

Available online at www.sciencedirect.com



**Remote Sensing** Environment

Remote Sensing of Environment 112 (2008) 186–202

www.elsevier.com/locate/rse

## Mapping leaf chlorophyll and leaf area index using inverse and forward canopy reflectance modeling and SPOT reflectance data

Rasmus Houborg<sup>a,\*</sup>, Eva Boegh<sup>b</sup>

<sup>a</sup> USDA-ARS, Hydrology and Remote Sensing Laboratory, BARC-WEST, Beltsville, MD 20705, United States b Roskilde University, Universitetsvej 1, DK-4000 Roskilde, Denmark

Received 14 November 2006; received in revised form 17 April 2007; accepted 22 April 2007

## Abstract

Reflectance data in the green, red and near-infrared wavelength region were acquired by the SPOT high resolution visible and geometric imaging instruments for an agricultural area in Denmark (56°N, 9°E) for the purpose of estimating leaf chlorophyll content ( $C_{ab}$ ) and green leaf area index (LAI). SPOT reflectance observations were atmospherically corrected using aerosol data from MODIS and profiles of air temperature, humidity and ozone from the Atmospheric Infrared Sounder (AIRS), and used as input for the inversion of a canopy reflectance model. Computationally efficient inversion schemes were developed for the retrieval of soil and land cover-specific parameters which were used to build multiple species and site dependent formulations relating the two biophysical properties of interest to vegetation indices or single spectral band reflectances. Subsequently, the family of model generated relationships, each a function of soil background and canopy characteristics, was employed for a fast pixel-wise mapping of  $C_{ab}$  and LAI.

The biophysical parameter retrieval scheme is completely automated and image-based and solves for the soil background reflectance signal, leaf mesophyll structure, specific dry matter content, Markov clumping characteristics,  $C_{ab}$  and LAI without utilizing calibration measurements.

Despite the high vulnerability of near-infrared reflectances  $(\rho_{\text{nir}})$  to variations in background properties, an efficient correction for background influences and a strong sensitivity of  $\rho_{\text{nit}}$  to LAI, caused LAI– $\rho_{\text{nit}}$  relationships to be very useful and preferable over LAI–NDVI relationships for LAI prediction when LAI>2. Reflectances in the green waveband ( $\rho_{\text{green}}$ ) were chosen for producing maps of  $C_{ab}$ .

The application of LAI–NDVI, LAI– $\rho_{\text{air}}$  and  $C_{ab}$ – $\rho_{\text{green}}$  relationships provided reliable quantitative estimates of  $C_{ab}$  and LAI for agricultural crops characterized by contrasting architectures and leaf biochemical constituents with overall root mean square deviations between estimates and in-situ measurements of 0.74 for LAI and 5.0  $\mu$ g cm<sup>-2</sup> for C<sub>ab</sub>.

The results of this study illustrate the non-uniqueness of spectral reflectance relationships and the potential of physically-based inverse and forward canopy reflectance modeling techniques for a reasonably fast and accurate retrieval of key biophysical parameters at regional scales. © 2007 Elsevier Inc. All rights reserved.

Keywords: Leaf chlorophyll; Leaf area index; SPOT; AIRS; MODIS; Spectral reflectances; Canopy reflectance model; Inverse modeling; Atmospheric correction; Markov clumping; Leaf mesophyll structure; Dry matter content; Green reflectance; Near-infrared reflectance; NDVI; Image-based application; Maize; Barley; Wheat

## 1. Introduction

Accurate quantitative estimates of leaf biochemical and canopy biophysical variables are important for land surface models quantifying the exchange of energy and matter between the land surface and the lower atmosphere. Key variables include the leaf area index (LAI), here defined as the single sided area of green, functioning leaves per unit ground, that exhibits a major control on transpiration and uptake of  $CO<sub>2</sub>$  by the canopy, and leaf chlorophyll content  $(C_{ab})$  that can assist in determining photosynthetic capacity and productivity (e.g. [Boegh et al., 2002; Nijs et al., 1995\)](#page--1-0).

Remotely sensed data in the reflective optical domain function as a unique cost-effective source for a detailed knowledge of the spatial and temporal variations of these key canopy characteristics. The shape and form of canopy reflectance

<sup>⁎</sup> Corresponding author. Tel.: +1 301 504 8902; fax: +1 301 504 8931. E-mail address: [rasmus.houborg@ars.usda.gov](mailto:rasmus.houborg@ars.usda.gov) (R. Houborg).

<sup>0034-4257/\$ -</sup> see front matter © 2007 Elsevier Inc. All rights reserved. doi:[10.1016/j.rse.2007.04.012](http://dx.doi.org/10.1016/j.rse.2007.04.012)

spectra depends on many factors such as vegetation structure, leaf biochemical composition, soil background, and the view and illumination geometry. For instance, LAI has a large impact on reflectance spectra especially in the near-infrared (NIR) while the visible part of the spectrum is strongly affected by leaf chlorophyll.

Remote sensing techniques to estimate vegetation characteristics from reflective optical measurements have either been based on the empirical–statistical approach that relates surface measurements of canopy variables to single spectral reflectances or vegetation indices (VI), or on the inversion of a physically based canopy reflectance (CR) model. Both approaches have their advantages and disadvantages. The potential of VIs for the determination of crop parameters have been demonstrated in numerous studies (e.g. [Broge &](#page--1-0) [Leblanc, 2001; Colombo et al., 2003; Gitelson et al., 2005;](#page--1-0) [Tucker, 1980\)](#page--1-0) and the simplicity and computational efficiency of the approach makes it highly desirable for large-scale remote sensing applications. However, a fundamental problem with the VI approach for estimating biophysical variables is its lack of generality. Since canopy reflectance depends on a complex interaction of several internal and external factors ([Baret, 1991\)](#page--1-0) that may vary significantly in time and space and from one crop type to another, no universal relationship between a single canopy variable and a spectral signature can be expected to exist. Consequently, spectral reflectance relationships will be site-, time-and crop-specific, making the use of a single relationship for an entire region unfeasible ([Baret & Guyot, 1991: Colombo et al., 2003; Gobron et al.,](#page--1-0) [1997\)](#page--1-0).

The physically-based models have proven to be a promising alternative as they describe the transfer and interaction of radiation inside the canopy based on physical laws and thus provide an explicit connection between the biophysical variables and the canopy reflectance. Different strategies have been proposed for the inversion of these models including numerical optimization methods (e.g. [Jacquemoud et al., 1995,](#page--1-0) [2000](#page--1-0)), look-up table approaches (e.g. [Combal et al., 2002;](#page--1-0) [Knyazikhin et al., 1998a,b; Weiss et al., 2000](#page--1-0)) and artificial neural network methods (e.g. [Bacour et al., 2006; Fang &](#page--1-0) [Liang, 2005; Walthall et al., 2004; Weiss & Baret, 1999](#page--1-0)). Lookup table and neural network approaches require a training database consisting of canopy reflectance spectra together with the corresponding biophysical variables, and their performances rely on the training database and the training process itself. Ideally, these approaches should be learned on experimental data which is not readily available for most places on the globe. The iterative optimization approach facilitates a direct retrieval of biophysical parameters from observed reflectances without the prior use of calibration or training data of any kind. However, this method suffers from its expensive computational requirement [\(Jacquemoud et al., 2000\)](#page--1-0) making the retrieval of biophysical variables unfeasible for large geographic areas. A limitation shared by all of the physicallybased models is the ill-posed nature of model inversion ([Atzberger, 2004; Combal et al., 2002](#page--1-0)); the fact that different combinations of canopy parameters may correspond to almost similar spectra. This makes the choice of the initial parameter values important, and some regularization of the inverse problem may be required implying the use of a priori knowledge or information on the spatial or temporal variability of key canopy parameters to constrain the inversion process ([Atzberger, 2004; Combal et al., 2002; Houborg et al., 2007](#page--1-0)).

The crop-specific sensitivity of spectral reflectance relationships to canopy geometry (e.g. leaf angle distribution and clumping) and leaf properties (e.g. dry matter and mesophyll structure) and the site-specific sensitivity to atmospheric and background influences must be properly accounted for in order to apply spectral reflectance relationships for the mapping of LAI and  $C_{ab}$ . In this study inverse and forward CR modeling techniques were combined for a pixel-wise estimation of LAI and  $C_{ab}$  from a family of spectral reflectance relationships. The relationships were derived separately for pre-classified land cover classes due to the dependence on land cover-specific parameters and were also made dependent on the soil background reflectance signal. To make LAI and  $C_{ab}$  estimates independent of in-situ and calibration data, the crop and sitespecific parameters needed to build the appropriate spectral reflectance relationships were retrieved from the inversion of a CR model employing the iterative optimization approach. Since the inversion of the CR model is computationally demanding the inversions were performed using reflectance observations averaged over several pixels. Additionally, pixel-wise inversions for the retrieval of LAI and  $C_{ab}$  were avoided making the scheme applicable for regional-scale use.

While the use of VI rather than single spectral reflectance relationships for estimating biophysical parameters tends to reduce the sensitivity to internal and external factors such as background and atmospheric influences, the translation of spectral reflectance data into a VI may also reduce the sensitivity to the parameter of interest. For instance, the widely used Normalized Difference Vegetation Index (NDVI) that combines reflectances in the near-infrared (NIR) and red waveband approaches a saturation level at intermediate values of LAI while NIR band reflectances remain sensitive to LAI in densely vegetated areas (e.g. [Huete et al., 2002; Knyazikhin](#page--1-0) [et al., 1998a](#page--1-0)). Several studies have demonstrated a maximum sensitivity of reflectances in the green (540–560 nm) and red edge (700–730 nm) spectrum to changing leaf chlorophyll concentrations (e.g. [Gitelson et al., 1996; Gitelson et al., 2005;](#page--1-0) [Houborg et al., 2007; Yoder & Pettigrew-Crosby, 1995\)](#page--1-0). However, VIs that combine leaf chlorophyll sensitive reflectances and  $\rho_{\text{nir}}$ , which is highly responsive to changing leaf biomass, are typically not correlated with leaf chlorophyll content due to a high variability of  $\rho_{\text{nir}}$  relative to chlorophyll sensitive reflectance data [\(Boegh et al., 2002\)](#page--1-0). In this study, the use of NIR band reflectances as predictors of LAI for intermediate to high vegetation densities was investigated while NDVI relationships were adopted for low vegetation densities. The mapping of leaf chlorophyll rather than total canopy chlorophyll was facilitated using relationships based on reflectances from the green waveband.

In this particular study, the turbid medium Markov chain CR model developed by [Kuusk \(1995, 2001\)](#page--1-0) coupled to the

Download English Version:

<https://daneshyari.com/en/article/4460545>

Download Persian Version:

<https://daneshyari.com/article/4460545>

[Daneshyari.com](https://daneshyari.com/)