



A method to the impact assessment of the returning grazing land to grassland project on regional eco-environmental vulnerability



Huaiyong Shao^{a,d,*}, Xiaofei Sun^a, Haoxue Wang^a, Xiaoxue Zhang^a, Zhiying Xiang^b, Rui Tan^a, Xuanyi Chen^a, Wei Xian^c, Jiaguo Qi^d

^a Key Laboratory of Geoscience Spatial Information Technology, Ministry of Land and Resources of China, Chengdu University of Technology, Chengdu 610059, Sichuan, China

^b School of Earth Sciences, Zhejiang University, Hangzhou 310027, Zhejiang, China

^c College of Resources and Environment, Chengdu University of Information Technology, Chengdu 610225, Sichuan, China

^d Center for Global Change and Earth Observations, Michigan State University, East Lansing 48823, MI, USA

ARTICLE INFO

Article history:

Received 15 June 2015

Received in revised form 21 October 2015

Accepted 23 October 2015

Available online 3 November 2015

Keywords:

Returning Grazing Land to Grassland Project (RGLGP)

Eco-environmental vulnerability

Projection pursuit model (PPM)

Geographic information system (GIS)

The Xianshui River Basin

ABSTRACT

The Chinese government has conducted the Returning Grazing Land to Grassland Project (RGLGP) across large portions of grasslands from western China since 2003. In order to explore and understand the impact in the grassland's eco-environment during the RGLGP, we utilized Projection Pursuit Model (PPM) and Geographic Information System (GIS) to develop a spatial assessment model to examine the ecological vulnerability of the grassland. Our results include five indications: (1) it is practical to apply the spatial PPM on ecological vulnerability assessment for the grassland. This methodology avoids creating an artificial hypothesis, thereby providing objective results that successfully execute a multi-index assessment process and analysis under non-linear systems in eco-environments; (2) the spatial PPM is not only capable of evaluating regional eco-environmental vulnerability in a quantitative way, but also can quantitatively demonstrate the degree of effect in each evaluation index for regional eco-environmental vulnerability; (3) the eco-environment of the Xianshui River Basin falls into the medium range level. The normalized difference vegetation index (NDVI) and land use cover and change (LUCC) crucially influence the Xianshui River Basin's eco-environmental vulnerability. Generally, in the Xianshui River Basin, regional eco-environmental conditions improved during 2000 and 2010. The RGLGP positively affected NDVI and LUCC structure, thereby promoting the enhancement of the regional eco-environment; (4) the Xianshui River Basin divides its ecological vulnerability across different levels; therefore our study investigates three ecological regions and proposes specific suggestions for each in order to assist in eco-environmental protection and rehabilitation; and lastly that (5) the spatial PPM established by this study has the potential to be applied on all types of grassland eco-environmental vulnerability assessments under the RGLGP and under the similar conditions in the Returning Agriculture Land to Forest Project (RALFP). However, when establishing an eco-environmental vulnerability assessment model, it is necessary to choose suitable evaluation indexes in accordance with regional eco-environmental characteristics.

© 2015 Elsevier Inc. All rights reserved.

1. Introduction

Stretching over 4×10^8 hm² of natural grassland, China is the home to the second largest grassland resource in the world (Hua and Squires, 2015). The grassland is the largest ecological system in China's mainland and has crucial ecological functions for national ecological security, including wind resistance and sand fixation, water and soil conservation, carbon conservation, air purification, climate regulation, biodiversity and more (Ministry of Agriculture, 2014). However, around 80% of the grassland locations are in arid, semi-arid, and alpine mountain regions of western China, with fragile eco-environments. At the same time, China has been suffering from some of the world's worst grassland

degradation since late 1960 (Liu and Diamond, 2005; Zheng et al., 2006). The degraded area increased by 15% each decade from the 1960s to the mid-2000s (Hua and Squires, 2015). Grassland degradation influences grassland ecosystem by weakening its ecological functions such as water and soil conservation, wind resistance, and sand fixation, which exacerbates the vulnerability of the grassland eco-environment (Han et al., 2008; MacDougall et al., 2013). Considering the severe grassland eco-environment deterioration in western China, the Chinese government has conducted the Returning Grazing Land to Grassland Project (RGLGP) in grassland-degraded areas since 2003, with plans to support it until 2020. The RGLGP aims to achieve grassland reservation and to improve its production, as well as promote the sustainable development between grassland eco-environment and local animal husbandry by establishing pasture fences, improved grass seeds, and by banning some pastures and delaying their measures. The investment of the project

* Corresponding author.

E-mail address: huaiyongshao@163.com (H. Shao).

was about 3.47 billion dollars from 2003 to 2014 (Ministry of Agriculture, 2014). Meanwhile, policy makers are eager to know the positive impact on the grassland eco-environment during the RGLGP. Therefore, a quantitative evaluation of the eco-environmental vulnerability in rangelands that compares the before and after effects of the RGLGP should be made (Chen et al., 2014; Hickie and Wade, 1998; Kværner et al., 2006; Manfré et al., 2013; Nautiyal and Kaechele, 2007; Shao et al., 2014; Tao et al., 2007; Tran et al., 2012; Toro et al., 2013). This evaluation can provide the quality of the RGLGP's performance and improve scientific recommendations for future RGLGPs.

Presently, a portion of methods are applied to analyze environmental vulnerability (Chen et al., 2015; Li et al., 2006; Shao et al., 2014). We have reviewed these models and have weighed their performance value. The health index/risk evaluation tool (HIRET) (Bien et al., 2004) was based on Geographic Information System (GIS), which evaluated and predicted the impact from land use planning on human health dynamically. Nevertheless, the impact factors and parameters were settled artificially in advance, which affected the precision of its result. And this model was established using GIS dataset overlay, which hardly processes and analyzes the nonlinear relations between diverse ecological impact factors. The land Suitability Index (LSI) assessment tool (Marull et al., 2007) presented us with the integrity and hierarchy of the land suitability assessment system; yet, it may simplify questions and be unable to express the non-linear characteristics of land suitability. The state-impact-state (SIS) model (Chen et al., 2014) described the dynamic process of change effectively in a regional eco-environment during the conduction of land use planning, combining fuzzy AHP (subjective method) with an entropy value (objective method) to decide the weight of each assessment. Nevertheless, how one can quantitatively address the degree of effect and contribution of both methods remains as a question to be further solved. The life cycle assessment (LCA) model (Loiseau et al., 2013) describes the process of change in eco-environmental systems, which is based on empiricism, and can be affected artificially. The landscape ecology method (Griffith et al., 2002; Wagner and Fortin, 2005; Wu, 2008) suits the spatial scale requirements of macroscopic research. It cannot provide precise indexes for landscape patterns and, as a result, it cannot clearly show the crucial factors that affect eco-environmental vulnerability nor express the non-linear characteristics of eco-environments. The fuzzy decision analysis (Navas et al., 2012; Parashar et al., 1997) applies accurate mathematical methods to fuzzy objects and obtains abundant assessment results. Yet, it requires complex calculation and has strong subjectivity when addressing the weight of evaluation indexes. The assessment result is likely to be too fuzzy, especially in the case of numerous indexes. The analytic hierarchy process (AHP) (Bottero et al., 2011; Sipahi and Timor, 2010; Tomás et al., 2009) has clear hierarchy but depends on artificial judgment, which may cause its results to vary widely across different individuals (Aryafar et al., 2013; Shao et al., 2014). A principal component analysis (Doukas et al., 2012; Villegas et al., 2013) integrates the approaches of quantitative and qualitative methods, but part of information is lost during the selection process and affects the evaluation results. The artificial neural network (ANN) (Mas et al., 2012; Mo et al., 2009; Nedic et al., 2014) is outstanding for its strong suitability; that is, the automatic adjusting of eco-environmental vulnerability evaluation indexes; however, it is also likely to create index over-training conditions or lack of training conditions, causing the inconformity between the model result and a real world situation (Castin et al., 2014; Kia et al., 2012). The Pressure-State-Response model (Chen et al., 2011; Hughey et al., 2004; Sekovski et al., 2012) presents the interactive relationship between human and eco-environments. While setting the index system for regional eco-environmental evaluation, this model still requires auxiliary models for calculation purposes. The environmental sensitivity areas (ESA) method (Jennings et al., 1988; Momtaz 2002; Gad and Lotfy, 2008) is sufficient for a simple data process and analysis in linear system; however, it is hard use it in a complex calculation in a nonlinear system. As shown above, various eco-environmental

vulnerability assessment methods have different characteristics and advantages, but these methods also have common problems. First, the evaluation process and the results of these methods are affected by artificial activity; therefore, the objectivity needs to be improved. Second, these methods do not properly reflect the nonlinear characteristics of eco-environmental systems affected by multiple factors. To solve this problem, it is necessary to develop a suitable nonlinear high-dimensional data processing system and a smoother regional eco-environmental vulnerability assessment methodology.

The Projection Pursuit Model (PPM) was first proposed by Friedman in 1974 as an effective way to analyze and process non-linear, non-normal high-dimensional data (Friedman and Turkey, 1974). The method has advantages of robustness, anti-interference and high accuracy as it does not need artificial activity to translate high-dimensional data into a result and automatically recognizes data structure, which could reflect the law of higher dimensional space (Barnett et al., 2014; Espezuza et al., 2014; Galeano et al., 2006; Gilliam et al., 2004; Ifarraguerri and Chang, 2000; Montanari and Lizzani, 2001; Pires and Branco, 2010). Yet, the complex space topology structure of high-dimensional data in PPM makes the optimal projection direction difficult to find, which is why optimizing the projection index key to a successful application of PPM (Yang et al., 2004). By obtaining real-time data from remote sensing (RS) technology, the eco-environmental vulnerability and its temporal and spatial variations are analyzed by using mathematical models and GIS, a method that is gradually becoming key to regional eco-environmental assessment (Huang et al., 2010; Kumar et al., 2015; Lioubimtseva and Henebry, 2009; Pavlickova and Vyskupova, 2015; Toro et al., 2012; Rapicetta and Zanon, 2009; Tran et al., 2010). Presently, PPM is used in selected research to assess the regional eco-environment (Christiansen 2009; Gao et al., 2012; Ghasemi and Zolfonoun, 2013; Wu et al., 2010b; Zhao et al., 2014), however, the combination of GIS and PPM has been scarcely applied to the regional eco-environmental vulnerability evaluation.

In light of need, we developed an eco-environmental vulnerability evaluation method by combining PPM with GIS and the Xianshui River Basin located in China, which was selected as a case study to validate the applicable feasibility of the model and to analyze the impact on regional eco-environmental vulnerability during the RGLGP. In this paper, we established an evaluation method for grassland areas and their eco-environmental vulnerability based on PPM and GIS in the 2nd section. And the eco-environmental vulnerability in the Xianshui River Basin in 2000 and 2010 are calculated by combining PPM with GIS in the 3rd section, the 4th section shows the influence that spatial and temporal distribution has on the Xianshui River Basin's eco-environmental vulnerability and that the project of reversing grazing land to non-grazing land has on eco-environmental vulnerability. And the 5th section reflects and discusses the advantages, restrictions, and the applications of this method. The 6th section comes to the main conclusions of our study.

2. Methods

The study on eco-environmental vulnerability under the RGLGP in grassland areas is based on the reasonable evaluation index system and the appropriate method. Finally, the changes in eco-environmental vulnerability before and after the implementation of the project are quantitatively calculated (Chen et al., 2014; Hou et al., 2015; Li et al., 2006). In this study, the establishment of the grassland eco-environmental vulnerability assessment methods contain the following steps: (1) construct an eco-environmental vulnerability assessment index system in grassland and pasture areas; (2) establishment the PPM space evaluation model of eco-environmental vulnerability in grassland and pasture areas; (3) use the classification method of the eco-environmental vulnerability assessment; and (4) conduct the quantitative analysis method of eco-environmental vulnerability.

Download English Version:

<https://daneshyari.com/en/article/1052684>

Download Persian Version:

<https://daneshyari.com/article/1052684>

[Daneshyari.com](https://daneshyari.com)