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Spatially constrained inversion of radiative transfer models for improved LAI mapping from future Sentinel-2 imagery

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ABSTRACT

The robust and accurate retrieval of vegetation biophysical variables using radiative transfer models (RTM) is seriously hampered by the ill-posedness of the inverse problem. With this research we further develop our previously published (object-based) inversion approach [Atzberger, 2004, RSE 93: 53–67] and evaluate it against simulated Sentinel-2 data. The proposed RTM inversion takes advantage of the geostatistical fact that the biophysical characteristics of nearby pixels are generally more similar than those at a larger distance. This leads to spectral co-variations in the n-dimensional spectral features space, which can be used for regularization purposes. A simple two-step inversion based on PROSPECT + SAIL generated look-up-tables is presented that can be easily adapted to other radiative transfer models. The approach takes into account the spectral signatures of adjacent pixels in gliding (3 × 3) windows. Using a set of leaf area index (LAI) measurements (n = 26) acquired over alfalfa, sugar beet and garlic crops of the Barrax test site (Spain), it is demonstrated that the proposed regularization using neighbourhood information yields more accurate results compared to the pixel-based inversion. With the proposed regularization, the RMSE between ground measured and Sentinel-2 derived LAI is 0.54 m^2/m^2 and hence significantly lower compared to the RMSE of the standard inversion approach (RMSE: 1.46 m^2/m^2) and also of higher accuracy compared to a scaled NDVI model (RMSE: 0.90 m^2/m^2). At the same time, a positive effect on the modelled leaf chlorophyll content (C_{ab}) is noticed, albeit too few field measurements were available for deriving statistically sound results. For the other retrieved biophysical parameters such as leaf dry matter content (C_m), soil brightness (α_{soil}) and average leaf angle (ALA) the proposed algorithm yields more plausible and spatially consistent results. Altogether the findings confirm the positive effect of regularizing the model inversion using spatial constraints. As for any other inversion strategy, the approach requires a RTM well suited for the crop under study. For three additional crops (maize, potatoes and sunflower), the forward modelling with field measured LAI did not match the observed signatures. Consequently, for these canopies both the standard and the object-based inversion failed.

1. Introduction

A continuous mapping of vegetation biophysical variables at high spatial and temporal frequency is serviceable in numerous applications such as for natural resource management, precision agriculture, forestry, Soil-Vegetation-Atmosphere Transfer (SVAT) modelling and hydrology (Asrar, 1989; Houborg et al., 2007). Of particular interest is the leaf area index (LAI) as plant leaves constitute the main surface available for energy and mass exchange between land surface and atmosphere (Asner et al., 2003; Moran et al., 1995). The regular and accurate mapping of LAI is therefore essential, but ground-based measurements are usually time-consuming as well as cost- and labour-intensive. As a promising alternative, Earth observation (EO) data from spaceborne/airborne sensors have been successfully adopted in the last decades, as demonstrated through a range of studies. The upcoming Sentinel-2 mission will further improve existing EO capabilities, as the sensors will have several advantageous spectral, spatial and temporal characteristics, compared to current satellite systems. With an envisaged ground sampling distance (GSD) of 10 m to 20 m for those bands to be exploited for the estimation of vegetation variables, Sentinel-2 sensors will be very suitable for precision agricultural applications. The high revisit frequency of only 5 days will additionally allow for multi-temporal information retrieval (Martimort et al., 2007).

Generally, the estimation procedures for biophysical variables from EO data can be grouped into two main categories: the first group involves empirical-statistical approaches, where regression models are calibrated against a set of *in situ* measurements. Most frequently, one of the many existing vegetation indices (VI) are used as predictors (Baret and Guyot, 1991; Glenn et al., 2008; Haboudane et al., 2004). Alternatively, predictor variables based on derivatives have been exploited such as the red edge position (REIP) (Baret et al., 1992; Cho et al., 2008; Darvishzadeh et al., 2009) or continuum-removed variables

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(Kokaly and Clark, 1999; Schlerf et al., 2010). To better exploit the full spectral information available, multi-variate (linear) regression models have been used, such as partial least squares regression (PLS) (Atzberger et al., 2010; Darvishzadeh et al., 2008a) or neural nets (e.g., Bacour et al., 2006; Danson et al., 2003). The main disadvantage of these empirical–statistical approaches is their limited transferability to different measurement conditions, sites and crop types. To minimize estimation uncertainties, large reference data sets are required for model calibration, rendering such approaches inappropriate for applications in large areas or for operational monitoring programs relying on regularly updated maps (Baret and Buis, 2008; Colombo et al., 2003).

With the advancement in developing radiative transfer models (RTM) simulating the spectral top-of-canopy bi-directional reflectance by means of physical principles, these limitations can be overcome. Therefore, the second group of estimation algorithms is based on RTM inversion techniques, which have been employed with success over various crops (e.g., Combal et al., 2002a; Vuolo et al., 2008), for (semi) natural vegetation (Darvishzadeh et al., 2008b), or in managed forests and plantations (Peddle et al., 2004; Schlerf and Atzberger, 2006).

Various techniques have been proposed to invert RTMs (Goel, 1989; Kimes et al., 2000; Liang, 2007). Traditionally, numerical optimization procedures were used (e.g. Goel and Thompson, 1984; Jacquemoud, 1993; Jacquemoud et al., 1995). Later, look-up-tables (LUT) (e.g. Combal et al., 2002a; Knyazikhin et al., 1999; Weiss et al., 2000), predictive equations (Le Maire et al., 2004, 2008; Yao et al., 2008), support vector machines (SVM) (Durbha et al., 2007) and neural nets (Atzberger, 2010; Weiss and Baret, 1999) have been applied. Comparative analyses demonstrated strengths and limitations of each inversion technique, depending on the dataset and the context of the application (Kimes et al., 2000; Richter et al., 2009).

One of the main difficulties in this context is the ill-posedness of the inversion (Combal et al., 2002b; Jacquemoud, 1993). The ill-posedness is mainly caused by the under-determined nature of the modelling schemes (Jacquemoud et al., 1995). At first, the number of unknown variables is generally higher than the number of independent radiometric measurements acquired (Baret and Buis, 2008). Secondly, different parameter combinations may yield almost identical spectral–directional signatures as the various model parameters may counterbalance each other (Atzberger, 2004; Darvishzadeh et al., 2008c; Jacquemoud and Baret, 1993). The problem is further amplified since neither the RTM nor the reflectance measurements are error-free (Baret and Buis, 2008). Altogether this may result in unstable and inaccurate inversion performances if no regularization is applied (Durbha et al., 2007).

Different strategies have been proposed to solve the problem (for an overview see Baret and Buis, 2008). In approaches based on LUT, several studies pointed out that the use of multiple solutions (instead of the single best solution) increases to some extent the robustness of the estimates. Another simple and straightforward solution consists in using *a priori* information about the retrieved variables (Baret and Buis, 2008; Combal et al., 2002b). Such constraints can be either implemented in the cost function leading to the Bayesian approach (Tarantola, 2005), or applied to the model input parameter ranges (Darvishzadeh et al., 2008a,b). Dorigo et al. (2009), for instance, coupled their RTM inversion with an automated land cover classification, adjusting the model input variables by means of predictive equations according to the respective land use classes. Houborg et al. (2009) used a coupled leaf, canopy and atmospheric radiative transfer model and applied an iterative inverse retrieval strategy. In this way, estimation of canopy characteristics could be regularized field/class-specific. As an alternative, the dimensionality of the data can be increased, using either spatio-temporal signatures (Lauvernet et al., 2008), multi-angular information (Goel, 1989; Vuolo et al., 2008) or a combination of different remote sensing data sets, such as from optical and microwave systems (Clevers and van Leeuwen, 1996). However, such additional information is not always available. Therefore, a strategy using neighbourhood information has been proposed and exploited by Atzberger (2004). In this "patch-ensemble" or "object-based" approach the covariances between spectral variables over a certain number of pixels representing the same class of object (e.g., an agricultural field) are analysed. The method requires therefore remotely sensed imagery with a spatial resolution sufficient enough to distinguish the different objects (such as provided by the future Sentinel-2 sensor). Relying on synthetic data, Atzberger (2004) demonstrated that the "object signature" contains valuable additional information to mitigate the compensation between LAI and the average leaf angle (ALA) in the inversion process. Positive effects of neighbourhood information and/or the use of per-field signatures are well known for land use and land cover classifications (Blaschke, 2010; Cremers et al., 2007; Guerif et al., 1996).

The main objective of the present study is to demonstrate the effectiveness of the object-based RTM inversion for the Sentinel-2 band setting and GSD using spectral data acquired by CHRIS/PROBA. The effectiveness of the proposed approach is assessed: (i) against reference LAI measurements (Barrax campaign), (ii) with respect to the spatial consistency of the retrieved biophysical fields, and (iii) through comparison of retrieval accuracies with those obtained from a standard RTM inversion approach and a simple empirical method using the Normalized Difference Vegetation Index (NDVI). The study is an extension of a previously published conference paper based on the same test data set (Atzberger and Richter, 2009). It further extends the original idea developed on synthetic data (Atzberger, 2004) and provides graphical illustrations of the underlying concept.

2. Materials and methods

2.1. Experimental site and observations

For the application of the proposed inversion technique, observations of the interdisciplinary ESA SPARC 2004 campaign (Moreno et al., 2004) were used. The field campaign was carried out in July 2004 at the Barrax site (N 30° 3′, W 2° 6′), an agricultural test area situated in the Castilla–La Mancha region, in southern Spain. Different satellite and airborne data were obtained concurrently with measurements of vegetation parameters for a range of crops, including alfalfa, maize, potatoes, sunflower, garlic and sugar beet. The crops were grown on large uniform land use units (Fig. 1), offering an ideal data basis for the study objectives.

Experiencing with the same data set, it was noticed through forward modelling that the PROSAIL radiative transfer model is not well

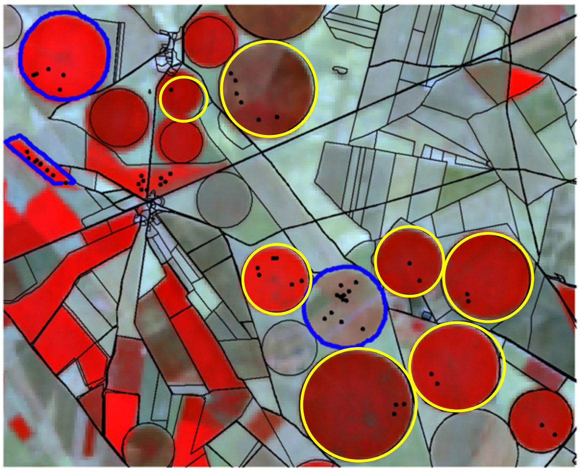

Fig. 1. Study area Barrax during the SPARC 2004 field campaign: CHRIS/PROBA image of 16 July 2004 at 11:25 UTC with the positions of LAI ground observations (black dots). The study mainly relies on the three fields with blue field boundaries. Results for three additional crops (in yellow) are presented in less detail.