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A physically-based model for retrieving foliar biochemistry and leaf orientation using close-range imaging spectroscopy

Sylvain Jay [a,*], Ryad Bendoula [a], Xavier Hadoux [b,c], Jean-Baptiste Féret [d], Nathalie Gorretta [a]

[a] Irstea, UMR ITAP, 361 rue J.F. Breton, 34196 Montpellier, France
[b] Centre for Eye Research Australia, Royal Victorian Eye and Ear Hospital, Melbourne, Australia
[c] Ophthalmology, University of Melbourne, Department of Surgery, Melbourne, Australia
[d] Irstea, UMR TETIS, Maison de la Télédétection, 500 rue J.F. Breton, 34093 Montpellier, France

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ABSTRACT

Radiative transfer models have long been used to characterize the foliar content at the leaf and canopy levels. However, they still do not apply well to close-range imaging spectroscopy, especially because directional effects are usually not taken into account. For this purpose, we introduce a physical approach to describe and simulate the variation in leaf reflectance observed at this scale. Two parameters are thus introduced to represent (1) specular reflection at the leaf surface and (2) local leaf orientation. The model, called COSINE (ClOse-range Spectral ImagiNg of lEaves), can be coupled with a directional–hemispherical reflectance model of leaf optical properties to relate the measured reflectance to the foliar content. In this study, we show that, when combining COSINE with the PROSPECT model, the overall PROCOSINE model allows for a robust submillimeter retrieval of foliar content based on numerical inversion and pseudo-bidirectional reflectance factor hyperspectral measurements.
The relevance of the added parameters is first shown through a sensitivity analysis performed in the visible and near-infrared (VNIR) and shortwave infrared (SWIR) ranges. PROCOSINE is then validated based on VNIR and SWIR hyperspectral images of various leaf species exhibiting different surface properties. Introducing these two parameters within the inversion allows us to obtain accurate maps of PROSPECT parameters, e.g., the chlorophyll content in the VNIR range, and the equivalent water thickness and leaf mass per area in the SWIR range. Through the estimation of light incident angle, the PROCOSINE inversion also provides information on leaf orientation, which is a critical parameter in vegetation remote sensing.

1. Introduction

Due to the strong interactions occurring between vegetation and the incoming optical radiation through absorption and scattering processes, hyperspectral remote sensing from satellites and aircrafts provides critical information to assess the spatial and temporal variabilities of vegetation status from local to global scales. This has led to a number of agricultural, environmental and ecological applications such as the retrieval of leaf pigments (Ustin et al., 2009; Zarco-Tejada, Miller, Morales, Berjón, & Aguera, 2004), the early detection of leaf diseases (Mahlein et al., 2013) or the mapping of forest biodiversity (Féret & Asner, 2014). As hyperspectral cameras are now becoming more affordable, close-range remote sensing data are also increasingly available to the scientific community. Compared with air- and satellite-borne data, they generally offer a submillimeter or millimeter spatial resolution, and they can be acquired at a higher temporal frequency, which is particularly interesting for precision agriculture. For example, these data can be used to identify plant pigments (Blackburn, 2007), freezing stress (Nicotra, Hofmann, Siebke, & Ball, 2003) or leaf diseases (Mahlein et al., 2013), each of which is of tremendous importance to follow up the plant physiological status. These images are generally processed by applying statistically-based methods to estimate various leaf biochemical properties (Jay, Hadoux, Gorretta, & Rabatel, 2014; Ji-Yong et al., 2012; Nicotra et al., 2003; Vigneau, Ecarnot, Rabatel, & Roumet, 2011). However, at this scale, a proper physical interpretation based on radiative transfer modeling is needed to describe the interactions between light and vegetation, especially for a spatially- and temporally-resolved quantification of pigments (Blackburn, 2007).

Vegetation radiative transfer models are physically-based and simulate light propagation within leaves and/or canopies, e.g., as a function of leaf biochemical constituents, leaf anatomy or canopy structure. Whenever possible, model inversion allows for the retrieval of the variables of interest, generally using iterative optimization, look-up tables, statistical methods or machine learning algorithms.

* Corresponding author.
E-mail addresses: sylvain.jay@irstea.fr (S. Jay), ryad.bendoula@irstea.fr (R. Bendoula), xavier@hadoux.com (X. Hadoux), jean-baptiste.feret@teledetection.fr (J.-B. Féret), nathalie.gorretta@irstea.fr (N. Gorretta).

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At the leaf level, these models range from simple plate models, to ray-tracing, radiosity and stochastic models that are computationally more difficult to invert (Dorigo et al., 2007). For instance, PROSPECT (Jacquemoud & Baret, 1990) is based on the generalized plate model, and is particularly well suited to estimate leaf biochemical constituents (e.g., chlorophyll content, water content and leaf mass per area) based on spectral measurements in the optical domain. The main reasons for the popularity of PROSPECT are its accuracy, its computational efficiency (resulting in fast iterative model inversion) and free distribution.

At the canopy level, various approaches of different complexities have been developed for radiative transfer modeling, e.g., turbid medium approaches (Verhoef, 1984), geometrical approaches (Chen & Leblanc, 1997) or the combination of both (Gastellu-Etchegorry, Demarez, Pinel, & Zagolski, 1996). Most of these models allow the canopy reflectance to be modeled as a function of parameters related to canopy structure (such as leaf area index or leaf inclination distribution function), leaf optical properties and sun-sensor geometry.

However, leaf and canopy radiative transfer models do not apply well to close-range imaging spectroscopy. For example, at the leaf level, the directional–hemispherical reflectance and transmittance simulated by PROSPECT (Jacquemoud & Baret, 1990) are usually measured with an integrating sphere, whose implementation is difficult (if not impossible) for every single pixel of hyperspectral images. As a result, PROSPECT cannot be inverted based on directional reflectance data as retrieved by a close-range hyperspectral camera, unless it is assumed that leaves are Lambertian (Buddenbaum & Hill, 2015) and in fully horizontal position, which is an unrealistic hypothesis. Indeed, in most cases, leaf reflectance exhibits some anisotropy (Bousquet, Lachérade, Jacquemoud, & Moya, 2005; Comar et al., 2012) and thus varies with respect to illumination and viewing angles. Furthermore, variation in leaf orientation prevent from achieving a proper reflectance correction for every pixel, because the reference surface used for reflectance correction is generally not submitted to the same local illumination conditions than leaf material.

At the canopy level, most radiative transfer models have to be applied to mixed pixels (containing both soil and leaf materials), for which effects of leaf composition, canopy structure, soil properties and viewing/illumination angles are integrated into a single spectrum. Canopy models are thus well suited for ground-based spectroradiometric measurements, as well as for air- and satellite-borne hyperspectral measurements, all of them being usually characterized by a spatial resolution coarser than one meter (Colombo et al., 2008; Schlemmer et al., 2013; Zarco-Tejada, Rueda, & Ustin, 2003). However, most canopy models are not suitable for simulating hyperspectral data characterized by a higher spatial resolution (up to submillimeter level) for which the assumption of mixed pixel does not hold.

In this study, we propose a physically-based model, called COSINE (ClOse-range Spectral ImagiNg of lEaves), that describes the additional spectral variability induced by directional effects and variation in leaf orientation. Combining COSINE with a leaf directional–hemispherical reflectance model such as PROSPECT allows the simulation of leaf reflectance according to our experimental conditions: submillimetric spatial resolution and a single light source assumed to be directional. When applied in inverse mode to close-range hyperspectral images, the overall PROCOSINE model enables the simultaneous retrieval of PROSPECT parameters (e.g., chlorophyll and water contents), bidirectional effects and leaf angle with respect to the light source.

The COSINE theory is described in Section 2. After recalling the necessary radiometric definitions, we develop a physically-based analytic expression of the reflectance quantity retrieved using close-range imaging spectroscopy. This expression is then related to PROSPECT to explain variations in leaf biochemistry and leaf anatomy. In Section 3, we present the data sets used in this article as well as details about model validation and sensitivity analysis. Results are presented and discussed in Section 4, and we finally draw some conclusions and perspectives in Section 5.

2. Theory

2.1. Radiometric considerations

2.1.1. Definitions

The definitions and notations of the main physical quantities used in this article and summarized in Table 1, are based on the initial terminology of Nicodemus, Richmond, Hsia, Ginsberg, and Limperis (1977), which has later been reviewed by Schaepman-Strub, Schaepman, Painter, Dangel, and Martonchik (2006).

The spectral radiance L is the radiant flux in a beam per unit wavelength, per unit area and per unit solid angle, and is expressed in the SI unit $[\mathrm{W \cdot sr^{-1} \cdot m^{-2} \cdot nm^{-1}}]$. This is the physical quantity measured by a hyperspectral imaging sensor after spectral calibration. The spectral irradiance E is the radiant flux in a beam per unit wavelength and per unit area and is expressed in $[\mathrm{W \cdot m^{-2} \cdot nm^{-1}}]$.

One of the main physical quantities used to describe angular patterns of reflected light is the bidirectional reflectance distribution function (BRDF) expressed in $[\mathrm{sr^{-1}}]$. It describes how a parallel beam of incident light from one direction in the hemisphere is reflected into another direction in the hemisphere:

$$f_r(\theta_s;\theta_v,\varphi_v;\lambda) = \frac{dL_r(\theta_s;\theta_v,\varphi_v;\lambda)}{dE_i(\theta_s;\lambda)} \tag{1}$$

where subscripts i and r refer to incoming and reflected lights respectively, θ_s and θ_v are respectively the illumination and viewing zenith angles, and φ_v is the viewing azimuth angle relatively to the illumination azimuth angle (see Fig. 1 for angle representation). The BRDF being the ratio of two infinitesimal quantities, it cannot theoretically be measured. However, its integration over the corresponding solid angles allows the derivation of many other measurable physical quantities.

Usually, the reflectance correction process does not consist in retrieving directly the reflectance (defined as the ratio of the leaving radiant exitance to the incident irradiance), but rather follows the definition of a reflectance factor. In the specific case of single illumination and viewing directions, the bidirectional reflectance factor (BRF, denoted by R) is given by the ratio of the radiant flux dL_r reflected from the area element dA to the radiant flux dL_r^{id} reflected from an ideal and diffuse surface of the same area dA under identical illumination and viewing geometries. It is

Table 1
Main parameters and acronyms.

Parameter	Definition [unit]
b_{spec}	Specular term [unitless]
C_{ab}	Chlorophyll a + b content [$\mathrm{\mu g \cdot cm^{-2}}$]
C_{bp}	Brown pigment content [unitless]
C_{cx}	Carotenoid content [$\mathrm{\mu g \cdot cm^{-2}}$]
C_m	Leaf mass per area [$\mathrm{g \cdot cm^{-2}}$]
C_w	Equivalent water thickness [cm]
E	Spectral irradiance [$\mathrm{W \cdot m^{-2} \cdot nm^{-1}}$]
f_r	Bidirectional reflectance distribution function (BRDF) [$\mathrm{sr^{-1}}$]
L	Spectral radiance [$\mathrm{W \cdot sr^{-1} \cdot m^{-2} \cdot nm^{-1}}$]
λ	Wavelength [nm]
N	Leaf structure parameter [unitless]
φ_l	Difference between illumination and leaf normal azimuth angles [°]
φ_v	Difference between illumination and viewing azimuth angles [°]
R	Bidirectional reflectance factor (BRF) [unitless]
R_{hsi}	Pseudo-bidirectional reflectance factor [unitless]
ρ	Directional–hemispherical reflectance (DHR) [unitless]
θ_i	Light incident angle (angle between the light source and the normal to the leaf) [°]
θ_l, θ_v, θ_s	Leaf normal, viewing and illumination zenith angles [°]
ϑ	PROCOSINE parameters
ϑ_{dhr}	Parameters of the leaf DHR model