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Original Research

Vulnerability of the Human-Environment System in Arid Regions: The Case of Xilingol Grassland in Northern China

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Abstract

The loss of biological and economic productivity in the dryland regions hinders the prospects of reducing poverty. The method of vulnerability assessment has been broadly employed to evaluate the potential impact of environmental change and pinpoint the future adaptations on regional or global levels, which could help in the identification and development of coping strategies for dryland regions. The present study provides a vulnerability assessment for the semiarid grasslands of the Xilingol, Mongolia Plateau – a typical dryland area that has been suffering from land degradation for a long period. An exposure-sensitivity index was calculated using Spatial Principal Component Analysis for 19 climate and anthropogenic indicators that had a strong correlation with observed grassland degradation. This indicator was compared with an adaptive capacity index, constructed using principal component analysis for 27 relevant variables from the aspects of location advantage, economic level, resources, and social efficiency. The results show that the northeastern part of Xilingol is least vulnerable due to more favorable and available natural resources, including high precipitation, productive grassland, etc., and greater economic development. By contrast, the areas in the southwest, with harsh environmental conditions and a poor socio-economic infrastructure, have the greatest vulnerability. These regions are in dire need for targeted adaptation measures to further decline in human well-being. Through analyzing the results of SPCA and PCA analysis, the entry points for vulnerability reduction were distinguished and the pertinent suggestions were clearly brought forward from the aspects of reducing exposure-sensitivity and improving adaptive capacity.

Keywords: vulnerability, adaptive capacity, environmental change, grassland degradation

Introduction

Drylands occupy 41% of Earth's land surface and are home to more than 2 billion people – a third of the human population in the year 2000 [1]. Drylands include all terrestrial regions where water scarcity limits the production of crops, forage, wood, and other ecosystem provisioning services. Worldwide 10-20% of drylands are degraded, i.e. suffer from the reduction or loss of the biological or economic productivity, threatening the world's poorest popula-

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tions and hindering prospects of reducing poverty [1]. Conflicts between economic development and environmental conservation are exacerbated by expanding populations and increased food demands [2], and climate change is likely to present further challenges to these already vulnerable regions [3]. The rural poor will suffer the most from these changes and will require a range of coping strategies to help them adapt to changing climates [4]. Vulnerability assessment can form a useful framework for identifying such strategies.

The concept of vulnerability was promoted in the Intergovernmental Panel on Climate Change (IPCC) Third Assessment Report [5], and has subsequently been applied in environmental change science [6], sustainability studies [7], and hazard and disaster research [8]. Vulnerability cannot be seen in isolation, and humans, as users, actors and managers of the system are not external, but integral elements of the coupled human environment system [9]. A region's vulnerability depends on its susceptibility to specific (e.g., drought) or integrated (e.g., drought and overgrazing in grassland) change, and its ability to cope with these changes. Vulnerability is therefore a function of the exposure to change, a system's sensitivity to these change (i.e. the degree to which the system is affected), and adaptive capacity, or ability to adjust to these changes.

In practice, it is often difficult to separate exposure and sensitivity, which are therefore often considered to be one single factor, such as exposure-sensitivity [10], or potential impact [6, 11]. In this paper, vulnerability is conceptually defined as a function of exposure-sensitivity and adaptive capacity. The analysis of exposure-sensitivity identifies regions facing the greatest potential impacts, where vulnerability can be reduced by lowering exposure and (or) by changing a system in terms of reducing the degree it is impacted through various direct and more indirect aspects. By contrast, adaptive capacity pinpoints regions where economic and human capitals are lowering vulnerability, and poverty alleviation measures can reduce vulnerability.

Many vulnerability assessments have focused on the future prediction on national or continental scales [12, 13]. By contrast, regional studies remain scarce and there is a need for the development of appropriate methods for analysis [14]. Moreover, pointing out the entry point for environmental management based on vulnerability research with the knowledge of ecological process and human adaptation could do more help in immediate environmental management decisions than projecting future vulnerability based on current or recent past analysis like most current research. Therefore, this paper presents a vulnerability assessment for the semiarid grasslands of Xilingol in northern China, a region that has seen degradation and marginalization for decades, and brings forward a method to pinpoint the sources of vulnerability. The methods presented here will provide a useful basis for regional vulnerability assessment and help in improving environmental management in the ecologically vulnerable area.

Study Area

The Xilingol League[1)] extends between 41°35'-46°47' N and 111º05'-120º01'E, in the Inner Mongolia Plateau, China (Fig. 1). Xilingol covers an area of about 203,000 km^2 and had a population of 909,500 at the end of 2000 [15]. Altitude ranges from 763 m to 1,750 m, declining from the southeast to the northeast with a mosaic of hilly mountains and low basins in the intermediate part. The area

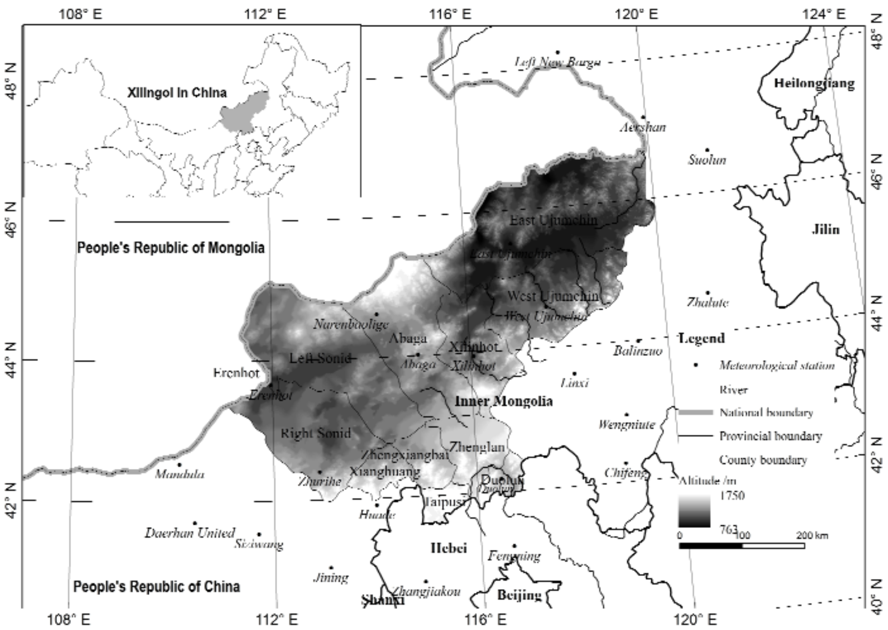

Fig. 1. Location and administrative regions of Xilingol League.

1) The administrative levels of league and banner are equivalent to prefecture and county, respectively. Hereafter, the subunits of Xilingol League are collectively referred to as counties.

is dominated by a continental middle temperate semi-arid climate, with a mean annual temperature between 1ºC and 2ºC and the growing season stretching from April to September. The rainfall temporally concentrates from July to September and the annual precipitation varies between around 400 mm in the southeast and lower than 200 mm in the southwest, while the potential mean annual evapotranspiration declines from 2,700 mm in the west to 1,500 mm in the southeast [16], which makes the west drier than the east. The rolling grasslands are categorized into three types, which follow a gradient from northeast to southwest: meadow steppe, typical steppe, and desert steppe [17].

Grassland is the major land use type of Xilingol, except the southeast, where farming and grazing co-exist due to a more favorable climate. The livelihoods of 60% of the Xilingol population depend on grazing and livestock products [18], which have been threatened by decades of grassland degradation. Around half of Xilingol grassland has been degraded to varying degrees between 1998 and 2003 [19]. In the past half century, the region saw a dramatic change from pastoral nomadic lifestyles to settled pastoralism, coinciding with rapid developments in animal husbandry. The increased number and the reduced mobility of herds make pasture broadly overgrazed and vegetation intensively stamped. Furthermore, poor grassland farming practices result in severe soil loss, which has greatly influenced livelihoods [20]. The ecological security of Xilingol grassland is even more fragile when global climate change is considered. While the projected temperature increase may be favorable, there are large uncertainties surrounding future fluctuations in precipitation [21]. The human disturbance in combination with the climate change in Xilingol caused severe grassland degradation, which is aggravated by shortage of scientific management and intervention mechanism for environmental improvement, or even fall into negative feedback under improper environmental management policies and causing further grassland deterioration. The current challenge of Xilingol environmental management is lack of planned adaptation strategies for vulnerability control on facing environmental change, while the biggest problem lies with the complicated correlation of vulnerability elements and the shortage of vulnerability research framework and practicable evaluation method. The paper started from analyzing the factors causing vulnerability, and committed to constructing the regional vulnerability appraisal system, which is expected to meet the need for environmental management of Xilingol and similar environmentally vulnerable areas.

Materials and Methods

The human-environmental system of Xilingol consists of a bio-geographical system and anthropogenic system and their interaction. This paper treats human-environmental system vulnerability under several inseparable stressors, including environmental changes leading by drought event, precipitation fluctuation, insect and rodent attack, and human management. And the human adaptive capacity is considered as regional ability to cope with such environmental changes and could be reflected and measured with social and economic statistical data.

Vulnerability reflects a normal feature of a region under a mean environmental condition that is greatly determined by the dominant environmental change factors. For Xilingol, precipitation is the most important determinant factor of environmental change. The year 2000 was chosen for the study because the precipitation of that year got close to the normal status after a decline from 1998 (383.9 mm) [22], and the precipitation of 2000 was quite near to the mean level (197.3 mm) in the last ten years.

This research attempts to quantify and map the vulnerability of the coupled human environmental system in Xilingol and comprises three steps, summarized in Fig. 2:

(1) Identifying the most important drivers of grassland degradation and using these drivers to assess the combined exposure-sensitivity index across the region.
(2) Assessing differences in adaptive capacity across the region by screening relevant indicators from the aspects of location advantage, economic level, resources, and social efficiency.
(3) Combining these insights to determine differences in vulnerability across Xilingol. These steps are described in more detail in the following sections.

All spatial analyses were carried out in ArcGIS (version 9.1), while non-spatial statistics were calculated using SPSS (version 14).

Step 1: Assessing Exposure-Sensitivity to Grassland Degradation

Quantifying Grassland Degradation

A first requirement for assessing the drivers affecting recent grassland degradation in Xilingol is a reliable spatial dataset quantifying the degradation. Although grassland degradation in Xilingol has been documented [15], such datasets are not available. A new dataset was therefore created using change in the normalized difference vegetation index (NDVI) derived from advanced a very high radiometer resolution (AVHRR) sensor onboard the National Oceanographic and Atmospheric Administration (NOAA) satellites. GIMMS AVHRR NDVI is broadly used in grassland monitoring on large scale [23], and its accuracy and applicability was confirmed broadly on Xilingol grassland classification and grass growth monitoring [24]. Change in grassland productivity is computed by comparing the NDVI data for 2000 with the undisturbed NDVI background. However, with a long history of human use, there is hardly any grassland left undisturbed [25]. A proxy for the undisturbed NDVI was therefore calculated based on the assumption that undisturbed conditions are associated with high NDVI values under the zonal climate condition. Since the highest values are probably caused by extreme precipitation events [26], the undisturbed NDVI proxy was calculated by cutting off the highest NDVI value of each

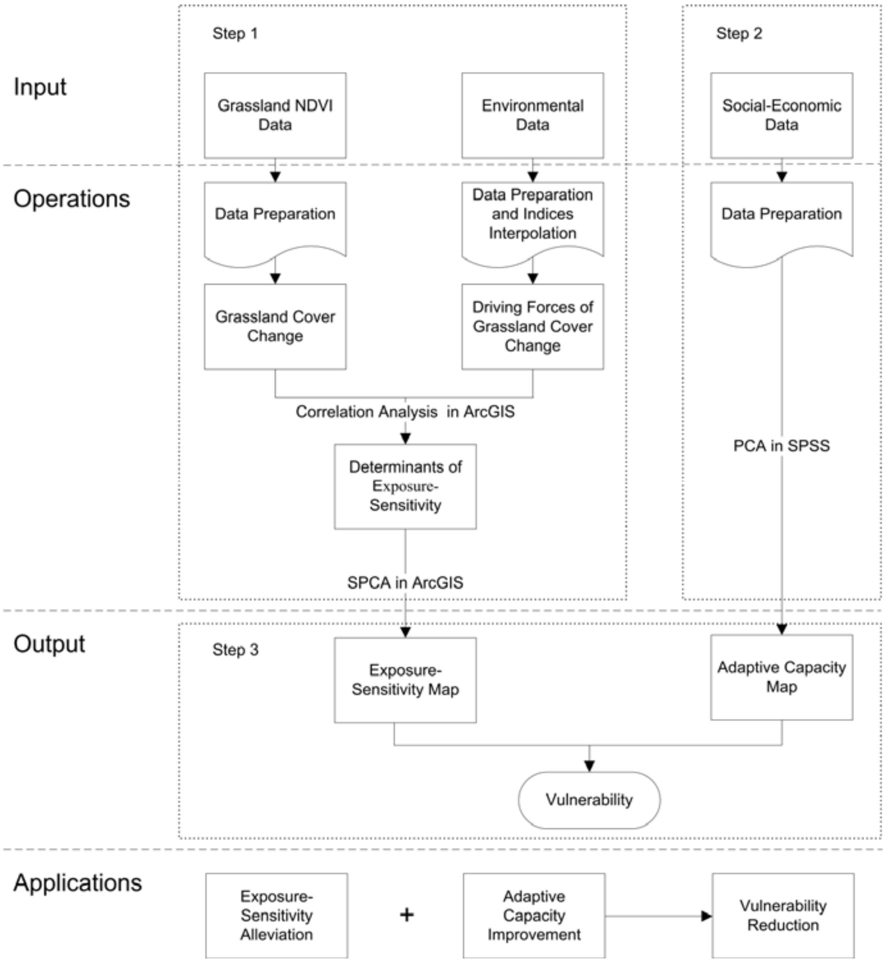

Fig. 2. Flowchart of the vulnerability research.

grid cell between 1981 and 2006 and averaging the next top 5 NDVI values. The grassland quality change for the year 2000 is then calculated by comparing the NDVI of 2000 with the undisturbed NDVI during the phase from 1981 to 2006.

Identifying Potential Drivers of Recent Grassland Degradation

A list of potential climatic, topographic, and anthropogenic drivers of grassland degradation was constructed following a literature review [27, 28] and based on the best available data sources.

Plant growth is affected by weather conditions of not only the growing season, but also the non-growing season, since plant growth responds to rainfall with a certain time lag [29]. We therefore define a growing year as the period from the beginning of the non-growing season to the end of the following growing season, (i.e. from the beginning of October till the end of the following September). However, due to the time lag, it is difficult to discriminate which indicators and which periods are most critical for plant growth and affect grassland degradation [23]. Eight periods (winter, spring, summer, February and March, winter and spring, non-growing season, growing season, and growth year) relating to plant growth were therefore chosen for the present analysis, for which monthly weather data (temperature, precipitation, evapotranspiration, and wind speed included) were extracted for 1999-2000. Data from 23 meteorological stations in and around Xilingol League (Fig. 1) were spatially extrapolated using ordinary kriging to produce a spatial dataset with 100 m resolution. Furthermore, an aridity index was calculated following Zhang et al. (Formula 1) [30].

$$K = \frac{0.16\sum_{j=1}^{n}\overline{t_{ij}} \times N_{ij}}{r} \tag{1}$$

...where K is the aridity index, $\overline{t_{ij}}$ represents the mean air temperature of meteorological station i in the month j, N_{ij} is the number of days in the month j.

Six topographic indictors were extracted from a 100m digital elevation model (DEM) that could potentially influence the distribution of grassland degradation, including altitude, slope degree, amplitude of landforms [31] (the differences between the highest and lowest point within 5 km), relative slope position [32], slope configuration [32], and the transformation of aspect [33].

Five indicators were identified to represent anthropogenic influence on grassland degradation, including distance to road, distance to nearest settlement, distance to nearest river (showing advantages of water accessibility), and integrated influence of housing and grazing intensity. The pastoralist settlement has resulted in sedentary grazing where, according to local shepherds, grazing activity generally radiates no further than 5 km from settlements. Simple indicators were therefore calculated for the distance to the nearest settlement, river, and road. Integrated influence of housing is a weighted indicator combining settlement size and distance to settlement. The grazing intensity index reflects human influence on vegetation growth [34]. The construction of this index is explained in Appendix 1.

Constructing the Exposure-Sensitivity Indicator

Spatial correlation analysis was used to identify the variables that correlated most strongly with the observed grassland change. The correlation coefficients were calculated based on the raster data of each indicator and the recent change in grassland productivity. Indicators with a higher correlation coefficient were considered as main driving forces of grassland degradation and used to construct the exposure-sensitivity index based on spatial principal components analysis (SPCA). Weak relations between grassland degradation and driving forces is attributed to several parameters, including regional heterogeneity, complexity of grassland change, and other factors that are difficult to incorporate here. Exposure-sensitivity was defined as the sum of the weighted principal components with an accumulative variance greater than 90% (Formula 2).

$$Exposure - sensitivity = \sum_{i=1}^{m} a_i \times SP_i \quad (2)$$

...where m is the number of principal components, SP_i is the No. i spatial principal component, and a_i demonstrates the corresponding % variance explained.

Step 2:
Assessing Adaptive Capacity

Adaptive capacity is defined as the ability of the coupled human environment system to cope with new or changing circumstances [35]. Adaptive capacity therefore helps to reduce the negative effects of the changing environment or to utilize positive effects. The potential components of adaptive capacity at the regional level include a lot of indicators. Here, we developed the adaptive capacity index to capture society's ability of a region to cope with changes and implement adaptation measures. Thus the variables of macro-economic, social development, public services, human resources, and administrative efficiency were selected as determinants of regional scale adaptive capacity. Especially the indicators of administrative efficiency were used to reflect the reaction capability, responding speed, and emergency handling ability of local governments. However, the regional governance in Xilingol comes from the same regime, and the only difference lies in the administrative level, so the two bigger cities of Xilinhot and Erenhot have more preponderance in adaptation to environmental change because of the higher administrative level than the other counties. In the end 27 distinguishable indicators were selected, which can be grouped in four categories: location, economic level, resources, and social efficiency (Table 1). Unfortunately, several factors identified in previous studies could not be included in the present study due to data limitations (e.g. population structure, disease, gender differentiation, and livelihood diversification).

The adaptive capacity index was calculated using PCA to reduce the number of indicators and eliminate the collinearity between variables. Adaptive capacity is calculated for each county, by summation of the weighted values of the principal components with a total explained variance over 90% (Formula 3).

$$Adaptive\ Capacity = \sum_{j=1}^{n} b_j \times PC_j \quad (3)$$

...where j is the number of principal components, PC_j is the score of No. j principal component, while b_j demonstrates the corresponding % variance explained.

Step 3:
Vulnerability Calculation and Mapping

Quantifying vulnerability is a great scientific challenge, especially because of the relationships between exposure, sensitivity, and adaptive capacity are not very well understood [36, 37]. However, it is clear that high-exposure sensitivity and low-adaptive capacity lead to high vulnerability and vice versa. It is therefore useful to explore relative rankings of the exposure-sensitivity and adaptive capacity indices for the different counties in Xilingol.

Results

Assessing Exposure-Sensitivity
of Recent Grassland Degradation

Through spatial correlation analysis, 19 of the 44 indicators with higher correlation coefficients with grassland cover change (Table 2) were enrolled into the SPCA to compose exposure-sensitivity index, including 15 climatic factors and 4 anthropogenic factors (the distance to the nearest river is treated as an anthropogenic factor for affecting the spatial distribution of human activity). The SPCA shows that 91.3% of the total variance of these 19 indicators could be represented by the first four components (Table 2). The correlation coefficient matrix between the SPCA components shows that the first component (SP1) is highly correlated with transpiration and wind speed. The mean annual transpiration of Xilingol is three times greater than precipitation, resulting in a large water deficiency, which is a key factor

Table 1. Factors and indicators used for calculating Xilingol adaptive capacity index.

Factor	Indicator (unit)	Adaptation mechanism	Data source
Location advantage	Distance to the nearest railway station (m) [a)]	Near rail station means great advantage for economic growth and fast access to goods and material supplies for emergent needs	Measured from traffic map of Inner Mongolia
	Soil erosion resistance (km^2) [b)]	Means the capability of local soil conditions for crop or forage production	China 1:4,000,000 Soil Database
	Mean Precipitation of each county (mm)	High rainfall could support better grass growth and favor regional adaptation.	Extracted from Precipitation of Xilingol, 2000
Economic level	GDP per capita (Yuan pp)	Reflecting individual capability for recovery from environmental change attack.	(Xilingol Statistic Bureau 2001)
	GDP (Yuan)	Region's economic power determine capability for adaptation and recoverage	(Xilingol Statistic Bureau 2001)
	Net income of rural resident (Yuan)	Reflecting the capability of the more vulnerable human group (rural peasants)	(Xilingol Statistic Bureau 2001)
	Non-agricultural GDP Percentage (%)	Showing the dependency of regional economics on agriculture: the higher of this indicator means the region will be more vulnerable under environmental change	(Xilingol Statistic Bureau 2001)
	GDP growth rate (%)	Showing the prospirity of regional economy.	(Xilingol Statistic Bureau 2001)
	Infrastructure construction investment (Yuan)	Infrastructure is a region's base for adaptation, increase of investment reflects the effort of perfection of regional infrastructure	(Xilingol Statistic Bureau 2001)
Resources	Grassland area (km^2)	Grassland is the basic natural resource for pasture living, more grassland means more income and high adaptive capacity of household.	(Xilingol Statistic Bureau 2001)
	Mean NDVI in each county	NDVI is used to reflect grassland quality, which is important besides grassland area	NDVI of Xilingol in 2000
	Grassland area Proportion in each county (%)	Reflecting the dependency of a region's agricultural economy on grassland	Calculation based on statistical data
	Livestock number by the end of year (head)	Total livestock quantity reflects the financial asset of a region	(Xilingol Statistic Bureau 2001)
	Medical staff quantity (person)	Reflecting the accessible medical services of the region	(Xilingol Statistic Bureau 2001)
	Population size (person)	A bigger population needs more resources and will be less flexible on adaptation	(Xilingol Statistic Bureau 2001)
	Proportion of vacant land (%) [c)]	Vacant land showing the potential of future land development	Desertification Map of China (1:4,000,000)
	Meat yield (pork, beef, and cotton) (kg)	High meat yield or stock means more help in the human adaptation for emergent need.	(Xilingol Statistic Bureau 2001)
Social efficiency	Population density (person/km^2)	Area with higher population density will exert heavier burden on regional ecology and need more resources for adaptation	(Xilingol Statistic Bureau 2001)
	Population growth rate (%)	High population growth means heavier pressure in the future on grassland	(Xilingol Statistic Bureau 2001)
	Non-agricultural population proportion (%)	Non-agricultural people is human resources for regional adaptation	(Xilingol Statistic Bureau 2001)
	Student quantity at primary and secondary school	Showing the people who could get knowledge from school education and tranfer the knowledge to others and benefit their family for better adaptation	(Xilingol Statistic Bureau 2001)
	Mean household size (person) [d)]	Families with more people will be better able to develop more strategies for adaptation under current resource distribution policies	(Xilingol Statistic Bureau 2001)
	Livestock death rate (%)	Showing the science and technology level of animal husbandry	(Xilingol Statistic Bureau 2001)
	Highway network density (km/km^2)	Highway plays an important role in population, goods, and material transportation.	Traffic map of Inner Mongolia, 2005

Table 1. Continued.

Factor	Indicator (unit)	Adaptation mechanism	Data source
Social efficiency	Electricity consumption per GDP unit (kWh/Yuan)	Low energy consumption level reflects more environmentally friendly economic development and less pressure on local environment	Calculation from (Xilingol Statistic Bureau 2001)
	Disposable income ratio between urban and rural residents	Reflecting the income gap of each sub-region, the region with less of an income gap are considered more socially stable during adaptation	(Xilingol Statistic Bureau 2001)
	Administrative ability [e)]	The administrative ability reflect the reaction capability, responding speed and emergency handling ability of local governments.	Assignment based on expert judgments

a) Average distance to the nearest rail station of all cells in a county
b) Summarizing the weighted area proportions of each soil type. The soil type is quantified by assigning values based on the content of organic matter and capacity to hold water and fertilizer. Grayzems soil: 8, chernozem soil: 6, chestnut soil: 4, brown soil: 2, bog soil: 7, grey meadow soil: 5, saline soil: 3, sandy soil: 1.
c) Including desertification land, salt and alkaline land, marshy land, etc.
d) Population number divided by household number
e) Xilinhot and Erenhot are assigned to 2 as two relative big cities; the remaining counties are 1 for small size

Table 2. Eigenvalues, contribution ratios, and the factor loading matrix of SPCA.

PCA component layer	Correlation coefficient [a)]	SP 1	SP 2	SP 3	SP 4
Eigenvalue	-	0.204	0.097	0.034	0.022
% variance explained	-	52.1	24.8	8.7	5.7
Cumulative % variance explained	-	52.1	76.9	85.6	91.3
Mean air temperature of spring	0.382	0.726	0.131	0.601	-0.005
Mean air temperature of winter and spring	0.302	0.791	0.319	0.373	-0.212
Mean air temperature of non-growing season	0.230	0.814	0.386	0.096	-0.273
Mean air temperature of February and March	0.435	0.758	0.476	0.393	0.013
Cumulative precipitation of winter and spring	0.368	0.307	0.799	-0.368	0.307
Cumulative transpiration of February and March	0.360	0.971	0.158	0.035	-0.047
Cumulative transpiration of non-growing season	0.373	0.969	0.103	-0.116	-0.008
Cumulative transpiration of spring	0.210	0.900	-0.380	-0.142	-0.034
Cumulative transpiration of winter	0.349	0.623	0.654	0.267	-0.042
Cumulative transpiration of winter and spring	0.261	0.941	-0.284	-0.114	-0.010
Distance to road	0.228	-0.094	-0.460	0.413	0.680
Cumulative precipitation of summer	0.230	-0.215	0.859	-0.135	0.199
Distance to river	0.278	0.555	-0.625	0.270	0.326
Cumulative precipitation of spring	0.384	0.300	0.824	-0.320	0.307
Average wind speed of winter	0.354	0.938	-0.202	-0.191	0.117
Distance to nearest resident point	0.239	-0.004	-0.309	0.075	0.592
Average wind speed of spring	0.219	0.852	-0.288	-0.333	0.096
Grazing intensity	-0.244	0.500	-0.311	-0.456	-0.192
Average wind speed of growth year	0.205	0.862	-0.313	-0.300	0.032

a) Indicators with correlation coefficient over 0.2 for grassland cover change at 0.1% level, n = 199042, SP – spatial principal component shaping the local environment. SP2, SP3, and SP4 correlate with precipitation (spring and summer), temperature (spring), and human driving forces (distance to nearest settlement and road), respectively. The exposure-sensitivity index is calculated by Formula 2, and shown in Fig. 3A. It increases in a radial pattern with a valley in the northwest and the peak value south of Right Sonid.

Adaptive Capacity of Each County

Four principal components had eigenvalues greater than 1.0, and explained more than 90% of the variation in the 27 input variables (Table 3). The correlation matrix shows that the first principal component (PC1) is more correlated with economic power, technology level, administration ability, and infrastructure, all of which reflect socio-economic efficiency. PC2 represents more information on economic disparity between rural areas and urban areas, the natural population growth rate and livestock development level, which could be labeled as rural economy and income disparity, while the last two components have higher correlations with human capital (PC3) and environment status (PC4).

The adaptive capacity index (Fig. 3B) was calculated using Formula 3. It shows that the counties with higher values of adaptive capacity are mainly located northeast of Xilingol, which is dominated by the productive meadow steppe and profitable stock breeding. By contrast, the counties with lower adaptive capacity are mainly located south of Xilingol, the eastern part of which belongs to the farming-pastoral zone with greater population density and fluctuating climate and the western part in the desert steppe area, where the rural livelihood is constrained by harsh climate and sparse vegetation. The other part of the region located in the typical steppe has intermediate adaptive capacity.

Vulnerability

Vulnerability is a function of exposure-sensitivity and adaptive capacity, but their relationship remains largely conceptual [38]. While this makes it difficult to construct meaningful vulnerability indicators, it remains useful to analyze exposure-sensitivity and adaptive capacity together. A vulnerability map was constructed by classifying and overlaying the spatial distribution of exposure-sensitivity and adaptive capacity (Fig. 4). The Exposure-sensitivity was classified into three types according to the breaking points (0.98 and 1.45) of the histogram plot, while the adaptive capacity was used to group all counties into three types by the scores (high >025, moderate: 0-0.25, low: <0). The hue of green, yellow, and red demonstrate the increase of exposure-sensitivity from low to high, and the saturation from light to dark represents the increase of adaptive capacity. Fig. 4 demonstrated that the counties in the southwest of Xilingol are more vulnerable than those in the northeastern part and should be given more attention in future regional and ecosystem management. The distribution patterns of vulnerability is in great accord with the differentiation of precipitation and grassland, for the precipitation decreased from the northeast to the southwest, while the grassland typology changed from meadow-steppe in the northeast and typical-steppe in the middle part to desert-steppe in the southwest part of the study area.

Discussion

Drivers of Grassland Degradation

Correlation analysis, used to discriminate the exposure-sensitivity indicators, forms a useful method to alleviate subjectivity in selecting indicators for vulnerability assessment [39]. However, the screening of driving factors remains very difficult; in this paper we used correlation coefficient to select the more relative indicators for further analysis. We selected the method of interpolation to construct spatial dataset of climatic date, and used the proxies to reflect the human influences by expertise and experience in the region. The drivers screening helped overcome the

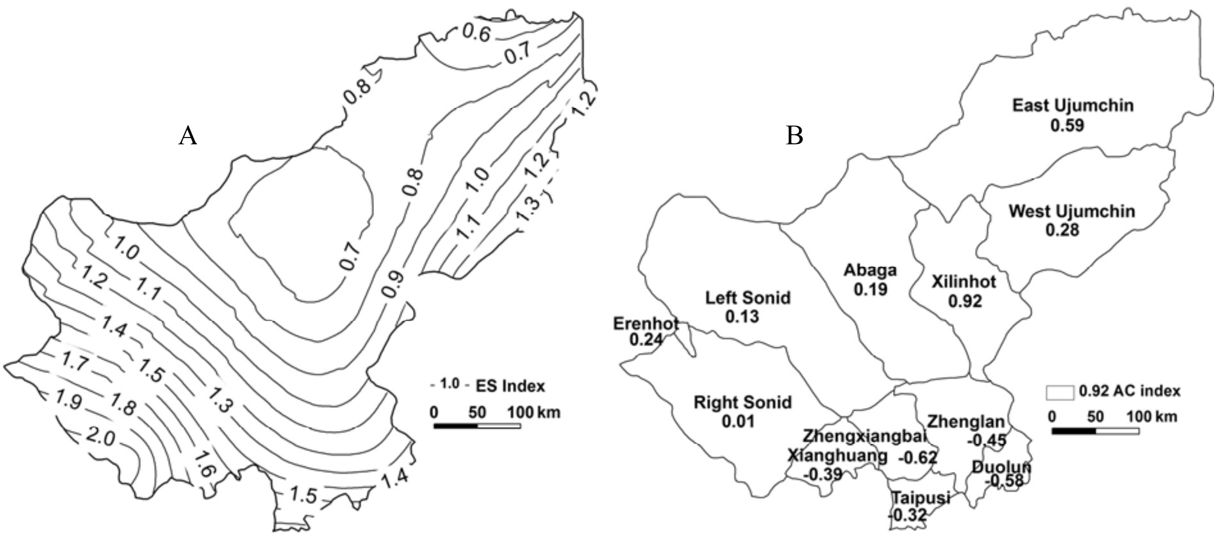

Fig. 3. Spatial distribution of exposure-sensitivity index (A) and adaptive capacity index of Xilingol (B).

Table 3. Eigenvalues, contribution, and correlation matrix of PCA.

Indicator	PC 1	PC 2	PC 3	PC 4
Total Eigenvalue	8.411	7.960	5.415	2.498
% variance explained	31.2	29.5	20.1	9.3
Cumulative % variance explained	31.2	60.7	80.8	90.1
Distance to the nearest railway station	-0.627*	0.604*	-0.100	0.284
Soil erosion resistance	-0.419	0.323	0.468	0.522
Precipitation	-0.457	-0.44	0.704**	-0.094
GDP per capita	0.559	0.806**	-0.044	0.004
GDP	0.546	0.577*	0.586*	-0.101
Net income of rural resident	-0.024	0.891***	-0.218	0.333
Percentage of GDP of non-agricultural industry	0.946***	-0.043	0.064	-0.032
Growth rate of GDP	0.693*	0.547	0.250	-0.145
Area of grassland	-0.400	0.793**	-0.268	0.054
Quality of grassland	-0.575	0.020	0.702*	0.242
Percentage of grassland over the total area	-0.603*	0.491	0.029	-0.594*
Livestock number by the end of year	-0.509	0.799**	-0.086	0.142
Medical staff number	0.429	0.560	0.654*	-0.163
Population size	0.056	-0.161	0.904***	0.219
Infrastructure construction investment	0.564	0.602*	0.496	-0.179
Proportion of vacant land	-0.394	0.050	-0.027	-0.713
Yield of meat (pig, cow, sheep, and goat)	-0.474	0.806**	0.099	0.127
Population density	0.338	-0.606*	0.439	0.526
Natural growth rate of population	0.468	0.805**	-0.154	0.029
Population of non-agricultural proportion	0.711**	0.305	-0.597*	0.120
Student population in primary and middle school	0.352	0.036	0.906***	0.102
Household size	-0.066	0.643*	0.654*	-0.149
Livestock death rate	0.890***	0.012	-0.376	0.135
Highway network density	0.862***	-0.299	-0.180	0.234
Energy consumption of unit GDP	0.453	-0.104	0.227	-0.719**
Ratio of disposable income between urban and rural residents	0.199	-0.832***	0.332	-0.099
Administrative ability	0.95***	0.204	0.011	0.062

***$P < 0.001$, **$P < 0.01$, *$P < 0.05$, n=10, PC – principal component

data gap in the research. However, refinement with field investigation may improve its explanatory power, as shown by Kawamura et al. [15].

Vulnerability Assessment Methods

The vulnerability assessment research is context-specific from the environmental, socio-economic, and institutional perspectives [40]. The PCA methods used in this study offer an objective method to construct indices for exposure-sensitivity and adaptive capacity [41, 42].

Vulnerability is a dynamic outcome of both environmental and social processes occurring at multiple scales [43]. Although location advantage indicators were included in the adaptive capacity analysis to reflect accessibility of outside resources, the present study reflected the cross-scale relations (e.g. links to national governance, or local communities) through macro level indicators from the economic and social aspects. For this research focused on the method for static vulnerability assessment, the absence of temporal vulnerable research under certain temporal contexts deserved further attention in future research.

This study has nevertheless demonstrated how straightforward methods can be used to quantify exposure-sensitivity and adaptive capacity, which can then be used to assess a region's vulnerability. The results provide a basis for developing strategies to alleviate the region's vulnerability, and also identify important directions for future research (i.e. incorporating future climate change scenario in the analysis).

Entry Point for Reducing Vulnerability

The ultimate goal of a vulnerability study is to provide insights that can be used to reduce vulnerability by identifying strategies that could decrease exposure-sensitivity, and/or improve adaptive capacity. The results of SPCA and PCA offer an angle to pinpoint the source of exposure-sensitivity and the advantages of adaptive capacity. From table 2 and table 3, the exposure-sensitivity and adaptive capacity are both mainly determined by the first two axes (SP1 and SP2, PC1 and PC2). So it is clear that the evapor-transpiration (SP1) and precipitation (SP2) play most important roles in determining the exposure-sensitivity index, while economic power and social efficiency (PC1) and rural economy and income disparity (SP2) greatly contribute to the adaptive capacity index. Therefore, more attention should be given to alleviating the influence of drought, and improve the regional and household economy. To pinpoint the concrete entry points to reduce vulnerability, the scores of each county about every component were divided into three categories by the quantity order, counties with high scores (top 4) would require particular attention (↑↑↑), while medium values (next 4) still indicate areas which need improvement (↑). In contrast, dimensions with low indicator values (bottom 4) would need to be stabilized to secure benefits from these relatively favorable conditions (●) (Table 4).

For the complexity of the human-environmental system, it is unfeasible to distinguish the strategies for reducing exposure sensitivity from those for improving adaptive capacity. So the combination of methods for reducing exposure sensitivity and improving adaptive capacity is needed for vulnerability reduction. For example, climate variables play an important role in vulnerability by determining the exposure-sensitivity index. However, the macro climate conditions could hardly be interfered with by humans. It is therefore necessary to implement adaptation strategies to reduce the dependency of human-environmental systems on the stochastic climate system by improving resistance and adaptive capacity. Such strategies include enhancing income diversity by developing activities outside the pastoral sector, establishing intensively managed grassland in suitable areas to produce fodder, or importing crop straws as fodder, etc. In addition, grazing intensity was identified as an important factor affecting exposure-sensitivity. So better grazing regulation is needed to control the stocking densities and its distribution for grassland protection.

Estimate of Accuracy

It is difficult to compose an explicit vulnerability index by precisely quantifying the relationship between exposure-sensitivity and adaptive capacity. Therefore, direct evaluation of the accuracy of the research remains impossible, but analyzing the qualitative relationship between exposure sensitivity and adaptive capacity could reflect the accuracy of the vulnerability research. As illustrated in Fig. 5, the counties in the northeast (e.g., East Ujumuchin, West

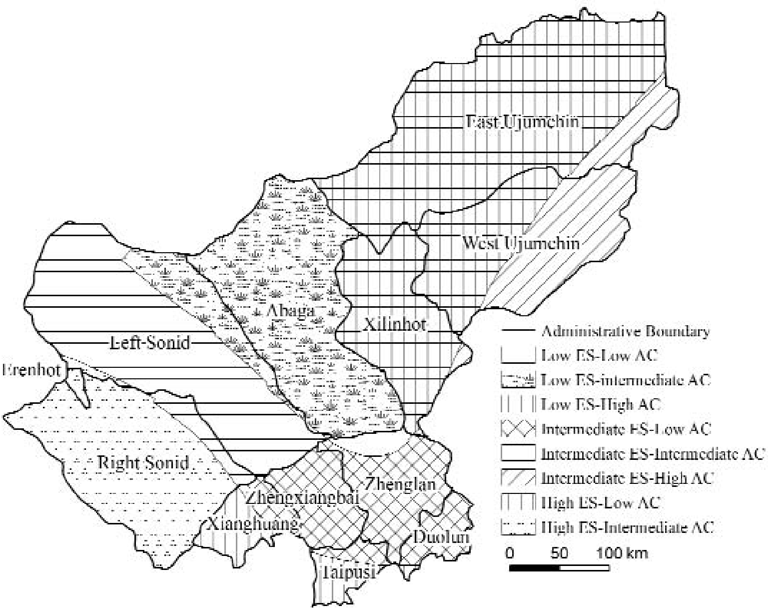

Fig. 4. Vulnerability regionalization of Xilingol league (ES – exposure-sensitivity; AC – adaptive capacity).

Table 4. Entry points for vulnerability reduction according to the indicator values at the SPCA and PCA components.

Ecological meaning	Score of exposure-sensitivity	SP1	SP2	SP3	SP4	Score of adaptive capacity	PC1	PC2	PC3	PC4
		Transpiration	Precipitation (spring and summer)	Temperature (spring)	Human driving forces		Economic power and social efficiency	Rural economy and income disparity	Human capital	Environmental stress
East Ujumchin	**0.78**	●	↑	↑	↑	**0.59**	●	●	↑	●
West Ujumchin	**1**	●	↑	↑↑↑	●	**0.28**	●	↑	↑↑↑	●
Abaga	**0.76**	●	●	↑	↑	**0.19**	●	↑↑↑	●	↑
Left Sonid	**1.15**	↑↑↑	●	↑	↑↑↑	**0.13**	●	↑↑↑	●	↑↑↑
Xilinhot	**0.76**	●	●	●	●	**0.92**	↑	●	↑	↑
Erenhot	**1.57**	↑↑↑	●	↑↑↑	●	0.24	↑	↑↑↑	●	●
Right Sonid	**1.74**	↑↑↑	↑	↑	●	**0.01**	↑	●	●	↑↑↑
Zhenglan	**1.11**	↑	↑↑↑	●	↑↑↑	**-0.45**	↑↑↑	↑	↑	↑↑↑
Zhengxiangbai	**1.22**	↑	↑	●	↑↑↑	**-0.62**	↑↑↑	↑	↑↑↑	↑↑↑
Xianghuang	**1.52**	↑↑↑	↑↑↑	●	↑↑↑	**-0.39**	↑	↑↑↑	↑	↑
Duolun	**1.33**	↑	↑↑↑	↑↑↑	↑	**-0.58**	↑↑↑	↑	↑↑↑	↑
Taipusi	**1.51**	↑	↑↑↑	↑↑↑	↑	**-0.32**	↑↑↑	●	↑↑↑	●

↑↑↑ – particular attention needed; ↑ – improvement needed; ● – stabilization needed

Ujumchin, and Xilinhot) located in the upper-left of Fig. 5 have a high adaptive capacity and low exposure-sensitivity, which means these regions are the least vulnerable. By contrast, the counties in desert meadow area (e.g., Erenhot) and farming-pastoral zone (e.g., Taipusi and Duolun) occupy the bottom-right, indicating greater vulnerability. Fig. 5 also shows that in Xilingol most counties with higher values for the exposure-sensitivity index have a low adaptive capacity, and vice versa. This is probably because the harsh environmental conditions resulting in high exposure-sensitivity cannot support the socio-economic infrastructure required for a greater adaptive capacity. Additionally, the vulnerability of Xilingol decreases from southwest to northeast, which is opposite the trend of annual mean precipitation (illustrated in study area section), which proved the fact that the drier areas are more vulnerable than the other areas.

Conclusions

This paper demonstrated a straightforward approach to regional vulnerability assessment that can be readily applied to other dryland regions. The analysis of exposure-sensitivity identifies regions facing the greatest potential impacts, where vulnerability can be reduced by lowering exposure. By contrast, adaptive capacity pinpoints regions where economic and human capitals are lowering vulnerability and poverty alleviation measures can reduce vulnerability.

The results show that northeastern Xilingol is least vulnerable due to a more favorable resource base and greater economic development (e.g., Xilingol, West Ujumchin, and East Ujumchin). By contrast, the counties in the southwest, with harsh environmental conditions and a poor socio-economic infrastructure, have the greatest vulnerability. These regions are in the direst need for targeted adaptation measures to a further decline in human well-being.

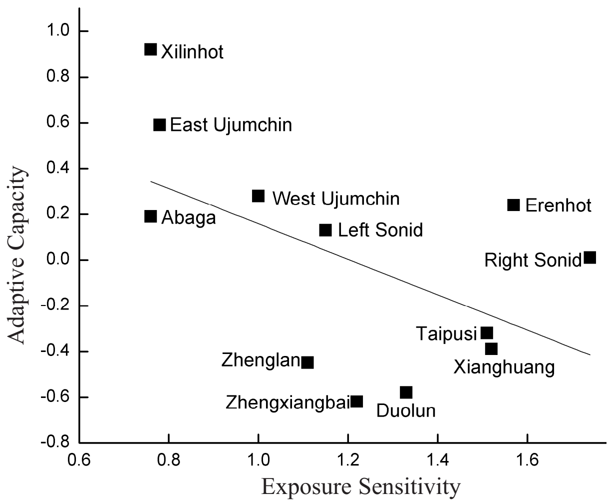

Fig. 5. Relationship between exposure sensitivity and adaptive capacity.

Appendix 1.
Indices for anthropogenic influence on grassland degradation

Grazing intensity index

Natural grassland productivity is mainly determined by hydrothermal status, while the real grassland status is controlled by natural condition and grazing activities. Thus the difference between potential and observed vegetation therefore represent the grazing effect. Here, the vegetation status is measured by NDVI and the grazing intensity index is calculated by subtracting the observed NDVI from the potential NDVI (Formula A2).

The aridity index K [30] is used to calculate the potential NDVI. The relationship between K and potential NDVI was determined experimentally, using 167 randomly selected points that are further than 5 km from settlements, and therefore less disturbed by grazing. The *K* value of each point is extracted from the grid data, and the relationship is demonstrated by Formula A3.

$$GI = NDVI_p - NDVI \quad \text{(A2)}$$

$$NDVI_p = 0.4032 \times K^{-0.2612} \quad \text{(A3)}$$

...where *GI* is grazing intensity, $NDVI_p$ and *NDVI* represent the potential and the observed *NDVI* separately, *K* represents the aridity index.

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