



Drivers of changes in ecosystem service values in Ganjiang upstream watershed



Meiqiu Chen^{a,b}, Yanfei Lu^{a,b,c,*}, Lin Ling^c, Yun Wan^c, Zhijun Luo^b, Hongsheng Huang^b

^a College of Landscape and Art, Jiangxi Agricultural University, 1101 Zhiming Road, Nanchang 330045, People's Republic of China

^b The Research Center on Rural Land Resources Use and Protection, Jiangxi Agriculture University, Nanchang 330045, People's Republic of China

^c College of Information and Engineering, Jiangxi Agricultural University, 1101 Zhiming Road, Nanchang 330045, People's Republic of China

ARTICLE INFO

Article history:

Received 13 January 2015

Received in revised form 15 March 2015

Accepted 6 April 2015

Keywords:

Ecosystem service value

Driving forces

Boosted regression tree

Ganjiang upstream watershed

ABSTRACT

Land use change and land-cover can influence ecological functions and ecosystem services. Based on Xie's coefficient of ecosystem service value, land use change in Ganjiang upstream watershed from the year 1990 to 2010 and the ecosystem service value caused by the land use change were quantitatively analyzed. Based on the statistical data and relevant research results, a gray correlation degree analysis was done between ecosystem services value (ESV) and its seven potential impact factors, i.e. Grain for Green program, population, gross domestic product (GDP), urbanization level, investment in fixed assets, the proportion of secondary industry and tertiary industry proportion. The boosted regression tree method was used to identify the driving factors for the changes of ESV during 1990–2010, 1990–1995, 1995–2000, 2000–2005 and 2005–2010 periods. The results showed that: (1) all seven indexes can affect the changes of ESV in Ganjiang upstream watershed during the study periods, (2) during 1990–2010 and from 2000 to 2005, the Grain for Green program is the most important factor influencing the ESV. The proportions of tertiary industry and GDP are the main factors influencing the ESV, whereas from 2000 to 2005 the main influential factor is GDP.

© 2015 Elsevier Ltd. All rights reserved.

Introduction

Ecosystem services represent the benefits of living organisms deriving from ecosystem functions that maintain the earth's life support system (Xie et al., 2003; Boyd and Banzhaf, 2007; Fisher et al., 2009; O'Farrell et al., 2011; Liu et al., 2012). Land use is closely linked to humans and nature. Land use change can directly impact biotic diversity worldwide, contributing to climate change, which is the primary source of soil degradation. And by altering ecosystem service, land use change may affect the ability of biological systems to support human needs. Land use and cover changes alter the structure and function of ecosystem (Lambin et al., 1999). Thus, the study of ecosystem service value changes caused by the change of land use and land cover has important implications.

The chief form of ecosystem alteration is land use change that has been highlighted as a key human-induced effect on ecosystems (Lambin et al., 2001, 2003). Various kinds of social and economic

factors can cause changes in ecosystem service value (ESV) (Ma et al., 2010). Land use change is the locally pervasive and globally significant ecological trend (Geist et al., 2006). However, because of the difference in the ecological environment of the regional natural resources, there exist considerable differences in the driving ability of social and economic factors (Wei et al., 2005). Costanza et al. (1998) conducted an evaluation on the global main types of ecological system service value, causing many scholars at home and abroad to study the theory, evaluation and accounting methods of ESV, the changes in driving force and application of ESV (Liu et al., 2003; Huang et al., 2007; Priess et al., 2007; Ricketts et al., 2008). There are many studies on the driving factors of ESV changes. However, studies are scarce on quantitative analysis of ESV changes especially on the driver at different stages of economic development and social and economic factors.

Ganjiang upstream watershed is the most important ecological barrier for Poyang lake watershed, in which the ESV is crucial for the regional sustainable development, related to the whole ecosystem health along the Poyang lake watershed. With the rapid development of economy, great changes have taken place in the land use and cover change of the region. Overall, the aim of the present study was to investigate the main driving factors of the ESV change in the Ganjiang river upstream watershed from the year 1990–2010.

* Corresponding author at: The Research Center on Rural Land Resources Use and Protection, Jiangxi Agriculture University, 1101 Zhiming Road, Nanchang 330045, People's Republic of China. Tel.: +86 79183813461.

E-mail address: cmqjxau@163.com (Y. Lu).

Methods

The study area

Gnjiang upstream watershed is located in the south of Jiangxi province in east China, and it occupies an area of about 35,699 km², of which 27,095 km² is the watershed area and the total length of rivers is 312 km. The watershed, lying on 113°54′–116°38′ E and 24°29′–27°09′ N, is in the transition zone between southeastern coast of China and central China, and is also one of the important channels to the southeast coast of the mainland. The watershed is characterized by a complex topography, and proximately 80% of the territory is occupied by hills and mountains. Annual rainfall in the watershed area varies between 1400 and 1800 mm. Ganjiang upstream watershed is rich in biological and mining resources, and it is one of many nonferrous metals bases in China. In this study, the scope of the study area straddles 16 counties, including Ruijing city, Zhanggong and Nankang districts, counties of Gan, Xinfeng, Dayu, Shangyou, Chongyi, Anyuan, Longnan, Quannan, Ningdu, Yudu, Xingguo, Huichang, and Shicheng. The location map of the study area is presented in Fig. 1.

Data sets

This study selected the following indicators for reflecting the development degree of social economy in Ganjiang upstream watershed, such as population, gross domestic product (GDP), urbanization level, investment in fixed assets, and the proportion of secondary and tertiary industries. In addition, Ganjiang upstream watershed began to carry out Grain for Green policy in 1999. Through the interpretation of remote sensing data analysis, it showed that the forest land area increased drastically after the Grain for Green project. Thus, the policy of Grain for Green exerted a great influence on the regional ESV. Thus, the Grain for Green policy has taken into account analyzing the driving factors of ESV. This study adopted gray correlation analysis and boosted regression tree (BRT) model to assess the drivers of ESV.

Gray correlation analysis

Gray relational analysis is an impacting measurement method in gray system theory that analyzes uncertain relations between one main factor and all the other factors in a given system. In the case when experiments are ambiguous or when the experimental method cannot be carried out exactly, gray analysis helps to compensate for the shortcomings in statistical regression (Ho and Lin, 2003). Gray relational analysis is actually a measurement of the absolute value of data difference between sequences, and it can be used to measure the approximate correlation between sequences (Fung, 2003).

The gray correlation analysis can complement the defects of mathematic statistic analysis methods. The gray approach can work with small amounts of irregular data. In addition, the inconsistency between quantitative and qualitative results would not happen. The basic concept of gray correlation analysis judges whether the relationship among data series sets is closely related to the similar degree of geometric shape of the data series curve. The closer the curves are, the greater the correlation among the relative data series (Yeh and Chen, 2004).

Boosted regression trees

We selected the BRT method to examine driving factors affecting the ESV, and then partitioned independent influences of driving factors. BRT is a multivariate technique based on binary decisions. BRT is one of several techniques that aim to improve the

performance of a single model by fitting many models and combining them for prediction. BRT uses two algorithms: “regression trees” is from the classification and regression tree (“decision tree”) group of models, and “boosting” builds and combines a collection of models (Elith et al., 2008). This method has powerful capacities for handling different classes of predictor variables (categorical, nominal and continuous) and distributions (Gaussian, Poisson, binomial and others), for accommodating missing data and outliers, and for automatically handling interaction effects between predictor variables (De'ath, 2007; Elith et al., 2008). Furthermore, this method has no prior assumptions about the independence of predictor variables. BRT can fit complex nonlinear relationships, and it is highly resistant to inclusion of large numbers of irrelevant predictor variables. More detailed description of the BRT method can be found in Hastie et al. (2009), and working guides in Ridgeway (2007) and Elith et al. (2008).

Parameter setting is a preliminary step in BRT modeling. The five parameters involved are determined-loss function (for minimizing squared error), learning rate, tree complexity, bagging fraction and *k*-fold cross-validation (Ridgeway, 2007; Elith et al., 2008; Zhang et al., 2012). The learning rate is a constant value applied to each individual regression tree for determining their contribution to the final model. Tree complexity gives the size of simple regression trees and maximum depth of variable interactions. The bag fraction introduces randomness into a model to reduce overfitting by random selection of a data portion for model training and validation. The cross-validation specifies the number of times to randomly divide the data for model fitting and validation. All BRT analyses were conducted by R software version 2.15.1 (R Development Core Team, 2012), using the “gbm” package (Ridgeway, 2012).

Results

Table 1 lists variables used to model ESV change in the Ganjiang river upstream watershed.

Analysis of ESV change

Combined with the ESV of Ganjiang upstream watershed from 1990 to 2005 (Chen et al., 2013), we calculated the ESV of Ganjiang upstream watershed in 2010 and the change value of ESV from 1990 to 2010, as shown in Table 2.

In various regions from 1990 to 2010, Shicheng county has the highest ESV change with 4.5×10^3 RMB hm⁻², followed by Shangyou county and Chongyi county with 4.1×10^3 RMB hm⁻², followed by Ruijin, Gan county, Dayu county, Nankang district, Huichang county, Yudu county, Quannan county, Xingguo county, Xinfeng county, Ningdu county, Anyuan county, Longnan county and Zhanggong district. The ESV of Shicheng county, Shangyou county and Chongyi county increased apparently. It showed that the ecological system of Ganjiang river source was continuously improved. The three counties are the largest area for conducting the Grain to Green policy.

Gray correlation coefficients of influential factor on ESV change

Gray correlation coefficients of influential factor on ESV change are listed in Table 3. It can be seen that all the gray correlation coefficients are greater than 0.5, indicating that the seven parameters are the driving factors affecting the ESV change of 16 counties of Ganjiang upstream watershed.

BRT analysis of ESV change driving factors

The influence of Grain to Green project, total population, GDP, urbanization level, fixed assets investment, and the proportion of

Download English Version:

<https://daneshyari.com/en/article/6548117>

Download Persian Version:

<https://daneshyari.com/article/6548117>

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