Simulating imaging spectrometer data: 3D forest modeling based on LiDAR and in situ data

Fabian D. Schneider, Reik Leiterer, Felix Morsdorf, Jean-Philippe Gastellu-Etchegorry, Nicolas Lauret, Norbert Pfeifer, Michael E. Schaepman

1. Introduction

Remote sensing offers the potential to study forest ecosystems by providing spatially and temporally distributed information on key biophysical and biochemical variables. The estimation of biochemical constituents of leaves from remotely sensed data is of high interest revealing insight on photosynthetic processes, plant health, plant functional types, and species composition. However, upsampling leaf level observations to canopy level is not a trivial task, in particular due to the inherent structural complexity of forests. A common solution for scaling spectral information is the use of physically-based radiative transfer models. We parameterize the Discrete Anisotropic Radiative Transfer (DART) model based on airborne and in situ measurements.

The study was performed on the Laegern site (47°28′53.2 E, 8°21′53.0 N, 43.0 N, 8°21′53.2 E, Switzerland), a temperate mixed forest characterized by steep slopes, a heterogeneous spectral background, and a high species diversity. Particularly the accurate 3D modeling of the complex canopy architecture is crucial to understand the interaction of photons with the vegetation canopy and its background. Two turbid medium based forest reconstruction approaches were developed and compared; namely based on a voxel grid and based on individual tree detection. Our study shows that the voxel grid based reconstruction yields better results. When using a pixel-wise comparison with the imaging spectrometer data, the voxel grid approach performed better ($R^2 = 0.48$, $\lambda = 780$ nm) than the individual tree approach ($R^2 = 0.34$, $\lambda = 780$ nm). Spatial patterns as compared to APEX data were similar, whereas absolute radiance values differed slightly, depending on wavelength. We provide a successful representation of a 3D radiative regime of a temperate mixed forest, suitable to simulate most spatial and spectral features of imaging spectrometer data. Limitations of the approach include the high spectral variability of leaf optical properties between and within species, which will be further addressed. The results also reveal the need of more accurate parameterizations of small-scale structures, such as needle clumping at shoot level as well as leaf angle.

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limitations. This can be achieved by comparing earth observation data with data, which is simulated using radiative transfer (RT) models in forward simulation mode to scale from leaf to sensor level.

RT models are physical models capable of describing the interaction of photons with the vegetation canopy and its background (Jacquemoud et al., 2009; Niemann, Quinn, Goodenough, Visintini, & Loos, 2012). One-dimensional (1D) models usually describe the canopy as a homogeneous turbid medium of randomly distributed infinitesimally small leaf elements (Monis & Saeki, 1953). These simple models were widely used in homogeneous vegetation stands, coupled with leaf RT models, and extended using multi-layered approaches (Jacquemoud et al., 2009). However, when modeling complex heterogeneous forest canopies with all their radiative processes, including multiple scattering or mutual shading, usually three-dimensional (3D) radiative transfer models are used (Koetz et al., 2004). 3D RT models describe the canopy architecture using individual three-dimensional volume elements (voxels), which are filled with smaller scale vegetation architectural features (such as stems, branches and leaves) and characterized by LOP, leaf area index (LAI), and leaf angle distribution (LAD). Finally, the coupling with an atmospheric model enables the simulation of a variety of illumination and observation angles, as well as different sensor configurations (Gastellu-Etchegorry, Grau, & Laurent, 2012).

A number of 3D radiative transfer models have been developed for this purpose, including FLIGHT (North, 1996), FLAIR (White, Miller, & Chen, 2001), and DART (Gastellu-Etchegorry, Demarez, Pinel, & Zagolski, 1996; Gastellu-Etchegorry et al., 2012). For example, Malenovský et al. (2008) and Verrelst et al. (2010) investigated the influence of woody elements on canopy reflectance using the DART and FLIGHT models, respectively. They used extensive field measurements to parameterize the 3D model environments and compared their results to high resolution imaging spectrometer data. However, both studies focused only on coniferous forest stands. Similar RT-based studies have not been carried out on temperate mixed forests, particularly with a forest architecture derived from airborne laser scanning (ALS) data. The use of ALS data is important, since the 3D heterogeneity of architectural forest properties is usually simplified in models, even though they play a critical role in reflectance simulations (Wang & Li, 2013).

A complete parameterization of the 3D canopy architecture remains challenging, but recent developments in light detection and ranging (LiDAR) offer new possibilities for area-wide retrieval of forest structural variables (van Leeuwen & Nieuwenhuis, 2010; Wulder et al., 2012). Full-waveform scanners allow us to detect multiple echoes from a single laser pulse and describe scattering properties with physical variables such as intensity and echo-width (Wagner, Hollaus, Briese, & Ducic, 2008; Wagner, Ullrich, Ducic, Melzer, & Studnicka, 2006). The resulting 3D point cloud can be used for individual tree detection in forests (Kaartinen et al., 2012; Morsdorf et al., 2004). Besides, attempts are made to estimate LAI from first and last returns based on gap fraction theory (Morsdorf, Kötz, Meier, Itten, & Allgöwer, 2006; Solberg et al., 2009) and more recently from multiple returns (Fleck et al., 2012). Terrestrial laser scanning (TLS) offers higher spatial resolution for retrieving forest structural parameters (Yang et al., 2013) or reconstructing single tree models (Eysn et al., 2013). However, TLS are restricted to field plot acquisitions and cannot cover larger areas, as compared to capabilities of ALS.

1.1. Aim and research objectives

In this paper, we model imaging spectrometer data using a forward simulation based on a 3D RT model with extensive in-situ measurements as well as ALS data and compare the model results with an imaging spectrometer data acquisition. The model is applied to a temperate mixed forest with a complex canopy structure. To model the canopy architecture, two approaches are compared: an individual tree based reconstruction and a voxel grid approach. Both approaches were fully parameterized using ALS data. The study made use of extensive in situ measurements, including TLS, spectral measurements of LOPs and background spectra originating from litter, mosses, and low growing vegetation. The Discrete Anisotropic Radiative Transfer (DART) model was used as 3D RT model (Gastellu-Etchegorry et al., 2012). The spectral bands were simulated and compared with the Airborne Prism Experiment (APEX) imaging spectrometer (Jehle et al., 2010).

The ultimate goal of this study is – once the RT model is fully parameterized – to inversely retrieve a set of variables from observations using look-up tables (LUTs), artificial neural networks (ANNs) (Vohland, Mader, & Dorigo, 2010), or direct radiance based approaches (Laurent, Verhoef, Clevers, & Schaepman, 2011b). However, the usually large number of free model parameters, model uncertainties, as well as instrument performance limitations and cross-correlations between adjacent bands of imaging spectrometer data acquisitions are limiting the applicability of such model inversions (Atzberger & Richter, 2012; Schaepman, 2009). Forward modeling is therefore a key requirement enabling to identify model and observational limitations, to finally better understand underlying physical processes, and provide relevant information for validation and calibration purposes.

2. Materials

2.1. Study area

The study area is a temperate mixed forest located on the south-facing slope of the Laegern mountain northwest of Zurich, Switzerland. It is an old-growth forest, characterized by high species diversity and a complex (i.e., multilayered) canopy structure. Mature beech (Fagus sylvatica) and Norway spruce (Picea abies) trees are predominant, growing on steep slopes with heterogeneous spectral background. A detailed description of the forest and environmental conditions can be found in Eugster et al. (2007).

The main scene covers an area of 300 × 300 m and is centered at 2 669 810 E, 1 259 060 N (CH1903 + LV95) ranging from 620 to 810 m above sea level (a.s.l.). It comprises a long-term forest ecosystem research site (LWF) of the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL) established in 2012 and a flux tower equipped with measurement units of FLUXNET (Baldocchi et al., 2001), AERONET (Holben et al., 1998), and the Swiss National Air Pollution Monitoring Network (NABEL).

Two subplots labeled S1 and S2 were defined within the main scene as representative sampling units of 40 × 40 m. S1 is located in the eastern part of the scene centered at 2 669 846 E, 1 259 040 N on 672 m a.s.l. It is covered by coniferous trees (P. abies, Abies alba) and deciduous trees (Fraxinus excelsior, F. sylvatica) in roughly equal parts. S2 is located in the western part of the scene centered at 2 669 690 E, 1 259 070 N on 701 m a.s.l. It represents a closed deciduous canopy mainly consisting of large beech trees and some smaller maple and ash trees (Acer pseudoplatanus, F. excelsior).

2.2. Field data

Deciduous leaves were collected at the Laegern site from ten individual trees of five species (A. pseudoplatanus, F. excelsior, F. sylvatica, Ulmus glabra, Tilia platyphyllos) on June 24th, 2009. To represent the vertical variability of leaf optical properties, leaf samples were taken from the upper, middle, and lower part of the crown representing sunlit, transitional, and shaded light conditions. Hemispherical–conical reflectance (HCRF, terminology following Schaepman-Strub, Schaepman, Painter, Dangel, & Martonchik, 2006) and transmittance were measured in the laboratory at three positions on the abaxial and adaxial side of the leaf. The measurements were performed using an integrating sphere coupled to a field spectroradiometer (ASD FieldSpec 3, Analytical Spectral Devices, USA). Spectral measurements of needle samples were available from an even-aged Norway spruce monoculture in the Šumava National Park, Czech Republic. Shoots of current year and
third year age classes were sampled from sunlit, transitional, and shaded parts of twelve mature trees. Needles were detached in the laboratory and immediately measured following Yáñez-Raußel, Malenovský, Clevers, and Schaepman (2014a), Yáñez-Raußel, Schaepman, Clevers, and Malenovský (2014b) and Rautiainen et al. (2012). The sampled trees were of the same species, growing under comparable environmental conditions, and having similar age and crown dimensions than the Norway spruce trees at the Laegern site.

Dominant ground components (leaf litter, needle litter, bare soil, rock, gravel, moss, understory vegetation up to 50 cm) and bark samples (beech, spruce, pine bark) were measured in the field using a field spectroradiometer (ASD FieldSpecPro). However, certain background was either located in shaded areas or suffered from substantial adjacency effects due to the proximity of large trees and a generally dense canopy. In such cases, the material was removed and measured under direct solar illumination or in the laboratory. Digital hemispherical photographs (DHPs) were taken under leaf on conditions at the two subplots S1 and S2 following the VALERI sampling scheme (Baret et al., 2003). True and effective plant area index (PAI) and the average leaf angle (ALA) were subsequently derived following (Weiss, Baret, Smith, Jonckheere, & Schaepman, 2002). Measurements of aerosol optical depth (AOD) and precipitable amount of water (PAW) were provided by the aerosol robotic network (AERONET) as level 2.0 quality-assured data (Holben et al., 1998).

2.4. Imaging spectrometer data

Imaging spectrometer data was acquired on June 16th, 2012 at 10:26 UTC under clear sky conditions using the APEX imaging spectrometer (Jehle et al., 2010). The Laegern site was covered by a single flight line with an off-nadir angle between 3.8° and 9.7°. Illumination and observation geometries at scene center are provided in Table 2. The average flight altitude was 4526 m a.s.l. resulting in a ground pixel size of 2 m. APEX recorded 299 spectral bands ranging from 376 nm to 2502 nm. The spectral sampling interval (SSI) varied between 2.5 nm and 13.9 nm and the full width at half maximum (FWHM) between 3.4 nm and 14.3 nm depending on wavelength.

Data preprocessing included traceable radiometric calibration, including compensation for spatial coregistration effects of the VNIR and SWIR detector, dark current and keystone correction (D’Odorico, Guanter, Schaepman, & Schläpfer, 2011; Hueni, Lenhard, Baumgartner, & Schaepman, 2013). The uncertainty of calibrated radiance values was lying within 0.5% and 3% in the range of 400 to 1900 nm and increasing subsequently up to 10% at 2400 nm. The noise equivalent detection limit of APEX was in the range of 0.5–1.0 mW m⁻² nm⁻¹ sr⁻¹ (Schläpfer & Schaepman, 2002). APEX data was georeferenced to the Swiss national grid CH1903 + and orthorectified using the nearest neighbor resampling in PARGE (Schläpfer & Richter, 2002; Schläpfer, Schaepman, & Itten, 1998). The geocorrection was based on the digital terrain model DHM25 of the Swiss Federal Office of Topography (Swisstopo, Switzerland).

3. Methods

3.1. Optical properties

Leaf optical properties were calculated for deciduous and coniferous trees. Since tree specific information about species or needle age classes were not available, a linear spectral forward mixing was applied to calculate the reflectance and transmittance spectra of sunlit, transitional, and shaded leaves and needles. The measured values were lying in the same range as literature based data (Combes et al., 2007; Wang & Li, 2012). Thus, the spectral measurements were used directly instead of using a forward run of the leaf optical properties model PROSPECT (Jacquemoud & Baret, 1990) to reduce the number of model parameters and possible model uncertainties. The broadleaf species composition used for spectral mixing was derived from forest inventory data of 617 trees: 50.8% beech, 19% maple, 10.7% elm, 10.5% linden and 9% ash. The composition of needle age classes was based on Lukeš, Rautiainen, Stenberg, and Malenovský (2011), summarized in Table 1.

The spectra of the four main classes of canopy background were based on the in situ spectrometer measurements. Understory vegetation up to 50 cm was defined being a mixture of 90% grass and shrubs and 10% mosses, unvegetated ground consisted of ½ bare soil and ½ gravel, whereas litter was composed of 85% leaf litter and 15% needle litter. Leaf spectra of the lowest crown layers were assigned to understory vegetation of 0.5 m up to 3 m. The composition of background components was determined from an inventory of forest floor characteristics and compared to a stratified plant sociological classification.

Table 1

<table>
<thead>
<tr>
<th>Crown layer</th>
<th>First year needles</th>
<th>Third year needles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top</td>
<td>41.5%</td>
<td>58.5%</td>
</tr>
<tr>
<td>Middle</td>
<td>13.6%</td>
<td>86.4%</td>
</tr>
<tr>
<td>Bottom</td>
<td>1.7%</td>
<td>98.3%</td>
</tr>
</tbody>
</table>
3.2. 3D forest reconstruction

3.2.1. Canopy background

The digital terrain model (DTM) was derived from ALS ground returns, which were extracted using an adaptive multi-scale algorithm based on (Evans & Hudak, 2007). An iterative filter process was used to select the ground return echoes and distinguish between height deviations caused by steep terrain and artificial objects or dense vegetation. The remaining points were interpolated to a $1 \times 1$ m DTM applying ordinary kriging.

Additionally, a classification of the four main classes of canopy background (see Section 3.1) was created from the ALS data. The classification was done on $1 \times 1$ m grid cells by investigating the point distribution, leaf-on to leaf-off variations, and quantitative statistical measures of the full-waveform variables within the vertical column of each cell (Leiterer, Mücke, Hollaus, Pfeifer, & Schaepman, 2013). Both DTM as well as ground cover classification were finally resampled to $2 \times 2$ m resolution for radiative transfer modeling. A majority resampling technique was used to remove single, misclassified pixels and match the spatial resolution of APEX.

3.2.2. Individual tree detection

To geometrically reconstruct the forest scene, the ALS point cloud was clustered into groups of ALS echoes presumably being reflected from a single tree. The clustering was based on the method described in Morsdorf et al. (2004) and compared to other methods in Kaartinen et al. (2012). Tree height and crown base height could be directly derived from the ALS returns of each cluster. Additionally, alpha shapes were calculated to derive crown specific metrics such as crown volume, projection area, and diameter in NS and WE direction (Vauhkonen, Tokola, Packalen, & Maltamo, 2009). Together with the tree positions, these crown variables were used to parameterize the geometric primitives (ellipsoids for deciduous trees, truncated cones for coniferous trees) used in radiative transfer modeling.

To distinguish deciduous from coniferous trees, within crown variations of the point distribution between leaf-on and leaf-off acquisitions were assessed. A tree was classified as deciduous, if the percentage of points lying in the uppermost $6$ m of the crown was varying more than $5\%$ between leaf-on and leaf-off acquisitions or if it was smaller than $10$ m. Otherwise, it was classified as coniferous tree.

Besides the crown geometry, the PAI was determined for each tree. The mean PAI of the in situ measurements was taken as a reference, as assessed after Fleck et al. (2012): $\text{PAI}_\text{local} = \frac{\sum e_{\text{veg}}}{\sum e_{\text{total}}}$

where $e_{\text{total}}$ are echoes within the projection area of the tree and $e_{\text{veg}} = e_{\text{total}} > 3$ m above ground. The vegetation ratio $r_{\text{veg}}$ was calculated on the leaf-on dataset to relatively distribute the PAI to the individual trees of the scene. The mean PAI of all trees was kept constant. Each crown was divided into three equally thick vertical layers (Fig. 1). The layering was introduced to assign different optical properties according to the differing light conditions within the crown. Additionally, a weight – calculated based on the vertical distribution of ALS points within the crown – was applied on the tree PAI for each crown layer to account for the vertical heterogeneity in the distribution of plant material.

3.2.3. Voxel grid parameterization

Instead of extracting individual trees, it is possible to directly derive a 3D voxel grid of PAI or plant area density (PAD) values from the ALS point cloud. Especially in a dense mixed forest, it is often difficult to separate individual trees from each other and approximating the crown shapes by ellipsoids or cones may be oversimplifying. Therefore, the voxel grid approach offers a way to model the 3D canopy architecture of a forest independently of pre-defined crown shapes.

The first step to derive the voxel grid was to calculate the PAI over the whole scene on $2 \times 2$ m grid cells. The PAI was calculated from leaf-on canopy and ground echoes in the vertical column of each cell based on Solberg et al. (2009), modified after Fleck et al. (2012):

$\text{PAI} = c \cdot \ln \left( \frac{1 - t_1 - \frac{1}{g_1} - t_2 - \frac{1}{g_2} - t_3 - \ldots - \frac{1}{g_7}}{1 - \frac{1}{g_1} - \frac{1}{g_2} - \frac{1}{g_3} - \ldots - \frac{1}{g_7}} \right), \quad (2)$

where $t_1, t_2, t_3, \ldots, t_7$ are the total number of echoes within the vertical column of pulses with $1, 2, 3, \ldots, 7$ returns and $g_1, g_2, g_3, \ldots, g_7$ are the number of ground echoes of pulses with $1, 2, 3, \ldots, 7$ returns respectively. Ground echoes were defined as echoes below $2$ m above ground. The calibration factor $c$ was derived by solving Eq. (2) for $c$ and replacing $\text{PAI}$ by $\text{PAI}_{\text{leaf}}$ which is the true PAI measured in situ under leaf-on conditions. Two calibration factors were calculated this way on subplots S1 and S2 and averaged for the use in Eq. (2). In very dense parts of the forest, it can happen that there are no ground echoes at all. In these situations, there will be a saturation of the PAI retrieval. Therefore, the denominator of zero was replaced by the smallest possible value greater than zero (e.g., being $\frac{1}{2}$ with a maximum number of $7$ returns per shot).

In a second step, the vertical distribution of plant material had to be determined by the analysis of the ALS point cloud of leaf-on and leaf-off acquisitions. Starting from the lowest point of the scene, each vertical column was divided into $2 \times 2 \times 2$ m sized voxels. The percentage of points in a voxel was calculated with respect to the total amount of points in the vertical column. The PAI of each voxel was then calculated accordingly, assuming that the vertical point distribution represented the canopy architecture.

A discrimination of coniferous and deciduous trees was applied on the $2 \times 2$ m grid as described in Section 3.2.2. Furthermore, three vertical crown layers were defined according to the vertical plant area distribution in the 3D voxel grid. $50\%$ of plant material was defined to be in the upper most layer of the canopy and $25\%$ in the lower two layers each. Therefore, most of the light is intercepted within the upper most
sulit layer, whereas the relative light transmission to the transitional and shaded layers can be less than 30% depending on the clumping of leaves or needles (Niinemets, 2009).

3.3. Radiative transfer model parameterization

The radiative transfer model used in this study was the DART model (DART v5.4.3). DART simulates three-dimensional heterogeneous landscapes in three operating modes: flux tracking, LiDAR, and Monte Carlo. Generally, a DART scene is built out of voxels with a predefined size. To simulate vegetation such as grass or tree crowns, voxels can be filled by turbid media parameterized by volume density, angular distribution, and optical properties. Moreover, DART offers the possibility to import detailed 3D models consisting of triangles with individual optical properties. A DART voxel can include vegetation turbid media as well as triangles with an arbitrary size, independent of the voxel size. In ray tracing, two types of radiation interaction are simulated: volume interaction within turbid voxels (Gastellu-Etchegorry, Martin, & Gascon, 2004) and surface interaction on triangles (Gastellu-Etchegorry, 2008). Further details of the DART model and examples of DART simulations can be found in Gastellu-Etchegorry et al. (2012).

Here, flux tracking was used in reflectance mode with the sun and the atmosphere as the only radiation sources. Optical properties described in Section 3.1 and the forest reconstruction described in Section 3.2 were used to parameterize the forest canopy, background, and terrain in DART. The established approach to simulate trees in DART is to use predefined crown shapes (e.g., ellipsoids, cones) filled by turbid media, which are voxelized internally by DART. Whereas most previous studies used generalized tree crowns and positioning of trees (e.g., Barbier, Couteron, Proux, Malhi, & Gastellu-Etchegorry, 2010; Malenovsky et al., 2013, 2008), every single tree was parameterized individually in this study as described in Section 3.2.2. This is called the individual tree approach. Additionally, a new approach was developed to directly parameterize the DART model from a voxel grid. The parameterization of the voxel grid is described in Section 3.2.3 and now referred to as voxel grid approach.

For both the individual tree and voxel grid approach, turbid media were used to model the vegetation volumes. Their leaf angle distribution was assumed to be spherical for coniferous trees, whereas the plagiophile distribution function was better suited to describe the LAD of broadleaved trees (terminology following de Wit, 1965). The decision to choose the plagiophile LAD was based on the average leaf angle of 45° measured at subplot S2 and supported by the findings of Pisek, Sonnentag, Richardson, and Mottus (2013).

Neither tree trunks nor branches were explicitly included in the model due to the lack of measurements over the whole scene. To study the effect of neglecting woody elements, over 70 geometrical models consisting of cylinders representing the stem and branches were extracted from the TLS point clouds on subplots S1 and S2. The tree skeletons together with the diameter of the stems and branches, thus cylinders, were digitized semi-automatically in the individual scans presented to the operator as range images. While manual interaction is required, the approach is robust in the presence of occlusions, registration errors, and wind (Eysn et al., 2013). After triangulation of the cylinders, the models of stems and branches can be added to the DART scene as 3D triangle meshes. Interactions of rays with woody elements are hence simulated on the basis of individual triangles, which are described by the optical properties of the bark.

To simulate the atmosphere, DART can be used with standard gas and aerosol models as contained in MODTRAN (Berstein & Roberston, 1989). We used the mid-latitude summer gas model and the rural aerosol model with a visibility of 23 km as a reference. The gas and aerosol models were then modified to meet the atmospheric conditions during the APEX overflight. Aerosol optical depth was adjusted based on the local measurement of the AERONET station at seven wavelengths (340, 380, 440, 500, 675, 870, 1020 nm). Besides the water vapor data provided by AERONET, the measurements of Rayleigh scattering were used to finalize the atmosphere parameterization. Sensor height, solar and viewing geometry were set according to the sun–earth-sensor geometries of the date and time of the APEX acquisition. The main model parameters of the 300 × 300 m scene are summarized in Table 2.

3.4. DART simulations

DART simulates images of radiance or reflectance at the top of canopy (TOC), top of atmosphere (TOA), and sensor altitude. For best comparability, the at-sensor radiance orthoimage was used as the main output. An orthoimage is the 2D distribution of radiance values for each pixel (x, y) and a given view direction (θv, φv). In order to create orthoimages, DART stores each radiative flux $\Phi_v(x, y, z, \theta_v, \phi_v)$ that exits the vertical column (x, y) reaching the top of canopy level. Radiance of the orthoimage at pixel $x, y$ for any view direction $(\theta_v, \phi_v)$ is (terminology following Schaepman-Strub et al., 2006):

$$L(x, y) = \sum_{\theta, \phi} \Phi_v(x, y, z, \theta_v, \phi_v) A_{\text{xy}} \cdot \cos \theta_v \cdot \phi_v \omega_v$$

Table 2

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atmosphere parameters</td>
<td></td>
</tr>
<tr>
<td>Sensor altitude</td>
<td>m a.s.l.</td>
</tr>
<tr>
<td>Aerosol optical depth</td>
<td>$\lambda$500 nm</td>
</tr>
<tr>
<td>Rayleigh optical depth</td>
<td>$\lambda$500 nm</td>
</tr>
<tr>
<td>Precipitable water</td>
<td>[cm]</td>
</tr>
<tr>
<td>DART specific parameters</td>
<td></td>
</tr>
<tr>
<td>Number of directions</td>
<td>100</td>
</tr>
<tr>
<td>Number of cell subcenters</td>
<td>400</td>
</tr>
<tr>
<td>Propagation threshold</td>
<td>W m$^{-2}$ sr$^{-1}$</td>
</tr>
</tbody>
</table>

Note:
- From north clockwise.
- At sea level.
- $A_{\text{xy}}$ is the area of pixel $(x, y)$.
- $\omega_v$ is the solid angle associated to direction $(\theta_v, \phi_v)$. The angles $\theta_v, \phi_v$ and $\omega_v$ depend on the horizontal location $(x, y)$ and also on the vertical location $z$, associated to each flux that leaves the column $(x, y)$ towards the sensor. Both the geometric representation in DART as well as the projection of the APEX data were based on the Swiss national grid CH1903+. The pixel size of $2 \times 2$ m was chosen to exactly match the spatial resolution of the projected APEX data.
Simulations were carried out for 281 bands on the two subplots S1 and S2 to cover the full spectral range of 400 to 2400 nm, whereas the whole 300 × 300 m scene was simulated with four selected wavelengths (533, 570, 680, 780 nm), allowing a distinct set of vegetation indices (PRI, NDVI) to be calculated. The simulations on the large scene and the two subscenes were once performed using the voxel grid approach and once using the individual tree approach. The other parameters were kept constant. The DART simulations are summarized in Table 3. Simulation time for 281 bands at subplot level (S1, S2) was 20 h, whereas the simulation of a single band at the scene level (300 × 300 m) took 21 h on a fast computer (6-core processor, 32 GB RAM). In the future, this constraint will be reduced by a multi-threading approach being implemented in the upcoming DART version (v5.4.7).

To be able to interpret the results, additional simulations were carried out on the two subplots S1 and S2 (see Table 3). For this, the parameterized DART scene based on the voxel grid was used as reference. To study the effect of neglecting woody elements, simulations with detailed 3D models of trunks and branches were carried out on S1 and S2. The 3D models were added to the subplots without adapting the PAI of voxels already filled by turbid media, leading to an overestimation of the scene PAI of 6.5% and 7.6% for S1 and S2 respectively. The influence of the background on the radiative regime was examined by replacing the background classification and the corresponding spectral properties by a black 100% absorbing background, since using a black background is a common simplification in radiative transfer modeling of forests (e.g., Knyazikhin et al., 2013). Additionally, the influence of the parameters used to describe the vegetation turbid media was studied by simulating the two subplots with the minimal and maximal canopy spectra and changing PAI and LAD values.

4. Results

4.1. Optical properties

The results of the linear spectral forward mixing of the optical properties of individual species are the mean reflectance and transmittance spectra of deciduous and coniferous trees, for both adaxial and abaxial sides of sunlit, transitional, and shaded leaves and needles, respectively. The mean adaxial spectra and the minimum and maximum values, measured among individual tree species and among different measurement positions on the leaf, are presented in Fig. 2. The optical properties of background components and barks are presented in Fig. 3.

4.2. 3D forest reconstruction

4.2.1. Canopy background

The canopy background, consisting of the DTM and the background cover classification, is shown in Fig. 4. Verification of the DTM, based on absolute DTM values derived from the TLS measurements at subplots S1 and S2, shows a mean vertical deviation of ±10 cm. The positional accuracy of the TLS derived DTM was evaluated based on 53 surveying points linked to accurately fixed control points of the Swiss national land survey. For the ground cover classification, a reference dataset derived from TLS data, field measurements, and a plant sociological classification were used to calculate accuracy measures based on Liu, Frazier, and Kumar (2007). An overall accuracy of ≈64% for all classes and a detection rate of understory vegetation of ≈89% are achieved (see Leiterer et al., 2013 for more details).

Table 3

DART simulations carried out on the whole scene (300 × 300 m) and subplots S1 and S2 (40 × 40 m).

<table>
<thead>
<tr>
<th>Scene size</th>
<th>Canopy</th>
<th>Background</th>
<th>Woody elements</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>300 × 300 m</td>
<td></td>
<td></td>
<td></td>
<td>4 spectral bands: 533.6 nm ± 3.9 nm 569.6 nm ± 3.0 nm 678.8 nm ± 2.2 nm 780.7 nm ± 3.2 nm</td>
</tr>
<tr>
<td>40 × 40 m</td>
<td></td>
<td></td>
<td></td>
<td>281 spectral bands: WVL: 400–2400 nm SSI: 2.5–13.9 nm FWHM: 3.4–14.3 nm</td>
</tr>
</tbody>
</table>

Additional simulations with a mean PAI of 3 and 7, an erectophile and planophile LAD, and minimal and maximal reflectance and transmittance of leaves and needles.
4.2.2. Individual tree and voxel grid parameterization

The mean PAI derived from in situ measurements at S1 and S2 is 5.05 ± 0.52 m² m⁻². This value was used as reference in the 3D forest reconstruction. The result of the individual tree approach is a 3D representation of the forest scene composed of 1526 deciduous and 312 coniferous trees. The individual trees and the PAI voxel grid of the 300 × 300 m scene are illustrated in Fig. 5. The two raster maps show the PAI values in 2D, whereas the values for the individual tree approach were derived after internal voxelization in DART.

The tree detection accuracy and the delineation of tree crown variables were assessed based on a stratified random sampling approach using TLS, orthoimages, and field-map system data. The commission and omission errors for the tree detection are 5.2% and 13.1% respectively, whereas deciduous trees are discriminated from coniferous trees with an overall accuracy of 89.7% and a Kappa coefficient of 0.74 (terminology following Liu et al., 2007). Because of sloped terrain, positional uncertainty using ALS results in a vertical tree height variation of ±1 m, as determined from the DTM and tree positions. Remaining uncertainties stemming from other error sources (e.g., underestimation of tree height as described in Morsdorf et al., 2004; Heurich, 2008) likely result in a total uncertainty up to 4 m. Crown dimensions show a high consistency using a cross-comparison with TLS measurements and orthoimages, but could not be verified quantitatively due to the complexity of the dense forest canopy.

4.3. Simulation results

4.3.1. Forest spectra

Spectrally contiguous radiance spectra (400–2400 nm) were simulated for two representative subplots S1 and S2 using the voxel grid approach. The inner 10 × 10 pixels of each plot were averaged, whereas a buffer of five pixels was disregarded due to possible boundary effects when using DART. The results of modeled mean at-sensor radiance ±

**Fig. 2.** Leaf optical properties of broadleaves (left) and needles (right): mean adaxial reflectance and transmittance (−) with minimum and maximum values (−−).

**Fig. 3.** Optical properties of understory vegetation up to 50 cm, litter, unvegetated ground (−) as well as deciduous and coniferous bark (−−).

**Fig. 4.** Four main classes of canopy background visualized on the digital terrain model.
Fig. 5. Reconstruction of the forest canopy by the individual tree (left) and the voxel grid approach (right) in 3D (above) and 2D (below). The 2D raster map shows the individual tree shapes after voxelization by DART. Rectangles indicate the locations of subplots S1 and S2.

Fig. 6. Mean at-sensor radiance ± standard deviations of APEX compared to the modeled output of DART on the two subplots S1 (left) and S2 (right). Plots of 40 × 40 m were simulated using the voxel grid approach, whereas the inner 20 × 20 m was used for this comparison to avoid border effects in RT modeling. Differences are calculated by subtracting the APEX from the DART signal.
standard deviations are presented in Fig. 6. When comparing the modeled spectra to at-sensor radiances measured by APEX, we detect general overestimation in the visible spectral range (VIS, 400–700 nm) and underestimation in the near infrared (NIR, 700–1100 nm). On subplot S1, mean at-sensor radiance simulated by DART differs by 4.98 mW m\(^{-2}\) nm\(^{-1}\) sr\(^{-1}\) from APEX on average. The mean relative difference is 37.3% in the VIS, 14.6% in the NIR range, and 37.6% in the shortwave infrared (SWIR, 1100–2400 nm). On subplot S2, the differences are larger, being 8.82 mW m\(^{-2}\) nm\(^{-1}\) sr\(^{-1}\) on average due to a strong difference in the NIR range. The relative difference is 35.4% in the VIS, 35.5% in the NIR, and 34.4% in the SWIR range.

4.3.2. Airborne remote sensing images

The simulated and measured airborne remote sensing images at 780 nm and the corresponding difference images at 533, 570, 680, and 780 nm are shown in Fig. 7 using the voxel grid approach and in Fig. 8.
using the individual tree approach. Averaging the inner 120 × 120 pixels of the difference images results in 9.41, 8.85, 9.50, and 36.65 mW m\(^{-2}\) nm\(^{-1}\) sr\(^{-1}\) mean difference at 533, 570, 680, and 780 nm respectively. A linear regression between the 120 ×120 APEX and DART pixels resulted in a coefficient of determination \((R^2)\) of 0.55, 0.56, 0.39, and 0.48 using the voxel grid approach and 0.41, 0.41, 0.29, and 0.34 using the individual tree approach at 533, 570, 680, and 780 nm.

4.3.3. Influence of scattering elements and turbid medium parameterization

The radiance spectra simulated using the individual tree approach, including woody elements, and a black background (see Table 3) were compared to the reference simulation, which itself is based on the voxel grid approach (Fig. 9). Using individual trees instead of the voxel grid approach leads to slightly smaller values in most bands. On S1, values are on average 4.6% and 6.3% smaller in the VIS and NIR.
Minor differences can be observed on the structurally more homogeneous subplot S2 with differences of 1.6% and 1.9% in the VIS and NIR range. Adding woody elements to the subplots has most influence in the NIR and SWIR range with a mean difference of 4.9% and 5.7% on S1, and 5.2% and 5.3% on S2. Using a black background has a relatively strong influence in all spectral bands. The radiance is on average 13.1%, 19.9%, and 30.4% smaller in the VIS, NIR, and SWIR range on S1, whereas it is 7.6%, 19.7%, and 27.0% smaller on S2 respectively.

Turbid media scatterers as used in DART are parameterized by using PAI, LAD, and LOP. Changing the values of these parameters strongly influences the simulated at-sensor radiances as a whole as well as in each individual spectral band. The result of simulations using a mean PAI of 3.0 and 7.0, with erectophile and planophile LAD functions, and using the minimum and maximum reflectance and transmittance spectra (see Fig. 2) is shown in Fig. 10. The strongest influence is caused by a change of leaf optical properties. The maximal reflectance and transmittance values are about 60%, 20%, and 25% higher in the VIS, NIR, and SWIR range than the input values used in the voxel grid reference simulation, resulting in an average increase of at-sensor radiances of 23.9%, 46.1%, and 29% on S1 and 30.3%, 47.9%, and 33.7% on S2. Minimal reflectance and transmittance values are about 50%, 20%, and 25% smaller in the VIS, NIR, and SWIR range, resulting in an average decrease of at-sensor radiances of 13.7%, 30.6%, and 22.5% on S1 and 17.5%, 34.4%, and 26.1% on S2. The influence of LAD on at-sensor radiance is strongest in the NIR spectral range, where a planophile function leads to an increase of 13.4% on S1 and 11.8% on S1 and an erectophile function leads to a decrease of 11.3% on S1 and 11.9% on S2. The influence of PAI is relatively small. A 40% higher PAI leads to a mean difference to
the voxel grid reference of 8% on S1 and 7% on S2 over the whole spectral range, whereas a 40% lower PAI leads to a mean difference to the reference of 19.2% on S1 and 19.1% on S2 over the whole spectral range.

5. Discussion

5.1. Leaf optical properties

Leaf optical properties are varying considerably among individual measurements, as indicated in Fig. 2 by the minimum and maximum values. These variations are primarily related to differences in leaf surface properties, internal leaf structure, biochemical constituents, and the LOP measurement process itself (Yáñez-Rausell et al., 2014a, 2004b). Leaf pigments mainly determine the optical properties in the VIS, being the important spectral range for plant photosynthesis (Asner, 1998). Scattering in the NIR range is primarily a function of the leaf structure (arrangement of cells, thickness of cell walls, etc.) and the dry matter content (Knyazikhin et al., 2013), whereas the SWIR range is mainly influenced by water, lignin, and cellulose (Kokaly et al., 2009).

In contrast, leaf surface reflectance is not restricted to certain wavelengths being a constant additive effect to scattering processes within the leaf (Niinemets, 2010). Interestingly enough, the strongest variation is present between measurements at different positions on the leaf (data not shown). Whether this is due to changing leaf interior or surface characteristics, or a combination of both, cannot be determined from the measurements. Dealing with the large variability of leaf optical properties and the disentanglement of signals from leaf surface and interior are current challenges in RT modeling, which are not met yet. Furthermore, there is a need for a more coherent approach to LOP measurements, since comparisons among studies are currently hampered by the large variability of leaf optical properties, internal leaf structure, biochemical constituents, and face characteristics, or a combination of both, cannot be determined from the measurements. Dealing with the large variability of leaf optical properties and the disentanglement of signals from leaf surface and interior are current challenges in RT modeling, which are not met yet. Furthermore, there is a need for a more coherent approach to LOP measurements, since comparisons among studies are currently hampered due to the fact that varying measurement techniques and units are used throughout the literature.

What is particularly addressed in this study are variations of optical properties along a vertical light extinction gradient within the canopy. These originate from the adaptation of the leaves’ efficiency of light interception to the light availability (Niinemets, 2010). Higher transmittance and lower reflectance in shaded compared to sunlit parts of the crown are the consequence, also observed by (Luček, Stenberg, Rautiainen, Möttus, & Vanhatalo, 2013) for boreal tree species. However, the change of LOPs along the light gradient is relatively small, since light harvesting is regulated not only by leaf-level traits but also by leaf area, leaf angle, and clumping within the canopy (Niinemets, 2010).

5.2. 3D forest reconstruction

3D canopy structure and background determine how radiation interacts with leaves, woody elements, and background components, affecting the sensitivity of canopy reflectance to leaf optical properties (Knyazikhin et al., 2013). The DTM, the canopy background (Fig. 4), and the canopy architecture (Fig. 5) are solely derived from ALS leaf-on and leaf-off data. This allows automating the forest reconstruction and applying it on various forest ecosystems ranging from plot to landscape level, given the availability of suitable ALS data.

The DTM shows a high level of detail, especially considering the density of the forest. Understory vegetation is mainly present in sparsely forested areas or forest edges and classified with high accuracy. Some occurrences can be observed in areas dominated by coniferous trees due to the higher canopy gap fraction. We observe a typical distribution of understory vegetation as described by Eriksson, Eklundh, Kuusk, and Nilson (2006). Main uncertainties in the classification of canopy background are stemming from the delineation of litter and unvegetated ground, mainly due to the similarity of the optical properties of organic material rich bare soil and litter.

The individual tree detection method applied in this study was reviewed and compared to other methods in Kaartinen et al. (2012). Even though we used a point cloud derived from full-waveform ALS data with a much higher point density, the resulting errors are comparable to the ones found by Kaartinen et al. (2012). The reason may lie in the complexity of the forest being characterized by a large number of understory, clustered, and multi-stemmed trees, which are difficult to detect. Thus there is a need for high-resolution, multitemporal ALS data in such complex forests, although some errors will remain saturating at high point densities.

Comparing the 2D PAI map of the individual tree to the one of the voxel grid approach shows the limitations of the former (Fig. 5). The general pattern is comparable, but the individual tree approach is not capable of describing the mostly closed canopy layer in a realistic way. The gap fraction is generally too high, whereas the plant material is clustered into small patches. The application of the voxel grid approach leads to a more realistic and coherent horizontal distribution of plant material. Moreover, the 3D canopy architecture derived using the voxel grid approach does better represent the underlying ALS point cloud, since tree crowns in a closed forest canopy can generally not be described sufficiently by using simple ellipsoidal or conical shapes.

Nevertheless, some limitations exist in the derivation of the vertical PAI distribution from ALS data. The vertical distribution of ALS points is influenced by the penetration rate of the laser beam through the forest canopy, which is dependent not only on the density of the canopy but also on the sensor and scanning characteristics (Côté et al., 2012; Naesset, 2009). A low flight altitude and overlapping flight strips result in high point densities and a variation of scan angles per unit area, reducing the effects of occlusion in dense parts of the forest. The combination of leaf-on with the leaf-off data further improves the ability to detect plant material in the lower parts of deciduous canopies, although limited to woody or evergreen elements. However, effects of occlusion—mainly expressed by reduced point densities in lower canopy parts—are still present and difficult to quantify. For the voxel grid approach, the logarithmic transformation in Eq. (2) is in accordance with Beer’s law and should yield a linear, non-intercept relation to effective PAI (Solberg et al., 2009). To be able to explicitly correct the laser light extinction through the canopy, further studies are needed to better model effects of occlusion by using physical models and assessing them in a quantitative fashion (e.g., Morsdorf, Nichol, Malthus, & Woodhouse, 2009).

5.3. Simulation results

Both DART and APEX at-sensor radiance spectra show typical atmospheric absorption features as expected (see Fig. 6). Atmospheric path radiance is strongest in the VIS part of the spectrum, adding to the reflected radiance from the forest canopy and background. The high atmospheric visibility during the APEX overflight was measured and confirmed by the AERONET station on the flux tower. However, the actual atmospheric absorption could still not be fully matched by basing our parameterization on MODTRAN’s standard atmospheres due to a skewed mix of absorbing and reflecting aerosol concentrations and the unknown distribution of aerosols in the vertical path. Hence, we observe a systematic shift of about 8–12 mW m−2 nm−1 sr−1 in the VIS due to enhanced atmospheric path radiance in the DART simulation.

The systematic shift of radiance values in the VIS is present in the difference images, however the spatial pattern remains consistent across space (Fig. 7). The results of Section 4.3.2 confirm our conclusion that the voxel grid approach is better suited to describe the complex 3D canopy architecture, even though there is a potential scale issue linked to clumping and voxel size (Béland et al., 2014). The difference images in Fig. 8 indicate strong local deviations from the APEX images due to the differing shape and arrangement of the individual trees. The concentration of plant material paired with the large gap fraction results in too many shaded canopy parts and partially enhanced radiance values in sunlit parts. Additionally, the influence of the canopy background is enhanced, especially in the red region where vegetation is mostly
In general, the influence of canopy background is higher than expected, even though considered negligible in other studies (c.f., Knayzikin et al., 2013). Modeling a black background has a much higher impact on the simulated radiance spectra than adding woody elements or using the individual tree compared to the voxel grid approach (see Section 4.3.3). This stresses the importance of an area-wide canopy background classification being necessary for a solid modeling approach at regional scale, where heterogeneous clumping occurs. The influence of woody elements was assessed before by others such as Malenovský et al. (2008). However, this was limited to using TOC reflectances in a different type of forest (less heterogeneity of the gap fraction), and using a different modeling approach. Nonetheless, our results are in agreement with the findings of Malenovský et al. (2008). Adding woody elements results in slightly lower radiance values at all wavelengths due to increased multiple scattering similar to the photon-trapping within a coniferous shoot (Rautiainen & Stenberg, 2005).

5.3.1. Voxel grid approach

Looking at the difference images in Fig. 7, the two bands at 533 and 570 nm show a similar homogeneous spatial difference pattern. This is important since these two wavelengths are used to describe the photosynthetic efficiency of plants (Garbulsky, Pehuelas, Gamon, Inoue, & Filella, 2011). Stronger differences can be observed locally, where the canopy has small gaps or glades. On one hand, these local differences can be explained by uncertainties in the spatial registration of the APEX data. At the border of sunlit and shaded crown parts, a shift of one pixel can already lead to strong differences when performing a pixel-wise comparison. On the other hand, there is a temporal difference between the ALS and the APEX acquisition of about two years, which can easily cause small differences in canopy structure.

Some differences in the scattering of understory exist at 680 nm, where the chlorophyll absorption of the vegetation is strongest. DART simulates higher radiance values on the forest glade located in the southwestern part of the scene, indicating that there was more absorbing vegetation present during the APEX overflight than modeled. If a small understory vegetation layer is modeled, the signal was more sensitive to the reflectance of the underlying soil being higher than that of vegetation in the red region. Additionally, the corresponding APEX band shows a low signal to noise ratio (SNR) due to the low radiant flux (see Schaepman, Schlapefer, & Mueller, 2002), leading to the weakest coefficient of determination of all four selected bands.

The most conspicuous spatial pattern is present at the 780 nm difference image. The distinct pattern of over- and understimation of APEX values corresponds with the distribution of coniferous and deciduous trees. This also explains the intensity differences between subplots S1 and S2 in the NIR range, since over- and understimation even out on S1 (Fig. 6). There are several possible reasons why the radiance of deciduous trees is simulated too low, whereas the signal of coniferous trees is too strong.

First, the rather strong absorption present in the NIR range of the deciduous leaf optical properties could explain the low radiance values in the simulation output (see Fig. 2). Secondly, the selection of leaf and needle samples is limited and does not represent the high spectral variability of the different tree species. Using only one mean spectrum per vertical crown layer for deciduous and one for coniferous tree species may be too generalizing, since the strong variations on the single leaf level scale up to the canopy level (Fig. 10). For example, the APEX image shows above-average radiance values in the southwestern part of the scene, where young beech trees are growing in a dense vegetation layer. This distinct type of vegetation is not modeled appropriately in the DART image, because specific LOPs of young trees are not considered in the model. In ongoing field work, the location, species, and diameter at breast height (DBH) of all trees are being determined to model individual tree species. Paired with more detailed LOP measurements (including measurements of biochemistry), we will be better able to understand how spectral differences among species and species’ development stages are influencing the model output.

Besides the optical properties, structural characteristics are known to have a strong influence in the NIR spectral range. Generally, the 3D architecture of the canopy is well modeled using the voxel grid approach, but our approach has its limits in the description of small-scale structures on the branch or shoot level. The clumping of needles into shoots is strongly influencing the scattering behavior of coniferous trees. Multiple scattering within shoots is considered to be the most important structural effect responsible for the low NIR reflectance of coniferous trees (Rautiainen & Stenberg, 2005). Therefore, the scattering and absorption of radiation are determined not only by the arrangement of shoots within crowns but also by the arrangement of needles within shoots, but neither the resulting absorption of radiation nor the shoot scattering phase function can be directly modeled by the turbid medium approach used in this study (Möttö et al., 2012; Rautiainen et al., 2012; Stenberg, Möttö, & Rautiainen, 2008).

A way to alternatively approximate the shoot-level clumping would be to reduce the voxel size by one order of magnitude (e.g., Malenovský et al., 2013, 2008) or to use shoots as basic scattering elements (e.g., van Leeuwen et al., 2013). To model the coniferous trees in a physically more consistent fashion, 3D models would need to be able resolving single needles (e.g., Côté et al., 2011, 2012). Theoretically, all of these approaches can be put into practice using DART, but are usually limited to smaller plots due to the high computational costs. Moreover, the parameterization is mainly based on TLS measurements and thus limited to plots accessible by foot. Our forest reconstruction approaches though are automated and applicable on the landscape level, wherever multi-temporal ALS data is available. A much simpler and therefore promising approach is the upscaling of coniferous needle spectra to shoot spectral albedo based on the spherically averaged silhouette to total area ratio (STAR), which could be included in future RT models (Möttö et al., 2012; Rautiainen et al., 2012).

Moreover, the LAD and PAI are the structural parameters used to parameterize the voxels filled by turbid media. It is not surprising that PAI variations have a comparably low impact on the modeled spectrum (Fig. 9), since they are known to be saturating in dense, closed canopies having a PAI \( \geq 3 \) (Baret & Guyot, 1991; Gitelson, 2004). Our results of Section 4.3.3 support previous findings about the LAD having a much stronger impact on canopy reflectance and at-sensor radiance (e.g., Ollinger, 2011; Laurent, Verhoef, Clevers, & Schaepman, 2011a). Applying a universal distribution function for deciduous and coniferous trees based on literature and ALA measurements is considered a good approximation, but still fails to account for the wide range of leaf angles observed within a tree (Falster & Westoby, 2003; Pisek et al., 2013).

Especially in closed canopies, the leaf angle distribution is assumed to be varying along the vertical canopy profile. Optimally, steeper leaf angles would prevail in the upper sunlit canopy parts, whereas flat leaves would be predominant in shaded understory layers (Niinemets, 1998, 2010). However, there are very few studies supporting these assumptions due to the difficulty and costs of measuring the large number of leaf angles needed to describe the variations among vertical crown layers and species (Pisek et al., 2013). Nonetheless, we recommend parameterizing LAD on different vertical canopy layers in future studies, since it would improve our model approaches for remotely sensed data and increase the ability of RT models to be inverted.

6. Conclusion and outlook

In this study we have reconstructed a temperate mixed forest using a high resolution canopy–atmosphere 3D RT model and compared it to imaging spectrometer data. To address the complex 3D canopy architecture, we developed and compared two forest reconstruction approaches: an individual tree based approach and a voxel grid approach. Our results show that the voxel grid approach performs
better than a parameterization based on individual trees. In a pixel-wise comparison with the imaging spectrometer data, the voxel grid approach better represented hotspots and shadows, leading to a slightly higher predictive power (R² = 0.48, λ780 nm) as when using the individual tree approach (R² = 0.34, λ780 nm). The images simulated using the voxel grid approach exhibit similar spatial patterns than the APEX images, whereas absolute radiance values are partially differing depending on particular wavelengths.

The work emphasized on two important constraining factors of the 3D RT model parameterization. Firstly, the high spectral variability of leaf optical properties needs to be considered not only along a vertical light extinction gradient within the canopy but also between individual species and leaves. For a specific leaf level simulation allowing to better understand spectral variations, an improved sampling of leaves and needles including validation will be needed. Secondly, the accurate parameterization of small-scale structures, such as the clumping of needles into shoots or the distribution of leaf angles is still a key challenge, even when using combined ALS and TLS approaches. Both have a particularly strong influence on the model output and therefore are critical for RT modeling of forests. Future model improvements might include a scaling approach. This would imply that voxels with high canopy clumping but little filling are modeled using a shoot scaling approach, since the turbid medium assumption might be violated (e.g., Rautiainen et al., 2012).

We conclude that our proposed method provides an advanced representation of the 3D radiative regime within a temperate mixed forest. This reconstruction is well capable of simulating most spectral and spatial features of imaging spectrometer data. The results indicate the potential to simulate future Earth observation missions, such as ESAs optical Sentinels (Malenovský et al., 2012). Limitations were discussed in detail and have to be considered for future research. Beyond this, our approach offers a wider range of possibilities for further investigations, namely the simulation of virtually any range of band combinations, permutations of parameter combinations, to even testing the effect of changing object composition of the scene (e.g., needle thinning effects and pigment shifts). Simulating a multitude of parameter combinations would support local and global sensitivity analysis and help to define priorities when running DART in an inverse mode. For more specific testing of the impact of structural effects, the model can be applied to mono-species stands, allowing to reduce uncertainties in the LOPs.

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