Fusion of imaging spectrometer and LIDAR data over combined radiative transfer models for forest canopy characterization

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1. Introduction

Vegetation controls a large part of the heat and mass fluxes within the terrestrial biosphere. The major physiological processes, such as evapotranspiration and photosynthesis, responsible within vegetation for energy and mass exchanges are driven by the canopy structure as well as the biochemistry of the foliage. For the understanding and monitoring of the typically heterogeneous and dynamic terrestrial biosphere a comprehensive and robust characterization of vegetation canopies is thus required (Sellers et al., 1997).

The vegetated land surface is often characterized by passive optical remote sensing sensors observing the spectral properties of the surface. The spectral information content is able to provide estimates on biophysical parameters, such as Leaf Area Index (LAI) and fractional cover, as well as on parameters related to the foliage biochemistry, such as the Fraction of Absorbed Photosynthetic Active Radiation (FAPAR), up to global scale (Myneni et al., 2002; Widlowski et al., 2001). Recently, the active optical system LIDAR started to provide information on the vertical distribution of canopy elements within a vegetation canopy (Drake et al., 2002b; Lefsky et al., 2002). While large footprint LIDAR capture the full vertical waveform over a canopy potentially form a spaceborne platform, airborne small footprint LIDAR can resolve the canopy structure up to a single tree (Harding et al., 2001; Hyyppa et al., 2001; Morsdorf et al.,...
The direct LIDAR observations of vertical canopy structure can thus present an independent information source complementing the spectral information content for a comprehensive canopy characterization (Gillespie et al., 2004; Hill & Thomson, 2005).

The complexity of a vegetation canopy and uncertainties related to measurements and retrieval algorithm cause the vegetation characterization by remote sensing to be an ill-posed problem (Combaf et al., 2003). The radiative transfer within a canopy depends on the complex 3-D canopy structure defined by the geometry, position and density of canopy elements as well as the optical properties of each canopy element (Goel & Thompson, 2000). Physically based Radiative Transfer Models (RTM) have been developed to describe the interaction of radiation with the diverse canopy components at foliage and canopy level (Govaerts, 1996; Jacquemoud & Baret, 1990; Kuusk & Nilson, 2000; Ni-Meister et al., 2001; Sun & Hanson, 2000). RTM provide thus an explicit connection between canopy variables, observation and illumination geometry and the resulting remote sensing signature. Nevertheless, assumptions and number of parameters of most invertible RTM rend them to an intrinsic undetermined system. This fact and measurement uncertainties lead to multiple possible solutions when RTM are inverted against remote sensing observations. For an improved retrieval of vegetation characteristics by RTM inversion, the number of independent information sources should thus be increased (Verstraete et al., 1996).

For the characterization of heterogeneous forest canopies we propose to exploit the independent information dimensions provided by the two earth observation systems imaging spectrometry and LIDAR. While the spectral measurements of imaging spectrometry bear information on the foliar biochemical composition and only an indirect link to the canopy structure, LIDAR observations provide direct measurements of the vertical and horizontal canopy structure. The LIDAR signal, e.g. recorded as full waveform, can thus improve the accuracy and robustness of RTM inversion based solely on spectral information by reducing the uncertainties related to canopy structure. On the other hand, accurate interpretation of the LIDAR signal depends on the spectral properties of canopy elements and background. The two sensors and their information dimension are thus mutually dependent but can also complement each other.

Radiative transfer modeling of the remote sensing signals as observed by imaging spectrometry and LIDAR is described by the same basic physical processes. Consequently, an interface between two RTM based on the same physical concept and sharing common input parameters can be established. A common forest stand parameterization is used by the two models to generate a combined spectral and LIDAR waveform signature of the respective canopy. RTM inversion based on a Look Up Table (LUT) comprising the combined remote sensing signatures of imaging spectrometry and LIDAR as a function of a common forest stand parameterization offers thus a simple approach to exploit synergistically these independent information dimensions. In the presented study prior information on the canopy structure derived from the LIDAR information helps to improve the retrieval performance. Similar approaches have been promoted using prior information derived from the spatial, temporal and directional information dimension of earth observation (Atzberger, 2004; Knyazikhin et al., 1998; Koetz et al., 2005; Widlowski et al., 2004).

The objective of the present research is to show the theoretical feasibility of an observation concept that fully exploits the information dimensions provided by the two earth observation systems imaging spectrometry and large footprint LIDAR to characterize a forest canopy. The exploitation of the two independent information sources ensures a robust parameter retrieval but also provides an enhanced canopy characterization, including the foliage biochemical content as well as the horizontal and vertical canopy structure. The methodology has been developed and evaluated on a synthetic data set, which allowed for a comprehensive validation over forest stands of changing age and under different environmental conditions generated by a forest growth model. The proposed approach finally also bears implications and shows potential for future multi-sensor earth observation platforms such as the proposed spaceborne mission Carbon-3D (Hese et al., 2005).

2. Radiative transfer models

The remote sensing signatures of forest canopies as observed by an imaging spectrometer and a large footprint LIDAR have been simulated by two separate Radiative Transfer Models (RTM). The use of the RTM has been twofold. They have been employed to generate by forward modeling an independent synthetic data set for validation purposes. Furthermore, the inversion of the two radiative transfer models provided the means for the proposed retrieval of vegetation canopy properties.

2.1. GeoSAIL

The hybrid radiative transfer model GeoSAIL (Huemmrich, 2001) describes the spectral canopy reflectance of a forest stand. The relatively simple GeoSAIL model was chosen due to its low computational costs and its comparable performance to e.g. the more sophisticated RTM FLIGHT (Kötz et al., 2004). The radiative transfer at foliage level is characterized by the PROSPECT model (Jacquemoud & Baret, 1990), which provides the foliage optical properties as a function of the biochemistry and is subsequently coupled with the canopy RTM. GeoSAIL describes the canopy reflectance of a complete scene including discontinuities in the canopy and shadowed scene components. GeoSAIL is a combination of a geometric model (Jasinski & Eagleson, 1990) with the SAIL model (Verhoef, 1984) that provides the reflectance and transmittance of the tree crowns. A SAIL version capable of dealing with unlimited number of bands and multiple canopy components, such as foliage and branches, was implemented (Kötz et al., 2004). The geometric model determines the fraction of the illuminated and shadowed scene components as a function of canopy coverage, crown shape and illumination angle. All trees are assumed to be identical with no crown overlap nor does the model account for mutual shading of crowns and foliage clumping.
2.2. LIDAR Waveform model

A three-dimensional (3D) waveform model was used to simulate LIDAR waveforms as a function of forest stand structure and sensor specifications (Sun & Ranson, 2000). The model constructs a 3D-representation of the observed forest stand taking into account the number and position of trees, tree height, crown geometry and shape as well as the exposition of the underlying topography. The crown itself is described as a turbid scattering medium parameterized by its foliage area volume density, the Ross–Nilson G-factor (Nilson, 1971) and the foliage reflectance. Finally, the ground reflectance needs to be defined for an accurate waveform simulation.

Within this study the original version of the LIDAR waveform model was adapted to allow for the input of LAI instead of the foliage area volume density. The updated model also calculates the fractional cover of the respective 3D stand representation used for the waveform simulation.

3. Data: generation of synthetic data set

A synthetic data set has been generated by linking the forest growth model ZELIG (Urban, 1990) to the two radiative transfer models described above. The linked models provided a comprehensive data set of the remote sensing signatures for an imaging spectrometer and a LIDAR over a wide range of forest stands. ZELIG simulations over time and for different sites in changing environmental settings described in detail highly variable canopy attributes, such as the canopy structure of the

Fig. 1. Simulated remote sensing signatures for the large footprint LIDAR LVIS (Blair et al., 1999) and the imaging spectrometer APEX (Nieke et al., 2005) (measurement uncertainties indicated by red error bars) over forest stands generated by the forest growth model ZELIG (stand ages: 5, 50, 100 years, soil type ADAMS).
studied forest stands. The ZELIG forest stand descriptions were used for the parameterization of the radiative transfer models. Forward simulations of the two radiative transfer models subsequently generated the remote sensing signatures of the forest stands as observed by an imaging spectrometer and large footprint LIDAR (see Fig. 1 as an example). Furthermore, typical measurement errors of the remote sensing data and uncertainties related to the radiative transfer models were as far as possible taken into account.

The synthetic data set avoids limitations due to the quantity, variability and accuracy of field sampling as well as the co-registration errors between field data and remote sensing observations. The ZELIG data set used here has already served well for similar studies of model simulation and data analyses (Kimes et al., 1997; Ranson et al., 1997).

3.1. Forest growth modeling: ZELIG simulations

A version of the forest growth model, ZELIG developed by Urban (1990) and modified by (Weishampel et al., 1999), was used to simulate the dynamics of the southern boreal/northern hardwood forest transition zone found at the International Paper’s Northern Experimental Forests (NEF) site located near Howland, Maine USA (45° 12’ N, 68° 45’ W). The model simulates the annual growth of each tree in a plot whose areal extent relates to the “gap” that is formed when a typical canopy dominant tree dies. The growth behavior of a species under ideal conditions (e.g., optimal temperature, soil moisture, light and nutrient availability) is estimated from silvicultural records available at each site. To implement the ZELIG model, site parameters, such as soil fertility and monthly values of temperature and precipitation, autecological parameters, tree height and diameter maxima as well as growth tolerances, were derived from empirical data and published sources. The implementation of the forest model ZELIG is described in greater detail in Ranson et al. (1997).

The ZELIG simulations were performed for ten different soil types over a time range of 250 years. Model results were recorded at 5-year intervals up to 100 years and at 25-year intervals up to 250 years. Soil types were used to provide a range of soil drainage conditions important for controlling forest growth and development in northern forests. More detailed information regarding soil types and characteristics was reported by Ranson et al. (2001). A number of 15 separate runs were performed for each soil type. Stochastic changes in tree mortality, regeneration and weather conditions integrated in ZELIG generated thus a range of stand responses. Furthermore, the drainage conditions typical for the different soil types caused a high diversity in forest structure observed in the resulting data set. For each simulated stand and time step total woody biomass, number of trees, LAI as well as for every tree absolute height, diameter at breast height (DBH) and species were recorded (Table 1). The spatial resolution of the ZELIG simulations was set to an area of 30 m × 30 m corresponding to the scale of the employed remote sensing data.

A total of 3900 forest stand simulations (10 soil types × 15 replications × 26 time steps) performed by ZELIG provided the

| Table 1 Parameter ranges describing the generation of the synthetic data set as well as the LUT for the subsequent RTM inversion |
|-----------------|-----------------|-----------------|
| Variable        | Units           | Synthetic data set | LUT |
|                 | Min.        | Max.         | Min.        | Max.         |
| Cab             | Foliage chlorophyll | µg/cm² | 35 | 80 | 35 | 80 |
| Cw              | Foliage water content | mg/cm² | 0.025 | 0.065 | 0.025 | 0.065 |
| Cdry            | Foliage dry matter | mg/cm² | 0.02 | 0.05 | 0.02 | 0.05 |
| LAI             | Leaf area index | – | 0.25 | 8.7 | 0.25 | 9 |
| fcover          | Fractional cover | % | 0.08 | 0.82 | 0.08 | 0.95 |
| Tree_z          | Max. tree height | m | 4.7 | 29.6 | 4 | 30 |
| C_ext           | Vert. crown exten. | m | 3.7 | 28.6 | 3.4 | 28.7 |

Additional parameters were fixed to model default or field measurement values: GeoSAIL parameterization: wood fraction \( n=0.09 \), crown height width ratio = 7.8, crown shape = cone, spectral properties of woody canopy elements and understory; Waveform model parameterization: foliage reflectance (\( \lambda \): 1064 nm)=0.215, background reflectance (\( \lambda \): 1064 nm)=0.152, crown shape: hemi-ellipsoid, G-factor = 0.5, tree number = 60 (for the LUT generation).

The structural canopy attributes for the subsequent parameterization of the radiative transfer models.

3.2. Remote sensing signatures

Two radiative transfer models were used to generate the remote sensing signatures of the simulated forest stands as observed by two sensors, an imaging spectrometer and a large footprint LIDAR. The radiative transfer models, GeoSAIL and the LIDAR waveform model, were parameterized with the structural canopy attributes produced by the forest growth model ZELIG. As the majority of simulated forest stands was dominated by coniferous species, homogenous conifer stands were assumed for the RTM parameterization.

3.2.1. Spectral canopy reflectance

The coupled radiative transfer models PROSPECT and GeoSAIL described the spectral canopy reflectance \( \rho(\lambda) \) as a function of foliage properties, canopy structure and instrument specifications. The canopy reflectance was simulated as observed from nadir in 299 spectral bands corresponding to the specification of the planned imaging spectrometer APEX (Table 2) (Nieke et al., 2005). APEX (Airborne Prism Experiment), initiated under the ESA PRODEX program, is an airborne dispersive pushbroom imaging spectrometer operating in the spectral range between 380–2500 nm. The illumination conditions were defined by a sun angle set to 45° and a diffuse radiation fraction of 15%.

The input parameters as required by PROSPECT were assumed within typical ranges for conifers and randomly distributed, since the forest growth model does not provide information on foliage biochemistry (Table 1, see Kötz et al., 2004 for details). The canopy structure parameters of the RTM, leaf area index (LAI) and fractional cover (fcover), were described by the stand attributes generated by the ZELIG simulations. The average inclination angle was parameterized
separately for green and woody canopy elements in GeoSAIL; spherical distribution was assumed for green, and plagiophile distribution for woody elements. The wood fraction and the crown height width ratio were set to values observed for the coniferous specie western hemlock (Tsuga heterophylla), (Huemmrich, 2001). The spectral properties of the background and woody canopy elements were characterized by ground spectroradiometric measurements within a coniferous forest as described in Kötz et al., 2004.

Within the radiative transfer representation of GeoSAIL, several assumptions such as omitting mutual shading and tree overlapping have been made. In order to take into account uncertainties related to model assumptions, a Gaussian noise of 15% was added respectively to the LAI and fcover values provided by ZELIG. The magnitude of model uncertainty was oriented relatively to observations made by (Wang et al., 2001).

Finally, radiometric noise was added to the simulated canopy reflectance to account for measurement uncertainties resulting from several error sources associated to the imaging spectrometer performance and the radiometric correction. The relative instrument noise was characterized according to the specified signal to noise ratio performance of APEX at medium radiance level (APEX wikispace). The radiometric calibration of the imaging spectrometer was assumed to reach an absolute accuracy of 3%. The error related to the inaccuracy of the atmospheric correction was assumed to result primarily from aerosol optical thickness uncertainties, and was therefore spectrally dependent. A 2% maximal error was assumed in the first band (385 nm). The error was propagated to the remaining wavelengths according to a $\lambda^{-1.3}$ law which is typical for continental aerosols (Richter & Schläpfer, 2002). Standard error propagation, combining the above single error sources, was applied to generate simulated but nevertheless authentic canopy reflectance.

### 3.2.2. LIDAR waveform

The above-described LIDAR waveform model generated the full LIDAR waveform signature over the simulated forest stands considering the specification of the large footprint LIDAR LVIS. The Laser Vegetation Imaging Sensor (LVIS) is an airborne, wide-swath mapping system developed at NASA’s Goddard Space Flight Center capable of recording the full waveform over 25-m diameter footprints Table 3 (Blair et al., 1999).

The parameterization of the LIDAR waveform model was based on the structural attributes generated from the forest growth model ZELIG. The forest growth model provided a comprehensive description of the simulated forest stands required by the waveform model, including number of trees within a stand, tree height, DBH and LAI. Although tree height was available from the ZELIG output, it was calculated from tree DBH and allometric relationships developed from field measurements (Ranson et al., 1997; Sun & Ranson, 2000). Crown geometry, defined by crown length and width, was subsequently calculated as function of tree height (Sun & Ranson, 2000). Trees were randomly positioned within the simulated forest stands. The foliage and background reflectance were provided by spectrometric measurements and the crown shape was approximated as a hemi-ellipsoid. The G-factor was set to the value of 0.5 representing a spherical foliage distribution typical for conifers. For the sake of simplicity the underlying terrain was assumed to be flat.

As an additional parameter the vertical crown extension within each forest stand was calculated as the difference between the maximal tree height and the lowest crown base. Uncertainties related to errors associated to this sensor and data processing could not be taken into account because of their insufficient characterization.

### 4. Methods: RTM inversion based on Look Up Tables (LUT)

The inversion of the two introduced radiative transfer models for the synergistic vegetation parameter estimation from LIDAR and imaging spectrometer data is based on a LUT approach. This is a conceptually very simple and efficient approach, which overcomes computational limitations as well as potentially the risk of local minimum convergence (Combal et al., 2002; Kimes et al., 2000). The approach also allows, due to its simplicity, the construction of a LUT comprising different remote sensing signatures of multiple sensors. Such a combined LUT is made possible by an interface between the two radiative transfer models. Common RTM parameters describing the canopy structure such as fractional cover, LAI and crown geometry establish a common forest stand parameterization used by each of the two models to generate a combined spectral and waveform signature of the respective canopy realization.

The LUT inversion approach can be split into two parts: (i) the generation of the LUT itself, and (ii) the selection of the
LUT solutions corresponding to a given measurement. The selection of the LUT solutions followed a sequential approach.

4.1. Generation of the LUT

The first step in generating a LUT was to sample the space of the input parameters of the two involved radiative transfer models (LUTp). A total of 100,000 canopy realizations had been generated following a uniform distribution and specific ranges for the respective canopy parameter (Table 1). Then, the two RTM, linked by common vegetation parameters (fcover, LAI), were used to simulate the corresponding remote sensing signature table (LUTs) for each canopy realization. The spectral properties of the background were also shared by both of the model parameterizations.

The parameterizations of the RTM for the LUT generation were in general defined accordingly to two previous experiments performed over a coniferous canopy, where each RTM was inverted separately (Koetz et al., 2006; Kötz et al., 2004). The LUT ranges were adapted to accommodate the conditions of the synthetic data set generated by ZELIG (Table 1). Note that the generation of the LUTp allowed the definition of some a priori information on the respective variable by constraining it to vary within limited ranges.

The parameterization of the LIDAR waveform model was modified in two major ways to improve the inversion performance relative to the study presented by Koetz et al. (2006). As already shown by the previous study and confirmed by inversion trials based on the ZELIG data set, the LAI estimations proved not to be stable. Strong correlation between the two canopy variables describing the canopy density, fcover and LAI, caused the LAI retrievals to deteriorate. The LAI was consequently fixed within the waveform model parameterization to a value of two, corresponding to an LAI of a well-developed canopy. A sensitivity study also showed a low sensitivity of the model simulations for variation of the LAI within the range of 1.5–3.5. Furthermore, the experience with the ZELIG data set showed a common occurrence of a more complex vertical structure within the canopy than has been considered up to now. The canopies of the ZELIG generated forest stands often exhibited a crown layer separated into two pronounced strata (e.g. Fig. 1). The tree height distribution of a forest stand parameterization was thus adapted for the LUT generation to mimic this behavior. Tree height distribution was now allowed to generate two strata, which could either overlap to one single stratum or form two vertically separated strata.

The measurement configurations used to generate the remote sensing signatures of LUTs considered the respective instrument specifications of the imaging spectrometer APEX and the large footprint LIDAR LVIS.

4.2. Selection of the solution

The selection of the solution within the LUT was achieved by a sequential approach consisting of two steps. The LIDAR waveform information was exploited in a first step delivering information on the vertical and horizontal canopy structure. Part of this information was used as prior information within the subsequent second step, the exploitation of spectral information. The coupling of the waveform and spectral information was based on the assumption that the LIDAR provided the most reliable estimates of fcover, due to its direct measurement principle of canopy structure.

4.2.1. Exploiting waveform information: definition of prior information

The solution of the waveform RTM inversion was found by minimizing the merit function ($\chi^2_{\text{wave}}$), defined as the simple squared-sum of distances between the reference waveform ($\omega_{\text{ref}}$) acquired by the LIDAR system and the simulated waveform ($\omega_{\text{sim}}$) found in the LUT (Eq. (1)).

$$\chi^2_{\text{wave}} = \sum_{j=1}^{n_{\text{bin}}} (\omega^j_{\text{ref}} - \omega^j_{\text{sim}})^2$$

where $n_{\text{bin}}$ is the number of bins of the digitized waveform.

However, given the ill-posed nature of a model inversion caused by measurement and model uncertainties, model inversion generally leads to a range of equally possible solutions (Combal et al., 2003). Thus, the LUT was first pre-selected following information provided by a direct assessment of the possible maximal tree height (Ni-Meister, 2005). Maximal tree height was assumed to be within ±10% of a height, where the waveform signal initially increased a noise threshold (Drake et al., 2002a). Furthermore, the pre-selected LUT was sorted accordingly to the merit function ($\chi^2_{\text{wave}}$) and the first ten canopy realizations (those with the minimal $\chi^2_{\text{wave}}$) were considered as possible solutions. The median of the possible solutions defined the final solution and their standard deviation the uncertainty of the inversion (Koetz et al., 2006).

4.2.2. Exploiting combined spectral and waveform information

The inversion of the GeoSAIL model was similarly solved as in the previous step by minimizing a simple distance criterion but was additionally restricted by prior information provided by the waveform RTM.

The spectral information was exploited by sorting the LUT according to the merit function $\chi^2_{\text{rad}}$. The spectral merit function was defined by the simple squared-sum of normalized differences between the reference reflectance $\rho_{\text{ref}}$ and the simulated reflectance $\rho_{\text{sim}}$ found in the LUTs (Eq. (2)).

$$\chi^2_{\text{rad}} = \sum_{j=1}^{n_{\text{b}}}(\rho^j_{\text{ref}} - \rho^j_{\text{sim}})^2$$

where $n_{\text{b}}$ is the number of bands of the spectrum recorded by the imaging spectrometer APEX.

The LIDAR waveform information was introduced to the retrieval process by restricting the LUT based on prior information of the canopy variable fcover. LUT entries have been constrained by the following criterion:

$$f_{\text{cover}} = f_{\text{cover}} + \Delta f_{\text{cover}}$$

where $f_{\text{cover}}$ represents the fractional cover as derived from the waveform information and $\Delta f_{\text{cover}}$ its uncertainty related
to the waveform model inversion. This simple way of introducing prior information to the inverse problem was made possible by the plain nature and the combined structure of the employed LUT approach.

Finally, the possible solutions considered were those that were within 20% of the best spectral match and considering the prior information on the pcover. The 20% threshold was derived after test and error trials and is consistent with findings proposed in earlier studies (Combal et al., 2002; Kötz et al., 2004). The median of possible solutions was considered as final solution and their standard deviation as the uncertainty of the model inversion.

5. Results and discussion: evaluation of RTM coupling strategy

The synthetic data set generated by the forest growth model ZELIG was used to evaluate the performance of the proposed method for a wide range of forest stands. First, the retrieval performance based solely on the information dimension provided by the LIDAR sensor was separately addressed. The improvement of the combined spectral and waveform information dimensions was subsequently evaluated relative to the spectral information performance. The simple root mean square error (RMSE) was calculated to quantify the agreement between
the respective reference and estimated parameter values. The correlation coefficient ($R^2$) of a linear regression was also presented. The results of the site over the soil type ADAMS, presented in the Figs. 2 and 3, are discussed in more detail. The overall performance of the proposed RTM inversion approach and its transfer to all of the considered soil types are presented in the Table 4. The results are grouped in Table 4 by soil type for convenience. ADAMS and DIXFIELD represent well drained soils while KINSMAN, PEACHMAN, SCANTIC and WESTBURY are considered poorly or very poorly drained. The remaining soils are of intermediate drainage class.

The inversion of the waveform RTM provided reliable estimates of model parameters describing the vertical as well as the horizontal canopy structure. The parameters were all retrieved with high correlation coefficients and low RMSE (Fig. 2, Table 4) two parameters describing the vertical canopy structure, maximal tree height and the vertical crown extension, showed similar performances. Both parameters were slightly underestimated which was most likely caused by missing the signal start of the highest tree top. Due to the nature of the employed merit function, low signals, as recorded from single tree tops extending over the canopy, received a relative low weight within the retrieval algorithm. The comparable values of the vertical crown extension relative to the maximal tree height also indicated that the observed forest stands exhibited a rather continuous vertical distribution of crowns down to the ground. The examples of ZELIG generated forest stands presented in Fig. 1 suggested such a vertical canopy structure. The horizontal structure represented by the canopy fractional cover showed some underestimation for low values as well as an overestimation for high values. Some of this behavior could be attributed to compensation of the fixed LAI parameter, which probably assumed a relative high crown density for sparse, younger stands and a relative low crown density for closed, mature stands. Nevertheless, this assumption was necessary for a stable inversion performance due to a strong inter-correlation between LAI and fcover. Finally, the overall high performance of the waveform model inversion has been only achieved by the implementation of a two strata canopy and a highly variable vertical tree height distribution into the LUT generation.

The combined RTM inversion performed well retrieving estimates of biophysical, LAI and fcover, and biochemical parameters, foliage content of chlorophyll and water, with significant correlation coefficients and low RMSE (Fig. 3B, Table 4). All parameters show linear relationships close to the 1:1 line. Only the LAI exhibits a significant scattering above an LAI value of five, consistent with the known saturation effect for this parameter in closed canopies. The introduction of prior information on the fcover parameter, derived from the waveform information content, clearly improved the retrieval performance relative to estimates based only on spectral information. The fcover estimates based on the combined RTM inversion resulted in a 22.2% (24.4%) lower RMSE and a 17% (15.4%) increase in terms of $R^2$, calculated over the stands of the ADAMS site (the total of all sites). The results for the soil type ADAMS, presented in Fig. 3, also indicated that most of the improvement was caused by the reduction of scattering for fcover greater than 0.5. The uncertainties of the RTM inversion for low fcover values have been also reduced. Relative to the fcover estimates based solely on waveform information content, the combined retrieval showed a more linear relationship causing an even lower RMSE. However, retrieval performance of the remaining parameters, especially the biochemistry, decreased by the introduction of prior information on the fcover. This had a number of different causes. First, the prior information on the fcover considerably reduced the number of available LUT entries, which consequently resulted in a lower probability to find a solution fitting the information content related to the biochemistry. Further, the prior information mostly improved the retrieval for closed canopies where estimation of foliage biochemistry is generally least affected by canopy structure (Zarco-Tejada et al., 2001). The RTM GeoSAIL also does not incorporate certain effects of canopy structure affecting the biochemistry estimation, such as mutual

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<th>Soil Types</th>
<th>LIDAR</th>
<th>Combined Imaging Spectroscopy / LIDAR</th>
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Overall performance as well as separate performances for ten different soil types are quantified as RMSE and $R^2$ between reference and estimated parameters. (Tree$_{z}$: max. tree height, C$_{ext}$: vertical crown extension, LAI: leaf Area index, fcover: fractional cover, Cab: Foliage chlorophyll content, Cw: Foliage water content).
shading and foliage clumping. Consequently, improvement of biochemistry retrievals by introduction of prior information on fcover was limited for this data set. Finally, the RTM inversion on the spectral information already provided good results since prior information on all parameters was introduced implicitly during the LUT generation and the synthetic data set assumed ideal measurement conditions. Nevertheless, in reality due to the important effect of the canopy architecture an improved characterization of the canopy structure by prior information should also enhance the capability to retrieve biochemistry from imaging spectroscopy (Asner, 1998; Dawson et al., 1999; Gastellu-Etchegorry & Bruniquel-Pinel, 2001).

The performance of the combined RTM inversion discussed above in more detail for the soil type ADAMS performed similar for the nine remaining soil types with different ecological conditions (Table 4). In spite of the changing soil types and the consequently differently evolving canopy structure, the retrieval remained stable and thus transferable among the sites. However, assumptions made for the generation of the synthetic data set, such as the constant background reflectance, a flat terrain and assumptions inherent to the two RTM, still limit the universality of the results.

6. Conclusions

Remote sensing of vegetation properties has been shown to be a generally ill-posed problem, partly due to the available indirect detection methods and measurement uncertainties but also due to the limited representation of the involved processes in the retrieval. This includes the inversion of RTM, because even physically based radiative transfer models have to be partly based on assumptions and parameterizations in order to be invertible. Consequently the introduction of prior or ancillary information into the retrieval process is a necessary and useful approach to increase the robustness of canopy parameter estimation by remote sensing. One promising way of deriving prior information is to exploit independent information dimensions provided by multiple sensors.

The presented study showed the feasibility and potential for the combined information exploitation of multiple sensors based on physically based radiative transfer modeling. The two information dimensions provided by imaging spectrometry and LIDAR were successfully used to derive a comprehensive canopy characterization, relevant for the assessment of biomass, productivity of vegetation and risk of natural hazards such as forest fires (Chuvieco, 2003; Sellers et al., 1997). The specific information content, inherent to the observations of the respective sensors, was able to complement the canopy characterization but also helped to stabilize the RTM inversion. Prior information derived from LIDAR observations helped to improve the retrieval performance of the canopy structure, which is in general only indirectly and thus with relative high uncertainties inferable from pure spectral information. The results of the study provided robust estimates of the vertical and horizontal canopy structure as well as biophysical and -chemical canopy parameters for a wide range of forest stands. The major limitation of the results was its validation relative to a synthetic data set based on simulations. Before an operational use of this observation concept it needs to be tested on actual measurements of the respective sensors and validated against a large variability of real field measurements. However, the generation of the data set by an ecologically sound forest growth model linked to physically based RTM ensured the reproduction of many processes important in reality. The advantage of a synthetic data set on the other hand is the wide range of forest stands conditions covered and avoiding limitations related to measurement errors. The explicit description of the canopy structure by the forest growth model also allowed for an increased understanding of the processes impacting the LIDAR waveform signal and thus led to an improved retrieval algorithm.

Although these findings are based on a synthetic data set and real measurements have to confirm them, they present a possible observation concept for future space-borne Earth-Observation platforms with multiple sensors. For example the proposed mission Carbon-3D, which is supposed to provide global biomass estimates, is based on similar observation techniques including an multi-spectral/-angular sensor and a large footprint LIDAR (Hese et al., 2005). The presented exploitation of multiple sensors could also be principally applied to existing space-borne instruments on separate platforms such as the imaging spectrometers Hyperion (Ungar et al., 2003) and CHRIS (Barnsley et al., 2004) as well as the large footprint LIDAR GLAS (Lefsky et al., 2005). However, the spatial resolution of GLAS is not adapted to the needs of vegetation studies and the revisiting frequency of the imaging spectrometers has to be increased for most applications. Finally, due to the simplicity and the generic nature of the coupled RTM strategy the approach could be easily extended to further information dimensions, such as provided by multiangular or microwave observations (Disney et al., 2006; Verstraete et al., 1996).

References


