Remote Sensing of Environment 140 (2014) 318–329

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Bayesian object-based estimation of LAI and chlorophyll from a simulated Sentinel-2 top-of-atmosphere radiance image

Valérie C.E. Laurent [a,c,*], Michael E. Schaepman [a], Wout Verhoef [b], Joerg Weyermann [a], Roberto O. Chávez [c]

[a] Remote Sensing Laboratories, University of Zurich, Winterthurerstrasse 190, CH-8057 Zurich, Switzerland
[b] Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands
[c] Laboratory of Geo-Information Science and Remote Sensing, Wageningen University, P.O. Box 47, 6700 AA Wageningen, The Netherlands

ARTICLE INFO

Article history:
Received 11 January 2013
Received in revised form 4 September 2013
Accepted 6 September 2013
Available online 1 October 2013

Keywords:
Top-of-atmosphere radiance
Sentinel-2
APEX
Variable estimation
Bayesian optimization
Object-based
Coupled model
Radiative transfer
SLC
MODTRAN4
Li–Ross
Nadir-normalization

ABSTRACT

Leaf area index (LAI) and chlorophyll content (Cab) are important vegetation variables which can be monitored using remote sensing (RS). Physically-based approaches have higher transferability and are therefore better suited than empirically-based approaches for estimating LAI and Cab at global scales. These approaches, however, require the inversion of radiative transfer (RT) models, which is an ill-posed and underdetermined problem. Four regularization methods have been proposed, allowing finding stable solutions: 1) model coupling, 2) using a priori information (e.g. Bayesian approaches), 3) spatial constraints (e.g. using objects), and 4) temporal constraints. For mono-temporal data, only the first three methods can be applied.

In an earlier study, we presented a Bayesian object-based algorithm for inverting the SLC-MODTRAN4 coupled canopy-atmosphere RT model, and compared it with a Bayesian LUT inversion. The results showed that the object-based approach provided more accurate LAI estimates. This study, however, heavily relied on expert knowledge about the objects and vegetation classes. Therefore, in this new contribution, we investigated the applicability of the Bayesian object-based inversion of the SLC-MODTRAN4 model to a situation where no such knowledge was available.

The case study used a 16×22 km^2 simulated top-of-atmosphere image of the upcoming Sentinel-2 sensor, covering the area near the city of Zurich, Switzerland. Seven APEX radiance images were nadir-normalized using the parametric Li–Ross model, spectrally and spatially resampled to Sentinel-2 specifications, geometrically corrected, and mosaicked. The atmospheric effects between APEX flight height and top-of-atmosphere level were added based on two MODTRAN4 simulations. The vegetation objects were identified and delineated using a segmentation algorithm, and classified in four levels of brightness in the visible domain. The LAI and Cab maps obtained from the Bayesian object-based inversion of the coupled SLC-MODTRAN4 model presented realistic spatial patterns. The impact of the parametric Li–Ross nadir-normalization was evaluated by comparing 1) the angular signatures of the SLC-MODTRAN4 and Li–Ross models, and 2) the LAI and Cab maps obtained from a Li–Ross nadir-normalized image (using nadir viewing geometry) and from the original image (using the original viewing geometry). The differences in angular signatures were small but systematic, and the differences between the LAI and Cab maps increased from the center towards the edges of the across-track direction. The results of this study contribute to preparing the RS community for the arrival of Sentinel-2 data in the near future, and generalize the applicability of the Bayesian object-based approach for estimating vegetation variables to cases where no field data are available.

1. Introduction

Global climate and carbon cycles are strongly influenced by the Earth's biosphere, and in particular by its vegetation component. Vegetation variables, such as leaf area index (LAI) and leaf chlorophyll content (Cab), are therefore important inputs in dynamic global vegetation models (DGVM) (Foley, Levis, Costa, Cramer, & Pollard, 2000). These vegetation inputs can be provided in a spatially continuous way and at global scale by satellite remote sensing (Bacour, Baret, Béal, Weiss, & Pavageau, 2006; Baret et al., 2007; Myneni et al., 2002).

Usually, remote sensing data are first atmospherically corrected to top-of-canopy (TOC) reflectance data before they are used for estimating the vegetation variables. The variables can be estimated by using two main approaches. Empirical approaches rely on statistical relationships between the vegetation variables and the TOC reflectance data. The

* Corresponding author at: Irstea, UMR TETIS, Maison de la Télédétection, 500 rue J.F. Breton, 34093 Montpellier Cedex 5, France. Tel.: +33 467558615; fax: +33 467548700.
E-mail addresses: valerie.laurent@geo.uzh.ch, valerie.laurent@teledetection.fr (V.C.E. Laurent), michael.schaepman@geo.uzh.ch (M.E. Schaepman), w.verhoef@utwente.nl (W. Verhoef), joerg.weyermann@geo.uzh.ch (J. Weyermann), roberto.chavez@wur.nl (R.O. Chávez).

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http://dx.doi.org/10.1016/j.rse.2013.09.005

statistical relationships, however, require extensive field data collection and are only valid for the specific conditions for which they were developed, including sensor, acquisition geometry, and vegetation type (Dorigo et al., 2007; Ustin et al., 2009). Physically based approaches rely on vegetation canopy reflectance models, which are mostly based on radiative transfer (RT) theory, and are therefore more general because they can be adapted for different sensors, acquisition geometry and be parameterized for various vegetation types (Gemmell, Varjo, Strandstrom, & Kuusk, 2002; Malenovský et al., 2008).

1.1. Physically-based estimation of vegetation variables

To estimate the vegetation variables from the TOC reflectance data, however, the canopy RT model has to be inverted. This inverse problem is ill-posed (Combal et al., 2002; Jacquemoud et al., 2009), and four types of regularization methods have been proposed (Baret & Buis, 2008): 1) coupling models, 2) using a priori data, 3) using spatial constraints and 4) using temporal constraints, or combinations of these.

Model coupling allows reducing the number of input parameters, thereby reducing the under-determined nature of the inversion (Baret & Buis, 2008). The maximum model coupling set-up involves soil, leaf, canopy, and atmosphere RT models. Using such a coupled model allows working directly with the top-of-atmosphere (TOA) radiance data, skipping the atmospheric correction step (Laurent, Verhoef, Clevers, & Schaepman, 2011a). The atmospheric correction requires inverting the atmospheric RT model, whereas, when working at TOA level, the atmospheric RT model is used in forward mode, which is more accurate and allows for better inclusion of canopy directional effects (Laurent, Verhoef, Clevers, & Schaepman, 2011b), topography and adjacency effects in the coupled canopy-atmosphere model. Despite the higher model complexity, the traditional inversion techniques can be used, and the same knowledge of the atmospheric parameters as in the atmospheric correction is sufficient.

A priori information allows restricting the variable space to a smaller subspace, thus facilitating the inversion (Combal et al., 2002). Bayesian approaches use the a priori data directly in the cost function, and have been widely used for estimating vegetation variables (Lavergne et al., 2007; Li, Gao, Wang, & Strahler, 2001; Pinty et al., 2007). Spatial constraints allow using the information contained in the neighbouring pixels in the inversion (Atzberger, 2004; Atzberger & Richter, 2012; Houborg, Anderson, & Daughtry, 2009), while temporal constraints allow using the information contained in a time series of remote sensing observations (Kötz, Baret, Poilve, & Hill, 2005; Lauvernet, Baret, Hascoët, Buis, & Le Dimet, 2008).

For a single RS image, the maximum regularization set-up involves a coupled canopy-atmosphere RT model, a priori information, and spatial constraints (Laurent, Verhoef, Damm, Schaepman, & Clevers, 2013).

1.2. Sentinel-2

Sentinel-2 is a scheduled multispectral and high spatial resolution mission which is part of the Global Monitoring for Environment and Security (GMES) program (Berger, Moreno, Johannessen, Levelt, & Hanssen, 2012; Drusch et al., 2012; Malenovský et al., 2012). The spectral and spatial characteristics for the Sentinel-2 mission have been specified so as to provide enhanced continuity for SPOT and Landsat missions in the visible (VIS), near infrared (NIR) and short-wave infrared (SWIR) spectral domains. The Multi Spectral Instrument (MSI) onboard Sentinel-2 will have 13 spectral bands in the range from 400 to 2400 nm, with pixel sizes of 10, 20, or 60 m, depending on the spectral band (Drusch et al., 2012; Sentinel-2 PDGS Project Team, 2011). The first of two satellites is planned to be launched in 2014. Until Sentinel-2 data are available, several studies have investigated the potential of Sentinel-2 for vegetation applications.

Most of the Sentinel-2 exploratory studies focussed on the spectral dimension, selecting appropriate bands from surrogate sensors such as CHRIS (Atzberger & Richter, 2012; Delegido, Verrelst, Alonso, & Moreno, 2011) and HyMap (Richter, Hank, Vuolo, Mauser, & D'Urso, 2012), or convolving the bands of hyperspectral sensors such as CASI (Richter, Atzberger, Vuolo, & D'Urso, 2011a; Richter, Atzberger, Vuolo, Weihs, & D'Urso, 2009) or field spectrometers (Clevers & Gitelson, 2013; Herrmann et al., 2011) to the Sentinel-2 bands. Limited by the spectral range of the surrogate sensor used, most of these studies were not able to simulate the blue and the SWIR Sentinel-2 bands in full.

Further, few studies included the varying pixel size in their simulated Sentinel-2 data (Richter, Wang, Bachmann, & Schläpfer, 2011b), and even fewer investigated the potential of the spatial characteristics of the Sentinel-2 data (Hedley, Roelfsema, Koetz, & Phinn, 2012; Verrelst et al., 2012). Only two studies made use of top-of-atmosphere simulated Sentinel-2 data, and they focussed on cloud detection and correction (Hagolle, Huc, Pascual, & Dedieu, 2010; Richter et al., 2011b), but not on vegetation.

Therefore, despite its potential use for supporting the development of (pre)processing algorithms in advance, a full TOA simulated image compliant with all spectral and spatial characteristics of the Sentinel-2 mission so far was still missing.

1.3. Objectives

The two main objectives of this study were to: 1) build a realistic TOA Sentinel-2 image with full spectral and spatial characteristics as specified in the Sentinel-2 documentation, and 2) estimate LAI and Cab from the Sentinel-2 image by inverting a coupled canopy-atmosphere RT model.

The particular spatial and spectral characteristics of Sentinel-2 can only be simulated using high resolution airborne imaging spectrometer data. APEX was chosen for this purpose because of its unprecedented spectral, spatial and radiometric resolution. Its continuous spectral coverage of the range 380 to 2500 nm (Jehle et al., 2010) allowed simulating all 13 Sentinel-2 bands. Each band was simulated with at least three APEX bands (D'Odorico, Gonsamo, Damm, & Schaepman, 2013), and each Sentinel-2 pixel was covered by at least nine APEX pixels. The signal-to-noise ratio (SNR) of APEX is also well above the expected SNR of Sentinel-2. Seven APEX images were normalized to nadir viewing before being spatially and spectrally resampled and mosaicked. The simulated Sentinel-2 image covers an area of 16×22 km^2 around the city of Zurich, Switzerland, which includes a wide range of land cover types (e.g., agriculture, forest, lakes, an airport and urban areas). In order to obtain the most accurate LAI and Cab estimates as possible from this single image, the Bayesian object-based approach of Laurent et al. (2013) was chosen, because it combines the strengths of model coupling, a priori data and spatial constraints regularization methods. This latter study, however, relied on manual digitization of the objects used to apply the spatial constraints and was based on extensive field data on vegetation classes and their associated a priori data. Therefore, two specific objectives were added to the main objectives: 1) evaluate the effect of the normalization to nadir viewing of the APEX images, and 2) propose an image-based approach for extracting objects, and a general vegetation classification associated with a priori data which does not require field data.

The results of this study contribute to preparing the RS community for the arrival of Sentinel-2 data in the near future, and generalize the applicability of the Bayesian object-based approach for estimating vegetation variables to cases where no field data are available, as is generally the case for studies in less accessible regions as well as global studies.