Ecological Indicators 40 (2014) 102–108

Contents lists available at ScienceDirect

Ecological Indicators

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

An improved indicator of simulated grassland production based on MODIS NDVI and GPP data: A case study in the Sichuan province, China

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ARTICLE INFO

Article history:
Received 20 June 2013
Received in revised form 10 January 2014
Accepted 14 January 2014

Keywords:
Grass production
NDVI
GPP
Fractional vegetation coverage

ABSTRACT

Grassland monitoring is important for both global change research and regional sustainable development. Gross primary production (GPP) is one of the key factors for understanding grass growing conditions. Methods for estimating GPP are plentiful, and the light use efficiency (LUE) model based on remote sensing data is widely used. The MODIS GPP product, which is employed by the National Aeronautics and Space Administration (NASA), is calculated using the LUE model and the surface reflection data from the Moderate Resolution Imaging Spectroradiometer onboard the Terra/Aqua satellite. The MODIS GPP product harbors its own uncertainties arising from the sources and parameters, such as FPAR and light use efficiency (ε). In this study, we propose an improved indicator for monitoring grassland based on MODIS GPP and NDVI data. Fractional vegetation coverage and the percentage of grass area (1 km^2) were used to reduce the mixed pixel effect. A function of NDVI was used to simulate the light use efficiency and FPAR. The modified GPP data were calculated and validated with in situ measured data from the Sichuan province, China, 2011. The results indicated that the modified GPP data were a more accurate indicator for monitoring grassland than previous indicators, and the precision of grass production simulated by $SsGPP_{ndvi}$ reached 85.6%. Spatial statistic results were consistent with the practical condition in most cases. Since MODIS data are available twice a day, the improved indicator can meet the actual requirement of grassland monitoring at regional scale.

1. Introduction

Grasslands represent one of the most widespread ecosystems worldwide and cover approximately 40% of emerged land (Suttie et al., 2005), which provides significant ecosystem services, carbon storage and forage production (Fry et al., 2013). It is also the largest terrestrial ecosystem in China, with approximately 400 million hm^2 of natural grasslands, accounting for 41.7% of China's total area (Xie et al., 2001; Xu et al., 2013). More than 100 million livestock are raised on those Chinese grasslands, and the desertification area now comprises 27.3% of the national land area, which is increasing by 2460 km^2 per year (Akiyama and Kawamura, 2007). Monitoring grass production is essential, for it is crucial for understanding growth conditions and evaluating carrying capacity to reduce pasture degradation and manage the grassland scientifically (Argenti et al., 2011). The gross primary production (GPP) is one of the primary monitoring indicators (Chen, 2008). GPP is defined as the overall carbon fixation rate through vegetative photosynthesis, which is used to quantify the amount of biomass produced within an ecosystem over a unit of time, regardless of the respiration amount (Monteith, 1972; Wu et al., 2010b). An accurate quantitative estimation of the spatial and temporal GPP distribution is critical for grassland monitoring and carbon exchange (Wu et al., 2009).

To achieve an accurate GPP, different estimation methods have been proposed. Remote sensing data have been extensively used to estimate the GPP not only for the ability to detect spatial and temporal changes but also for the consistent and systematic vegetation and ecosystem observations (Di Bella et al., 2004; Wu et al., 2010a). The light use efficiency (LUE) model proposed by Monteith (1972) is one of the most widely used methods for estimating GPP based on remote sensing data. It is one of the many methods which may have potential to adequately address spatial and temporal dynamics of GPP (Seaquist et al., 2003; Turner et al., 2005; Yuan et al., 2007; Rossini et al., 2012; Wu et al., 2009).

Since 1999, the National Aeronautics and Space Administration (NASA) has provided GPP estimates for the entire globe based on

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http://dx.doi.org/10.1016/j.ecolind.2014.01.015

the Moderate Resolution Imaging Spectroradiometer (MODIS) 1 km products (Running et al., 2000, 2004). The MODIS GPP algorithm was based on the LUE model (Lee et al., 2011). Reasonable spatial patterns and logical temporal variability across a diverse range of biomes and climate regimes were generated using the current MODIS GPP algorithm (Gitelson et al., 2012). However, the MODIS GPP data sets harbor uncertainties arising from sources, such as the input data sets and the parameters specified to describe plant biophysical behavior (Gebremichael and Barros, 2006).

The MODIS GPP was derived from the absorbed photosynthetically active radiation (APAR) multiplied by the light use efficiency (ε). The APAR was calculated from the photosynthetically active radiation (PAR) multiplied by the absorbed photosynthetically active radiation (FPAR) fraction. The FPAR provided by the MOD15 product was subject to the uncertainties due to several factors, including the atmospheric conditions, view angle geometry, leaf area index (LAI) and canopy heterogeneity (Fensholt et al., 2004; Gebremichael and Barros, 2006; Heinsch et al., 2006). ε was ε_{max}, which was derived from the Biome Parameter Look Up Table (BPLUT) and modified by the daily minimum temperature (TMIN) and vapor pressure deficit (VPD). The ε_{max}, TMIN and VPD relied on a simple look-up table approach, based on model outputs rather than observations, which also contribute to the uncertainties (Running et al., 2000; Turner et al., 2003). The ε_{max} was assumed as a constant, which reduced the ability to detect species-specific differences (Gitelson et al., 2012). The land cover classes employed in the MODIS GPP algorithm may be too general, and thus the spatial resolution of the MODIS GPP data may be too coarse to apply at a local scale (Zhao et al., 2005).

Several studies have suggested that vegetation indices (VIs) are highly correlated with the light use efficiency as well as the FPAR (Inoue et al., 2008; Viña and Gitelson, 2005; Wang et al., 2004). Recent publications have demonstrated that VIs were reliable proxies for both the ε and FPAR, and a strong relationship was observed between the GPP and the product of VI × VI × PAR (Gitelson et al., 2012; Wu et al., 2010a,b).

Given these drawbacks, an improved indicator for simulating grass production was proposed based on the MODIS GPP and NDVI data. The Sichuan province was chosen for the case study site as it is one of the most important pastoral areas in China, comprising 43% of the grassland area. VI × VI was used to modify the MODIS GPP product, and the normalized difference vegetation index (NDVI), derived from the MOD15 product, was the selected VI for the Sichuan grassland in this study. The fractional vegetation coverage and percentage of grass area in 1 km^2 were used to reduce the mixed pixel effect. Then, MODIS GPP data and modified MODIS GPP data were both employed in the correlation analysis of the grass production with field-measured data.

2. Materials and methods

2.1. Study area

The Sichuan province in Southwest China is one of the country's primary pasture areas. Grassland accounts for 43% of total area of the province, whereas available natural grassland accounts for 85% of the total grassland area (Zhou et al., 2004). Most of the grassland (78%) is distributed in the Northwest Sichuan province, at the southeastern edge of the Tibetan plateau, where the Yangtze and Yellow Rivers flow at an average elevation from 3000 m to over 4500 m. The mean annual temperature varies from −1.6 °C to 3.3 °C. The average monthly precipitation is 78.4 mm, and approximately 90% of the precipitation falls in the growing season from April to October. The alpine meadow, alpine shrub meadow, alpine marsh grass and mountain woodland grass are the four primary grassland types, and the subalpine meadow is the dominant soil type (Zhang et al., 2011). Fig. 1 demonstrates the distribution of the four main grass types and the distribution of the sampling regions in the Sichuan province.

Table 1
Detailed information of survey data.

Grassland type	Sample points	Minimum value of AFY (kg/ha)	Maximum value of AFY (kg/ha)
Alpine meadow	85	3850	9040
Alpine marsh grass	25	1040	10,780
Alpine shrub meadow	25	1304	9029
Mountain woodland grass	25	2260	4995
All	160	1040	10,780

2.2. Data acquisition

2.2.1. In situ measurements

The in situ measured data used in this study were derived from the grassland resource survey of the Sichuan province in 2011, which was conducted by the Sichuan Grassland General Work Station, China. The survey data were collected from the middle of July to the end of August, when the grassland was at the peak of its growing season. Information, such as grassland type, actual fresh yield (AFY, kg/ha) (presented in Table 1), selection date, longitude and latitude, was surveyed based on the grassland type and located with a global positioning system (GPS). The four primary grass types, alpine meadow, alpine shrub meadow, alpine marsh grass and mountain woodland grass, were studied. The data collected from the survey points (160) that could be categorized into the four grass types were selected, thus totaling 25 alpine shrub meadow samples, 25 alpine marsh grass samples and 25 mountain woodland grass samples and 85 alpine meadow samples, which accounted for 49% of the total grass area.

2.2.2. MODIS data

The MODIS/Terra 16-day 1 km NDVI products MOD13A2 (d209-d225) and 8-day 1 km GPP products MOD17A2 (d209-d233) were obtained from the NASA website (ftp://e4ftl01.cr.usgs.gov/) from July 20th to August 28th 2011, which is consistent with date of the field measured data. The maximum values for the two NDVI images were extracted to compose the mNDVI during the study period, whereas the sGPP (g cm^{-2} d^{-1}) was obtained by summing the four GPP images. The mNDVI and sGPP were expressed as:

$$\mathrm{mNDVI} = \max(\mathrm{NDVI}_{\mathrm{DOY}_1}) \quad (1)$$

$$\mathrm{sGPP} = \mathrm{sum}(\mathrm{GPP}_{\mathrm{DOY}_2}) \quad (2)$$

where DOY_1 is 209 and 225, and DOY_2 is 209, 217, 225 and 233.

2.2.3. Fractional vegetation coverage (FVC)

Considering the mixed pixels, the image pixels can be represented as the parts coved with vegetation and parts covered without vegetation (Zribi et al., 2003). It is assumed that the NDVI of each pixel is composed of the two parts, covered with vegetation and without vegetation (Li et al., 2004). Then, the fractional vegetation cover of the pixel is calculated using the following formula (3):

$$f_{\mathrm{ndvi}} = \frac{\mathrm{NDVI} - \mathrm{NDVI}_{\mathrm{min}}}{\mathrm{NDVI}_{\mathrm{max}} - \mathrm{NDVI}_{\mathrm{min}}} \quad (3)$$

where $\mathrm{NDVI}_{\mathrm{min}}$ is the minimum NDVI for the mNDVI image and $\mathrm{NDVI}_{\mathrm{max}}$ is the maximum.

The fractional vegetation coverage (FVC) was utilized to reduce the error of the actual fresh yield in the range of 1 km^2 obtained by sample estimation.