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Estimating forest variables from top-of-atmosphere radiance satellite measurements using coupled radiative transfer models

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ABSTRACT

Traditionally, it is necessary to pre-process remote sensing data to obtain top of canopy (TOC) reflectances before applying physically-based model inversion techniques to estimate forest variables. Corrections for atmospheric, adjacency, topography, and surface directional effects are applied sequentially and independently, accumulating errors into the TOC reflectance data, which are then further used in the inversion process. This paper presents a proof of concept for demonstrating the direct use of measured top-of-atmosphere (TOA) radiance data to estimate forest biophysical and biochemical variables, by using a coupled canopy–atmosphere radiative transfer model. Advantages of this approach are that no atmospheric correction is needed and that atmospheric, adjacency, topography, and surface directional effects can be directly and more accurately included in the forward modelling.

In the case study, we applied both TOC and TOA approaches to three Norway spruce stands in Eastern Czech Republic. We used the SLC soil–leaf–canopy model and the MODTRAN4 atmosphere model. For the TOA approach, the physical coupling between canopy and atmosphere was performed using a generic method based on the 4-stream radiative transfer theory which enables full use of the directional reflectance components provided by SLC. The method uses three runs of the atmosphere model for Lambertian surfaces, and thus avoids running the atmosphere model for each new simulation. We used local sensitivity analysis and singular value decomposition to determine which variables could be estimated, namely: canopy cover, fraction of bark, needle chlorophyll, and dry matter content. TOC and TOA approaches resulted in different sets of estimates, but had comparable performance. The TOC approach, however, was at its best potential because of the flatness and homogeneity of the area. On the contrary, the capacities of the TOA approach would be better exploited in heterogeneous rugged areas. We conclude that, having similar performance, the TOA approach should be preferred in situations where minimizing the pre-processing is important, such as in data assimilation and multi-sensor studies.

1. Introduction

Forests are important ecosystems on Earth: they cover about 30% of the land surface (FAO, 2006), provide a wide range of services and have a major influence on the global climate. Dynamic global vegetation models (DGVM) increasingly require forest biophysical and biochemical variables, such as leaf area index (LAI), fractional vegetation cover (fCover), and chlorophyll content, as inputs. These variables can be estimated and monitored using remotely sensed data (Bacour et al., 2006a; Baret et al., 2007; Myneni et al., 2002).

Traditionally, remote sensing data are pre-processed to obtain top-of-canopy (TOC) reflectance data, which are then used to estimate forest variables. We refer to this approach as the TOC approach.

Several categories of methods can be used to estimate forest variables: (semi-) empirical and physically-based are amongst the most frequently used. Empirical methods rely on statistical correlations between image information and forest variables. They depend on many local characteristics, such as vegetation type, background reflectance, sun–target–sensor geometry, and sensor spectral bands, and are therefore site and time specific (Dorigo et al., 2007; Ustin et al., 2009).

Physically-based methods are more general because they rely on physical relationships (Gemmell et al., 2002; Malenovský et al., 2008). Most of these methods use canopy reflectance models based on the radiative transfer (RT) theory. To estimate forest variables, the canopy RT model has to be inverted. The inversion, however, is not straightforward because it is an ill-posed and ill-conditioned problem

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due to the limited information content of the radiometric signal (Jacquemoud et al., 2009) and to measurement and model uncertainties (Combal et al., 2002).

The ill-posedness of the inversion can be reduced by using regularization methods: prior information, spatial (Atzberger, 2004) and temporal constraints (Lauvernet et al., 2008) allow reducing the variable search space, and model coupling allows decreasing the number of free variables (Baret & Buis, 2008; Jacquemoud et al., 2009).

The TOC approach has proven to be successful in the last decades, enabling the production of high level data products (Garrigues et al., 2008; Yang et al., 2006), which are now being used as inputs for DGVMs. Pre-processing of remote sensing data to TOC reflectances, however, is still a cumbersome task, and each pre-processing step has a number of limitations.

Atmospheric correction often relies on the inversion of an atmospheric RT model, which is a limitation in itself because this inversion is ill-posed. In practice, most operational methods use look up tables (LUT) to perform the inversion, leading to frequent interpolation between LUT entries (Guanter et al., 2009; Richter, 2009). In addition, it is often necessary to assume that the surface is Lambertian, which is generally not true, especially for forests (Bicheron & Leroy, 2000). In heterogeneous scenes, adjacency effects are usually dealt with by spatially filtering the image, which is not completely accurate because the measured pixel data are affected by the adjacency effects through the atmospheric point-spread function. Topographic effects are influenced by factors such as sky view factor, surface anisotropy, and lower boundary conditions of the atmosphere, which makes their correction complex (Richter & Schläpfer, 2002), especially for forest environments (Soenen et al., 2005). Finally, for images with a large field of view (Schlerf et al., 2005), for image mosaicking (Schaaf et al., 2002) or multi-temporal studies (Bacour et al., 2006b), it may be necessary to correct for surface directional effects, which are described by the bi-directional reflectance distribution function (BRDF). Correcting for BRDF effects is not consistent with the Lambertian surface assumption used in other pre-processing steps.

Usually, corrections for atmospheric, topographic, adjacency, and directional effects are applied sequentially and independently. In addition to error propagation issues, sequential processing does not reflect the physical interactions between these effects (Gao et al., 2009). Because all these effects are inter-related, it is not possible to correct for each effect without making simplifying assumptions about the others or using an explicit physically-based approach.

Following a proper pre-processing sequence, hemispherical–conical reflectance factor (HCRF) (Schaepman-Strub et al., 2006) data can be derived. Based on the assumption that there are no directional effects within the very small instantaneous field of view of satellite sensors, HCRF is commonly used as an approximation of the hemispherical–directional reflectance factor (HDRF). Most studies, however, use the bi-directional reflectance factor (BRF) output of the canopy RT model in the model inversion (Dorigo et al., 2007; Malenovský et al., 2008; Verhoef & Bach, 2007; Verrelst et al., 2010). This mismatch between the two quantities compared, is another inherent limitation of the TOC approach.

Finally, the estimation of forest variables is subject to errors both in the simulations, because of modelling errors and parameter uncertainties, and in the reference TOC reflectance data, because of the error propagation in the pre-processing chain (Rahman, 2001).

Because most limitations of the TOC approach arise from the need to correct the remote sensing data from top of atmosphere (TOA) to TOC level, a solution is to use the TOA data directly (Verhoef & Bach, 2003a). This requires coupling the canopy and atmosphere models to assess the canopy variables from the TOA level. This coupling also enables the inclusion of surface BRDF, adjacency and topography effects in the model. Thus, the forward modelling of the coupled surface–atmosphere system is more accurate than applying a series of corrections as in the TOC approach. In addition, the coupled model simulates the TOA radiance, which is the physical quantity measured by the sensor. Therefore, by including sensor properties such as spectral bands, spatial and spectral resolution, and modulation transfer functions in the modelling, the simulations can be directly compared with the measurements (Verhoef & Bach, 2003b), and the coupled model can be inverted directly against the measured radiance data to estimate the forest variables. Finally, in the TOA approach, all modelling errors and parameter uncertainties are contained in the simulation, which makes it easier to study their impact on the estimates. Table 1 presents a comparison of the pre-processing and modelling steps between the TOC and TOA approaches.

Coupled canopy–atmosphere models already exist (Börner et al., 2001; Fourty & Baret, 1997; Gastellu-Etchegorry et al., 2004; Rahman et al., 1993; Verhoef & Bach, 2007). Their ability to simulate sensor-like data has been used for sensor feasibility studies (Schläpfer &

Table 1
Comparison of pre-processing and modelling efforts required in the TOC and TOA approaches.

		TOC approach	TOA approach
Observations (preprocessing)	Radiometric	Radiometric calibration	Radiometric calibration
	Geometric terrain	Geometric correction Ortho-rectification	Geometric correction Ortho-rectification
	Correction to TOC reflectance	Atmospheric correction: inversion of atmosphere model using a LUT and assuming Lambertian surface Filter for adjacency effect Correct topography effects Correct BRDF effects	None
	Physical quantity	HCRF approximates HDRF	Radiance
	Errors	Measurement + modelling + assumptions errors + error propagation	Measurement errors
Simulations	Coupled RT models	Soil, leaf, bark, canopy	Soil, leaf, bark, canopy, atmosphere
	Effects	Surface BRDF Topography Adjacency	Surface BRDF Topography Adjacency Atmospheric
	Model output	TOC BRF	TOA radiance
	Errors	Modelling errors	Modelling errors
Comparison	Simulation vs observation	Approximation: HCRF ~ HDRF ~ BRF	Direct