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Method for evaluating ecological vulnerability under climate change based on remote sensing: A case study

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ABSTRACT

Ecological vulnerability assessment is essential to environmental and resource management, especially given recent global warming concerns. However, evaluation of ecological vulnerability over large areas is difficult and complex because it is affected by many variables, including natural factors and human activities. Here, we propose a novel method to evaluate the vulnerability of an eco-environment with a typical ecologically fragile region, the northern and southern foothills of the Yinshan Mountains of Inner Mongolia, China (NSFYM), as a case study. The proposed method is based on the definition of the IPCC framework and remote sensing. The results showed that the ecological vulnerability in the NSFYM was moderate or high and had distinct regional variations in spatial distribution. Overall, 29% of the seriously and highly vulnerable areas appeared mainly in the highlands, where the natural conditions are poor and human activities have been developing rapidly. Additionally, 31% of the medium vulnerable levels occurred in the low lands, probably in response to agricultural practices. The areas that were found to have high ecological vulnerability exhibited high degrees of exposure and sensitivity and weak adaptive capacity and vice versa, consistent with the current understanding of the characteristics of ecological vulnerability. The integrated method proposed here will be useful for protection of eco-environments under climate change and proper planning for land use in the future.

1. Introduction

The self-adjustment capability of ecosystems has been progressively declining because of global climate change, rapidly increasing population, and the irrational use of natural resources. Ecological vulnerability is a natural attribute of ecosystems that can be used as an indicator for self-adjustment capability. Currently, this vulnerability is a topic of growing concern and has become an issue of considerable interest in the field of global environmental change and sustainable development (Linder et al., 2010; Xu et al., 2015). An ecosystem always maintains a stable state when it can bear the external pressures from nature and humans, otherwise it would become vulnerable and begin to degrade. Ecological vulnerability is a critical indicator for measuring the quality of the ecological environment that has become an important systematic tool in the research field of climate change. The third assessment report (AR3) (2001) of the Intergovernmental Panel on Climate Change (IPCC) first presented the concepts of the impact, adaptation and vulnerability of climate change, proposing that it is important to consider ecological vulnerability in the context of climate change. The fourth (AR4) (2007) and fifth assessment reports (AR5) (2014) further emphasized those concepts. Subsequently, the assessment of ecological vulnerability has become an important research topic in the field of global climate change.

Although ecological vulnerability has recently attracted a great deal of attention, there are few widely accepted definitions of it under climate change. In AR3, vulnerability is defined as "the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes, which is a function of the character, magnitude and rate of climate change and variation to which a system is exposed to, its sensitivity, and its adaptive capacity" (IPCC, 2001). Based on this definition, ecological vulnerability has received increasing attention from many researchers in a variety of research fields (Simenlton et al., 2009; Zheng et al., 2012). These studies have revealed that an ecological system 1) is inherently unstable, 2) sensitive to interference and environmental change, and 3) has difficulty returning to its original state (Pei et al., 2015). Currently, ecological vulnerability is broadly identified as the natural attributes of an ecosystem that have sensitivity and adaptive capacity to resist natural and man-made disturbances at spatiotemporal scales and experience difficultly returning to the natural, original and sustainable state (Brown et al., 2016; Xu et al.,

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2015).

Three approaches, the comprehensive index method, the quantitative evaluation model method, and the scenario analysis method, have been advanced in different systems and at different spatial and temporal scales to assess the vulnerability in the context of climate change (Thang et al., 2016). Among these approaches, the comprehensive index method has been used by most researchers (Nguyen et al., 2016; Wilhelmi and Wilhite, 2002; Abbas and Fahim, 2014; Nazari et al., 2015) and is the main evaluation method. However, the comprehensive index method is susceptible to indicator selection and weight determination from subjective factors. Quantitative evaluation models have also been developed, such as the improved Lund-Potsdam-Jena (LPJ) dynamic vegetation model (Zhao and Wu, 2013), the Carbon Exchange between Vegetation, Soil, and Atmosphere (CEVSA) model (Yu, 2014), and the Pressure-State-Response (PSR) model (Wang et al., 2015), focusing on changes in ecological vulnerability from natural, socio-economic, and environmental aspects. Although quantitative evaluation models can reduce the influence of subjective judgements, their application is still limited because of their complexity. The scenario analysis method, which is a relatively new method for assessing vulnerability to climate change, has significant advantages that include its ability to predict the degree of future ecological vulnerability and changes in vulnerability under diverse scenarios (Abbas and Fahim, 2014; Woznicki et al., 2016). However, its main disadvantage is that it requires large quantities of historical data. Recently, remote sensing has increasingly been applied to evaluate ecological vulnerability and characterize the distribution of vulnerable areas. When compared to the aforementioned areas, remote sensing is arguably one of the most important technologies available for collecting biological parameters across broad geographic extents. Image access has surged over the last several decades, spatial, spectral, and temporal resolution of observations have increased, and data archives cover increasingly longer time periods, which altogether have enabled more detailed assessments of ecological environments than ever before. The strong advantages of remote sensing include systematic acquisition setup, the spatially explicit nature of measurements, and their consistency across political borders (Kuemmerle et al., 2013). For example, Bai et al. (2009) used remote sensing technology to develop an index system of ecological vulnerability in Qinghai Lake by selecting eight indicators that included NDVI, soil moisture, soil brightness, elevation, slope, temperature, precipitation and land use. Yang (2011) constructed an index system of ecological vulnerability in the Huangshan district of Anhui province based on data from SPOT_VGT NDVI and Landsat TM. However, the application of remote sensing for ecological vulnerability assessment is still in the exploratory stage, and needs to be improved.

The above analyses show that, although many studies have conducted vulnerability assessment, few have been based on the IPCC framework. Dong et al. (2015) proposed a quantitative assessment method for agricultural vulnerability under climate change according to IPCC framework, but it is based on the analysis of historical data. Accordingly, it would be worth exploring methods for assessing vulnerability under climate change based on remote sensing technology. This study aims to propose a feasible method for evaluating ecological vulnerability based on remote sensing under climate change. The results presented herein enrich vulnerability theory, and will facilitate construction of indicative, operational and scientific models, as well as standardization of ecological vulnerability evaluations.

2. Study area

The northern and southern foothills of the Yinshan Mountains (NSFYM) belong to one of the most sensitive areas to climate change in the world and play a vital role in the ecological security of Northern China; therefore, this region has received intense attention in studies of the responses of terrestrial ecosystems to climate change (Hou, 2013; Wei, 2011; Meng et al., 2010). The NSFYM, which is situated in the middle of the Inner Mongolia Autonomous Region, China, has a typical moderate temperate semiarid climate, complex physical geographical features and vulnerable eco-environments. Abundant sunlight, low temperatures, frequent drought, short winters, long summers, and stronger winds in winter and spring occur in this region (Pang, 2011). The mean annual rainfall is approximately 200–400 mm, and this gradually increases from west to east. Additionally, 70% of the rainfall occurs from the warmer July to September period. The annual evaporation is around 8–10 times higher than the average rainfall, and the free-frost period is normally 100–120 days (Wu et al., 2008). Potatoes, corn and spring wheat are the main crops grown in the area, which has a short growing period.

The NSFYM comprises 18 counties and/or districts: Huade, Shangdu, Chahar Right Back Banner, Chahar Right Middle Banner, Chahar Right Front Banner, Jining, Xinghe, Zhuozi, Fengzhen, Liangcheng, Hohhot, Wuchuan, Guyang, Tumd Left Banner, Tumd Right Banner, Tuoketuo, Helinger, and Qingshuihe (Fig. 1).

Studies have shown that the average temperature has increased in this region by 0.3 °C over the last 40 years, while the annual rainfall has trended downwards (Chen et al., 2007; Yan et al., 2008). The warming and drying climatic change trend has become increasingly severe and gradually led to grassland degradation, soil erosion, and land desertification. Therefore, it is essential to assess the ecological vulnerability that is occurring under climatic change in this region.

3. Data and methods

3.1. Data

3.1.1. Data sources

The meteorological data were collected from the China Meteorological Science Data Sharing Service Network (http://cdc.cma.gov.cn/), and include monthly precipitation data for the 18 counties in the NSFYM during 1992–2012. Because the relative soil humidity data are incomplete, this study selected ten-day data from the meteorological stations of Wuchuan County, Guyang County, Chahar Right Back Banner, Xinghe County, Chahar Right Front Banner, Tumd Left Banner, Tumd Right Banner, Hohhot Urban District and Qingshuihe County.

The remote sensing data were MOD09Q1, which are eight-day surface reflectance data at a spatial resolution of 250 m, and the original image projection method was SIN projection. The data were selected from the 105th day to the 305th day and downloaded from the USGS Data Center (https://www.usgs.gov/). Each MOD09Q1 image element contained L2G data for an 8-day period, with the exception of instances of high coverage, low clouds, cloud shadows or the influence of aerosol concentrations.

3.1.2. Data manipulation

The surface reflectance data are level three (L3) MODIS products, which had already been mapped to the specified projection coordinates using radiometric and geometric corrections. Therefore, this study dealt with the mosaic, projection and format conversion of the remote sensing images using MRT software supported by NASA and ENVI. The sinusoidal projection coordinates were converted to Albers Conical Equal Area projection coordinates using the nearest neighbour re-sampling method, which maintains the brightness values of original MODIS images and has fast computational speeds for re-projection and re-sampling. In addition, the Interactive Data Language (IDL) software language program was used to perform image-clipping and band operations, as well as to calculate NDVI.

3.2. Methods

3.2.1. Ecological vulnerability evaluation

Ecological vulnerability is an intrinsic characteristic of ecosystems that represents the state of an ecosystem under disturbance or stress. Based on the definition of vulnerability by the IPCC framework, the arid-ecological vulnerability is suggested as the degree of damage to an ecosystem under varying degrees of drought. This index primarily consists of ecological exposure degree, ecological sensitivity and

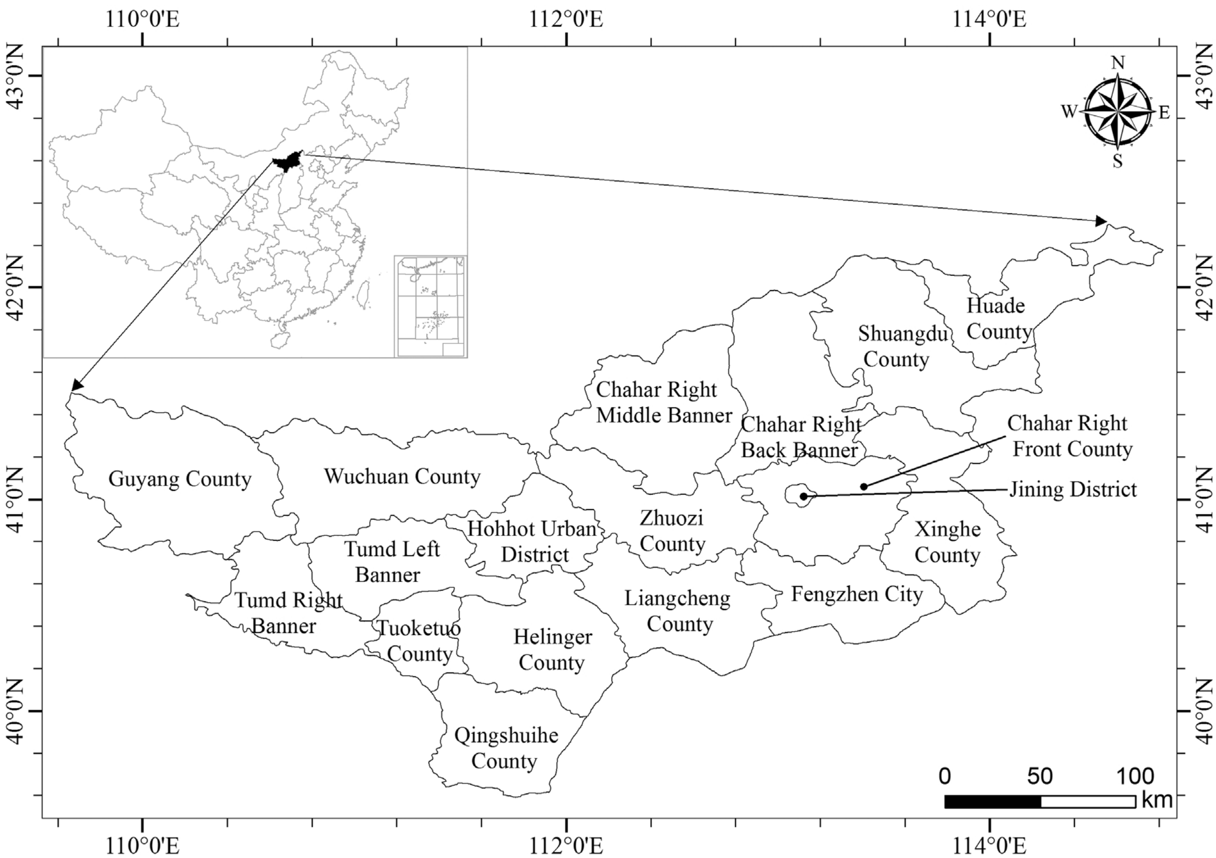

Fig. 1. Location of the northern and southern foothills of Yinshan Mountain.

ecological adaptive capacity. Ecological exposure degree is the degree to which the ecosystem is affected by external pressures such as droughts. Ecological sensitivity is the ability of an ecosystem to respond under different degrees of drought. Ecological adaptive capacity is the ability for self-adjustment under the external forces of drought. The assessment of ecological vulnerability is a comprehensive performance of the quantitative characteristics of ecological vulnerability that is also evaluated under a framework of ecological exposure, ecological sensitivity and ecological adaptive capacity (Brown et al., 2016). This value was calculated using Eq. (1) (Peng et al., 2016; Dong et al., 2015):

$$EV = \frac{EE \times ES}{EA} \tag{1}$$

where EV, EE, ES and EA are ecological vulnerability, ecological exposure degree, ecological sensitivity and ecological adaptive capacity, respectively.

3.2.2. Ecological exposure degree

Ecological exposure degree, which describes the degree to which an ecosystem is exposed to drought environments, is related to drought frequency and intensity, and comprehensively reflects the degree to which an ecosystem is affected by drought at a specific spatiotemporal scale. Temporally, the effects of droughts on ecosystems either continuously increase or gradually decrease. Spatially, ecological exposure degree reflects the reactions of ecosystems to light or heavy droughts and emphasizes drought intensity level. Generally, drought indexes, such as the standard precipitation index, percentage of precipitation anomalies and crop-water and surface water supply indexes, are used to evaluate the drought states of ecosystems (Andrea et al., 2014; Shen et al., 2013; Hou et al., 2002). Among those indexes, the standard precipitation index (SPI), which is widely accepted and has been applied by many researchers (Zarch et al., 2014; Dutta et al., 2015; Shah et al., 2015), is among the indicators used to illustrate the probability of the occurrence of precipitation within a certain period and is suitable for monitoring and assessing local climate conditions on a monthly scale (General Administration of quality supervision, 2008). The average value of the standard precipitation index and the trend rate of the standardized precipitation index were used in this study to evaluate the ecological exposure degree under climate drought based on precipitation in the study area from 1992 to 2012 as follows:

$$EE = \text{average}_{SPI} \times \text{slope}_{SPI} = \text{average}_{SPI} \times \frac{n\sum_{i=1}^{n} SPI_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} SPL_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2} \tag{2}$$

where *EE* is ecological exposure degree, $average_{SPI}$ is the average value of the standard precipitation index after standardized treatment of the original data, $slope_{SPI}$ is the trend rate of the standardized precipitation index after standardized treatment of the original data, SPI_i is the standard precipitation index in year i, and *i* is the serial number of the year, where i = 1, 2, 3,..., n.

3.2.3. Ecological sensitivity

Ecological sensitivity, which is the ability of an ecosystem to respond to different degrees of drought, emphasizes the possibility of imbalances in ecosystems. The sensitivity coefficient method proposed by McCuen, 1974 was applied to evaluate ecological sensitivity in the context of climate change and is an important indicator used to measure the effects of independent variables such as temperature, precipitation, and humidity on dependent variables. Many studies have used ratios of variations in potential evapotranspiration and meteorological elements to reflect the ecosystem sensitivity under climate change (Yin et al., 2010). In this study, sensitivity was calculated as follows:

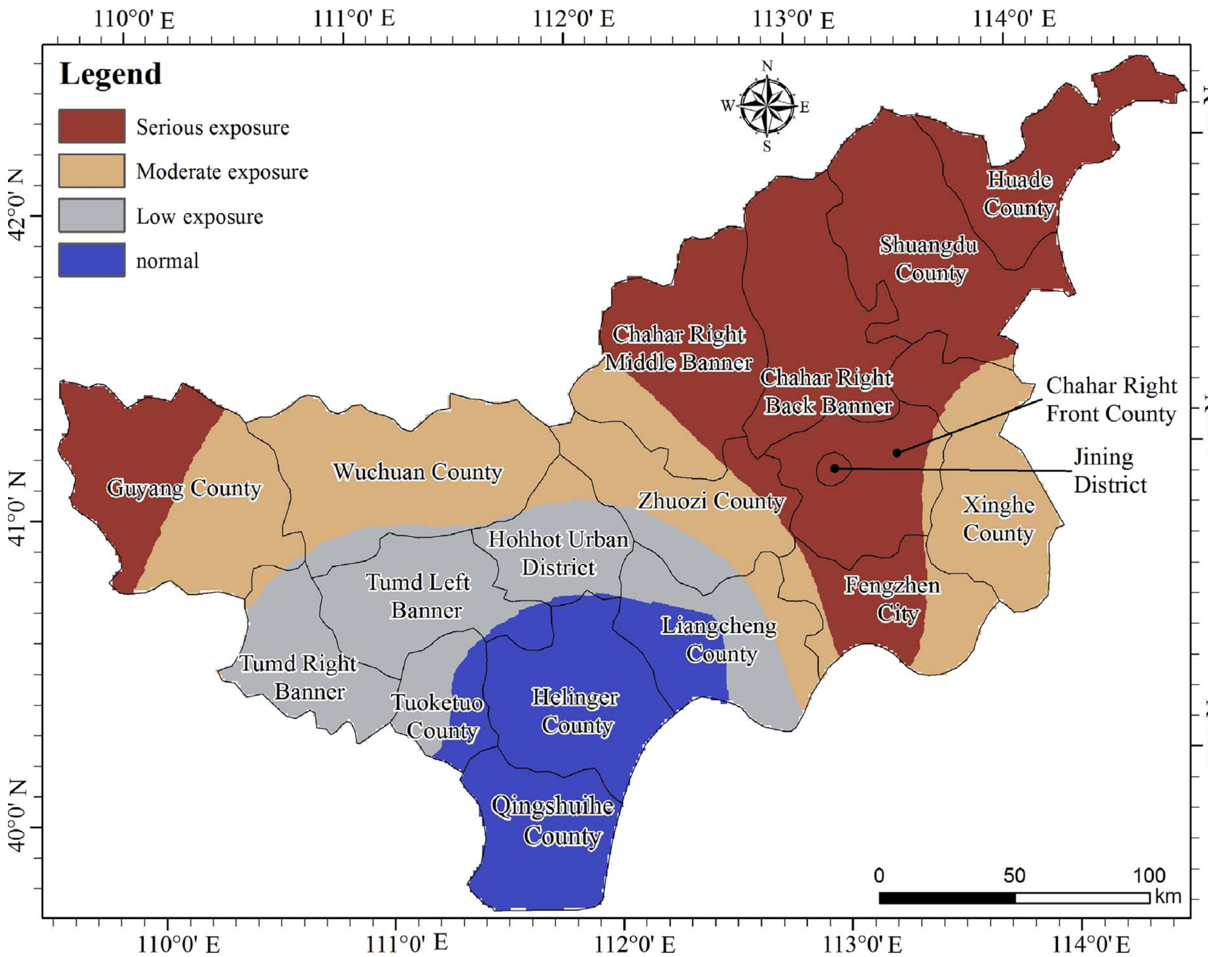

Fig. 2. Spatial distribution of ecological exposure degree in the study area.

$$ES = SA \times RC,$$

$$SA = \lim_{\Delta x \to 0}\left(\frac{\Delta SM/SM}{\Delta P/P}\right) = \left(\frac{\partial SM}{\partial P} \times \frac{P}{SM}\right), \quad \text{and}$$

$$RC = \frac{n \times Trend_P}{Average_P} \tag{3}$$

where ES is ecological sensitivity, SA is the sensitivity coefficient of relative soil humidity to precipitation, RC is the change rate of relative soil humidity, SM is the relative soil humidity, P is the precipitation per year, $Trend_p$ is the rate of change of precipitation, $Average_p$ is the average precipitation, and n is the number of years from 1992 to 2012 ($n = 21$).

3.2.4. Ecological adaptive capacity

Ecological adaptive capacity is the ability of an ecosystem to mitigate the impact of drought through its own anti-interference mechanisms or artificial measures. Vegetation growth status is a direct and obvious indicator of natural ecosystems under drought conditions (Smith et al., 2014). The normalized difference vegetation index (NDVI), which is among the most effective indices used to characterize vegetation change, has been widely used to investigate vegetation growth and dynamic changes (Bajocco et al., 2012; Pei et al., 2015; Birtwistle et al., 2016). In this study, changes in vegetation growth were used to evaluate ecological adaptive capacity based on MODIS-NDVI data and calculated using the following equation:

$$EA = VG \times GP,$$

$$VG = \frac{slope_{NDVI} \times average_{NDVI}}{SD_{NDVI}}, \quad \text{and}$$

$$GP = \left|\frac{1}{T_n\text{-}T_1}\right|, \tag{4}$$

where EA is ecological adaptive capacity, VG is the stability of vegetation growth, GP is the stability of vegetation green degree, $slope_{NDVI}$ is the tendency rate of NDVI after standardized treatment, $average_{NDVI}$ is the average value of NDVI after standardized treatment, SD_{NDVI} is the standard deviation of NDVI after standardized treatment, T_1 is the time value of the vegetation green period in the first year after standardized treatment, and T_n is the time value of the vegetation green period in the last year after standardized treatment.

3.2.5. Classification method

Based on the method mentioned above, final synthesis maps of ecological exposure degree, ecological sensitivity, ecological adaptive capacity and ecological vulnerability were produced and classified as serious, heavy, moderate, low or normal based on the Natural Interval Classification method (Nguyen et al., 2016) of ArcGIS.

4. Results

4.1. Spatial distribution of ecological exposure degree

As shown in Fig. 2, the ecological exposure degree in the NSFYM decreased gradually from east to west and north to south. The serious exposure impacts accounted for 40% of the total area, and were primarily located in the northern NSFYM. The distribution corresponded

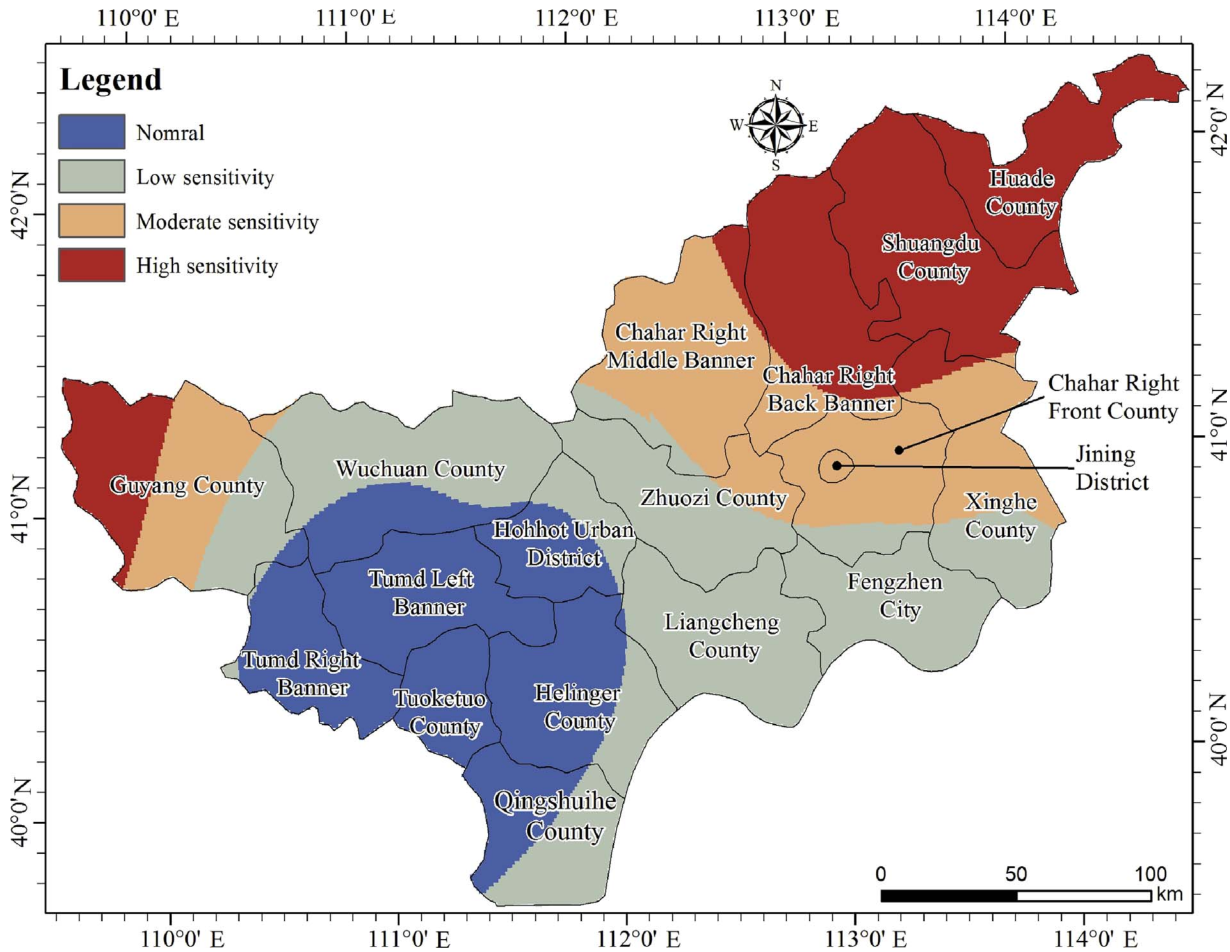

Fig. 3. Spatial distribution of ecological sensitivity in the study area.

to very poor precipitation and high wind speed. Annual precipitation of Huade County was only 312 mm, which was lower than the average 383 mm of the study area, and the maximum wind speed was faster than that of other counties or districts. The moderate exposure areas accounted for 28% of the total area, and were mainly found in the southeast and northwest, where there was relatively little precipitation. The low and normal exposure degree values accounted for the remaining 32% of the total area. These values were mainly found in the middle and south, where there was more rainfall and lower wind. For example, the annual precipitation was 387.3 mm and the maximum wind speed was 4.95 (Unit: m/s) in Qingshuihe County. The average ecological exposure degree in the NSFYM was moderate to serious.

4.2. Spatial distribution of ecological sensitivity

As shown in Fig. 3, the ecological sensitivity in the NSFYM clearly increased from southwest to northeast. Generally speaking, the NSFYM was characterized by a relatively low level of ecological sensitivity. The classes of normal and low sensitivity, which accounted for 23% and 33% of the total areas, respectively, were mainly situated in the southwest and south. The moderate level was mainly distributed in the east, where there was low soil moisture. For example, the standard deviation of soil moisture of Chahar Right Black Banner was 11.9, while that of Wuchuan County was only 8.5. The areas of serious sensitivity were primarily located in the northernmost region of NSFYM, accounting for 23% of the total areas, where land was characterized by higher wind speed and less rainfall. Moreover, higher wind speed led to intensified evapotranspiration and less effective irrigation in areas of low precipitation, which made it difficult to keep soil moisture stable under the shortage of precipitation. When compared with the degree of ecological exposure, the areas of serious and moderate sensitivity were fairly consistent with the areas of serious and moderate ecological exposure degree, indicating that the ecological sensitivity increased with increasing ecological exposure degree.

4.3. Spatial distribution of ecological adaptive capacity

As shown in Fig. 4, the area of low adaptive capacity accounted for 12% of the total area. Most of this land was located in the westernmost portion of the region, where the land was most seriously deteriorated and characterized by shortage of water, high wind and less vegetation cover. General adaptive capacity was observed in 38% of the total area, primarily in northern Wuchuan County, southern Qingshuihe County and Chahar Right Back Banner. Half of the moderate and high levels were distributed in the west and the east, respectively, accounting for 30% and 20% of the total areas. The areas characterized by moderate and high adaptive capacity were the main agricultural production areas of the NSFYM, in which crops grew relatively well because there was sufficient water from rain and irrigation, and little wind speed. In general, vegetation growth reflected the ecological adaptive capacity of the region, while the ecological adaptive capacity was at general and moderate levels.

4.4. Spatial distribution of ecological vulnerability

The spatial distribution of ecological vulnerability (Fig. 5) shows that the ecological environment of NSFYM was in a highly fragile state, as the degree of ecological vulnerability was high and the ability to

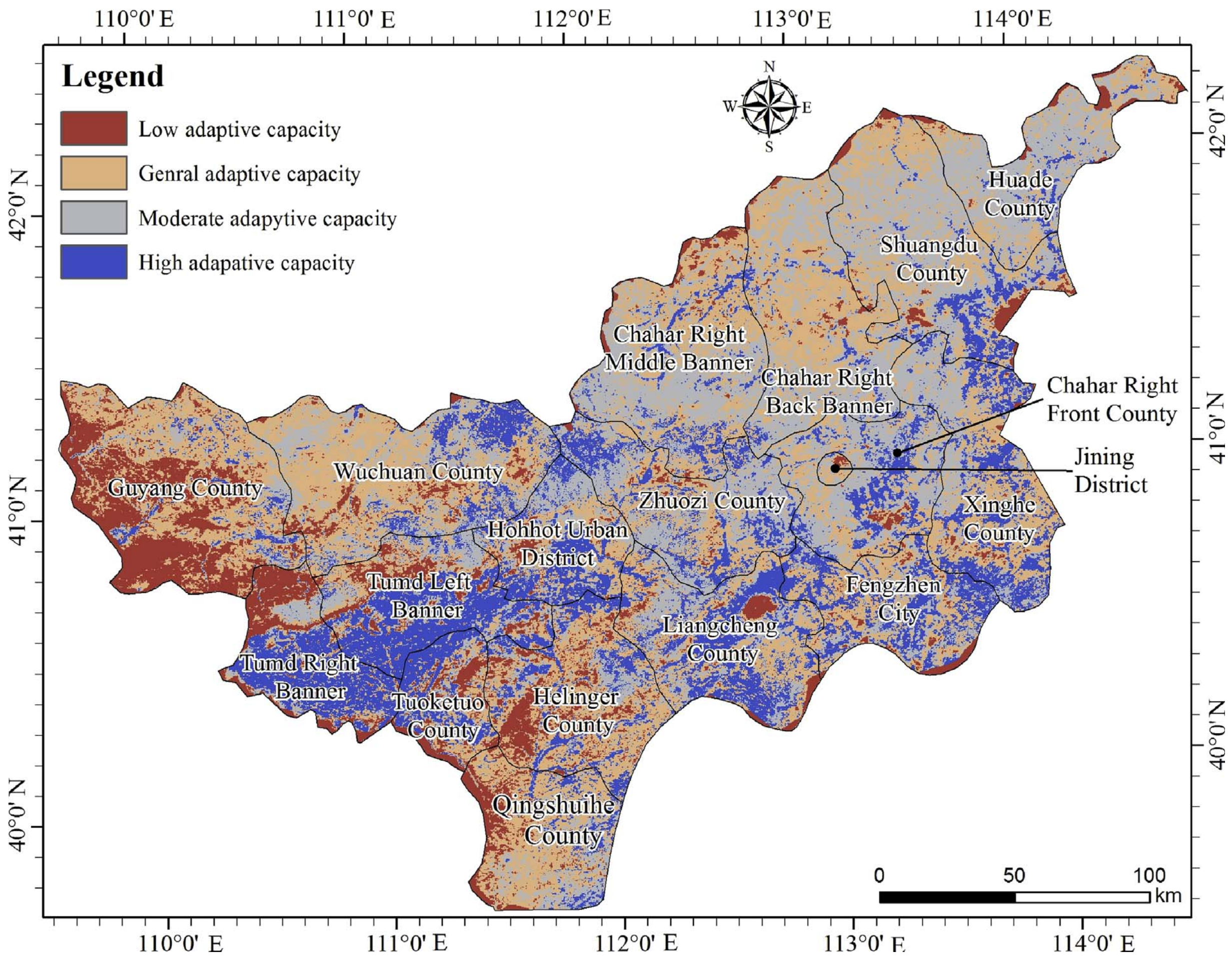

Fig. 4. Spatial distribution of ecological adaptive capacity in the study area.

withstand external disturbances was poor. The ecological vulnerability of the NSFYM clearly declined from northeast to southwest, which was consistent with changes in topography and annual precipitation. Areas of serious vulnerability appeared in the north, accounting for 11% of the total area in high vulnerability regions that bordered each other, and 21% of the total area. The regions usually suffered from hazardous climate conditions and had the most serious vegetation degradation because the soil was very thin with poor fertility. Moreover, these areas received less than 400 mm of rainfall annually, which was insufficient for cultivation of grain crops, and wind erosion in these areas was severe. Areas of moderate vulnerability accounted for 28% of the total area and were found in the southeast, where precipitation was relatively scarce, although the degree and extent of drought were less severe. Moreover, wind erosion and irrigation conditions were slightly better in this region than in areas of serious vulnerability. Additionally, 40% of low and normal vulnerable levels were located in the middle and southern areas, where there was low terrain, plains and a large effective irrigation area. Overall, 40% of the total area was classified as having low and normal vulnerability, with relatively low ecological exposure and ecological sensitivity. In these areas, the growth of vegetation did not degenerate, but increased obviously, making this portion of the study site as the optimal ecological area.

5. Discussion

5.1. Causal analysis of ecological vulnerability

Analysis of the natural and economic conditions of different ecosystem vulnerability areas indicate that the areas of higher ecological vulnerability always show higher ecological exposure, higher ecological sensitivity, and lower ecological adaptive capacity, and vice versa. This is because the vulnerability in a relatively good natural environment is always lower than that in a weak environment. Based on the types of land use and topography in the NSFYM, cultivated lands (the main type of land use) were in normal and low vulnerability areas, which were located in the plains and the main agricultural production areas, while grasslands were in areas of serious and high vulnerability, which were located in regions of low hills used for mixed pastoral agriculture. For example, the area of normal vulnerability in the Tumd Right Banner in 2010 consisted of 1.03 million hectares, accounting for 43.5% of the total land area. However, in areas of serious and high vulnerability in Huade County in 2010, the grasslands occupied 1.56 million hectares, accounting for 61% of the total land area. Secondly, there was a positive correlation between social economic development and ecological vulnerability. For example, the total output value was 7.07 billion Renminbi (RMB), and the per capita income of urban and rural residents reached 19,618 RMB and 6902 RMB, respectively, in areas of serious and high vulnerability in Chahar Right Back Banner in 2010, but the total output value was 21.6 billion RMB and the per capita income of urban and rural residents reached 24.600 RMB and 12,400 RMB, respectively, in the areas of normal vulnerability in Tumd Left Banner in 2010. Finally, human activities such as increased irrigation facilities and the implementation of farmland to forests eased ecological vulnerability to a certain extent. For example, the ratio of effective irrigation was more than 60% for cultivated land in the normal area of Tuoketuo County in 2010, while this ratio was less than 20% for cultivated land in areas of serious and high vulnerability in Huade County in 2010.

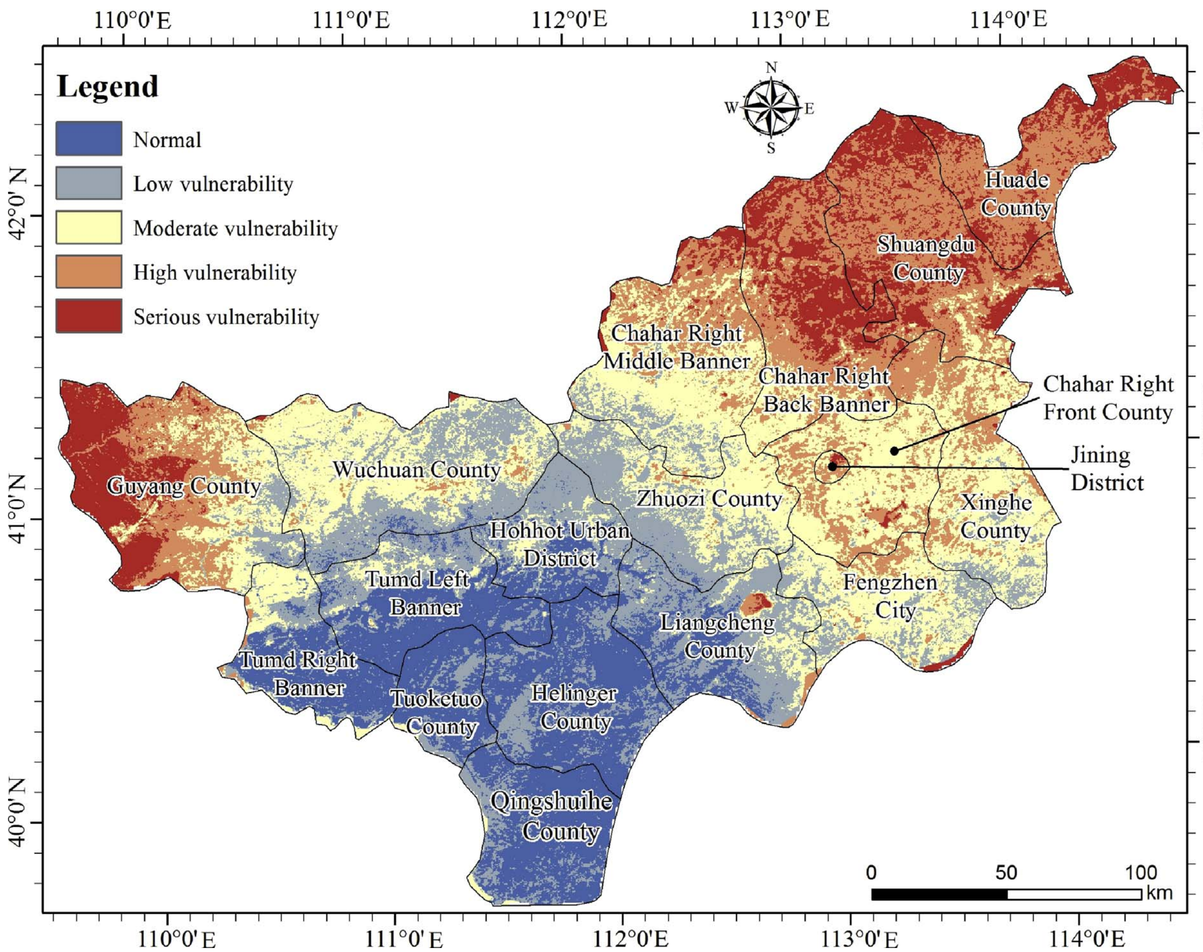

Fig. 5. Spatial distribution of ecological vulnerability in the study area.

Based on these results, the areas of heavy vulnerability were mainly found in the northern and westernmost portion of the NSFYM. It is estimated that about 30% of the total cultivated area, which supports 24% of the rural population and 20% of the livestock in NSFYM, respectively, is under threat of serious and high vulnerability to climate change. Accordingly, it is suggested that these areas be transformed into ecological conservation areas, and that local governments and farmers be obliged to take protective measures, such as increasing vegetation cover to reduce wind erosion, reducing the number of grazing animals in spring and autumn, and improving the agricultural infrastructure.

5.2. Rationality of the model

Ecological vulnerability reflects the comprehensive effects of natural and human activities in an area (Suresh et al., 2016; Abbas and Fahim, 2014; Meng et al., 2010). Therefore, assessments of ecological vulnerability under climate change should be made using comprehensive methods to evaluate the status of ecosystems based on the interaction of the natural environment and human activities. Because the study area is located in an arid and semi-arid area, where the ecological environment is mainly confined by natural factors, especially precipitation, only natural factors were considered in this study, and the impact of drought on the local ecological environment was highlighted. The proposed assessment model used here provided a viable method of assessing the major influencing factors of ecological vulnerability based on the IPCC definition of ecological vulnerability to evaluate the state of the ecosystem under climatic drought using historical data from 1992 to 2012 and MOD09Q1 images. The analysis process indicates that the degree of vulnerability was mainly determined by exposure, sensitivity and adaptive capacity. If a particular area had higher exposure and sensitivity, but the adaptive capacity was relatively low, its vulnerability was evident (Pei et al., 2015), and vice versa. For example, Guyang County (located in the western part of the NSFYM) had high exposure and high sensitivity with low adaptive capacity, thus, its vulnerability was high. From a field investigation in 2015, we know that soil depletion, precipitation deficiencies and serious desertification have been caused by wind erosion in this area (Hou, 2013). Therefore, the results of the assessment model in this study were consistent with the physical site conditions.

Moreover, the assessment method adopted in this study differs from conventional methods because it is based on remote sensing to provide biological parameters, such as NDVI, and is not merely dependent on the meteorological statistics. Vegetation growth is a direct and obvious indicator of the status of the natural ecological system with regards to drought, and NDVI is among the most commonly used monitors of crop growth and vegetation phenology via remote sensing, making it an effective tool. This method extends the technical measures of ecological vulnerability assessment.

5.3. Uncertainties

Given its general consistency with the IPCC's conceptual framework for climate change vulnerability assessment, the theory-driven approach proposed in this study can be compared with existing results from more popular scenario-based projections. However, uncertainty exists in any assessment of vulnerability to climate change and is driven by the number of sources for both the ecological and socio-economic processes of the evaluation (El-Zein and Tonmoy, 2015). This study primarily focused on precipitation, relative soil humidity and vegetation variability under drought in the NSFYM, and did not consider the influences of socioeconomic aspects.

A common challenge for indicator-based vulnerability assessments is undertaking a comprehensive and balanced consideration of the important processes, but some suitable indicators may be omitted because of data deficiencies (El-Zein and Tonmoy, 2015). In this study, we focused on precipitation and did not consider the impacts of temperature variability on ecological vulnerability, which might be a critical reason for the occasional differences between our results and those of other related studies. Therefore, a limitation of the study is that it fails to provide such critical information regarding vulnerability assessment.

6. Conclusions

In this study, a method for assessing ecological vulnerability according to the definition in the IPCC report on climate change was advanced using MODIS images to retrieve environmental variables such as NDVI with NSFYM as a case study. The results showed that the overall ecological vulnerability of the NSFYM was currently moderate or high. Areas of serious and high vulnerability were mainly in the northeastern and northwestern NSFYM because of the relatively poor natural conditions. Overall, 28% of the areas with moderate vulnerability appeared in the middle part of the NSFYM, while 40% of the areas with low and normal vulnerability occurred in the southern part of the study area. We found that areas with higher ecological fragility always showed higher levels of exposure degree, higher sensitivity, and lower adaptive capacity, while areas of lower ecological fragility areas always had lower levels of exposure degree, lower sensitivity, and higher adaptive capacity. The assessment method proposed herein can be applied to other regions by adjusting the factors relevant to the concerned variables required.

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