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Quantitative assess the driving forces on the grassland degradation in the Qinghai–Tibet Plateau, in China

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ABSTRACT

Grassland degradation in the Qinghai–Tibet Plateau (QTP), has attracted considerable concern because of its negative influence on the development of the local economy and the ecological security of China. Climate and human activities are considered as the main driving forces of grassland degradation. However, distinguishing their respective contributions to grassland degradation is a challenge. This study used the Carnegie–Ames–Stanford Approach model, which coupling remote sensing (e.g. NDVI, LAI, near and mid-infrared bands) and meteorological data (precipitation, temperature and radiation), was adopted to simulate the actual and potential NPP in the QTP from 2001 to 2013. The difference between potential NPP and actual NPP was used to represent the influence of human activities. Results showed that nearly 38.8% of the total grassland area underwent degradation, whereas 61.2% experienced restoration. Furthermore, 56.7% of the degraded grassland areas were influenced by climate, and 19.9% were affected by human activities. The restored areas induced by human activities, climate variation, and the combination of the two factors accounted for 28.6%, 12.8% and 19.9% with an increases in NPP of 5923.4, 3188.1 and 5959.2 GgC, respectively. Therefore, climate was the principal driving force of grassland degradation, whereas human activities were the dominant factor in grassland restoration. Climate and human activities, as the potential driving force in grassland NPP variations, should be fully understood by a long term monitoring and the main causes exploring in its dynamics. In addition, the uncertainty of the driving forces should be clarifying immediately in the future, and provide scientific basis for policies and plans making in grassland management.

1. Introduction

As one of the most common vegetation types, i.e., accounting for 20% of the land surface area of the world, grassland has a key role in ecology, food security (Conant et al., 2001), carbon balancing, and global climate change (Piao et al., 2009). The grassland in China covers approximately 4 million km^2, which is nearly 40% of the country's land area. Global warming and increasing human activities have significantly affected the natural ecosystems in many regions of the world (Gao et al., 2013). In China, approximately 90% of the total grassland area has been degraded to a certain extent (Nan, 2005) because of global warming (Yu et al., 2012), population growth (Nan, 2005), and excessive land use (Harris, 2010). To date, numerous studies have been conducted to analyze grassland degradation worldwide (Harris, 2010).

The Qinghai–Tibet Plateau (QTP), which is one of the largest and most unique geographical units on Earth, has a mean elevation of more than 4000 m above sea level (a.s.l.). This plateau is known as the "third pole" of the Earth and has a significant role in maintaining the ecological security of China (Qiu, 2008) and the global carbon cycle (Piao et al., 2012; Zhao et al., 2006), accounting for approximately 2.5% of the global soil carbon pool (Genxu et al., 2002). The region is approximately 2.5 million km^2, which is nearly 25% of the area of China. Grassland is the dominant vegetation type in the QTP and nearly half (44%) of grasslands in China, which is also accounts for 6% of the total grassland areas of the world (Scurlock and Hall, 1998; Tan et al., 2010). The grassland ecosystem in the QTP is extremely sensitive to climate variation and human activities because of its vulnerability and the alpine condition in the region (Kato et al., 2004; Piao et al., 2006).

Climate and human activities are considered the main driving forces of grassland degradation (Chen et al., 2014; Chen et al., 2013; Wessels et al., 2008). Distinguishing between the contributions of these two

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factors is difficult but is urgently required in quantitative methods for assessing the respective effects of climate and human activities on grassland degradation (Wang et al., 2010; Wessels et al., 2008). Currently, the newly Landsat-8 satellite was employed to detect the grassland degradation in the QTP (Fassnacht et al., 2015), other indirect methods that are used to assess the influence of human activities on ecosystems include the normalized difference vegetation index (NDVI), Wessels (Wessels et al., 2004) proposed a Land capability units coupling NDVI method, making it possible to distinguish natural physical variations from human influences; and Li applied a using the NDVI-based residual trend method to investigate the human and climate forces in vegetation changes in inner Mongolia (Li et al., 2012). Rojstaczer (Rojstaczer et al., 2001) incorporates contemporary data to estimate human use of terrestrial net primary production to measure of human impact on the biosphere and hydrosphere. While, Harberl (Haberl et al., 2007) presents a comprehensive assessment of global human appropriation of net primary productivity to estimate human impact on ecosystems. Several studies have assessed the contributions of these two factors by selecting net primary production (NPP) as an indicator because of its significance in indicating grassland degradation and the status of ecological processes. Xu's work focused on the desertification, and the assessing methods were built based on the slope of NPP and scenarios simulation (Xu et al., 2009), Zhou and Gang expanded study region to global and regional scale, and this method was applied to detect grassland degradation (Gang et al., 2014; Zhou et al., 2015). Consequently, NPP coupled scenario simulation methodology has been successfully applied in detecting land degradation.

Degradation is not only a retrogressive succession process of the grassland ecosystem under the influences of human activities and natural factors (Li, 1997), but also a relative state on the time series. Identifying the respective contributions of climate and human activities is important because the main driving force, location, and extent of grassland degradation should be primarily clarified. The former studies have only identified human activities in the regions affected by land degradation, and the respective roles of climate and human activities in land degradation remain unclear (Haberl et al., 2007; Li et al., 2012; Wessels et al., 2004), and the recent studies devoted to differentiate the relative contribution in grassland productivities dynamics. However, it still remains uncertain to calculate potential NPP by using the statistic model (Gang et al., 2014; Zhou et al., 2015). In this study, NPP was selected as the indicator to analyze the relative role of driving factors in grassland productivity dynamics in which minimal attention has been given to the grassland ecosystem of the QTP despite the importance of this region. Consequently, a scenario simulation method was established on the basis of the slope of NPP. We integrated Carnegie–Ames–Stanford Approach (CASA) model to simulate actual NPP and potential NPP to reflect grassland degradation and restoration, and reduce the uncertainties remained in the methodology. Most importantly, the principal driving forces of grassland degradation or restoration, their corresponding NPP variations, and the extent of the affected area were identified over time in the QTP. All these works were designed to provide theoretical and methodological bases for policy making and optimizing ecosystem management in grasslands.

2. Materials and methods

2.1. Study area

The QTP is located in southwest China (26.5–39.5°N, 78.3–103.1°E). This plateau has an average altitude of 4000 m a.s.l. Alpine and sub-alpine meadows are the dominant vegetation types in the QTP (covers over 40% of the plateau area) (Bartholomé and Belward, 2005). Other grassland types include alpine and sub-alpine meadow, meadow, alpine and sub-alpine plain grasslands, as well as slope grassland, plain grassland and desert grassland (Fig. 1). The mean temperature in the QTP is generally lower than −10 °C during the coldest month and lower than 10 °C during the warmest month (Piao et al., 2011). The QTP has experienced significant warming since the mid-1950s, with the mean annual temperature increasing by 0.3 °C per decade (Piao et al., 2012). The southeast QTP is the wettest area with an annual precipitation over 1000 mm. Meanwhile, annual precipitation in the driest northwest area is less than 50 mm (Zheng, 1996). The QTP is essentially the source of all of the major rivers in Asia, including the Yangtze River, the Yellow River, and the Lancang River, which are considered as "China water tower".

2.2. Remote sensing data

The Moderate-resolution imaging spectroradiometer (MODIS) MOD13A2 and MOD15A2 dataset products from 2001 to 2013, with a spatial resolution of 1 km and a temporal scale of 16 days, were obtained from the Level 1 and Atmosphere Archive and Distribution System Web of NASA (http://ladsweb.nascom.nasa.gov/data/search.html). The MOD13A2 dataset used in the study including NDVI, near and mid-infrared bands while the MOD15A2 dataset including LAI. The NDVI dataset was successful applied in estimation of actual evapotranspiration and achieved valuable outcome recently (Rahimi et al., 2015). The maximum value composite method (Holben, 1986) was employed to merge the days in the NDVI and LAI data and to generate monthly data. Moreover, the LAI dataset was performed minimum value composite to retrieve the input parameter. Radiation correction and geometric correction were already performed on the original NDVI dataset. The coordinate and projection system used were the World Geodetic System 1984 and the Albers equal area conic projection respectively.

2.3. Meteorological data

The meteorological data used included the average monthly temperature data and monthly precipitation data from 97 meteorological stations, as well as the total solar radiation data from 11 stations in study area from 2001 to 2013. These data were collected from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). The meteorological data were then interpolated by using the ordinary Kriging interpolation method to generate monthly raster data with a spatial resolution of 1 km. The coordinate system and projection were the same as those for remote sensing data. The radiation and temperature based method has been successfully applied in estimating evapotranspiration and achieved fruitful outcomes (Valipour, 2015a; Valipour, 2015c; Valipour and Eslamian, 2014). Moreover, the radiation-based method was proved that could obtain highest precision of estimation in the parameters if used for suitable and specific weather conditions (Valipour, 2015b; Valipour, 2015d). Notably, radiation-based method provides a guideline of potential application of radiation and temperature data. The current study also used the potential advantage of radiation and temperature datasets for specific weather condition, expecting to obtain promising results.

2.4. Grassland classification data

The Global Land Cover 2000 (GLC2000) was produced by an international partnership that consisted of 30 research groups under the coordination of the Joint Research Center of the European Commission in 2000 (Bartholomé and Belward, 2005). The GLC2000 database was based on the data from the VEGETATION sensor placed on-board SPOT 4 and comprise 22 land cover classes with a resolution of 1 km. The study area was extracted from the GLC2000 database and classes 8–12 and 22 were selected as grasslands. The GLC2000 database is available at http://bioval.jrc.ec.europa.eu/products/glc2000/data_access.php.