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Modeling grassland aboveground biomass using a pure vegetation index

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ABSTRACT

Remote sensing can be the most effective means of scaling up grassland aboveground biomass (AGB) from the sample scale to the regional scale. Among the remote-sensing approaches, statistical models based on the vegetation index (VI) are frequently used to retrieve grassland AGB because of their simplicity and reliability. However, these types of models have never been comprehensively optimized to overcome VI insensitivity and soil effects. Because grassland AGB is related to grassland type, in our research the integrated orderly classification system for grassland (IOCSG) was used to differentiate grassland types. The study area, located in Inner Mongolia, China, included desert steppe, typical steppe and meadow steppe. A pure VI (PVI) was extracted from the normal VI using spectral mixture analysis (SMA). Using a proportional relationship, PVI models were then constructed based on grassland type. The results demonstrated that the PVI models can have clear advantages over the more commonly used VI models. They simplify the parameterization of VI models and thus enhance models constructed for different regions with different remote sensing data sources. Notably, detailed differentiation of grassland types can improve the accuracy of AGB estimates. The methodology proposed in this study is particularly beneficial for AGB estimates at a national scale, especially for countries such as China with many grassland types.

1. Introduction

Grassland is a renewable resource and provides the feed source for a sizable portion of animal production (Calanca and Fuhrer, 2005; Finger et al., 2010; Soussana and Lüscher, 2006). Furthermore, it plays an important role in biodiversity conservation and soil protection as well as in the global carbon cycle (Fang et al., 2010; Lehmann et al., 2004; Piao et al., 2007; Scurlock et al., 2002; Yang et al., 2009). Unfortunately, due to high-intensity use, grasslands have been degraded worldwide in the past decades (Chen et al., 2007; Kawamura et al., 2005b; Li et al., 2007). It is reported that over 90% of grassland in Inner Mongolia is facing substantial degradation as evidenced by reductions in grassland herbage mass and area (Jiang et al., 2006).

In a pasture area, the amount of grassland aboveground biomass (AGB) determines forage availability and herbivore carrying capacity (Jobbágy et al., 2002; Mutanga et al., 2004; Yahdjian and Sala, 2006). Timely and accurate monitoring of the quantity of grassland AGB can provide the scientific data to regulate stocking rates (SR) for sustainable use of grassland resources (Tueller, 1989; Wang et al., 2006). Although field surveys provide the most accurate method for obtaining grassland AGB data, they are too time-consuming and costly over large areas (Xie et al., 2009). Satellite remote sensing offers a more effective means of collecting regional and global data in a continuous spatio-temporal context (Hall et al., 1995; Moreau et al., 2003). It has been widely used to estimate vegetation biomass or productivity, particularly at a regional scale (Fang et al., 2003; Paruelo et al., 1997; Piao et al., 2004).

Using satellite remote sensing to estimate vegetation biomass can be traced to the 1970s (Rouse et al., 1974). Launch of the NOAA-6 satellite in June 1979 was particularly important enabling, for example, estimates of vegetation biomass for semi-arid grassland savannas in Senegal (Tucker et al., 1983, 1985) and for woodland savannas in Botswana (Prince and Tucker, 1986). Later satellites such as Landsat, SPOT and Terra provided additional choices for biomass estimation using remote sensing techniques (Anaya et al., 2009; Li et al., 2013; Roy and Ravan, 1996).

Using remote-sensing to estimate grassland AGB requires establishing a relationship to scale-up from ground surveys of sample field plots to regional scale remote sensing data obtained over the

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same period as the field surveys (Anaya et al., 2009; Todd et al., 1998a). Since vegetation indices (VI) are optical measures of vegetation canopy 'greenness,' which is a composite of properties such as leaf chlorophyll, leaf area and canopy cover (Tucker and Sellers, 1986), VI-based statistical models are frequently used to construct this scaling relationship (Curran and Steven, 1983; Friedl et al., 1994; Hunt et al., 2003; Paruelo et al., 1997; Psomas et al., 2011). Of the many VIs which have been proposed, the ratio vegetation index (RVI), the normalized difference vegetation index (NDVI), the modified soil adjusted vegetation index (MSAVI) and the enhanced vegetation index (EVI) are most commonly employed (Beeri et al., 2007; Gao et al., 2013; Jianlong et al., 1998; Todd et al., 1998b). However, these VIs have been criticized for their relative insensitivity in more heavily vegetated areas (Li et al., 2014; Mutanga and Skidmore, 2004). The solution proposed here is to incorporate ecological zoning in the VI estimates. Additionally, variability in soil background reflectance has a strong effect on 'greenness' indices (Huete et al., 1984, 1985). The solution proposed for this problem is to exclude information on the soil from the VIs for a pixel.

Given these issues, the objectives of this study are: (1) to improve the ability of VI for modeling grassland AGB at a regional scale by incorporating climate-based ecological zoning, (2) to establish soil-excluded VI-based models for estimates of grassland AGB, and (3) to demonstrate the methodology's effectiveness by applying it to two different remote sensing products, Moderate-resolution Imaging Spectroradiometer (MODIS) and Landsat 8 data.

2. Methodology

2.1. Study area

The study area in the Inner Mongolian grasslands of northern China (Fig. 1) is characterized by a temperate continental monsoon climate with mean annual temperatures decreasing from about 9 °C in the southwest to −5 °C in the northeast. The annual rainfall varies from 40 to 580 mm, 80% of which occurs during the growing season (May–October). Topographically, the area is dominated by plateaus with the Ordos, Xilingole and Hulun Buir plateaus arrayed from the southwest to the northeast with an overall mean elevations of about 1000 m. Based on the dominant species, which are primarily determined by rainfall, the grassland can be classified into three major types from west to east: desert steppe, typical steppe and meadow steppe (Gong Li et al., 2000; Kawamura et al., 2005a; Li et al., 2014). Meadow steppe occurs in the eastern part of the study area. The dominant species are *Stipa baicalensis* and *Filifolium sibiricum*. Typical steppe is located in the center, dominated by *Leymus chinensis* and *Stipa grandis*. Desert steppe is distributed in the west. Because of limited rainfall, most areas are relatively sparsely vegetated and the ecological environment is fragile.

2.2. Sampling design and remote sensing data

To enable the comparison of different remote sensing data sources for estimating grassland AGB, a hierarchical design was used for selecting field plots. Each first level sample plot was 100 m × 100 m, which is well-suited for the 250 m resolution MODIS data. Five 10 m × 10 m sample plots, distributed along both diagonals of the first-level sample plots, comprised the second level for use with the 30 m resolution Landsat 8 data. Similarly, five 1 m × 1 m quadrats are arrayed within the second level sample plots to create the third level (Fig. 1).

The ground survey was executed from July 20 to August 10, 2013. Location of the survey plots relative to the different vegetation types was guided by vegetation maps (at a scale of 1:1 million) compiled by a committee of the Chinese Academy of Sciences in 2001. The primary content of the survey included aboveground biomass (AGB) and fractional vegetation cover (FVC). AGB was acquired by weighing fresh grass harvested in the quadrats, whereas FVC was acquired by classifying fisheye camera photographs. The AGB values for the 10 m × 10 m sample plots were obtained by averaging the fresh grass measures over the five 1 m × 1 m quadrats, and then the 10 m × 10 m sample plots were averaged up to the 100 m × 100 m level. A Trimble Geo XT 6000 GNSS receiver, capable of providing real-time positioning with submeter accuracy, was used to obtain the coordinates for these sample plots. In total, data for 48 100 m × 100 m sample plots and 240 10 m × 10 m sample plots were obtained.

Table 1
Thermal zonal landscapes (Ren et al., 2008).

Thermal grades	>0 °C annual cumulative temp. (°C)	Suitable thermal zone
Frigid	<1300	(Alpine) Frigid zone
Cold temperate	1300–2300	Cold temperate zone
Cool temperate	2300–3700	Cool temperate zone
Warm temperate	3700–5300	Warm temperate zone
Warm	5300–6200	Temperate subtropics
Subtropical	6200–8000	Equatorial subtropics
Tropical	>8000	Tropics

The remote sensing data were derived from the MODIS 8-Day product (MOD09Q1), which has two reflectance bands, a red band (620–670 nm) and a near-infrared band (841–875 nm), at a spatial resolution of 250 m. The Landsat 8 Level 1 Operational Land Imager (OLI) data products, the second remote sensing data source, have a resolution of 30 m. For this study, the MOD09Q1 data were collected on the accrued days of 97 (April 7) and 217 (August 5), 2013, and the OLI data for the period July 20–August 15, 2013 (Li et al., 2014).

The MOD09Q1 data have undergone atmospheric radiometric correction. For the OLI data, atmospheric radiometric correction was conducted using the FLAASH module in the ENVI 5.0 sp3 software package. Then, spectral reflectance values were extracted for the MOD09Q1 and OLI data using, respectively, 72 m and 7.2 m radii drawn from the coordinates of the center of the sample plots.

2.3. Determination of grassland types

The accuracy of AGB estimates from satellites is limited by the spatial, spectral, and radiometric resolutions inherent in the remotely sensed data (Lu, 2006). However, incorporation of grassland type should improve these estimates. This is particularly valuable at the regional scale, especially in China, which has many grassland types, including alpine meadow, tundra, steppe and desert (Ren et al., 2008).

A grassland ecosystem is highly influenced by climate, land form and soil type, fauna and flora, and human activities. Ren et al. (2008) analyzed the relative stability of these parameters in grassland classification and suggested that bioclimate has a greater stability than soil characteristics and vegetation. Consequently, grassland types in China were classified using indictors of bioclimate following the integrated orderly classification system of grassland (IOCSG) proposed by Ren et al. This system quantifies bioclimate using >0 °C annual cumulative temperature and a moisture index (i.e., *K*-value) expressed as

$$K = \frac{r}{0.1\sum\theta} \quad (1)$$

where r is annual rainfall, and $\sum\theta$ is the >0 °C annual cumulative temperature, that is, bio-temperature. Zonal landscapes are then related via gradations based on >0 °C annual cumulative temperature (Table 1) and the *K*-value (Table 2). Table 1 mainly reflects