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 crops, with a root mean square error (RMSE) of approximately 0.62 m² 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 m² m⁻² and an RRMSE of approximately 13.6%. The results demonstrate that additional directional information improves the performance of LAI estimation.

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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.
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 m² m⁻² for maize, 4.0–4.8 m² m⁻² for potato, and 1.9–4.8 m² 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
Table 1: Acquisition time and sun-sensor geometry of the flight lines L1 and L2.

<table>
<thead>
<tr>
<th>Flight line</th>
<th>Local time</th>
<th>SZA</th>
<th>SAA</th>
<th>VZA*</th>
<th>VAA</th>
<th>Orientation</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>14:43</td>
<td>42.8°</td>
<td>227.5°</td>
<td>0.2°</td>
<td>4.7°</td>
<td>1.9°</td>
</tr>
<tr>
<td>L2</td>
<td>14:53</td>
<td>44.2°</td>
<td>230.5°</td>
<td>0.9°</td>
<td>5.4°</td>
<td>3°</td>
</tr>
</tbody>
</table>

* Minimum, maximum, and mean VZA values of sample plots in the flight lines L1 and L2.

The PROSPECT model simulates the leaf hemispherical transmittance and reflectance as a function of four structural and biochemical leaf parameters: leaf structure parameter \( N \) (unitless), leaf chlorophyll \( a + b \) concentration \( C_{ab} \) (\( \mu g \) cm\(^{-2} \)), equivalent water thickness \( C_w \) (cm), and dry matter content \( C_m \) (g cm\(^{-2} \)). The leaf optical properties (leaf reflectance and transmittance) simulated by the PROSPECT model are then inputted into the SAIL model. The SAIL model simulates the top-of-the-canopy reflectance as a function of eight input parameters: LAI (m\(^2\) m\(^{-2} \)), average leaf angle \( \text{ALA} \) (deg) of an ellipsoidal leaf angle distribution function (Campbell, 1990), fraction of diffuse incoming solar radiation \( \text{sky} \) (unitless), wavelength-dependent canopy background reflectance (i.e., soil reflectance, hot-spot size parameter \( \text{hot} \) (mm\(^{-1} \)) (Kuusk, 1995), sun zenith angle \( \theta_s \) (deg), sensor viewing angle \( \theta_v \) (deg), and relative azimuth angle \( \phi \) (deg) between the sensor and sun.

To account for the variations in soil brightness induced by soil moisture and surface roughness, a soil brightness parameter \( \text{scale} \) was used to scale and shape an average soil spectrum (Darvishzadeh et al., 2012):

\[
R_s = \text{scale} \times R_s
\]

where \( R_s \) and \( R_t \) are the average soil spectrum before and after scaling, respectively.

To generate the LUT, the PROSAIL model was run in forward mode to simulate canopy reflectance for an appropriate number of parameter combinations. An LUT size of 100,000 parameter combinations was found to achieve a good compromise between the computer resource requirement and the accuracy of canopy variable estimation (Weiss et al., 2000). The same LUT was used for the LAI estimation of all three crops. The 100,000 parameter combinations were randomly generated with uniform distributions and specific ranges for the variables in Table 2:

\[
V(n) = \min (+\max - \min) \times \text{rand}(n)
\]

where \( V \) is the variable, \( n \) is the number of parameter combinations, \( \text{rand} \) is the uniform random number generator, and \( \min \) and \( \max \) are the minimum and maximum of the variable, respectively.

The ranges (minimum and maximum) of the variables (Table 2) were selected in accordance with previous studies (Darvishzadeh et al., 2011; Koetz et al., 2005; Richter et al., 2011; Si et al., 2012). The parameter \text{sky} \ depends on atmospheric conditions, the solar zenith angle, and wavelength. Because it has only a very small influence on canopy reflectance, \text{sky} \ was fixed at 0.1 across all

Table 2: Ranges of the input variables for the PROSAIL model for the generation of the LUT.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Abbr.</th>
<th>Unit</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leaf structure parameter</td>
<td>( N )</td>
<td>Unitless</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Leaf chlorophyll concentration</td>
<td>( C_{ab} )</td>
<td>( \mu g ) cm(^{-2} )</td>
<td>20</td>
<td>70</td>
</tr>
<tr>
<td>Dry matter content</td>
<td>( C_m )</td>
<td>cm</td>
<td>0.004</td>
<td>0.007</td>
</tr>
<tr>
<td>Equivalent water thickness</td>
<td>( C_w )</td>
<td>cm(^{-2} )</td>
<td>0.005</td>
<td>0.03</td>
</tr>
<tr>
<td>Leaf area index</td>
<td>LAI</td>
<td>m(^2) m(^{-2} )</td>
<td>0.001</td>
<td>6</td>
</tr>
<tr>
<td>Average leaf angle</td>
<td>( \text{ALA} )</td>
<td>Deg</td>
<td>30</td>
<td>70</td>
</tr>
<tr>
<td>Hot-spot size parameter</td>
<td>( \text{hot} )</td>
<td>mm(^{-1} )</td>
<td>0.05</td>
<td>1</td>
</tr>
<tr>
<td>Soil brightness parameter</td>
<td>scale</td>
<td>Unitless</td>
<td>0.5</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Fig. 1. Subset images of the flight lines (a) L1 (west–east) and (b) L2 (east–west) acquired over the study area. Plus signs denote LAI sample plots. Two additional LAI sample plots (not shown) exist outside the subset of the L2 image.
wavelengths, as in previous studies (Atzberger and Richter, 2012; Darvishzadeh et al., 2008b; Richter et al., 2009; Vuolo et al., 2008). A soil reflectance spectrum corresponding to an average of local measurements was used to characterize the background reflectance. Sun-sensor geometry corresponding to the situation of the UAV-HYPER data acquisitions (see Table 1).

2.3.2. Inversion of the LUT

To select the solution of the inverse problem, the LUT is sorted in terms of the cost function $X_{\text{RMSE}}$ corresponding to the RMSE between the measured reflectance $R_{\text{measured}}$ and the simulated reflectance $R_{\text{simulated}}$ found in the LUT (Combal et al., 2002a; Vohland et al., 2010):

$$X_{\text{RMSE}} = \sqrt{\frac{1}{n_d \cdot n_b} \sum_{i=1}^{n_d} \sum_{j=1}^{n_b} (R_{\text{measured}}^{i,j} - R_{\text{simulated}}^{i,j})^2}$$

where $n_d$ is the number of viewing directions and $n_b$ is the number of bands.

The solution is found by identifying the set of variables in the LUT that minimize the $X_{\text{RMSE}}$ value. However, because measurement errors and model inadequacies make this an ill-posed problem, the solution may not be unique. For this reason, the solution is the average of the parameter combinations that yield within 20% of the smallest $X_{\text{RMSE}}$ value. The 20% threshold is consistent with the optimum number adopted by previous studies (e.g., Dorigo, 2012; Koetz et al., 2005; Vohland et al., 2010).

3. Results

3.1. LAI estimation from single-angle observations

The LUT-based inversion of the PROSAIL model was performed to estimate LAI from the single-angle observations (SAOs) L1 and L2. The LAI was averaged over 3 × 3 pixel windows centered at each sample plot. The estimated LAs from the SAOs L1 and L2 versus the in situ LAI measurements are shown in Fig. 2(a) and (b), respectively, and are summarized in Table 3. Horizontal error bars denote ±1 standard deviation of the in situ LAI measurements at each sample plot. Vertical error bars indicate ±1 standard deviation of the estimated LAI in the 3 × 3 pixel windows centered at each sample plot. The accuracy of the LAI estimation was evaluated in terms of the RMSE and relative RMSE, where RMSE is the RMSE divided by the average of the in situ LAI measurements.

As displayed in Fig. 2, the estimated LAI from the SAO L1 slightly overestimated the in situ LAI measurements for some sample plots where LAI values exceeded 3.5, with RMSE of 0.55 m² m⁻² and RMSE of 14.3%, whereas the estimated LAI from the SAO L2 slightly underestimated the in situ LAI measurements for some sample plots, with RMSE of 0.51 m² m⁻² and RMSE of 13.6%. Table 3 shows the accuracy of the LAI estimation from the SAOs L1 and L2 for maize, potato, sunflower, and all crops. For the SAO L1, the RMSE value decreases from 0.62 m² m⁻² for potato and 0.58 m² m⁻² for maize to 0.45 m² m⁻² for sunflower, whereas the RMSE value decreases from 21.1% for maize and 14.2% for potato to 10.6% for sunflower. For the SAO L2, the RMSE value decreases from 0.96 m² m⁻² for maize and 0.39 m² m⁻² for sunflower to 0.22 m² m⁻² for potato, whereas the RMSE value decreases from 31.1% for maize and 10.3% for sunflower to 5.2% for potato.

3.2. LAI estimation from dual-angle observations

The two overlapping flight lines L1 and L2 provide an opportunity to estimate LAI from dual-angle observations (DAOs). Prior to applying the model inversion to estimate LAI from the DAO, it is necessary to evaluate whether the LAI estimation from the SAOs L1 and L2 is robust. Fig. 3 shows the estimated LAI from the SAO L1 versus the estimated LAI from the SAO L2 for 7 sample plots in the overlapping area of the two flight lines. There are discrepancies between the LAI estimated from the SAOs L1 and L2: the estimated LAI from the SAO L1 is higher than that from the SAO L2 for the 7 sample plots. These results indicate that integrating the SAOs L1 and L2 simultaneously into the inversion scheme may improve the accuracy of LAI estimation.

To further check whether including a second observation angle adds the angular anisotropy information, anisotropy index versus wavelength for the 7 sample plots is shown in Fig. 4. The specific
The definition of the anisotropy index can be found in Sandmeier et al. (1998). In our study, the anisotropy index is calculated as the ratio of surface reflectance of the SAOs L1 and L2 for each of the 7 sample plots. As the surface reflectance of these 7 samples plots retrieved from SAOs L1 and L2 below approximately 0.52 μm is very small (<0.05), their ratio may lead to high (>4.0) or low (<1.0) anisotropy index values. Considering the uncertainties involved in the surface reflectance retrieval, the anisotropy index below approximately 0.52 μm should be taken with caution here. As seen from Fig. 4, the values of the anisotropy index range from approximately 1.2 to 2.0 in the wavelength range between approximately 0.52 and 0.7 μm. There are relative strong anisotropy effects around 0.7 μm (red region) and relative low anisotropy effects around 0.56 μm (green region) for some sample plots due to the strong chlorophyll absorbance in red region and low in green region (Sandmeier et al., 1998). The values of the anisotropy index are lower than approximately 1.2 in the spectral region above approximately 0.7 μm due to the multiple scattering effects which reduce the contrast between shadowed and illuminated canopy components and result in small anisotropy effects (Dorigo, 2012).

The accuracy of LAI estimation from the DAO for all crops is shown in Fig. 5. Horizontal error bars are ±1 standard deviation of the in situ LAI measurements at each sample plot. Vertical error bars represent ±1 standard deviation of the estimated LAI in 3 × 3 pixel windows centered at each sample plot. A comparison of the accuracy of LAI estimation between the SAO and the DAO was performed in the overlapping area of the flight lines. There are 7 sample plots in this area, with the measured LAI values ranging from 3.0 to 4.8 m² m⁻². The accuracy of LAI estimation from the DAO was evaluated using these 7 sample plots. In addition, the accuracy of LAI estimation from the SAOs L1 and L2 was also re-calculated using these 7 sample plots. These results are shown in Table 4. The accuracy of LAI estimation from the DAO is slightly higher than that from the SAOs L1 and L2. The RMSE value decreases from 0.61 m² m⁻² for the SAO L1 and 0.62 m² m⁻² for the SAO L2 to 0.55 m² m⁻² for the DAO. Moreover, the RRMS value decreases from 15.1% for the SAO L1 and 15.5% for the SAO L2 to 13.6% for the DAO.

3.3. Comparison between different LUT sizes

To analyze the influence of different LUT sizes on the accuracy of LAI estimation, two more LUTs with sizes of 50,000 and 250,000 were generated using the same uniform distributions and ranges of the variables as the LUT with a size of 100,000. The LAI estimation was performed for the SAO and the DAO using different LUT sizes. The results are shown in Table 5. There is no significant difference between the accuracy of LAI estimation using different LUT sizes. Similar results were obtained by Darvishzadeh et al. (2012), who used three different LUT sizes (50,000, 100,000, and 250,000) to estimate canopy chlorophyll content. They concluded that the size of the LUT was not significantly important for canopy chlorophyll content retrieval when the inverse problem had more than 100 viable solutions. In addition, Richter et al. (2009) compared two LUTs with sizes of 100,000 and 200,000 for LAI estimation and found that the larger LUT did not improve the accuracy of the LAI.

### Table 4

Accuracy of LAI estimation from single-angle observations (SAOs) and dual-angle observations (DAOs). RRMS is the RMSE divided by the average of the in situ LAI measurements.

<table>
<thead>
<tr>
<th>Data</th>
<th>RMSE (m² m⁻²)</th>
<th>RRMS (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAO L1</td>
<td>0.61</td>
<td>15.1</td>
</tr>
<tr>
<td>SAO L2</td>
<td>0.62</td>
<td>15.5</td>
</tr>
<tr>
<td>DAO</td>
<td>0.55</td>
<td>13.6</td>
</tr>
</tbody>
</table>
Table 5
Accuracy of LAI estimation from single-angle observations (SAOs) and dual-angle observations (DAOs) using different LUT sizes. RRMSE is the RMSE divided by the average of the in situ LAI measurements.

<table>
<thead>
<tr>
<th>Data</th>
<th>50,000</th>
<th>100,000</th>
<th>250,000</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE (m² m⁻²)</td>
<td>RRMSE (%)</td>
<td>RMSE (m² m⁻²)</td>
</tr>
<tr>
<td>SAO L1</td>
<td>0.60</td>
<td>14.9</td>
<td>0.61</td>
</tr>
<tr>
<td>SAO L2</td>
<td>0.63</td>
<td>15.5</td>
<td>0.62</td>
</tr>
<tr>
<td>DAO</td>
<td>0.55</td>
<td>13.6</td>
<td>0.55</td>
</tr>
</tbody>
</table>

estimation. Therefore, following Weiss et al. (2000), this study uses an LUT size of 100,000 – a good compromise between accuracy and computer resources – to estimate the LAI from the SAO and the DAO.

3.4. Comparison of different cost functions

To assess the influence of different cost functions on the accuracy of LAI estimation, a second cost function was also used in the model inversion. This cost function, \( X_{\text{RRMSE}} \), corresponds to the RRMSE between the measured reflectance \( R_{\text{measured}} \) and the simulated reflectance \( R_{\text{simulated}} \) found in the LUT (Weiss et al., 2000):

\[
X_{\text{RRMSE}} = \sqrt{\frac{1}{n_d \cdot n_r} \sum_{i=1}^{n_d} \sum_{j=1}^{n_r} \left( \frac{R_{i,j}^{\text{measured}} - R_{i,j}^{\text{simulated}}}{R_{i,j}^{\text{measured}}} \right)^2}
\] (4)

Fig. 6(a) and (b) show the in situ LAI measurements versus the estimated LAI from the SAOs L1 and L2 using the cost function \( X_{\text{RRMSE}} \). The RMSE and RRMSE values are 0.82 m² m⁻² and 21.3% for the SAO L1, and 0.60 m² m⁻² and 16.0% for the SAO L2. As the difference between Fig. 6(a) and (b) and Fig. 2(a) and (b) shows, the LAI estimation using the cost function \( X_{\text{RRMSE}} \) is less accurate than that using the cost function \( X_{\text{RMSE}} \). As the difference between Fig. 6(c) and Fig. 5 shows, similar results are achieved for the DAO: the RMSE and RRMSE values are 0.66 m² m⁻² and 16.4% for the cost function \( X_{\text{RMSE}} \), and 0.55 m² m⁻² and 13.6% for the cost function \( X_{\text{RRMSE}} \). Because of its better accuracy, we used the cost function \( X_{\text{RMSE}} \) more often in this study.

4. Discussion

4.1. Impact of row crops on the model inversion

Fig. 2 indicates that the estimated LAI from the SAO L1 was often slightly greater than the measured LAI for LAI values above 3.5, whereas the estimated LAI from the SAO L2 was often slightly less than the measured LAI. These results may be because the PROSAIL model does not take into account the shading effect of row crops (Dorigo, 2012). The shading effect results in enhanced reflectance in the backward scattering direction (the perspective of SAO L1) and in reduced reflectance in the forward scattering direction (the perspective of SAO L2), as observed in Fig. 7. Similar results were obtained by Schlerf and Artzberger (2012) and Verrelst et al. (2012), who used the multi-angular CHRIS/PROBA data to estimate LAI.

The results shown in Fig. 2 also demonstrate a significant underestimation in the estimated LAI for maize. This may be because the PROSAIL model was initially developed for canopies for which the turbid medium assumption, where the leaves are randomly distributed within the canopy volume (Jacquemoud et al., 2009), is valid. The canopy characteristics of maize deviate from this assumption. Maize, a typical row crop, is affected by leaf clumping, which the PROSAIL model does not take into account. Therefore, the PROSAIL model underestimated maize LAI compared to the in situ LAI measurements. Similar results were described in other studies (e.g., Richter et al., 2009, 2011). To reduce the effect of
row structure on the estimation of LAI for maize, Yao et al. (2008) proposed to use a row structure model for early growth stage (before elongation) and a homogeneous canopy model for later growth stage (after elongation).

LAI estimation for potato and sunflower yielded lower RMSE values than for maize. This result may be because potato and sunflower fields exhibited more homogeneous coverage than maize fields. Except for one sunflower sample plot, the measured LAI values for potato and sunflower are higher than 4 m² m⁻², whereas those for maize are lower than 3.5 m² m⁻². Consequently, the soil background has a smaller influence on the LAI estimation for potato and sunflower fields than for maize fields.

Improving the accuracy of LAI estimation for row crops requires hybrid turbid/geometrical models that take row structure into account. For example, coupling the improved PROSPECT model (Feret et al., 2008) with a canopy reflectance model accounting for row structure (e.g., Zhao et al., 2010) will improve the accuracy of LAI estimation. Nevertheless, the inversion of such a model requires high parameterization loads, which come at the expense of conceptual and computational complexity.

4.2. Impact of the ill-posed inverse problem

The LUT-based inversion of the PROSAIL model is, by nature, an ill-posed problem because various combinations of canopy parameters may yield similar spectra. Combal et al. (2002a) showed that the use of a priori information is an efficient way to solve the ill-posed problem and to improve the accuracy of LAI estimation. Later studies used a priori information on the distributions and ranges of the variables to regularize the ill-posed inverse problem (Darvishzadeh et al., 2008b; Si et al., 2012). In this study, we use the approximate ranges from the in situ measurements of the parameters LAI and ALA as a priori information to generate the LUT. The sun zenith angle, the sensor viewing angle, and the relative azimuth angle were fixed at the sun-sensor geometry of the UAV-HYPER data acquisitions, but the other input parameters were constrained a priori to ranges defined by the results of previous studies.

Due to the lack of a priori information on variables for each separate crop species, we generated the same LUT for maize, potato, and sunflower. However, the differences in the accuracy of LAI estimation demonstrate that the use of a well-adapted parameter input set for each crop species may improve the accuracy of LAI estimation. To constrain the ranges of variables, Dorigo et al. (2009) and Verrelst et al. (2012) used land cover classification to construct a specific LUT for each vegetation class.

Selecting the cost function of the model inversion is a critical step in solving the ill-posed inverse problem. Meroni et al. (2004) showed that better accuracy was achieved using a cost function that included radiometric and priori information than using a cost function that included only radiometric information. However, often, only limited information about the crop status in an agricultural area is available, so the cost functions in this study were often constrained by radiometric information only. We compared two cost functions $\chi_{RMSE}$ (Eq. (3)) and $\chi_{RRMSE}$ (Eq. (4)). The accuracy of LAI estimation using the cost function $\chi_{RMSE}$ was higher than that using the cost function $\chi_{RRMSE}$.

The use of multi-angle observations instead of just the nadir view has also proven to be an efficient way to constrain the ill-posed problem. This aspect is discussed in the following section.

4.3. Multi-angle observations

Table 5 shows that the DAO gave a more accurate LAI estimation than did the SAO. The results are consistent with those obtained by Dorigo (2012), Meroni et al. (2004), Vuolo et al. (2008), and Yang et al. (2011), who showed that directional information improves the accuracy of LAI estimation. There were only two angle observations available for each pixel in this study, and their angular anisotropy differed by only small amounts. Consequently, the RMSE (RRMSE) value of the LAI estimation from the DAO was only approximately 0.05 m² m⁻² (2%) lower than that from the SAO. If more angle observations can be acquired for each pixel, the accuracy of LAI estimation may be further improved. However, more angle observations may also add to the uncertainty of the LAI estimation. For example, Dorigo (2012) showed that including the +55° viewing angle of the CHRIS/PROBA in the inversion scheme dramatically reduced the

![Fig. 7. Measured surface reflectance from single-angle observations L1 and L2 for (a) maize, (b) potato, and (c) sunflower.](image)
accuracy of LAI estimation. Therefore, optimal directional sampling is necessary to obtain high accuracy of LAI estimation.

5. Conclusions

This study investigated the performance of LUT-based inversion of the PROSAIL model for LAI estimation from the UAV-HYPAR data. LAI estimation was performed along two overlapping flight lines, L1 and L2, in a study area over three typical row crops: maize, potato, and sunflower. In situ LAI measurements were also collected. The estimated LAI was evaluated against the in situ LAI measurements in terms of the RMSE and RRMSE. For the SAO L1, the best-performing crop was sunflower, with an RMSE of 0.45 m² m⁻² and an RRMSE of 10.6%, and the worst-performing crop was potato, with an RMSE of 0.62 m² m⁻² and an RRMSE of 14.2%. For the SAO L2, the best accuracy was achieved for potato, with an RMSE of 0.22 m² m⁻² and an RRMSE of 5.2%, whereas the worst accuracy was achieved for maize, with an RMSE of 0.96 m² m⁻² and an RRMSE of 31.1%. Nevertheless, the accuracy of LAI estimation for all crops was similar for the SAOs L1 and L2. These results indicate that the PROSAIL model is suitable for LAI estimation for these three crops with reasonable accuracy in terms of the RMSE and RRMSE.

The UAV-HYPAR data in the area where the flight lines overlapped provided an opportunity to estimate LAI from the DAo. The estimated LAI from the SAO and the DAo were compared against the in situ LAI measurements. The RMSE (RMSE) value was approximately 0.62 m² m⁻² (15.5%) for the SAO and approximately 0.55 m² m⁻² (13.6%) for the DAo. These results show that using the DAo rather than the SAO improves the accuracy of LAI. The effects of different LUT sizes on the accuracy of LAI estimation were also investigated. The results demonstrate that the size of the LUT does not affect the accuracy of the LAI estimation. The impact of different cost functions on the accuracy of LAI estimation was also analyzed. The results showed that the choice of cost function influences the accuracy of LAI estimation.

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