Science of the Total Environment 563–564 (2016) 210–220

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Vegetation dynamics and its driving forces from climate change and human activities in the Three-River Source Region, China from 1982 to 2012

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HIGHLIGHTS

- Partitioned the contributions of human activities and climate change to NPP trends.
- The relationships of different climate factors and NPP were analyzed quantitatively.
- Radiation was the most important climate factor of NPP interannual variation.
- After 2001, the climate conditions changed from benefit for vegetation to negative.
- Whereas the effect of human activities changed from negative to positive after 2001.

ARTICLE INFO

Article history:
Received 25 April 2015
Received in revised form 25 March 2016
Accepted 28 March 2016
Available online xxxx

Editor: Simon Pollard

Keywords:
Net primary productivity (NPP)
Interannual variation
Climate change
Human activities
Quantitative assessment
Driving factors

ABSTRACT

The Three-River Source Region (TRSR), a region with key importance to the ecological security of China, has undergone climate changes and a shift in human activities driven by a series of ecological restoration projects in recent decades. To reveal the spatiotemporal dynamics of vegetation dynamics and calculate the contributions of driving factors in the TRSR across different periods from 1982 to 2012, net primary productivity (NPP) estimated using the Carnegie–Ames–Stanford approach model was used to assess the status of vegetation. The actual effects of different climatic variation trends on interannual variation in NPP were analyzed. Furthermore, the relationships of NPP with different climate factors and human activities were analyzed quantitatively. Results showed the following: from 1982 to 2012, the average NPP in the study area was 187.37 g cm^{-2} yr^{-1}. The average NPP exhibited a fluctuation but presented a generally increasing trend over the 31-year study period, with an increase rate of 1.31 g cm^{-2} yr^{-2}. During the entire study period, the average contributions of temperature, precipitation, and solar radiation to NPP interannual variation over the entire region were 0.58, 0.73, and 0.09 g cm^{-2} yr^{-2}, respectively. Radiation was the climate factor with the greatest influence on NPP interannual variation. The factor that restricted NPP increase changed from temperature and radiation to precipitation. The average contributions of climate change and human activities to NPP interannual variation were 1.40 g cm^{-2} yr^{-2} and −0.08 g cm^{-2} yr^{-2}, respectively. From 1982 to 2000, the general climate conditions were favorable to vegetation recovery, whereas human activities had a weaker negative impact on vegetation growth. From 2001 to 2012, climate conditions began to have a negative impact on vegetation growth, whereas human activities made a favorable impact on vegetation recovery.

1. Introduction

Net primary productivity (NPP) is originally defined as the amount of photosynthetically fixed carbon available to the first heterotrophic level in an ecosystem (Field et al., 1998). NPP is an indicator of the extent of vegetation light utilization under natural conditions (Yu et al., 2009). It is also an important indicator of the health and ecological balance of an ecosystem, as well as a key element for assessing carbon sink and ecological regulatory behavior (Gao et al., 2009). A decline in vegetation productivity is the major manifestation of vegetation degradation, whereas NPP is an important indicator of productivity. In recent years, many studies of NPP have been conducted in recent years (Nemani et al., 2003; Hein et al., 2011; Mu et al., 2013a; Zhou et al., 2015; Wu et al., 2014; Yang et al., 2014), which explored the long-term monitoring of vegetation dynamics in terrestrial ecosystems, on

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http://dx.doi.org/10.1016/j.scitotenv.2016.03.223

both local and global scales. Terrestrial ecosystems are susceptible to the combined effects of climate conditions and human activities (Esser, 1987; Haberl, 1997). With aggravating global climate change and increasing human activities (Vitousek, 1994; IPCC, 2007), quantifying the influence of different driving factors on vegetation dynamics has become an important issue to formulate countermeasures and management policies. To date, several efforts have been devoted to separately quantify the influence of climatic and anthropogenic factors on an ecosystem within a specific region (Wessels et al., 2004; Wu et al., 2014; Mu et al., 2013a, 2013b; Nayak et al., 2013; Chen et al., 2014).

China is currently confronted by severe grassland degradation (Akiyama and Kawamura, 2007; Harris, 2010). A series of policies that addressed this problem was launched in the early 21st century, such like the Grain to Green Program (GTGP, which is usually explained as "replacing cropping and livestock grazing in fragile areas with trees and grass") and the Grazing Withdrawal Program (GWP, which is aimed to conserve grassland through banning of grazing, rotational grazing or converting grazing land to cultivated pasture) (Wang et al., 2007b; Liu et al., 2008a; Mu et al., 2013b). The effect of such policies became a major concern of the society. The Three-River Source Region (TRSR), which lies in the hinterland of the Tibetan Plateau, is dominated by natural grasslands (Chang et al., 2014). The region is not only an important ecological barrier of China, but it also has a sensitive and fragile ecological environment (Liu et al., 2014). In the past decades, the TRSR has attracted considerable attention because of its grassland degradation problem (Liu et al., 2008b; Wang et al., 2009; Liu et al., 2014). The climate conditions and human activities in this region have obviously changed. For the past decades, the TRSR has suffered from climate warming, which has been aggravated in the 21st century. Since the national nature reserve was designated in the TRSR in the early 21st century, a series of ecological protection policies and projects has been implemented in this area (Fang, 2013; Tong et al., 2014). However, only a few studies have been conducted to quantitatively analyze the relationships of vegetation growth with climate factors and human activities in the TRSR (Qian et al., 2010; Liu et al., 2014), particularly to compare the differences in such relationships across different periods or to distinguish the effects of various climate factors.

Therefore, this study attempts to accurately simulate the spatiotemporal evaluation of the dynamics of vegetation NPP in the TRSR for the past 31 years (1982–2012) and to distinguish the effects of various driving factors on vegetation dynamics. The NPP in the TRSR is estimated by the Carnegie–Ames–Stanford approach (CASA) model and used as an indicator of vegetation dynamics. Furthermore, the spatiotemporal dynamics of vegetation NPPs across different periods of the 21st century are analyzed. The cumulative effects of different driving factors on NPP interannual variation are determined. Our aim is to provide an accurate method for evaluating the health status of the vegetation conditions in the TRSR and the effects of ecosystem protection projects. The findings can be used to promote sustainable utilization, ecological construction, and policy formulation in the TRSR.

2. Materials and methods

2.1. Study area

The TRSR is the headstream of three major rivers (i.e., the Yangtze River, the Yellow River, and the Lantsang River) in East Asia, and around 40% of the world's population depends on, or is influenced by these rivers (Foggin, 2008). The TRSR covers an area of 350,000 km^2, of which the source region of the Yangtze River is 150,000 km^2, that of the Yellow River is 90,000 km^2, and that of the Lantsang River is 30,000 km^2. The area of other inland river basins is 60,000 km^2. The original natural vegetation and the soil rich in organic matter in the TRSR fulfill significant water conservation functions. This region supplies 25% of the total water of the Yangtze River, 49% of the total water of the Yellow River, and 15% of the total water of the Lantsang River (Zhang et al., 2012). Thus, the TRSR is known as the "Water Tower of China". The TRSR is mainly constituted of mountainous landforms with altitudes ranging from 3335 m to 6564 m. The major mountains include the East Kunlun Mountain and its branch the Aemye Machhen Range, the Bayan Har Mountain, and the Tanggula Mountain. This region features a fluctuating terrain, dense river networks, numerous rivers, extensive snowy mountains, and crisscrossing glaciers. The TRSR has a typical high-altitude continental climate, with small annual temperature difference, large diurnal temperature range, and a notably decreasing trend of heat and water from southeast to northwest. The growing season in this region is from May to September. The population is approximately 568,000, and most of the residents are Tibetan with a nomadic lifestyle (Harris, 2010). The grassland is the primary ecosystem in the TRSR. The main grassland types are alpine meadow and alpine steppe (Fan et al., 2010). As mentioned in Section 1, the TRSR has attracted considerable attention in the past decades because of its grassland degradation problem. With a deteriorating regional ecosystem and a decline in water conservation function, the life of the residents in this region is threatened. In addition, the ecological security of the Yangtze River basin, the Yellow River basin, and even the Southeast Asia region is in danger.

2.2. Data source and processing

2.2.1. Climate data

The climate data used in this study are the 1982–2012 data on monthly average temperature, monthly precipitation, solar radiation, and altitude from 50 standard weather stations in the TRSR and its surrounding area, which are provided by the Meteorological Data Sharing Service System of China. This data was interpolated by using ANUSPLIN version 4.2 software to regular monthly data layers with the spatial resolution same as NDVI data. Given the fluctuating terrain and sparse meteorological stations in the TRSR, common interpolation methods cannot achieve high precision (Li et al., 2003), thus, interferences to NPP calculation and data analysis are introduced as subsequent treatments. To solve this problem, ANUSPLIN (a software program developed by the Australian National University for the spatial interpolation of climate data using a thin plate smoothing spline) (Hutchinson, 2001), is used in this study for interpolation. It has been proved be more appropriate for spatial interpolation of climate than other methods in the TRSR (Peng et al., 2010).

2.2.2. Remote sensing data

To create a long time series of NDVI data set from 1982 to 2012, two kinds of NDVI sources are used. The NDVI data of 1982–2000 are the Global Inventory Modeling and Mapping Studies (GIMMS) NDVI data produced by the Global Land Cover Facility of the University of Maryland, with an original spatial resolution of 8 km. During the preparation of this data set, its creators performed radiation correction, geometric correction, and cloud filtering to improve data accuracy. In our study, the GIMMS–NDVI data are resampled to have a spatial resolution of 1 km. Meanwhile, the remote sensing data of 2001–2012 are the MODIS 13A2 data, with a spatial resolution of 1 km. The MODIS–NDVI data are subjected to format conversion and reprojection in our study; spatial splicing and resampling are also performed. Using the 16-d MODIS–NDVI data, monthly NDVI data are obtained via the maximum-value composite (MVC) procedure.

Using the Spector–Grant filtering method, which is a denoising technique for NDVI data, the two types of NDVI data are smoothed and filtered. Given that the two types of MODIS data by GIMMS are acquired using different sensors, conducting a consistency test between them is necessary. The two types of data overlap in 84 months (2000–2006). A correlation analysis of the monthly average NDVI indicates that the correlation coefficient is 0.87 ($P < 0.001$). Thus, the two types of data are significantly consistent at the regional scale. The linear regression equation between the two types of data for each pixel is established using the recursive least square method with the overlapped data, and the average R^2 of all pixels is 0.84 ($P < 0.001$). The GIMMS–NDVI data