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Inversion of the PROSAIL model to estimate leaf area index of maize, potato, and sunflower fields from unmanned aerial vehicle hyperspectral data

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ABSTRACT

Leaf area index (LAI) is a key variable for modeling energy and mass exchange between the land surface and the atmosphere. Inversion of physically based radiative transfer models is the most established technique for estimating LAI from remotely sensed data. This study aims to evaluate the suitability of the PROSAIL model for LAI estimation of three typical row crops (maize, potato, and sunflower) from unmanned aerial vehicle (UAV) hyperspectral data. LAI was estimated using a look-up table (LUT) based on the inversion of the PROSAIL model. The estimated LAI was evaluated against *in situ* LAI measurements. The results indicated that the LUT-based inversion of the PROSAIL model was suitable for LAI estimation of these three crops, with a root mean square error (RMSE) of approximately 0.62 $m^2\ m^{-2}$, and a relative RMSE (RRMSE) of approximately 15.5%. Dual-angle observations were also used to estimate LAI and proved to be more accurate than single-angle observations, with an RMSE of approximately 0.55 $m^2\ m^{-2}$ and an RRMSE of approximately 13.6%. The results demonstrate that additional directional information improves the performance of LAI estimation.

1. Introduction

Leaf area index (LAI), defined as the total one-sided area of leaves per unit of ground area (Bréda, 2003), is a key parameter in a wide range of biological and physical processes (Gower et al., 1999; Li et al., 2009; Myneni et al., 2002). For instance, the monitoring and mapping of LAI is vital for modeling energy and mass exchange between the land surface and the atmosphere (Asner et al., 2003; Running et al., 1999; Li et al., 2009). Remote sensing provides a cost-effective method to estimate LAI over extended regions. There are two main approaches for estimating LAI from remotely sensed data: statistical and physical approaches (Baret and Buis, 2008; Dorigo et al., 2007; Kimes et al., 2000). The statistical approaches are based on empirical relationships between ground-based LAI measurements and spectral vegetation indices (Darvishzadeh et al., 2008a; Haboudane et al., 2004). The physical approaches are based on radiative transfer model (RTM) inversion (Combal et al., 2002a; Meroni et al., 2004). The inversion of RTMs has been integrated multi-angular sensors (Dorigo, 2012; Meroni et al., 2004; Vuolo et al., 2008).

Three different techniques are commonly used for the inversion of RTMs: iterative optimization techniques (Jacquemoud et al., 1995; Meroni et al., 2004; Vohland et al., 2010), look-up tables (LUTs) (Darvishzadeh et al., 2012; Dorigo, 2012; Richter et al., 2011), and neural networks (NNs) (Atzberger, 2004; Bacour et al., 2006; Baret et al., 2007). Several studies have found that LUTs and NNs delivered the best accuracy and speed in the inversion of RTMs (Richter et al., 2009; Weiss et al., 2000). The inversion of RTMs is, by nature, an ill-posed problem for two main reasons (Atzberger, 2004; Combal et al., 2002a). One reason is that various combinations of canopy biophysical variables may produce similar canopy reflectance spectra. The other is that measurement and model uncertainties may induce large inaccuracy in the simulated reflectance spectra.

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Different strategies have been proposed to solve the ill-posed inverse problem (Li et al., 2013a, 2013b). For LUT-based inversion methods, the use of multiple solutions (rather than the single best solution) modestly increases the robustness of LAI estimation (Darvishzadeh et al., 2011; Weiss et al., 2000). The exploitation of *a priori* knowledge, *e.g.*, on the ranges and distributions of variables (Darvishzadeh et al., 2008b; Si et al., 2012) and on land cover classification (Dorigo et al., 2009; Verrelst et al., 2012), is another way to constrain solutions to the ill-posed problem and to improve the accuracy of LAI estimation. Moreover, the use of multi-angle observations has also been shown to improve the accuracy of LAI estimation (Dorigo, 2012; Meroni et al., 2004; Vuolo et al., 2008).

Because of its ease of use and general robustness, the PROSAIL model has been used to estimate LAI over fields of agricultural crops such as sugar beet (Combal et al., 2002b; Jacquemoud et al., 1995), maize (Koetz et al., 2005; Yang et al., 2012), and alfalfa (Bacour et al., 2002; Vuolo et al., 2008). However, relatively few investigations have been performed over potato and sunflower fields. The objective of this study is twofold: (i) to further evaluate the suitability of the PROSAIL model for LAI estimation of maize, potato, and sunflower fields in northern China using the LUT approach; and (ii) to compare the performance of LAI estimation from single- and dual-angle observations against *in situ* measurements. This paper is organized as follows. The study area, data, and methods are described in Section 2. The results are presented in Section 3 and discussed in Section 4. Conclusions are drawn in the last section.

2. Materials and methods

2.1. Study area

To evaluate a potential calibration and validation test field for future hyperspectral sensors, a comprehensive field campaign was conducted over the Baotou test site (Inner Mongolia, China, 40.88° N, 109.53° E) on 3 September 2011. The Baotou test site has an average ground elevation of approximately 1.3 km above sea level. The test site receives little precipitation and has a high percentage of cloud-free days. This area has a continental climate that is characterized by four seasons and a large diurnal temperature variation. The yearly average temperature is 6–7 °C, and the average annual rainfall is 200–250 mm. The main agricultural crops of this region are maize, potato, and sunflower, and all three require irrigation.

2.2. Data

2.2.1. In situ measurements

Four reference targets, which were 15 m × 15 m and with nominal reflectance of 20%, 30%, 40%, and 50%, were placed on a soil background over the study area. These four targets were used to perform the radiometric calibration of unmanned aerial vehicle (UAV) hyperspectral sensor. *In situ* surface reflectance spectra of these four targets were collected with an SVC HR-1024 field-portable spectroradiometer at the time of UAV hyperspectral data acquisition. The spectroradiometer has 1024 channels covering the spectral range from 350 to 2500 nm with spectral resolution of 3.5 nm at 700 nm wavelength, 9.5 nm at 1500 nm wavelength, and 6.5 nm at 2100 nm wavelength. Before and after each target measurement, a reference measurement was collected with a white Spectralon reference panel. The spectra were measured in absolute radiance mode at nadir. The raw spectra of each target were scaled with the reference measurements to produce reflectance spectra. Five measurements of each target were averaged to yield a representative reflectance spectrum.

Atmospheric measurements were collected with an automatic CIMEL CE318 sunphotometer at the time of the UAV hyperspectral data acquisition. The sunphotometer has nine channels at nominal wavelengths of 340, 380, 440, 500, 670, 870, 936, 1020, and 1640 nm. Measurements at 936 nm were used to derive columnar water vapor (CWV) (Bruegge et al., 1992) with the coefficients simulated by MODTRAN (Halthore et al., 1997). Aerosol optical depth (AOD) at 550 nm was derived from the other channels using the Ångström law, following the method of Estellés et al. (2006). The measured values of AOD at 550 nm and CWV at the time of UAV hyperspectral data acquisition were 0.18 and 1.7 g cm^{-2}, respectively. These values were used as inputs to atmospheric radiative transfer models such as MODTRAN to perform atmospheric corrections on the UAV hyperspectral data.

In situ LAI measurements were collected with the Plant Canopy Analyzer LAI-2200 instrument under overcast sky conditions on 2 September 2011. The average LAI was calculated in each sample plot based on the one above-canopy measurement and five below-canopy measurements. When LAI measurements were conducted, the sun was kept behind the operator and the operator used a view restrictor of 45°. No corrections were performed to account for leaf clumping or the influence of non-photosynthetic plant components (*e.g.*, stems). A total of 14 LAI measurements were performed: 4 on maize, 4 on potato, and 6 on sunflower plots. The measured LAI values ranged from 2.4 to 3.2 m^2 m^{-2} for maize, 4.0–4.8 m^2 m^{-2} for potato, and 1.9–4.8 m^2 m^{-2} for sunflower. The *in situ* LAI measurements were used to evaluate the accuracy of LAI estimation from hyperspectral data.

2.2.2. UAV hyperspectral data

Two flight lines were acquired by a new hyperspectral sensor over the study area on 3 September 2011 from approximately 14:40 to 15:00 local time. This hyperspectral sensor is referred to as UAV-HYPER and was installed on a UAV. The UAV-HYPER sensor contains 128 bands that cover the spectral range from 350 to 1030 nm, with a bandwidth of 5 nm and a field of view of 11.5°. During the campaign, the operational altitude of the UAV-HYPER sensor was approximately 3.5 km above ground level, which gave a spatial resolution of approximately 0.7 m.

The two flight lines L1 (west–east) and L2 (east–west) overlap. The observation details of these two flight lines are summarized in Table 1, and subset images of the two flight lines are shown in Fig. 1. There are 10 sample plots located along flight line L1, 11 along flight line L2, and 7 in the overlapping area.

Pre-processing of the UAV-HYPER data includes the assessment of the signal-to-noise ratio (SNR), radiometric calibration, and atmospheric and geometric corrections. Some bands of the UAV-HYPER sensor have low SNR values. A method based on local means and local standard deviations of small imaging blocks was used to estimate SNR from the UAV-HYPER data (Gao, 1993). To minimize the effect of low SNR on the LAI retrieval, 32 bands with SNR values lower than 40 were discarded from further analysis: bands 1–12 (395.3–450.0 nm) and bands 109–128 (932.5–1027.0 nm). The radiometric calibration coefficients were determined using the four reference targets. The atmospheric correction was performed using a MODTRAN-based LUT method informed by atmospheric parameters collected at the time of the UAV-HYPER data acquisitions (Duan et al., 2013). The geometric correction was performed using differential GPS-derived ground control points. A second-order polynomial transformation with nearest-neighbor interpolation was used for the geometric correction, which achieved a geometric accuracy of approximately one pixel.

2.3. Method

2.3.1. Generation of the LUT

The PROSAIL model (Jacquemoud et al., 2009), which couples the PROSPECT leaf optical properties model (Jacquemoud and