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A radiative transfer model-based method for the estimation of grassland aboveground biomass

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ABSTRACT

This paper presents a novel method to derive grassland aboveground biomass (AGB) based on the PROSAILH (PROSPECT + SAILH) radiative transfer model (RTM). Two variables, leaf area index (LAI, $m^2 m^{-2}$, defined as a one-side leaf area per unit of horizontal ground area) and dry matter content (DMC, $g cm^{-2}$, defined as the dry matter per leaf area), were retrieved using PROSAILH and reflectance data from Landsat 8 OLI product. The result of LAI × DMC was regarded as the estimated grassland AGB according to their definitions. The well-known ill-posed inversion problem when inverting PROSAILH was alleviated using ecological criteria to constrain the simulation scenario and therefore the number of simulated spectra. A case study of the presented method was applied to a plateau grassland in China to estimate its AGB. The results were compared to those obtained using an exponential regression, a partial least squares regression (PLSR) and an artificial neural networks (ANN). The RTM-based method offered higher accuracy (R^2 = 0.64 and RMSE = 42.67 $g m^{-2}$) than the exponential regression (R^2 = 0.48 and RMSE = 41.65 $g m^{-2}$) and the ANN (R^2 = 0.43 and RMSE = 46.26 $g m^{-2}$). However, the proposed method offered similar performance than PLSR as presented better determination coefficient than PLSR (R^2 = 0.55) but higher RMSE (RMSE = 37.79 $g m^{-2}$). Although it is still necessary to test these methodologies in other areas, the RTM-based method offers greater robustness and reproducibility to estimate grassland AGB at large scale without the need to collect field measurements and therefore is considered the most promising methodology.

1. Introduction

Aboveground biomass (AGB) determines biosphere–atmosphere interactions, and it is key to our understanding of the terrestrial carbon balance (Anaya et al., 2009; Cartus et al., 2012; He et al., 2015; Houghton, 2005; Liu et al., 2015; Su et al., 2016). A spatial and temporal assessment of AGB at different stages can be used to determine which processes drive changes in the global carbon cycle and can help land managers to develop strategies for climate change mitigation (Yan et al., 2015). Although field surveys provide the most accurate method for obtaining grassland AGB, they are too time-consuming and costly over large areas (Paul et al., 2013; Xie et al., 2009). Remote sensing can provide a uniquely effective and efficient means of achieving this end due to its high temporal and spatial resolution image of large landscape observation (Barrachina et al., 2015; Chen et al., 2015; Fassnacht et al., 2014; Lu, 2006).

Different methods exist to estimate AGB using different remote sensing data: (*i*) light detection and ranging (LiDAR) data (Chen, 2015; Tsui et al., 2012), (*ii*) synthetic aperture radar (SAR) data (Baghdadi et al., 2015; Englhart et al., 2011; Liu et al., 2015), (*iii*) optical satellite data (Cho et al., 2007; Cho and Skidmore, 2009; Ramoelo et al., 2015; Doraiswamy et al., 2005; Liu et al., 2010; Tian et al., 2012), and (*iv*) multi-sensor data (Clevers and van Leeuwen, 1996; Koch, 2010; Li et al., 2015; Su et al., 2016; Zhang et al., 2014). LiDAR is an active sensing technology which uses a laser (light amplification by stimulated emission of radiation) to transmit a light pulse towards a target and a receiver to measure the backscattered or reflected light from that target (Cho et al., 2012; Lefsky et al., 2005). The LiDAR data have shown great potential for the retrieval of vegetation biophysical parameters that are largely related to AGB, such as vegetation height, volume and structure

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(Lefsky et al., 2005; Zolkos et al., 2013). However, LiDAR data are generally used for forest and shrub AGB mapping (Boudreau et al., 2008; Cho et al., 2012; Lefsky et al., 2005; Zolkos et al., 2013) and as far as we know there are not studies focused on grassland AGB. Moreover, it is not suitable in applications for large regions because wall-to-wall coverage of large areas with LiDAR is impractical (Cartus et al., 2012; Liu et al., 2015). SAR data also showed great potential for AGB mapping by using its intensity information, polarized information and phase information, such as the development of polarimetric SAR (PolSAR), SAR interferometry (InSAR) and polarimetric SAR interferometry (PolInSAR) (Cartus et al., 2012; Cloude and Papathanassiou, 1998; Liu et al., 2015; Solberg et al., 2013). Svoray and Shoshany (2002) derived biomass in a semi-arid grassland region by modifying the water-cloud model. Moreau and Le Toan (2003) utilized SAR data as a function of plant biomass at homogeneous areas. However, the use of SAR data remains challenging due to its high costs and lack generality for the application of the empirically based equations to large scale. Moreover, the SAR data are hypersensitive to the underlying surface in grasslands, which will sufficiently influence the accuracy of AGB estimations (Hajj et al., 2014).

With regard to the use of optical satellite data to estimate AGB, the primary methods are empirical approaches, including vegetation indices regression (Anderson et al., 1993; Zheng et al., 2004, 2007), partial least squares regression (PLSR) (Cho et al., 2007), artificial neural networks (ANN) (Xie et al., 2009) and machine learning algorithms (Clevers et al., 2007). The vegetation indices regression method was to establish the relationship (such as linear fitting, exponential regression, polynomial regression, etc.) between vegetation indices and vegetation variables of interest, and with this relationship, the target variables can be derived. PLSR is a method for relating two data matrices, X and Y, by a linear multivariate model, but goes beyond traditional regression in that it models also the structure of X and Y. This method derives its usefulness from its ability to analyze data with many, noisy, collinear, and even incomplete variables in both X and Y (Wold et al., 2001). The ANN and machine learning algorithms need a training database consisting of canopy reflectance spectra together with the corresponding vegetation parameters, and their performance largely relies on the training database and the training process itself (Houborg et al., 2009). Generally, these methods are empirical and indirect (Koch, 2010) as they relate AGB with other directly retrieved vegetation parameters, such as height and crown closure. Consequently, these methods are limited to a certain region and time and, being indirect, they may introduce extra uncertainties in the estimation of AGB.

Another method for the estimation of AGB is the model-data assimilation approach which incorporates field and multiple remote sensing data into dynamic mechanistic models, such as the CERES-Wheat (Godwin et al., 1989) and World Food Studies (WOFOST) model (Diepen et al., 1989; Ma et al., 2013a, 2013b). This approach has increasingly been used for crop growth monitoring and AGB or yield prediction, with considerable success (He et al., 2015; Huang et al., 2016, 2015a). However, these dynamic mechanistic models are hard to parameterize due to the large requirement of input parameters, and the iterative optimizing process is time-consuming, especially for the four-dimensional variational algorithm (4D-Var) (Quan et al., 2015b; Talagrand and Courtier, 1987).

Optical satellite data and radiative transfer model (RTM) inversion techniques have been widely used to retrieve vegetation biophysical and biochemical variables, such as leaf area index (LAI) (Houborg et al., 2007; Quan et al., 2014), canopy water content (Quan et al., 2015a), canopy or leaf chlorophyll content (Darvishzadeh et al., 2008b; Yin et al., 2016) and fuel moisture content (Quan et al., 2015b; Yebra and Chuvieco, 2009b; Yebra et al., 2013). RTM inversion techniques have proven to be a promising way to retrieve bio-physical and bio-chemical variables because compared with the empirical methods, RTM are more universal as they are based on physical laws that provide explicit relations between canopy properties and spectra (Houborg et al., 2009, 2007; Quan et al., 2015a; Yebra et al., 2013, 2008). Thus, these RTM-based approaches have the advantage of reproducibility. However, to date, no study has explored the use of RTM inversion techniques for the estimation of grassland AGB.

In this paper, a novel method based on the PROSAILH (PROSPECT and SAILH) RTM (hereafter referred as RTM-based method) was explored to estimate grassland AGB from two model parameters: LAI ($m^2 m^{-2}$, defined as a one-side leaf area per unit of horizontal ground area) and dry matter content (DMC, $g cm^{-2}$, defined as the dry matter per leaf area). To test the performance of this method vs. the traditional empirical methods, the exponential regression, PLSR and ANN were also implemented. A case study of the proposed methods was applied to a plateau grassland in China to estimate its AGB, and the results were validated using the field measurements.

2. Materials and methods

2.1. Study area and data

2.1.1. Study area and sampling

The study area is the Qinghai Lake watershed, located in Qinghai Province, China (36° 15′–38° 20′ N, 97° 50′–101° 22′ E) (Fig. 1). This watershed is a closed inland basin surrounded by mountains, with an area of approximately 29,600 km^2. The watershed ranges in elevation from 3194 m to 5174 m with annual mean temperatures between −1.10 °C and 0.80 °C. The annual precipitation is between 324.50 mm and 412.80 mm, and the majority of the precipitation falls during the period from May to September. Due to its unique geographic location, geomorphic features, climate conditions and saline-alkali soil, the Qinghai Lake watershed forms a complex habitat with diverse grass species.

The field surveys were carried out in late July 2014 and early August 2015 in collaboration with the Qinghai Ecosystem Remote Sensing Monitoring Centre (http://www.qherc.org/). The sampling plots were selected based on the image of 1:100,0000 grassland cover types in Qinghai province, China. A total of 135 30 × 30 m plots were sampled. A GPS was used to locate their geographical positions. For each plot, LAI was obtained from fish-eye photographs and the CAN-EYE V6.3.8 analysis software. Three pictures were taken in the diagonal direction of each plot. In each plot, 3 subplots (0.5 × 0.5 m) were randomly selected to destructively sample the aboveground grass by removing all grass to the ground level. The collected samples were transported to the laboratory, oven-dried for 24 h at 105 °C (Matthews, 2010) and weighed (dry weight).

2.1.2. Satellite data and pre-processing

Landsat 8 Operational Land Imager (OLI) products acquired within the field survey periods were used as the source of reflectance data to carry out the RTM inversion. The Landsat 8 OLI sensor images the Earth every 16 days at a pixel size of 30 m × 30 m (same size as the field plots). The data were downloaded from the United States Geological Survey (USGS) (http://glovis.usgs.gov/). A total of five Landsat-8 OLI scenes per date were needed to completely cover the Qinghai Lake watershed. Only images covered by less than 70% cloud were selected and downloaded. The images were atmospherically corrected using the FLAASH tool in the ENVI (version 5.2) image processing software (Matthew et al., 2000). FLAASH is structured based on the MODTRAN (MODerate resolution atmospheric TRANsmission) atmospheric RTM, which can be