China, variable rainfall, wind and drought exposure in its high-altitude grasslands are the main causes of vulnerability (Leng, 1994; Li *et al*., 2003; Liu and Diamond, 2005). In the present study, we took the middle Inner Monglia, the temperate farming-grazing transitional zone in the northern China as an example. This region is threatened by serious drought and is very sensitive to climate change. This study focused on vulnerability under adaptive management to mitigate the effects of drought. The objective was to evaluate the various vulnerabilities and the spatial differences in counties in the middle Inner Mongolia (MIM) of China and to investigate the relationships between the determinants by reanalyzing the index structure and by a zonation method.

2 Methodology

2.1 Study area

As shown in Fig. 1, the middle Inner Mongolia (MIM) Autonomous Region (38°–49°N, 107°–119°E) is located in the north of China, including 74 counties located in Hulunbuir City, Hinggan League, Tongliao City, Chifeng City, Xilin Gol League, Ulanqab City, Baotou City, Hohhot City, Bayannur City, Wuhai City and Ordos City (Fig. 1). The region has a long history of land use and hazard modeling. One of the main focuses currently discussed is the efficiency of environmental management for balancing the local ecological fragility with land use requirements for socioeconomic development. The government has embarked on several environmental programs for nearly 20 years, such as grassland restoration, prohibition of grazing in degraded areas and implementation of ecosystem services conservation to improve land productivity (Leng, 1994; Song and Zhang, 2007).

Middle Inner Mongolia encompasses most of the farming-grazing transitional zone in China and is very sensitive to climate fluctuation and anthropogenic impact. The grassland forms a continuum through the southern Da Hinggan Mountains and across the Inner Mongolia Plateau to the south of the Ordos Plateau and the Loess Plateau. Cultivation of grains is markedly restricted to a few locations suitable for agriculture, which further exacerbates hydrologic scarcity in the semi-arid ecosystem by consuming much of the underground water. The population is over 1.63×10^7 across the total area of 698 537 km^2. The population density is about 24 persons/km^2, very small compared to other parts of China (Inner Mongolia Autonomous Region Bureau of Statistics, 2007). The main landscape is high plains, most of which are located on the Mongolia Plateau with an average altitude of 1000 m. Annual solar radiation increases from northeast to southwest, and precipitation decreases from northeast to southwest. Mean annual precipitation ranges from less than 50 mm to more than 450 mm, showing a strong northeast-southwest gradient. Desertification of the land, as one of the biggest chal-

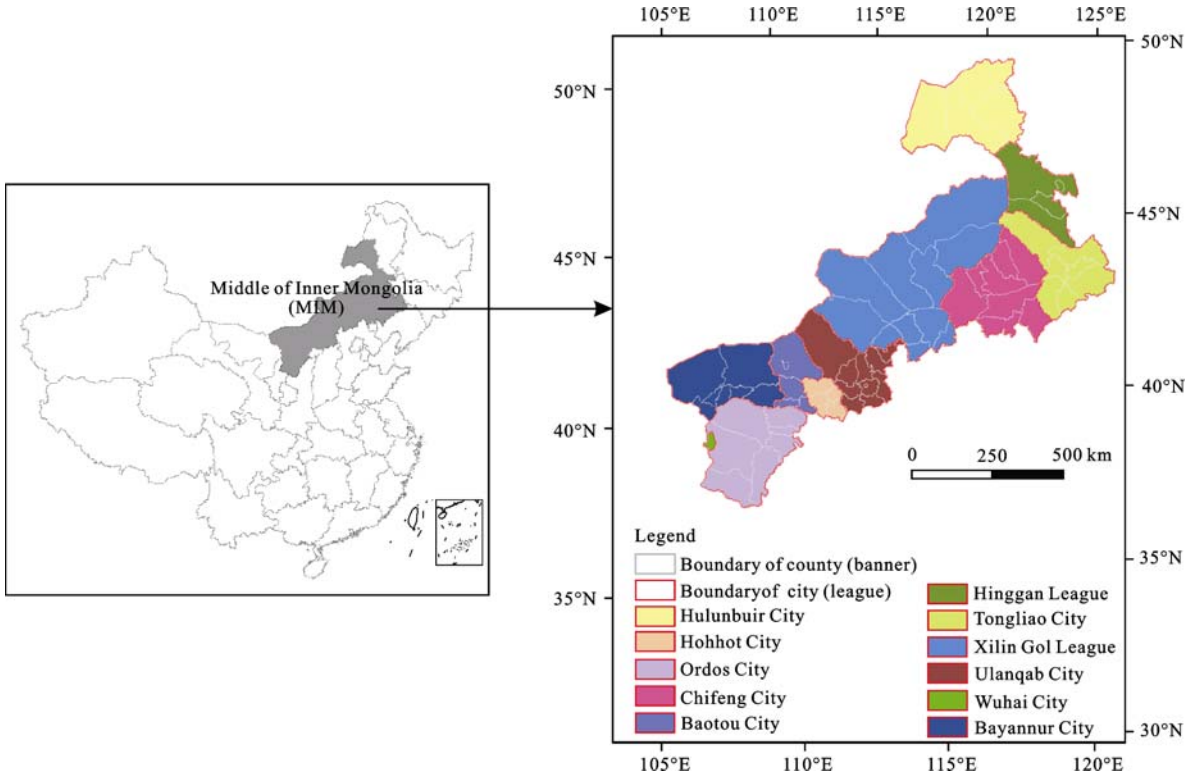


Fig. 1 Location of study area in China

lenges for sustainable development, is mostly caused by meteorological drought (Li *et al*., 2003; Song and Zhang, 2007).

2.2 Data and processing

The basic analysis unit of this study is at county (banner) level, and multiple social and environmental variables were compiled as the attributes of the 74 counties (Table 1). To render them suitable for spatial analysis, we created indicators from the original variables using county as the unit of analysis. Both Geographical Information System (GIS) analysis and geographical mathematical methods were used in the development of the database.

2.3 Vulnerability assessment model

Three dimensions were constructed in the vulnerability assessing diagram: exposure, sensitivity and adaptive capacity. Conceptual interactions and modules are depicted in Fig. 2. It is intrinsic that the definition of vulnerability must always linked to specific hazards (Blaikie *et al*., 1994). While in this case, meteorological drought, as a key stress, is a driving force of regional vulnerability, and is a more potential starting point for analysis as a consequence of climate changes.

Table 1 Description of data used in this study

Type & date	Indicator	Source
Vegetation (1998–2008)	Standard deviation of normalized difference vegetation index (NDVI)	Spot/vegetation images from Institute of Technology in Belgium Flemish (VITO) (1 km by 1 km) (http://www.vito.be/VITO/EN/HomepageAdmin/Home)
Climate (1958–2008)	Coefficient of variance of precipitation, coefficient of variance of temperature, precipitation index	Daily maximum /minimum /average precipitation and temperature data of meteorological stations from National Meteorology Bureau of China (http://cdc.bjmb.gov.cn)
Digital Elevation Model (2000)	Elevation	U.S Geological Survey GTOPO30 DEM (1 km by 1 km) (http://www.usgs.gov/pubprod/data.html#data)
Socioeconomic data (2006)	Per capita cultivated area, physicians per 1000 persons, ratio between agricultural and industrial output, technologists per 1000 persons, per capita savings deposits, per capita business volume of Post and Telecom Service (access to information), population density, per capita GDP	Statistical Yearbook of China (Nationa Bureau of Statistics of China, 2007) and statistical information of counties and cities in Inner Mongolia provided by Inner Mongolia Autonomous Region Bureau of Statistics

Exposure measures the extent, duration or frequency of a stress on a system. Drought is the central risk in the study area and is therefore chosen as the exposure variable, meteorological index on regional precipitation is used to detect the temporal climate changes and its spatial distribution. Sensitivity is the degree to which a system is affected by a stress or perturbation, either positively or negatively. It is an inherent property of the human-environment system prior to perturbation and is influenced by both ecological and socioeconomic conditions. Adaptive capacity is the ability of system to cope with actual or expected stress, including the ability of the system to initiate measures to prevent future damage and/or to extend the range of conditions to which it is adapted (Brooks *et al*., 2005; Smit and Wandel, 2006), and it may also be a function of several factors, including income, education, information, skills, infrastructural access and management capabilities (McCarthy *et al*., 2001; Tol and Yohe, 2007).

According to the conceptual correlations of vulnerability and its three dimensions, as depicted by the red or green arrows in Fig. 2, vulnerability was composed of two positively affected dimensions, i.e., exposure and sensitivity, and one negatively mitigating factor, i.e., adaptive capacity. Therefore, the most vulnerable county was characterized with a low adaptive capacity, a high drought exposure and a high sensitivity to environment fluctuations. The vulnerability index (*VI*) can be defined as follows:

$$VI = EI + SI - AI \tag{1}$$

Single index of each vulnerability dimension was produced to represent each facet. Sensitivity index (*SI*) and adaptive capacity index (*AI*) were obtained by principle component analysis. Exposure index (*EI*) was indicated by standardized precipitation index (*SPI*). According to the scheme of the indexing method, the calculation based on indexes of three dimensions is as follows:

$$VI = -SPI + SI - AI \tag{2}$$

where *EI* has been replaced by the negative *SPI*, because negative *SPI* denotes drought events and positive *SPI* denotes moist conditions. *EI* equals *SPI* rescaled to a range between 0 and 1 with the extreme values standardization method.

What we should note is that all the indexes involved in the model were values for measurement of spatial diff-

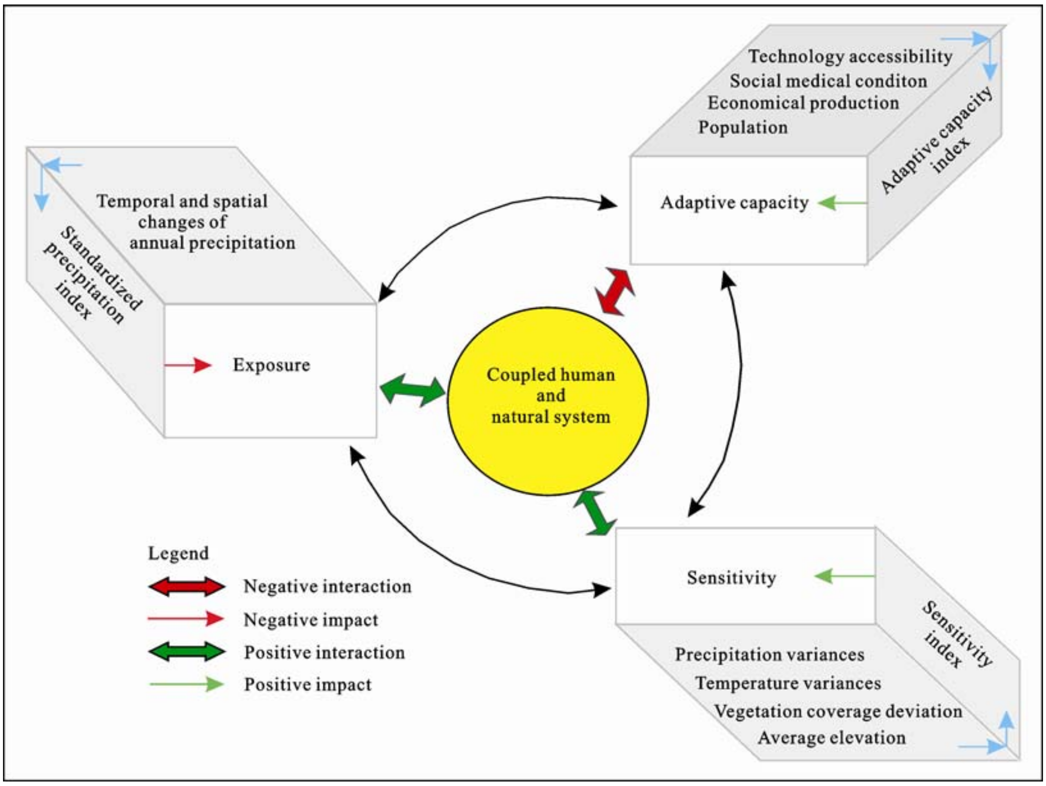


Fig. 2 Module of vulnerability assessment based on exposure, sensitivity and adaptive capacity

erentiation rather than the true values representing the specific conditions of certain counties. That is to say, comparison between indexes is only suitable for counties in the study area.

2.4 Exposure index calculation

When climate change and shortage of precipitation are considered, the annual precipitation and its variability become the keys to measure how much a region is exposed to threat. Exposure in this case is the occurrence of drought events due to absence of precipitation, which is a common phenomenon in this semi-arid area. While, certainly, rising of temperature could also manifest drought stress, but it is more subjects to vary with micro-geomorphology and hardly to capture by the data set available from remote sensing images at a medium scale (Birkmann, 2007).

Index indicating the amount of precipitation and its pattern is widely used for measuring exposure, especially when analyzing the stochastic characteristic of precipitation. Single index host its advantage on both telling the spatial divergence of potential threats on a straight way and more applicable to sample contrast. In the present study, SPI was used as a virtual value to measure the degree of regional drought stress by quantitative description methods. It could be used to define how eco-environmental vulnerability changes with external threats when the counties are similar in their natural and geographical conditions.

SPI is a simple indicator of exposure to drought at different time scales with spatial homogeneity, and has been used in many studies related to drought hazard based on the probability of precipitation in a given time period (Mckee *et al*., 1993; Wu *et al*., 2001; 2007). The SPI allocates a single numeric value to the precipitation so that comparisons can be made across regions with different climates. In this case, SPI of each county was calculated from a time series of annual precipitation data for 50 years between 1958 and 2008 as follows:

$$SPI_i = \frac{P_i - \overline{P}}{P_{\mathrm{std}}} \tag{3}$$

where P_i is the average precipitation for county i (1, 2, 3, 4, …, 74) since 1958 to 2008; $\overline{P}$ is the average precipitation in the study area and P_{std} is the standard deviation value of precipitation derived from the climate records for nearly 50 years. Negative values obtained from this equation indicate precipitation deficit (drought events), while positive values represent wet conditions (Mckee *et al*., 1993). The SPI was rescaled to a range between 0 and 1 to obtain the EI as follows by the extreme values standardization method. A similar rescaling process was also used to formulate AI and SI to make sure they had similar impacts on VI by inspection of the different magnitudes of related indicators.

2.5 Sensitivity and adaptive capacity indexes calculation

Sensitivity indexes are involved with a number of natural indicators such as temperature, precipitation, NDVI and elevation. The indexes are highly interactive through coupled ecological processes, so principal components analysis (PCA) was used to analyze the correlations among the data through SPSS 16. Apart from dealing with data redundancy, PCA also provides an objective basis for weighting the indices, which is crucial for the overall evaluation criteria.

The steps in the PCA method are as follows: 1) standardize primary data; 2) extract principle components by PCA in SPSS 16; 3) compute eigenvalues β_i of matrix R and its corresponding eigenvectors α_i; 4) group α_i by linear combination to extract two to three principal components; 5) rotate the component matrix by the variation max standardizing method with Kaiser normalization; candidate indicators with lower scores than needed will fail to be significant enough in the principle component; 6) according to their eigenvalues β_i and the component scores of each county, obtain the new scores of each county. Then an evaluation function can be set up to compute an integrated index on the basis of selected components (Li *et al*., 2006; Braimoh, 2009).

Principal components analysis was also used in analyzing the adaptive capacity to deal with the highly interrelated social-economic indicators, which played the most important role in improving the capacity to adapt to changes and to mitigate harm in ecosystem management. According to the PCA, components and their weights could be defined. The cumulative index of county i could be calculated as follows:

$$I_i = \sum \alpha_j \times S_{ij} \quad (i = 1,\ 2,\ 3,\ \ldots,\ 74)$$

in which

$$\sum \alpha_j = 1 \tag{4}$$

where I_i is the sensitivity or adaptive index of county i resulting from a linear combination of principle components; α_j is the weight of principle j obtained from the component scores, and S_{ij} is the value of the principle component j of county i calculated as follows:

$$S_{ij} = \sum \beta_m \times X_m \left(\beta_m > \alpha\right) \tag{5}$$

where X_m is the indicator m in principle j; β_m indicates the correlation significance between the indicator and the principle, displaying the contribution to the principle j; α is a dependent variables, which varies with interpretation of components analysis. Indicators with β_m greater than the threshold α will be taken into account。

3 Results and Analyses

3.1 Sensitivity index

We specifically introduce the indices that could be used to measure the variability of a certain array of data by calculating its coefficient of variance (CV). The CV was calculated as the ratio of the standard deviation index (x^*) to the average of an estimated series value $\overline{x}$. The variable x could be a time series of climate, e.g., temperature or precipitation; it also could be a series of the vegetation index of a certain area during the years.

From the PCA, two components were extracted. Indicators with a weight β_m greater than 0.6 were taken into account and are noted with an asterisk in Table 2. Two principal components accounted for about 73% of the variability in the data. The first component has a high loading on temperature, precipitation and NDVI variation and could therefore be referred to as 'climate-land cover sensitivity'. The second component is highly correlated with altitude and could be referred to as 'elevation sensitivity'. Each of the two components was weighted based on its relative contribution to total variance (Table 2) and integrated to produce the sensitivity map.

Rescaling of the indices, including SI, to a range between 0 and 1 was performed to standardize the SI to make sure that each dimension had a similar effect on vulnerability. The most sensitive counties are located in the area near Mongolia (as shown in red zone of Fig. 3b), where the continental climate characteristics are more obvious. The less sensitive areas have better vegetation coverage and are dominated by agro-pastoral activities.

Table 2 Principal component loadings on indicators of sensitivity

Indicator	Component 1	Component 2
Coefficient of variance of precipitation	0.79*	0.36
Coefficient of variance of temperature	–0.92*	–0.05
Elevation	0.08	0.89*
Coefficient of variance of NDVI	0.61*	–0.38
Weight (α)	0.63	0.37

Note: * represents that indicators with a weight β_m greater than 0.6

3.2 Adaptive capacity index

After the PCA, three components were included in the index calculation. Considering the meaning of each indicator and the components, indicators with a weight β_m greater than 0.56 are noted with an asterisk in Table 3.

Three components account for over 66% of the variability in the adaptive capacity data. The first component has a high loading on per capita cultivated land area, ratio of agriculture and industry output, and population density. It can therefore be referred to as a 'population-economic production' factor. The second component has a high loading on per capita savings deposit and access to information and can therefore be referred to as a 'income-information access' factor. The last component is highly positively correlated with number of technologists and per capita GDP and can be referred to as a 'skills and total productivity' factor.

Rescaling of the indices to a range between 0 and 1 was also carried out to standardize the AI and SI. Thus, the three indices of vulnerability are statistically similar and range between 0 and 1. The highest adaptive capacity occurs for the Ordos Region in the southwestern part of the MIM (Fig. 3c), encompassing the highest industrial production and per capita GDP emanating from a relatively rich natural resources and energy industry. Medium adaptive capacity is associated mostly with counties in the middle part of MIM, which includes predominantly urbanized areas with higher levels of social infrastructure compared to rural areas. Perhaps the reason is that regionally important ecological effects of projected land-use change are still limited to major urban areas, while there is a demand for initiatives to promote high ecological adaptation in rural areas (Jackson *et al.*, 2004).

3.3 Vulnerability indices

As all the vulnerability indexes were rescaled to the range between 0 and 1, their spreads were measured by

Table 3 Principal component loadings on indicators of adaptive capacity

Indicator	Component 1	Component 2	Component 3
Per capita cultivated land area	0.83*	–0.08	–0.03
Physicians per 1000 persons	–0.28	0.46	–0.41
Ratio of agriculture and industry output	0.90*	0.09	0.01
Technologists per 1000 persons	–0.08	0.17	0.85*
Per capita savings deposit	0.00	0.82*	0.36
Per capita business volume of post and telecom service	0.03	0.87*	0.14
Population density	0.56*	–0.06	0.16
Per capita GDP	0.20	0.19	0.74*
Weight (α)	0.37	0.33	0.30

Note: * represents that indicators with a weight β_m greater than 0.56

calculating their inter-quartile range (IQR), with the results shown in Table 4.

The value of the IQR is important when two sets of similar data are compared. First we divide each value of EI, SI and AI into four equal parts, and then the lines marking each division are quartiles. The IQR is a robust statistic with the advantage of excluding extreme values. It equals to the distance between the top of the lower quartile and the bottom of the upper quartile of a distribution. The median is the corresponding measure of tendency. It equals to the midhinge, which is the average of the first and third quartiles and is thus a measure of location. The closer the clustering of values around the median, the smaller the IQR.

The spread of the three components measured by the IQR is in the order sensitivity > exposure > adaptive capacity. The fact that adaptive capacity index has the lowest values in both IQR and mean value is a quantitative manifestation of unequally development of regional economy. About 50% of the counties have rescaled exposure indexes of at least 0.54, as shown in Table 4, which indicates a climate-dominated vulnerability pattern. Precipitation is the most important factor in shaping the vulnerability to climate changes on a regional level, as most of these counties are covered with semi-arid steppe or desert and face threats from grassland degradation and desertification. Cumulative distribution functions of the vulnerability components indicate that 75% of the counties have a rescaled AI of 0.36, reflecting uneven economic development in MIM among other factors. The rescaled median AI of 0.24 suggests that adaptive capacity is generally low across the counties. The low adaptive capacity is potentially a manifestation of underdeveloped social services and relatively simple economic structure. Rescaled median SI was at least 0.39, and a moderately high IQR suggests that most of the counties in the study area are naturally sensitive to drought. Proximity to deserts and scarcity of water and low coverage of vegetation both contribute to the sensitivity to disturbances.

Table 4 Quartiles of vulnerability indices

Index	Percentile			Inter-quartile range
	25th	Median	75th	
Exposure index	0.35	0.54	0.73	0.38
Sensitivity index	0.22	0.45	0.68	0.46
Adaptive capacity index	0.12	0.24	0.36	0.24
Vulnerability index	0.30	0.45	0.60	0.30

3.4 Vulnerability mapping

To compare the spatial differences of vulnerability indices, we classified the values into five levels of three dimensions by a geometrical interval method: high, medium high, medium, moderate low, low (Fig. 3). This classification method is a scheme whereby the class breaks are based upon class intervals for minimizing the square sum of element per class. This ensured that each class range had approximately the same number of values, and it can even work reasonably well on data that are not normally distributed.

The map of exposure to drought indicates that counties in the western part are more exposed to drought hazard (Fig. 3a). Interior land is more exposed than counties nearer to the eastern part, the region near the sea. The higher exposure index indicates more severe drought. Coincidentally, counties in the western part also have low adaptive capacity due to underdeveloped social economics that consequently increase their vulnerability.

As shown in Fig. 3b, counties in Ordos City and Bayannur City were also most frequently influenced by multiple climate variances coupled with instability in land coverage and thus showed the highest value of sensitivity index.

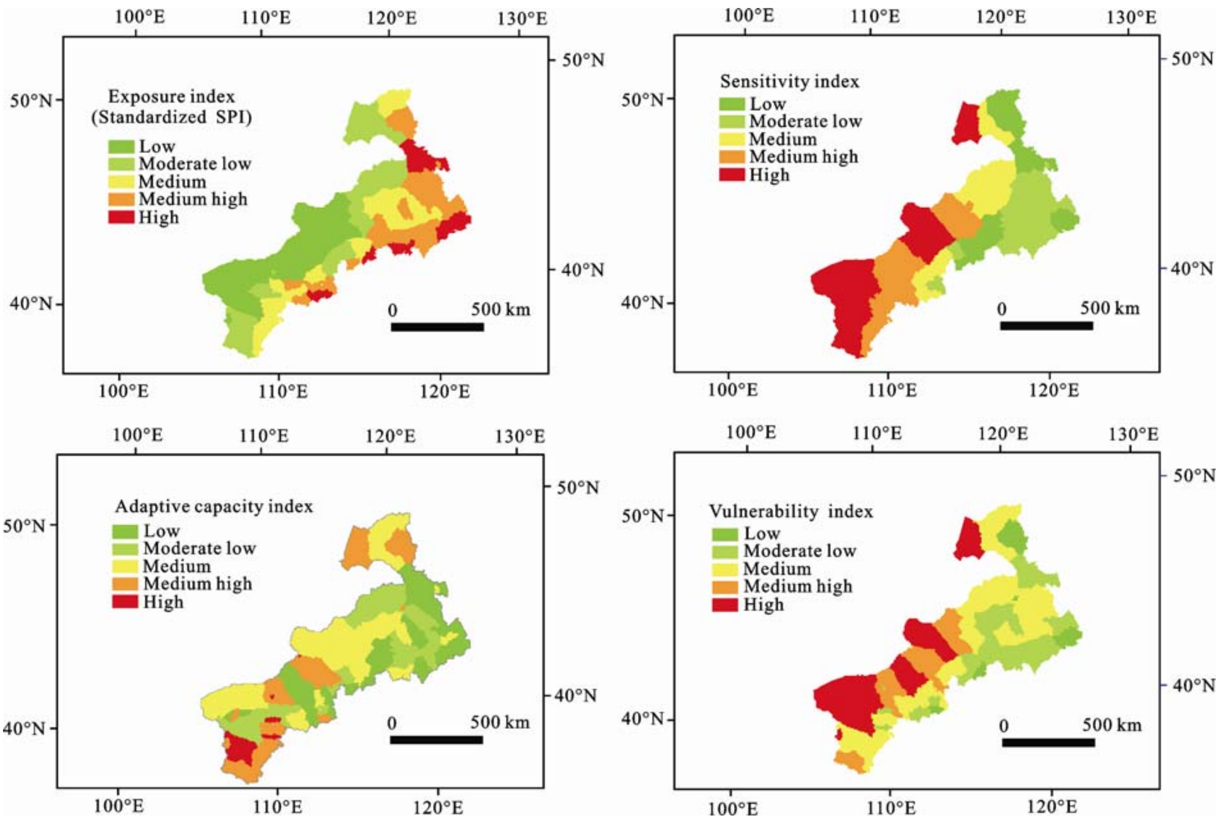
Potentially the most adaptive counties are located in the eastern part with humid climate and relatively well-developed farming as shown in Fig. 3c, including Fengzhen City in Ulanqab City, Ewenki Autonomous Banner in Hulunbuir City, Holin Gol City, Horqin Right Wing Rear Banner in Tongliao City, Duolun County in and Taibus Banner in Xilin Gol League. Different activities have various blends of adaptive capacity. In some cases, high sensitivity and low adaptive capacity may lead to large residual vulnerability. On the other hand, a strong adaptive capacity may mean that residual risks are small or non-existent in other counties.

The VI results indicating that the most exposed inner land areas were the most fragile are depicted in Fig. 3d. Counties with the highest VI are mostly located in Bayannur City and Hulunbuir City, including Hanggin Rear Banner, Urad Rear Banner, Urad Middle Banner, Dengkou County, Wuyuan County and Xin Barag Right Banner. The counties are located in inland Inner Mongolia and have an arid climate. They are mostly covered by dry grassland and desert grassland, and the economy is relatively underdeveloped, the main agricultural production relying on animal husbandry, overgrazing and other inappropriate land uses that cause serious land degradation and desertification. In contrast, most of the municipal districts are found to be less vulnerable, probably because they are less dependent on agricultural production and have greater adaptively originating from high technology development and information accessibility. Examples include Dongsheng City, Chifeng City and Baotou City.

3.5 Vulnerability zoning

A zoning method for understanding the characteristics of the region as a whole is important. Spatial differentiation drafting by zones, defining the quantitative boundary values, has been applied in many previous studies.

The triangular chart was initially introduced by the



Exposure, sensitivity and adaptive capacity were all standardized to range between 0 and 1

Fig. 3 Distribution of exposure, sensitivity, adaptive capacity, vulnerability indexes classified by geometrical interval method

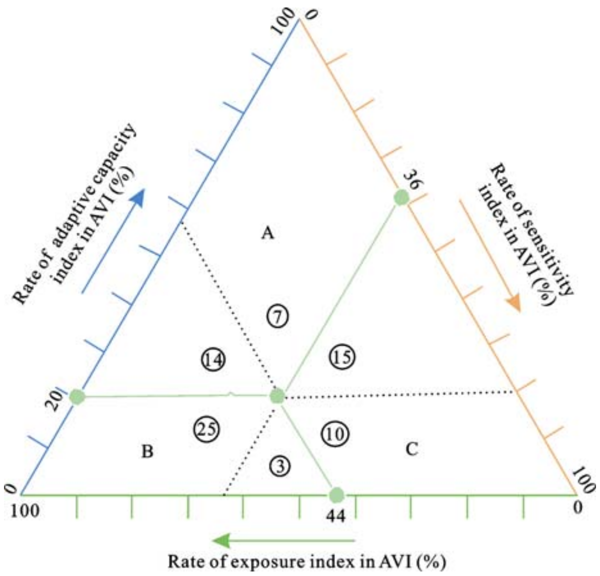
United States Department of Agriculture (USDA) to classify soil types by giving names to various combinations of clay, sand and silt before it was widely used in measuring types of one thing based upon multiple combinations of the other three measures.

In Fig. 4, there are three orientations of the percentages on the sides of the triangle. The numbers are arranged symmetrically around the perimeter. Perimeters, either on the left or right or at the bottom of the chart, represent different numbers corresponding to the percentages of three measures. Intersection of three lines corresponding to three proportions should be identified before classifying. All of the percent will add up to 100%.

In this study, the composition of VI was analyzed in depth by comparison between the absolute values of dimensional indices. Different structures of contribution of each index to the summary of the three values of AI, SPI and SI were depicted in an equilateral triangle map (Fig. 4). AVI denotes the summary of EI, SI and AI. Each side of the triangle represents the perimeter of the rate of each index divided by AVI, with a range between 0 and 100%. The bottom, right and left sides of the triangular are respectively standing for REI (ratio of EI divided by AVI), RSI (ratio of SI divided by AVI) and RAI (ratio of AI divided by AVI). The range position of counties on the triangular map could be defined by a coordinate system as REI, RSI, and RAI.

The intersection of the three lines indicating the mean values of REI, RSI and RAI (REI = 44%, RSI = 36%, RAI = 20%) were drawn to define the six crossing areas in the triangle representing six combination types of vulnerability index. The number of counties in each category is given in the circles in the crossing ranges in Fig. 4 and in the last row of Table 5. Considering the regional character and the assessment results, three categories (A, B and C) representing different sources of regional vulnerability were drawn according to the perimeters given in Table 5.

Thirty-nine counties were located in zone B (Fig. 5), 25 of which were in the ranges of REI ≥ 44%, RSI < 36% and RAI < 20% (as shown in lower left corner of Fig. 4). This result implies a high exposure impact on the evaluation result of vulnerability, a low influence from adaptive management and sensitivity to change. A more effective strategy to improve social economical mitigation of the process could be a key solution to this problem in MIM at present.



Numbers in circles mean number of counties; AVI is summary of absolute value of adaptive capacity index (AI), exposure index (EI) and sensitivity index (SI)

Fig. 4 Triangular map of vulnerability index structure

Table 5 Categories of vulnerability zones based on structure of triangular map of absolute values of vulnerability indexes

Zone code	Vulnerability zone	Index structure (%)			Number of counties	
		REI	RSI	RAI		
A	Adaptive and sensitivity inter-acted	0–44	0–36	≥20	7	21
		≥44	0–36	≥20	14	
B	Exposure dominated	≥44	0–36	0–20	25	28
		≥44	≥36	0–20	3	
C	Sensitivity dominated	0–44	≥36	0–20	10	25
		0–44	≥36	≥20	15	

Notes: AVI is summary of absolute value of adaptive capacity index (AI), exposure index (EI) and sensitivity index (SI); RAI is rate of AI in AVI; SPI is standardized precipitation index; REI is rate of SPI in AVI; RSI is rate of SI in AVI. Each vulnerability zone includes two parts separated by extension line of average index value (gray dotted line in Fig. 4)

4 Discussion

There is evidence that natural drought frequencies and shortage of precipitation still dominated the overall region, as shown in the analysis of vulnerability zones and vulnerability index structure. Investigation of the influence of exposure to drought in the region is especially important.

In this study, we will divide the study area into three climate zones based on differences in SPI. The SPI value of each county is depicted in Fig. 3a, which indi-

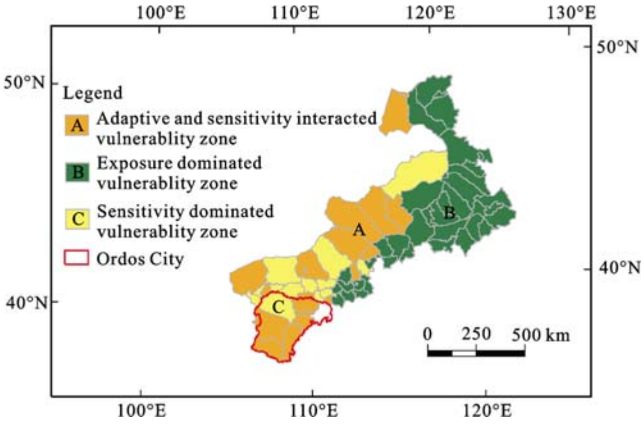


Fig. 5 Vulnerability zone divided according to triangular structure of indices

cates that the counties most exposed to drought are located in the western part. Considering the situation in the specific region and practical utilization, three threshold levels of drought intensity were calculated to redefine the boundaries of dry/moist climate defined by negative/positive SPI as depicted in the climate zone map (Fig. 6). Consistent definition of drought categories and SPI threshold can be found in other studies (Guttman, 1998; Li *et al*., 2003; Wu *et al*., 2007; Zhang *et al*., 2007). According to Mckee *et al*. (1993) study of drought intensity categories based on SPI, 2/3 of the counties in MIM were experiencing moderate drought, with SPI ranging from –1.63 to 1.64. According to Table 6, moderate drought climate zone was the counties with SPI values lower than –0.84, where are frequently influenced by drought threats. Mild drought climate zone was defined as those with SPI values between –0.84 and 0.65, where faced with seasonally occurring drought and relatively low precipitation. Counties located in the eastern part were relatively humid with SPI values higher than 0.65.

A surprising relationship is found when the two zones in Fig. 5 and Fig. 6 are compared. The three climate zones obtained from SPI values revealed a remarkably similar trend of different formation of vulnerability sources. Counties in the least exposed humid zone and mildly drought zone were also experiencing exposure-dominated vulnerability. In other words, exposure differences played a major role in regional differentiation. A conclusion that could be drawn is that more precise forecasting of the mechanism of drought events could play an important role in vulnerability prevention.

The exposure extent of widespread drought hazard is envisioned as the main initiating process of the regional vulnerability, while the potential difference in the capacity to adapt to changes is the main cause of its spatial differences. Counties that are most exposed to the drought hazard in zone I (in Fig. 6) show two types of vulnerability (roughly corresponding to zones A and B in Fig. 5): the effectively adaptive ones and the sensitivity-dominated ones. Half of them were more affected by the higher values of AI, indicating a more developed adaptive capacity in zone A.

Assessment results also indicate that although all the indicators were based upon county unit, there is a tendency for the index distribution to extend to a regional scale. Considering the high spatial correlation in sensitivity and exposure elements, it is difficult to explain this relative vulnerability of the relatively fragmented vulnerability zones. Thus, a reasonable inference would be that there is the potential derived from the regional adaptive management that increased the spatial fragmentation in vulnerability. In fact, many scholars have proposed the role of adaptive management on its scale effect. Jones *et al*. (2007) indicated that mitigative and adaptive capacity do not share the same scale, that is, adaptive capacity is expressed locally, whereas mitigative capacity is different for each activity and location but needs to be aggregated at the global scale to properly assess its potential benefits in reducing climate hazards. This can be seen as an explanation of social-economic factors that extend out of the county and also as a demand for mitigation, which can be exercised at the local scale through the exercise of mitigative capacity.

One of the best examples can be found in Ordos City as shown by the red line in Fig. 5 and Fig. 6. Located in the southwest of MIM and experiencing an unprecedented rate of development since 1990, Ordos leads the regional economic development, mostly benefiting from the abundant reserves of mineral and energy resources. However, the advantages also bring with them intense destruction of land resources. Extensive interventions have increased its frangibility by increasing its sensitivity. For example, variation of vegetation coverage due to mineral exploration has been witnessed in the Ordos region during this period.

A possible explanation for the moderate vulnerability in Ordos shown in Fig. 3d is that restoration programs significantly enhance adaptive capacity (Fig. 3c), even though Ordos is located in the most sensitive and highly exposed area. Since 2002, ecological restoration, such as return of farmland to grassland, has slowed ecological deterioration and desertification. Restoration programs have been supported by huge government investment (Song and Zhang, 2007). The history of Ordos foreshadows a more favorable future in ecosystem management, and it is also a reminder of an issue in regional economic development. A locally concentrated application of development strategies invariably brings with it intensive pressure on ecosystems, or necessitating a reallocation of resources and funding. This may imply that different environmental impacts from these regional economic strategies through a region's history should be taken into consideration in the future research. Models should not only present regional comparisons within certain current social-economical patterns, but also provide adjusted patterns with the feedback between sensitive ecosystems and better ecological restoration and environmental protection.

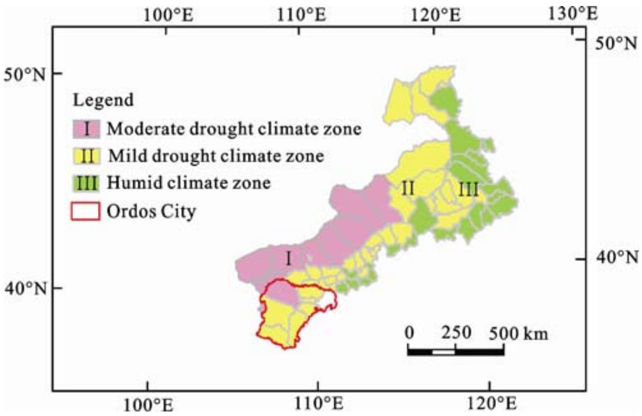


Fig. 6 Climate zone defined according to value of standardized precipitation index (SPI)

Table 6 Climate zones defined according to standardized precipitation index (SPI)

Code	SPI value	Climate zone	Number of counties	Description
I	–1.63– –0.84	Moderate drought climate zone	12	Exposed to drought threats, dry and water shortage
II	–0.84–0.65	Mildly drought climate zone	34	Seasonally influenced by drought events, dry climate, low precipitation
III	0.65–1.64	Humid climate zone	28	Occasionally threatened by drought, more surface water

5 Conclusions

Vulnerability quantification is not easy for hardly accessed information and uncertain endpoint. Complexity urges us to build a convincing standard method, and application brings a need for a clear but not simple solution.

The results indicated that vulnerability to the drought in the study area was at a medial level, and its distribution was highly correlated with regional precipitation. Based on the triangular map of index structure, key factors in shaping the vulnerability were identified. Exposure is the dominated factor of vulnerability. In addition, further investigation of the interaction mechanism of social and ecological factors and their effects provides evidences for adaptive management which could mitigate the frangibility of ecosystem although it is usually encompassed with economic status and functioned only at a local scale. A combination of exposure, sensitivity and adaptive capacity based on geographical statistical methods and GIS analysis function is a robust frame for vulnerability assessment, and could be applied to various geographical backgrounds, certifying the method of vulnerability assessment of CHANS.

Additionally, we found that the evaluation criteria might be effective in validating the spatial differentiation but potentially ineffective because of the limited time scope of the analysis. The main actions in the further researches may include: 1) Vulnerability reducing actions increased potential adaptive capacity at the local level. Potential calibrations on indices will increase the reliability a lot since accurate vegetation/soil and other spatial GIS-based data are not available at county level. 2) Assumptions may affect the results, especially the definition of drought as the main regional exposure to climate change. For example, climate change scenarios can hardly be explicitly calculated and depicted in the comprehensive analysis, as demonstrated by the fact that multiple causes and response strategies were hardly indicated by the statistical data. 3) Time span of the research limits the evaluation, as drought is very sensitive to it. Longer-term observation in the study area will reduce this uncertainty. Factors such as land use policies and ecological conservation strategies are the key measures of drought hazard in a social-ecological system, and always have long-lasting and time-lagged impacts on regional adaptive capacity. Despite these shortcomings, it also indicates possible directions taken by adding a historical view and future simulation to the criterion.

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